Enhancing Network Performance in Mixed Motorcycle Traffic: Leveraging Route Choice Behavior of Motorcyclists through Traffic Information Provision

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Abstract

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The dissertation addresses congestion mitigation and traffic performance enhancement in motorcycle-dependent mixed traffic environments by developing traffic control strategies that leverage insights into motorcycle riders' route choice behaviors. Motorcycles dominate the traffic landscape in many regions, especially in Southeast Asia, due to their smaller size and agility. These attributes allow motorcycles to navigate through traffic in ways that cars cannot, significantly affecting overall traffic flow. The research begins with a comprehensive literature review of the unique characteristics of motorcycles compared to other vehicles. Unlike four-wheeled vehicles, motorcycles maneuver with agility, exploiting smaller gaps, which impacts traffic dynamics, especially in regions where they constitute a large proportion of the vehicle population. In such environments, motorcycles account for a significant share of the traffic, which is typically driven by their economic benefits, operational flexibility, and ability to navigate congested urban areas more efficiently than larger vehicles. However, such dominance also brings challenges such as increased congestion concerns, necessitating tailored traffic management strategies. The research underscores the importance of developing tailored traffic control measures that address the specific behaviors and needs of motorcycle riders.

Despite the critical role of motorcycle route choices, research in this area remains scarce, with existing studies predominantly focusing on passenger cars. One sub-objective of the present dissertation aims to understand the decision-making processes underlying riders' route selection and their subsequent impact on traffic systems. This analysis involves investigating external stimuli, including the provision of real-time traffic information systems, which are seldom available in countries heavily reliant on motorcycles. A novel approach is introduced by dynamically incorporating real-time traffic reports into traffic management, focusing on the strategic use of Variable Message Signs (VMS) in non-highway contexts—an area typically overlooked. The methodology involves multiple phases, beginning with the modeling and analysis of the route choice behavior of motorcycle riders. These phases consider road topology, travel attributes, and the availability of VMS. Significant findings from this phase discover the impactful role of traffic information on motorcycle route selection, with 35.6% of study participants altering their routes in response to VMS recommendations, indicating the strong influence of traffic information on motorcycle route selection. Expanding information coverage from toll roads to urban roads encourages more informed decision-making and equitable traffic distribution. The route choice modeling and analysis also integrate individual socioeconomic and motorcycle riding characteristics into the model, highlighting the heterogeneity among motorcycle riders. Factors such as gender, age, occupation, purpose of travel, and driving frequency were discovered to significantly affect their routing decisions. Riders using motorcycles for professional services like taxi and delivery prefer shortcuts to save time, while senior riders prioritize safety by avoiding narrow and high-disruption areas. This nuanced understanding of diverse rider preferences is essential for developing more effective and responsive traffic management systems that cater to the varied needs of motorcycle users. Overall, the

findings reveal how targeted measures for motorcycles can lead to more informed route choices, better travel performance, and broader traffic improvements.

To enrich the understanding of motorcycle route selection behavior, the current research also explores a link-based choice model, marking another key academic contribution. Such dynamic decision-making route choice behavior is then integrated into the microscopic simulation model using AIMSUN Next 23 software, which captures individual vehicle behaviors and interactions, accurately reflecting the mobility patterns of specific network regions. This integration allows for a nuanced analysis of how individual decisions impact broader traffic patterns, providing a deeper insight into the collective effects of individual route choices on overall traffic congestion and flow. The dissertation successfully presents a reliable micro-simulation model tailored for motorcycle-dependent areas by modifying various crucial aspects in this instance, including road network topology, traffic demand, and driver behavior, to align with empirical observation data. The iterative calibration and validation processes confirm the model's accuracy, effectively demonstrating its capacity to represent traffic dynamics in environments with significant non-lane-based two-wheeled vehicles. The simulation model also includes a pre-defined route choice function derived from the previously formulated link-based discrete choice model. Such adaptability was substantiated by a 27.59% improvement in the statistical accuracy measures during the model's validation, underscoring the importance of an accurate route choice function. The increase in the model's accuracy reveals that motorcycles dynamically adjust their routes in response to evolving traffic conditions rather than merely following the shortest path. This improvement revealed a more realistic representation of the decision-making process in route selection, further illustrating how traffic information profoundly influences travel decisions and enabling the traffic microscopic simulation model to describe this adaptable route choice behavior effectively.

The dissertation not only extends beyond theoretical exploration but also applies practically, demonstrating how route choice modeling and traffic simulations can significantly enhance traffic management strategies in typical traffic patterns found in this context. A macroscopic analysis then becomes imperative for understanding network performance. The Macroscopic Fundamental Diagram (MFD) serves as an effective tool not only for modeling the traffic performance of large-scale 'neighborhoods' but also for assessing traffic control measures by aggregating the behavior of traffic flow and density. Utilizing the MFD allows for a thorough assessment of the current traffic infrastructure and the identification of improvement areas to optimize traffic flow. This strategic application aids in pinpointing specific areas where interventions could yield the most benefit, thus facilitating targeted enhancements in traffic management. However, the standard MFD has not yet been fully adjusted to conditions in regions dominated by motorcycles. Adapting the MFD to these specific conditions is essential, particularly where conventional homogeneous traffic measurements fall short, such as the tendency of motorcycles to disregard lane markings. This adaptation integrates Motorcycle Equivalent Units (MEU) and area occupancy metrics, creating a framework for analyzing traffic dynamics in environments where motorcycles are predominant. The MFD concept allows for a macroscopic view of traffic performance, capturing the relationship between traffic density and flow at a network level. By integrating MEU and area occupancy metrics, the recalibrated MFD offers a more accurate representation of traffic dynamics in environments where motorcycles are predominant.

The data analysis within the study area revealed an extreme surge in traffic during the morning peak, leading to significant congestion and delays. Such tendencies in traffic distribution underscore the need for effective traffic control strategies tailored to manage the distinct behaviors of motorcycles. As the study focuses on dynamic control strategies, traffic information provision is proposed, assessing scenarios based on the scope of its coverage, availability, and accessibility of these reports. This approach aims to bridge the gap between current traffic management practices and the unique demands of motorcycle-heavy traffic, fostering a more responsive infrastructure. Subsequently, the microscopic simulation model evaluates existing conditions and the effectiveness of proposed scenarios, using the recalibrated MFD to identify the most effective traffic control measures. The outputs of the simulation run across various scenarios led to the findings that without specific traffic interventions, network capacity remains limited. However, targeted information, when made universally accessible and available, notably improves network performance, highlighting the necessity of comprehensive real-time traffic reports. While targeted information on major roads rapidly enhances traffic flow, broader dissemination takes longer but eventually leads to substantial systemic improvements. This gradation in response times underscores the importance of strategic placement of traffic advisories to optimize their effectiveness. Importantly, higher compliance rates notably enhance network performance, achieving peak efficiency at full compliance with maximized trip production and network utilization.

The effectiveness of traffic control measures heavily depends on drivers' adherence to provided traffic information. The analysis showed that as compliance rates increased from 0% to 100%, network capacity improved significantly, with an 84% increase in overall capacity. Partial compliance already yielded notable benefits, while full compliance led to optimal traffic distribution and utilization. The study also explored the distinct behaviors of motorcycles and their impact on traffic systems, with car compliance held constant at 30%. The findings revealed that at lower compliance levels, network capacity was higher when motorcycle compliance fluctuated. However, at higher compliance rates, greater capacities were observed when both motorcycles and cars had fluctuating compliance. This interaction highlights the delicate balance needed in traffic management systems to accommodate the varying compliance levels of different vehicle types. This suggests that managing motorcycle behavior can significantly improve network performance even without altering car compliance rates. Consistent improvements in compliance for both motorcycles and cars were shown to maximize traffic efficiency and capacity. To sum up, the strategic integration of advanced traffic systems, focusing on dynamic control and behavioral adjustments, can substantially enhance traffic management in motorcycle-dependent cities. However, it should be noted that accurate, timely traffic information and strong compliance rates play a crucial role in achieving efficient traffic management. Effective communication and engagement with all road users are vital to maintaining high compliance rates and ensuring the success of these traffic management strategies. These findings advocate for strategic education and the integration of advanced traffic systems, which are critical for maximizing network efficiency.

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Abbreviations

Term	Description
AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
ATIS	Advanced Traffic Information Systems
BIC	Bayesian Information Criterion
CBD	Central Business Districts
CDF	Cumulative Distribution Function
CNL	Cross Nested Logit
DCE	Discrete Choice Experiments
DTA	Dynamic Traffic Assignment
DUE	Dynamic User Equilibrium
ETC	Electronic Toll Collection
GMFD	Generalized Macroscopic Fundamental Diagram
GPS	Global Positioning System
IIA	Independence of Irrelevant Alternatives
i.i.d	Independent and Identically Distributed
KS	Kolmogorov-Smirnov
MAE	Mean Absolute Error
MEU	Motorcycle Equivalent Unit
MFD	Macroscopic Fundamental Diagram
MNL	Multinomial Logit Model
MXL	Mixed Logit Model
NL	Nested Logit
OD	Origin-Destination
OSM	Open Street Map
PCU	Passenger Car Unit
PSL	Path Size Logit Model
RL	Recursive Logit
RMSE	Root Mean Square Error
RP	Revealed Preference
RUM	Random Utility Maximization
SP	Stated Preference
SRC	Stochastic Route Choice
VMS	Variable Message Sign

Chapter 1

Introduction

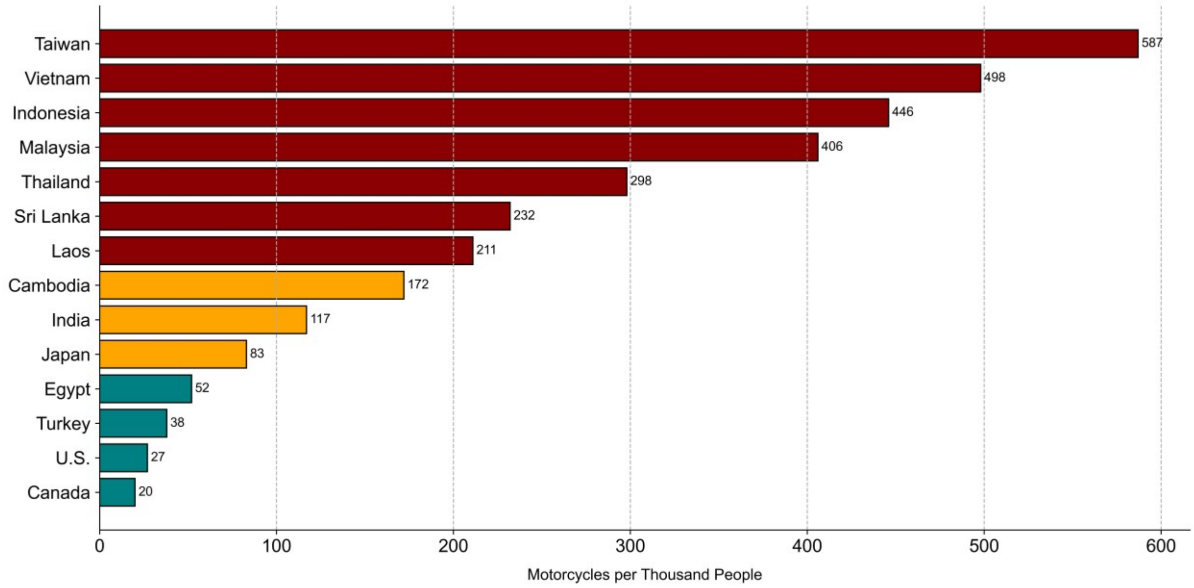
1.1 Background

Motorcycles (alternatively known as motorbikes, scooters, or mopeds) are defined as two-wheeled motorized vehicles steered through handlebars and possess unique properties compared to automobiles, particularly regarding flexibility, adaptability, and affordability. These advantages stem from their lightweight design and compact structure, allowing seamless navigation across various terrains and traffic. The small size further contributes to their maneuvering capabilities, enabling riders to filter through congested lanes and swerve between vehicles without adhering to lane markings, and navigate narrow streets that are often inaccessible to larger vehicles. This agility allows them to utilize small gaps between cars and obstacles, maximizing their utility and efficiency. The cost-effectiveness, including lower fuel consumption and maintenance costs, makes them an attractive option for many commuters, especially in regions with high traffic congestion and limited public transportation options. These characteristics collectively underscore the pivotal role motorcycles play in urban mobility.

In many parts of Asia, motorcycles are not merely a convenient mode of transport but a necessity, constituting about 79% of all motorized vehicles. (H. H. Nguyen, 2013). Approximately, Europe follows this trend at 9%, South America at 5%, the Middle East at 3%, and both North America and Africa at 3% and 2%, respectively (H. H. Nguyen, 2013), based on data compiled by the World Health Organization (WHO), as cited by Chiu and Guerra (2023). The widespread prevalence of motorcycles emphasizes the substantial role motorcycles serve in shaping transportation frameworks. This high proportion reflects not only vehicles' behavior but also the challenges encountered, where infrastructure often struggles to keep pace with travel demand. Countries like Indonesia, Taiwan, Vietnam, Malaysia, and Thailand are thus categorized as motorcycle-dependent nations, as illustrated in the motorcycle ownership charts in Figure 1-1. The popularity of motorcycles suggests that their prominence in these regions is likely to persist, although not without complications. In urban networks, where road space is limited and often overburdened, congestion becomes an inevitable issue, necessitating demand regulation and congestion mitigation. The concept of mixed traffic—varied vehicles sharing the same space—further complicates this situation, resulting in inefficient traffic flow and frequent gridlock. To effectively manage these issues, it is crucial to understand the behavior of motorcycle riders, particularly in terms of route choice, which is fundamental to effective traffic management (Oguchi et al., 2003). Therefore, this dissertation conducts a comprehensive analysis of motorcycle route choice behavior in the context of motorcycle-dependent cities, an area not extensively covered in the existing literature.

Nevertheless, it is believed that these travel decisions are influenced not only by the attributes of each route option but also by some external stimuli, including the availability and presentation of traffic information. The dissemination of such information is crucial in assisting road users to make more efficient route choices (Toledo & Beinhaker, 2006). Among the various mediums for traffic broadcast, Variable Message Signs (VMSs) have emerged as a particularly effective means. The impact of traffic information on route selection is profound. It effectively manages travel demand by guiding drivers to choose less congested routes, thereby minimizing delays and reducing the potential for vehicle conflicts (Balakrishna et al., 2013). As an Advanced Traffic Information System (ATIS) component, VMS is well-suited for conveying updates on traffic conditions and alerts about incidents downstream or any occurrence that could create delays, thereby facilitating a more balanced distribution of traffic flow across the network (Peeta & Gedela, 2001). This technology contributes to congestion alleviation (Poulopoulou & Spyropoulou, 2019) by delivering essential travel information, including real-time traffic reports, recommended routes, and incident locations (Zhong et al., 2012), enhancing travel efficiency and aiding in informed route selection (Ma et al., 2014).

Figure 1-1 Motorcycle ownership in 2018 (adopted from Chiu and Guerra, 2023).



Despite the apparent advantages of traffic information systems described above, their deployment has predominantly been limited to toll roads and highways in developing countries, but in places like Ho Chi Minh City and Taipei, there have been attempts to implement such devices on a select few major roads that accommodate both motorcycles and automobiles. This restricted use of the VMSs could undermine the trust and confidence of road users, potentially diminishing their perceived reliability. Expanding the utilization of these devices beyond highways is expected to substantially improve traffic performance by making real-time reports accessible to more road users. Such efforts aim to regulate the influx of motorcycles into congested areas, ultimately managing the flow but also ensuring efficient travel mobility. Accordingly, this dissertation explores the applicability and implication of this control measure on traffic performance, drawing on findings from motorcycle riders' route choice analysis.

To accomplish these objectives, macroscopic analysis is key for understanding specific traffic patterns and developing tailored management strategies. In this regard, the Macroscopic Fundamental Diagram (MFD), initially proposed by Daganzo (2007), serves as an effective tool for modeling the traffic performance of large-scale 'neighborhoods' by aggregating traffic flow and density. Previous research has shown the practicality of the MFD in evaluating transportation network performance and in assessing traffic control measures (e.g., Keyvan-Ekbatani et al., 2013; Zheng et al., 2012). Unlike traditional models focusing on individual road segments, the MFD represents the relationship between the number of vehicles inside the network and the rate at which vehicles have successfully reached their destination, making it an essential tool for real-time traffic control. Thus, the establishment of a well-defined MFD for a network is fundamental to developing effective control strategies that alleviate congestion (Zheng et al., 2013). For road networks in regions reliant on two-wheeled, non-lane-based vehicles, effectively understanding and analyzing heterogeneous traffic patterns requires moving beyond conventional homogeneous traffic approaches, as traditional models necessitate substantial adaptations for mixed traffic conditions (M. & Verma, 2016). This underscores the need for customized approaches that address the unique characteristics of mixed traffic. Thus, in addition to the route choice behavior analysis of motorcycle riders, the present study also refines and applies the MFD to mixed motorcycle traffic in evaluating the whole system and proposing appropriate control measures.

1.2 Research Objectives and Scope

This dissertation centers on two questions arising from the issues discussed in the background: What factors drive motorcycle riders' preferences when selecting routes, and how do these preferences impact network traffic performance? The study aims to unpack these dynamics to better inform the development of traffic control strategies in this context. Accordingly, the aims and scope of the dissertation are elaborated upon, outlining the specific objectives and the extent of the research undertaken.

1.2.1 Objectives

The primary goal is to mitigate congestion in mixed traffic predominantly composed of motorcycles through the formulation and assessment of traffic control strategies based on the route choice behaviors of motorcycle riders. The objectives are broken down into several specific components as follows.

- **Estimation**. The initial direction is to develop route choice models for motorcycle riders by assessing the impact of road network topology and travel attributes, along with external stimuli—such as traffic information and management policies—on their route selection process.
- **Modeling**. The outputs derived from route choice analysis are employed as calibration parameters for driving behavior in the development of a microscopic simulation model. This model is then statistically validated against the actual network region. The study evaluates traffic performance under existing conditions while also simulating the installation of traffic control scenarios.
- **Evaluation**. Given the heterogeneous traffic composition, characterizing traffic flow in motorcycle-dependent regions requires substantial adaptations from conventional homogeneous measurements. This consideration also extends to the distinct nature of motorcycles, which frequently deviate from following lane markings. The study ultimately aims to establish MFDs for mixed motorcycle trafficto provide a more accurate tool for comprehensive traffic analysis.
- **Application**. The study shows the practicality of the proposed methods and models by applying them to real networks and datasets, showcasing the traffic control effectiveness in actual scenarios.

1.2.2 Scope

This dissertation is concentrated on exploring and enhancing mixed traffic flow in motorcycle-dependent regions, with a specific emphasis on urban environments in Southeast Asia. It encompasses the development and application route choice models, the modeling of microscopic traffic simulation, and the introduction of tailored traffic management strategies.

1.3 Research Contributions

The following significant contributions were expected in the fields of travel behavior, traffic flow analysis, and traffic management, particularly focusing on mixed motorcycle traffic. These academic and practical contributions not only address existing research gaps but also introduce novel concepts, methodologies, and strategies to enhance the understanding and management of traffic.

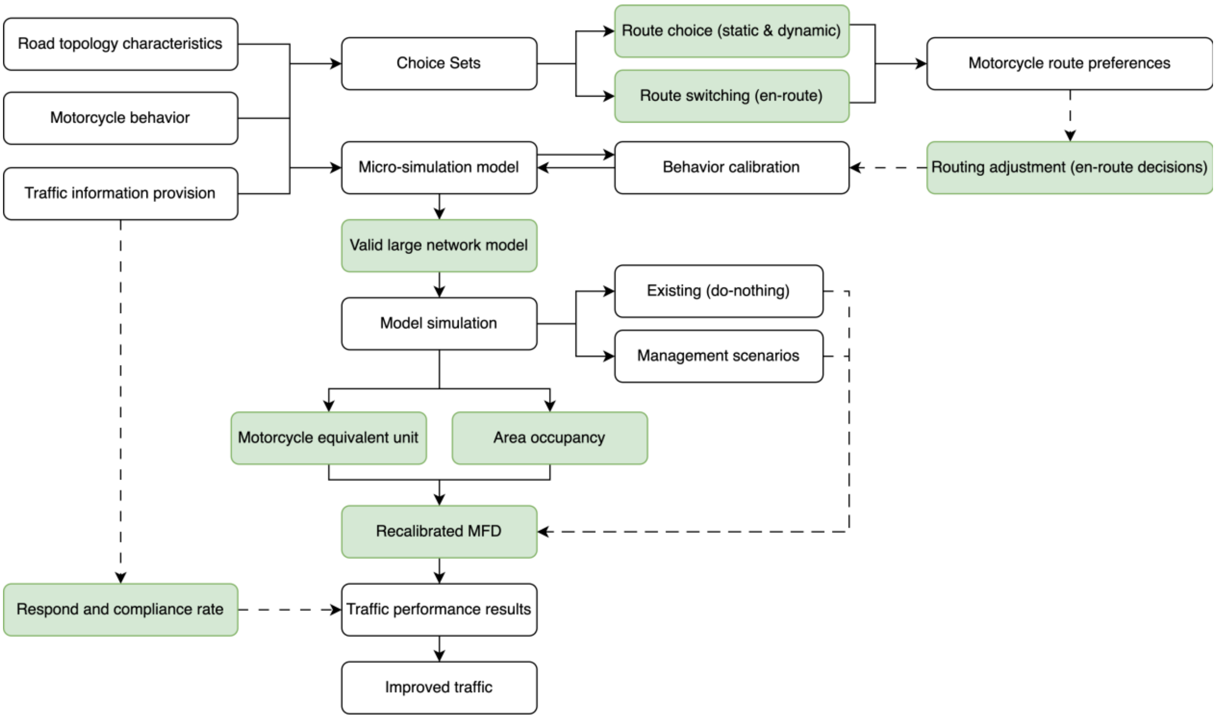
1. **Novel Analysis of Motorcycle Route Choice Behavior**. This dissertation pioneers in bridging the literature gap on motorcycle route choice analysis, which remains scarce compared to the extensive studies on cars. The findings provide new insights into motorcycle behavior, their necessity for and reaction to traffic information, and the subsequent implications on traffic.
2. **Microscopic Simulation for Large-Scale Mixed Traffic Networks**. A microscopic simulation model is presented, notable academically for its detailed representation of mixed traffic dynamics within large network infrastructures, acknowledging the complexity due to the high granularity of data and extensive parameter requirements. Practically, it offers refined calibration and validation techniques that enhance the reliability of traffic analysis in motorcycle-dependent regions.
3. **Integration of Route Choice Function and Traffic Simulation Model**. A notable aspect here is the successful integration of a discrete choice model-based route choice function within the microscopic simulation framework, which improves the theoretical comprehension and modeling of mixed traffic behavior and dynamics. The integration is fundamental for the precise portrayal of driver decision-making, significantly enhancing model validation. It ensures the simulation's accuracy in mirroring actual traffic patterns, which is crucial for reliable traffic analysis.
4. **Implementation of Traffic Management Strategies for Motorcycles**. A key component of this research is the introduction of real-time traffic information provision, designed as dynamic control strategies specifically tailored for motorcycle riders in cities with heavy motorcycle reliance. This study is among the first to empirically demonstrate the impacts of such strategies on overall traffic flow. The findings highlight that targeted measures for motorcycles can lead to more informed route choices, enhanced travel performance, and broader traffic improvements.
5. **Refined Traffic Flow Characteristic Measurement**. The research adjusts the measurement of traffic flow characteristics to better accommodate heterogeneous traffic environments dominated by motorcycles. By integrating the concepts of Motorcycle Equivalent Unit (MEU) and area occupancy, this study offers a more refined approach to analyzing traffic under these conditions.
6. **Application of Mixed Macroscopic Fundamental Diagram (MFD)**. Another significant contribution stems from the application of the redefined MFD in assessing mixed motorcycle traffic, addressing a notable gap in the literature for such environments. The study effectively demonstrates how the MFD can capture the complex dynamics of mixed traffic flows.

1.4 Research Framework

This section details the research framework and the specific challenges addressed throughout the dissertation, as summarized in the flowchart in Figure 1-2. The dissertation begins with an observation of the road topology and the intrinsic characteristics of motorcycles, both of which are pivotal in shaping traffic dynamics. It leverages previous findings on the benefits of real-time traffic updates in easing congestion and enhancing performance to explore traffic information systems in this setting. The study addresses unique road configurations and motorcycle rider behaviors in such settings, acknowledging the complexity and variability of mixed traffic conditions. It develops comprehensive route choice models for motorcycles—the predominant vehicle type—to delineate their decision-making processes in both static and dynamic scenarios. Additionally, it investigates route-switching behavior, capturing situations where riders decide to change their paths in response to evolving traffic conditions.

The understanding of motorcycle route preferences and routing adjustments (en-route decisions) is then integrated into the simulation model through the calibration of driving behaviors. This calibration and validation are meticulously refined through iterative feedback, ensuring the model closely mirrors real traffic patterns. The resulting valid and reliable model, which is still scarce in the context of large-scale networks in the literature due to its extensive parameter requirements and detailed modeling, facilitates the next analysis of mixed traffic. This dissertation analyzes traffic network performance, contrasting existing conditions with optimized traffic control scenarios to alleviate congestion in the study area. Key to this analysis is the modification of the standard MFD by integrating MEU and area occupancy metrics, providing refined measurements for mixed traffic environments with high non-lane-based vehicle mobility. The analysis concludes with a performance evaluation, comparing proposed strategies against current conditions. It emphasizes the significance of traffic information systems for motorcycles and underscores the critical importance of user response and compliance rates.

Figure 1-2 Overview of the research.



1.5 Dissertation Outline

The remainder of the dissertation is structured as follows:

- **Chapter 2**. This chapter comprehensively reviews existing literature to establish a theoretical framework, covering topics like route choice behavior, mixed traffic systems, traffic models, and the concept of MFD. It also identifies research gaps and outlines the overall research structure.
- **Chapter 3**. This chapter details the modeling and analysis of the route choice of motorcycle riders. It includes discussions on data collection, analytical approaches, model estimation techniques, and the results obtained. The chapter concludes with a discussion of the implications of these findings.
- **Chapter 4**. This chapter explains traffic microscopic simulation modeling thoroughly. It covers the methodology, data preparation, and experiment settings, including model calibration and validation.
- **Chapter 5**. This chapter focuses on the evaluation and management strategies for mixed motorcycle traffic. It includes the methodology, adaptations for analyzing such environments, network performance evaluation, and discussions on traffic control strategies and policy development.
- **Chapter 6**. This final chapter provides concluding remarks, highlights research novelty, discusses contributions, acknowledges study limitations, as well as outlines future research implications.

Chapter 2

Literature Review

2.1 Introduction

Amid rapid urbanization and escalating congestion, mixed traffic conditions have become widespread, especially in Southeast Asia, where motorcycles play a significant role. Motorcycles are not just agile transport modes but integral to local mobility. Shiomi et al. (2012) identified two key characteristics of such traffic landscapes: the fluid movement of vehicles, particularly motorcycles, unconstrained by lane markings, and the distinct interactions between cars and motorcycles due to their differing properties. As detailed by Lee (2007), these differences include factors like field of view, size, weight, maneuvering capabilities, turning radii, and acceleration/deceleration features, summarized in Table 2-1.

Table 2-1 Summary of the distinctive attributes of motorcycles and passenger cars (Lee, 2007).

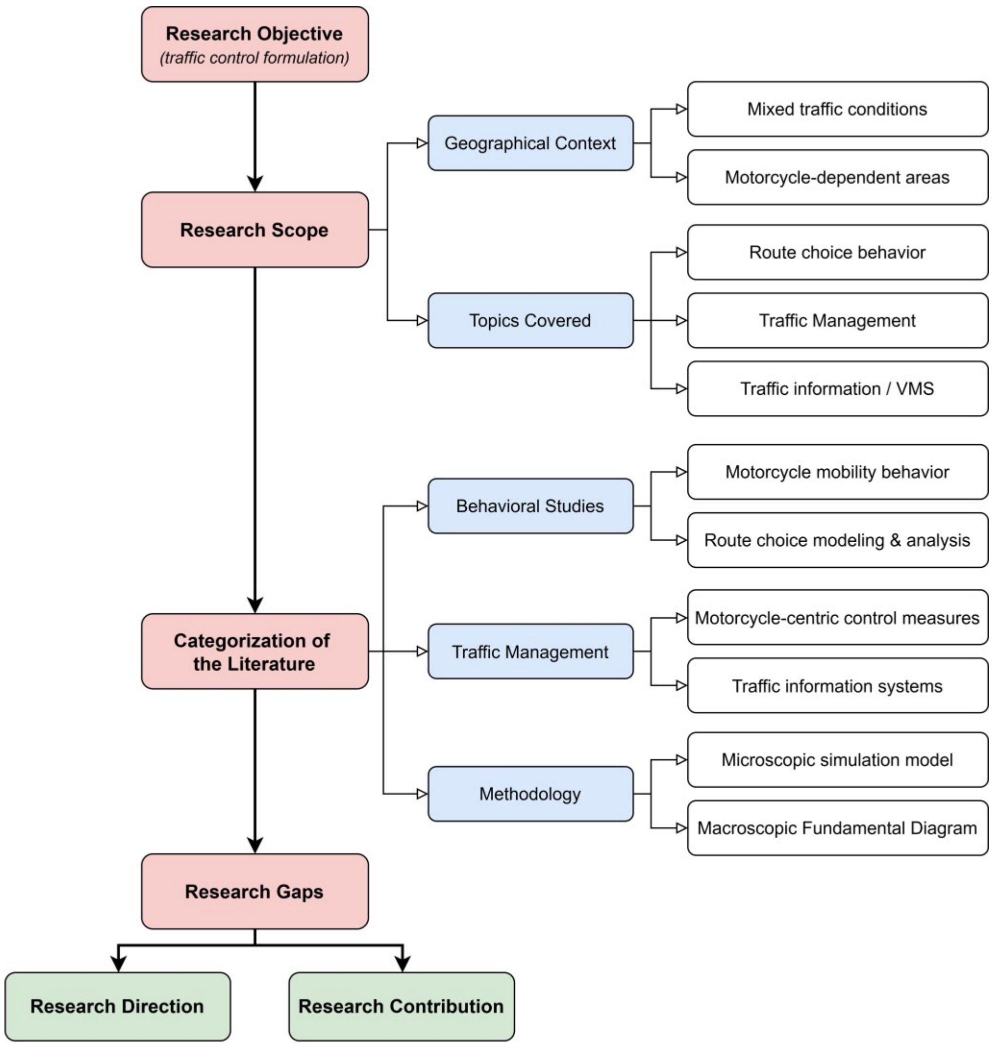
Indicators	Motorcycles	Passenger Cars
Field of view	Wider	Restricted by windshield, doors, and cabin
Size	Compact (0.75m width × 1.60m length)	Larger (1.60m width × 4.30m length)
Maneuvering	Handlebar and rider's body	Steering wheel
Turning radii	Smaller	Larger
Acceleration	Quick at green traffic lights	Slower at low speeds, faster > 40 km/h
Reaction time	0.52s typical	0.70–0.80s alert, 1.25–1.5s unexpected
Headway	Motorcycles had 0.6 to 0.9 times shorter headways on highways	
Spacing	Extremely narrow gaps are acceptable for motorcycle riders	
Speed	Motorcycles are faster at the green light start and on narrow roads	

Motorcycle-dependent cities, as the name implies, lean heavily on motorcycles as a primary mode of transportation. Minh et al. (2007) characterizes it as those with lower income, high-density land use, and a high share of motorcycles. As also identified by Khuat (2006), three indicators should be considered to specify a this condition: vehicle ownership rates, the availability of alternative transport options, and the prevalence of motorcycle usage. Yet, the presence of a significant number of motorcycles brings forth a set of challenges that need to be addressed. Integrating motorcycles and cars on roads often leads to unique interactions and requires specialized traffic management techniques.

Typically, motorcycle riders exhibit an active driving style, seizing opportunities to move forward (Martin et al., 2001) while appearing in movement patterns that differ from those of cars. Lee (2007) identified several distinct natures that define motorcycle mobility characteristics, including oblique following (where riders follow vehicles at an angle); filtering through slow or stationary traffic; swerving, which is the act of making sudden, sharp turns; moving to the front of a queue, often seen at traffic signals; and lane sharing, where they travel alongside another vehicle within the same lane. Trinh et al. (2021), through a case study ofHo Chi Minh City, Vietnam, highlighted the adaptability of motorcycles, noting their continuous speed and direction adjustments, limited maneuverability at higher speeds, and a shorter critical gap of around 1.25 seconds compared to lane-based vehicles.

Figure 2-1 illustrates the strategic framework of the literature review process employed in this dissertation, organizing the systematic approach taken in reviewing the literature.

Figure 2-1 Strategic framework of the literature review process.



To conclude, Chapter 2 offers an extensive overview of various aspects related to mixed traffic patterns in motorcycle-dependent regions. It begins by exploring literature on route choice behaviors, including their scope, modeling approaches, and findings, while also examining how traffic information dissemination can influence rider decisions. The chapter further reviews the dynamics and modeling of mixed traffic, with a focus on micro-simulation. It assesses varying network scales and coverage to understand the implications of different modeling strategies. A particular focus is given to the MFD method as an instrumental tool for traffic assessment, with a review of its application in various case studies. Additionally, the chapter discusses global and motorcycle-specific traffic management, as well as novel proposed strategies, defining the current state of traffic control. It identifies research gaps, presents research motivation, and outlines the general study's framework, offering a solid foundation for understanding the complexities of motorcycle traffic within broader transportation systems.

2.2 Route Choice Behavior

Route choice constitutes a daily decision undertaken by travelers to select a specific route according to various attributes associated with the available alternatives (Bapat et al., 2017). Previous studies have emphasized that a wide range of variables impact the route choice decision (Prato, 2009). Bovy and Stern (1990) classified the factors influencing this behavior into four major categories as follows.

- Route attributes (e.g., road characteristics, traffic conditions, and environmental concerns)
- Personal characteristics of the driver
- Trip characteristics (e.g., trip purpose, mode of transportation, and forth)
- Other circumstances (e.g., weather conditions, time of day, and traffic information)

Modeling route choice behavior is beneficial for numerous reasons, as Prato (2009) mainly asserted in a review of route choice problems. First, it permits the assessment of drivers' perceptions and preferences regarding route features. Second, it enables the prediction of behavior under different hypothetical and future scenarios (Frejinger, 2008; Prato, 2009). Finally, it helps to identify how drivers respond and comply with traffic information (Prato, 2009), as well as determine the impact of policies (Hartman, 2012). Route choice models also serve multiple transport applications, including planning and demand forecasting (Prato, 2009), particularly for mapping traffic flow patterns on road networks (Oyama, 2017), as well as evaluating travelers' perceptions of different route attributes and their relevance to sociodemographic characteristics (Frejinger, 2008). Additionally, the model plays a pivotal role in understanding and predicting travel choices within transportation networks (Oyama, 2017).

Despite its significance, the literature on motorcycle route choice behavior remains limited compared to that of cars (e.g., Dia & Panwai, 2006; Diop et al., 2020; Mai et al., 2015), bicycles (e.g., Ghanayim & Bekhor, 2018; Menghini et al., 2010; Zimmermann et al., 2017), or trucks (e.g., Schreiner et al., 2007; Tahlyan et al., 2017). To the authors' knowledge, only two studies exist. First, Schreiner et al. (2007) studied 167 sampled motorcycle riders in Ho Chi Minh City, and using the maximum route overlapping method by Hyodo et al. (2000), found that only speed limit was a significant factor, while pavement type and value of time had no effect. Nonetheless, this study primarily focused on trucks, applying the same method and model to motorcycle cases as a secondary analysis. Second, Turner (2009) identified the cognitive aspect of routing decisions of motorcycle delivery couriers in London, who should be familiar with the network and capable of traveling freely without GPS navigation. The study assessed the angularity effect on 2425 individual trips made by 50 samples, revealing a preference for routes with the shortest angular path over those with the minimum block distance. This suggests that turns significantly impact the cognitive distance and route choices of motorcycle riders.

2.2.1 Route Choice Models

Two distinct methodologies can be adopted in modeling and analyzing route choice: static and dynamic discrete choice models. These two approaches will be further explained in the following sub-sections.

2.2.1.1 Static Discrete Choice Models

Regarding methodological applicability, route choice behavior has been studied using various approaches. Given that individuals decide on route choice instinctively (Bovy & Stern, 1990), the discrete choice model, based on the random utility maximization framework, is a good fit. This model enables the estimation of parameters that characterize drivers' routing decisions, including the binary logit (e.g., Dia & Panwai, 2006; Vacca et al., 2019), multinomial logit (e.g., Ghanayim & Bekhor, 2018; Ton et al., 2017), ordered logit (e.g., Mannering et al., 1994), probit model (e.g., Ben-Akiva et al., 2004; Choocharukul & Wikijpaisarn, 2013), ordered probit (e.g., Spyropoulou & Antoniou, 2015). The logit model implies that random error terms have a Gumbel distribution, whereas the probit model assumes that the error terms are in the normal distribution. Nevertheless, some earlier studies indicated that the underlying premise of the Multinomial Logit (MNL) model was irrelevant to route selection.

Based on the structure of the model, the extension of the standard logit can be divided into three groups (Prashker & Bekhor, 2004). The first group involves modifications to the specifications of the MNL model to improve the estimation accuracy. An essential aspect of this adjustment is including overlapping path correction terms into the utility, a crucial consideration in route choice scenarios. For instance, Ghanayim and Bekhor (2018) utilized a combination of GPS and household survey data to apply both C-logit and Path-Size Logit (PSL) to model the route preference of cyclists in Tel Aviv, Israel. Similarly, prior research has also employed the C-logit model (e.g., Ben-Akiva et al., 2004; Frejinger & Bierlaire, 2007) and PSL model (e.g., Menghini et al., 2010) to investigate the route choice behavior of cars or bicycles. In another study, Frejinger and Bierlaire (2007) utilized GPS-based data from nearly 200 vehicles in the Swedish city of Borlänge to capture correlation structures within subnetworks in route choice models. Recent research by Łukawska et al. (2023) further advanced this approach with a joint PSL model, addressing the overestimation of overlapping path probabilities to more accurately capture the route preferences of cyclists in Copenhagen. Second, further relaxing the irrelevant assumption underlying the MNL model, nested logit (Abdel-Aty, 1998) is a simple approach that demonstrates significant deviations from the Independence of Irrelevant Alternatives (IIA) property while keeping most of the computational simplicity of the MNL model (Börsch-Supan, 1987). Finally, the Mixed Logit (MXL), an advanced and flexible discrete choice model that can approximate a wide variety of random utility models, is yet another enhancement of the standard logit. As Bekhor et al. (2002) revealed that the MXL produced a better overall fit than the MNL and PSL models, this model structure has become popular in predicting route choice behavior (e.g., Bekhor et al., 2002; Ben-Akiva et al., 2004; McFadden & Train, 2000; Vacca et al., 2019). Prato et al. (2014), using the GPS data in the Greater Copenhagen region, presented a novel approach by introducing a mixed-PSL model to assess the values of congestion and reliability based on observed route choice behaviors of car drivers. The results demonstrated that both the value of time and congestion were significantly higher during peak periods, possibly due to higher penalties for being late and intensified time constraints. The study also uncovered variations in drivers' responses to congestion and uncertainty across peak and off-peak times.

2.2.1.2 Dynamic Discrete Choice Models

The static model, an extension of the cross-sectional specification, has been extensively applied to describe route choice behavior but has notable limitations: it fails to capture serial correlation and dynamic decisions of road users. While incorporating unobserved factors through panel effects can address the issue of serial correlation by relaxing the assumption of independence across time, the static model still overlooks en-route decisions, assuming travelers make route choices only at the trip's origin (referred to as a pre-trip route choice) while disregarding the possibility of en-route decisions that could lead to route diversion (Li et al., 2014). This gap highlights the need for a dynamic route choice model, where decisions made in one period influence those in the next. Thus, the utility of an alternative at a given time t is only affected by the decision made at the time $t-1$. Instead of explaining the behavior of selecting a pre-trip choice, dynamic choice models encompass the decision-making process for an en-route preference and update the driver's perception of route attributes (Oyama & Hato, 2017).

In this framework, the Recursive Logit (RL) model by Fosgerau et al. (2013) formulates route choices as a sequence of link selections based on a deterministic Markov decision process with an Independent and Identically Distributed (i.i.d.) Gumbel distribution. This approach eliminates the need for route enumeration and simplifies the generation of choice sets, which can be nearly infinite, thus addressing two key challenges in path-based route choice models: defining choice sets and modeling correlated utilities (De Moraes Ramos et al., 2020). Since decision-makers select the outgoing link that maximizes the utility at each node rather than a single route (Kaneko et al., 2018), this model structure corresponds to a static model with an unrestricted choice set. In summary, the RL model is well-suited for identifying the response of motorcycle riders towards traffic information as an en-route routing decision, dynamically reflecting their sequential and forward-looking decision-making processes by integrating the value function into the utility function of each link (Oyama & Hato, 2017). This capability effectively addresses the aforementioned second constraint associated with static models.

The efficient computation and consistent estimates of the RL model with unrestricted choice sets (Fosgerau et al., 2013) have led to a vast array of extensions and applications. These include the nested recursive logit model (Mai et al., 2015), the incorporation of a discount factor of expected downstream utility (Oyama & Hato, 2017), the inclusion of non-link additive attributes in investigating bike route choice behavior (Zimmermann et al., 2017), and a multimodal route choice model (de Freitas, 2018). Moreover, a prism-based approach has been explored to capture positive utility and address violations of feasible conditions for the value function (Oyama, 2023). In 2017, Zimmermann et al. analyzed a link-based route choice model for bicycles using GPS data in Eugene, Oregon. As the data contained over 40,000 network links, an RL model was adopted to eliminate the need to generate choice sets of paths. However, the equivalent structure of the RL and MNL models causes IIA property issues, leading to the employment of two specifications: one with nesting and one without, following the NRL model—an extension of the RL introduced by Mai et al. (2015). Despite the requirement of exclusively involving additive link attributes in the RL model (Fosgerau et al., 2013), the research innovatively incorporated non-link additive attributes, such as slope, by interacting them with link length in the utility function. The outcomes disclosed that factors such as distance, traffic volume, slope, crossings, and the presence of bicycle facilities significantly affect the route choices made by cyclists.

Using vehicle trajectory data from the ETC 2.0 dataset of the Tokyo Metropolitan Area, Kaneko et al. (2018) developed an RL model that accounted for drivers' awareness of the following link, aiming to increase the stability of the model estimations. The model was divided into four groups determined by trip length across nine different road types ranging from highways to minor roads. Road attributes, like distance, width, travel time, cost, and two dummy variables indicating U-turns and right-turn angles, were assessed to identify car drivers' route preferences. The study found that link awareness could be omitted for relatively short trips where drivers are familiar with the roads. In a separate study, de Freitas (2018) applied an RL model to a multimodal network in Zurich, using Swiss mobility micro-census data. This pioneering application marked the first use of an RL model for multimodal analysis, offering a more realistic evaluation by considering various transportation modes and the trade-offs between them.

Van Oijen et al. (2020) utilized data from spatially fixed proximity sensors in Assen, Netherlands, to develop a methodology for estimating RL model parameters, specifically analyzing pedestrian route choices during the TT Assen music festival. It was revealed that the recursive method falls short in estimating model parameters or predicting link flows in scenarios where networks are heavily equipped with sensors, highlighting the importance of strategic sensor placement for accurate travel predictions. Knies et al. (2022) further refined the RL model's structure by incorporating choice aversion into user behavior using GPS data from Borlänge, Sweden, following a similar approach as Fosgerau et al. (2013) and Mai et al. (2015). This was accomplished by adding a penalty term that reflects the choice set at each network node, allowing the model to relax IIA assumptions of standard logit that are irrelevant in route choice cases when pathways overlap, such as the link-size correction term.

In summary, the existing literature has primarily examined link-based route choices within three transportation modes: cars, trucks, and bicycles. This emphasis has left a notable gap that the present study intends to fill. Despite the routing decision characterization estimated by the static model, research into motorcycle route preferences remains limited compared to the extensive studies on automobiles.

2.2.2 Route Choice in a Traffic Information Environment

The route choice analysis in response to traffic information provision has traditionally incorporated the economic theory of random utility maximization (M. Ben-Akiva & Lerman, 2018). Some previous studies have appraised route choice behavior in the presence of traffic information circumstances. Ma et al. (2014) performed a stated preference survey in Beijing to identify factors contributing to drivers' compliance with VMS-displayed information. An MNL model was explored, and the finding was that individual characteristics, such as gender, drivers' experiences, vehicle types, driving personality, travel frequency, and familiarity, contribute to the drivers' propensity for route deviation. It was also found that most drivers prefer a graphical VMS compared to its counterpart. Moreover, the study suggested the necessity of including more detailed information on current devices, such as travel time and delays. Zhao et al. (2020) gathered 3462 behavioral answers from local private and taxi drivers via a stated preference experiment. The model estimate was done using random-parameter logistic regression models to observe the effects of different VMS designs on the drivers' route preferences. It was found that VMS traffic accident information was more influential than either congestion or road construction. However, the individual characteristics accounted for were confined to the demographic data and did not include more predictably impactful variables, such as yearly driving distance and driver personality.

Moghaddam et al. (2019) combined a questionnaire survey with a driving simulator experiment involving various traffic and driving conditions, information provision, and reliability level scenarios. This study evaluated route choice behavior concerning perceptions and their response to travel time information. Based on the estimates of binary and multinomial logit, as well as multinomial probit models, it was disclosed that trip purpose, travel time reliability, and income are the most influencing variables on drivers' route preferences and their compliance with traffic information. However, this study did not account for the correction of overlapping links. Furthermore, using the case of southwest Brisbane, Australia, Dia and Panwai (2006) conducted a comparative study of two different estimation approaches. It was revealed that the performance of Artificial Neural Network models outperforms the binary logit model in describing drivers' route choice and compliance with traffic information. Different styles of traffic information, including qualitative and quantitative delay information, were evaluated under real-time conditions of predicted delay and prescriptive best alternate routes.

2.3 Route Switching Behavior

As individual characteristics and perceptions contribute significantly to routing decisions (Frejinger, 2008), different vehicles may opt for various routes between the same Origin-Destination (O-D) based on their perceived utility, which is a combination of observable and unobservable factors (Vacca et al., 2019; Vacca & Meloni, 2015). In addition, even after selecting a pre-trip route, real-time conditions or individual urgencies may prompt travelers to switch from their original path, known as en-route choices, indicating the contrast between the current and expected best routes (Chen & Mahmassani, 2009).

Numerous earlier studies have analyzed the propensity of road users to deviate from their pre-trip route choice (e.g., Long et al., 2021; Vacca et al., 2019; Zhao et al., 2020). Khattak et al. (1993a) conducted seminal work on this topic, identifying en-route route switching as a response to incident-induced congestion, using survey data from Chicago car commuters. It was found that the likelihood of altering routes increased when delays were communicated through real-time radio traffic reports rather than direct observation. Additionally, factors such as socioeconomic status, travel time, delay length, perceptions of congestion, and knowledge of the area significantly influenced route-switching decisions. However, when alternative routes were unfamiliar or perceived as risky, drivers were less likely to switch. Khattak et al. (1993b) then analyzed the decision of drivers in downtown Chicago to divert to alternate routes and return to the regular route afterward in reaction to the incident report. The estimation of the NL and the (joint) MNL models demonstrated that the probability of switching increased with information about greater delays and longer travel times on the regular route, affected by personal experiences. Moreover, drivers with longer trips were more inclined to revert to their usual route.

Using a stated preference experiment, Khattak et al. (1994) further emphasized the analysis in the San Francisco Bay area, California. It was found that commuters tend to switch routes if the travel information presented is more comprehensive, especially when equipped with quantitative real-time information on their regular route, in addition to travel time information about the alternative route. Together with their knowledge and familiarity with other routes available, commuters' choices to switch routes also depend on their personal characteristics and the weather conditions. Abdel-Aty (1998), moreover, recognized drivers' decisions toward traffic incident information transmitted by the ATIS in real-time. The behavioral responses were acquired through a telephone survey of 564 morning commuters in Los Angeles by offering respondents three travel choices: staying on their current route, switching to a new route, or switching to a path around the affected area. A nested logit model was estimated, and it ultimately proved the superiority of this multivariate extreme value model over the classic logit, as it accounted for unobserved attributes shared across alternatives.

Jou et al. (2005) examined the node-to-node propensity to switch routes on Taiwan's freeway by giving distinct patterns of real-time traffic information, including qualitative, quantitative, qualitative guidance, and quantitative guidance. Multinomial Probit models based on the bounded rationality principle were estimated, with travel time and cost as explanatory variables. The outputs showed that real-time traffic information with route guidance is preferred. Regarding socioeconomic characteristics, male drivers and those with a higher income have a stronger tendency to switch routes, whereas senior drivers are less likely to do so. It was also confirmed that providing real-time traffic information can effectively reduce congestion, allowing drivers to make more informed choices. Similarly, as further elaborated by the recent study, Long et al. (2021) provided diverse information patterns for commuters to capture their route-switching preferences, i.e., historical descriptive information, real-time descriptive information, historical travel time information, and real-time travel time information. The switching threshold was evaluated using bounded rationality theory and calibrated by estimating a probit regression model. As a result, the dissimilarity of switching thresholds in various information displays was proven, showing a lower edge for real-time information than historical information.

Kattan et al. (2010) evaluated the drivers' responses and the variables affecting their compliance with VMS incident information. In a survey of 500 commuters in Calgary, Canada, approximately 63.3% stated that the VMS message prompted them to adjust their trip choices. An estimation of a latent discrete choice model discovered that driver experience, network familiarity, travel time, distance, travel purpose, and complementary information sources significantly impact route-switching behavior. Yan and Wu (2014) used a driving simulator experiment to assess the impact of drivers' characteristics and VMS attributes (i.e., location and presentation format) on their routing decisions, speed control, and lane changing. It was discovered that the age, gender, and profession of drivers all had a crucial role in shaping these behaviors. Moreover, the estimation outcomes indicated that drivers preferred the graphical VMS over the text-only style. Vacca and Meloni (2015) estimated a route-switching model with a mixed logit specification employing GPS-based data of trips in Cagliari, Italy, to identify the major factors, whether road properties or individual characteristics, that drive variations in route selection for identical O-D pair. The research determined that gender, age, income, driving age, perception of time, the number of traffic lights per kilometer, and the percentage of highways affect drivers' decisions to switch routes. Further extended by Vacca et al. (2019), a comparison of two distinct model structures, binary logit, and mixed binary logit models, was elaborated to ensure the best-fit model without accounting for the existence of external stimuli. The inclusion of habit and learning effect variables captured the unobserved attributes, which turned out to have a great influence on the route-switching tendency. The travel habits of drivers led to less desire to change routes, while the learning effect was generated because of the accumulation of prior experiences. Moreover, traffic delay and distance were shown to have negative coefficients, confirming drivers' disutility toward longer routes.

In summary, Table 2-2 lists existing research that discusses route-switching behavior. Among contrast to the studies mentioned above that explore route switching of travelers, none have specifically examined this sort of behavior within the context of motorcycles, revealing a notable gap in the literature. This gap could potentially be attributed to the fact that VMS is typically placed merely on freeways in motorcycle-dependent cities, restricting riders from accessing this information.

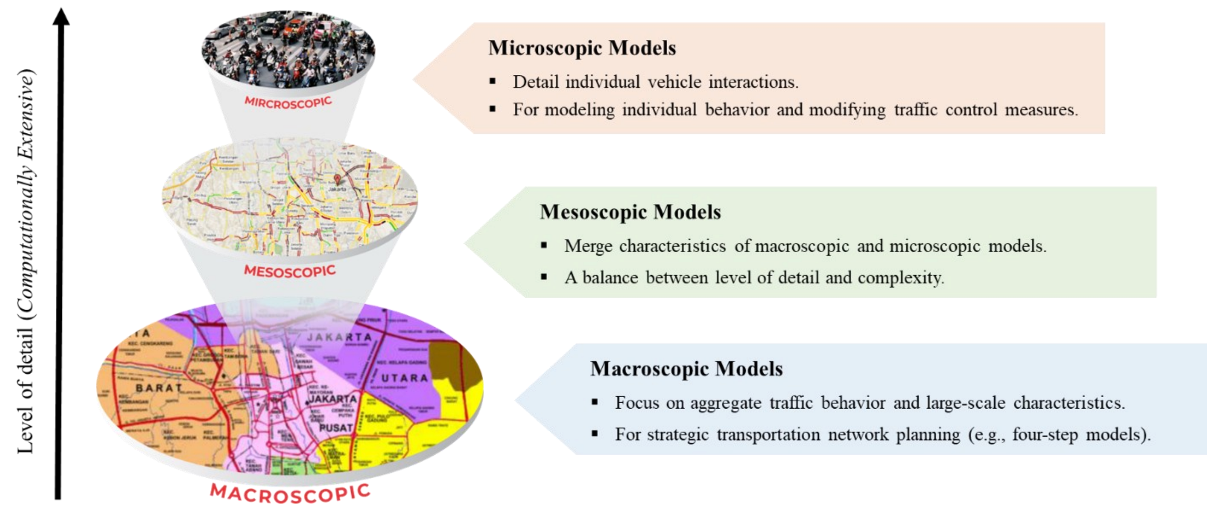
Table 2-2 Recent existing studies on route switching model.

Authors	Case Study	Objective	Data	Method	Findings
Long et al. (2021)	Xi'an, China.	Evaluating the threshold at which drivers decide to switch routes in response to various patterns of traffic information.	Experiment	Bounded rationality, Probit regression	The switching threshold is lower for real-time information than for historical information. Due to the information's unreliability, drivers often underestimate the informed travel time.
Diop et al. (2020)	Dalian City, China	Analyzing how driver acceptance of VMS affects route-switching behavior.	SP	A combination of the Technology Acceptance Model and the Hybrid Choice Model	The content of a VMS should be as complete as possible to aid drivers in making better travel decisions. Socioeconomic variables, including age, gender, income, driving experience, and route selection style, affect perceptions of VMS.
Long et al. (2020)	Xi'an, China	Investigating the route-switching behavior based on group classification.	SP and RP	Latent class model (LCM) and ordinal logistic model	Route-switching behavior is affected by various factors, including drivers' ages, experience levels, personalities, and travel frequency.
Zhao et al. (2020)	China	Assessing VMS impact on route choices among five driver groups with similar demographics, experience, education, employment, and income.	SP	Logistic regression models (fixed and random parameters)	The impact of accident information on VMS was more significant than congestion or roadwork. When an alternative route was given, less-experienced male drivers with free employment and less-experienced female drivers with at least a bachelor's degree were favored to switch routes.
Vacca and Meloni (2015)	Cagliari, Italy	Determining key factors affecting route choice for a consistent O-D pair.	GPS	Mixed logit model	A driver's propensity to switch routes depends on several variables, including gender, age, income, driving age, perception of time, traffic lights per kilometer, and the proportion of freeways.
Ma et al. (2014)	Beijing, China	Identifying variables that contribute to VMS compliance.	SP	Multinomial logit model	Driver characteristics, i.e., gender, driving experience, vehicle type, personality, frequency of travel, and familiarity, influence route switching.
Tiratanapakhom et al. (2014)	Tokyo expressway, Japan	Evaluating route selection and switching in response to traffic information.	ETC	Mixed multinomial logit model	Different degrees of congestion information generate varying responses from drivers.

2.4 Mixed Traffic and Modeling Review

The investigation of traffic flow is stratified into three primary levels of analysis: macroscopic, mesoscopic, and microscopic, each with distinct focuses and methodologies. Figure 2-2 visually summarizes these differences, illustrating the specific scope and application of each model type.

Figure 2-2 Hierarchical framework of analysis: macro-, meso-, and micro- simulation models.



Macroscopic models examine the aggregate behavior of traffic flow, focusing on large-scale aspects such as congestion, delay, and queue formation (Mohan & Ramadurai, 2013), which are ideal for strategic transport planning. These models represent traffic flow in terms of groups or platoons of vehicles, employing key variables like speed, density, and flow to establish an equilibrium relationship (Wierbos et al., 2021). Microscopic models, on the other hand, focus on individual vehicle interactions (Mohan & Ramadurai, 2013), which is imperative for understanding and predicting the behavior of each drivers and vehicles. Most traffic flow can be represented by microscopic models that track each vehicle individually (Thonhofer et al., 2018), making them a preferred method for offering precise assessments of network conditions, traffic controls, and policy impacts. Despite their detailed analysis capability, their application to network-wide studies is constrained by computational complexity and extensive parameter requirements, which pose challenges in model calibration (Thonhofer et al., 2018). To mitigate these challenges, commercial software like PTV VISSIM (e.g., Hu et al., 2020), AIMSUN (e.g., Tsubota et al., 2014), and Paramics (e.g., Oketch and Carrick, 2005), are commonly used for developing microscopic models. Meanwhile, mesoscopic models blend macroscopic and microscopic elements (Z. H. Khan & Gulliver, 2018), representing traffic as groups of vehicles or individual vehicles (Mohan & Ramadurai, 2013), striking a balance between detail and complexity, and are suited for scenarios requiring detailed traffic behavior analysis without the computational demands of microscopic models.

2.4.1 Mixed Traffic Characteristics

According to M. and Verma (2016), mixed traffic, often termed heterogeneous traffic, is a form of 'heterogeneous disordered' traffic that occurs when various types of vehicles with differing static and dynamic characteristics share the same road space, resulting in asynchronous movements. Factors such as the absence of lane discipline (Luo et al., 2014; M. & Verma, 2016), disparities in vehicle dimensions (Khan & Maini, 1999), the presence of motorized and non-motorized vehicles (Khan & Maini, 1999; Luo et al., 2014), as well as a mix of fast- and slow-moving vehicles (Khan & Maini, 1999), further characterize this traffic condition. Trinh et al. (2021) identified two primary factors behind the occurrence of mixed traffic: the performance rule and the emergence of small vehicles. The integration of such diverse vehicles creates a complex environment for traffic management and analysis. Figure 2-3 illustrates the contrasting actual circumstances between homogeneous and heterogeneous traffic.

Figure 2-3 Types of traffic patterns: (a) homogeneous traffic, and (b) heterogeneous traffic.

(a)

(b)

The pioneered work by Khan and Maini (1999) investigated the complexities of modeling heterogeneous traffic flow in developing countries, where motorized and non-motorized vehicles share the same right-of-way. Acknowledging the limitations in existing traffic flow models predominantly suited for homogenous traffic, the study provided a review of several studies on mixed, non-lane-based traffic in India, Bangladesh, and Indonesia. It emphasized the necessity for specialized models to address the unique characteristics of heterogeneous traffic, such as diverse traffic composition, driver behavior, roadway geometry, and vehicular interactions. In addition, the paper explored various methodologies, including macroscopic flow relationships and simulation models, to better understand mixed traffic systems and stressed the importance of considering specific features like vehicle size, maneuverability, and lateral movements in traffic flow characterizations.

The essence of mixed traffic is rooted in the dynamic interactions among various types of vehicles, resulting in unique traffic flow patterns that markedly impact factors like speed, density, and the overall capacity of the roads. Motorcycles, in particular, exhibit distinct behaviors compared to automobiles. As lane restrictions do not bind them, they are adept at swerving and filtering between lanes, taking advantage of small gaps between vehicles and obstacles to optimize mobility. This agility allows motorcycles to travel flexibly in any direction, enabling them to traverse congested roads with greater efficiency. Kov and Yai (2010) evaluated this mixed traffic context, focusing on the impact of light vehicles. The study was conducted in downtown Phnom Penh, where motorcycles accounted for about 70% of all vehicles. In addition to assessing traffic performance, the perception of motorcycle riders regarding safety issues was also determined. The study's findings revealed that in this setting, the speed of light vehicles, along with road capacity, is decreasing. Additionally, with the rise in the proportion of light vehicles, motorcycle speeds saw a corresponding reduction. This decline was paralleled by restricting the freedom of motorcycle riders to select their lateral position within the traffic flow. Trinh et al. (2021) recently examined the microscopic traffic characteristics of a roundabout in Vietnam. The study discovered that motorcycles show continuous speed and direction alterations during their travel within the roundabout, which highlights their ability to adapt to changing traffic conditions. However, it was observed that their speed limits the maneuverability behavior. Furthermore, the analysis showed that motorcycles maintain a clear space around them while navigating the roundabout.

2.4.2 Review of Mixed Traffic Modeling Approaches

The study of mixed traffic flow modeling has been extensively explored through numerous research efforts. One must recall that Edie (1963) established a generalized framework for defining traffic flow characteristics independent of the measurement approach, capturing vehicle movements within a specific time-space continuum where vehicle trajectories are observed (Suvin & Mallikarjuna, 2018). This method permits the assessment of flow and density by aggregating spatial and temporal data, a technique that remains relevant across diverse traffic analyses. Edie (1963) emphasized the importance of considering the lateral dimension to account for vehicle heterogeneity and the lack of lane discipline. Building upon Edie's work, Suvin and Mallikarjuna (2018) extended the generalized definitions by introducing the time period as an additional space dimension. This modification allows for a more thorough description of mixed traffic, further enhancing the applicability of the traffic flow analysis.

Lee (2007) employed an agent-based simulation model to examine motorcycle behavior in mixed traffic, mainly in networks where motorcycles constitute a significant proportion. This approach enabled a detailed representation of individual motorcycle agents within a traffic system. By compiling data from field observations and existing literature, the model accurately reflected real-world traffic scenarios. The methodology involved creating simulation scenarios that imitate typical urban traffic conditions, with a specific concentration on the distinctive characteristics of motorcycle movement, such as lane splitting and weaving. The model underwent thorough testing and calibration to ensure its validity, discovering the complexity and unique nature of motorcycle behavior in traffic related to acceleration, deceleration, and lane changing, which must be considered in traffic modeling.

Nguyen and Hanaoka (2011) used the social force model, typically applied to pedestrian dynamics, to describe mixed motorcycle traffic, exploring motorcycle interactions and the psychological behaviors influencing riders in congested situations. The model was validated using microscopic data from video footage at a Hanoi intersection, with parameters estimated through a non-linear regression method. The results demonstrated that this approach could effectively estimate the speed and direction choices of motorcycles, proving its utility in mixed traffic analysis. Furthered by Shiomi et al. (2012), a novel microscopic model to analyze traffic flow in environments where motorcycles are predominant was presented. This model employs a non-lane-based discrete choice approach that focuses on motorcycle and car interactions. The methodology is effective due to its capability to accurately depict the flexible movements of motorcycles, as well as its adeptness in capturing drivers' perceptions of their traffic situation. For validation purposes, the model was applied to vehicle trajectory data collected from an intersection in Hanoi. The study utilized Cross-Nested Logit (CNL) and Nested Logit (NL) models for estimating motorcycle and car behavior, respectively. The study confirmed the model's reliability and accuracy, highlighting that motorcycle riders are more alert to surrounding cars, while car drivers generally pay less attention to motorcycles, which is in line with Nguyen and Hanaoka (2011). This discrepancy in attention levels can potentially create hazardous situations for motorcycle riders.

Sarkar et al. (2020) established microscopic modeling framework specifically for heterogeneous traffic, where drivers disregard lane markings and perceive the entire road space. The research introduced a two-step hierarchical framework consisting of area selection and vehicle movement. The first step involved using the MNL model to select the area-based movement direction of the subject vehicle, with the choice space divided into realistic radial cones representing possible directions, and attributes defined by angular deviation, spacing, and relative speed. The second step applied a Modified Intelligent Driving Model to simulate the vehicle's next position along the selected direction from step one. Both steps were calibrated using real data, with the model parameters simulated stochastically through an empirical distribution. The combination of these steps defined the vehicle's trajectory, and the framework proved effective in simulating and managing mixed traffic flows in non-lane-based environments, as validated by comparing macroscopic properties between simulated and real datasets.

Furthermore, Chiou et al. (2015) presented a macro-micro model designed to simulate mixed traffic flow, specifically addressing the challenge of accurately modeling environments where both cars and motorcycles coexist. The model converts upstream macroscopic traffic flow into downstream microscopic flow, accounting for the lateral drifts and transverse crossings of motorcycles. The model's validity was tested using field data from a section of an intersection in Hanoi. Field data from a Hanoi intersection validated the model, showing promising performance despite higher error rates for simulated motorcycle flows on inner lanes, where motorcycles are prohibited. In a recent study, Wierbos et al. (2021) tackled mixed bicycle-car traffic modeling, where interactions between these classes significantly affect traffic flow. By implementing class-specific speed functions, the model dynamically adjusts speed based on the density of bicycles and cars. The study introduced a multi-class macroscopic traffic flow model that utilizes the approach above, incorporating space headway for both vehicles and bicycles, allowing for precise travel time estimation across various scenarios. The model's capacity to adapt to varying conditions by promptly switching to the fastest-moving class is crucial in congested scenarios where cyclists can maneuver more effectively than automobiles.

2.4.3 Review of Micro-Simulation Traffic Modeling

The present study employs a microscopic simulation model, recognizing its advantages for detailed traffic analysis. According to the classification of network sizes in traffic modeling by Elesawey and Sayed (2011), the current study qualifies as a large-scale network model, given its expansive scope encompassing over 100 intersections. This contrasts with small-sized models, which typically focus on an isolated intersection or a series of sequentially connected junctions within a corridor, and medium-sized models, which handle up to 100 intersections. The complexity of this study is further heightened by its focus on a motorcycle-dependent area where the road hierarchy includes a broad range, from major thoroughfares to narrow shortcuts and alleys commonly found in developing countries.

Balakrishna et al. (2007) pioneered the calibration of microscopic simulation models for large networks, utilizing aggregate data to estimate demand and supply parameters, as demonstrated in their case study of Lower Westchester County, New York, which included 1,767 links. The study highlighted the reliance on aggregate calibration, often due to the difficulty of obtaining disaggregated data and the resulting simplifications and trial-and-error methods used. Their work, particularly with the MITSimLab model, significantly contributed to the field by developing a systematic approach that allows for comprehensive calibration using general traffic measurements, thus overcoming the limitations of linear approximations like assignment matrices. However, the study acknowledges the complexity and computational intensity of simulating large-scale networks, often requiring the estimation of only a select group of parameters. Using the same simulation platform, moreover, Jha et al. (2004) developed and calibrated a large-scale microscopic model for Irvine, California, featuring 298 nodes and 618 links. The study enhanced model performance by fine-tuning driving behaviors, travel patterns, and O-D flows through iterative optimization. While this approach provided a precise representation of traffic conditions, it faced challenges related to model complexity and computational demands. Traditionally, microscopic analysis has centered on homogeneous traffic for decades, often overlooking the complex conditions prevalent in Asian contexts. Complementing this research, Hourdakis et al. (2003) advanced the field by proposing a systematic methodology for calibrating such models, exemplified through freeway sections in Minneapolis. Their research showed the efficacy of manual and automated calibration across three layers, aligning simulated data with actual conditions to improve model reliability. Nonetheless, the exclusive focus on freeways concerns its adaptability for varied simulation objectives. Toledo et al. (2003) further contributed by calibrating the MITSIMLab model for a motorway network in Stockholm, focusing on driving behavior using aggregate data. Their iterative approach aimed to match simulated outputs with observed traffic flow but was limited to a single urban corridor.

Oketch and Carrick (2005) calibrated a micro-simulation model for the Niagara Falls network using Paramics, comparing field data with simulation outcomes for traffic volumes, turning movements, travel times, and queue lengths. Their work highlighted the model's adaptability for network analysis, despite challenges in validating complex human behaviors. Hollander and Liu (2008) reviewed calibration principles and methods for microscopic modeling and simulation, emphasizing the need for accurate parameter adjustments to enhance predictive accuracy. Elesawey and Sayed (2011) validated micro-simulation models for medium-sized networks, covering 23 streets and 115 intersections in downtown Vancouver. While effective in matching actual travel times, their methodology focused on medium-sized networks, potentially limiting its applicability to larger or more diverse traffic systems.

Overall, the existing literature, as reviewed earlier, primarily centers on homogeneous traffic. However, a shift towards mixed traffic analysis was observed in Muniruzzaman et al. (2016), who included local modes of transportation (i.e., rickshaws, human haulers, bicycles) in the development of a VISSIM simulation model for the Moghbazar-Kakrail Corridor of Dhaka City, Bangladesh. However, the study lacked detail on the calibration process, merely listing parameters such as standstill distance, headway time, following behavior, speed impact, oscillation, lane change, overtaking, and lateral distances at different speeds. Bhattacharyya et al. (2020) further explored VISSIM calibration in a signalized corridor in Kolkata, India, including modes like rickshaws and buses. The mode-specific travel time distribution calibration findings affirmed the method's effectiveness in representing the non-lane-based mixed traffic dynamics, though the focus on a single intersection limits broader applicability. Similarly, Kumar et al. (2012) developed a driving cycle micro-simulation model to assess emissions and fuel consumption in Edinburgh, Scotland. Despite successful calibration, the study encountered challenges due to the sensitivity of micro-simulation and the extensive parameterization required.

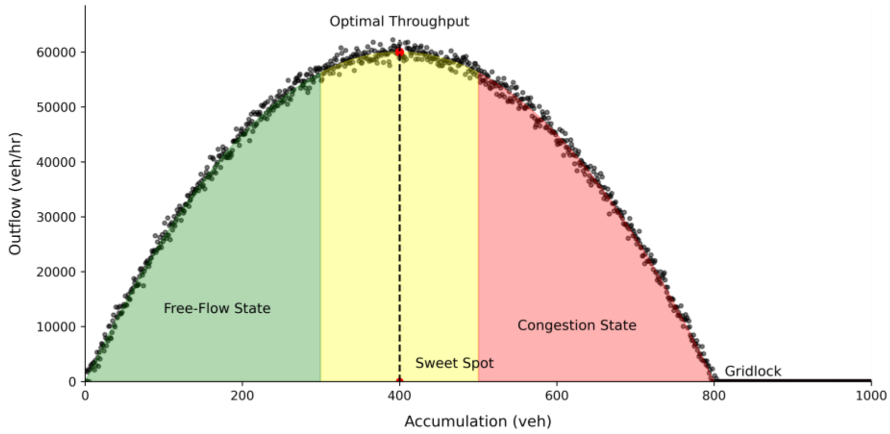
Notably, the literature mostly discusses freeway networks in developed countries, with scant attention to motorcycles and mixed traffic dynamics in developing areas. This critical gap underscores the need for comprehensive research in this domain, which is addressed in the present study.

2.5 Macroscopic Fundamental Diagram

The MFD has revolutionized traffic analysis by broadening the scope of the conventional fundamental diagram from individual road segments to entire networks. Introduced by Daganzo (2007) and expanded upon by Geroliminis and Daganzo (2007, 2008), the MFD provides a holistic representation of primary traffic characteristics—flow, density, and speed—across a network. This enables an assessment of 'neighborhood' network performance, identifying critical areas for improvement. The MFD establishes a relationship between the number of vehicles within the network (referred to as trip production on the X-axis) and the rate at which vehicles successfully reach their destination (referred to as accumulation on the Y-axis). In relatively homogeneous congestion areas, a well-defined MFD emerges (Geroliminis & Daganzo, 2007), where average traffic flow initially increases with rising density. However, as network homogeneity decreases, traffic production may also diminish (Knoop et al., 2014). The trend persists until it reaches a critical threshold, as illustrated in the yellow region of Figure 2-4. This point represents the network's capacity—the maximum flow rates the network can sustain. Prior to reaching this capacity, the network operates in a free-flow state, with low vehicle numbers and low outflow. Beyond this capacity, as the network shifts into a congestion state, further density increases can lead to congestion or potential gridlocks, inversely affecting outflow. Earlier studies have indicated that even at the same space-mean density level, the space-mean flow can decrease as the standard deviation of density increases (Mazloumian et al., 2010), as cited by Wang (2016). Understanding this transition between free-flow and congested states is fundamental for effective traffic management.

Leclercq et al. (2014) emphasize the predominance of the MFD in efficiently monitoring road networks, as well as offering a simple and aggregate model approach to network dynamics (Knoop & Hoogendoorn, 2013; Zheng et al., 2013). This foundational relationship between traffic density and flow became a vital tool for gauging a network's level of service and an instrumental access control measure in urban locations with complex layouts (Geroliminis & Daganzo, 2007, 2008). Its relevance is further shown by its utility in evaluating traffic characteristics, as shown through the performance diagram that illustrates the relationship between volume and density throughout an extensive network. Flow rate, the measure of the number of vehicles passing a point within a specific time frame, is essential in evaluating the impact of traffic control measures. Meanwhile, density, defined as the number of vehicles per unit length of roadway, is another key metric crucial for designing and managing road capacity effectively.

Figure 2-4 Macroscopic Fundamental Diagram.



Wang (2016) categorized three fundamental groups that influence the configuration of the MFD. The first group involves road network infrastructure, including network topology (Ambühl et al., 2018; Geroliminis & Daganzo, 2008), and spatial congestion distribution (Daganzo et al., 2011), both of which significantly affect the shape and scatter of the MFD. Traffic management strategies, according to Ji et al. (2010), have a profound impact on establishing a well-defined MFD, with Qian (2009) highlighting the relevance of ramp metering and Geroliminis and Daganzo (2007, 2008) examining the impact of traffic signal control. Keyvan-Ekbatani et al. (2016) further elaborate on how perimeter control and traffic guidance systems can alter the MFD, while Zheng et al. (2012) showcase the practical application of the MFD in formulating congestion pricing strategies. The second group pertains to the characteristics of user behavior. Drivers' route choice, contributing to the inhomogeneity of traffic distribution, is another key element, as discussed by Geroliminis and Daganzo (2008) and expounded upon by Daganzo et al. (2011) and Ambühl et al. (2018). In addition, Wang et al. (2015) explored how road network demand and supply conditions impact the stability of the MFD, with Mazloumian et al. (2010) noting the significance of traffic variability on the contour of the MFD. The last group considers the impact of unforeseen events. Incidents such as road traffic accidents (Ji et al., 2014) and different time periods (Knoop et al., 2014) can all markedly affect MFD stability. These groups collectively inform the comprehensive indicator of road network performance under varying conditions and influences.

Geroliminis and Daganzo (2008) conducted a pioneering field experiment to validate the existence of an urban-scale MFD in downtown Yokohama, Japan. Utilizing fixed detectors and GPS-equipped taxis, the study achieved extensive network coverage, confirming that space-mean speeds and densities closely followed the proposed MFD curve, with deviations attributed to experimental errors. Furthermore, the experiment established a consistent relationship between space-mean flows and trip completion rates, introducing a dynamic measure of network accessibility. Notably, the MFD exhibited resilience to fluctuations in traffic demand, showing that network outflow remained primarily influenced by vehicle accumulation and exhibited a regular pattern despite variations in the O-D matrix. This research underscores the MFD's utility in enhancing traffic management and system accessibility.

Geroliminis and Sun (2011) further expanded the research scope, including both downtown Yokohama and the twin cities metropolitan area freeway network in Minnesota, to identify the properties that enable a network to maintain a well-defined MFD with low scatter. This study holds significant potential for traffic control schemes, such as pricing and perimeter control, which are crucial for alleviating congestion and enhancing mobility. The findings challenged previous assumptions by revealing that a well-defined MFD with low scatter can exist when the spatial distribution of traffic density remains consistent across different time intervals with the same average network density, rather than requiring evenly distributed congestion. Additionally, the study shows a notable element of freeway networks that may not consistently demonstrate well-defined MFDs due to hysteresis effects, in contrast to arterial networks. Such hysteresis loops with high variability in the MFD may fundamentally arise from the uneven spatial distribution of traffic density across the network (Mazloumian et al., 2010).

Qian (2009) explores the application of the MFD in the metropolitan area of Amsterdam. Due to limited empirical data, traffic-flow characteristic variables for deriving an MFD were generated using a simulation model. The RBV model initially used reveals anomalies, including lower flow during congestion resolution and the absence of a congestion branch, attributed to measurement location discrepancies and the model's assumption of constant flow during congestion. Consequently, the RBV model proved inadequate for MFD derivation. Subsequently, the VISSIM model was employed, which successfully demonstrated the presence of congestion branches in MFDs, showing that while flow drops during congestion resolution, critical density and maximum flow information can still be accurately extracted. The study further investigated the impact of dynamic traffic management measures on MFDs, uncovering varying effects of ramp metering and extra lanes on different road segments. Although the MFD performed less favorably than conventional methods in terms of accuracy and visualization, it was concluded that the MFD could still be effectively used alongside traditional approaches to enhance the reliability of evaluations on the effects of traffic measures on motorways.

Hu et al. (2020) presented a novel approach to the discrete transportation network design problem using the MFD concept, concentrating on improving network capacity. A bi-level programming model was developed, where the upper level determines the optimal links to be added for maximizing network capacity, subject to budget constraints, and the lower level assigns flows based on user equilibrium theory. To manage the model complexity, traffic flow distribution calculations under Dynamic User Equilibrium (DUE) were integrated with VISSIM-COM-Python interaction. This method shapes MFDs and utilizes a k-means clustering algorithm to compute network capacity. The study, tested on the Sioux Falls network, demonstrated the effectiveness of this MFD-based approach in addressing network design challenges, especially under stochastic OD demands. However, the shape and scatter varied significantly with changing demands, likely due to the inclusion of a heterogeneous network. This finding aligns with some prior research (e.g., Daganzo et al., 2011; Ji et al., 2010) yet diverges from others (Geroliminis & Daganzo, 2007, 2008; Geroliminis & Sun, 2011). The uneven distribution of demand may give rise to hysteresis loops within the MFD (Daganzo et al., 2011; Mazloumian et al., 2010).

Ji et al. (2018) introduced a method for deriving an MFD by integrating data from probe vehicles and loop detector counts, specifically targeting Changsha, China, using data from April 2013 and 2015. This approach addressed the failure of loop detectors in certain network areas, relying on a subset of network links to generate an MFD for effective traffic monitoring and control. This concept was previously explored by Keyvan-Ekbatani et al. (2013) in a simulated network. Ortigosa et al. (2015) further expanded this subject matter by determining which specific links should be assessed to optimize the number and placement of traffic detectors for deriving a functional MFD. The well-defined MFD resulting from this study demonstrated the feasibility of using partial traffic data to construct a representative MFD, offering a novel solution for traffic management, especially in scenarios where monitoring capabilities are limited and complete data collection is not feasible. Tsubota et al. (2014) then integrated data from multiple sources—Bluetooth devices, loop detectors, and signal phase timing—to present an empirical framework for constructing the MFD for the arterials in Brisbane, Australia. This method captured varying density levels within the MFD, providing a clearer understanding of network traffic conditions. The study assessed different MFDs across the entire network and in several sub-regions, using spatial partitioning to accurately reflect network performance. This partitioning was instrumental in identifying congestion patterns and pinpointing specific ar traffic bottlenecks. The findings highlighted the heterogeneity of congestion and the importance of network partitioning in maintaining traffic homogeneity during peak hours, which is vital for implementing successful traffic management measures and effective monitoring, including incident detection.

The advancement in MFD research was carried out by Geroliminis et al. (2014), who developed an MFD tailored for mixed bi-modal networks, consisting of cars and buses, in downtown San Francisco. Data on traffic flow and density were gathered at five-minute intervals over a 5.5-hour duration using the AIMSUN microscopic simulator, which facilitated the construction of a three-dimensional passenger MFD (3D-pMFD) across more than 20 scenarios that reflected a range of demand characteristics. The findings indicated that a static bus car unit equivalent value was inadequate to capture the effect of buses on congestion, necessitating a dynamic, derivative-based traffic analysis approach. Furthermore, the study demonstrated that segmenting the network into a finite number of regions could reveal critical traffic flow characteristics, particularly flow heterogeneity. Finally, the study proposed multiple traffic management strategies to regulate the high density of buses based on these insights.

Similarly, Huang et al. (2022) further explored the traffic dynamics of cars and bicycles within three selected networks in Shanghai, China, by establishing a bi-modal three-dimensional MFD using data from taxi floating vehicles, loop detectors, bicycle-sharing statistics, and video recordings from August 2016. They introduced the bicycle equivalent unit to quantify the combined flow of bicycles and cars, aiming to calculate the total network flow. Nonetheless, the congested branches of the 3D-MFDs were not clearly identified due to data limitations. Knoop and Hoogendoorn (2013) introduced a new perspective on traffic flow theory with the generalized-MFD (GMFD), which incorporates additional dimensions such as traffic production, accumulation, and the spatial distribution of traffic density. The GMFD is particularly useful for understanding traffic patterns in densely populated urban areas, capturing more complex dynamics by considering how traffic is distributed across the network. Using empirical data from freeway networks in Amsterdam, the study demonstrated the practical applications of the GMFD concept with two significant findings. First, the GMFD can easily explain the formation of hysteresis loops in traffic flow, which is the phenomenon where the traffic state follows different paths in the flow-density diagram during the onset and dissipation of congestion. Second, the GMFD enables precise predictions of traffic production under certain levels of accumulation.

Nonetheless, there is a notable lack of network performance analysis in Southeast Asian countries using the MFD method, despite the region's frequent traffic issues, largely due to the high volume of private vehicles exacerbating congestion. Suwanno et al. (2021) conducted one of the few studies in this context, focusing on the Sukhumvit District in Bangkok, Thailand. The research aimed to quantify the impact of floods on traffic, utilizing Thailand's open data in 2019, including vehicle and mobile probe data, specifically analyzing taxi traffic from 5 a.m. to 12 a.m. on weekdays, while excluding freeway data from the datasets. Findings revealed that flood levels and network traffic operations significantly influenced the MFD shape. A mesoscopic model simulated vehicle movements, providing insights into dynamic traffic conditions and evaluating traffic control schemes. However, the study's limitation is its exclusion of mixed traffic considerations, which is crucial in Thailand due to high motorcycle usage (see Figure 1-1). The complex nature of mixed traffic in Southeast Asia, characterized by surging mobility demands and constrained size of street networks, underscores the necessity for comprehensive analysis and effective management solutions—objectives that this study aims to address.

2.6 Traffic Management Approaches

This section explores a variety of traffic control measures and outlines the strategies currently proposed.

2.6.1 Global Implemented Strategies

As mentioned in Section 2.5, mixed traffic poses challenges for many cities worldwide, each with its unique traffic composition. This has led to the development of various traffic management strategies to regulate and streamline these disordered environments, including:

1) **Traffic Calming Measures**. Countries like the United Kingdom and Australia employ this scheme, especially in residential areas, to slow down vehicles and prioritize the safety of all road users, particularly pedestrians and cyclists. Measures include speed humps, chicanes, and curb extensions.
2) **Dedicated Lanes**. Dedicated Bus Rapid Transit (BRT) lanes are widely used in Brazil and Colombia to enhance safety and reduce delays, while Indonesia, Malaysia, and Japan employ semi-BRT systems due to traffic intersections. Dedicated bicycle lanes, prevalent in Denmark, Germany, and the Netherlands, aim to reduce accidents, although compliance issues arise in cities like Jakarta, where motorcycles often misuse these lanes.
3) **Zone Restriction**. Some cities have demarcated zones to restrict specific vehicular movements, such as pedestrian-only areas in Central Business Districts (CBDs) for safety and motorcycle-free zones to maintain consistent traffic speeds.
4) **Mixed Traffic Lanes**. Several metropolitan areas have designated lanes catering to various vehicle types, providing a more efficient and structured approach to traffic management. Several regions of India are equipped with dedicated lanes mostly designated for auto-rickshaws and two-wheelers.
5) **Grade Separation**. Structures like overpasses, underpasses, and flyovers segregate different traffic types, reducing congestion and collision points, as seen in cities like Los Angeles, Beijing, and Shanghai, which utilize multi-tiered road systems with elevated highways.
6) **Traffic Signal Prioritization**. This strategy favors particular transport modes. For example, buses might receive an advanced green signal at traffic intersections.
7) **Advanced Traffic Management Systems (ATMS)**. Incorporating technology such as cameras, sensors, and data analytics, ATMSs offer real-time traffic oversight. These systems dynamically adjust signal timings and relay instant traffic updates to commuters. Singapore, for instance, has integrated an extensive network of cameras and sensors for advanced traffic management.

2.6.2 Motorcycle-Centric Strategies

Shifting focus from broad regulation schemes to motorcycle-specific strategies is crucial, especially in Asia. Recognizing their distinct dynamics, several countries have implemented tailored traffic management measures to enhance safety and efficiency for riders, as follows.

1) **Dedicated Motorcycle Lanes**. Malaysia pioneered exclusive motorcycle lanes on major highways in the 1990s to reduce accidents involving motorcyclists, ultimately decreasing collisions in several areas. A study by Radin Sohadi et al. (2000) on a 30-km motorcycle lane in Selangor showed a 39% reduction in motorcycle accidents. This strategy is consistent with previous research, specifically that the rationale behind it was to segregate motorcycles from the main traffic streams (Saini et al., 2022). Similar strategies have been adopted in Taiwan, Indonesia, Thailand, and the Philippines.
2) **Motorcycle Restrictions**. Some cities have restricted motorcycles on specific roads or during certain times to reduce congestion and pollution. However, these bans often led to longer travel times and met significant resistance, especially in countries like Vietnam and India, where motorcycles are a primary mode of transport.
3) **Restrictions on Lane Splitting**. Lane splitting, where motorcycles navigate between lanes of slower or stopped traffic, is legal in regions like California, where it is believed to reduce rear-end collisions and ease traffic. However, the practice is controversial, with some countries supporting it as a traffic solution while others impose strict regulations or bans due to safety concerns.
4) **Motorcycle Boxes at Intersections**. Cities like Portland in the United States and several Asian regions, including Taiwan, have introduced bike boxes at intersections. These designated spaces at traffic signals reduce the likelihood of crashes by providing a safer start for two-wheelers.
5) **Motorcycle Two-Stage Left Turn Waiting Area**. In Taipei, two-stage left turn waiting areas allow riders to stop at red signals before completing their turn, improving safety during signal transitions.

6) **Fast- and Slow-Speed Lanes**. To optimize the efficiency of vehicle movement in mixed traffic, Indonesia has designated fast and slow lanes, separating high-speed automobiles from motorcycles to decrease potential accidents. These lanes were purposefully created to accommodate a significant number of motorcycles while maintaining the flow of the traffic stream.
7) **Motorcycle-Only Parking Zones**. The UK and Japan have designated parking zones for motorcycles, leveraging their compact size to enhance space efficiency and reduce parking conflicts.
8) **Road Pricing**. In some countries, road pricing is used to mitigate congestion by imposing fees on vehicles in heavily trafficked areas. Motorcycles often receive exemptions or lower rates, though some cities, including Singapore, London, Stockholm, and Oslo, also impose fees on motorcycles.

2.6.3 Novel Proposed Strategies

Expanding upon the successful global traffic management strategies discussed in Chapter 1, this study proposes two novel approaches tailored for motorcycle-dominated environments: the provision of traffic information and the installation of ramp metering on non-freeway roads. These measures are specifically designed to manage and control motorcycle flow effectively, addressing the unique challenges they present in this settings. The following subsections provide detailed discussions of these strategies.

2.6.3.1 Variable Message Sign

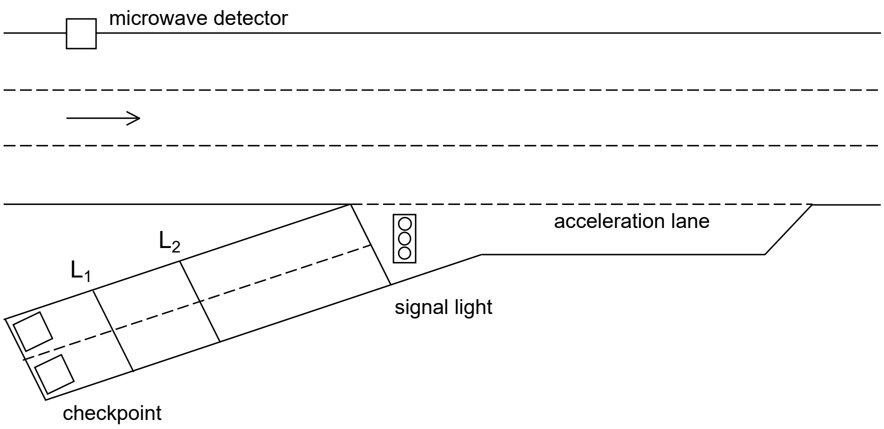
Variable Message Sign (VMS), also referred to as Dynamic Message Sign, is an electronic board device typically placed on a road segment to broadcast traffic reports or provide advance warnings of incidents, for instance, congestion, roadwork, accidents, or any other occurrences that may create either recurring or nonrecurring delays. According to Chatterjee and Mcdonald (2004), VMS is an effective tool for managing demand, reducing trip times, improving traffic flow, and addressing environmental concerns. The provision of traffic information is believed to aid drivers in making more efficient route choices by diminishing trip uncertainty (Levinson, 2003) and minimizing time and cost losses along the way.

Multiple studies have shown the critical relevance of VMS-displayed information in enhancing traffic systems (Jou et al., 2005; Zhao et al., 2020) by minimizing travel time and delays (Ackaah, 2019). This leads to a more balanced distribution of vehicles across road networks (Zhao et al., 2020), contributing to an increase in the network capacity and a reduction in congestion (Abdel-Aty, 1998; Ackaah, 2019; Amiri & Li, 2022; Jou et al., 2005). Particularly noteworthy is a study by (Bature & Georgakis, 2016), which reported a 38.37% increase in the capacity of the CBD in Kaduna, Nigeria, due to VMS implementation, effectively addressing persistent congestion. Serving as an advanced traffic guidance system, VMS is also able to influence drivers' preferences in either normal or congested traffic conditions (Peeta et al., 2000) by providing route recommendations that help avoid heavy traffic (Yan & Wu, 2014), thereby reducing emissions and fuel consumption (Ackaah, 2019). From a road safety perspective, real-time traffic information that warns about an impending incident can lower the probability of vehicle collision occurrences (Zavareh et al., 2017) and guide road users away from routes affected by incidents (Abdel-Aty, 1998). Furthermore, as highlighted by Amiri and Li (2022), VMS strengthens traffic resilience, denoting the capability to sustain functionality under disruptive conditions.

2.6.3.2 Ramp Metering

Ramp metering was first implemented in 1963 on the Eisenhower Expressway in Chicago, where a police officer manually controlled traffic flow. The U.S. Department of Transportation's Federal Highway Administration (2020) defines ramp meters as a kind of traffic lights that is strategically placed on freeway on-ramps that operate with much shorter cycle times than typical signals. The operational mechanism of this system entails the fragmentation of vehicle platoons at on-ramps, resulting in the alleviation of localized congestion (Jacobson et al., 2006), which is deemed the most direct and efficient countermeasure (Papageorgiou et al., 2003). Therefore, the frequency of vehicles entering the mainline traffic stream can be controlled by permitting only a single vehicle or a small batch of vehicles to enter the mainline during each green phase. This strategy effectively addresses the 'capacity drop' issue arising from merging activities, ultimately reducing the time vehicles remain in the system (Papageorgiou et al., 2003). The components and operational mechanisms of ramp metering are depicted in Figure 2-5.

Figure 2-5 Ramp metering scheme.



Ramp metering offers an effective solution for stabilizing and smoothing mainline traffic flow by addressing disturbances that often lead to stop-and-go scenarios (Arnold, 1998). This measure manages bottlenecks and delays—typically caused by vehicles competing for gaps—by either preventing these situations or diverting congestion to the ramp (Arnold, 1998), thereby accelerating mainline traffic. Its benefits include preserving mainline capacity, preventing upstream ramp blockages, and significantly reducing network travel time by half (Papageorgiou & Kotsialos, 2002). Additionally, prior research highlights improvements in travel time reliability (Bhouri et al., 2013; Shehada & Kondyli, 2019), increased throughput, and diminished severity of capacity issues (Arnold, 1998; Shehada & Kondyli, 2019). From a safety perspective, ramp metering enhances safety along freeway corridors by mitigating turbulence in merge areas and stabilizing speed variations (Federal Highway Administration, 2020).

On the whole, this notion has been further elaborated upon by the Federal Highway Administration (2020), highlighting the benefits of ramp metering, including:

1) **Reducing travel time and congestion**: Ramp metering reduces travel times and delays, and alleviates congestion, thus enhancing mobility across the freeway and improving traffic throughput.
2) **Enhancing safety**: By helping to break up the platoons of vehicles entering the freeway, ramp metering contributes to reducing accidents, making the road safer for all users.
3) **Improving traffic flow**: Ramp metering systems help smooth out traffic flow and prevent disruptive patterns, resulting in more predictable and efficient travel.
4) **Reducing emissions and fuel consumption**: The deployment of ramp metering provides the environmental benefits of lowering vehicle emissions and fuel consumption on the freeway.

In contrast, Arnold (1998) also discussed potential drawbacks of ramp metering, notably the risk of traffic spillback onto local streets due to excessive ramp demand (Cazorla et al., 2022). This situation may disrupt traffic flow on arterial roads. As queues at the metered ramps grow and green light intervals lengthen, drivers may divert to alternate routes. Such diversions are particularly common for short-distance trips with available uncongested parallel routes, leading to increased 'through traffic' on local streets. Hence, effective ramp metering requires precise identification of bottlenecks and control parameters using both historical and real-time data (Cazorla et al., 2022).

2.7 Discussion

This section synthesizes the insights from the literature review, recognizing the identified gaps, clarifying the motivations behind the study, and outlining an overview of the research framework.

2.7.1 Research Gap

The literature review conducted in this chapter highlights several crucial research gaps across empirical, conceptual, and methodological aspects, mainly focusing on motorcycle-dependent environments. These gaps, outlined below, underscore the specific areas this study aims to address and contribute to.

1) **Motorcycle Route Choice Model**: Despite the prevalence of motorcycles in Asian countries, there is a notable lack of studies addressing the route choice behavior of motorcycle riders. Existing research on route selection is scarce and predominantly focuses on passenger cars, bicycles, or trucks, overlooking the unique behaviors of riders in motorcycle-dependent areas.
2) **Microscopic Simulation Model:** Current microscopic simulation models in the literature primarily address small-scale networks, often limited to specific road segments or intersections. While studies on medium-sized networks are more frequent, there is a notable deficiency in large-scale network modeling, especially under mixed motorcycle traffic. Developing accurate microscopic simulation models for these scenarios remains an emerging research area.
3) **Macroscopic Analysis and Evaluation**: The research extends into the realm of macroscopic analysis in Southeast Asian contexts, aiming to pioneer the development of MFD for mixed motorcycle traffic. The existing literature lacks such specialized applications, and where MFD models exist, they do not account for the unique characteristics of non-lane-based, heterogeneous traffic that includes motorcycles. In the big picture, there is also a significant research gap in applying MFDs within such contexts, where motorcycle prevalence significantly differs from patterns in developed countries. This area requires more in-depth exploration and understanding.
4) **Dynamic Traffic Control for Motorcycle-Dependent Cities:** The study advocates for dynamic traffic control mechanisms using real-time information tailored to managing motorcycles in mixed traffic. In Indonesia, for example, VMS usage is constrained to toll roads in the Greater Jakarta Metropolitan Area (locally known as Jabodetabek, an abbreviation for Jakarta-Bogor-Depok-Tangerang-Bekasi), which are inaccessible to motorcycles. These current systems offer limited functionality and fail to deliver traffic updates, potentially diminishing driver confidence and the perceived reliability of the messages. Yet, this situation is common within motorcycle-dependent cities. In addition, ramp metering—a strategy proven to maintain flows at capacity levels—has not been adapted for urban streets. This study suggests applying the core concept of ramp metering on arterial roads to regulate motorcycle ingress and maintain optimal traffic flow and speeds.

2.7.2 Research Motivation

following motivations drive this research, emphasizing the need to understand and enhance motorcycle-dependent traffic systems, where conventional traffic management practices often fall short. These motivations underscore the urgency of aligning traffic control strategies with the dynamic traffic patterns in this context, offering both immediate solutions and a foundation for long-term strategic planning.

1) **Mobility Improvement**. As urban centers expand, the reliance on motorcycles for flexible modes grows, necessitating adapted traffic control measures to ensure efficiency for all road users.
2) **Congestion Impact**. Tackling congestion by optimizing traffic flow is essential for improving mobility and reducing the losses linked to prolonged travel times and increased operational costs.
3) **Technological Advancements**. Modern traffic management technologies, such as VMS and ramp metering, offer untapped potential in urban settings where motorcycles dominate.

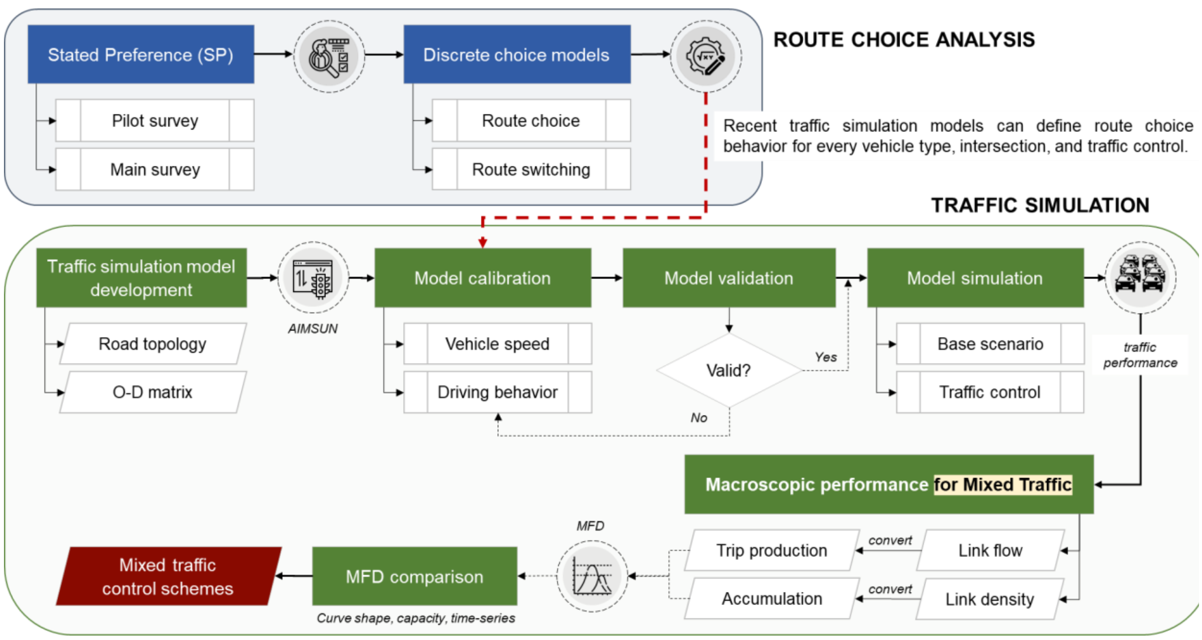
4) **Policy Development**. Findings from this research could provide empirical evidence to guide policymakers and urban planners in designing and implementing traffic management strategies tailored to the unique patterns of motorcycle-dominated traffic.

2.7.3 Research General Framework

The research framework presented in the flowchart in Figure 2-6 outlines a systematic approach to addressing the intricacies of traffic flow in motorcycle-dependent areas. The process initiates with stated preference surveys, which are crucial for capturing the behavioral tendencies of motorcycle riders, particularly focusing on factors that influence their route selection and switching behaviors. This foundational step is pivotal for understanding their decision-making processes, which are then used to develop accurate models and set the stage for subsequent analysis.

Following the relevant data collection and analysis, a microscopic traffic simulation model is constructed, incorporating essential factors such as road topology, traffic demand, and driving behaviors to mirror real-world conditions closely. The model then undergoes calibration to fine-tune parameters, ensuring high fidelity with empirical observations. Model validation is a pivotal checkpoint where the accuracy of the simulation is scrutinized—if discrepancies arise, recalibration is performed. Once validated, the simulation phase investigates the effectiveness of current traffic conditions and proposed control measures. This involves a detailed analysis of traffic performance indicators under various scenarios. The research then transitions to a macroscopic analysis, employing the MFD to generate network performance metrics. This phase evaluates traffic flow attributes on a larger scale, such as trip production, link flow, and density, and involves contrasting simulation results with various hypothetical scenarios. Additionally, it includes analyzing curve shapes, capacities, and temporal data trends to compare the effectiveness of different traffic management scenarios. The culmination of this framework is the evaluation of mixed traffic control schemes. This final step involves formulating and appraising some strategies that are not only effective in managing flows but are also specifically tailored to the unique mixed traffic conditions prevalent in motorcycle-dependent environments. This comprehensive approach ensures that the strategies developed are contextually relevant and practically viable.

Figure 2-6 Research framework.



Chapter 3

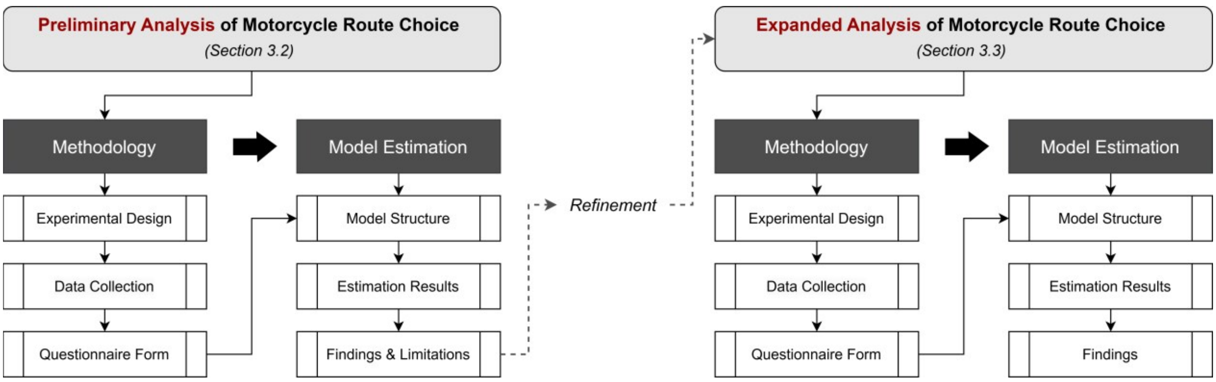
Route Choice Analysis of Motorcycle Riders

3.1 Introduction

Understanding the patterns of route selection behavior is one critical aspect of devising traffic control schemes, particularly under mixed traffic conditions. This chapter focuses on route choice analysis, specifically targeting the preferences of motorcycle riders in areas where motorcycle traffic prevails.

To enhance clarity, Figure 3-1 provides a structured framework outlining the analytical process of motorcycle route choice within this chapter, which aids in understanding how each component builds upon previous efforts to foster a comprehensive evaluation of motorcycle riders' route choices.

Figure 3-1 Analytical framework of motorcycle route choice behavior



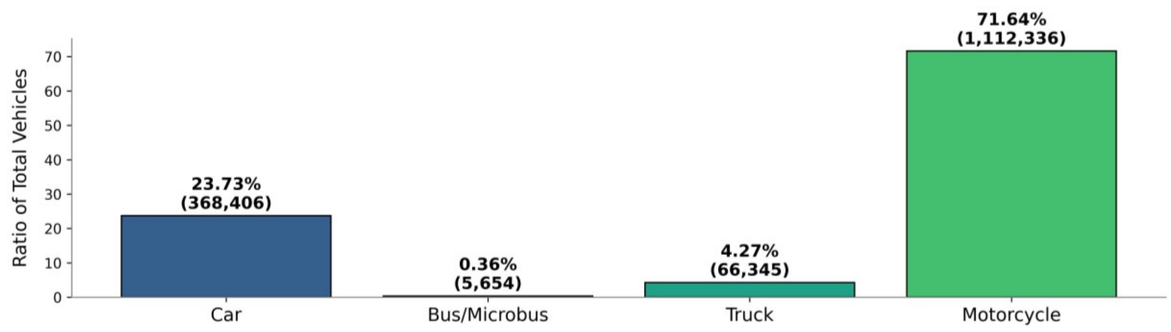
The diagram visually represents the sequential approach taken in this research, beginning with the preliminary analysis in Section 3.2. This initial phase was conducted to assess the significance of route choice behaviors of motorcycle riders, an area not extensively researched despite the high prevalence of these vehicles. The results from this preliminary phase are then referenced, and the identified limitations are addressed in the expanded analysis in Section 3.3. This progression includes a refinement stage, where methodologies and experimental designs are further developed based on initial findings. This thorough evaluation is crucial for understanding how various factors, including road attributes, travel properties, individual characteristics, and external stimuli such as traffic information provision and traffic control measures, may shape motorcycle riders' routing decisions. Finally, the discussion in Section 3.4 connects the findings to a deeper analysis of sensitivity and probability, while also exploring their broader implications, thereby enriching our understanding of route choice behaviors in areas with a high concentration of motorcycle traffic. Overall, the knowledge derived from this study aims to inform the formulation of traffic management strategies discussed in the subsequent chapters.

3.1.1 Case Study

As shown in Figure 1-1, Indonesia is among the top countries worldwide for the highest rate of motorcycle ownership. Therefore, Bandung City, the capital of West Java Province, was chosen for the route choice analysis in this chapter due to its representative mobility patterns in this context. Covering a land area of 167.31 km^2, Bandung, with a population of 2,452,943 in 2021, is the fourth most populous city in the country, resulting in a density of 14,388/km^2 (Bandung Central Bureau of Statistics, 2022).

Bandung caters to its own residents' transportation needs and absorbs trips from nearby regions within its administrative boundaries. These include Cimahi City, Bandung Regency, West Bandung Regency, and Sumedang Regency. This phenomenon has led to the establishment of the third-largest metropolitan area in Indonesia, the Greater Bandung region, with a population of 8,872,957 inhabitants. Even more, its proximity to Jakarta, located approximately 200 kilometers away, attracts many weekend travelers, further exacerbating traffic issues. The severe traffic jams in Bandung are also caused by the heavy reliance on private vehicles, particularly motorcycles. Out of the registered motorized vehicles in the city, a substantial portion are motorcycles, accounting for about 57.94% of the residents aged 17 and older, the minimum age in Indonesia to possess a driver's license. Managing this massive fraction of motorcycles is crucial to improving traffic performance by analyzing and comprehending their travel patterns. The overall distribution of motorized vehicles in Bandung is illustrated in Figure 3-2.

Figure 3-2 Mode share of Bandung City (Bandung Central Bureau of Statistics, 2022).



In Bandung City, the deployment of real-time traffic information systems like VMSs is primarily confined to toll roads, where existing devices provide reports for upcoming routes but lack further detail, as seen in Figure 3-3. Unfortunately, such arrangements exclude motorcycle riders, who are prohibited from using highways, from accessing traffic information. This limitation highlights a significant gap in disseminating essential traffic updates to a key segment of road users in motorcycle-dependent cities.

Figure 3-3 Qualitative information on the VMS in Indonesian toll roads.

3.1.2 Data Collection Technique

The literature review shows that route preferences can be collected through various techniques, depending on the research objective and data accessibility. For instance, the Stated Preference (SP) survey (e.g., Ma et al., 2014; Spyropoulou & Antoniou, 2015; Wardman et al., 1996), GPS data (e.g., Vacca et al., 2019), a combination of SP and Revealed Preference (RP) surveys (e.g., Poulopoulou & Spyropoulou, 2019), and driving simulator experiments (e.g., Ardeshiri et al., 2015; Roca et al., 2018; Yan & Wu, 2014), as well as a combination of questionnaire surveys and driving simulators (e.g., Zhong et al., 2012). These varied approaches may affect the accuracy and precision of the data differently.

The case study area, Bandung City, as detailed in the previous subsection, lacks real-time traffic reports on all road types except for toll roads, which motorcycles are not authorized to use—a common practice in motorcycle-dependent countries. Consequently, due to the absence of actual data on route choices for motorcycle riders towards such devices, an SP experiment was deemed an appropriate data collection technique to identify and understand the behavioral responses in route selection. As a well-known approach for investigating drivers' route choice behavior, this survey provides decision-makers with a series of attribute combinations from real-world and hypothetical alternatives (Moghaddam et al., 2019). The primary advantage of the SP method over RP, which relies on observed behavior, is its ability to capture choices in non-existent markets and anticipate future demand (de Freitas, 2018) through the predefined choice set. Furthermore, it proves efficient regarding time and cost (Ma et al., 2014), allowing respondents to determine their route preferences by comparing trade-offs among available alternatives (de Freitas, 2018). Additionally, Wardman et al. (1996) highlighted that one of the principal benefits of applying the SP experiment is its capacity to avoid collinearity and inadequate variation of the critical variable of interest while also enabling the capture of multiple observations from a single individual.

In this research, SP surveys were designed to understand the response of motorcycle riders toward the traffic information displayed by the VMS when making route choice decisions by offering a series of hypothetical controlled scenarios. In order to ensure validity, data collection occurred in two steps: a pilot survey and a main survey. The former was conducted to test the questionnaire design and gather opinions from motorcycle riders. The refined questionnaire form was then employed in the main survey, incorporating a more extensive range of explanatory variables and a larger sample size. The subsequent sections provide a detailed discussion of the experimental design formulated for these surveys.

3.2 Preliminary Analysis of Motorcycle Route Choice Behavior

The dissertation initiated a preliminary analysis aimed at confirming the existence of distinct route choice behaviors among motorcycle riders. Additionally, it sought to identify the key factors influencing these behaviors. This foundational research sets the groundwork for a broader-scale analysis and the development of a more comprehensive model to accurately represent and capture motorcycle riders' route decision-making. This section provides a detailed elaboration on this initial study, highlighting the significant insights gained and their implications for the subsequent stages of the research.

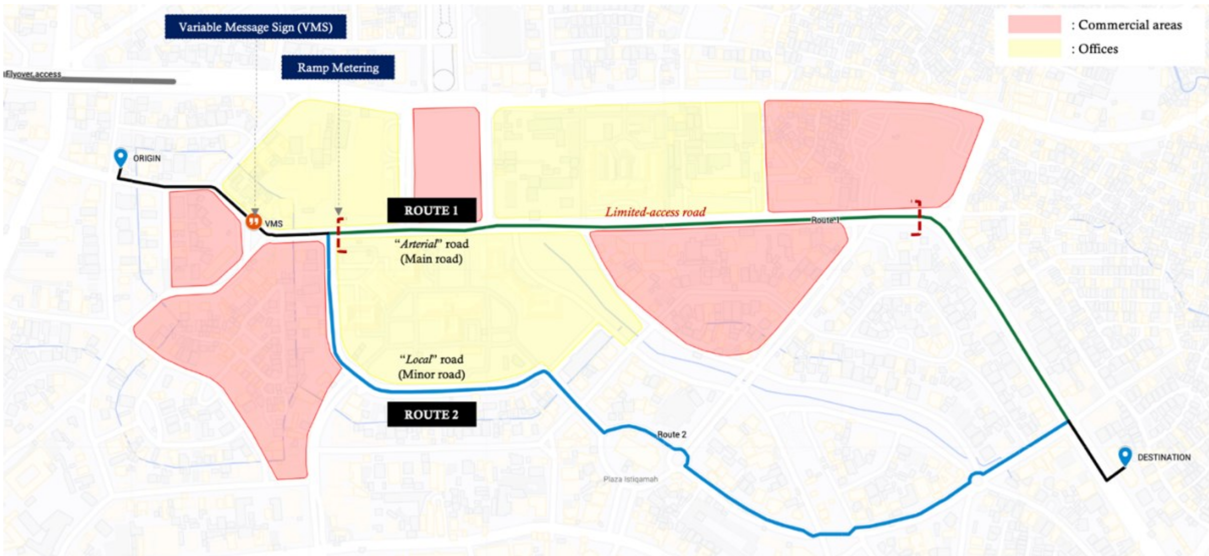
3.2.1 Methodology

This section provides a detailed explanation of the methodology applied in the preliminary analysis, including the experimental design, questionnaire, and the statistical properties of the sample obtained.

3.2.1.1 Experimental Design

The questionnaire for this preliminary experiment outlined a network configuration with two routes of differing functionality, situated in busy areas, generally office and commercial zones. The choice set generation process, which involves determining alternative routes between O-D pairs, is an essential process in route choice analysis. Respondents were asked to envision themselves riding a motorcycle from an origin location to a designated destination, as illustrated in Figure 3-4. In this scenario, as motorcycle riders, respondents had to choose one of the predefined route choices (either Route 1 "arterial road" or Route 2 "local road") in accordance with their personal preferences and the given alternative attributes. The underlying assumption in the labeled choice experiment is that Route 1 is primarily an arterial road that traverses the CBD area. Typically, this major road has a relatively faster speed (30 to 35 mph), greater capacity with a minimum road width of 8 meters, and fewer intersections to diminish traffic delay. Arterial roads are designed to facilitate traffic between city centers at the highest possible level of service. On the contrary, Route 2 is a local road that connects local secondary roads with arteries through collector roads. It has a lower speed limit (25 mph) and a maximum road width of 5 meters, primarily accommodating short trips through neighborhoods and providing local access.

Figure 3-4 Alternative routes in the SP survey.



Referring to the findings of Long et al. (2021), the threshold in the travel time difference for drivers to change routes, assuming both inertia and habit are zero, ranges from 0.012 hours (7.2 seconds) to 0.053 hours (3 minutes and 11 seconds) when real-time travel time is made available. Consequently, it was supposed that every participant had prior knowledge of the average travel time to the destination through Route 1 (8 minutes) and Route 2 (10 minutes), as the aforementioned significant difference in travel time. Respondents were expected to heed traffic information broadcast from the VMS, strategically located just before the intersection of the two routes (see Figure 3-4). All explanatory variables accounted for in this research were delivered to the respondents through VMS content, including traffic flow conditions (light, moderate, heavy), and the estimated waiting time owing to the installation of a ramp meter (0, 3, 5 minutes) which marks the predicted time a motorcycle would have to wait on the ramp before entering the main road. However, in some stated choices, traffic conditions were substituted with travel time information to portray traffic situations numerically.

With respect to the experimental design formulation, it was understandably challenging to evaluate all 27 full factorials of stated choices for each respondent. Thus, a block design consisting of five hypothetical scenarios was established, as listed in Table 3-1. These treatment combinations were verified to reflect the actual settings adequately. Since the road functions were not put into the same categories, it is essential to point out that the same level of vehicle flow on Routes 1 and 2 might lead to different traffic performance. Notably, this analysis is a preliminary step toward identifying the key features influencing the route choice of motorcycle riders on a more extensive scope.

Table 3-1 The combination of attributes of each alternative was given in the SP survey.

Treatment combinations	Traffic flow conditions		Waiting time at a ramp meter (Route 1)
	Route 1 "*Arterial road*"	Route 2 "*Local road*"	
1	Moderate	Heavy	3 minutes
2	Light	Moderate	5 minutes
3	Heavy	Moderate	0 minutes
4	Heavy	Heavy	3 minutes
5	Moderate	Light	0 minutes

It must be recognized that the manner in which road users utilize VMS information is highly determined by the substance and presentation format (Zhao et al., 2020). Further highlighted by Yan and Wu (2014) and Ma et al. (2014), it was disclosed that road users favor graphical VMS over the text-only style, which contributes more positively to traffic performance. This conclusion aligns with the findings of a study by Choocharukul and Wikijpaisarn (2013), who determined that color-coded traffic information that distinguishes the level of traffic congestion can significantly influence drivers' decisions. Graphic-based VMS, afterwards referred to as pictogram, is pointed out by its effectiveness for several reasons: (1) the ability to be read from twice as far as text, (2) the capacity to synthesize complex road and traffic situations, and (3) the potential to be a universal language that is easily understood (Arbaiza & Lucas-Alba, 2012). Pictograms are easier to interpret than lengthy text messages (Roca et al., 2018) and enable quicker reading and response times (Chatterjee & Mcdonald, 2004).

In line with these findings, the experiment in this study employed a dual-format VMS, integrating pictograms with a color-coded congestion level system and text-based messages to convey traffic information to motorcycle riders. Figure 3-5 presents VMS examples provided to survey participants.

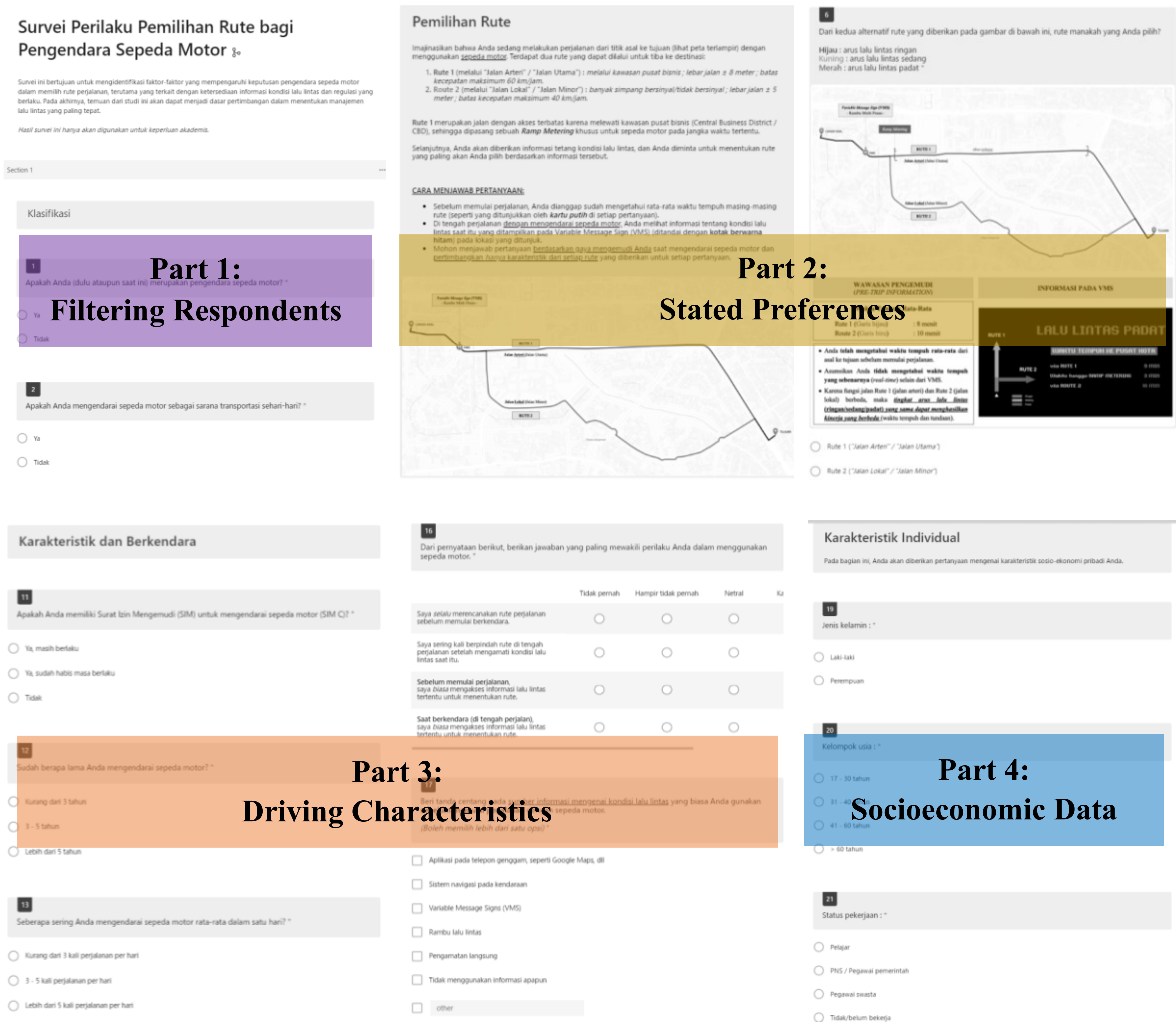
Figure 3-5 Examples of VMS were given in the SP survey of the preliminary study.

3.2.1.2 Questionnaire Form

Building on the experimental design discussed above, the questionnaire forms used in the preliminary experiment are presented in Figure 3-6. This questionnaire, created using Microsoft Forms, was distributed through social media platforms to collect the motorcycle riders' behaviors and perspectives.

The initial part focuses on screening and categorizing respondents based on their status as motorcycle riders, including primary usage, such as commuting or service provision. It also provides a brief introduction to VMS and ramp metering concepts, which are relatively novel in the Indonesian context. Subsequent sections present stated choice scenarios to capture their route selection behaviors. The final part collects essential personal data, encompassing socioeconomic aspects (gender, age, occupation, education level, and income) and riding characteristics (driver's license ownership, driving age, frequency, riding style, regular travel purpose, and exposure to traffic information).

Figure 3-6 Questionnaire design for the preliminary experiment.



3.2.1.3 Sample Characteristics

Out of 160 Indonesians respondents, a total of 135 (84.4%) were motorcycle riders, with the remaining 15.6% removed from the dataset. Each respondent was given five stated choices, resulting in a dataset of 675 observations, which was then analyzed to capture the decision-making patterns while selecting the routes. Table 3-2 presents a breakdown of the socioeconomic and driving factors of the respondents.

The preliminary survey outcomes show that most questionnaires were filled out by motorcycle commuters (93.8%), with 37.8% also riding for professional purposes, such as motorcycle taxis ('ojek') and delivery couriers. Regarding prior knowledge, 52.6% had heard of VMSs, whereas only 17.8% were aware of ramp metering. Among all respondents, about 13.3% did not possess a valid driving license when the survey was administered. In terms of driving experience, over two-thirds had ridden for over five years and drove less than three times daily. Overall, more than half of the respondents stated they steadily rode motorcycles, indicating moderate aggressiveness. Approximately 36.1% rode motorcycles to work, 19.8% for grocery shopping, and 1% merely for wandering around the city. In the case of socioeconomic characteristics, the respondents were predominantly male (68.5%), aged between 17 and 30 years (86.7%), or had a bachelor's degree (54.1%). Over half of them worked in the private sector, including entrepreneurs and freelancers, while one-fourth were public workers, such as civil servants, state-owned enterprise employees, lecturers, and doctors. Moreover, about 39.3% were classified as having a middle-low income (IDR 5,000,001 to IDR 10,000,000), while 6.7% had no income.

Table 3-2 Socioeconomic and motorcycle riding characteristics (preliminary survey).

Socioeconomic - Gender	N	%
1: Male	89	65.9
2: Female	46	34.1
Socioeconomic - Age	**N**	**%**
1: 17 - 30 years old	117	86.7
2: 31 - 40 years old	13	9.6
3: 41 - 60 years old	4	3.0
5: > 60 years old	1	0.7
Socioeconomic - Occupation	**N**	**%**
1: Unemployed	6	4.4
2: Student	19	14.1
3: Government employee	37	27.4
4: Private sector	73	54.1
Socioeconomic - Education Level	**N**	**%**
1: Middle school or less	2	1.5
2: High school	13	9.6
3: Undergraduate	75	55.6
4: Graduate	45	33.3
Socioeconomic - Monthly Income	**N**	**%**
1: No income	9	6.7
2: ≤ IDR 5,000,000	41	30.4
3: IDR 5,000,001–IDR 10,000,000	53	39.3
4: IDR 10,000,001–IDR 15,000,000	22	16.3
5: > IDR 15,000,000	10	7.4
Driving - Commuter	**N**	**%**
1: Yes	123	91.1
2: No	12	8.9

Driving - Service Provider	N	%
1: Yes	51	37.8
2: No	84	62.2
Driving - Driving license ownership	**N**	**%**
1: Valid	117	86.7
2: Expired	8	5.9
3: None	10	7.4
Driving - Driving Age	**N**	**%**
1: < 3 year	17	12.6
2: 3 - 5 years	12	8.9
3: > 5 years	106	78.5
Driving - Driving Frequency	**N**	**%**
1: < 3 times/day	83	61.5
2: 3 - 5 times/day	43	31.9
3: > 5 times/day	9	6.7
Driving style	**N**	**%**
1: Risky	24	17.8
2: Steady	76	56.3
3: Conservative	35	25.9
Driving - Travel Purpose	**N**	**%**
1: Work	104	36.1
2: School	38	13.2
3: Recreational / Entertainment	36	12.5
4: Social activities	50	17.4
5: Groceries / Shopping	57	19.8
6: Other	3	1

Along with individual characteristics, the questionnaire survey was also circulated to identify the attitudes of motorcycle riders in planning and undertaking their mobilization in terms of route choice decisions, as well as the utilization of traffic information sources, as illustrated in Figure 3-7. It was found that about 3% of respondents never planned their route before departure, while 40.7% frequently and 39.3% always planned their trips in advance. Approximately two-thirds of riders often adjust routes in response to traffic circumstances, with only 2.2% rarely doing so. Concerning the use of traffic guidance, slightly more riders access particular sources before their ride than during it, supporting the study's premise that motorcycle riders often seek traffic information before or while riding.

Figure 3-8 depicts the extent to which motorcycle riders utilize various sources of traffic information when making decisions about their routes. The study discovered that mobile phone applications, such as Google Maps, are the most popular choice for monitoring real-time traffic conditions, with 52% of respondents using them before departure and 39% while riding a motorcycle on the road. Nearly one-third of the participants exhibit a tendency to choose travel routes based on direct observations, whereas the subsequent percentage of those who depend on street signs for route selection follows closely behind. A small fraction (0.44%) occasionally engages in conversations with acquaintances to gather information about possible routes before embarking on a trip.

Figure 3-7 The SP survey results on the attitude of motorcycle riders towards route choice.

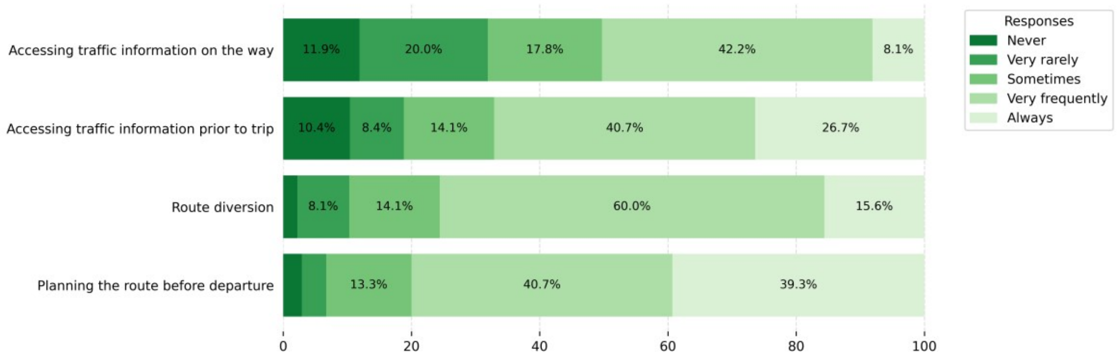
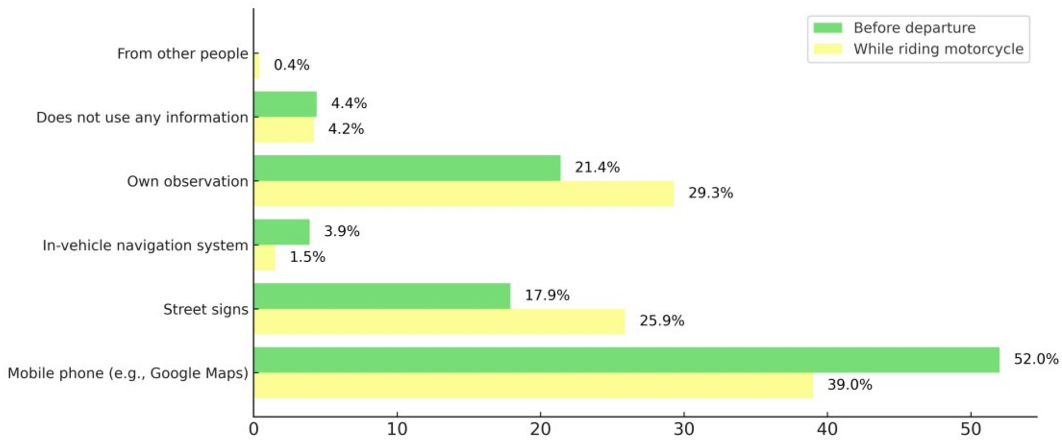


Figure 3-8 The SP survey results on sources of information about traffic conditions.



The survey results are then analyzed using cross-tabulation and hypothesis testing for categorical variables, as detailed in Table 3-3. From the SP hypothetical choices, 69% of respondents who are professional riders preferred the arterial (Route 1), while the rest chose Route 2. In addition, 91.7% of respondents who selected Route 1 were motorcycle commuters, while another 5.4% who were not. This preference likely stems from arterial roads experiencing fewer disruptions, leading to increased speed and capacity. Among those preferring Route 1, 33.4% frequently switch routes, and about half usually plan their trips prior to departure. Moreover, 52.8% gathered traffic information before riding, whereas more than half of those who chose Route 2 did not, likely due to greater familiarity with the local area. In terms of exposure to traffic reports when riding, only one-third who rarely access traffic data opt for Route 2, indicating a preference for the greater certainty of arterial routes with regard to time and space.

A nonparametric chi-square test was applied to verify whether the listed variables in Table 3-3 influence riders' route preferences. The null hypothesis (H_0) posits that the factors in the rows and the response variables in the columns (route preference for Route 1 or 2) are independent. This hypothesis can be rejected if two conditions are met: (1) the p-value is less than the significance level (α); and (2) the chi-square value (χ^2) exceeds its critical margin. The test reveals that, in this particular group, using motorcycles for service provision likely impacts route choice decisions. Similarly, riders' tendencies to observe traffic information sources, either before departure or during a trip, also relate to their route preferences. These findings suggest a need to further explore the correlation between these parameters and route choices by estimating discrete choice model specifications, elaborated in the next subsection.

Table 3-3 Cross-tabulation analysis of the riders' attitude towards route choice.

	Variables	Levels	Percentage	Route 1	Route 2	Total	Sig.	χ^2	Hypothesis Test
1	Motorcycle use for service providers	Yes	Count	176	79	255	0.04	3.98	Reject H_0 at 95% confidence interval
			% within *route choice*	69.0%	31.0%	100%			
			% within *variable 1*	40.6%	32.8%				
		No	Count	258	162	420			
			% within *route choice*	61.4%	38.6%	100%			
			% within *variable 1*	59.4%	67.2%				
2	Motorcycle use for commuting	Yes	Count	398	217	615	0.47	0.53	Cannot reject H_0 at 90% confidence interval
			% within *route choice*	64.7%	35.3%	100%			
			% within *variable 2*	91.7%	90.0%				
		No	Count	36	24	60			
			% within *route choice*	60.0%	40.0%	100%			
			% within *variable 2*	8.3%	10.0%				
3	Planning the route before motorcycle riding	Yes	Count	246	129	375	0.54	3.20	Cannot reject H_0 at 90% confidence interval
			% within *route choice*	65.6%	34.4%	100%			
			% within *variable 3*	56.7%	53.5%				
		No	Count	188	112	300			
			% within *route choice*	62.7%	37.3%	100%			
			% within *variable 3*	43.3%	46.5%				
4	Route switching tendency	Yes	Count	145	70	215	0.24	5.35	Cannot reject H_0 at 90% confidence interval
			% within *route choice*	67.4%	32.6%	100%			
			% within *variable 4*	33.4%	29.0%				
		No	Count	289	171	460			
			% within *route choice*	62.8%	37.2%	100%			
			% within *variable 4*	66.6%	71.0%				
5	Accessing traffic information before departure	Yes	Count	229	116	345	0.00	20.03	Reject H_0 at 95% confidence interval
			% within *route choice*	66.4%	33.6%	100%			
			% within *variable 5*	52.8%	48.1%				
		No	Count	205	125	330			
			% within *route choice*	62.1%	37.8%	100%			
			% within *variable 5*	47.2%	51.9%				
6	Accessing traffic information on the trip	Yes	Count	172	83	255	0.05	9.33	Reject H_0 at 95% confidence interval
			% within *route choice*	67.5%	32.5%	100%			
			% within *variable 6*	39.6%	34.4%				
		No	Count	262	158	420			
			% within *route choice*	62.4%	37.6%	100%			
			% within *variable 6*	60.4%	65.6%				

3.2.2 Route Choice Model

3.2.2.1 Model Structure

A discrete choice model was developed to estimate motorcycle rider behavior using the open-source discrete choice analysis tool, BIOGEME (Bierlaire, 2020), which adopts a random utility model. The preliminary SP survey provided respondents with two route options—Route 1 ("arterials") and Route 2 ("local road")—leading to the adoption of a logit model with binary specifications to assess the influence of predetermined attributes on their preferred route. The binary logit model was initially introduced to estimate the size and direction of the relationship between dependent and explanatory variables, due to its simplicity and ease of calculation. In this model, individual preferences are characterized by the attractiveness or utility of each alternative (Sheffi, 1985), where the decision maker is expected to choose the alternative with the highest utility. Equations (3.1) and (3.2) define the utility (U_{in}) of an individual n for alternative i, comprising a systematic component (V_{in}) and an additive error term (ε_{in}).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{3.1}$$

$$V_{in} = \beta' x_{in} = \sum_{k=1}^{K} \beta_k \, x_{ink} \tag{3.2}$$

where,

k : an index for observable variables

β : coefficient of the explanatory variable (marginal utilities)

x_{ink} : vector of explanatory variables k related to the alternative i by the individual n

Furthermore, the choice probability (P_{in}) of each alternative can be calculated by applying Equation (3.3) or, for the binary specifications, Equation (3.4).

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j=1}^{I} e^{V_{jn}}} \tag{3.3}$$

$$P_{in} = \frac{e^{V_{in}}}{e^{V_{in}} + e^{V_{jn}}} = \frac{1}{1 - e^{V_{jn} - V_{in}}} \tag{3.4}$$

While the binary logit model is straightforward to estimate, its independence of the IIA properties is considered irrelevant in route choice contexts, where substitution patterns require greater flexibility. McFadden and Train (2000) assert that the mixed logit is highly adaptable, capable of estimating any random utility model while addressing the IIA limitation of the standard logit. Further stated by Hess and Polak (2009), this sort of model structure accommodates random taste variation among individuals and accounts for serial correlations in repeated choice observations within panel data, leading to more accurate and reliable behavioral predictions compared to fixed-coefficient models. As a result, this study also proposed a mixed binary logit model to capture the correlations across alternatives, as commonly observed in route choice scenarios. This model specification in a binary response aligns with the method taken by Vacca et al. (2019), which will contribute to expanding the literature.

To address the assumption of the i.i.d. properties of the error term across alternatives i, individuals n, and time t, the stochastic component is decomposed into two additive parts. One component exhibits the correlation across alternatives and heteroskedasticity, while the other retains an i.i.d. extreme value distribution across alternatives and individuals, as represented in Equation (3.5). The inclusion of α_{in}, a random term with a zero mean whose distribution across motorcycle riders and route alternatives typically depends on underlying parameters and observable data, is intended to account for latent variables that remain consistent over time. Whereas ε'_{int} is a random term with zero mean that is independent of underlying parameters or data and is identically distributed across alternatives.

$$\varepsilon_{int} = \alpha_{in} + \varepsilon'_{int} \tag{3.5}$$

The utility that individual n derives from alternative i in choice situation t is transformed, as shown in Equation (3.6). The mixed logit model assumes a general distribution for the parameter α (taste of heterogeneity), which may take the forms of normal, lognormal, or triangular distribution and an i.i.d. extreme value for ε' properties (Hensher & Greene, 2003).

$$U_{int} = \beta' X_{int} + \alpha_{in} + \varepsilon'_{int} \qquad \forall\, i, t \tag{3.6}$$

Suppose there is an inertia in individual choices that drives them to stick with the previously selected alternative until the other alternative provides a higher utility, captured by Equation (3.7).

$$V_{int} = \alpha Y_{in(t-1)} + \beta X_{int} \tag{3.7}$$

where Y_{int} equals 1 if the individual n chose an alternative i in choice situation t, and 0 otherwise. The negative sign of α indicates that an individual gains higher utility by choosing a different alternative than in the last period. Train (2009) also emphasized that the lagged dependent variable $Y_{in(t-1)}$ is uncorrelated with the error term ε_{int} due to the nature of independence over time in the logit model.

In addition, the probability of the mixed logit model, which integrates the standard logit model over a specified distribution of random parameters, is expressed as follows (Hess & Polak, 2009).

$$P(n, i) = \int L_i(\beta, z_n) f(\beta|\theta)\, d\beta \tag{3.8}$$

where z_n is the matrix of the attributes of alternatives encountered by the individual n, while $f(\beta|\theta)$ is the density function of β given certain parameters of the distribution θ.

Finally, the function $L_i(\beta, z_n)$ portrays the probability of the conditional logit model, as demonstrated by Equation (3.9) below.

$$L_i(\beta, z_n) = \frac{e^{\beta' z_{ni}}}{\sum_{j=1}^{I} e^{\beta' z_{ni}}} \tag{3.9}$$

3.2.2.2 Estimation Results

The preliminary results of motorcycle riders' route choice behavior is summarized in Table 3-4. The models incorporate both the attributes of the alternatives and the socioeconomic variables of decision-makers. While the former can vary, the individual characteristics remain constant across alternatives and are integrated as main effects on the utility function of the second alternative (local road).

The first model, referred to as Model 1, includes generic attributes in a binary logit specification, without distinguishing distinctive features among alternatives. The estimation revealed that traffic flow conditions have a statistically significant impact on motorcycle riders' route choices, with an inverse relationship indicating greater disutility for routes with denser traffic volumes, aligning with the initial hypothesis. The positive sign of the Alternative-Specific Constant (ASC) implies that Route 1 (the main road) was selected more frequently than Route 2 (the local road). According to Hess and Polak (2009), when SP data is employed, the ASCs capture at least two effects: one is substantive effects related to actual preferences, and the other is linked to the SP survey design. However, when the ramp metering system was implemented and activated on Route 1, the waiting time a motorcycle rider must endure to access this route was found to be negligible, as it does not significantly influence riders' routing decisions. As a result, this variable was omitted from the models. The observed outcome might perhaps be attributed to the limited awareness among study participants, with only 17.8% having previously heard of ramp metering, and motorcycle riders are less likely to be bothered by a 5-minute wait on a ramp. Further studies are required to evaluate this particular attribute category on a larger scale.

In order to overcome the limitation of the binary logit model, the mixed logit model was adopted by introducing error terms that account for correlations between choices. This method effectively breaches the standard logit model's assumption of independent observations by allowing for correlated responses (Hensher & Greene, 2003). Withh only two alternatives offered, the mixture model is a mixed binary logit model, referred to as Model 2. The hypothetical stated choices questionnaire included multiple observations per participant, leading to serial correlations that share unobserved factors among these observations. Consequently, it became necessary to develop a model capable of accommodating a series of observed choices and their inherent correlations. Since the integral configuration of the mixed logit choice models generally lacks a closed-form solution, a Monte Carlo simulation with a specified number of draws was employed for parameter estimation. In this analysis, 2000 Halton draws (Halton, 1960) were used for parameter estimation in BIOGEME (Bierlaire, 2020), deemed sufficient, given the number of random parameters and the correlation between attributes and alternatives.

Table 3-4 Model estimation results from preliminary analysis.

	Model 1 (Binary logit)				Model 2 (Mixed binary logit)			
	Est.	t-test	Sig.		Est.	t-test	Sig.	
Estimated parameters								
Constant (ASC Route 1)	0.62	0.99	0.32		0.70	1.08	0.28	
Traffic flow conditions	-1.15	-4.09	0.00	***	-1.26	-4.27	0.00	***
Waiting time on the ramp	-0.26	-0.77	0.44	-	-0.27	-0.85	0.40	-
Individual characteristics								
Gender	-0.46	-2.34	0.02	**	-0.55	-2.12	0.03	**
Age group (17 – 30 years old)	-0.63	-2.27	0.02	**	-0.44	-0.56	0.57	-
Age group (31 – 40 years old)	-0.72	-1.98	0.05	**	-0.52	-0.59	0.56	-
Age group (> 60 years old)	2.26	2.66	0.01	***	2.68	3.18	0.00	***
Occupation (public servant)	-0.46	-2.04	0.04	**	-0.62	-1.39	0.16	-
Occupation (unemployed)	1.20	3.29	0.01	***	1.32	4.16	0.00	***
Education (middle high or less)	-1.54	-1.21	0.23	-	-1.69	-1.99	0.05	**
Education (senior high school)	-0.71	-1.94	0.05	*	-0.82	-1.60	0.11	-
Motorcycles for the service provider	-0.35	-1.82	0.07	*	-0.41	-1.79	0.07	*
Driving license ownership	-0.72	-2.50	0.01	***	-0.59	-1.53	0.13	-
Driving frequency	0.35	2.40	0.02	**	0.39	2.15	0.03	**
Travel purpose (work)	-0.42	-1.83	0.07	*	-0.58	-1.85	0.06	*
Driving style (conservative)	-0.60	-2.64	0.01	***	-0.68	-2.24	0.03	**
Error terms								
Panel effect - Route 1	-	-	-		-0.54	-2.15	0.03	**
Panel effect - Route 2	-	-	-		0.57	2.28	0.02	**
Model fit statistics								
Final log-likelihood			-369.287				-365.586	
Init log-likelihood			-467.874				-467.874	
Rho-square (init)			0.211				0.219	
Rho-square-bar (init)			0.174				0.178	
Akaike Information Criterion			772.574				769.172	
Bayesian Information Criterion			849.325				824.372	
Number of parameters			17				19	
Number of draws			-				1000	
Number of respondents			135				135	
Number of observations			675				675	

*** Significant at 1%, p-value (0.00–0.01); ** Significant at 5%, p-value (0.01–0.05); * Significant at 10%, p-value (0.05–0.10); - Not relevant

The results listed in Table 3-4 show that the agent effects included in the mixed binary logit model are significant for both routes, effectively capturing intrinsic correlations between observations from the same respondent. As expected, motorcycle riders generally prefer Route 1 over Route 2 to reach the destination, likely due to the common belief that major roads typically offer higher capacity and fewer traffic disruptions. In the case when a specific traffic policy aimed at smoothing traffic streams is applied, the estimated waiting time on the ramp to access an arterial road was found to be insignificant, mirroring the situation in Model 1. This implies that respondents did not consider the waiting time on the ramp to be a crucial attribute in their route preferences; hence, this variable was also excluded from the model. To summarize, the statistical parameters of the mixed binary logit model suggest that it outperforms the standard logit, as indicated by better-fitting values for key indicators such as log-likelihood, pseudo-R-squared (ρ^2), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Incorporating individual characteristics into the utility function further enhances model fit. Hypothesis testing results support this conclusion, showing that the restricted model can be rejected since the likelihood ratio exceeds the chi-square value (-2LL = 7.402; $\chi^2_{95\%,2}$ = 5.99).

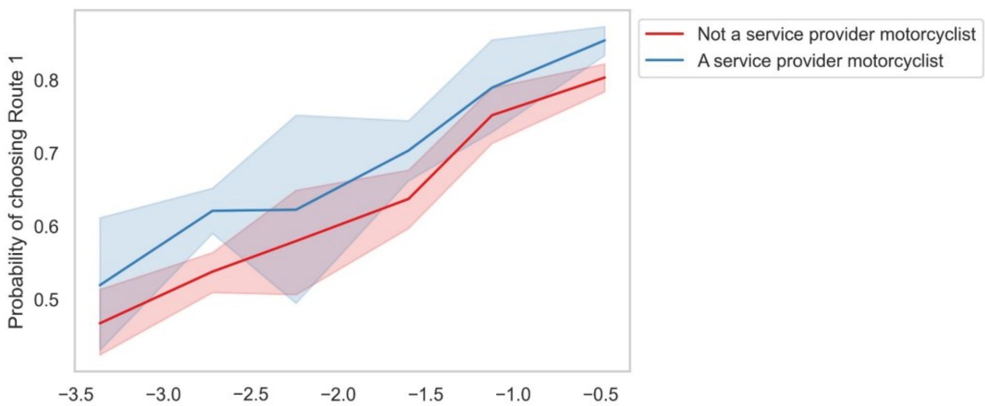
Table 3-5 Final results of motorcycle route choice model (Preliminary analysis).

	Est.	t-test	Sig.
Estimated parameters			
Constant (ASC Route 1)	0.28	0.55	0.58
Traffic flow conditions	-1.05	-7.33	0
Gender	-0.52	-1.92	0.055
Occupation (unemployed)	1.53	5.17	0
Education (middle-high school)	-1.45	-1.97	0.049
Motorcycles for the service provider	-0.50	-1.86	0.062
Driving frequency	0.36	1.99	0.046
Travel purpose (work)	-0.53	-1.66	0.097
Driving style (conservative)	-0.83	-2.67	0.008
Error terms			
Panel effect - Route 1	0.68	3.83	0
Panel effect - Route 2	-0.40	-0.45	0.041
Model fit statistics			
LL (β)		-370.921	
LL (ASC)		-467.874	
ρ^2		0.207	
Adjusted ρ^2		0.182	
AIC		765.841	
BIC		800.704	
Number of parameters		11	
Number of draws		2000	

Alternative-specific variance models were also tested using a normal distribution, but this approach did not reveal significant variance among alternatives. Thus, the null hypothesis—that the variance of unobserved components differs across alternatives—cannot be rejected, and the constants of each alternative are not randomly distributed. In addition, attempts were made to include random coefficients to capture taste variation across individuals. The traffic flow conditions variable was considered with both normal and lognormal distributions. Although the normal distribution model showed better statistical fit, it incorrectly suggested that 19.23% of respondents preferred routes with heavy traffic. On the other hand, assuming a lognormal distribution yielded a non-significant model specification, despite aligning with the expectation that people generally avoid congested routes. Ultimately, neither alternative-specific variance models nor random coefficients produced statistically significant estimates or improved the model fit for motorcycle riders' route choice behavior. The final model pertaining to this preliminary investigation is presented in Table 3-5.

This research categorizes individual characteristics into driving and socioeconomic factors. The model estimation reveals that gender, occupation, and education substantially affect motorcycle riders' route choices. In line with Dia and Panwai (2006), income levels do not appear to affect these decisions, possibly due to the diverse economic backgrounds of motorcycle users. The use of motorcycles for professional purposes, such as taxis or delivery services, strongly impacts route preferences, with a negative marginal utility indicating a tendency towards arterial routes. This preference, likely driven by the need for efficiency and reliability, is further supported by the probability logit curve in Figure 3-9, which shows a higher likelihood of choosing arterial routes within a 95% confidence interval. These riders prioritize reliable routes, even if it involves some waiting, whereas local streets, with their frequent intersections and interrupted traffic, are more prone to delays and unpredictable travel times.

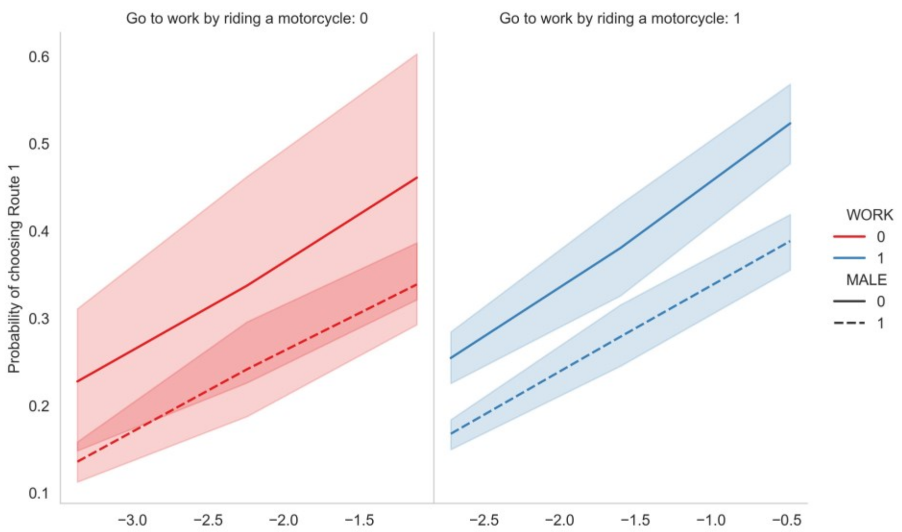
Figure 3-9 Probability of professional motorcycle rides selecting arterial roads.



In terms of driving characteristics, the study found that the average number of times a respondent rides a motorcycle daily influences their route choice behavior, as also observed by Choocharukul and Wikijpaisarn (2013) in a related study focusing on passenger cars. Individuals who engage in more regular motorcycle riding tend to show a stronger preference for the local road as opposed to the arterial route. This outcome is expected given that a significant proportion of participants (about 67%) who ride motorcycles more than five times daily rely heavily on specific traffic information sources. As a result, they are more likely to be exposed to VMS information that provides specific instructions for the duration of time motorcycle riders should wait at a designated on-ramp. Concerning driving style, conservative riders showed a strong preference for Route 1, as indicated by the negative coefficient in the model. This aligns with the expectation that cautious drivers choose less hazardous conditions. Supporting this, only 5.71% of conservative riders consistently alter their routes, and 62.86% usually plan their route before starting a trip. The chi-square test further confirms the link between driving style and route choice. It is important to acknowledge that 13.3% of participants lacked a valid license at the

A similar trend arises concerning the variable representing the riding purpose. The positive coefficient indicates that respondents who commute to work by motorcycle (indicated by the dummy variable) prefer arterial roads over local roads. This preference likely stems from the fact that individuals commuting to work cannot afford to be late, even when facing unforeseen circumstances. Moreover, the model estimates reveal that gender has a substantial effect on routing decisions, aligning with the conclusions drawn from prior research on car drivers (Yan & Wu, 2014; Zhong et al., 2012). Male riders exhibit a stronger preference for Route 1, and vice versa. From a gender and travel purpose standpoint, this may be explained by the fact that more than two-thirds of respondents commuting to work by motorcycle are male (64.5%), as are 54.9% of the professional riders surveyed. The chi-square test confirms a statistically significant relationship between gender and these variables. Figure 3-10 shows the probability of individuals riding motorcycles to work, which is also differentiated by gender (coded as 1 for male respondents; otherwise, 0), with the x-axis indicating the utility function of choice ($x_i\beta$).

Figure 3-10 Probability of selecting Route 1 based on travel purpose and gender.



3.2.3 Findings and Implications

The preliminary study successfully confirmed the existence of route choice behaviors among motorcycle riders and identified essential factors influencing these behaviors. Key findings from this analysis revealed that riders tend to avoid denser roads, highlighting the significant influence of traffic flow on route choice. Additionally, socioeconomic factors such as daily riding frequency, commuting purpose, riding style, gender, unemployment status, and education level significantly impacted route decisions. These insights emphasize the importance of considering both traffic conditions and individual characteristics in modeling their route choice behavior. The analysis also explored adapting the ramp metering concept for urban roads to manage motorcycle traffic flow by shifting delays and queues to the ramp. Nonetheless, model estimation indicated that waiting time on the ramp did not affect the route preferences of motorcycle riders. As this was an initial examination, further research is required to better understand and validate this traffic control strategy, incorporating a wider array of attributes.

However, the preliminary analysis identified several limitations. The alternative routes provided in the experimental design were insufficient for accurately reflecting the complex network topology typical of motorcycle-dependent areas. Additionally, the explanatory variables tested were still limited, necessitating further exploration of factors that may influence motorcycle route choices. To overcome the limitations, the expanded analysis discussed in the next section develops a hypothetical network structure with a broader range of alternative routes, more closely representing real-world conditions. It also expands the set of explanatory variables to include a wider array of road configurations, traffic conditions, and individual characteristics. Furthermore, the expanded analysis tests route switching behavior and dynamic routing decision models to better capture motorcycle riders' en-route decision-making in response to real-time traffic information. In summary, the findings from the preliminary analysis inform the expanded study, enabling the development of a more comprehensive model of motorcycle route choice behavior, which is essential for devising traffic management strategies.

3.3 Expanded Analysis of Motorcycle Route Choice Behavior

Building on the preliminary analysis in Section 3.2, this study refines the methodologies to overcome identified limitations, enabling a further analysis that provides deeper insights into behavioral patterns.

3.3.1 Methodology

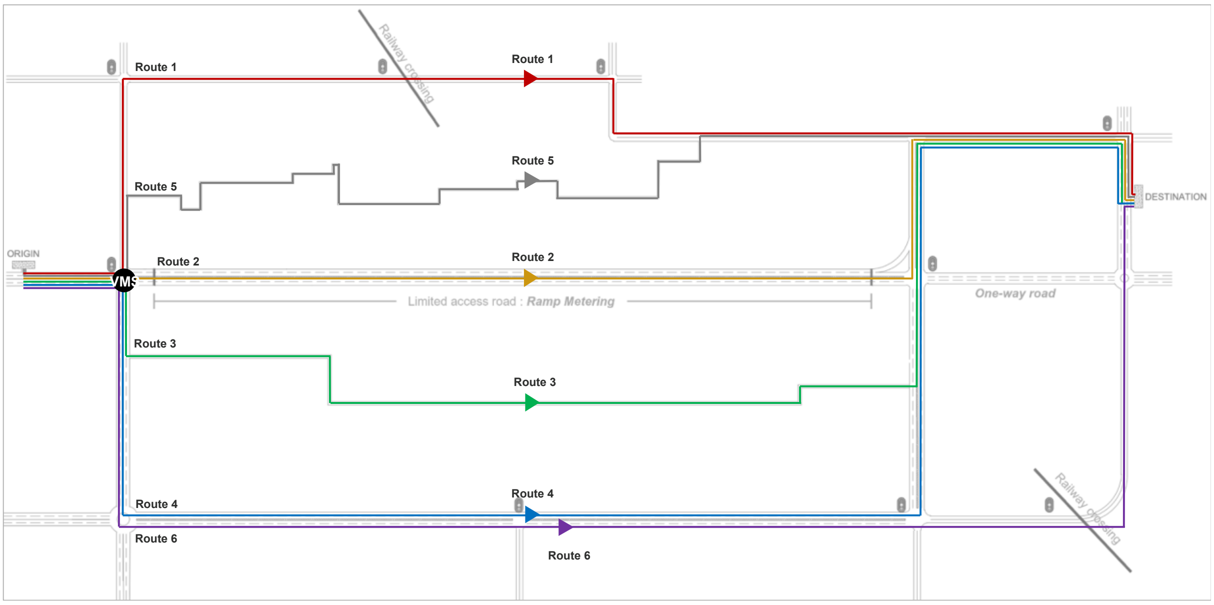
This section highlights the experimental design for the SP method, the data collection process, and the model structure applied in the expanded analysis of motorcycle riders' route choice behavior.

3.3.1.1 Experimental Design

A web-based SP was conducted with respect to the possibility of respondents better comprehending the questionnaire due to the more clearly articulated survey components (Ma et al., 2014). Numerous variables affect the route preferences of road users, for instance, individuals' perceptions of route attributes, preferences for these attributes, and specific decision rules (Li et al., 2014). In this case, three primary categories were considered about motorcycle riders' behavior: (1) route physical attributes (i.e., distance, road width, number of signalized junctions, and road features like the presence of railway crossings, and ramp metering); (2) trip properties (i.e., traffic conditions, travel time, delay); and (3) individual characteristics (socioeconomic and driving). It must be emphasized that several of the above-mentioned attributes are given to riders through VMS as traffic information is one of the main influences on the route selection (Bovy & Stern, 1990). Moreover, the selection of explanatory variables for the model was tailored to the distinct road network patterns of developing countries, which are characterized by numerous shortcut roads, often narrow and winding. This approach accounts for the unique properties of motorcycles, such as their small size, which enables them to pass through all types of roads easily.

In light of the above considerations, Figure 3-11 below shows the network configuration presented to the sampled motorcycle riders to analyze their preferred route.

Figure 3-11 Hypothetical networks in the SP experiment.



Wardman et al. (1996) emphasize that selecting route alternatives in the SP should ensure that the hypothetical network includes a variety of route configurations, a broad range of travel circumstances, and more thoroughly considered trade-offs between variables than in binary choices. Therefore, each proposed route incorporates a diverse combination of road types and attributes that attempt to closely replicate actual conditions. For instance, shortcut roads appear on Routes 3 and 5 in varying proportions, while Routes 2 and 4 offer the most extensive traffic capacity with minimal disturbances. Vehicles on Routes 1 and 6 must pass a railway crossing gate, a common traffic-delaying infrastructure in Indonesia, where over 400 crossings in Bandung alone contribute to delays and long queues, some of which are unattended. The VMS is strategically positioned at a specific distance from the intersection (as indicated by the marked black circle), with the assumption that all respondents are aware of the traffic conditions displayed. Respondents were then instructed to imagine themselves riding a motorcycle from home to their workplace, with six possible routes available, each characterized by the constant attributes listed in Table 3-6. Notably, every motorcycle rider in the study had access to the same set of route options.

Table 3-6 Attributes of route alternatives.

	Distance (km)	Avg. lane width (m)	Min. lane width (m)	Free-flow TT (mins)	Traffic signals	Ramp metering	Railway crossings	Shortcut roads
Route 1	4.25	3.68	3.25	5.50	4	No	Yes	No
Route 2	4.00	7.00	3.25	4.00	2	Yes	No	No
Route 3	4.75	3.60	2.00	7.00	3	No	No	Yes
Route 4	5.25	6.96	3.25	6.00	5	No	No	No
Route 5	4.50	2.57	1.25	8.00	2	No	No	Yes
Route 6	5.00	6.43	3.50	5.50	3	No	Yes	No

In addition to the attributes that remained constant in all SP observations, several route-specific properties were considered to predictably affect riders' routing decisions. These include traffic flow conditions, travel time, waiting time at on-ramps during ramp metering, duration of gate closures at railway crossings, and the number of motorcycles ahead on the route. Each attribute's relevance to the alternatives corresponds to the network topology shown in Figure 3-11, with a detailed breakdown in Table 3-7. Such attributes were statistically designed for the survey with unlabeled choices using R programming, following the Discrete Choice Experiments (DCE) method developed by (Aizaki et al., 2014). Hence, the variability in travel time for each observation and alternative was generated using the former method, acknowledging travel time's significant impact on route choic (Bovy & Stern, 1990).

Table 3-7 Alternative attributes and levels of attributes.

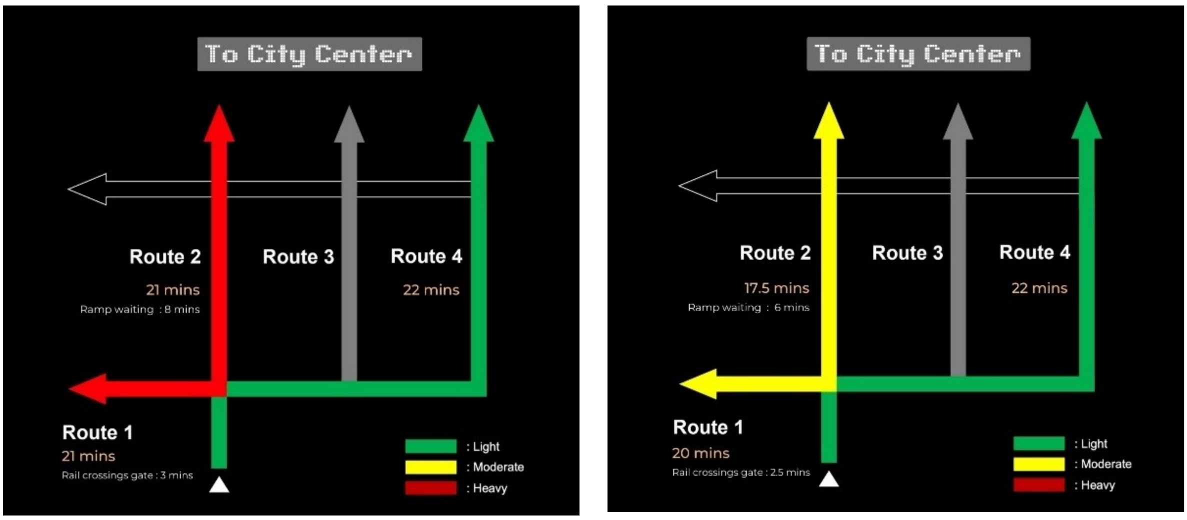
Attributes	Levels
Traffic flow conditions	0: unknown, 1: light, 2: moderate, 3: heavy
Waiting time at ramp metering	0: none, 1: 2.0 mins, 2: 4.0 mins, 3: 6.0 mins, 4: 8.0 mins
Delay in railway crossing gate closure	0: none, 1: 2.5 mins, 2: 3.0 mins, 3: 3.5 mins, 4: 4.0 mins
Traffic lights (minutes/cycle/intersection)	0: none, 1: 1.0 mins, 2: 1.5 mins, 3: 2.0 mins, 4: 2.5 mins
Traffic delay variability	0: +0%, 1: +2.5%, 2: +5.0%, 3: +7.5%, 4: +10.0%
Preceding motorcycles took the route	0: none, 1: 1 person, 2: 2-3 people, 3: 4-5 people, 4: >5 people

The experimental design initially included 768 attribute combinations, which were streamlined to 24 balanced observations. To prevent fatigue-related bias, the design was divided into three sets of questionnaires, each containing an equal number of queries, as presented in Table 3-8. Notably, Routes 3 and 5 are narrow alleys where it is presumed that the sensor equipment has not yet recognized the traffic performance. Unrealistic SP tasks with inadequate independent variations were promptly eliminated. The final design consisted of three sets, each with eight stated choices, randomly distributed to motorcycle riders in Bandung, who were then asked to select their preferred route in each scenario.

Table 3-8 Final experimental design.

		Traffic flow conditions				Travel time (mins)				Rail-cross delay (mins)		Ramp meter (mins)	Preceding riders
		R1	R2	R4	R6	R1	R2	R4	R6	R1	R6	R2	R5
Set 1	No.1	1	1	3	1	22.5	19.0	24.5	17.5	3.5	2.5	8	2
Set 1	No.2	2	3	1	2	25.5	18.5	21.0	19.0	3.0	3.0	4	4
Set 1	No.3	3	3	2	1	22.5	21.0	21.5	19.0	3.0	4.0	8	1
Set 1	No.4	2	3	2	3	21.0	14.0	20.5	20.0	2.5	3.5	4	4
Set 1	No.5	2	1	3	3	25.0	18.5	27.5	21.5	3.0	3.0	4	2
Set 1	No.6	3	1	3	2	22.0	17.5	21.5	18.0	4.0	3.0	6	3
Set 1	No.7	3	2	1	1	20.0	12.0	24.0	20.5	2.5	2.5	2	1
Set 1	No.8	1	2	2	2	26.5	20.0	24.0	21.0	3.5	3.5	6	3
Set 2	No.1	1	2	1	2	22.0	14.5	21.5	18.0	3.5	3.0	2	3
Set 2	No.2	3	2	2	2	23.5	19.0	21.0	17.0	3.5	3.5	8	4
Set 2	No.3	2	1	2	3	23.5	14.0	21.0	18.0	4.0	3.5	2	2
Set 2	No.4	1	3	3	1	24.5	18.5	20.5	17.0	3.5	2.5	6	2
Set 2	No.5	1	2	3	3	19.0	17.5	16.5	15.5	4.0	4.0	8	1
Set 2	No.6	3	1	1	3	23.0	15.0	24.0	20.5	4.0	2.5	4	3
Set 2	No.7	2	2	1	1	20.0	17.5	22.0	20.5	2.5	4.0	6	1
Set 2	No.8	1	1	2	1	22.0	13.0	23.0	21.0	3.0	2.5	2	4
Set 3	No.1	3	2	3	1	22.5	18.0	20.0	17.0	3.0	3.5	8	3
Set 3	No.2	2	1	1	3	18.5	18.5	22.5	17.5	2.5	4.0	6	4
Set 3	No.3	1	3	1	1	24.5	12.0	19.5	19.5	4.0	3.5	2	1
Set 3	No.4	2	3	3	3	22.0	15.5	20.0	18.0	4.0	2.5	4	3
Set 3	No.5	1	3	2	1	23.0	19.5	25.5	22.0	2.5	4.0	6	2
Set 3	No.6	3	1	2	3	24.5	14.0	24.0	22.0	3.5	4.0	4	2
Set 3	No.7	3	3	1	2	21.0	21.0	22.0	19.5	3.0	3.0	8	4
Set 3	No.8	2	2	3	2	19.5	13.0	24.0	20.0	2.5	3.0	2	1

Figure 3-12 Example of VMS information given in the SP experiment.



As established in the preliminary study (described in Section 3.2.1.1), the expanded experiment also employed a combination of graphic and text-based formats for VMS, as depicted in Figure 3-12. Time-related variables are displayed in minutes with respect to their significance; Long et al. (2021) revealed that road users tend to choose routes with the shortest indicated travel times over descriptively presented options. The color-coded map indicates traffic flow conditions: a green arrow signifies light traffic (volume capacity ratio less than 0.5), yellow indicates moderate traffic (volume capacity ratio between 0.5 and 0.8), and red denotes severe congestion (volume capacity ratio greater than 0.8), while a gray arrow marks shortcut routes not evaluated by ATIS devices for traffic performance.

3.3.1.2 Questionnaire Form

Following the design of the discrete choice experiment, three questionnaire sets were simultaneously distributed to randomly selected motorcycle riders in Bandung City from October 28 to 30, 2022. The distribution was facilitated by a professional panel agency, which also handled the screening and filtering process to ensure that respondents met the predetermined criteria for study participants. Each questionnaire comprised eight observations, along with the collection of respondent characteristics.

Figure 3-13 Questionnaire design for the main experiment.

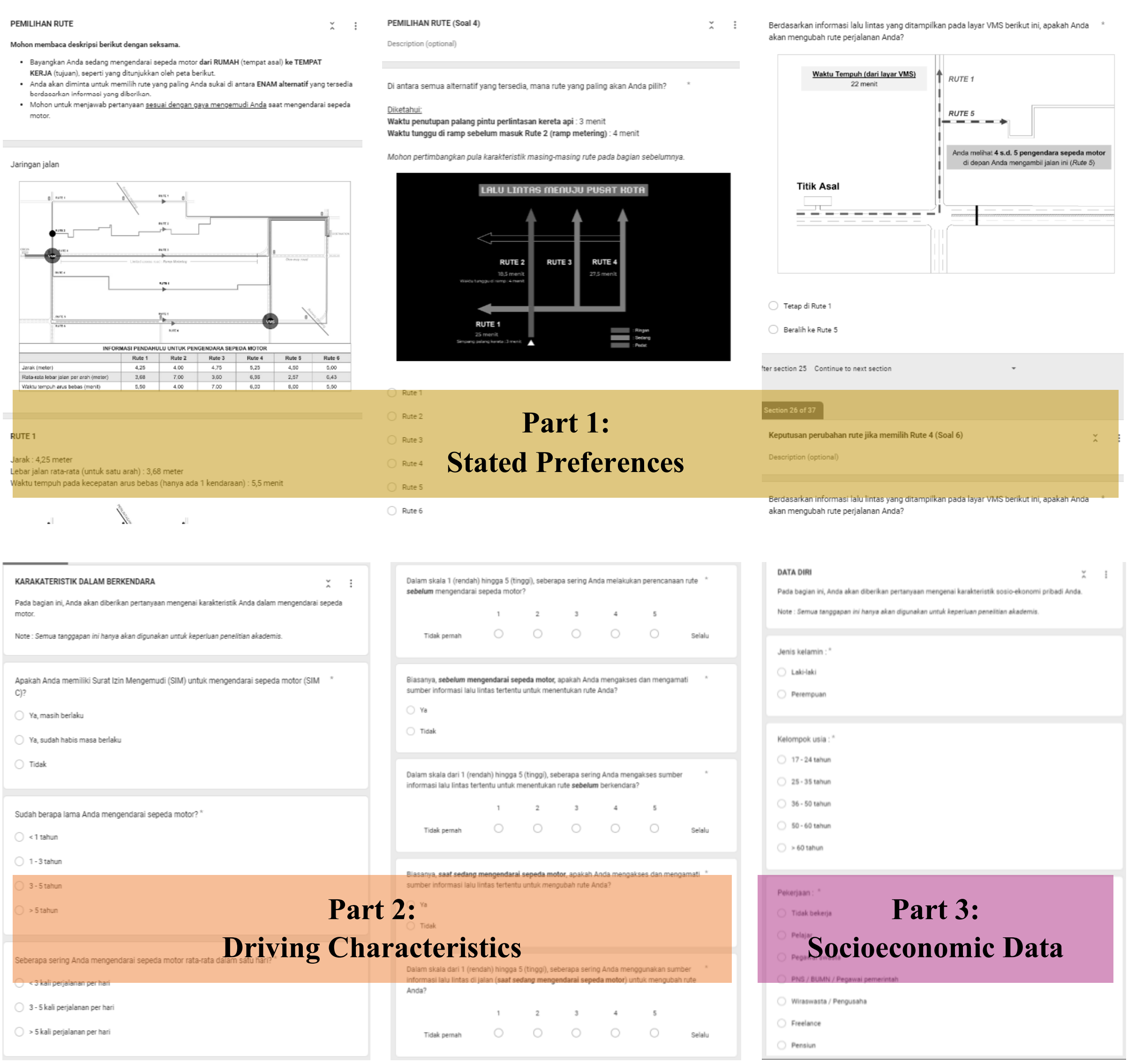


Figure 3-13 illustrates the structured questionnaire design used in the primary experiment. The layout is segmented into three distinct segments, the details of which are listed below.

1) **Stated Preference Experiments**: Each experiment varied key factors such as trip duration, traffic conditions, and delays from ramp meters or railway crossings.
2) **Motorcycle Riding Characteristics**: This includes questions like riding experience, motorcycle use frequency, license ownership, riding style, travel purposes, and exposure to traffic information.
3) **Personal Data Collection**: The final section gathers basic personal data, focusing on socioeconomic attributes like gender, age, occupation, educational background, and income levels.

3.3.1.3 Sample Characteristics

The overall socioeconomic characteristics of the 301 sampled motorcycle riders are comprehensively summarized in Table 3-9, providing a detailed breakdown of the demographic data collected.

Table 3-9 Socioeconomic and motorcycle riding characteristics (expanded survey)

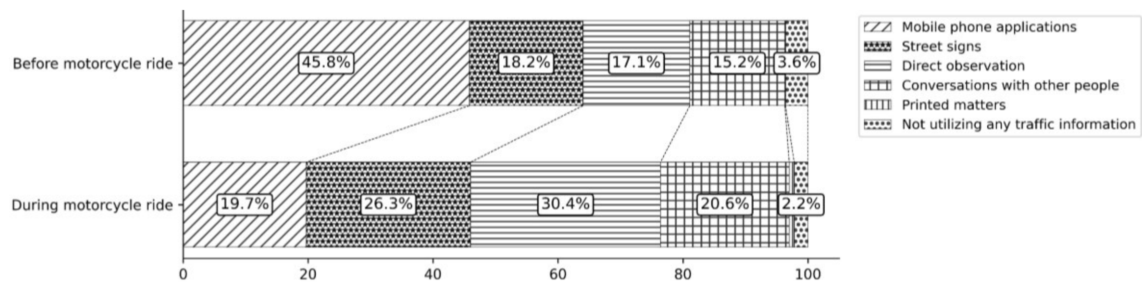
Socioeconomic - Gender	N	%	Driving - Commuter	N	%
1: Male	104	34.6	1: Yes	291	96.7
2: Female	197	65.5	2: No	10	3.3
Socioeconomic - Age	N	%	Driving - Service Provider	N	%
1: 17 - 24 years old	151	50.2	1: Yes	117	38.9
2: 25 - 35 years old	94	31.2	2: No	184	61.1
3: 36 - 50 years old	41	13.6	Driving - Heard about VMS	N	%
4: 51 - 60 years old	13	4.3	1: Yes	195	64.8
5: > 60 years old	2	0.7	2: No	106	35.2
Socioeconomic - Occupation	N	%	Driving - Heard about Ramp Metering	N	%
1: Unemployed	13	4.3	1: Yes	166	55.2
2: Student	110	36.5	2: No	135	44.9
3: Government employee	12	4.0	Driving - Driving license ownership	N	%
4: Private sector	107	35.6	1: Valid	260	86.4
5: Freelancer	32	10.6	2: Expired	11	3.7
6: Self-employed	25	8.3	3: None	30	10.0
7: Retired	2	0.7	Driving - Driving Age	N	%
Socioeconomic - Education Level	N	%	1: < 1 year	32	10.6
1: Middle school or less	16	5.3	2: 1 - 3 years	97	32.2
2: High school	168	55.8	3: 3 - 5 years	79	26.3
3: Undergraduate	111	36.9	4: > 5 years	93	30.9
4: Graduate	6	2.0	Driving - Driving Frequency	N	%
Socioeconomic - Monthly Income	N	%	1: < 3 times/day	139	46.2
1: No income	68	22.6	2: 3 - 5 times/day	117	38.9
2: ≤ IDR 5,000,000	168	55.8	3: > 5 times/day	45	15.0
3: IDR 5,000,001–IDR 10,000,000	48	16.0	Driving - Travel Purpose	N	%
4: IDR 10,000,001–IDR 15,000,000	15	5.0	1: Work	169	32.5
5: > IDR 15,000,000	2	0.7	2: School	119	22.9
Socioeconomic - Transport Expense	N	%	3: Recreational / Entertainment	101	19.4
1: ≤ IDR 1,000,000	213	70.8	4: Groceries / Shopping	125	24.0
2: IDR 1,000,001–IDR 3,000,000	78	25.9	5: Children's drop-offs/pick-ups	5	1.0
3: IDR 3,000,001–IDR 5,000,000	10	3.3	6: Go to the nearest shop/stalls	1	0.2

Over two-thirds of the respondents are female (65.45%), slightly higher than the proportion of female residents within the legal driving age in Bandung city (49.90%). However, due to the lack of publicly accessible data on the statistical characteristics of motorcycle riders in Indonesia, sample validation and verification cannot be performed. The questionnaire forms were primarily completed by motorcycle riders aged between 17 and 24 years, with more than one-third identifying as students. a diverse range of occupations, with 35.55% working in the private sector, 10.63% as freelancers, 8.31% as self-employed (e.g., entrepreneurs), and 3.99% as public servants, alongside a small percentage who are unemployed or retired. Over half of the respondents had completed high school, and 36.88% held a bachelor's degree. Regarding personal income, more than half earned less than IDR 5,000,000 per month; meanwhile, approximately 23% had no income during the survey. Therefore, most riders allocate transportation expenditures less than IDR 1,000,000 per month, and none spend above IDR 5,000,000.

In addition, Table 3-9 illustrates respondents' characteristics related to their motorcycle usage. Of the 301 survey participants, only ten are not regular commuters—those who typically ride between home and work. This is in accordance with the predominant purposes of motorcycle use, which are to travel to work (32.50%), school (22.88%), and the grocery store (24.04%). Some also ride motorcycles for leisure activities (19.42%) and drop off and pick up children from school, which is very common in Indonesia. Moreover, approximately 38.87% use motorcycles professionally as service vehicles, for example, motorcycle taxis and delivery couriers, which have become increasingly widespread in Indonesia during the last five years to transport people, goods, or food. Concerning awareness, about 64.78% and 55.15% of respondents have heard about VMS and ramp metering, respectively. The distribution of driving ages among motorcycle riders is relatively balanced, except for those with less than one year of experience, who account for only 10% of respondents. Regarding driving frequency, nearly half ride motorcycles fewer than three times a day, while 38.87% ride between three and five times daily. The majority hold a valid driving license, though nearly 10% have never obtained one.

Regarding information exposure, the study found that a significant portion of respondents—approximately 80% before the trip and 78% during the trip—access certain sources. Figure 3-14 illustrates the diversity of these information types and the distinct patterns of access during each period.

Figure 3-14. Sources of traffic information utilized before and during the motorcycle ride.



Before embarking on their trip, most surveyed motorcycle riders rely on smartphone applications like Google Maps for effective route planning, underscoring the convenience and accessibility of digital navigation tools during the preparation phase. In contrast, preferences for traffic information sources during the trip shift significantly. Direct observations become the primary information source, as the ability to visually assess traffic conditions in real time allows riders to make quick decisions and adapt to changing situations. Following direct observations, motorcycle riders rely heavily on street signs to navigate their route, highlighting the importance of clear and accurate signage for providing real-time guidance. It is important to note that the limited use of smartphones for real-time information during the trip is often due to the challenges and safety concerns associated with accessing such data while riding. Meanwhile, in-vehicle navigation systems are not commonly equipped in motorcycles in Indonesia.

3.3.2 Route Choice Model (Path-based Analysis)

3.3.2.1 Model Structure

The process of modeling route choice behavior begins with identifying various route alternatives and creating a choice set, as outlined in the preceding subsection. The MNL model is the most commonly used for route choice analysis. Standard logit models operate under two primary assumptions: (1) the error components adhere to the Gumbel distribution (extreme value type I), and (2) they are identically and independently distributed, with uniform fixed variances (Sheffi, 1985) across alternatives. These assumptions, however, limit the model's ability to capture correlations between different route options. The utility function (U_{in}) of the standard logit model is derived by computing marginal utilities from a range of explanatory variables. The formulation of these utilities aligns with Equations (3.1) and (3.2), which are essential for quantifying the utility or preference associated with each route alternative, considering the evaluated attributes of the routes and the individual characteristics of motorcycle riders.

Despite the simple calculation of the MNL model, this approach restricts the assumption that the error terms are i.i.d. extreme value type 1 following Gumbel distribution, which is not appropriate for predicting route choice behavior since it cannot account for similarities across route alternatives (Bekhor et al., 2002). Thus, the modification of the standard logit in the form of C-logit and PSL models included a correction of the utility for overlapping paths in an effort to overcome this shortcoming. Frejinger and Bierlaire (2007) reported that the PSL model with the generalized PS formulation statistically surpasses the C-logit estimate with the utility expressed in Equation (3.10).

$$U_{in} = V_{in} + \beta_{PS} \ln PS_{in} + \varepsilon_{in} \tag{3.10}$$

where,

β_{PS} : coefficient of path-size correction
PS_{in} : path-size factor for route i and motorcyclist n

The attribute of path size, which was derived directly from route alternatives and the geometry of network configurations, can be defined as an original or generalized formulation, as specified in Equations (3.11) and (3.12), respectively (Frejinger & Bierlaire, 2007).

$$PS_{in} = \sum_{a \epsilon \Gamma_i} \frac{L_a}{L_i} \frac{1}{\sum_{j \in C_n} \delta_{ai}} \tag{3.11}$$

$$PS_{in} = \sum_{a \epsilon \Gamma_i} \frac{L_a}{L_i} \frac{1}{\sum_{j \in C_n} \left(\frac{L_i}{L_j}\right)^{\varphi} \delta_{ai}} \tag{3.12}$$

where,

Γ_i : set of all links of the route i,
L_a : length of the link a,
L_i : length of the route i,
C_n : choice set for the motorcycle rider n,
δ_{ai} : link and route incidence dummy, equals 1 if the link a is on route i and otherwise, and
φ : positive scaling term for adjusting the effect of overlapping routes.

Further emphasized by Frejinger and Bierlaire (2007), the IIA property of the standard logit is not suitable for route choice problems in light of the inevitability of overlapping paths, prompting the development of variants or generalizations of the model specifications. The study explored the MXL model—an extension of the MNL model, comparing its efficacy with the MNL and PSL models. Duncan et al. (2020) described how MXL models address route correlations by separating random error terms into two components: (1) i.i.d. extreme value variables, maintaining the logit structure, and (2) Gaussian distributed variable terms, capturing the interdependencies among routes. This is intended to relax the assumption that i.i.d. error terms are independent across alternatives, individuals, and time.

A wide variety of MXL specifications can be estimated, including the logit kernel, random parameter, error component, heteroskedastic, and hybrid logit (Duncan et al., 2020), depending on where the variances of random terms are allowed. Hence, the MXL model was claimed to be a highly adaptable discrete choice model that can approximate any random utility model and is easily generalized to account for multiple choice observations, such as those seen in panel data (McFadden & Train, 2000). The MXL model does not possess a closed-form expression, as it is derived from the integrals of standard logit probabilities over a density of parameters (Train, 2009). Consequently, solving the route choice probabilities of the MXL model necessitates a simulation computation, such as Monte Carlo. Equation (3.13) shows the choice probability of the MXL model assessed at β's with the mixing distribution of $f(\beta|\theta)$, where θ represents the parameter distribution of variables.

$$P_{in} = \int L_{in}(\beta)\, f(\beta|\theta)\, d\beta \tag{3.13}$$

$$L_{in}(\beta) = \frac{e^{\beta' X_{in}}}{\sum_{j=1}^{J} \beta' X_{jn}} \tag{3.14}$$

where,

$L_{in}(\beta)$: the probability of the standard logit at parameters β

$f(\beta)$: a density functions

In the case where utility is linear in β, then the $V_{in}\beta$ can be substituted to $\beta' X_{in}$. As a result, the probability of the MXL model is modified as follows (Train, 2009).

$$P_{in} = \int \left(\frac{e^{\beta' X_{in}}}{\sum_j e^{\beta' X_{jn}}} \right) f(\beta)\, d\beta \tag{3.15}$$

The issue of overlapping paths in route choice analysis introduces error components that capture correlations among the utilities for various alternatives, as indicated in Equation (3.16) (Train, 2009). Nonetheless, implementing this type of MXL model, which categorizes alternatives that share the unobserved attributes, will predictably restrict the applicability of the estimated parameter results on real networks, for instance, to calibrate and validate the simulation model as the network may be modified. For this reason, Multivariate Extreme Value models, such as nested logit and cross-nested logit, were also not explored for estimating riders' route preferences in these unlabeled choices.

$$U_{in} = \beta' X_{in} + \mu_n' z_{in} + \varepsilon_{in} \tag{3.16}$$

where,

μ_n : a vector of random terms with zero mean

z_{in} : error components of the utility of route i for motorcycle rider n

As a result, heteroskedastic logit was adopted to generate a better estimate of the route choice behavior of motorcycle riders by enabling the variance of unobserved factors to differ for each alternative. The estimation was performed using the open-source BIOGEME software (Bierlaire, 2020). The utility function is substantially identical to what is specified in the MNL model (see Equation 1), except for the fact that ε_{in} is distributed independently of extreme value with variance $(\theta_i \pi)^2/6$ (Train, 2009). The choice probabilities for this model can be calculated with Equation (3.17) (Bhat, 1995).

$$P_{in} = \int \left[\prod_{i \neq j} e^{-e^{-\left(V_{in} - V_{jn} + \theta_i w\right)/\theta_j}} \right] e^{-e^{-w}} e^{-w}\, dw \tag{3.17}$$

where,

w : $\varepsilon_{in}/\theta_i$

$e^{-e^{-w}} e^{-w}$: extreme value density

3.3.2.2 Estimation Results

The analysis of motorcycle riders' route choices initially started by estimating a classic MNL model based on the stated preference experiment. In contrast to a labeled DCE, in which an attribute can be an alternative-specific attribute, the application of unlabeled choice experiments requires only generic parameters (Aizaki et al., 2014). Therefore, in estimating the route choice behavior of motorcycle riders for this study, the alternative-specific parameters that distinguish explanatory variables across alternatives in utility functions were not considered. Frejinger (2008) asserted that a route choice model could investigate the perceptions of road users toward different route attributes and individual characteristics. Further emphasized by Zhao et al. (2020), driver characteristics have a notable influence on their routing decisions under various traffic information provisions. Hence, the socioeconomic and riding characteristics of the 301 sampled motorcycle riders in the SP experiment were incorporated into the systematic utility as either interaction or main effects, intended to capture the taste of heterogeneity across individuals. It should be highlighted that, unlike route properties, the characteristics of the decision-makers do not vary among the alternatives.

Greene and Hensher (2007) noted two main issues with the MNL model. First, the assumption of the i.i.d. extreme value type I is exceedingly restricted and leads to the IIA property of the model. Next, the standard logit model is incapable of capturing choice heterogeneity that is not reflected in individual characteristics and i.i.d. disturbances. In fact, the variance of the error term might arise depending on the geographic regions, data sets, time, or other factors (Train, 2009). Since the MNL model assumes that riders interpret each route as a different independent alternative, further extension of the MNL model was necessary to address these concerns. The PSL model was initially estimated to correct the overlapping links between routes, which is unavoidable in the case of route choice analysis. Nevertheless, the PSL model retains the characteristics of the standard logit, including the irrelevant IIA property. Consequently, the model was then modified and improved into the MXL model in light of its capacity to account for observed and unobserved heterogeneity from a different range of sources. The overall scale of utility was established by normalizing one of the variances and then estimating the remaining variances with the normalized one (Train, 2009).

Table 3-10 presents a comparative summary of estimation results for the route choice behavior of motorcycle riders under the VMS environment, utilizing the abovementioned distinct models (see Figure 3-11). These estimations employed a new flattening panel data feature of BIOGEME 3.2.10 (Bierlaire, 2020), which can address potential serial correlation from multiple survey observations for a single individual. The first model provided is the MNL with 20 parameters for 2408 observations, not accounting for unobserved random terms. The second, a PSL model with 21 parameters, addresses the critical issue of overlapping paths in route choice analysis. The third model represents a mixed PSL incorporating 26 parameters, where the ASCs are assumed to be randomly distributed, allowing the unobserved components of each alternative to have a different variance. This approach relaxes the traditional assumption that all alternatives share identical error distributions, instead enabling the error components for every alternative to be independent. For identification purposes, the overall utility scale was derived by normalizing the ASC of Route 1 into zero. This route was selected as a benchmark due to its minimum variance, with estimates for the remaining alternatives calculated relative to Route 1. The significant standard deviations of ASCs indicate the presence of unobserved preference heterogeneity among respondents for specific routes. These ASCs reflect the tendency of each route when all other variables are at their baseline, representing the baseline utility of selecting a particular route before considering other attributes. A negative ASC for a route implies a baseline aversion toward that alternative when other attributes are held constant. It is also noteworthy that the standard deviations for the alternatives are generally larger than their mean values, suggesting that treating the high variability in ASCs as random variables rather than fixed constants might yield a more accurate representation. Meanwhile, the negative sign of the ASC standard deviations is irrelevant, as the variance of the distribution corresponds to the square of the parameter.

Table 3-10 Path-based model estimation results from expanded analysis (t-value in the parentheses).

Estimated Parameters	MNL		PSL		Mixed PSL	
Constants						
ASC (Route 1)	-		-		-	
ASC (Route 1) standard deviation	-		-		-	
ASC (Route 2)	-1.48 (-7.11)	***	-1.31 (-5.30)	***	0.21 (0.72)	-
ASC (Route 2) standard deviation	-		-		0.58 (5.56)	***
ASC (Route 3)	-3.43 (-12.22)	***	-3.31 (-9.06)	***	-4.82 (-12.96)	***
ASC (Route 3) standard deviation	-		-		1.89 (8.70)	***
ASC (Route 4)	0.75 (5.85)	***	0.66 (5.38)	***	1.76 (10.91)	***
ASC (Route 4) standard deviation	-		-		0.68 (5.23)	***
ASC (Route 5)	-3.64 (-11.5)	***	-3.28 (-7.88)	***	-4.83 (-12.56)	***
ASC (Route 5) standard deviation	-		-		1.24 (9.48)	***
ASC (Route 6)	-0.67 (-7.18)	***	-0.62 (-6.79)	***	-0.03 (-0.22)	-
ASC (Route 6) standard deviation	-		-		-1.23 (-6.89)	***
Road attributes						
Distance (kilometers)	-2.01 (-23.18)	***	-1.96 (-14.83)	***	-1.93 (-12.31)	***
Minimum road width per direction (kilometers)	4×10^{-4} (15.22)	***	4×10^{-4} (13.89)	***	0.02 (2.75)	***
Traffic flow conditions	-0.97 (-24.44)	***	-0.97 (-24.44)	***	-1.08 (-16.79)	***
Average travel time (minutes)	-0.10 (-4.75)	***	-0.10 (-4.75)	***	-0.10 (-4.88)	***
Waiting time at a ramp meter (minutes)	-0.08 (-3.86)	***	-0.08 (-3.87)	***	-0.09 (-4.46)	***
Interaction effects						
Shortcut portions (given the motorcycle's use as a service vehicle)	0.47 (2.48)	***	0.52 (2.71)	***	0.72 (1.87)	*
Number of preceding motorcycles (given a male rider)	0.16 (3.54)	***	0.14 (2.90)	***	0.11 (1.67)	*
Railway crossing delay (given a rider plans a route before a trip)	-0.11 (-2.70)	***	-0.11 (-2.70)	***	-0.08 (-1.44)	-
Number of signalized junctions (given riding age of < 3 years)	-0.13 (-3.37)	***	-0.14 (-3.51)	***	-0.13 (-2.51)	**

Estimated Parameters	MNL		PSL		Mixed PSL	
Socioeconomic characteristics						
Riding > 5 times/day (towards the non-ramp metering routes)	-0.24 (-1.86)	*	-0.25 (-1.89)	*	-0.22 (-1.31)	-
Age group (17 - 24 years old) toward shortcut roads	0.02 (0.12)	-	0.54 (2.82)	***	0.04 (0.15)	-
Age group (25 - 35 years old) toward shortcut roads	0.18 (1.16)	-	0.09 (0.63)	-	0.25 (1.04)	-
Age group (36 - 50 years old) toward shortcut roads	0.41 (2.35)	**	0.13 (0.74)	-	0.54 (1.84)	*
Age group (51 - 60 years old) toward shortcut roads	-0.91 (-2.83)	***	-1.18 (-3.20)	***	-1.08 (-1.96)	*
Age group (> 60 years old) toward shortcut roads	-6.78 (-24.86)	***	-7.39 (-23.83)	***	-9.31 (-14.11)	***
Overlapping path correction						
Path-size factor	-		0.46 (6.14)	***	0.941 (12.09)	***
Model fit statistics						
Null log-likelihood (LL_0)	-7331.210		-7331.210		-	
Initial log-likelihood (LL_{ASC})	-4314.557		-4314.557		-4314.557	
Final log-likelihood (LL_β)	-3394.072		-3390.095		-2921.405	
Likelihood ratio test (LLR_β)	1840.969		1848.924		2786.303	
Rho-square (ρ^2)	0.213		0.214		0.254	
Rho-square-bar (adjusted ρ^2)	0.209		0.210		0.248	
Akaike Information Criterion (AIC)	6828.144		6822.189		6492.090	
Bayesian Information Criterion (BIC)	6943.875		6943.707		6588.475	
Number of parameters	20		21		26	
Number of respondents	301		301		301	
Number of observations	2408		2408		2408	
Number of draws	-		-		1000	

*** Significant at 1%, p-value (0.00–0.01); ** Significant at 5%, p-value (0.01–0.05); * Significant at 10%, p-value (0.05–0.10); - Not relevant

The standard logit model was first developed as a benchmark for upgrading the model's fit. Referring to the statistical parameters of the three models presented in Table 3-10, it was found that the PSL slightly outperforms the MNL model in characterizing the route choice behavior of motorcycle riders, which was initially pointed out by the higher adjusted pseudo-R-square (ρ^2) parameter, as well as lower AIC and BIC values. At the final convergence, the log-likelihood of the MNL and PSL models are -3394.072 and 3390.095, respectively, necessitating a likelihood ratio test to statistically confirm the hypothesis by accounting for both restricted and unrestricted models, as shown in the equation below.

$$-2\left(L(\hat{\beta}_R) - L(\hat{\beta}_{UN})\right) \sim \chi^2 \tag{3.26}$$

At a 5% significance level, the PSL model demonstrated a significantly better fit than the MNL, with an LRT value of 7.954, surpassing the critical chi-square threshold ($\chi^2_{95\%,1}$= 3.84). The path-size correction term, incorporated to account for correlations between routes, proved significant and enhanced the accuracy of behavior predictions. This underscores the necessity of addressing route correlations to avoid biased demand estimates and misguided policies. However, it was believed that the likelihood estimation of the PSL model remained overestimated, although the multiple observations for a single respondent have been relaxed by the flattening panel data. The mixed PSL was then introduced by permitting the variance of error terms for each alternative to be distributed differently, as indicated by the addition of standard deviations of ASCs. As with the PSL model, a likelihood ratio test was also performed to establish the validity of the hypothesis that the model was better fitted than the first two previous models. With a final log-likelihood of -3390.095 for the PSL model and -3220.045 for the mixed PSL model, the test finally concludes that the null hypothesis cannot be rejected, and the latter yielded statistically better estimates (-2LL = 340.1; $\chi^2_{95\%,2}$= 11.07). The model increased the overall goodness-of-fit of the MNL and PSL models, as demonstrated by the higher adjusted pseudo-R-square (ρ^2) parameter of 0.248. It is worth mentioning that multiple model structures were assessed to accurately estimate the route choice model of motorcycle riders. Nonetheless, the model with the underlying assumption that the ASCs are randomly distributed while also consider thecorrection of overlapping paths has proven to be particularly effective in capturing the complexities of route selection.

The MNL model estimation results indicate that path distance significantly impacts riders' route preferences, with the negative coefficient signifying a strong disutility for longer routes, consistent with previous studies (e.g., Ghanayim & Bekhor, 2018; Ton et al., 2017). Traffic conditions displayed on VMS also substantially impacted route choices, confirming a general preference for avoiding denser traffic. Travel time was also found to be a significant factor, aligning with Ardeshiri et al. (2015). It is important to note that the free-flow travel time variable was not incorporated in the model due to its strong correlation with other attributes, as was initially hypothesized. The results of the magnitude of marginal utility between travel time and traffic flow conditions, however, contradicted the findings of Xu et al. (2011). It was observed that travel time information presented by the VMS had a higher impact on drivers' route choices than traffic congestion, but the current research disclosed the opposite. This may be because a color-coded display of real-time traffic performance in the VMS enables drivers to interpret and react more quickly than a text-based format for travel time, facilitating the process of riders making trade-offs among alternatives. Additionally, the time spent waiting at on-ramps for arterial access on Route 2 was statistically significant, with a negative value indicating a preference for shorter waits. Nonetheless, the preliminary study determined that this attribute did not affect motorcycle riders' route choices due to the attribute levels being too tight and not having enough scatter. Other potential delays, such as the duration of traffic signal cycles, did not significantly influence route choice behavior.

Despite the flexibility and accessibility motorcycles offer in terms of size and maneuverability, riders generally prefer broader roads. On the contrary, respondents who ride motorcycles for service professions have a positive marginal utility value toward shortcuts, driven by the need to save time as their jobs often require quick pickups and drop-offs. Among respondents who plan their routes before starting a trip (about 86%), the duration of rail crossing gate closures significantly impacts their routing decisions, with a negative covariate indicating a disutility towards longer waiting times. Likewise, riders with less than three years of experience tend to avoid routes with multiple signalized intersections, likely to steer clear of stop-and-go traffic and the additional cognitive effort required. This aligns with the initial belief that riders prefer to avoid delays. The analysis also reveals that male riders are more inclined to follow routes with a higher number of motorcycles ahead on the same path, possibly indicating a greater trust in following other road users, irrespective of their familiarity with the route or or awareness of its traffic conditions. These findings are crucial for identifying specific patterns among targeted VMS users and will be instrumental in succeeding analyses of VMS implementation on urban roadways.

As age group variables linked with the systematic utility of Routes 3 and 5, parameters disclosed that riders over 50 prefer routes with fewer shortcuts. This preference may stem from the nature of shortcut routes in Indonesia, which often include alleyways and narrow roads through residential areas, traditional markets, or along riverbanks. These routes, while less congested, are prone to disruptions from items, people, animals, carts, or other motorcycles, affecting traffic safety. Conversely, the positive coefficients for younger age groups indicate a preference for routes with a higher proportion of shortcuts. Nonetheless, since this study only considers shortcut roads in terms of size and space, further studies should explore additional shortcut characteristics, such as land use, roadside activity, the existence of bridges, and other obstacles that may influence route choice. Furthermore, riders with high mobility exhibit a disutility for routes with ramp metering due to the mandatory waiting times imposed by this traffic management scheme, which could increase overall travel time despite the road's larger capacity. In contrast to Zhao et al. (2020), however, some variables were found to not affect the route choice behavior of motorcycle riders, as in line with earlier studies showing the insignificance of gender (e.g., Moghaddam et al., 2019; Zhong et al., 2012), income (e.g., Dia & Panwai, 2006; Wang et al., 2017), education levels (e.g., Dia & Panwai, 2006; Wang et al., 2017), and occupations (e.g., Wang et al., 2017). This lack of significance may reflect the diverse socio-economic backgrounds of motorcycle users in developing countries, where motorcycles are widely used across various social strata.

3.3.3 Route Choice Model (Link-based Analysis)

While the path-based analysis provides a comprehensive overview of route selections, the link-based analysis is equally vital for understanding the decisions riders make at individual road segments.

3.3.3.1 Model Structure

A concise overview of the RL model, adopted to investigate how traffic information impacts riders' link choices, is provided, following the notation defined by Fosgerau et al. (2013). The model assumes that decision-makers select states to maximize the utility of the outgoing link at each node, considering elements, including instantaneous utility, expected maximum utility to the destination, and error terms.

Following the methodology of Fosgerau et al. (2013), a network denoted as $G = (A, \upsilon)$ was introduced, where A representing a set of links and υ nodes. For each link $k \in A$, the series of outgoing links from the sink node of k is denoted by $A(k)$. Given that the two links a and k belong to the A link set $(a, k \in A)$, the instantaneous utility $u_n(a|k)$ earned by traveler n in choosing the subsequent link a, given the current state k, is expressed in Equation (3.18), with μ as a scale parameter and β as the vector of parameters. Since the random terms pertaining to instantaneous utilities conform to an i.i.d. extreme value type I (denoted as $\varepsilon_n(a)$ with zero mean), the model is equivalent to the MNL model specification.

$$u_n(a|k;\beta) = v_n(a|k;\beta) + \mu\varepsilon_n(a) \tag{3.18}$$

Given the current state represented by the link k, the decision regarding the action a is made to minimize both the instantaneous utility at the link a and the expected downstream utility until the destination. While this concept aligns with the notion of a Markov decision process, it differs crucially from traditional Markov chains in that the choice is not stochastic but rather deterministic (de Freitas, 2018). Upon reaching the absorption state for the destination, defined by expanding the network with dummy links d, the trip will end. Considering the set of all links is $\tilde{A} = A \cup \{d\}$, the deterministic utility for all links k for which destination d is the sink node becomes $v(d|k) = 0$.

In addition to the instantaneous utility, the expected downstream utility is considered to derive the maximum utility for successive link choices. By solving the Bellman equation (Bellman, 2010), the expected utility from the selected link a to the destination d is specified as the value function $V^d(a)$.

$$V_n^d(k;\beta) = \mathbb{E}\left[\max_{a\in A(k)}\left(v_n(a|k;\beta) + \mu\varepsilon_n(a) + V_n^d(a;\beta)\right)\right] \ \forall k \in A \tag{3.19}$$

The value function may be rewritten as the logsum below (Williams, 1977).

$$V_n^d(k;\beta) = \begin{cases} \mu \ln \sum_{a\in A} \delta(a|k) e^{\frac{1}{\mu}\left(v_n(a|k)+V_n^d(a)\right)} & \forall k \in A \\ 0 & k = d \end{cases} \tag{3.20}$$

The exponential of the function above needs to be rewritten in matrix form, yielding the following linear equation to gain the value function for each destination.

$$M_{ka} = \begin{cases} e^{\frac{1}{\mu}\left(v_n(a|k)+V_n^d(a)\right)} & a \in A(k) \\ 0 & otherwise \end{cases} \tag{3.21}$$

$$\mathrm{z} = \mathrm{Mz} + \mathrm{b} \ \Leftrightarrow \ (\mathbf{I} - \mathbf{M})\mathbf{z} = \mathbf{b} \tag{3.22}$$

where $\mathbf{z}\left(\left||\tilde{A}| \times 1\right|\right)$ is a vector with elements $z_k = e^{\frac{1}{\mu}V(k)}$, $\mathbf{M}\left(\left||\tilde{A}| \times |\tilde{A}|\right|\right)$ indicates the incidence matrix describing instantaneous utilities, $\mathbf{I}\left(\left||\tilde{A}| \times |\tilde{A}|\right|\right)$ as the identity matrix, and $\mathbf{b}\left(\left||\tilde{A}| \times 1\right|\right)$ is a vector with elements of the form $b_d = 1$ and $b_k = 0$ for $k \neq d$.

The probability of selecting the subsequent link $a \in A(k)$ for a given state, based on the utility function in Equation (3.19), is computed as follows. This formula aligns with the logit model.

$$P_n^d(a|k) = \frac{e^{\frac{1}{\mu}\left(v_n(a|k)+V_n^d(a)\right)}}{\sum_{a'\in A(k)} e^{\frac{1}{\mu}\left(v_n(a'|k)+V_n^d(a')\right)}} = e^{\frac{1}{\mu}\left(v_n(a|k)+V(a)-V(k)\right)} \tag{3.23}$$

Based on the Markov property, Fosgerau et al. (2013) determined the probability of choosing a path σ by calculating Equation (3.23), with a path defined as a sequence of links $\sigma = \{k_0, \ldots, k_I\} \in A(k_i)$, where k_0 is the origin and $k_I = d$ (absorbing link). This formulation corresponds to the choice probability of the path-based model, specifically MNL, encompassing an infinite number of alternatives.

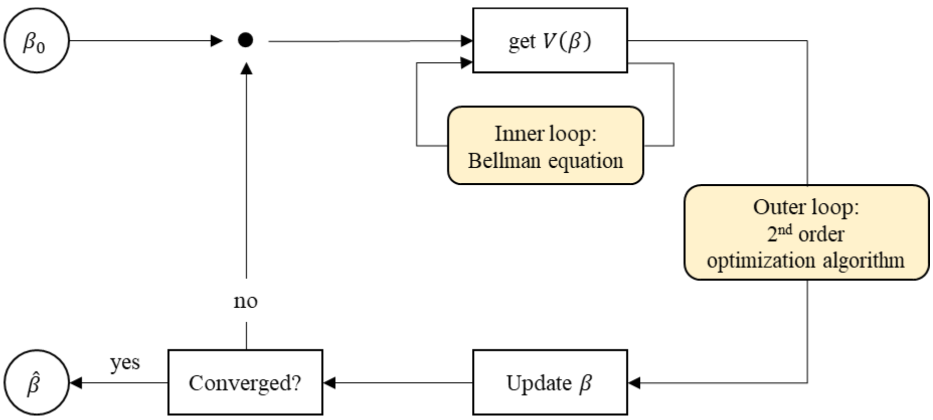
$$P_n^d(\sigma) = \prod_{i=0}^{I-1} P\left(k_{i+1}|k_j\right) = \frac{e^{\frac{1}{\mu}v(\sigma)}}{e^{\frac{1}{\mu}V(k_0)}} \tag{3.24}$$

The RL path probabilities can be solved by maximum likelihood, with the unconstrained nonlinear optimization algorithm BFGS—regarded as the best for this purpose (Train, 2009; de Freitas, 2018)—applied to search the parameter space (Fosgerau et al., 2013). Since the linear system in Equation (3.22) lacks a solution for all parameter values (a constrained optimization problem), Fosgerau et al. (2013) suggest starting from a feasible point and being conservative in the first step size of the line search algorithm, leading to the log-likelihood function that is defined for observations $n = 1, \ldots, N$.

$$LL(\beta) = \ln \prod_{n=1}^{N} P(\sigma_n) = \frac{1}{\mu}\sum_{n=1}^{N}\sum_{i=0}^{I-1} v(k_{i+1}|k_i) - V(k_0) \tag{3.25}$$

Figure 3-15 shows the maximum likelihood estimation framework, combining an inner algorithm that uses the Bellman equation $[z = (I - M)^{-1}b]$ to solve the value function for each parameter, and an outer algorithm that maximizes the likelihood function over the parameter space $\left[\max_{\beta} LL\left(\beta, z(\beta)\right)\right]$.

Figure 3-15 Maximum likelihood estimation framework.



Adapted and redrawn from Zimmermann et al. (2017)

3.3.3.2 Estimation Results

Recursive route choice models achieve efficiency by framing the path choice problem as a parametric Markov Decision Process and using dynamic programming to solve its embedded shortest path problem (Zimmermann & Frejinger, 2020). This approach allows for a more profound understanding of route selections, as it involves a sequence of link choice decisions. The process of estimating the RL model is discussed in this subsection, following the utility function outlined below.

$$u_n(a|k) = v_n(a|k;\beta) + \mu\varepsilon_n(a) + V_n^d(a) \tag{3.27}$$

Referring to the RL model structure, the instantaneous utility function of the model is specified as follows, where LL_a and LW_a represent the length and width of the link a in kilometers, TT_a is the travel time in minutes, and TF_a corresponds to the traffic flow condition of the link a, which consists of three different levels: light, moderate, and heavy traffic. Second, the dummy variable RM_a refers to the existence of ramp metering implementation on the link a is also incorporated into the model.

$$v_n(a|k) = \beta_{LL}\, LL_a + \beta_{TT}\, TT_a + \beta_{TF}\, TF_a + \beta_{RM}\, RM_a \tag{3.28}$$

Figure 3-16 illustrates the hypothetical network configurations established within the link-based context, serving as a point of reference for the dynamic route choice analysis. Following this setup, the estimation of the RL model was performed using the BFGS Hessian, an iterative method designed for handling unconstrained nonlinear optimization problems, and implemented using R programming.

Figure 3-16 Link-based definitions of the road network settings.

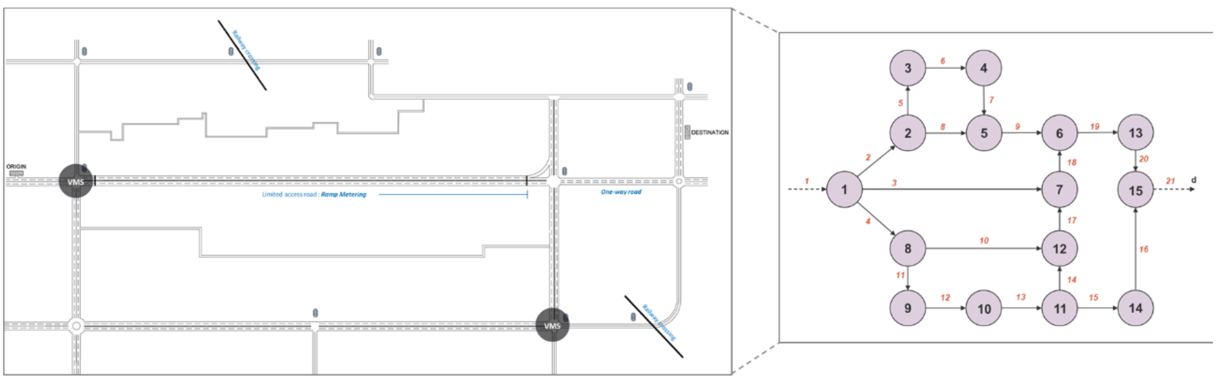


Table 3-11 summarizes the convergent estimation of the RL model. The outcomes derived offer a set of valuable statistical parameters that serve as indicators for evaluating the model's fitting accuracy in representing the behavior of riders when selecting their route within a link-based context. The final log-likelihood value serves as a benchmark, highlighting the goodness of fit to the observed data.

Table 3-11 Link-based model estimation results from expanded analysis.

	Est.	t-value	Pr (> t)	
Estimated parameters				
Link length	-1.582	-8.625	0.000	**
Travel time	-0.039	-2.290	0.022	*
Traffic flow conditions	-5.304	-57.800	0.000	**
Ramp metering (dummy)	-1.013	-12.160	0.000	**
Model fit statistics				
Null log-likelihood (LL_0)		-9506.175		
Final log-likelihood (LL_β)		-4224.296		
Rho-square (ρ^2)		0.556		
Rho-square-bar (Adj. ρ^2)		0.555		
Number of samples		301		
Number of observations		2408		

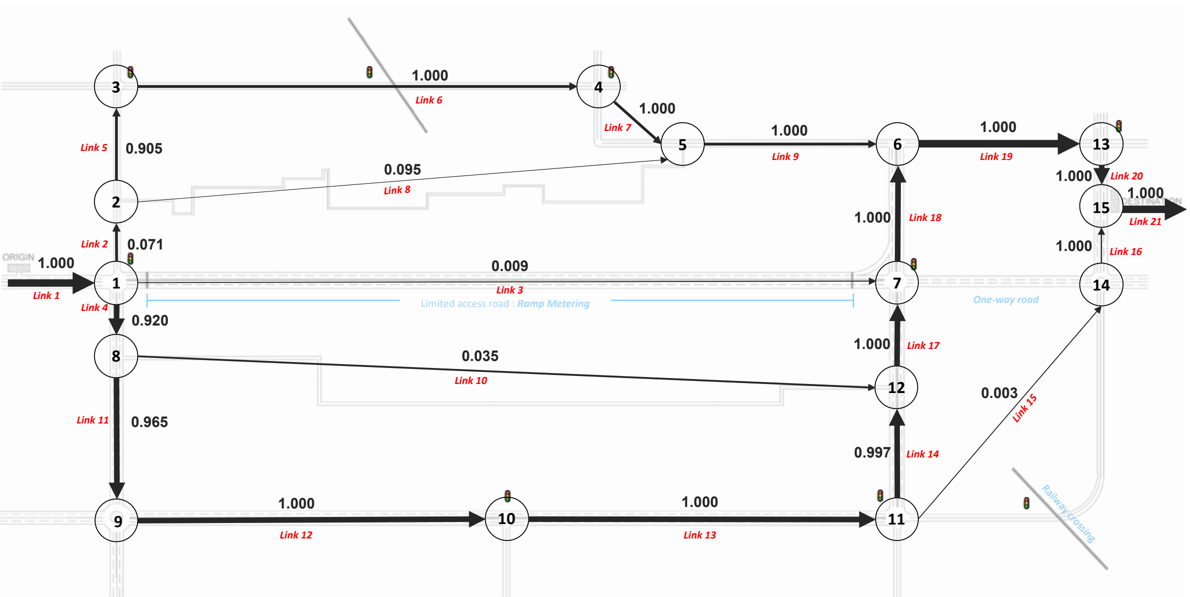
** Significant at 1%, p-value (0.00–0.01); * Significant at 5%, p-value (0.01–0.05); - Not relevant

The results showed that the vital variable governing riders' decision-making process was identified to be traffic flow conditions, signifying its paramount importance when choosing a link. This was closely followed by considerations of distance and travel time, underscoring the hierarchy of their priorities. In general, it was observed that all the link-additive attributes incorporated into the model exhibited statistical significance, revealing a notable influence on the choices to pick the outgoing link. These variables consistently demonstrated the expected direction of the marginal utility coefficients, affirming their relevance in shaping the travel decision-making process of motorcycle riders. Several variables on the link characteristics were evaluated within the model framework. However, certain attributes, including road width, signalized intersections (as indicated by the dummy variable), and total delay along the particular link, demonstrated insignificance in affecting the decision-making process of motorcycle riders when picking the subsequent link a based on the current state k. These variables were then excluded from the model. This lack of significance could potentially be attributed to the comprehensive information provided by the VMS, which effectively conveyed details about travel time and traffic flow degree, thereby offering a clear depiction of subsequent link traffic conditions. As a result, riders might not consider additional delays arising from road features or regulations, such as railway crossings and traffic signals, since the VMS has already provided thorough insights. The classification of a link as a shortcut was also determined to be insignificant, implying that it does not hold substantial weight in riders' considerations when choosing the upcoming link. Even though it is common practice among them in developing countries to opt for narrow roads to shorten the trip, this behavior might be limited to specific demographics. This observation could be clarified by taking individual characteristics into account as interaction effects on the utility function that shapes riders' preferences, requiring further refinements in the methodology used for link-based route choice analysis.

Earlier studies have established that the estimation of the RL model demonstrated equivalence with the MNL model across the set of feasible paths (Fosgerau et al., 2013; Zimmermann et al., 2017). The marginal utilities produced from the MNL model estimation, however, should not be directly compared to those of the RL model due to the distinct approaches taken in their utility functions within the model structure. Fundamentally, the MNL model pertains to the decision-makers selecting a route that maximizes utility for an entire trip, from origin to destination. In contrast, the RL model specification signifies that the decision-maker considers not only the utility derived from selecting the next state but also anticipates possible future choices when deciding the outgoing link. The maximization of these combined utilities occurs for each node. While the former (instantaneous utility) outlined in the RL model can essentially be solved by the MNL model, the latter (expected downstream utility) is addressed through Bellman equations. Another significant distinction lies in how alternatives are defined. In the MNL model, the alternatives are specified as entire routes from origin to destination, while the RL model treats alternatives as individual links or road sections. This fundamental difference results in distinct modeling considerations: the MNL model involves selecting a single choice for each trip, while the RL model captures sequences of link choices. This contrast in how alternatives are characterized highlights the ability of the RL model to better capture the intricate decision-making process of motorbike riders. This is particularly relevant considering motorcycles' high flexibility and maneuverability, allowing them to execute en-route route choices quickly. As a result, the RL model offers a more accurate representation of individuals' route preferences in real-world scenarios. Nevertheless, it is important to mention that, the outcomes of the MNL and RL models serve distinct functionalities when applied to the traffic simulation model, as elaborated upon in Chapter 4.

The probabilities of selecting a particular link in the RL model are computed using Equation 3.23, which determines the likelihood of choosing an action a given the current state k and the destination d. These results are compiled and presented in Figure 3-17. Unlike the path-based model, where a single route is chosen for each O-D pair, the link-based analysis involves a sequence of choices, with the probability calculated at each node. Participants make decisions regarding their outgoing link at four distinct locations based on their previous link choice, some of which are influenced by VMS traffic reports. The thicker arrow symbolizes the most preferred route, where the product of individual link choice probabilities can be converted into the overall path choice probability. While this route may be longer from a path-selection perspective, it offers greater capacity than other routes in the network.

Figure 3-17 Link choice probabilities results.



3.3.4 Route switching model

This section aims to identify the route-switching behavior of motorcycle riders when exposed to traffic information and the variables influencing their decision to change routes. A binary logit model was employed to present riders with two choices upon receiving traffic information: either continue on their current route or switch to an alternative route suggested by VMS. The model estimation results, which account for road attributes, trip characteristics, and individual traits, are listed in Table 3-12. Only variables with a significant impact on riders' propensity to switch routes were retained in the model.

Table 3-12 Estimation results in binary logit model specifications.

Estimated parameters	Interaction to utility	Binary logit model			
		Est.	t-test	p-value	
Constants					
ASC (stay on the current route)		-	-	-	
ASC (switch to the alternative route)		-1.551	-4.564	0.000	***
Road attributes					
Distance (meters)		-0.003	-2.788	0.005	***
Minimum road width / direction (meters)		1.783	2.419	0.016	**
Traffic flow conditions		-0.571	-5.449	0.000	***
Average travel time (minutes)		-0.085	-1.858	0.063	*
Information on the alternate route					
No information available (dummy)	V_{switch}	-0.792	-2.418	0.016	**
Provision of route guidance (dummy)	V_{switch}	0.479	2.518	0.012	**
Socioeconomic characteristics					
Age group (17 - 24 years old)	V_{stay}	-0.951	-3.976	0.000	***
Age group (25 - 35 years old)	V_{stay}	-1.178	-6.070	0.000	***
Age group (36 - 50 years old)	V_{stay}	-1.259	-5.538	0.000	***
Age group (51 - 60 years old)	V_{stay}	-0.947	-2.285	0.022	**
Age group (> 60 years old)	V_{stay}	5.887	11.192	0.000	***
Occupation as a government employee	V_{stay}	1.052	2.207	0.027	**
Occupation as a student	V_{stay}	-0.415	-1.813	0.070	*
Do not own a driving license	V_{stay}	0.804	2.647	0.008	***
Hold a master's degree toward	V_{switch}	1.614	2.715	0.007	***
Access information sources during a trip	V_{switch}	0.326	1.688	0.091	*
Model fit statistics					
Null log-likelihood (LL_0)			-982.159		
Initial log-likelihood (LL_{ASC})			-619.674		
Final log-likelihood (LL_β)			-535.535		
Likelihood ratio test (LLR_β)			161.276		
Rho-square (ρ^2)			0.136		
Rho-square-bar (adjusted ρ^2)			0.104		
Akaike Information Criterion (AIC)			1111.071		
Bayesian Information Criterion (BIC)			1206.985		
Number of parameters			17		
Number of observations			894		

*** Significant at 1%, p-value (0.00–0.01); ** Significant at 5%, p-value (0.01–0.05); * Significant at 10%, p-value (0.05–0.10); - Not relevant

The ASC reflects the average effect on the utility of all factors not included in the model (Train, 2009). As one alternative must be normalized to 1 in the model estimation, the negative sign of the ASC of the 'switching' alternative implies that respondents are less likely to switch routes. The statistical indicators represented an adequate model for describing the route-switching propensity of motorcycle riders. The performance of the binary logit with the specification of alternative-specific attributes has been assessed in comparison to that of generic attributes. With 5 degrees of freedom and a significance level of 10%, the likelihood ratio test rejects the null hypothesis that the latter creates a better-fitting model, as denoted by the lower likelihood ratio of 5.479 compared to the chi-square ($\chi^2_{95\%,6}$ = 11.07).

Consistent with the findings of Diop et al. (2020) about the impact of individual characteristics on routing decisions, hypothesis testing shows that including these factors may statistically enhance the model fit. The likelihood ratio test results confirm that the model listed in Table 3-12 outperforms the model that excluded socioeconomic and riding characteristics (-2LL = 25.23; $\chi^2_{95\%,12}$ = 21.03). Moreover, since the error terms associated with observations derived from the same individual share a large number of unobserved variables, the emergence of serial correlation becomes inevitable. Hence, the flattening panel data function in BIOGEME 3.2.10 (Bierlaire, 2020) was applied to relax this issue. This function accommodates the heterogeneity among individuals without sacrificing the simplicity of the logit structure by incorporating the respondent identifier into the model specification code. In addition, since the study contributes a novel analysis of riders' route switching behavior, the recognition of distinct trends for each attribute referred to the routing preferences of car drivers in the literature.

As expected, the distance to the destination, whether via the current or an alternative route, significantly affects riders' routing decisions, contrary to the conclusion of Vacca and Meloni (2015). The negative coefficient implies that riders prefer not to change routes when the alternate route has a longer link length, in line with Vacca et al. (2019) and Kattan et al. (2010) for the case of car drivers. Despite the maneuverability of these two-wheeler vehicles, the model reveals that they have high utility toward route switching if the alternative road has a wider lane. This preference may stem from the discomfort of passing through narrow roads, such as shortcuts and alleys, which are often disrupted by human activities or topological features like bridges and rivers. It was discovered, however, that the number of traffic signals along the route had no effect on encouraging riders to switch routes.

Regarding trip attributes, travel time has a substantial negative impact on the likelihood of motorcycle riders switching routes, confirming aversion to routes with longer travel times. When an alternate route provides shorter travel times, it is inferred that riders desire to alter routes. Unlike Vacca and Meloni (2015), the finding is consistent with Khattak et al. (1993), who stated that road users tend to switch when given real-time quantitative travel time information for both their regular route and the alternative. The impact of traffic flow conditions—classified as light, moderate, and heavy—was also examined. The binary logit model revealed that traffic flow information significantly influences riders' decisions to switch routes, supporting the *a priori* belief that route switching is preferable when it saves time and distance, thereby preventing delays. Furthermore, the existence of route recommendations encourages riders to switch routes more efficiently. The positive coefficient indicates that riders are eager to switch when given route guidance, enabling them to make more informed choices. Earlier, the research by Diop et al. (2020) highlighted that the provision of guidance increased the rate of route switching. This strategy would greatly improve traffic performance, particularly considering that the percentage of road users who change their routes typically remains below 40% (Erke et al., 2007). In comparison, when no traffic information is available, for instance, in the case of the alternative route on shortcut roads that often lack sensor equipment, riders are more likely to stay on their current route, avoiding the uncertainty and potential delays associated with less predictable paths. Nonetheless, regardless of the number of riders in front of an individual who switches routes, this rider was not affected to divert, as indicated by the insignificant coefficient for this variable in the estimation model.

In terms of individual characteristics, the age of the riders significantly influences motorcycle route preferences, aligning with findings in the literature (e.g., Diop et al., 2020; Long et al., 2020; Yan & Wu, 2014) that observed similar trends among car drivers. As shown in Table 3-12, riders aged between 17 and 60 exhibit a strong propensity for route switching, unlike those over 60, who prefer to stick to their existing routes, in line with Jou et al. (2005). This age-related difference in behavior may be attributed to the typical conservative driving style of older individuals, who tend to prioritize caution and safety. It should be mentioned that this study did not evaluate the behavior of individuals under 17, as they are below the legal driving age in Indonesia. In addition, those without a valid driver's license, whether expired or never obtained, are more likely to stay on their initial route, likely to avoid encounters with law enforcement. Consistent with previous research on passenger car route choice (e.g., Diop et al., 2020; Vacca & Meloni, 2015), it was discovered that monthly income and transport expenditure did not influence motorcycle riders' decisions to switch routes. Occupation was shown to have a significant influence on their route-switching behavior. Unlike government employees, who prefer to remain on the present route, students greatly desire to change routes, likely due to the tendency of younger individuals to ride more aggressively and take risks. Moreover, the habit of accessing traffic information sources while riding to determine their travel path resulted in a higher urge for route switching.

3.4 Discussion

This section reflects upon the insights drawn from analyzing motorcycle riders' route choices and switching behavior. The study highlights key decision-making processes and emphasizes the potential for tailored traffic management strategies. It is important to acknowledge that these findings are based on hypothetical responses from an SP survey and may not fully reflect real-world behaviors.

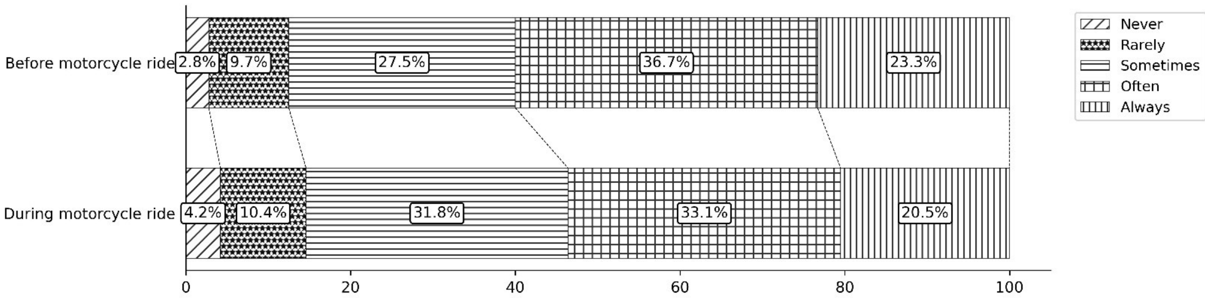
3.4.1 Motorcycle Route Choice: Strategic Insights and Behavioral Implications

As comprehensive analysis of motorcycle riders' route choice behavior reveals key factors that strongly impact their decision-making in selecting routes and identifies a variety of implications, as follows.

First, recognizing motorcycles' unique properties compared to automobiles, it was hypothesized that VMS strategies for urban roads should differ from those on highways, especially in motorcycle-dependent regions. The findings suggest that when VMS broadcasts include variables that significantly influence route choices, riders demonstrate greater flexibility, such as opting for route deviations. This has practical implications; for instance, VMS should provide reports not just on main routes but also on local roads, concurrently helping lessen the probability of congestion on major roads.

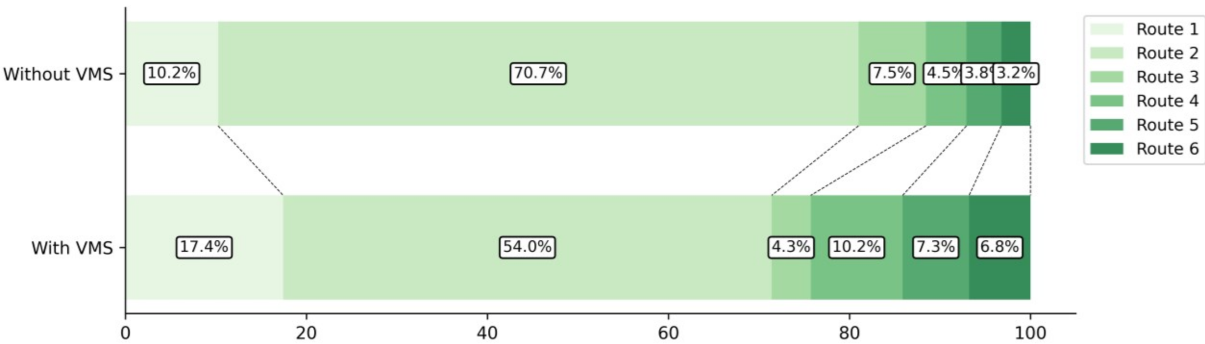
Second, the survey uncovered that more than two-thirds of motorcycle riders in Bandung actively seek out traffic information sources while riding, as shown in Figure 3-18. This pattern emerged from the SP survey, which not only gathered behavioral responses to stated choice scenarios but also inquired about habits relevant to motorcycle riding. Respondents were asked to rate their frequency of utilizing any traffic information sources before and during rides on a scale from 1, signifying 'never,' to 5, meaning 'always'. The data underlines an apparent demand for accessible and reliable traffic updates to facilitate informed decision-making. Thus, given the earlier-discussed benefits, VMS remains a valuable and safer means of delivering traffic updates in motorcycle-dependent cities, instrumental in controlling mixed traffic and optimizing the traffic stream through route guidance. It is important to through that using smartphones while driving, even for navigation, is legally prohibited in several countries, including Vietnam and Indonesia (Article 287 Paragraph (1) Law of the Republic of Indonesia Number 22 of 2009), primarily due to the high risk of distraction-related accidents. Smartphones, despite offering thorough information, pose elevated risks when riding (Truong et al., 2019), as they impair physical maneuverability and slow reaction times. Studies have confirmed that navigation applications can lead to chaos and confusion, undermine traditional traffic information systems, and lead to unexpected surges in local cut-through traffic (Macfarlane, 2019). Furthermore, Dong et al. (2019) found that smartphone navigation could diminish a driver's field of view, reducing the attention span directed at the road. Although some riders attempt to mitigate these risks by mounting smartphones on their handlebars, this method introduces additional dangers due to non-ergonomic positioning. Often, the setup fails to provide eye-level viewing, compelling them to shift focus from the road, which increases hazards and potentially leads to discomfort and instability while riding. Moreover, adjusting the device for optimal viewing proves challenging, making VMS a more viable option. VMS displays information clearly from a distance, enabling drivers to quickly obtain necessary details without diverting attention from the road. Moreover, from a traffic management perspective, VMS consistently outperforms smartphones in delivering real-time updates under specific circumstances (Macfarlane, 2019).

Figure 3-18 Frequency of accessing traffic information.



The considerations highlighted above underscore the urgent need for the installation of VMS on urban roads in motorcycle-dependent cities. This technology not only ensures that motorcycle riders receive crucial traffic updates safely, but it also provides route suggestions and early alerts about potential incidents that could lead to delays. The importance of VMS in this context is further emphasized by a numerical analysis of changes in choice probabilities, as illustrated in Figure 3-19.

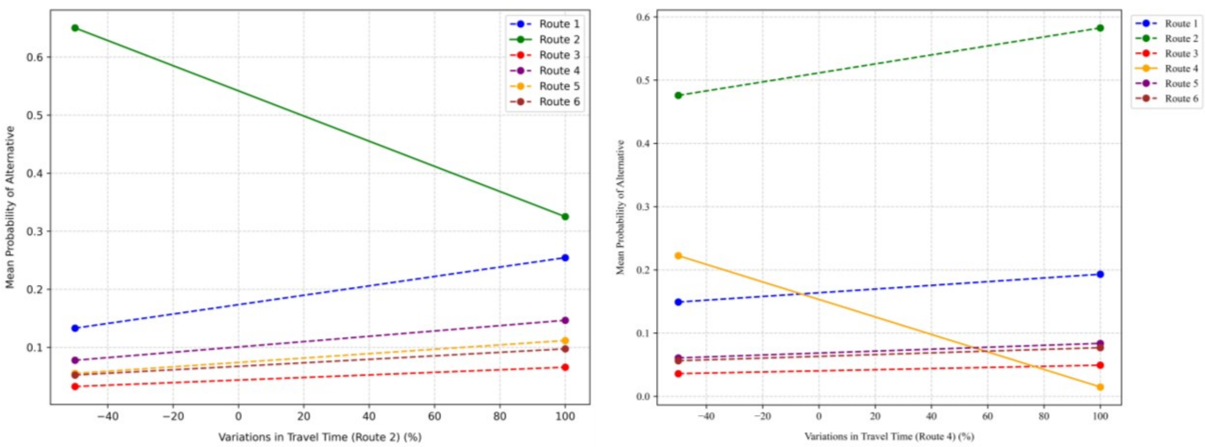
Figure 3-19 Choice probabilities of routing decisions (with and without VMS).



Derived from the integrals of standard logit probabilities over a parameter density, the MXL model lacks a closed-form expression (Train, 2009), necessitating Monte Carlo simulation. Before receiving traffic information, over two-thirds of motorcycle riders drift toward the shortest route (Route 2) and avoid long-distance routes (Route 4). Whereas after acquiring information through VMS about travel time, delay, and congestion levels, their tendencies of routing decisions significantly diverge. For example, there is a notable increase in the preference for Routes 4 and 6, which are longer than other alternatives and were initially less favored when no traffic report was available. Once informed about better traffic conditions on these routes through VMS, motorcyclists shift their preferences accordingly. Thus, it can be concluded that VMS is indispensable in optimizing the transportation system and enhancing overall travel experiences by distributing motorcycle traffic across varying routes.

Figure 3-20(a) illustrates a sensitivity analysis of travel time on Route 2, confirming its significant trend on route preference. According to the results of the SP experiment, motorcyclists show a strong preference for Route 2, attributed to its major road, shorter distances, and more comfortable travel conditions compared to other alternatives. Nevertheless, increases in travel time on this route, possibly due to peak-hour traffic, could diminish its attractiveness, resulting in a more even distribution of traffic across alternatives and helping to maintain vehicle speeds on this arterial road. In such scenarios, there is a notable increase in preference for Route 1 relative to other routes, likely because it is also shorter and runs parallel to Route 2, aligning with findings that distance is crucial in motorcycle riders' route selection (see Table 3-10). Conversely, a significant reduction in travel time on Route 2 would lead approximately 10% of motorcyclists to choose other routes, emphasizing the importance of disseminating traffic information to achieve more balanced road networks and prevent congestion. Meanwhile, the sensitivity analysis of travel time for Route 4 (see Figure 3-20(b)) exhibits a steeper gradient, signifying a greater influence of this attribute on motorcyclists' routing decisions. If travel time doubles, almost no motorcyclist would choose this route, given its status as the longest option in the choice set. Travel time is a pivotal factor in motorcyclists' decision-making, particularly when VMS broadcasts this information along with traffic flow conditions. Routes not covered by VMS, specifically Routes 3 and 5, are less popular, potentially causing traffic imbalances and the risk of gridlock on major roads. This situation highlights the challenge of maintaining and enhancing road performance.

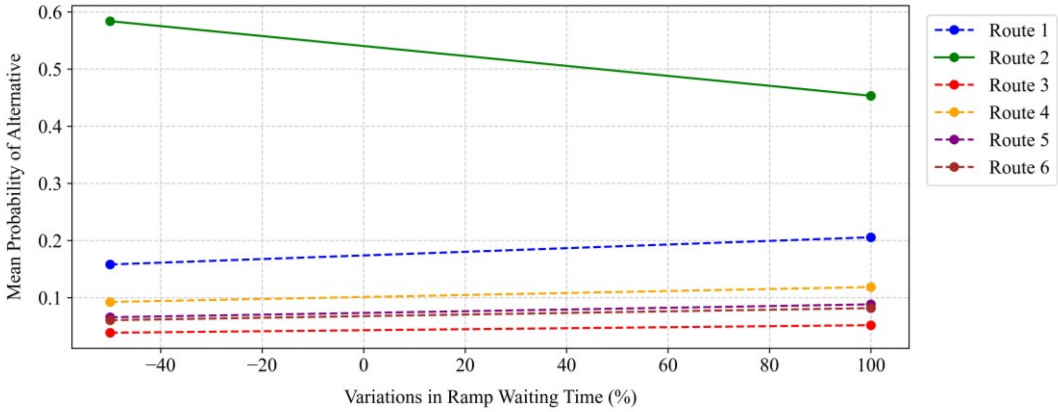
Figure 3-20 Sensitivity analysis of travel time for alternatives: (a) Route 2, and (b) Route 4.



(a) (b)

Third, the discrete choice model estimation determined to what extent road properties affect routing decisions under the VMS environment. As expected, riders favor routes with shorter distances and trip times. While traffic conditions significantly persuade their preferences, this information is only accessible through real-time devices, underscoring the need for VMS implementation on urban roads frequented by motorcycles. In addition to the relevance of traffic information provision, this research is essential in proposing new traffic management strategies to enhance traffic performance in motorcycle-dependent cities, including adopting ramp metering on arterial roads—an approach previously reserved for highways. Motorcycle riders' aversion to longer waiting times confirms the effectiveness of ramp metering in distributing vehicles evenly across various road types, smoothing flow, maintaining speeds, and preventing stop-and-go movements that escalate conflicts. Figure 3-21 presents a sensitivity analysis, illustrating how riders' disutility increases with longer ramp metering waiting times. In contrast, in scenarios where ramp metering is not activated, riders tend to mobilize towards major roads, increasing the risk of severe congestion. Furthermore, it has been revealed that individual characteristics significantly influence their route choices in response to VMS. While addressing these varied personal attributes in the planning and execution of VMS poses a challenge, it is crucial, as the effectiveness of VMS heavily depends on how individual riders perceive and comply with the provided information.

Figure 3-21 Sensitivity analysis of the attribute waiting time at a ramp meter.

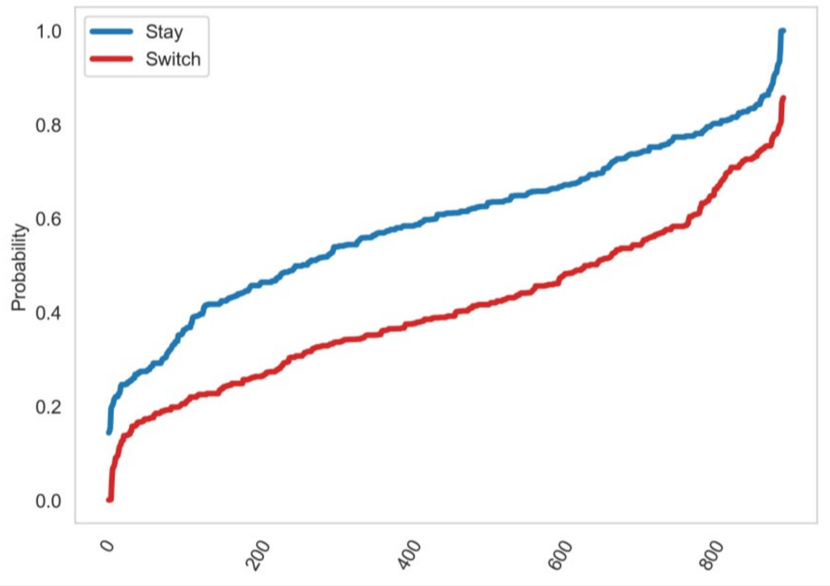


3.4.2 Motorcycle Route Switching: Strategic Insights and Behavioral Implications

The current subsection discusses the substantial implications arising from the analysis of motorcycle riders' route switching behavior, complementing the insights gained from their route choice behavior.

First, the interpretation of the estimated model parameters evaluates how motorcycle riders make trade-offs in choosing their routes, which will serve as an essential reference for optimizing network performance. Second, the provision of traffic information has been proven valuable for motorcycle riders' routing decisions, as they may select a better en-route route choice. Additionally, incorporating route guidance into the traffic information on VMS is an effort to prevent vehicles from entering congested areas, for example, due to the recurrently heavy traffic flows that could create delays. This vital function of VMS may assist in balancing the distribution of vehicles throughout networks, particularly in developing countries where motorcycles are the predominant mode of transportation. Figure 3-22 shows that the compliance rate of motorcycle riders with VMS is high enough to disperse traffic flow across networks. In the end, infrastructure utilization can be maximized without the obligation to construct new roads, ultimately reducing traffic blockages and increasing vehicle speeds.

Figure 3-22 Choice probability of route switching decision.



However, the installation of VMS in Indonesia is still restricted to highways in the Greater Jakarta Metropolitan Area, and these technological devices do not transmit real-time traffic indicators, such as travel time or travel delay. Instead, the existing VMS merely distributes a qualitative level of traffic congestion, which may reduce the reliance of road users on the information. As a result, drivers still do not get the most benefit from VMS. Therefore, in addition to initially equipping the networks with sensor devices to generate real-time traffic data, installing the VMS on urban roadways was also necessary so motorcycle riders could access it and be notified of upcoming situations. As hypothesized, given the higher flexibility and adaptability of these two-wheeled vehicles, a different implementation approach for VMS in mixed traffic is necessary. Although different vehicle types will utilize the provided traffic information, the VMS should account for the unique properties of all user groups to effectively affect their routing decisions and direct them to the less congested routes. In the case of motorcycles, the VMS system should cover traffic updates not only on the arterial road but also on local roads, allowing riders to abbreviate their trip while minimizing the potential for a gridlock mechanism on the main road.

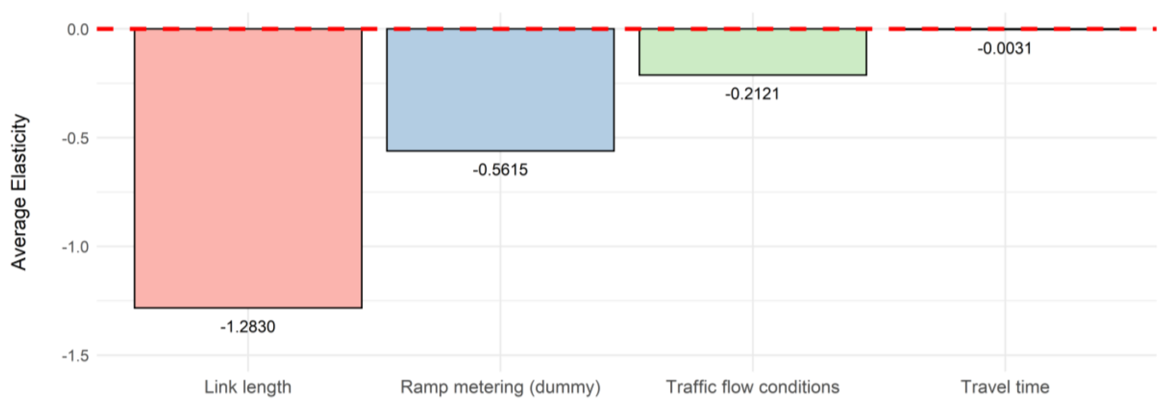
Moreover, VMS should be presented as comprehensive as possible, containing sufficient updates to assist drivers in making proper routing selections with ease (Diop et al., 2020). The strong correlation between VMS messages and driver route-switching behavior can be utilized as a control strategy to mitigate traffic jams (Peeta & Gedela, 2001). As a whole, comprehending this sort of behavioral change allows the optimization of network performance evaluation and strengthens traffic policies.

3.4.3 Sensitivity and Elasticity in Link-Choice Behavior

This section explores the implications drawn from the analysis of riders' link choice behavior, further enriching the comprehension of the implications obtained from elasticity and sensitivity analyses.

Elasticity analysis, rooted in microeconomics, measures the responsiveness of route choice to changes in road network attributes. This research calculated elasticity values using data from 24 stated choices gathered from 301 individuals, applying the method of direct elasticity linked to the collected MNL model. This quantified the impact of attribute changes on the probability of link selection by motorcycle riders, as illustrated in Figure 3-23. The graph shows a visual summary of the attributes that significantly influence routing decisions and captures the sensitivity to changes. In particular, negative average elasticity values imply that increases in an attribute's value tend to reduce the likelihood of choosing a link, a relationship consistently depicted below a red dashed line in the graph.

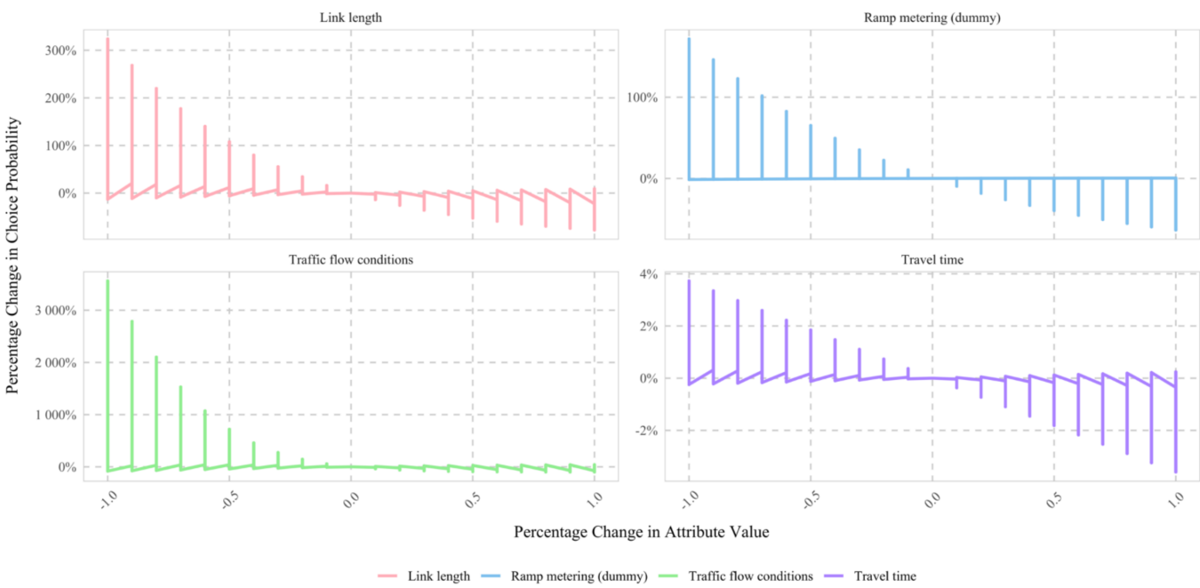
Figure 3-23 Elasticity analysis.



The elasticity analysis revealed that link length is highly elastic, with each 1% increase reducing the probability of a motorcycle rider choosing that link by approximately 1.28%. Conversely, other attributes demonstrated inelasticity (values lower than 1.0), demonstrating that while these factors influence the route preferences, the degree of sensibility is comparatively lesser. This analysis is crucial for forecasting riders' responses to road network changes, playing a vital role in strategic transport planning. Nonetheless, there is a divergence between attributes with high marginal utilities and those with significant elasticity trends; traffic flow conditions primarily influence the former, while link distance affects the latter more. Coefficients in model estimation represent the strength and direction of the relationship between an independent and dependent variable, holding all other variables constant. A higher coefficient suggests a stronger impact of that attribute per unit change. Elasticity measures the percentage change in choice probability for a 1% change in an attribute, which can vary based on factors like data range, attribute distribution, and base value. Unlike coefficients, elasticity is unit-free, making it a relative measure of effect, whereas coefficients provide an absolute measure of impact.

To verify the model's reliability and understand how different attributes affect link choice probabilities, a sensitivity analysis was performed. The results are presented in a series of graphs in Figure 3-24, which each chart the percentage change in attribute value against its impact on link choice probability. The horizontal axis represents the adjustment factors applied to the attribute values, ranging from -50% to +100%, where 0% denotes the baseline. The vertical axis quantifies the proportional change in the likelihood of selecting an outgoing link, where positive values indicate an increase and negative values denote a decrease in choice probability relative to the baseline. The analysis discovered that travel time has the least effect on link choice probabilities, whereas traffic flow is highly sensitive, showing a marked increase in preference for links with improved conditions.

Figure 3-24 Sensitivity analysis.



3.4.4 Predictive Modeling with Recursive Logit

The section underscores the significance of traffic prediction as an important implication of the analysis, particularly highlighting the efficiency of the dynamic route choice model specified in the RL model. This proficiency stems from consistent parameter estimation, unbound by choice set restrictions sets (Fosgerau et al., 2013; Zimmermann et al., 2017). The RL model's accurate prediction of traffic patterns and flows, crucial for managing urban traffic dynamics, gives it a distinct advantage over other models.

Therefore, traffic flows mobilized across each link were predicted in this study using the trip production volume based on the number of observations in the SP experiment. Within the graphical framework illustrated in Figure 3-25, the formulation in Equation (3.29) was employed to generate link flows from multiple origin nodes directed towards a single destination node (Fosgerau et al., 2013).

$$F_n^d(a) = G_n^d(a) \sum_{k \in A} P_n^d(a|k)\, F(k) \tag{3.29}$$

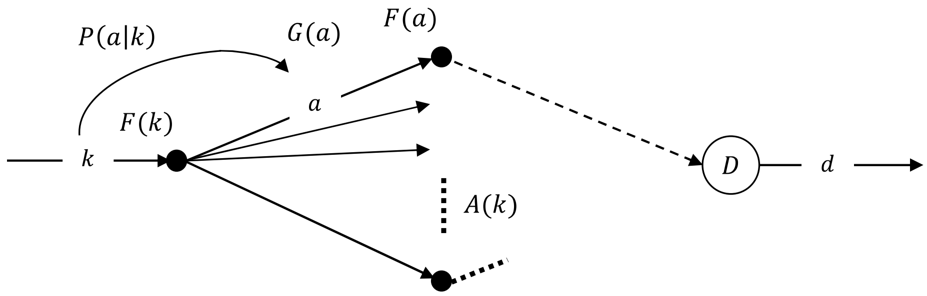
where,

P^d : link choice probabilities $\forall k, a \in A$

G^d : demand originating at $a \in A$ and ending at d

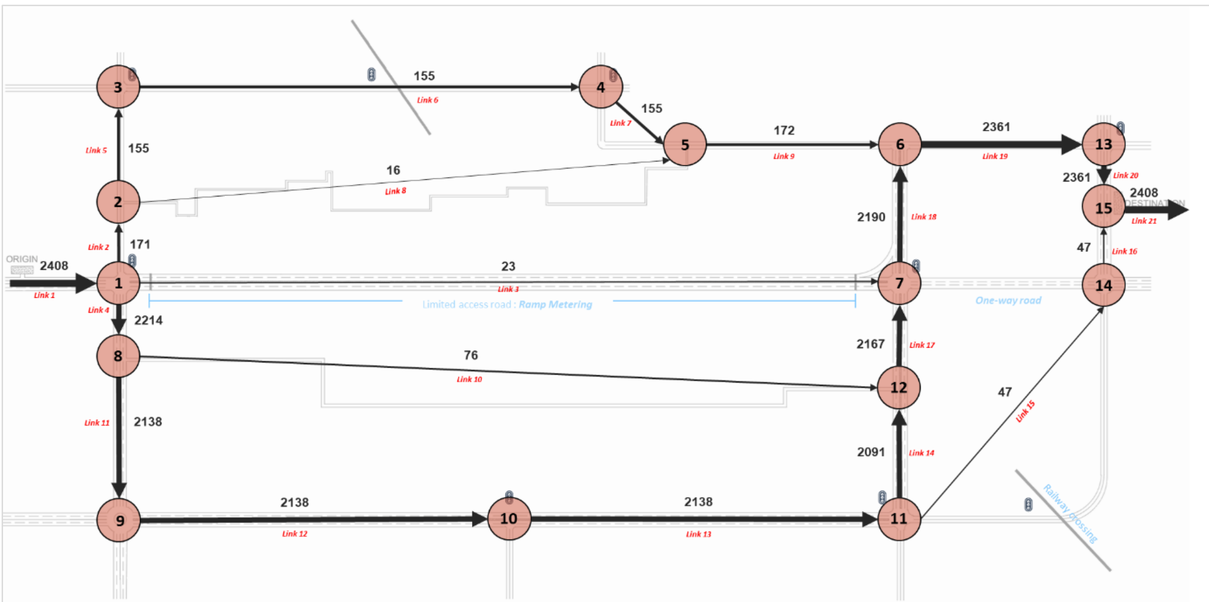
F^d : expected flows towards d on $a \in A$

Figure 3-25 Framework for traffic flow prediction.



Therefore, the traffic flows mobilized within each link of the experimental network were also predicted in this article using the outcomes from prior analysis. The trip production volume was assumed to be the equivalent of the number of observations gathered from the SP experiment, which amounted to 2,408 individuals. As a result, the expected link flow outputs were obtained, as depicted in Figure 3-26. Corresponding to the choice probabilities analysis results, it was determined that out of 2,408 motorbike riders beginning their trip from the origin point, 2,214 opted for routes leading to the south of the network (link 4), 171 chose routes heading north (link 2), and the remaining participants selected the road section with ramp metering (link 3). This approach not only leverages the predictive strength of the RL model but also provides insights into the potential distribution of flows across the network.

Figure 3-26 Traffic prediction results.



3.5 Summary

This chapter estimates the route choice behavior of motorcycle riders in motorcycle-dependent traffic, addressing a gap in the current body of literature. The analysis is structured in layers and employs two main data sources; the investigation begins with a preliminary pilot survey to capture riders' perceptions and confirm the validity of the stated choice questionnaires that inform the subsequent primary survey. The research develops a tailored traffic control strategy that integrates VMS and ramp metering—a scheme specially designed for the demands of mixed traffic settings with high usage of motorcycles. Both static and dynamic discrete choice models are considered. The introduction of ramp metering on non-highway roads and VMS in this context represents a novel aspect. Specifically, the proposed ramp metering strategy is designed to regulate the entry of motorcycles onto arterial roads, ensuring the flow remains within capacity limits to avert congestion. Meanwhile, the deployment of VMS equips riders to make more informed travel decisions, leading to an investigation of route switching and link-choice behaviors to identify the factors influencing route preferences and the extent of their impact.

The study explored the impact of different road attributes and the specialized behavior of motorcycle usage on routing decisions, aiming to capture riders' decision-making processes. Employing an SP survey, the research enabled them to consider hypothetical scenarios and evaluate potential responses to VMS, which is not always possible with RP data. The findings suggest that distance is the primary factor influencing motorcycle route choice, with congestion rates and travel time also being significant considerations. The integration of VMS messages that offer travel times and a color-coded saturation map gives a comprehensive overview. The data reveal that riders are flexible in their road type usage, often leveraging narrower pathways typical in developing countries. The implementation of ramp metering has been observed to encourage riders to consider different alternative routes, potentially leading to a more balanced traffic distribution across the network. Furthermore, the provision of VMS influences riders' willingness to change routes upon gaining information about the conditions on other available paths. However, it is noted that senior riders, characterized by their cautious driving approach, are more likely to stick with their initial route plan. In conclusion, the findings gleaned from this chapter will be integrated into the subsequent traffic simulation modeling and analysis, where the strategies for managing motorcycle traffic within mixed traffic environments are evaluated.

Chapter 4

Traffic Microscopic Simulation Model

4.1 Introduction

Chapter 4 explores the complex domain of microscopic simulation modeling for mixed traffic flow, establishing a foundation for performance evaluation and proposing traffic control strategies that are further detailed in the subsequent chapter. This chapter extends the route choice analysis from the earlier chapter, applying these findings to refine the calibration of driving behavior in mixed traffic within simulation models. Using AIMSUN as a pivotal tool in this process, the micro-simulation model adeptly replicates drivers' decision-making processes, covering aspects like route selection and response to traffic information, and simulates the implementation of various traffic management strategies and infrastructural modifications (Balakrishna et al., 2007). The capacity of the AIMSUN model to demonstrate the interactions and conflicts among vehicles surpasses traditional methods, proving essential in the distinct context of motorcycle-dependent settings. Through dynamic representations, the utilization of a simulation model enables a thorough observation of how different factors influence traffic patterns, facilitating the exploration of hypothetical scenarios and providing an assessment of their potential impacts without necessitating expensive or disruptive real-world implementations.

The methodological approach and experimental settings applied in this study are detailed in Section 4.2, which encompasses the case study, structural framework, and fundamental mechanisms used in AIMSUN. The development of the microscopic simulation model for Ninh Kiều District is outlined in Section 4.4, elaborating on the construction, calibration, and validation of the model. Data preparation is discussed in Section 4.3, covering data processing methods, secondary data analysis, and primary survey data collection. The discussion in Section 4.5 critically evaluates the outputs from these models and explores their practical implications, study contributions, and underlying assumptions. The chapter concludes in Section 4.6 with a summary that synthesizes key findings.

4.2 Methodology

The methodology of this research centers on microscopic simulation using AIMSUN Next version 23.0 software, which stands for Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks. This advanced simulation platform is particularly adept at emulating the dynamic and fluid movement of vehicles in environments where conventional lane-following is not the norm, making it highly relevant to the study's context of mixed traffic conditions where motorcycles are prevalent.

AIMSUN, developed by Transport Simulation Systems Ltd. (TSS), distinguishes itself through its multifaceted capabilities, making it adaptable for handling different traffic network complexities. It integrates a range of functionalities, including travel demand modeling, as well as macroscopic, mesoscopic, and microscopic analysis, combined with a hybrid-level simulator (Barceló & Casas, 2005). One of the distinctive strengths of AIMSUN, compared to other simulation models, lies in its integrated framework, which facilitates the seamless fusion of different scales within a singular model. This integration ensures a holistic understanding of any traffic scenario, from high-level strategic planning to detailed operational analysis. With its advanced tools for real-time traffic prediction and management, AIMSUN aids in formulating strategies for incident management, adaptive signal control, and traffic management systems. Overall, this study leverages the advanced capabilities of the AIMSUN to provide a detailed and thorough evaluation of traffic flow dynamics, particularly in motorcycle-dependent urban environments, aiming to develop traffic management solutions that cater to their unique challenges.

4.2.1 Case Study

4.2.1.1 Background of Case Study Selection

The selection of a case study underpins the relevance of empirical research, including when it pertains to urban mobility and the pursuit of effective traffic management solutions. In this context, the criteria hinge on the distinct nature of the region's traffic dynamics and the significant presence of motorcycles as a primary mode of transportation, alongside the accessibility of pertinent data for analysis. Preparing a simulation model requires a substantial amount of fundamental information, and the availability of extensive data from Cần Thơ, Vietnam, facilitates the development and calibration of the model. This study's estimated route choice model for motorcycle riders, detailed in Chapter 3, is designed to represent their behavior accurately in Southeast Asian countries, providing a valuable framework for broader applications due to the similar characteristics of motorcycle-dependent traffic across these regions. In this regard, Vietnam emerges as a particularly fitting subject for study.

The transportation view in Vietnam is characterized by one of the highest rates of motorcycle ownership globally, with motorcycles accounting for about 85% of all vehicles (Tonko & Gidwani, 2018), as shown in Figure 1-1. This dominant use of motorcycles is not merely a cultural feature but also a result of socio-economic factors and urban planning decisions that have historically favored motorcycles as an economical and flexible option. However, this reliance also brings considerable challenges while offering agility and convenience. The urban centers frequently grapple with congestion, where the high volume of motorcycles interacts with other modes of transport, leading to complex and often chaotic traffic flows. The National Traffic Safety Committee reports that congestion causes annual economic losses of around 30,000 billion VND, equivalent to 1.34 billion USD (D. T. Nguyen & Kajita, 2018), underscoring the urgency for efficient traffic management strategies.

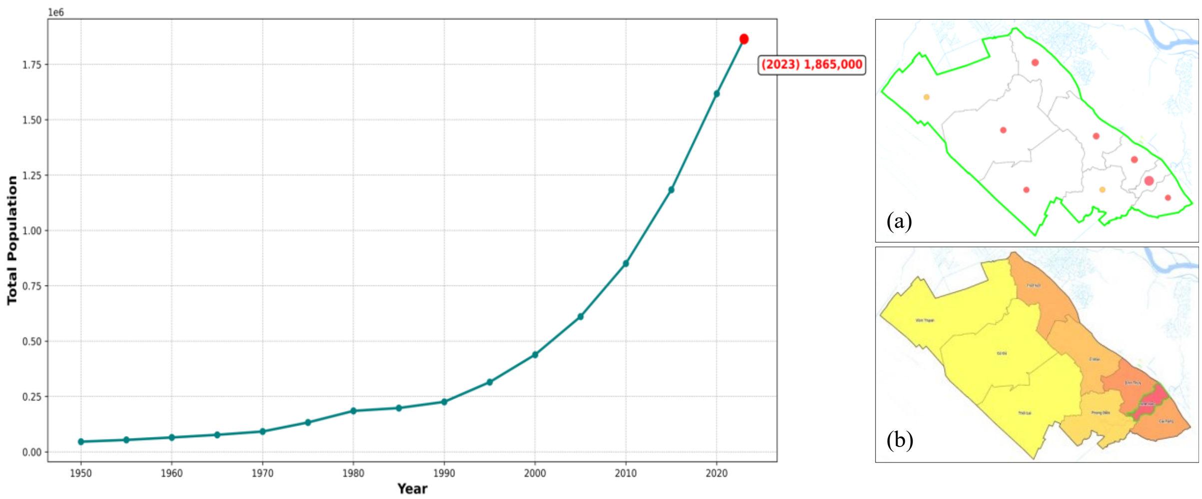
4.2.1.2 Overview of the Area of Analysis

Vietnam spans approximately 331,212 square kilometers and has a diverse population of 97.47 million as of 2021, leading to a density of about 295 inhabitants per square kilometer. Transportation in Vietnam is a mix of traditional and modern elements (Vietnam General Statistics Office, 2022). While bicycles were once the dominant mode of transport, especially in smaller towns and rural areas, they now account for only about 5–7% of travel, having been largely supplanted by motorcycles and motor scooters. Motorcycles are particularly prevalent in cities, accounting for roughly 80–85% of the overall traffic due to their compact size and cost-effectiveness. Public buses are vital in urban commuting, comprising about 5–10% of daily travel, while metro systems are emerging in major cities, marking a trend toward mass rapid transit. Cars and taxis, while growing in numbers, especially with the rise of ride-sharing platforms, constitute 7–10% of the transportation matrix in urban areas. However, this percentage is expected to rise with the expanding middle class and increased car affordability.

Descending toward the southern part of Vietnam reveals Cần Thơ City, located on the right bank of the Hau River and serves as a key urban center in the Mekong Delta region. As the fourth largest city by population in Vietnam, Cần Thơ houses around 1,252,348 inhabitants as of 2022, with a significant majority, 70.5%, residing in urban areas, while the remaining 29.5% dwell in rural locales (Vietnam General Statistics Office, 2022). Covering an area of approximately 1,438.96 square kilometers, Cần

Thơ has a population density of 870 people per square kilometer. It features a multifaceted transportation network that significantly contributes to the connectivity throughout the Mekong Delta. The dominant mode of transportation is motorcycles, reflecting a widespread preference seen across the country. Cần Thơ's administrative divisions include five urban districts and four rural ones. The Ninh Kiều District, in particular, is noted for its high population density, which is pointed out in Figure 4-1. Hence, Ninh Kiều becomes a significant area of interest for the current scope of the analysis.

Figure 4-1 Population – Growth trends and district classification by (a) size and (b) density.



Generated by https://www.citypopulation.de/en/vietnam/cantho/

For a socio-demographic overview, Table 4-1 compiles characteristics of the 13 wards in Ninh Kiều District, detailing area size, population, density, and number of employed individuals and students.

Table 4-1 Socio-demographic characteristics of the Ninh Kiều District (Source: secondary data).

Ward	Area (km^2)	Population	Density (p/km^2)	Employees (p)	Students (p)
An Bình	7.221	19,463	2,385	15,026	2,955
An Cư	0.639	19,060	27,380	12,292	2,189
An Hòa	1.735	32,872	17,043	24,767	2,991
An Hội	0.324	8,420	24,133	5,843	1,279
An Khánh	4.642	25,637	4,958	18,558	2,893
An Lạc	0.469	13,154	26,285	9,603	1,010
An Nghiệp	0.355	10,131	26,121	6,260	1,553
An Phú	0.471	14,106	27,476	10,297	2,142
Cái Khế	7.028	26,902	3,491	21,346	1,085
Hưng Lợi	3.412	38,462	10,361	27,592	2,840
Tân An	0.569	7,185	11,663	5,317	1,091
Thới Bình	0.552	16,473	27,339	11,795	1,528
Xuân Khánh	2.041	34,783	15,939	25,689	2,282
Ninh Kiều	29.460	266,648	8,276	194,385	25,838

Ninh Kiều District, strategically positioned along the Bassac River, is the administrative and commercial center of Cần Thơ's city, where the majority of the city's municipal offices are located. To the south, it interfaces with the Cái Răng district via three large bridges that serve as critical arteries for the flow of traffic. To the north, Ninh Kiều is bordered by Bình Thủy District, while Phong Điền forms its western periphery. The 2019 census documented Ninh Kiều's population at 280,494, spread over an area of 29.46 square kilometers, resulting in a density of 9,599 individuals per square kilometers (Vietnam Central Population and Housing Census Steering Committee, 2020).

The road network in this area is distinguished by varying road types (see Figure 4-2). Trunk roads, which facilitate major through traffic, constitute 6.87% of the network. Secondary roads, which connect major arteries to smaller streets and service moderately dense areas, represent 18.48%. Tertiary roads, often providing access to residential and less commercialized zones, make up 27.91% of the network. The remaining, residential roads, primarily accommodating local traffic within neighborhoods, comprise the largest share at 46.74%. This configuration reflects the dominance of small roads typical in developing countries, accommodating two-wheeled vehicle needs within densely populated urban areas.

Figure 4-2 Distribution of road types in Ninh Kiều District: Trunk, secondary, and tertiary roads.

(a) Trunk Roads

(b) Secondary Roads

(c) Tertiary Roads

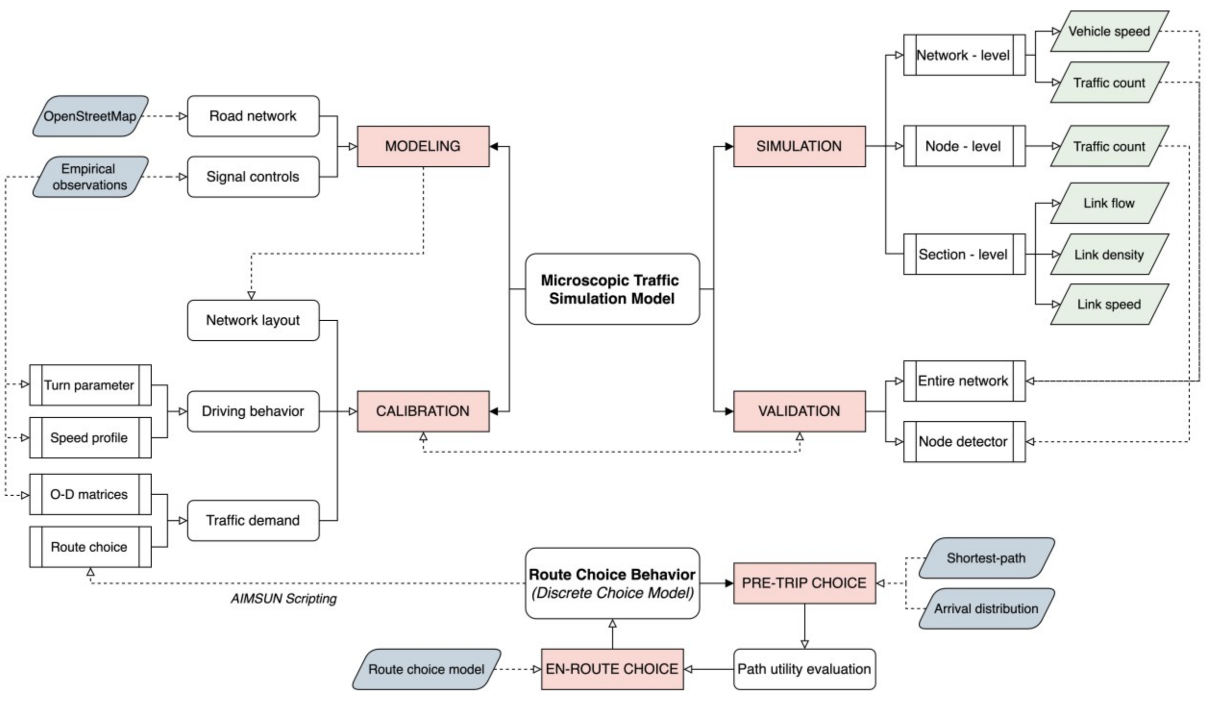
(d) Residential Roads

4.2.2 Structural Framework

An overview of the methodological framework employed in this chapter, shown in Figure 4-3, is a multi-phased process designed to simulate and analyze heterogeneous traffic patterns. It shows the essence of the workflow involved in developing the micro-simulation model, emphasizing the incorporation of the route choice model to accurately describe driver behavior and demand distribution across the network.

The flowchart delineates the structured process of developing a microscopic traffic simulation model, capturing the comprehensive steps from data acquisition to model validation. The modeling phase begins with the construction of the road network, informed by data from OpenStreetMap (OSM) and supplemented by empirical observations such as signal controls. It transitions into calibration, where network layout adjustments are made, and crucial parameters are defined, including turn parameters, speed profiles, O-D matrices, and traffic demand. These are fine-tuned based on driving behaviors, speed profiles, and route choices. Subsequent to calibration is the simulation stage, which assesses network performance indicators like vehicle speed, traffic counts, flow, density, and speed at varying scales: network, node, and section levels. The model goes through a statistical validation phase where simulated results are scrutinized against empirical observation data from the entire network and specific node detectors, ensuring the model's accuracy and reliability for further analysis. Embedded within this process is the route choice mechanism, which includes pre-trip and en-route decision-making based on a discrete choice model. Pre-trip choices involve the evaluation of shortest paths and arrival distributions, while en-route choices consider the utility of different paths. The system's flexibility is further enhanced by the API scripting feature in the AIMSUN, which allows for custom route choice algorithms, integrating real-time data and simulating adaptive driver behavior. This integrative approach encapsulates the dynamics of route selection, modeling the complexity of driver decisions in an urban traffic context. By leveraging the API's capabilities, the simulation dynamically adjusts to changing traffic conditions, ensuring a high level of accuracy in traffic forecasting.

Figure 4-3 Workflow of integration between route choice model and micro-simulation model.



The model underwent iterative calibration and validation following the GEH statistic, a key metric for quantifying discrepancies between simulated and observed data to confirm the statistical acceptance of the model. This process is crucial to address potential variances introduced by the model's parameters and assumptions. While the GEH shares a mathematical resemblance to a chi-squared test, it is noteworthy that this method is not a true statistical test. Instead, it is an empirical formula that is advantageous in evaluating traffic models' performance. The formula for calculating the GEH is outlined as follows, where S and O represent the simulated and observed traffic data, respectively.

$$GEH = \sqrt{\frac{2\,(S-O)^2}{(S+O)}} \tag{4.1}$$

Moreover, in traffic simulation studies, where randomness or stochastic elements such as vehicle arrival times, driver behavior, vehicle interactions, and traffic conditions play a significant role, it is acknowledged that different outputs can emerge from each run. This variability underscores the insufficiency of conducting a single simulation to fully capture the comprehensive range of possible outcomes. It is critical, therefore, to determine an adequate number of replications to ensure the statistical reliability of the outputs. Multiple runs allow for a thorough assessment of the results under a variety of conditions, offering a more accurate representation of average traffic patterns and behaviors.

The inclusion of multiple replications is essential to account for small deviations from specified values, effectively capturing the variability and stochastic nature of traffic. As noted by Hourdakis et al. (2003), repeating simulation runs a number of times is a practical approach to reduce the impact of these deviations. The requisite number of replications depends on the study's objectives, the detail level of the simulation model, and the expected variability in traffic patterns, especially when evaluating unpredictable or infrequent events. Finding the right balance between computational resources and the desired accuracy of simulation outcomes is key in determining the optimal number of replications. Initial statistical analysis of replications can assess result consistency; high consistency might reduce the need for additional runs, while significant variability may require more replications to ensure robust conclusions. The decision on the number of replications should be informed by statistical criteria, such as confidence intervals or the coefficient of variation, to confirm the reliability and representativeness of the simulation results. This method strengthens the credibility of using simulation outcomes for further traffic analysis, effectively reflecting the intricacies of traffic flow and congestion with statistical confidence. Accordingly, Equation (4.2) aids in the computation of the necessary number of simulation replications (R) to achieve a specified confidence level in the mean estimated value of a traffic metric (Chu et al., 2003; Hollander & Liu, 2008; Toledo & Koutsopoulos, 2004).

$$R = \left(\frac{s \cdot t_{\alpha/2}}{\bar{x} \cdot \varepsilon}\right)^2 \tag{4.2}$$

where,

s	: standard deviation of the examined traffic measure
$\bar{x}$	: mean of the traffic measure
ε	: the required accuracy (allowable error), specified as a fraction of the mean $\bar{x}$
$t_{\alpha/2}$	: critical value of the t-test distribution at the confidence level 1-a

4.2.3 Fundamental Mechanism in the AIMSUN

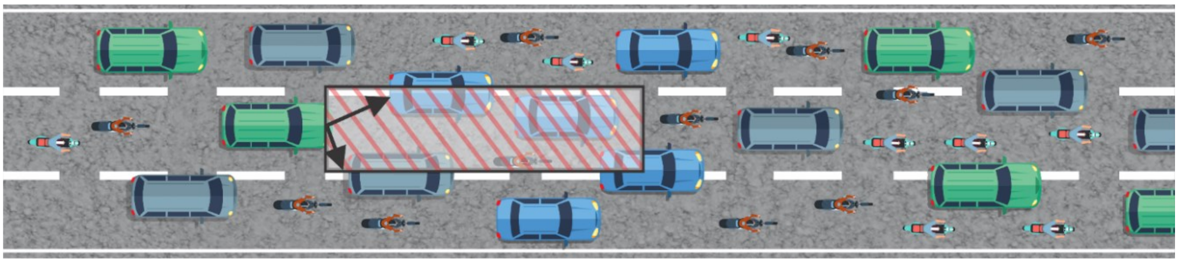
AIMSUN stands out as an advanced simulation tool that encapsulates complex mechanisms to model and forecast traffic dynamics, with its ability to simulate mixed conditions being a primary reason for its selection in this study. In such settings, the dynamic interactions among different vehicle types profoundly affect the traffic flow patterns. This section discusses the key mechanisms of simulation within AIMSUN, highlighting its proficiency in simulating non-lane-based scenarios, detailing the nuances of lane-changing and car-following behaviors, and outlining the process of route selection.

4.2.3.1 Non-Lane-Based Traffic Simulation

In AIMSUN, simulating non-lane-based vehicles provides a more realistic depiction of traffic flow, essential in environments where traditional lane-following behaviors do not adequately represent vehicle interactions. This approach is crucial for capturing the fluid nature of traffic, especially where multiple motorcycles often share lane space. The model's flexibility in simulating non-lane-based movements, tailored to specific vehicle types and road sections, is key to reflecting the distinctive maneuvers of motorcycles, which navigate more freely within and between lanes compared to larger vehicles.

To effectively capture the lateral dynamics of vehicles, particularly motorcycles, AIMSUN introduces specific parameters that govern lateral spacing and movements, such as *'Lateral Clearance*' and '*Maximum Lateral Speed*'. These parameters facilitate the modeling of motorcycles' lateral agility, reflecting their ability to navigate through traffic with a different set of constraints than those applied to cars and larger vehicles. The AIMSUN framework is engineered to avoid lateral oscillations, fostering realistic traffic flow by permitting vehicles to adjust their lateral position during each simulation step based on their current movement and recent lateral changes. This process contributes to smooth and stable traffic conditions, as illustrated by the non-lane-based behavior shown in Figure 4-4.

Figure 4-4 Illustration of non-lane-based behavior in AIMSUN.



4.2.3.2 Lane-Changing Model

Lane-changing in the simulation context for motorcycle-dependent areas reflects the complexity of moving between lanes, influenced by factors like speed, proximity to other vehicles, and driver behavior. This process incorporates tendencies to switch lanes for route optimization or speed improvement, considering the surrounding traffic's cooperation. The model also accounts for drivers' propensity to enter shorter gaps during lane changes, reflecting a range of driving styles from cautious to aggressive.

The AIMSUN simulation incorporates the Gipps model to represent the psychological and physical factors influencing lane-changing decisions. By evaluating drivers' motivations for route-following, speed objectives, and the practicality of maneuvers, the model facilitates realistic simulations of vehicles negotiating tight traffic and executing timely lane changes. It addresses the nuances of driving behavior, including the ability to navigate into narrowing gaps and the need for sudden speed adjustments, providing a real representation of on-road dynamics. Vehicles in the simulation initiate lane changes and overtaking based on speed differentials and traffic flow, simulating drivers returning to original lanes to prevent unnecessary obstructions. AIMSUN also models different driving styles, from cautious to aggressive, by simulating the anticipation of road conditions and corresponding assertive lane changes. It incorporates a safety parameter, ensuring overtaking occurs only under safe conditions. This approach to simulating vehicle dynamics enhances the realism of traffic flow.

4.2.3.3 Route Selection

The route choice mechanism in AIMSUN traffic simulation is a critical component for modeling driver behavior and traffic flow dynamics. Governed by the shortest path calculation at designated route choice intervals, it generates the shortest path tree for each destination centroid. This includes turning penalties and assigning cost labels to links, facilitating a detailed mapping of route choices.

The simulation initiates with an assessment of initial link costs, which are then dynamically updated in subsequent intervals to reflect changing traffic conditions. The dynamic traffic assignment method includes the calculation of initial shortest paths using predefined costs, the simulation of traffic over designated intervals, and the updating of paths based on the observed travel times. Additionally, the concept of initial K-Shortest Paths is employed to provide multiple routing alternatives at the onset of the simulation, enhancing the model's ability to anticipate traffic distribution. This method incrementally assigns traffic demand across these paths, recalculating and updating paths as the simulation progresses based on the evolving traffic conditions and link cost functions.

Path selection operates by estimating flow rates along different routes, simulating a driver's decision-making process among a set of available paths. This is achieved through discrete route choice models or user-defined assignments, where drivers are initially assigned paths upon entering the system, with the option to update their route choices en-route as new alternatives present themselves. Path selection calculates the likelihood of each available path, leading to drivers randomly choosing based on these probabilities. This mechanism is part of the dynamic traffic assignment process, where initial paths are determined using preset costs and subsequently updated based on travel times derived from the simulation. The simulation process alternates between calculating the shortest paths and updating them, taking into account the actual travel times or any predefined factors in the route choice function.

In essence, the route selection mechanism in AIMSUN dynamically interweaves initial route assignments with real-time updates to paths based on evolving traffic conditions, ensuring that the simulation accurately mirrors the complexity and variability of real-world traffic scenarios.

4.2.3.4 Calibration of Simulation Parameters for Motorcycle Dynamics

In the realm of traffic simulation, calibration of vehicle behavior is crucial for reflecting the traffic patterns observed in such environments. The simulation parameters for vehicles, which are carefully adjusted within AIMSUN, play a pivotal role in this process. The efficacy of AIMSUN's simulation is rooted in its extensive array of tunable parameters, which can be calibrated to mirror the distinctive traits of motorcycle traffic. The calibration process extends beyond mere scaling to incorporate a detailed comprehension of riders' behaviors. Motorcycles are known for their flexibility and maneuverability, which necessitate specified simulation parameters compared to larger vehicles. Motorcyclists exhibit distinct driving behaviors, such as the propensity to utilize smaller gaps, filter through traffic, require less space to maneuver, and operate in close proximity to other vehicles. To capture these behaviors, the model facilitates precise adjustments to parameters like clearance and following distance.

One of the key adjustments involves the spacing between vehicles. Motorcycles, due to their smaller footprint, do not adhere to the same spacing rules as larger vehicles. In simulation, this is reflected by allowing motorcycles to operate with reduced spacing requirements, both laterally and in the following distance. This flexibility in movement is further enhanced by the adjustments made to the parameters governing the vehicles' response to traffic signals and guidance systems. Motorcycles in these simulations are often given a higher responsiveness level, which allows them to react more quickly to changing traffic conditions, a common characteristic observed in the actual behavior. Moreover, the AIMSUN modeling capabilities consider the rapid acceleration and agile deceleration typical of motorcycles, differentiating them from cars and larger vehicles. The calibration of these dynamic models is essential to capture the riders' ability to swiftly respond to changing traffic conditions.

AIMSUN also offers specialized features for simulating non-lane-based movements, including behaviors such as lane splitting and filtering, which are not commonly permitted or possible for other vehicle types. The parameters governing these behaviors are carefully adjusted to enable motorcycles to navigate between lanes, enhancing the realism of the simulation. Intersections and merging scenarios are other areas where the flexibility of the AIMSUN in parameter adjustment proves invaluable. Motorcycles often can yield or merge within much shorter time frames than cars, which is reflected in how they are modeled in the software. By calibrating these parameters, AIMSUN can effectively simulate the quick and dynamic interactions of motorcycles at these critical points in the traffic network.

In conclusion, the calibration of vehicle-specific parameters for motorcycles within traffic simulations is a complex but essential process. It ensures that the resulting models can effectively replicate the dynamic traffic patterns found in motorcycle-dependent areas.

4.3 Data Preparation

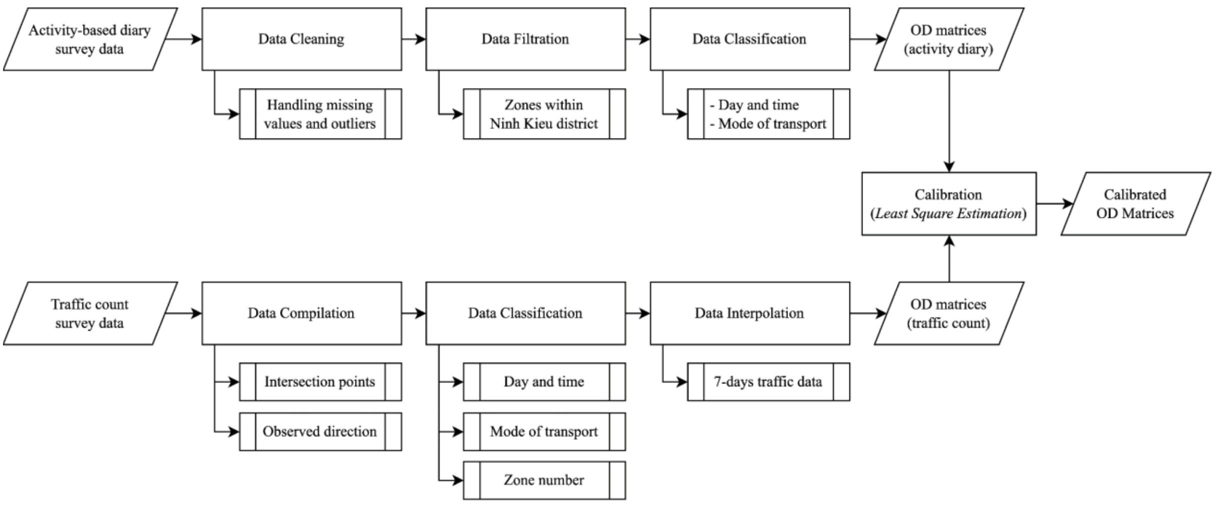
Data collection and processing are crucial for conducting a reliable and precise analysis. The present research draws on secondary traffic data for Cần Thơ City, provided by the "*Sustainable Urban Public Transport and Central Area Traffic Management Study for Cần Thơ City*," carried out from 2019 to 2020. However, the acquired data necessitated further refinement to align with the specific criteria in this study. Two datasets were employed: activity-based diary data and traffic count data from several major intersections. In addition to that, the study also incorporated field observations and measurements of traffic signal cycles and phase timing, enhancing the traffic conditions information in the study area.

Therefore, this section delves into the processing techniques applied to these datasets, addressing the strengths and constraints, to prepare the data for subsequent stages of analysis. The details of the procedures used and the outcomes obtained from the data preparation process are also discussed.

4.3.1 Data Processing Method

The structured methodology for data preparation, as visualized in Figure 4-5, commenced with separate processing streams for the activity diary data and the traffic count survey data. This approach allowed for tailored cleaning procedures for each data type, ensuring the preservation of their singular attributes.

Figure 4-5 A framework of survey data processing.



For the activity-based diary data, the process began with data cleaning, a crucial step to address discrepancies and rectify any inconsistencies present in the dataset. This phase involved handling missing values and outliers that could potentially skew the study's outcomes. The following stage, data filtration, narrowed the focus to zones within the Ninh Kiều District, ensuring that the analysis would be pertinent to the study's targeted area. Subsequent classification of the data was based on the day and time of travel, as well as the mode of transport, which are critical factors in understanding travel patterns and demands. In parallel, the traffic count survey data underwent a compilation phase, where data from intersection points were collated, including the observed direction of traffic flow. This dataset was then classified according to similar temporal and spatial parameters, along with the mode of transport and zone numbers, aligning it with the diary data. Data interpolation was employed to fill in gaps within the seven-day traffic dataset, which helped in constructing a complete picture of the weekly traffic trends.

The ultimate stage of this preparation was the calibration process, utilizing Least Square Estimation, to synthesize the data from both streams into calibrated O-D matrices. These matrices were crucial for the subsequent modeling and simulation phases, as they provided a quantitative foundation for predicting traffic flows, ensuring reliable inputs for the traffic models were achieved.

4.3.2 Secondary Data Analysis

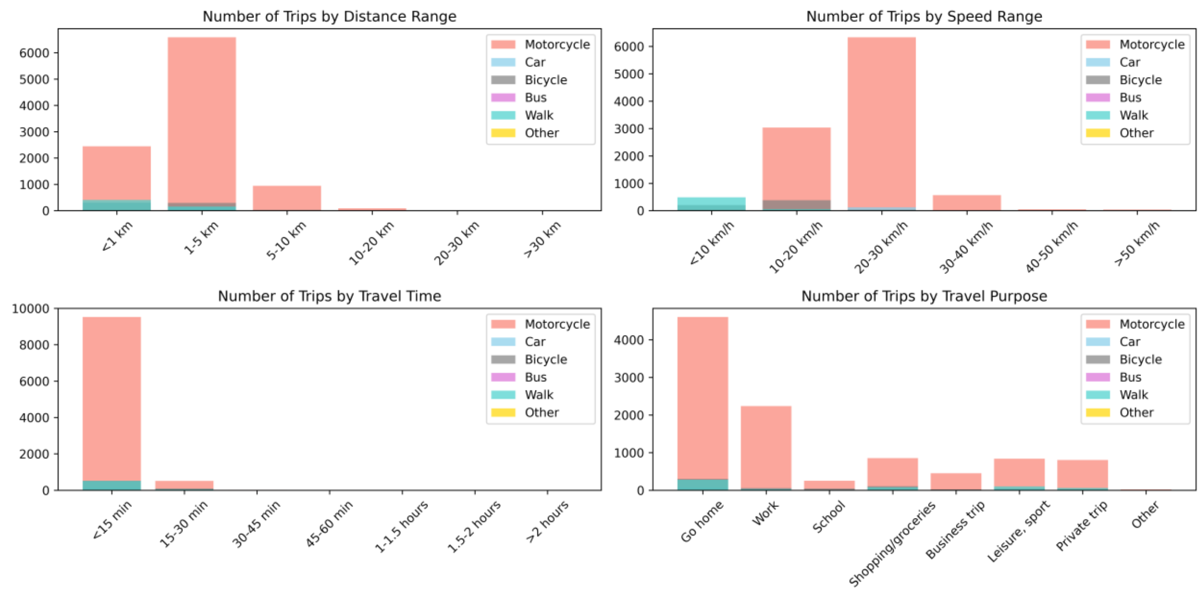
This section elaborates on the detailed processing and analysis of data from activity-diary surveys and traffic count surveys, examining their characteristics, patterns, and trends.

4.3.2.1 Activity-based Diary Survey Data

The activity diary survey data was systematically gathered over a period of seven days from a representative sample of residents in Cần Thơ city. A total of 5,841 participants were asked to maintain a diary in which they recorded detailed information about every trip they made during this time period. For each journey, they provided data detailing the purpose of their travels. This covered varied motives, ranging from routine tasks like returning home and commuting to work or school, as well as to more specific errands such as shopping, business trips, leisure, sports, personal affairs, and other activities. The investigation further enriched the data by documenting the characteristics of the trips, encompassing some essential metrics such as the distance they traveled, speed, and trip duration of each trip.

Figure 4-6 graphically depicts segmented data across Ninh Kiều District, respectively, highlighting distance, speed, travel time, and trip purpose for respective modes of transportation. The trend reveals a pronounced preference for motorcycles in both regions, with usage significantly surpassing that of cars, bicycles, and buses. This suggests a dependency on motorcycles, likely attributed to their adaptability and ease of navigation in urban areas. The infrequent use of buses may point to underdeveloped public transport infrastructure and services. Walking, while not predominant, still constitutes a notable share of local travel. The majority of recorded trips are short, typically under 15 minutes and less than 5 kilometers, primarily for commuting between home and work.

Figure 4-6 Classification overview of activity diary survey data for Ninh Kiều District.



Regarding the mode of transportation, survey participants also reported their chosen mode: walking, bicycles, motorcycles (distinguishing between passenger and driver roles), motorcycle taxis (online services), passenger cars (as either passenger or driver), car taxis (online services), urban buses, contract buses, and other modes. Nevertheless, for the ease of subsequent analysis, the multiple sub-categories of motorcycles and cars were merged into broader categories: 'motorcycle' and 'car', respectively. Specifically, within the Ninh Kiều District, the data comprised 11,465 entries: 10,071 for motorcycles, with motorcycles accounting for 10,071, passenger cars for 180, walking for 573, bicycles for 619, and the remaining 22 entries falling under various other transportation modes.

In accordance with the methodology framework in Section 4.2.2, the survey data pertaining to activity diary patterns underwent a transformation to be represented in the form of O-D matrices, relying on the pre-defined zones present within the dataset. The starting and ending locations of each trip were denoted using zone numbers, as indicated in the following map (see Figure 4-7). Any trips that extended beyond these designated zones were categorized as external trips, providing a complete picture of travel patterns, encompassing traffic in the Ninh Kiều District. The study mapped out 35 internal zones and included an additional 7 to capture external travel within the district's geographical boundaries.

Figure 4-7 Definition of zone numbers in the activity diary survey data.

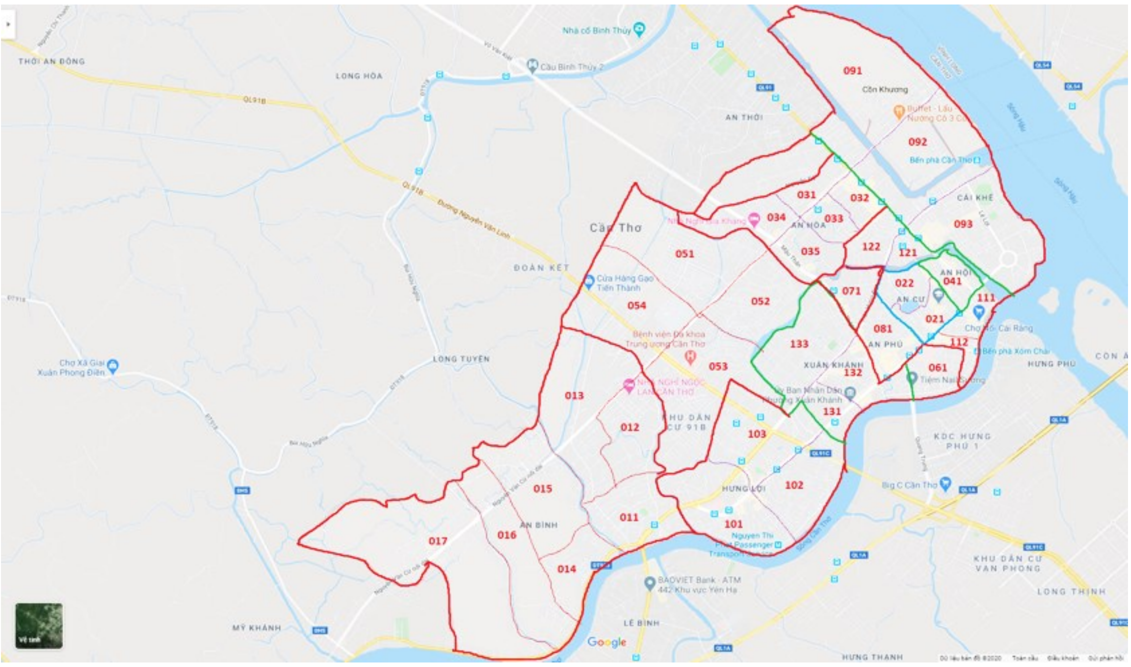
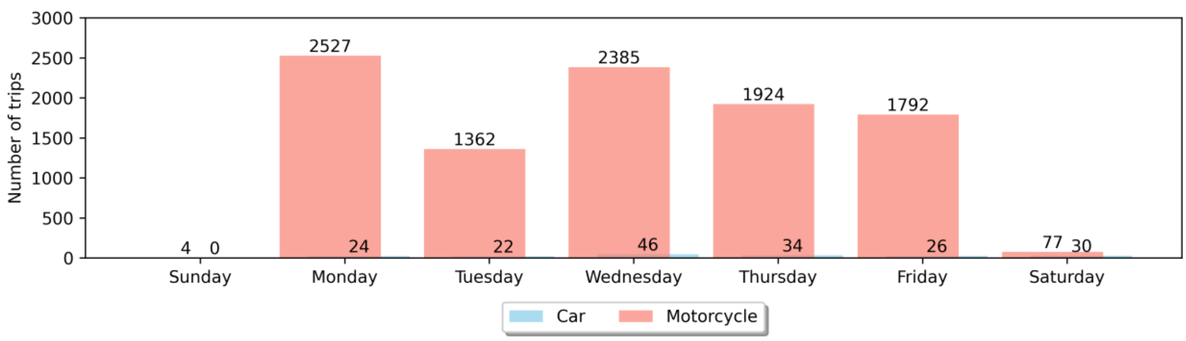


Figure 4-8 Summary of activity-based diary survey data in Ninh Kiều District.



The process began with extensive data cleaning to remove any missing values and outliers, focusing on the Ninh Kiều District. This step was essential to ensure data quality and relevance to the study's objectives. It was assumed that each journey between a single O-D pair represented a unique trip, irrespective of multiple trips made by an individual during a given day. It should also be highlighted that trips undertaken using transportation modes other than cars and motorcycles were not considered. Subsequently, the O-D matrices were systematically organized by the specific days of each trip and the mode of transportation used, which is visually summarized in Figure 4-8. A detailed breakdown of the refined O-D matrices, extracted from the activity diary survey data is available in Appendix A.

4.3.2.2 Traffic Count Survey Data

Another secondary data comprised traffic count surveys from 12 major intersections within Ninh Kiều District, detailing traffic flow in various driving directions for each road arm, as shown in Figure 4-9.

Data collection was carried out continuously over 24 hours each day using video recording methods in 5-minute intervals, capturing daily fluctuations in traffic, ranging from early-morning commuters to late-night traffic. This observation spanned three days, from the 23rd to the 25th of February 2020, covering both a weekend day (Sunday) and working days (Monday and Tuesday) to capture a holistic perspective on varying traffic patterns. The data categorization reflected the traffic composition, sorting vehicles by type and size into several groups. These encompassed bicycles, motorcycles, cars (seating less than eight passengers), taxis, larger cars (seating capacity up to 25), buses (more than 25 seats), public buses, light goods vehicles (LGVs under 4 tons), heavy goods vehicles (HGVs between 4 and 10 tons), HGVs over 10 tons, containers, and other types like tricycles.

Figure 4-9 Distribution of traffic count monitoring locations in Ninh Kiều District.

Figure 4-10 shows an example of both the setup for the traffic count survey and the resulting data collected at the Ba Tháng Hai - Nguyễn Văn Linh intersection, with color-coded lines depicting the paths of vehicles and a table detailing the hourly traffic volume. Following this, Figure 4-11 and Figure 4-12 present the layouts of the observed turning percentages for cars and motorcycles, respectively.

Figure 4-10 Traffic count data at Ba Tháng Hai - Nguyễn Văn Linh intersection.

From	To	Bicycle	Motorcycle	Car (< 8 seats)	Taxi	Bus (<=25 seats)	Bus (> 25 seats)	Public Bus	Small Truck (< 4T)	Medium Truck (4-10 T)	Large Truck (>=10 T)	Container	Other (Tricycle)
00:00:00	01:00:00	0	317	2	0	0	0	0	2	2	0	0	0
01:00:00	02:00:00	0	356	6	2	0	0	0	2	0	0	0	0
02:00:00	03:00:00	0	320	5	1	3	0	0	3	4	0	0	0
03:00:00	04:00:00	0	314	10	2	0	0	0	4	3	0	0	0
04:00:00	05:00:00	0	380	7	5	1	1	0	8	6	2	1	0
05:00:00	06:00:00	4	498	9	5	1	3	0	7	4	0	2	0
06:00:00	07:00:00	6	948	15	4	4	7	0	3	5	3	1	0
07:00:00	08:00:00	2	1433	45	7	6	1	0	11	17	13	4	1
08:00:00	09:00:00	0	1504	61	15	7	0	0	12	44	23	4	1
09:00:00	10:00:00	0	1469	82	9	2	0	0	12	42	31	8	0
10:00:00	11:00:00	0	1557	97	10	0	0	0	11	36	24	12	0
11:00:00	12:00:00	0	1869	109	10	5	1	0	12	28	14	15	2
12:00:00	13:00:00	0	1176	68	5	0	0	0	13	32	16	18	1
13:00:00	14:00:00	0	1109	80	6	6	3	0	11	29	12	9	2
14:00:00	15:00:00	0	956	82	5	2	5	0	34	42	5	7	0
15:00:00	16:00:00	0	1098	89	10	5	0	0	37	42	3	3	2
16:00:00	17:00:00	0	1579	74	11	6	0	0	11	34	9	11	0
17:00:00	18:00:00	0	2879	106	1	4	1	0	19	28	8	6	0
18:00:00	19:00:00	0	1738	98	0	2	0	0	6	27	2	4	2
19:00:00	20:00:00	0	1702	112	0	1	0	0	11	20	10	5	0
20:00:00	21:00:00	3	1339	101	0	1	0	0	9	7	4	1	0
21:00:00	22:00:00	1	1396	87	5	1	1	0	8	6	6	2	0
22:00:00	23:00:00	0	1233	37	7	1	0	0	4	3	5	1	0
23:00:00	00:00:00	2	404	21	5	0	0	0	0	0	1	1	0

Figure 4-11 Car turning percentage at Ba Tháng Hai - Nguyễn Văn Linh intersection.

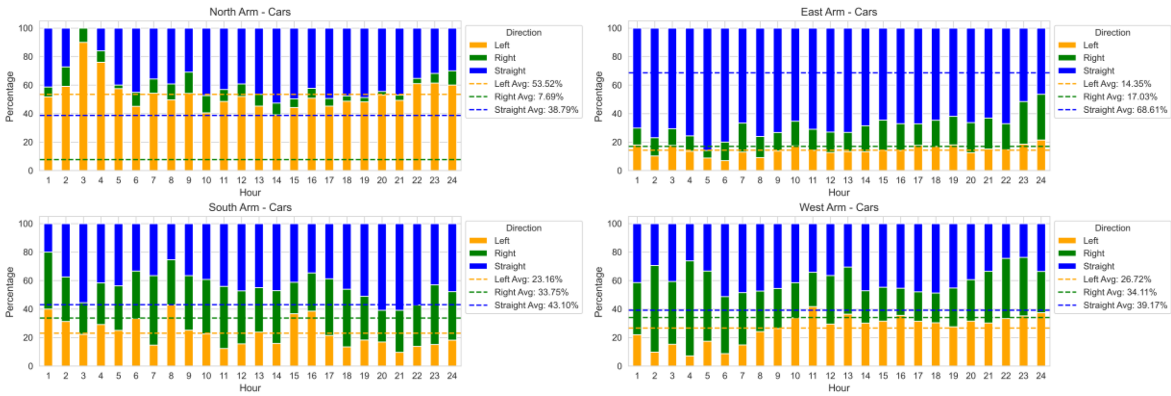
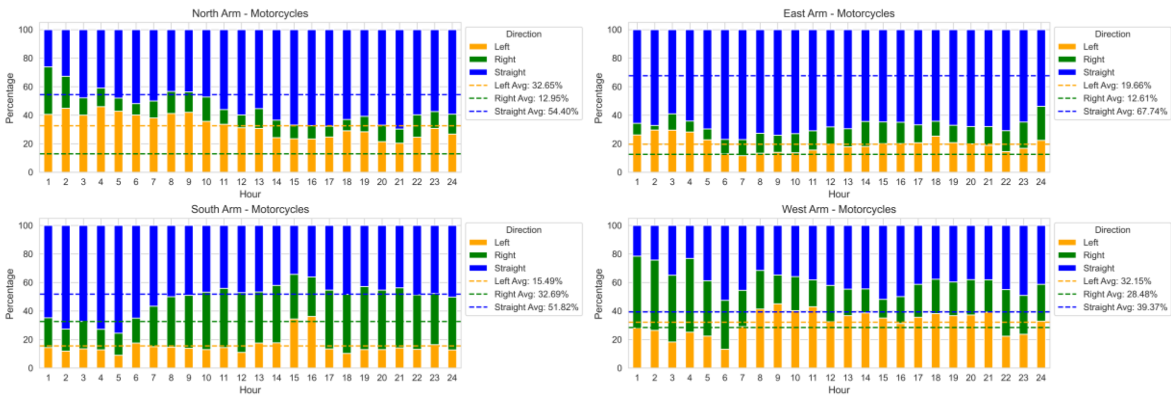
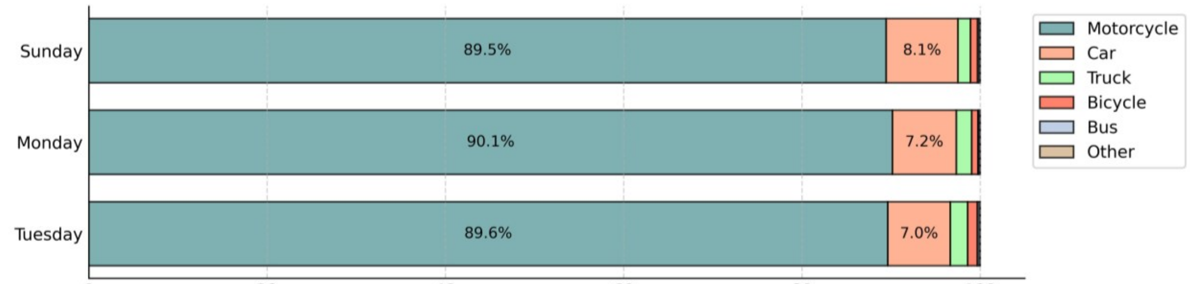


Figure 4-12 Motorcycle turning percentage at Ba Tháng Hai - Nguyễn Văn Linh intersection.



The data compiled facilitated the calculation of modal shares, displayed in Figure 4-13. As expected, motorcycles emerged as the dominant mode of transport in Ninh Kiều District, comprising nearly 90% of the total traffic monitored across the three-day survey. Passenger cars accounted for an average of 7.4%, while trucks, buses, bicycles, and other vehicle types, made up a minor portion of the traffic composition. Accordingly, the subsequent analysis focused exclusively on motorcycles and cars.

Figure 4-13 Mode share from traffic count survey data in Ninh Kiều District.



	Motorcycle	Car	Truck	Bicycle	Bus	Other
Sunday	89.5%	8.1%	1.4%	0.8%	0.2%	0.1%
Monday	90.1%	7.2%	1.7%	0.7%	0.2%	0.1%
Tuesday	89.6%	7.0%	1.9%	1.1%	0.2%	0.1%

Overall, Figure 4-14 provides a graphic summary of the traffic count data, explicitly highlighting the flow of cars and motorcycles across 12 surveyed intersections. This aggregation pinpoints Monday as the peak traffic day, consistent with the typical start of the workweek. Conversely, Sunday records the least traffic, reflecting the weekend's reduced activity. For a thorough tabulation of traffic counts at each intersection, refer to the detailed tables provided in Appendix B.

Figure 4-14 Summary of traffic count data in Ninh Kiều District.

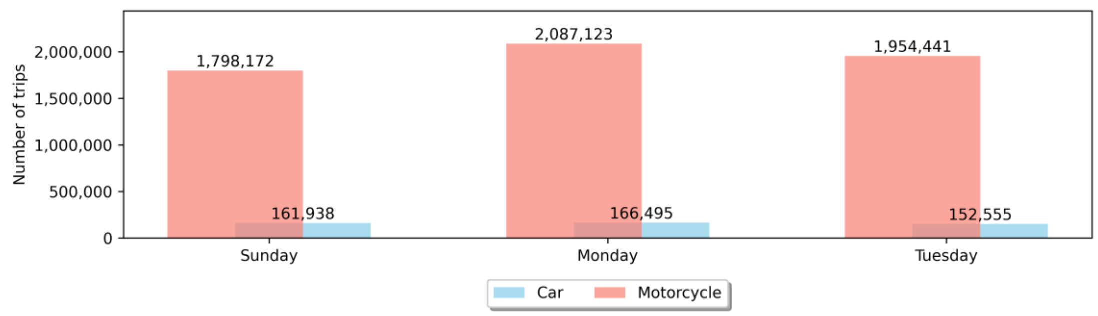
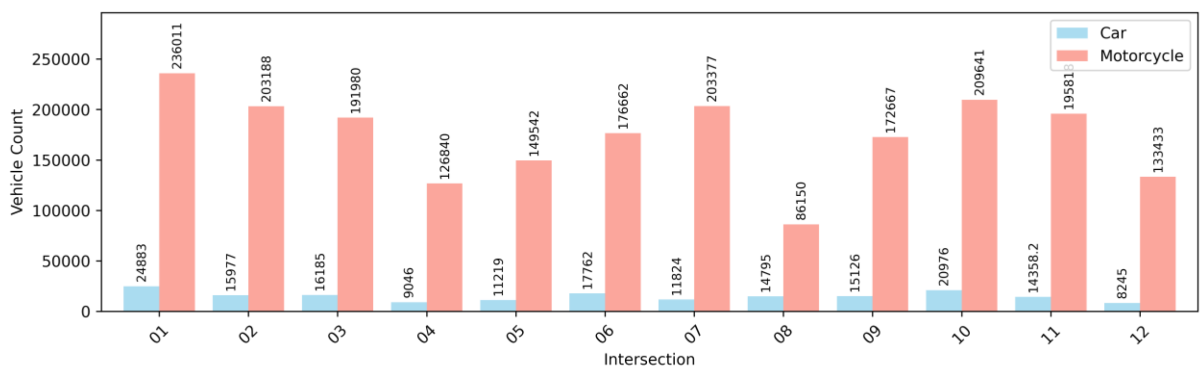


Figure 4-15 Aggregated traffic counts data across intersections.



In addition, Figure 4-15 presents the 24-hour aggregated vehicle counts for cars and motorcycles across each major intersection during the highest traffic volume recorded on Monday—the busiest day observed in the survey period. The intersection identifiers correspond with those listed in Figure 4-9. The hourly traffic volume graph from traffic count data from a survey on Monday, February 24th, 2020. For further analysis, traffic count survey data was systematically organized by zones, aligning with zone numbers depicted in Figure 4-7.

4.3.2.3 Calibrated Traffic Demand Results

The chart in Figure 4-16 provides a summary of the calibrated O-D matrices for traffic flow between zones within the study area, which were generated based on the workflow detailed in Figure 4-5 and derived from processing the two data sources previously discussed.

The calibrated traffic data mentioned above were used as inputs to develop the microscopic traffic simulation model, revealing distinct traffic patterns in the Ninh Kiều District. Mondays are marked as the busiest day of the week, showing a peak in trip volume. A notable observation from the data is the prevalence of motorcycles, accounting for approximately 90% of the traffic volume. This finding aligns with Vietnam's status as the country with the highest rate of motorcycle ownership globally (Tonko & Gidwani, 2018), underscoring the motorcycle's role as the primary mode in the region. For a granular analysis of trip production and attraction in each ward of Ninh Kiều District, refer to Figure 4-17.

Figure 4-16 Calibrated car and motorcycle trips in Ninh Kiều District.

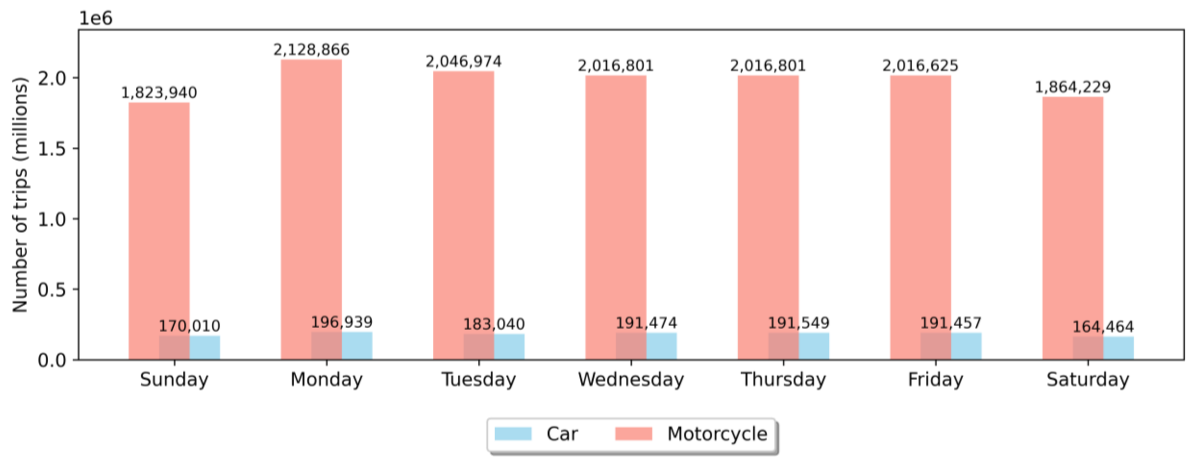
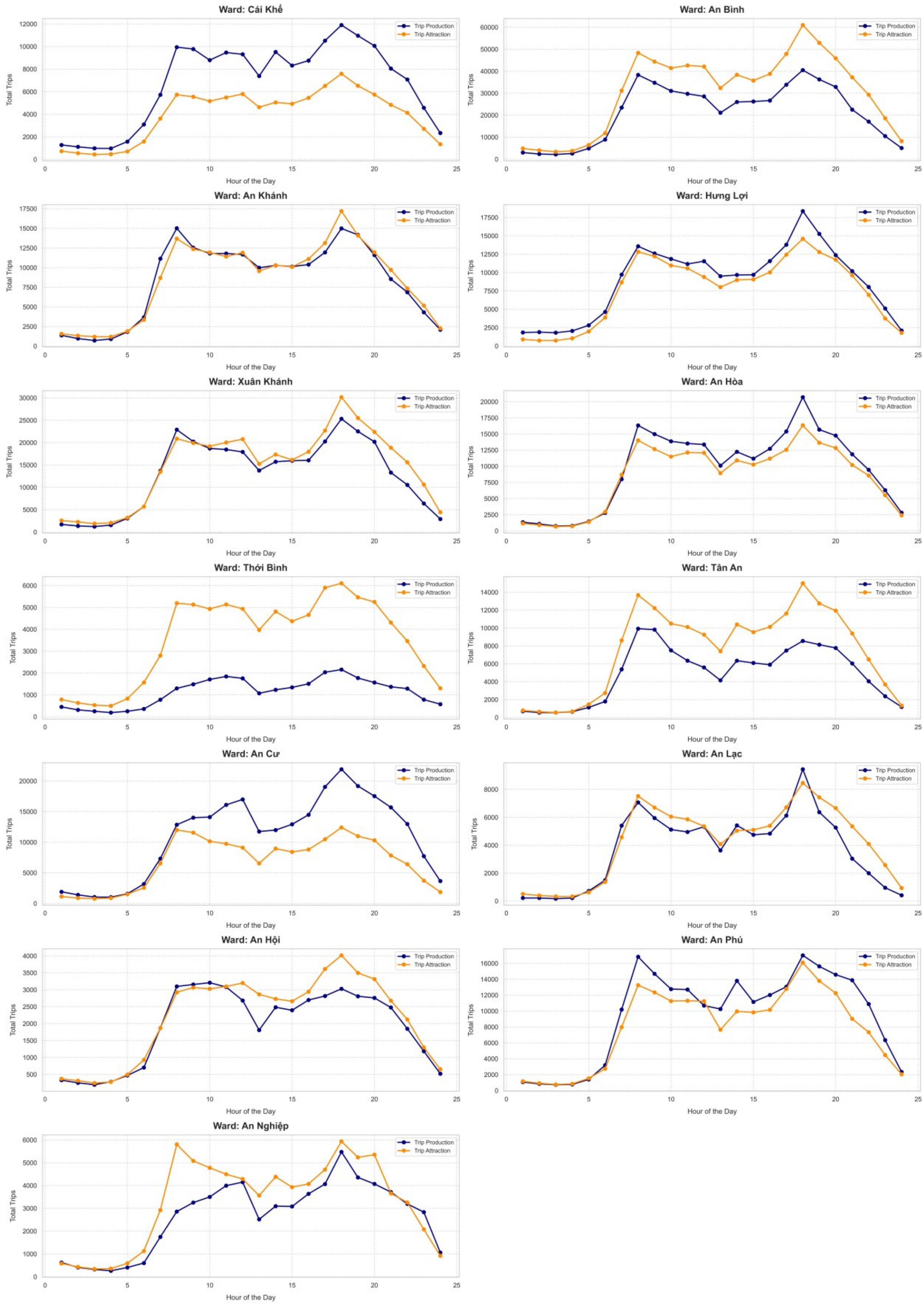


Table 4-2 then presents a comparative summary of daily trip counts for cars and motorcycles, capturing the data prior to and subsequent to calibration adjustments of traffic demand. Initially, trip data were compiled from a combination of activity diary surveys and traffic counts, whereas after adjustments, the updated trip counts reflect refined data from the two data sources and the integration of external trips. The adjustments result in a notable increase in recorded trips, with the total number of daily trips for cars and motorcycles post-adjustment standing at 196,939 and 2,128,866, respectively.

Table 4-2 Comparison of Monday vehicle trips before and after adjustments.

	Pre-adjustments (activity-diary + traffic count)	Post-adjustments
Total number of trips for cars	24 + 166,495	196,939
Total number of trips for motorcycles	2,527 + 2,087,123	2,128,866

Figure 4-17 Daily trip production and attraction patterns across wards in Ninh Kiều District.



4.3.3 Primary Survey Data

In addition to secondary data acquisition, the study conducted a primary survey on March 2nd, 2024, to perform field observations and gather empirical data. Figure 4-18 demonstrates how motorcycles dominate the traffic streams in Ninh Kiều District, with the observed roads mostly lacking distinct lane demarcations. This supports the fluid, non-lane-based riding habits of motorcyclists.

Figure 4-18 Field observations of traffic conditions in Ninh Kiều District.

The main target of this survey was to record the configurations of traffic signals at 27 intersections within the study area, as depicted in Figure 4-19, which shows the spatial distribution of these intersections on a map: red points for signalized intersections and blue for roundabouts without signals.

Figure 4-19 Map of traffic signal observations in Ninh Kiều District.

Primary data covered details on the phases and cycles of traffic signals at these intersections, selected based on geographic spread, size, and strategic relevance to the district's traffic network. The data collection methodology included on-site observations—manually recording signal timings—and traffic flow video analysis, which provided details on the signal timings and clarified the geometric layout of the roadways. This detailed documentation is integrated into the AIMSUN model for calibration to replicate actual network conditions accurately. The analysis revealed that intersections typically operate on either two or four phases, with the latter used at busier junctions to accommodate extended green times for left turns, in accordance with right-hand driving rules. It was also noted that right turns, particularly by motorcycles, often disregard red signal phases—a common occurrence in many developing countries. A significant finding was the lack of designated signal timings for pedestrian crossings across the district, highlighting prevalent jaywalking in these urban settings. Examples of two-phase and four-phase traffic signal configurations are shown in Figure 4-20 and

Figure 4-21, respectively, with further details on the remaining intersections provided in Appendix C.

Figure 4-20 Illustration of a two-phase traffic signal system at an intersection.

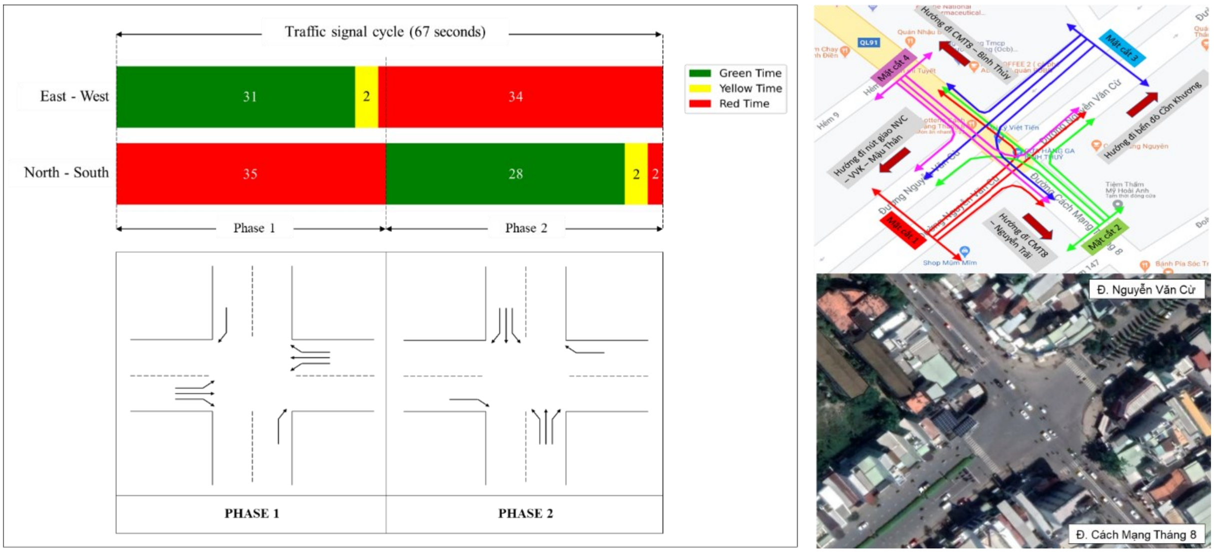
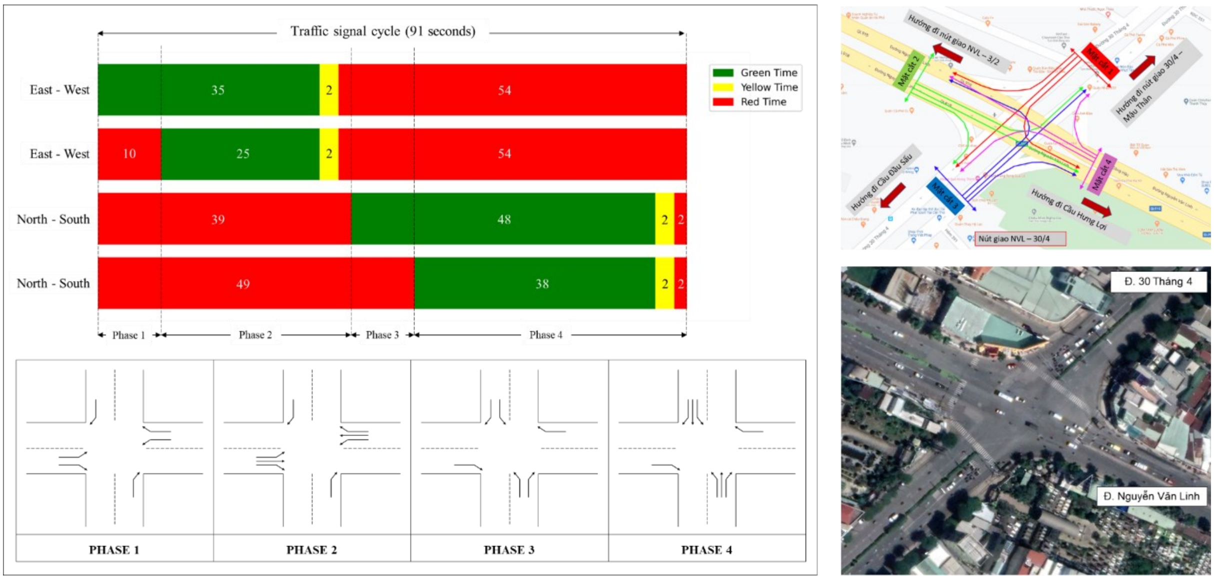


Figure 4-21 Illustration of a four-phase traffic signal system at an intersection.



4.4 Experiment Settings

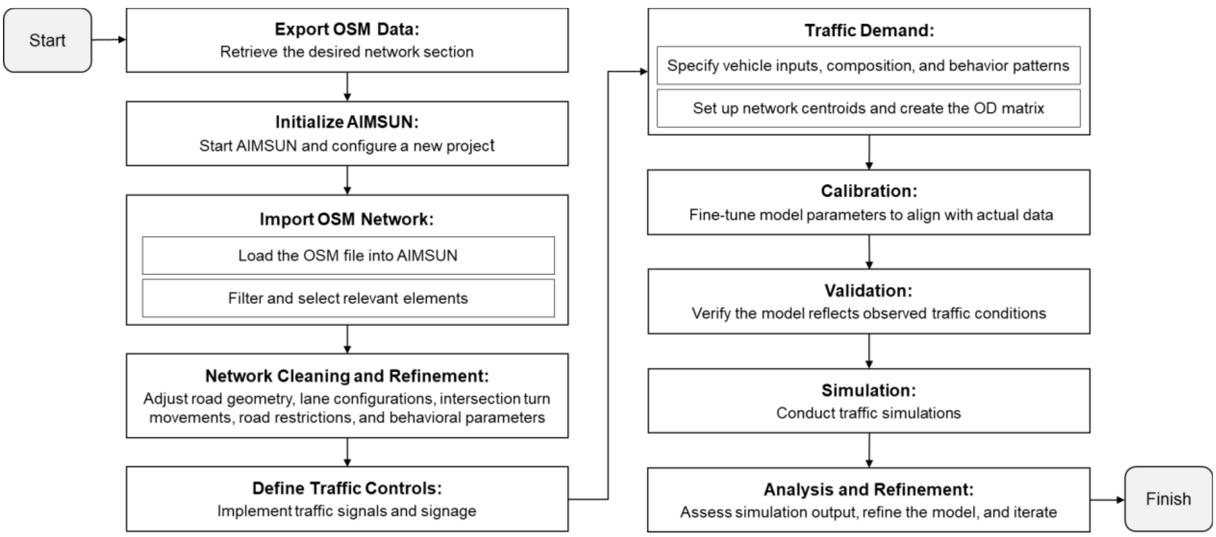
The study utilized microscopic traffic simulation, recognized for its effectiveness in addressing a variety of challenges (Chu et al., 2003), as a principal technique for analyzing the traffic system in this context. This model is indispensable in transportation planning and analysis, adeptly capturing the movements of individual vehicles and their interactions with the infrastructure and one another. It examines the micro-level behaviors of road users and conducts detailed assessments of evolving network conditions. This granular approach offers a sharper analysis compared to models with different levels of detail, facilitating accurate assessments of traffic control, road design changes, and the effects of new transportation schemes. The micro-simulation model also effectively replicates drivers' decision-making processes, including route selection and responses to information, and models the implementation of traffic management strategies, technologies, and infrastructure (Balakrishna et al., 2007).

This section outlines the development, calibration, and validation of the model, establishing a framework for analyzing mixed motorcycle traffic. This comprehensive preparation ensures the simulation closely reflects real conditions and provides a reliable base for analyzing various scenarios.

4.4.1 Development of the Traffic Microsimulation Model

Figure 4-22 shows the structured workflow employed to develop the AIMSUN micro-simulation model, systematically detailing each step of the process as outlined in section 4.2.1. The model development begins with the extraction of OSM data, which provides geographic and infrastructural information essential for precisely representing the actual road topology. This initial step involves transforming the real-world network into a format that is compatible with the AIMSUN simulation environment, where road segments are defined as links, intersections as nodes, and traffic origins and destinations as zones.

Figure 4-22 Development process of traffic micro-simulation model.



Within this simulation environment, AIMSUN models driver behavior using predefined parameters for car-following, lane-changing, and gap acceptance, shaped by the Gipps model (Gipps, 1981). This model considers safety distances and rates of acceleration and deceleration, realistically depicting drivers striving to achieve their desired speeds, influenced by vehicle characteristics and the behavior of leading vehicles. Following network setup, the model undergoes calibration and validation phases to ensure it accurately and statistically reflects real-world conditions. Figure 4-23 visualizes the AIMSUN model of the study area, with further details on these processes in subsequent subsections.

Figure 4-23 AIMSUN simulation model of the Ninh Kiều District.

4.4.2 Model Calibration

Developing a microscopic traffic simulation requires accurately representing roadway layouts, traffic control systems, and driver-vehicle interactions. While the software provides a set of default parameters for these aspects, customizing them to match the specific characteristics of each study network is crucial through calibration—a detailed, iterative process to adjust the simulation model's parameters to mirror actual conditions (Hourdakis et al., 2003). The primary goal is to fine-tune input parameters to minimize discrepancies between simulated traffic flow and field measurements, a process complemented by a validation phase to confirm the accuracy of the simulation outcomes. The calibration process, performed through trial and error, was necessitated by the extensive array of undefined parameters and the considerable computational workload involved in conducting traffic simulations.

This study places particular emphasis on calibrating behavioral models that depict driving behaviors and cognitive processes involved in route selection, highlighting the importance of accurately modeling driving behavior, especially in motorcycle-dependent environments. However, not all parameters require calibration. Hollander and Liu (2008) suggest that directly measurable parameters, like vehicle dimension, typically do not require calibration and often rely on the default settings offered by micro-simulation models. In this study, the range of vehicle types and their respective dimensions incorporated into the AIMSUN model are presented in Table 4-3. Similarly, parameters that fall outside the research scope or are not contextually relevant to the study's focus are not calibrated. This includes pedestrian-related parameters, those pertaining to autonomous vehicles and public transport operations, and environmental factors like the impact of vehicle engines, engine types, and fuel consumption.

This section discusses the calibration of three primary components of the microscopic simulation model: road network topology, traffic demand, and driver behavior. Each aspect is detailed below.

Table 4-3 Vehicle types and their dimensions in the AIMSUN simulation model.

Vehicle Type	3D Shapes		Range of Length
Motorcycles			1.50 – 2.50 meter
Cars			3.50 – 4.00 meter
			4.00 – 4.20 meter

4.4.2.1 Road Network Topology

The calibration of the simulation model begins by defining the study area and creating a detailed geometric representation of the road network, including segments, intersections, and turning movements. Such detailed configurations are crucial, as they influence vehicle flow, route selection, and network capacity, ultimately shaping the integrity of simulation outputs essential for traffic analysis.

In the initial calibration phase, redundant road segments like certain local pathways and footpaths, were removed to streamline the focus, guided by land use and connectivity considerations. The next step was to adjust road geometry to match actual conditions, such as lane numbers and widths, and apply vehicular restrictions according to traffic rules. Disjointed road segments were then merged to form a coherent link structure. Further refinements included specifying behaviors for each road segment based on vehicular limitations and observed traffic regulations, and adjusting intersection configurations to include traffic signals, priority rules, and other controls. These modifications resulted in a refined representation of the network while ensuring that the selected level of detail and spatial boundaries comprehensively cover the traffic system. The increase in O-D zones post-calibration indicates a more detailed mapping of traffic patterns, and the integration of external trip flows into and out of the area.

Figure 4-24 Transformation of road configuration: (a) pre-calibration, and (b) post-calibration.

(a) (b)

Figure 4-24 shows a visual comparison, showcasing the road network's evolution from its initial to its calibrated state, thereby underlining the substantial improvements in road topology representation. Alongside road topology, the micro-simulation model integrates traffic management schemes that influence vehicle speeds and regulate permissible turns. It also encompasses traffic signal control schemes, incorporating detailed settings of signal phasing, timing sequences, and offset alignments, as documented from the primary data in section 4.3.3, all of which significantly affect the flow of traffic. The calibration process further involves setting up additional control measures, such as roadside detectors, traffic signs, and VMS, to collect real-time traffic data and provide drivers with information. This integration of controls and data ensures that the simulation model operates with a high level of accuracy and utility, serving as a foundation for generating reliable solutions to traffic issues.

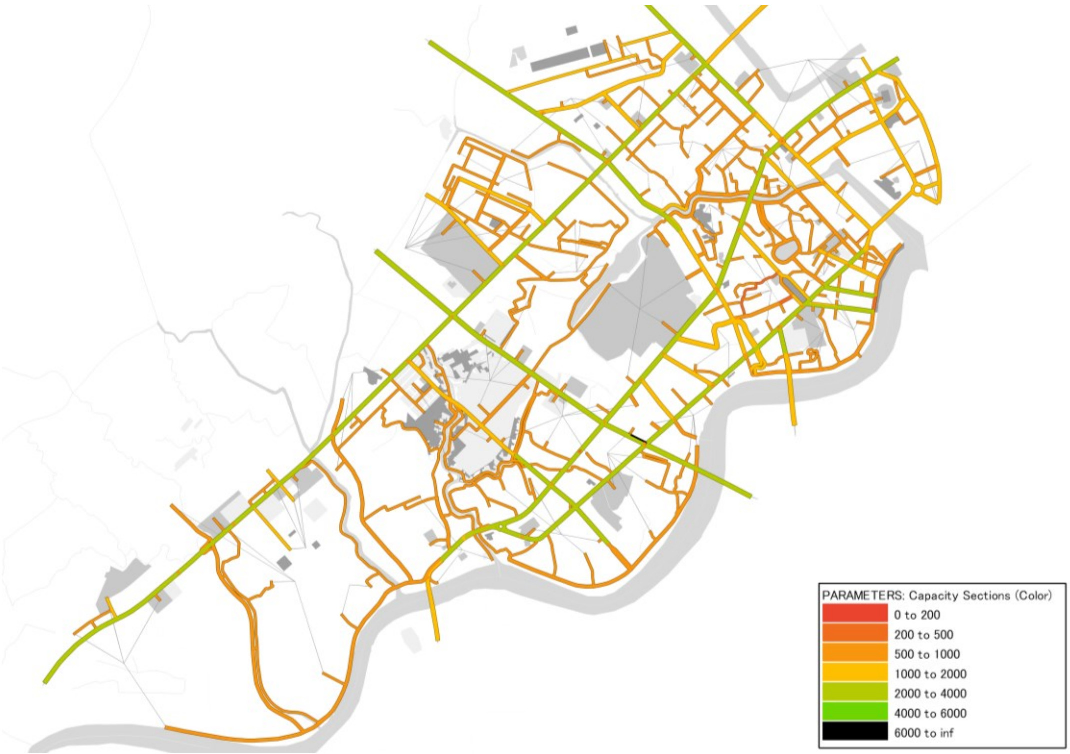
Overall, Table 4-4 presents a comparative summary of network elements within the simulation model, quantifying the modifications performed during the calibration process. It contrasts the initial state of the network—derived from raw OSM data—with the refined configuration post-calibration, underscoring the adjustments to the numbers of links, nodes, and O-D zones. Additionally, Figure 4-25 and Figure 4-26 display the calibrated network layout, classified based on road types and section capacities, respectively. The importance of calibrating network topology is highlighted by its influence on the shape and dynamics of the MFD (Ambühl et al., 2018), along with its interaction with traffic signal control mechanisms (Geroliminis & Daganzo, 2008). This calibration is critical in accurately representing the network's structural and operational characteristics within the simulation model.

Table 4-4 Summary of network configuration adjustments before and after calibration.

	Pre-calibration	Post-calibration
Number of links	10,065	1,533
Number of nodes	3,313	519
Number of origin-destination zones	35	42

Figure 4-25 AIMSUN model calibration - Network topology by road type.

Figure 4-26 AIMSUN model calibration - Network topology by section capacity.



4.4.2.2 Traffic Demand

In calibrating vehicle demand, this study primarily relies on aggregate data measurements from traffic count surveys and activity diary surveys. Although disaggregated data would allow for more precise calibration, their high collection costs and limited availability often limit their practical use.

A. Origin-Destination Matrix

Establishing input flow patterns at the entry points of the road network is a critical component of traffic demand calibration, vital for simulating both the ingress and subsequent traffic distribution within the simulation environment. Thus, organizing hourly O-D matrices for different vehicle classes plays a pivotal role in this context, providing a detailed representation of traffic flows and enhancing simulation realism. These matrices detail trips between O-D pairs over specific time intervals, providing a temporal breakdown of travel demand across the network. This aids in simulating traffic volumes at different times and understanding network travel patterns. Secondary survey data pinpoints Monday as the peak traffic day in Ninh Kiều District (see Figure 4-16), which then becomes the focus of this study. Origins and destinations, defined by zoning partition numbers shown in Figure 4-7, including the first 35 zones for internal traffic and the last seven for external traffic. Table 4-5 exemplifies the O-D matrix for motorcycles, which dominate traffic with an average of 91.57%, and cars make up the remaining 8.43%. For a more detailed hourly breakdown of these O-D matrices, please refer to Appendix D.

Overall, to summarize the 24-hour O-D matrices, Figure 4-27 illustrates the hourly distribution of car and motorcycle volumes throughout an entire day, derived from calibrated demand data. This refined dataset serves as the primary input for the microscopic simulation model. The graph reveals two peak periods: the morning rush from 07:30 AM to 10:00 AM and the evening rush between 05:00 PM and 07:30 PM. These peaks align with conventional work commute times, mirroring the daily influx of individuals traveling to and from their workplaces.

Table 4-5 Example of hourly O-D matrix for motorcycles.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133	Ext. 1	Ext. 2	Ext. 3	Ext. 4	Ext. 5	Ext. 6	Ext. 7	Total
11	0	2	2	2	2	2	2	2	2	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	30	30	2	2	1	1	3	3	3	3	2	2	2	2	2	2	2	134
12	2	0	2	2	2	2	2	3	3	3	3	3	3	1	1	1	8	14	8	1	1	1	1	2	2	2	2	6	2	1	1	3	3	3	3	2	2	2	2	2	2	2	111
13	2	2	0	2	2	2	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	3	3	3	3	3	2	2	2	2	2	2	82
14	2	2	2	0	2	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	3	3	3	3	3	3	1	1	1	1	1	79
15	2	2	2	2	0	1	1	1	1	1	1	1	1	1	2	2	4	4	6	6	6	7	7	4	4	2	2	2	2	3	5	5	6	6	6	6	5	2	2	1	1	1	126
16	2	2	2	2	3	0	1	1	1	1	1	2	2	2	2	2	4	4	6	6	6	7	7	5	5	2	2	4	3	3	6	6	7	7	6	6	5	3	3	1	1	1	142
17	2	2	2	3	3	1	0	1	2	2	2	3	4	4	4	4	6	6	7	7	6	8	7	5	5	2	2	4	3	4	6	6	8	8	6	6	5	3	3	2	3	1	168
21	2	2	2	3	3	1	1	0	10	3	3	4	5	5	33	4	6	6	7	103	10	140	7	5	39	2	2	4	6	16	33	6	44	132	7	55	20	3	3	10	10	1	758
22	2	2	2	3	3	1	1	2	0	3	15	4	5	5	33	4	6	6	7	7	6	8	7	5	33	2	2	4	3	4	33	15	8	8	7	3	6	4	4	2	1	1	277
31	2	3	3	3	3	1	1	2	3	0	24	11	15	4	6	29	29	8	25	8	7	9	2	2	5	2	2	4	3	4	6	13	8	8	7	8	6	4	4	2	3	6	295
32	1	1	1	1	1	1	1	2	3	14	0	14	14	9	7	8	9	9	10	9	8	9	4	4	5	3	3	4	3	4	6	6	8	9	7	6	6	4	4	2	1	1	222
33	1	1	1	1	2	2	2	3	4	5	3	0	7	8	7	7	6	6	6	5	4	4	2	2	2	2	2	3	3	3	3	3	4	3	2	18	8	2	18	1	1	1	168
34	2	2	2	2	3	3	2	3	4	5	20	20	0	42	7	13	37	6	13	5	24	4	2	2	2	1	2	1	2	2	2	2	3	2	2	3	3	3	3	1	1	1	259
35	2	2	27	2	3	3	2	3	4	12	6	5	20	0	6	35	5	5	27	4	4	3	3	12	2	1	2	1	1	1	1	2	3	3	3	3	3	3	3	2	1	1	231
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52	3	3	4	4	5	5	3	4	3	3	16	16	4	38	5	8	0	5	7	5	15	3	3	3	4	3	4	4	4	5	4	4	4	3	15	3	10	3	2	1	3	6	247
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61	1	1	2	2	3	3	2	3	3	2	3	3	4	5	5	5	7	6	7	0	5	43	4	3	4	5	8	8	34	34	13	14	10	10	10	10	8	5	2	2	1	1	301
71	1	1	2	2	3	3	2	2	2	2	2	2	2	20	4	4	20	5	6	6	0	3	4	3	4	5	8	8	8	11	13	14	57	60	77	11	8	5	3	2	6	1	402
81	1	1	2	2	3	4	3	13	2	4	5	5	5	16	5	5	7	9	8	88	27	0	8	7	5	7	9	53	73	81	18	19	62	81	31	3	6	3	6	10	2	6	705
91	2	2	2	2	2	3	3	4	4	9	5	5	9	9	3	3	5	7	7	7	8	8	0	6	5	6	8	10	12	15	19	20	18	16	14	11	8	5	3	2	6	6	299
92	2	2	2	2	2	3	3	4	4	2	5	5	4	4	4	4	6	7	6	7	8	7	2	0	5	7	8	9	11	15	20	5	20	19	16	26	6	8	3	2	2	1	278
93	2	2	2	3	3	4	4	25	32	4	60	5	4	4	55	12	14	16	15	15	106	11	32	60	0	9	10	11	25	18	136	106	24	22	20	6	6	13	3	2	2	1	904
101	27	2	2	27	3	3	27	4	4	4	4	4	4	4	8	12	12	6	13	13	14	9	6	7	6	0	6	6	9	13	16	18	35	35	16	14	10	5	3	2	1	1	415
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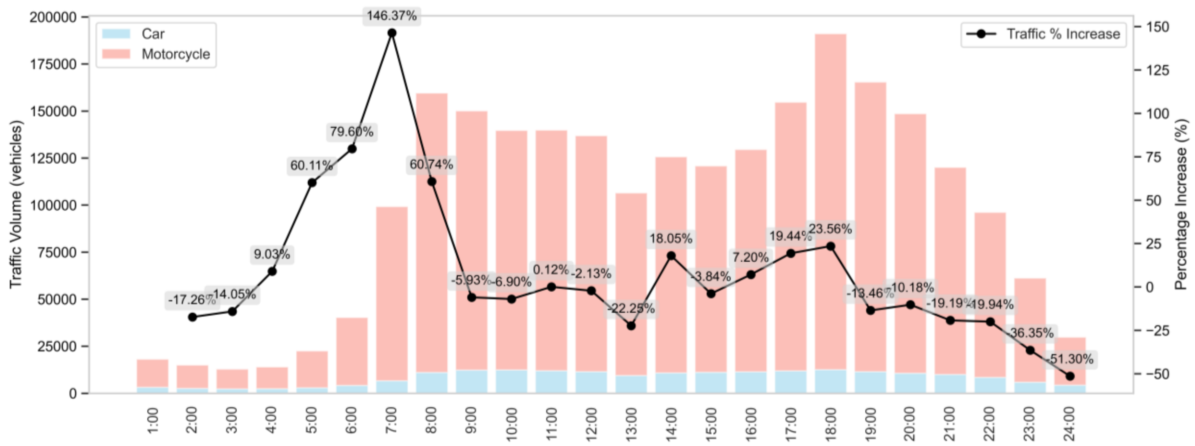
103	2	2	13	2	13	13	2	8	8	8	7	6	4	4	8	13	13	212	201	15	16	11	8	9	8	53	53	0	10	13	17	19	132	132	106	3	9	5	3	2	2	1	1166
111	2	2	2	3	5	7	7	6	6	6	5	4	1	2	7	11	11	11	13	13	13	9	6	7	8	6	6	6	0	9	12	14	14	14	13	13	9	5	2	1	1	6	298
112	1	1	1	1	4	7	6	116	85	6	6	5	2	2	32	12	13	13	17	10	17	95	11	12	13	8	9	10	32	0	14	16	16	10	14	14	3	6	2	15	10	1	668
121	1	1	1	1	5	9	8	8	8	8	8	6	2	2	7	11	12	13	18	18	18	15	12	13	13	8	9	9	9	9	0	14	14	13	12	12	9	5	2	2	1	3	349
122	3	3	4	4	4	8	8	8	36	8	9	6	2	2	2	2	3	4	10	10	10	36	12	23	41	7	7	8	7	6	53	0	6	5	5	3	5	3	2	2	2	1	380
131	3	3	3	4	5	9	9	10	25	10	10	7	3	26	3	3	4	8	10	40	48	113	13	13	13	42	42	50	8	32	7	7	0	59	75	5	5	3	2	2	2	3	739
132	3	3	3	4	3	6	6	56	42	6	7	5	2	2	6	2	3	4	8	9	14	55	11	12	12	7	7	8	10	13	6	6	7	0	14	6	6	4	3	2	6	3	392
133	3	3	3	4	3	6	6	6	13	6	7	5	2	2	3	2	3	3	9	8	13	25	12	12	12	10	8	26	7	6	6	7	6	17	0	7	7	10	4	3	2	3	300
Ext. 1	3	3	3	4	3	5	5	52	6	8	3	18	3	3	20	3	3	13	8	3	9	3	10	33	8	6	10	3	6	5	5	6	6	6	7	0	6	18	3	3	6	3	331
Ext. 2	3	3	3	3	3	5	5	23	6	6	6	6	2	2	2	2	6	2	4	4	5	6	5	10	6	4	4	3	3	3	3	3	3	3	4	8	0	36	4	3	3	1	216
Ext. 3	2	3	3	1	2	3	3	3	4	4	4	3	2	3	3	2	2	2	2	3	3	3	4	8	13	3	4	3	3	3	3	2	8	3	6	18	36	0	4	3	3	6	193
Ext. 4	2	3	3	1	2	3	3	3	4	4	4	18	2	2	3	2	3	2	2	2	3	6	3	3	3	3	3	3	2	2	2	2	2	3	4	4	4	4	0	4	3	2	133
Ext. 5	2	2	3	1	1	1	2	10	2	2	2	1	1	2	2	1	1	1	2	2	2	10	2	2	2	2	8	2	1	15	3	2	2	2	3	3	3	3	4	0	10	3	125
Ext. 6	2	2	3	1	1	1	3	10	1	3	1	1	1	1	8	1	3	1	1	2	6	2	6	2	2	1	2	2	1	10	2	2	6	6	2	3	2	3	3	8	0	20	138
Ext. 7	2	2	2	1	1	1	1	1	1	6	1	1	1	1	3	3	6	1	3	1	1	6	6	1	1	1	1	1	6	2	2	2	3	3	3	3	1	6	2	8	18	0	116
Total	108	105	179	124	149	187	190	466	365	199	290	232	172	265	335	283	343	531	535	482	478	743	251	324	318	277	332	371	344	440	520	425	644	795	614	372	274	217	131	126	135	112	13783

Figure 4-27 Hourly distribution of traffic demand in Ninh Kiều District.



B. Route Choice

Dynamic Traffic Assignment (DTA) models handle the complex task of modeling time-varying link or path flows as they evolve within the network (Mahmassani, 2001). They simulate route choices based on a diverse range of factors and preferences, ensuring that simulated traffic distribution matches observed conditions. This aligns with the decision-making processes of individual road users when selecting routes, emphasizing the unique nature of route choice of motorcyclists compared to car drivers.

The AIMSUN simulation model utilizes Stochastic Route Choice (SRC) and Dynamic User Equilibrium (DUE) algorithms for DTA operation. The DUE algorithm iteratively balances travel times for each O-D pair and pre-defined departure time, aiming for uniform and reduced durations for all trips initiated within the same time frame. The SRC algorithm, on the other hand, calculates the least cost path at the end of each predefined departure time interval, allocating vehicles across these and previous paths in accordance with a discrete choice function. This approach accounts for the behavioral patterns, information compliance, and route preferences of motorcycle riders, as discussed in Chapter 3. Given the absence of pre-defined paths from primary and secondary data, the study uses a stochastic route choice model to simulate path selection, instead of employing O-D or path-assignment routes. The simulation starts by routing vehicles according to the model specified in subsection 3.3.2.1 and allows for mid-journey path adjustments as conditions change, following the link-based route selection process in subsection 3.3.2.2. The route choice model integration into the AIMSUN, as methodologically framed in Figure 4-3, is performed through scripting with Python interfacing with simulation elements. The pseudocode applied is presented in Table 4-6. Initially, pre-trip route choices follow the shortest path principle, but as vehicles enter the network, real-time traffic data may prompt route adjustments. The SRC algorithm captures these dynamics by evaluating route utility and facilitating en-route adjustments as conditions evolve, effectively representing the probabilistic nature of route selection.

In summary, the components mentioned above for traffic demand calibration, encompassing input flow patterns, time-sliced OD matrices, and DTA models, each contribute differently to refining the micro-simulation model. These components collectively enhance the model's ability to represent the qualitative aspects of driver behavior and network dynamics.

Table 4-6 Pseudocode for route choice function in AIMSUN.

Algorithm: Route Choice API Function
Procedure **RCF** (context, manager, paths, currentPathIndex)
Initialize scaleFactor
Initialize *probability* to 0
Initialize *numPath* to the number of paths
while there are paths to evaluate
Calculate *currentPathCost*
for each path in paths except the current path
Calculate and compare *currentPathCost* and *otherPathCost*
Update *probability*
end for
if a better route is found
Update *currentPathIndex*
end if
end while
return true if a route was found, false otherwise
End Procedure

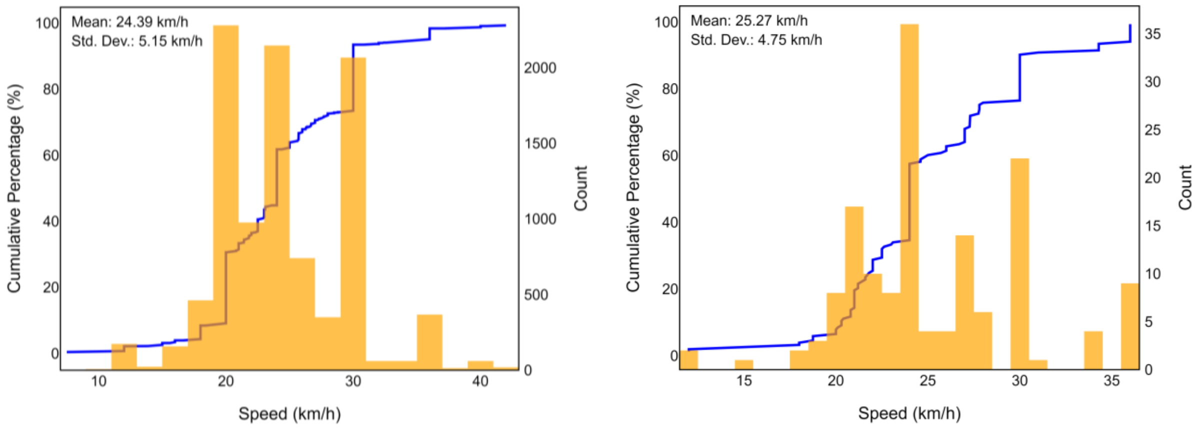
4.4.2.3 Driver Behavior

Particular attention must be given to driver behavior components, especially for motorcycle driving patterns, which are distinct from the more lane-disciplined behavior of cars. The subsequent subsections detail the specific calibration parameters employed to closely reflect these distinct driving behaviors.

A. Vehicle Speed Distribution

One essential aspect in calibrating driver behavior is understanding speed distribution, for which profiles were developed from data in the activity diary and vehicle speed sampling surveys. To ensure integrity, the data cleaning process follows the 68-95-99.7% empirical rule, which stipulates that in a normal distribution, approximately 68%, 95%, and 99.7% of the data points fall within one, two, and three standard deviations from the mean, respectively. This three-sigma rule helps identify and exclude outliers, refining the dataset to include representative speed measurements and effectively filtering out anomalies that could skew analysis outcomes. Figure 4-28 displays the resulting cumulative percentages and histograms for the speed distributions of motorcycles and cars in Ninh Kiều District.

Figure 4-28 Speed distribution profiles for (a) motorcycles, and (b) cars.



(a) (b)

Figure 4-28(a) exhibits a steeper rise in the speed distribution for motorcycles at the lower end of the speed spectrum, suggesting that motorcycles typically travel within a narrow speed range, with many maintaining lower speeds. This trend indicates motorcycle usage in dense urban settings, where agility and frequent maneuvering through traffic naturally lead to slower speeds. Meanwhile, Figure 4-28(b) shows a more gradual slope in car speed distribution, indicating a more consistent speed pattern across vehicles, indicative of more uniform road conditions. To sum up, Table 4-7 provides an overview of the statistical characteristics of speed distributions for motorcycles and cars.

Table 4-7 Speed distribution characteristics.

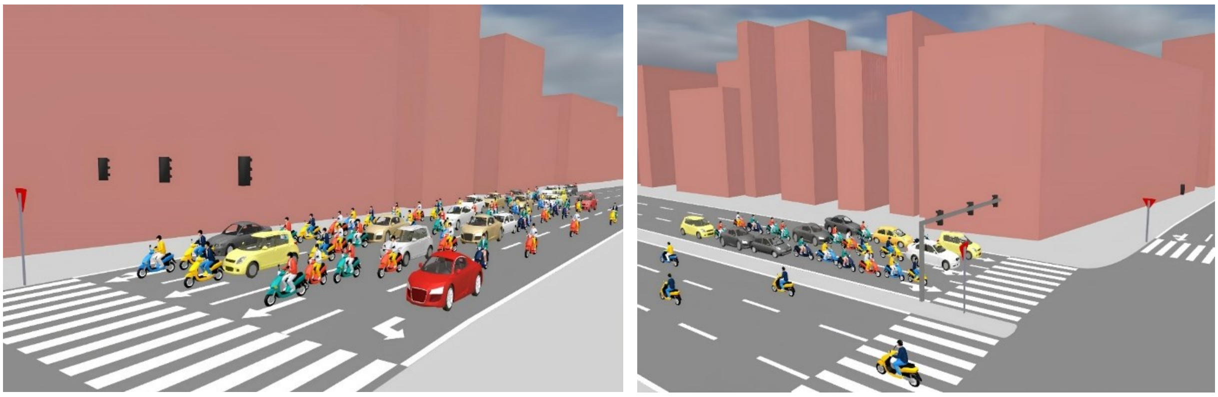
Vehicle type	Proportion (%)	Vehicle speed (km/hour)			
		Mean	Minimum	Maximum	Std. deviation
Car	8.43	25.26	8.19	42.55	4.77
Motorcycle	91.57	24.39	7.01	42.02	5.14

B. Motorcycle Non-Lane-Based Behavior

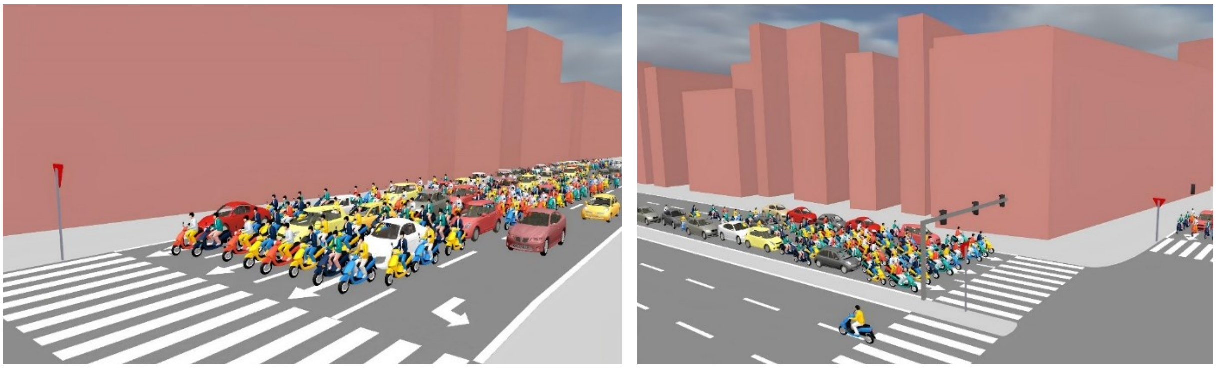
Motorcycle lateral movement patterns, marked by frequent disregard for lane markings, have been precisely specified within the model to ensure an accurate representation of the distinctive spatial dynamics that motorcycles contribute to overall traffic flow. By implementing this feature for designated vehicle types and throughout various segments of the traffic network, the model accounts for lateral clearance among all road users. To further capture the intricacies of mixed traffic, a parameter for impromptu lane-changing behavior is included to simulate vehicles moving into gaps not advised by the car-following algorithm, typical of the assertive driving seen in high-density motorcycle environments. As a result, vehicles performing such maneuvers, whether changing lanes or reacting to others doing so, may experience deceleration rates that surpass their usual maximum capabilities.

Figure 4-29 provides a visual comparison of vehicle behavior calibration, showcasing the differences before and after the applied adjustments. Initially, panel (a) illustrates the pre-calibration scenario where motorcycles rigidly adhere to lane demarcations, a portrayal that fails to reflect the fluid movement typical of motorcycle-dependent cities. This discrepancy underscores the essential need for calibration that integrates the true nature of motorcycle riding behavior. In contrast, the lower panel (b) reveals the post-calibration condition, where the model has been fine-tuned to represent the dynamic and flexible lane usage of motorcycles, portraying their propensity to weave through tighter spaces.

Figure 4-29 Calibration of non-lane-based behavior.



(a) Pre-calibration



(b) Post-calibration

C. Turn Parameters

Gap acceptance during turning movements at unsignalized intersections is another crucial parameter that requires further adjustments. Relying on default software settings—typically designed for vehicle behaviors in developed countries—may lead to inaccuracies, for example, simulations depicting motorcycles waiting for completely clear paths at intersections. This differs from the aggressive behavior observed in motorcycle-dependent cities, where riders often exploit smaller gaps that larger vehicles would avoid, weaving through traffic.

However, capturing motorcycle rider behaviors accurately poses a significant challenge. A practical solution is adopting parameters from contextually relevant previous studies, a common strategy in traffic model calibration (Hollander & Liu, 2008). For instance, research by Ibrahim and Sanik (2007) in Malaysia reportedgap acceptance times of 3.7 seconds for cars and 3.2 seconds for motorcycles, highlighting the shorter waiting times due to motorcycles' nimbleness and smaller size. Similarly, studies in India (Patil & Sangole, 2016) identified gap acceptance times of 3.65 seconds for cars and 3 seconds for motorcycles. In contrast, drivers in developed countries tend to have longer gap acceptance times—7.1 seconds in the UK (Robbins et al., 2018) and 7.6 seconds in the US (Tupper, 2011)—highlighting a more cautious approach at intersections. Considering that the traffic conditions in Vietnam closely resemble those of Malaysia, as shown by high motorcycle ownership rates in Figure 1-1, leveraging established parameters from these studies is particularly pertinent for this research. This approach helps ensure that the model represents the bold, risk-taking behavior at unsignalized intersections.

Table 4-8 lists an example of parameter adjustments for primary roads in the AIMSUN model, comparing changes from pre-calibration defaults to post-calibration values.

Table 4-8 Calibration of simulation parameters for primary road - before and after comparison.

	Unit	Pre-calibration	Post-calibration
Turn parameters			
1) Initial safety margin	second	3.00	2.00
2) Final safety margin	second	1.00	0.50
3) Initial yield time factor	-	1.00	0.70
4) Final yield time factor	-	2.00	1.30
5) Visibility to yield	meter	30.00	20.00
6) Visibility along main stream	meter	60.00	40.00
7) Look-ahead distance	meter	300.00	250.00
8) Critical look-ahead distance	meter	40.00	25.00
Section parameters			
1) Imprudent lane changing	-	-	✓
2) Allow vehicles non-lane-based behavior	-	-	✓
Vehicle parameters			
1) Reaction time - cars	second	0.80	0.62
2) Reaction time - motorcycles	second	0.45	0.44
3) Lateral clearance - cars	meter	0.50	0.40
4) Lateral clearance - motorcycles	meter	0.50	0.30

Calibrating gap acceptance behavior for turning movements involves fine-tuning key parameters specific to each road type, rather than applying global parameters, to significantly influence how vehicles navigate through unsignalized intersections. This includes setting the distance at which vehicles begin to consider gap acceptance (refers to the 'Visibility to Yield' parameter). A smaller value suggests more aggressive driving, with drivers making decisions closer to the junction, as is common in developing countries where drivers often rely on shorter distances at intersections. Similarly, the extent to which drivers look ahead on the conflicting road is adjusted to account for the shorter lookout distances prevalent in congested settings (refers to the 'Visibility along Main Stream' parameter). This adjustment reflects the need for drivers, especially motorcyclists, to make quick and efficient navigation decisions within limited visibility, typical in densely populated areas with mixed traffic conditions.

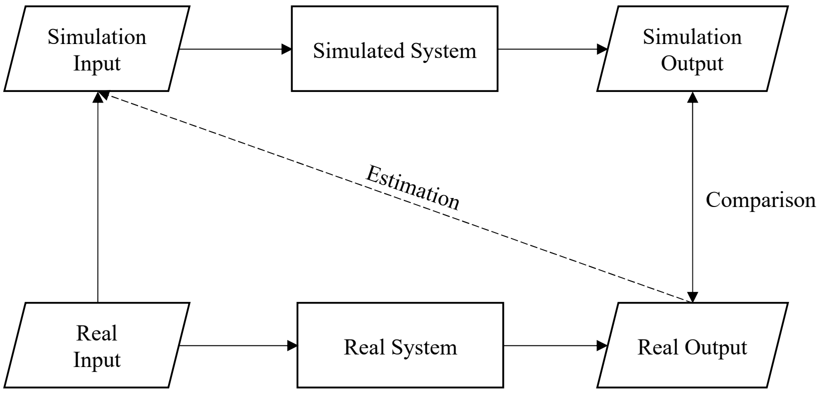
Moreover, the calibration modifies the safety margins required by drivers both before initiating and after completing a turn (refer to 'Initial Safety Margin' and 'Final Safety Margin' parameters). In the context of aggressive driving conditions prevalent in motorcycle-dense cities, these margins are reduced to reflect drivers' readiness to accept shorter gaps. This emphasizes the need for swift navigation and the willingness to take risks, characteristic of the driving culture in such environments. Lastly, the parameters that influence the assessment time a vehicle needs when approaching a turn are also calibrated (refer to 'Initial Yield Time Factor' and 'Final Yield Time Factor' parameters). Lower values imply quicker decision-making processes, with drivers using actual gap sizes and minimal additional buffer time. This calibration reflects the reality where drivers, especially those on motorcycles known for their agility and ability to navigate through tight spaces, utilize the actual sizes of gaps available without relying on significant additional buffer times. Such adjustments ensure the AIMSUN model more accurately simulates the aggressive, quick-paced, and risky behaviors of drivers in developing countries, providing a reliable basis for traffic analysis and management solutions in these environments.

4.4.3 Model Validation

Model validation is an essential phase in traffic simulation, evaluating the extent to which the model represents the real-world system. It entails comparing simulation outcomes with empirical observations to detect and minimize inconsistencies (Hourdakis et al., 2003). This phase, carried out through a trial-and-error procedure to calibrate parameters and measure discrepancies, not only enhances the model's precision but also verifies its utility. Key areas of focus include correcting for variances caused by errors in demand estimation, inaccuracies in route selection mechanisms, variations in driver behavior patterns, and potential flaws in the data collection (Doan et al., 1999). Toledo and Koutsopoulos (2004) outline a general framework for validating the model, as illustrated in Figure 4-30**.**

The validation strategy uses measures of fit and statistical analysis to quantitatively assess the congruence between simulated outcomes and actual data, identifying systematic deviations that may necessitate model adjustments. The next subsections detail the procedures and criteria used to validate the simulation model, focusing on two distinct levels: the entire network and individual intersections.

Figure 4-30 Aggregate model validation process.



Adapted and redrawn from Toledo and Koutsopoulos (2004)

4.4.3.1 Choosing Performance Measures

Selecting appropriate measures of performance is of utmost importance as they shape the validation framework and set the criteria against which simulated outcomes are compared to observed data. The success of validation largely depends on these comparative measurements (Hourdakis et al., 2003); for example, volume, speed, and occupancy or density are sufficient for freeways, while ramps benefit from including queue size. Validation success is also determined by goodness-of-fit measures, such as hypothesis testing (e.g., t-test), percentage error (e.g., Root-mean-square Error of Prediction), correlation coefficients, and Theil's inequality coefficient. These measures collectively evaluate how closely the simulation matches observed data, guiding necessary adjustments to improve accuracy.

In this study, traffic flow is the primary reference variable for model validation, providing a direct and quantifiable means. Observed data were derived from traffic count surveys conducted at 12 intersections within the study area (see Figure 4-9), recording vehicle numbers over specific periods. Correspondingly, simulated traffic data were obtained from virtual detectors in the AIMSUN, positioned to mirror these locations for direct comparison. The validation process, therefore, involves comparing observed and simulated traffic flows at these intersections, using key performance indicators such as average vehicle counts, peak hour flows, and traffic densities. Discrepancies are analyzed to identify deviations, prompting iterative refinements and adjustments to model parameters during calibration.

The calibration and validation efforts in this dissertation targeted data from midnight to 8 a.m. to capture the early morning traffic surge in Cần Thơ City. Activity-diary survey data reveals a pronounced early morning commuter trend, with 61.2% of employed individuals starting work between 3 a.m. and 7 a.m. This demand is compounded by the fact that 60.6% of students travel to school primarily between 6 a.m. and 7 a.m., representing 85.6% of all school-related trips documented. This results in a significant congestion peak, with a 146.37% increase in traffic volume from 6 a.m. to 7 a.m. Consequently, focusing on this initial traffic spike contributes to better understanding and addressing the most challenging conditions of the area's daily traffic patterns, where higher accuracy of the simulation model is needed.

4.4.3.2 Validation in Network-Level

Table 4-9 presents the results from an 8-hour simulation period, highlighting critical indicators such as average speed and total traffic volume, along with their GEH values calculated using Equation (4.1). Since all GEH values fall within acceptable ranges, which are below 5—a threshold indicating strong agreement between simulated and observed data—the model is deemed statistically validated. This underscores its reliability in accurately representing traffic dynamics within Ninh Kiều District.

Table 4-9 Validation of the overall network simulation against empirical data.

Indicators	Observed	Simulated	Rel. Difference (%)	GEH
Mean speed - cars (km/h)	23.97	25.26	5.38	0.26
Mean speed - motorcycles (km/h)	24.19	24.39	0.83	0.04
Throughput - cars (veh)	35,837	36,120	0.79	1.49
Throughput - motorcycles (veh)	350,415	353,373	0.84	4.99

4.4.3.3 Validation in Intersection-Level

In this detailed intersection-level validation, observed vehicle counts were compared with those recorded by the simulation model's internal detectors at corresponding points. Figure 4-31 visually illustrates this comparison, displaying hourly volumes for each road arm at the surveyed intersections.

Figure 4-31 Model validation at intersection-level.

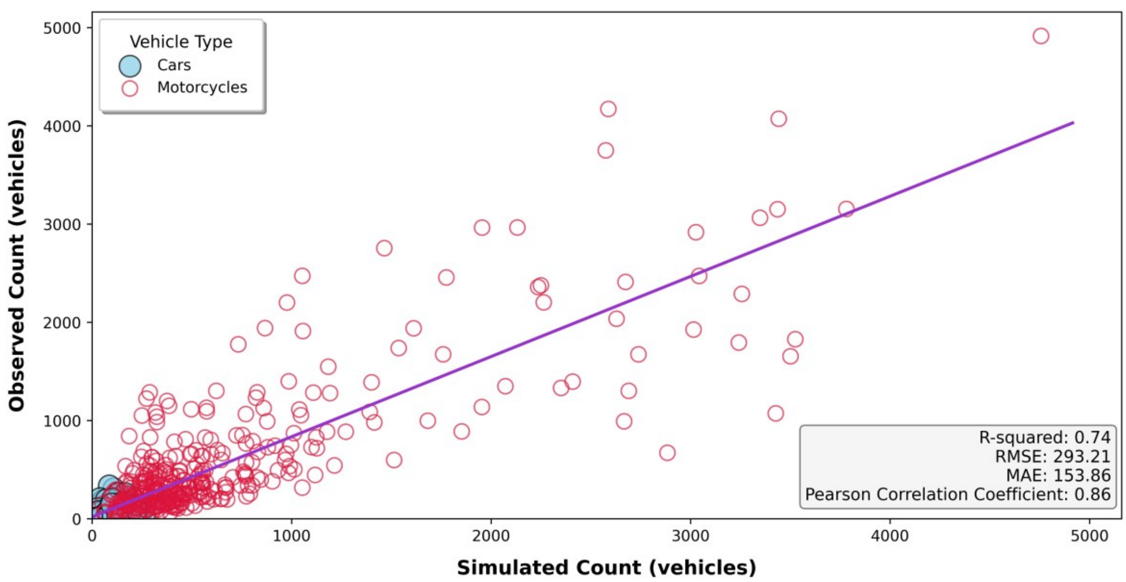


Table 4-10 presents the statistical analysis results to quantify the accuracy of the developed model. The goodness-of-fit, reflected by an R-squared value of 0.74, indicates the model's ability to explain a substantial portion of the observed traffic variance, signifying its effectiveness in capturing traffic patterns within its predictive framework. Further validation is achieved through the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics, which the formulas as follows:

$$RMSE = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N}(x_i - y_i)^2} \tag{4.3}$$

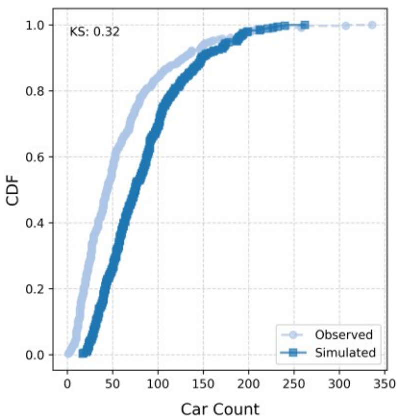
$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \tag{4.4}$$

An RMSE of 293.21 indicates the dispersion of residuals, revealing the concentration of predictions around actual observations—a lower value here suggests tight clustering and high model precision. The MAE of 153.86 represents the average error between simulated and observed data, providing a direct measure of average prediction error. A Pearson Correlation Coefficient of 0.86 shows a strong positive relationship between observed and simulated vehicle counts, showing model reliability. The GEH statistic was also evaluated, showing that 60.56% of data points had a GEH below 5, affirming the high precision of the developed micro-simulation model. The remaining 39.44% of data points, with GEH values between 5 and 10, indicate a moderate match that, while higher, is still within an acceptable range and does not compromise the model's practical applicability. Importantly, no data points exceeded a GEH of 10, eliminating concerns over substantial discrepancies. These findings conclude the model's capability to capture traffic behavior in the Ninh Kiều District, validating its use for traffic analysis.

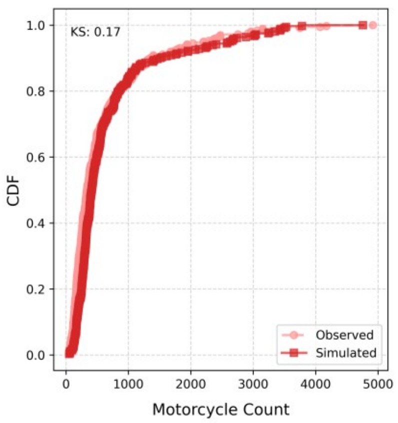
Table 4-10 Summary of statistical validation and goodness-of-fit measures.

Metrics	Values
Coefficient of determination (R^2)	0.74
Root Mean Square Error (RMSE)	293.21
Mean Absolute Error (MAE)	153.86
Pearson correlation coefficient	0.86
GEH < 5	60.56%
5 < GEH < 10	39.44%
Average GEH	4.77

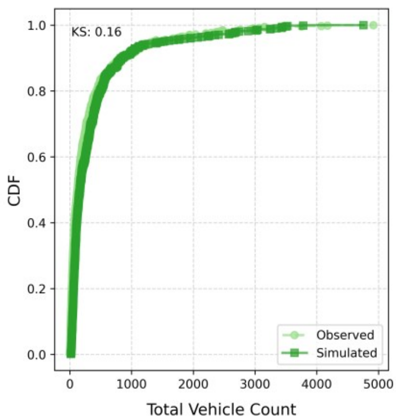
Figure 4-32 Cumulative distribution function (CDF) - Comparing simulated and observed data.



(a) Car Traffic



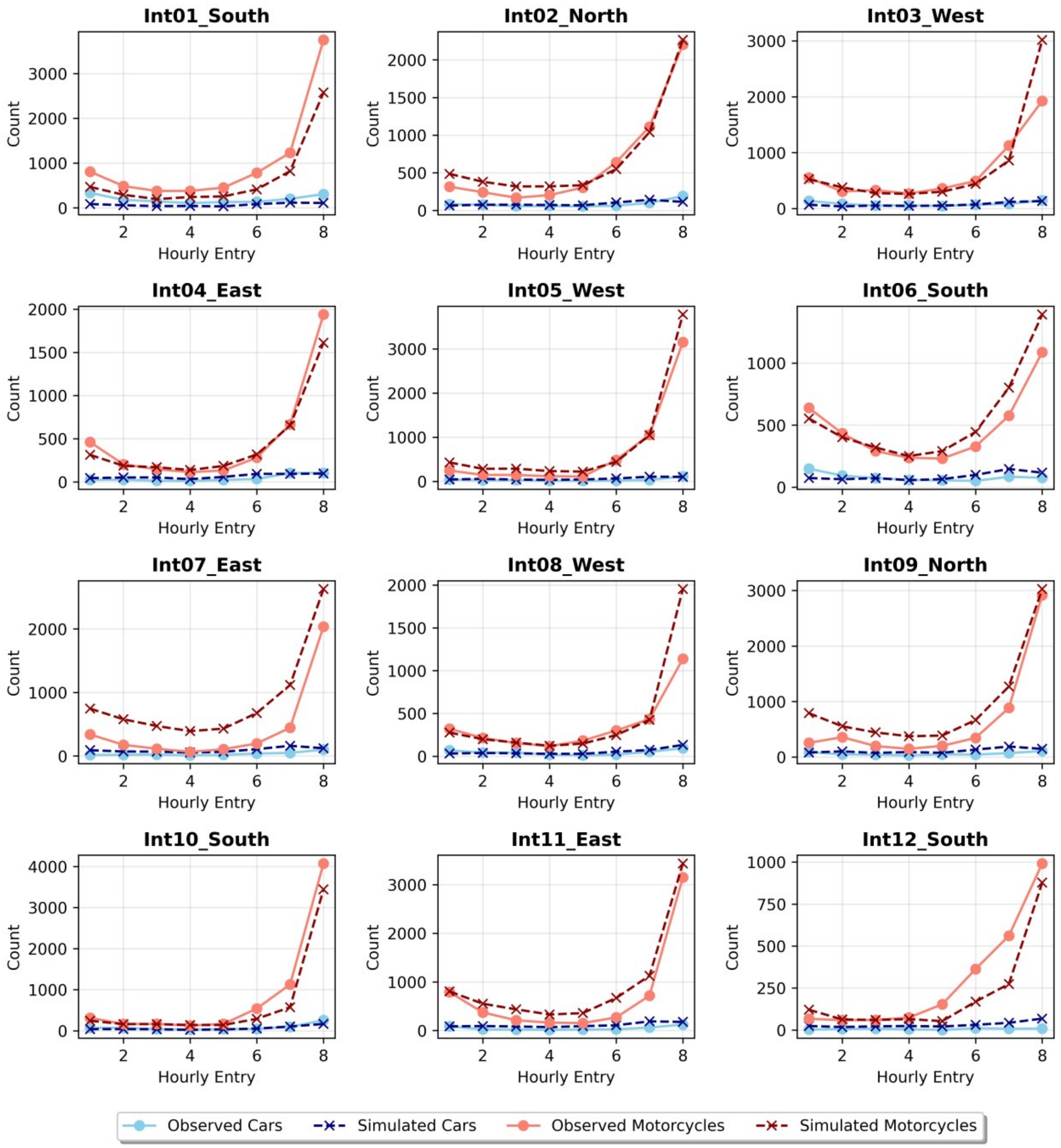
(b) Motorcycle Traffic



(c) Total Vehicle

Furthermore, to augment statistical validation, the Cumulative Distribution Function (CDF) is calculated, indicating the probability that a value falls within a specified range. It is particularly useful for comparing the entire distribution of simulated traffic counts against observed data, both visually and quantitatively. Figure 4-32 presents CDF graphs for validation at the intersection level, with each plot corresponding to a specific vehicle type: cars, motorcycles, and the total vehicle counts. The close alignment of simulated and observed data distributions demonstrates the model's high accuracy in replicating real traffic patterns. In addition, the Kolmogorov-Smirnov (KS) statistic is computed to quantitatively assess the correspondence between simulated and observed traffic volumes for cars, motorcycles, and the aggregate vehicle count. The KS statistic measures the maximum deviation between the empirical CDF of real data and the simulation-derived CDF. Lower KS values, as shown in Figure 4-32, denote a strong congruence between these data sets, confirming the model developed for Ninh Kiều District is accurately calibrated and reflective of observed traffic conditions.

Figure 4-33 Time-series analysis for model validation at intersection-level.



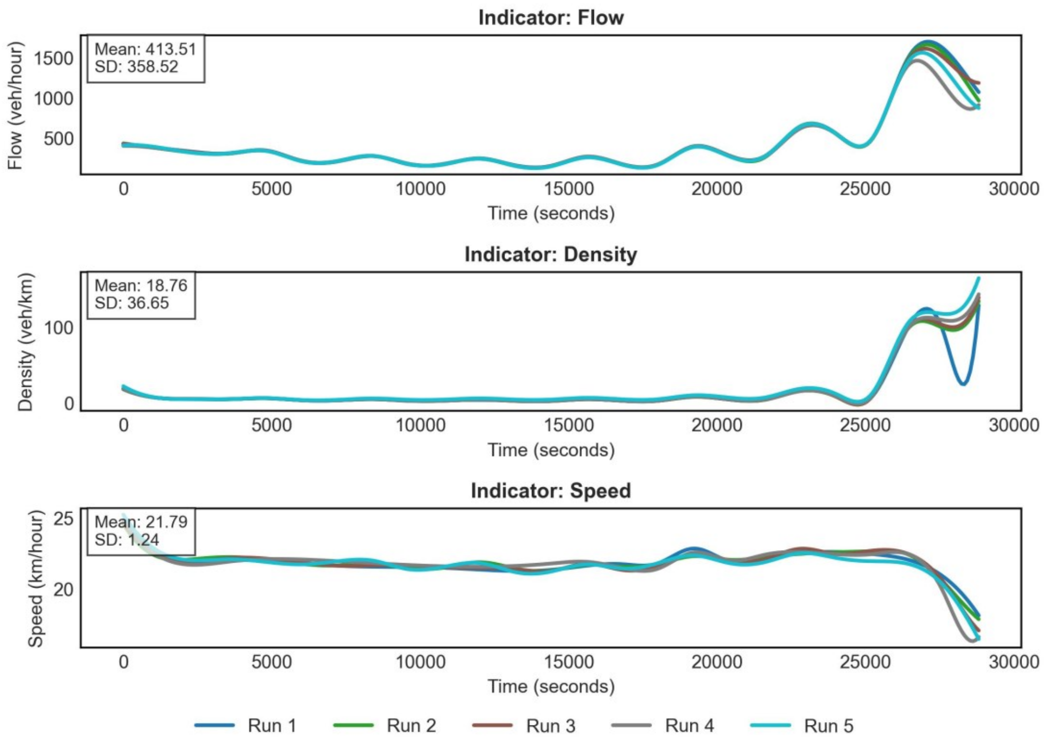
For detailed calibration and validation, a time-series analysis was conducted to provide an in-depth examination of the traffic count data from specific periods and locations. Comparisons from a number of road arms across the surveyed intersections are illustrated in Figure 4-33. In general, the time-series plots show a high alignment between observed and simulated vehicle counts, especially during peak hours. The simulation model effectively captures traffic dynamics for both cars and motorcycles, based on the Monday traffic count survey in Ninh Kieu District, reflecting realistic traffic patterns throughout the day. However, it should be acknowledged that some discrepancies still exist, with occasional overestimation or underestimation of vehicle volumes. Despite these inconsistencies, the average GEH statistic for the model is 4.77 (see Table 4-10), indicating satisfactory overall performance.

4.4.3.4 Number of Replications

To address the random variation in the micro-simulation model, Hollander and Liu (2008) suggested that the number of simulation runs required to evaluate the fitness of a single candidate solution varies between 1 and 20. Following the methodology described in Section 4.2.2, this study initiated with five simulation replications performed in AIMSUN. Figure 4-34 illustrates several traffic characteristics measured during these simulations, showing the variation in traffic flow, density, and vehicle speed across different times of the day. Such variation between the runs is expected due to the stochastic nature of traffic flow and the randomness introduced by individual driver behavior in the simulation model.

To determine the necessary number of simulation runs, Equation (4.2) from the methodology section was used. Analysis revealed that traffic flow, highly variable, required five runs to achieve reliable data. Density, with moderate variability, needed four runs for consistency. Speed, being the most stable indicator with low standard deviation, only required one run. Since the number of runs necessary for robust validation differs depending on the traffic indicator, the study opts for a maximum of five runs to ensure validity across all measures accounting for the most variable indicator (traffic flow) to guarantee reliable predictive capabilities for real-world traffic conditions.

Figure 4-34 Plots in different simulation replications.



4.5 Discussion

This chapter discusses the development of a reliable microscopic traffic simulation model tailored for Ninh Kiều District, revealing the complexities of applying such models to large-scale, mixed-traffic networks dominated by motorcycles—a topic less explored in current literature. As noted by Elesawey and Sayed (2011), applying such a model to extensive or high-density networks, like the one in this study, significantly increases its complexity. Simulating the behavior of individual vehicles demands substantial computational resources, leading to prolonged processing times (Balakrishna et al., 2007; Jha et al., 2004). Moreover, the model accuracy hinges on the availability of detailed data on vehicle movements, driver behaviors, and road conditions, which, as Kumar et al. (2012) and Jayakrishnan et al. (2001) point out, makes data collection and integration challenging and demanding task.

Additionally, the practical utility of micro-simulation models requires careful calibration and validation against actual data, a process that is inherently complex and time-consuming. Elesawey and Sayed (2011) and Jayakrishnan et al. (2001) emphasize the critical role of extensive empirical data collection in constructing, calibrating, and validating these models. Further complicating this process is the need to accurately define driver behavior, which requires capturing the diverse reactions, decisions, and interactions among drivers. This modeling challenge, necessitating the management of a broad range of parameters due to human behavior variability, adds to the complexities of micro-scale modeling (Balakrishna et al., 2007; Elesawey & Sayed, 2011; Jayakrishnan et al., 2001). Such detailed behavioral modeling is crucial for enhancing the realism and efficacy of the simulation models, making them more reflective of actual driving patterns and interactions in traffic systems.

In this section, the research contributions are identified, and the limitations of the study in the realm of microscopic traffic simulation modeling and analysis are acknowledged.

4.5.1 Study Contributions

This study represents a significant advancement in traffic simulation by delivering a reliable microscopic model designed for motorcycle-dependent environments, filling a gap in the literature concerning the application of such models in large network settings. An academic contribution is the integration of route choice models within the simulation framework, enriching the theoretical understanding of mixed motorcycle traffic patterns. This model extends beyond traditional simulations that typically rely on static pre-trip planning assumptions by incorporating dynamic route choice behavior. From a practical perspective, the study delves into the methodologies, challenges, and implications associated with enhancing model accuracy, providing insights into the practical applications.

Figure 4-35 visually contrasts the calibrated and non-calibrated route choice models by comparing simulated and observed traffic counts at the road arms in 12 intersections within Ninh Kiều District. This illustration emphasizes the impact of route choice adjustments while maintaining consistency in other simulation parameters. When vehicles are modeled to select routes based on the shortest path alone, without access to current traffic information—reflecting static, pre-trip planning—this constitutes the uncalibrated model condition. Conversely, the calibrated model incorporates dynamic route selection, allowing vehicles to adjust their paths based on changing travel times and traffic conditions.

The refinement of route choice calibration yields substantial advancements, as reflected in the enhanced statistical metrics detailed in Table 4-11. Notable improvements include increased R-squared and Pearson Correlation Coefficient values, along with significant reductions in RMSE and MAE, all indicative of a higher fidelity in mirroring actual traffic patterns. The accurate depiction of drivers' decision-making processes, which enhances model validity by 27.6%, demonstrates that motorcycle riders do not strictly adhere to the shortest path principle; instead, they dynamically adjust their routes in response to real-time traffic conditions. In conclusion, the results underline the necessity for traffic simulation models to align with observed behaviors in the targeted population, ensuring that further traffic analysis is both theoretically valid and highly representative of actual conditions.

Figure 4-35 Comparative validation of calibrated vs. non-calibrated route choice functions.

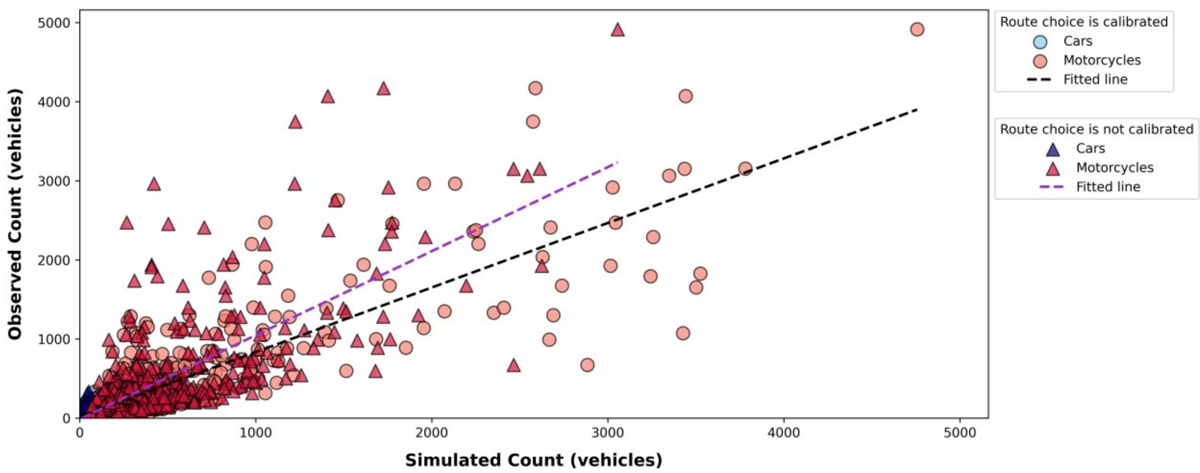


Table 4-11 Statistical measures for calibrated and non-calibrated route choice models.

Metrics	Shortest Path	Route choice model (En-route)
Coefficient of determination (R^2)	0.58	0.74
Root mean square error (RMSE)	372.48	293.21
Mean absolute error (MAE)	192.44	153.86
Pearson correlation coefficient	0.76	0.86

4.5.2 Assumptions in Model Development

This dissertation acknowledges the assumptions and limitations of microscopic simulation modeling, particularly for large-sized networks and mixed traffic. The detailed nature of microscopic models poses challenges to the accurate depiction of individual vehicle behaviors in complex traffic environments.

The computational intensity of microscopic models often restricts their application in city-wide network studies due to the extensive parameters required, which are difficult to estimate and calibrate , potentially constraining their utility (Thonhofer et al., 2018). Additionally, the model's reliance on established results from previous studies for setting up detailed driving behaviors, such as reaction times and gap acceptance, may hinder its adaptation to locale-specific driving patterns. In terms of data and model scope, the study area, which is not covered by Google Street View, required estimates of certain network configurations that were not fully available from OSM data. For instance, the widths and lane counts of some roads were estimated using bird's-eye views from Google Maps satellite imagery to fill gaps where precise, up-to-date geographic data were lacking. Moreover, the model exclusively considers cars and motorcycles, omitting other transportation modes such as public transit, cycling, or walking, which constitute about 3% of the mode share. This exclusion may potentially affect the traffic analysis's applicability, as it does not account for the interactions among these modes.

Regarding behavioral assumptions, the complexity of modeling detailed driving behaviors, such as car-following and lane-changing, often necessitates reliance on approximations. Such data ideally derives from detailed trajectory or video recording observational studies, which, despite the intensive calibration process requiring extensive empirical data collection, have successfully established a valid micro-simulation model that closely represents the dynamics of motorcycle-dependent environments. However, the model does not account for the lateral movement behaviors of motorcycles, including lane changes and maneuvering around obstacles. This omission could lead to an incomplete representation of actual conditions. Ultimately, while the model offers valuable findings, these limitations highlight areas for future direction. Further studies should include more extensive data collection, expand the types of traffic behaviors modeled, and enhance the model's generalizability across different contexts.

4.5.3 Practical Implications

The development of a microscopic simulation model for Ninh Kiều Districtoffers profound implications for understanding and managing motorcycle traffic in regions heavily dependent on two-wheeled vehicles. This model, carefully calibrated on the AIMSUN, provides a sophisticated tool capable of capturing the unique dynamics of motorcycle behavior, which is essential for devising effective traffic management strategies in such environments. Motorcycles, with their agility and compact size, pose distinct challenges and opportunities in traffic management, often maneuvering through smaller gaps and flouting conventional traffic rules like lane discipline. This ability significantly impacts traffic flow and necessitates a specialized approach to traffic simulation and management.

The model's capability to reflect the aforementioned behaviors—through detailed adjustments in network configuration, vehicle demand, and driver behavior—enables a realistic representation of the observed conditions. It particularly highlights the route choice behavior of motorcycle riders, who often adjust their routes based on real-time conditions rather than following the shortest paths. This challenges traditional car-centric route choice models and underscores the need for strategies tailored to the fluid nature of motorcycle movements. The integration of a predefined route choice function from a link-based discrete choice model notably enhances the model's accuracy in simulating decision-making processes. These simulations serve as a vital tool for city planners, enabling them to test traffic control measures in a virtual environment, thereby facilitating the implementation of effective traffic solutions without the need for costly and disruptive physical changes. Additionally, the model aids infrastructure development by identifying bottlenecks and simulating various traffic scenarios. Preparations are made to utilize this model for further evaluations, which will be discussed in the next chapter.

4.6 Summary

This chapter outlines the development of a microscopic simulation model for Ninh Kiều District in the AIMSUN software. Through iterative and rigorous calibration, the model was fine-tuned to precisely configure network settings, traffic demand, and driver behavior—factors crucial to influencing network flow and performance metrics. A novel aspect is the integration of a predefined route choice function from a link-based discrete choice model, which improved the simulation of route choice mechanisms by accurately estimating how drivers respond to dynamic road conditions. This improvement has been validated statistically, showing that motorcycles often dynamically adjust their routes based on real-time conditions, rather than simply following the shortest path. This model is especially relevant for motorcycle-dependent regions, where it captures the distinctive patterns of mixed motorcycle traffic, including their ability to maneuver through smaller gaps and significantly impact overall traffic flow.

Moving forward, the micro-simulation model developed for Ninh Kiều District will be leveraged in the subsequent chapter to evaluate proposed management strategies. This application will contribute to developing solutions to enhance the overall performance of motorcycle-dependent environments.

Chapter 5

Evaluation of Traffic Control Strategies

5.1 Introduction

Macroscopic models, in outlining traffic characteristics, employ deterministic relationships between speed, flow, and density, offering a framework for understanding traffic behavior (Wong et al., 2016). However, congestion on a single road segment can lead to broader network disruptions, as Ji et al. (2018) noted, thereby necessitating a management approach that considers the macroscopic state of the entire network rather than isolated segments. In response, the Macroscopic Fundamental Diagram (MFD) represents a revolutionary perspective to understanding urban traffic dynamics, offering a global view of the network performance that stands in contrast to traditional, segment-based analyses.

This chapter undertakes a thorough exploration of the MFD, particularly its application in heterogeneous, motorcycle-dependent traffic environments like those in Ninh Kiều District, Cần Thơ City, Vietnam. Such environments substantially differ from the homogeneous traffic conditions typically seen on highways and controlled-access roads. Given the non-lane-based movements characteristic of these areas, traditional traffic flow theories and models—designed for homogeneous traffic—prove inadequate without significant modifications. As M. and Verma (2016) emphasize that the complexity of mixed traffic systems demands tailored methodologies for accurate characterization and analysis. Building on the stable and elegant properties of the MFD, noted by Hu et al. (2020), this chapter, therefore, seeks to refine these methodologies to develop network strategies that can adapt to future stochastic demands in motorcycle-dependent areas. The research explores how the conventional MFD can be recalibrated to account for the unique dynamics of mixed traffic in motorcycle-dependent cities, integrating novel concepts such as the Motorcycle Equivalent Unit (MEU) and area occupancy.

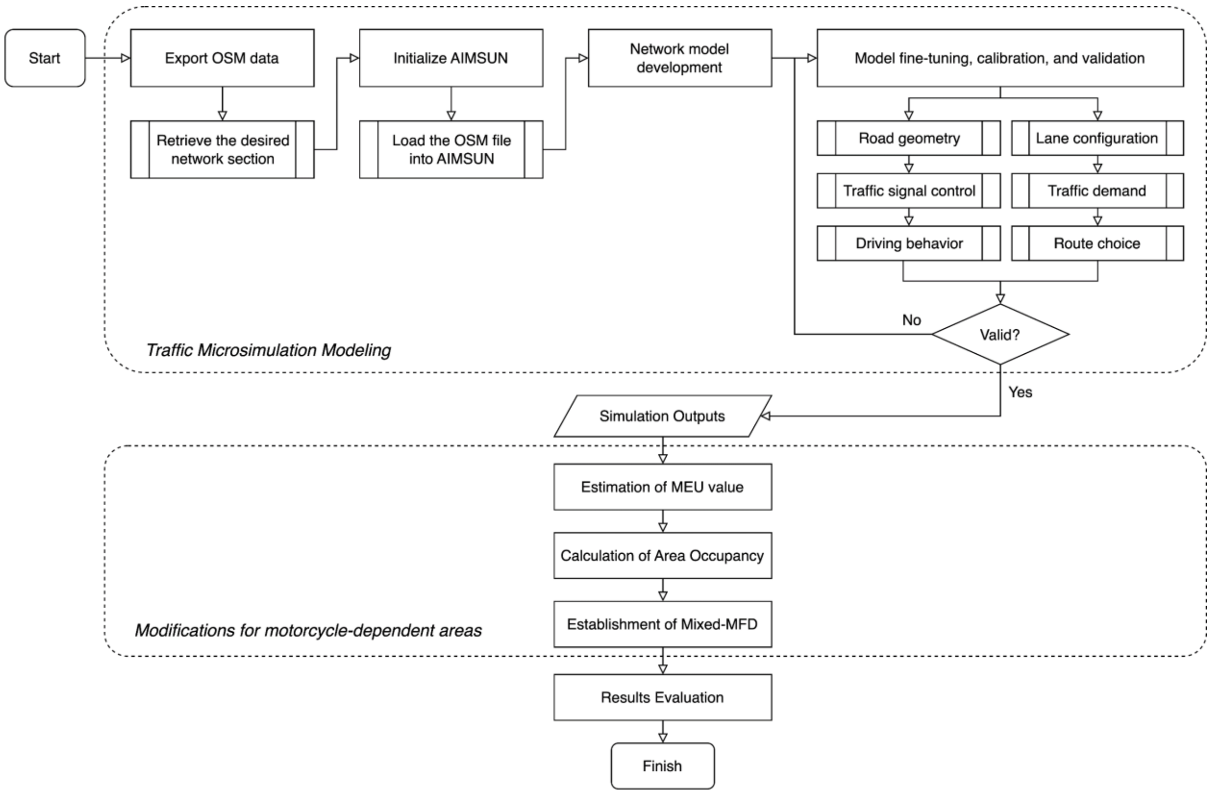
Structured in several sections, this chapter begins with a detailed methodology (Section 5.2). It continues with adaptation methods for mixed motorcycle traffic analysis (Section 5.3), which includes the development of the MEU metrics and the concept of area occupancy, detailing their applications in managing motorcycle-dependent traffic. The chapter advances with a network performance evaluation (Section 5.4), where it assesses existing traffic conditions and different traffic control strategies across various scenarios. The discussion section (Section 5.5) further elaborates on the macroscopic impact of traffic information and compliance rates, as well as the formulation of traffic management policies. The chapter culminates with a summary and concluding remarks on the research findings (Section 5.6).

5.2 Methodology

This section outlines the theoretical frameworks and empirical approaches utilized for evaluating network performance and proposing effective traffic control measures, employing a redefined MFD suited to heterogeneous traffic environments of Ninh Kiều District. The traffic dynamics marked by a significant volume of motorcycles are addressed through an integration of the MEU and area occupancy into the application of the MFD. Figure 5-1 illustrates a flowchart delineating the systematic approach encompassing traffic simulation, measurement, and analysis, executed through AIMSUN software.

The process commences with the extraction of data from OSM file, establishing a foundational layer upon which the AIMSUN model is constructed. Attention to the detailed mapping of the road network, from traffic controls to movement patterns, is paramount to ensure fidelity to the empirical conditions specific to this motorcycle-dependent district. With the model in place, a calibration aligns it with real-world behaviors, informed by extensive empirical data collection, while subsequent validation is rooted in its consistency with observed traffic conditions. Upon validation, the simulation yields essential data that guides the refinement of the evaluation process. This fine-tuning involves critical computations, such as the estimation of the MEU metrics and the determination of area occupancy, which are integral to tailoring the MFD for the specific context. The results lead to a thorough and detailed evaluation, with the refined MFD at its core, ensuring that the final traffic model serves as a precise tool for analyzing and understanding traffic patterns in areas heavily dependent on motorcycles. Through this approach, the dissertation develops a traffic model that not only aligns with the theoretical aspects of traffic science but also proves highly relevant in practical, real-world settings.

Figure 5-1 A methodological framework for simulation modeling and analysis of mixed traffic.



The MFD describes the relationship between the number of vehicles within the, known as trip production, and the rate at which these vehicles reach their destinations, known as accumulation. Geroliminis and Daganzo (2008) then suggested formulas to quantify these concepts at an aggregate level by weighting the link flow (q_i) and density (k_i) of each link i by its length (l_i), as shown detailed in Equations (5.1) and (5.2), respectively.

$$q_{MFD} = \frac{\sum_i q_i \cdot l_i}{\sum_i l_i} \tag{5.1}$$

$$k_{MFD} = \frac{\sum_i k_i \cdot l_i}{\sum_i l_i} \tag{5.2}$$

The peak of trip production rate signifies the capacity of the road network, whereas the accumulation at this point represents the critical density. The data plots in the area of the MFD graph preceding the capacity are included in the free-flow state, which occurs when only a few vehicles use the network. In contrast, the plots beyond the capacity point depict the congestion/gridlock state, in which vehicles continue to block each other as the number of vehicles keeps increasing.

Through this methodology, the chapter lays the foundation for an in-depth analysis that not only advances academic understanding but also provides actionable insights for practitioners. The integration of empirical data, simulation modeling, and the recalibration of established traffic analysis techniques culminates in a methodology that is both theoretically sound and practically relevant. It highlights the need for customized analysis frameworks in mixed traffic settings, ultimately proposing a modified MFD as a key instrument for assessing the network performance in motorcycle-dependent cities.

5.3 Adaptation Methods for Mixed Motorcycle Traffic Analysis

The study of traffic flow modeling has traditionally relied on simplifying heterogeneous traffic into an equivalent stream of passenger cars using the Passenger Car Unit (PCU) concept, reflecting homogeneous traffic conditions. This approach, foundational in traffic engineering, is exemplified by Chandra and Sikdar (2000) and further explored by Chandra and Kumar (2003), who examined the effects of carriageway width on road capacity under varied traffic conditions across India. Their research, focusing on vehicle speed in PCUs across ten road sections in northern and eastern India, highlighted the limitations of PCUs in encapsulating the complex dynamics introduced by motorcycles. Furthermore, the limitations of conventional traffic modeling become particularly evident in scenarios lacking lane discipline, a common characteristic of motorcycle traffic. These unique conditions indicate that traffic analysis cannot be approached in the same manner as homogeneous traffic.

Despite these advancements, there remains a lack of macro-scale application of these concepts. Current MFD models primarily cater to homogeneous traffic with strict lane adherence and often overlook the variable nature of traffic in motorcycle-dependent regions. This section seeks to bridge this gap by expanding the use of MEU and area occupancy metrics to broader contexts, with the goal of developing a mixed-traffic MFD that more accurately reflects the unique traffic patterns in this context. The following subsections detail the adaptation of MEU and area occupancy for mixed motorcycle traffic analysis, crucial for understanding and managing the dynamic interactions in these environments.

5.3.1 Adaptation Motorcycle-Heavy Traffic: The MEU Approach

In cities with predominant motorcycle traffic, the management of heterogeneous traffic requires an adapted approach, leading to the development of the concept of motorcycle equivalent units (MEU). The need to transition to a more normalized metric is also underscored by Gani et al. (2017), who highlighted that the PCU method was insufficient to accurately represent the vehicle variance within the mixed traffic composition on a specific arterial road in Makassar City, Indonesia. Tan et al. (2018) further emphasized this perspective in the case of Vietnam, as also the focus of the current study, where the low car-to-motorcycle ratio complicates traffic planning using PCUs. Instead, MEUs are more beneficial for capacity estimation in traffic streams where motorcycles significantly outnumber cars.

The abundance of motorcycles and their capacity to maneuver through tight spaces result in traffic patterns not adequately represented by PCU-based models. Arasan and Arkatkar (2008) revealed that the relevance of PCUs varies with traffic composition changes in mixed-traffic settings, underscoring the limited applicability of PCUs and the importance of MEUs. Addressing this, Minh et al. (2005) introduced the MEU, developed from videotaped traffic data in Hanoi, which better captures the dynamic characteristics of motorcycle mobility compared to cars and larger vehicles. This standardized method provides a more accurate measure of road usage, essential for effective traffic management and infrastructure planning in motorcycle-dependent cities, ensuring realistic representation of mixed traffic conditions and addressing the specific needs of such environments.

The concept of the MEU, an evolution of the traditional PCU, is especially relevant for road sections with dense motorcycle traffic. It establishes a correlation between the speed and spatial occupancy of different transportation modes relative to motorcycles, offering a refined assessment of their influence on traffic flow and congestion. This concept extends the methodology developed by Chandra and Kumar (2003) for calculating PCU, which was further refined by Minh et al. (2005) using videotaped data from four road sections in Hanoi, Vietnam. In this study, focusing on the vehicular mix of cars and motorcycles, this advanced formulation is employed through Equation (5.3) to quantify the comparative impact of passenger cars in relation to motorcycles on roadway usage, providing a crucial scalar metric in the context of Ninh Kiều District, where motorcycles account for 90% of traffic.

$$MEU_{car} = \frac{V_{mc} / V_{pc}}{A_{mc} / A_{pc}} \tag{5.3}$$

where,

MEU_{car} : motorcycle equivalent unit for passenger cars,

V_{mc} , V_{pc} : mean stream speed for motorcycles and passenger cars, and

A_{mc} , A_{pc} : projected rectangular area on the road for motorcycles and passenger cars.

The computation of the MEU relies significantly on vehicle mean stream speed, which becomes crucial in heterogeneous traffic conditions where vehicle types display a broad range of speeds. Unlike homogeneous traffic, where speeds are mostly consistent, the mixed nature necessitates a distinct calculation method that takes into account the varying speeds and the number of each type of vehicle present. It is worth noting that traditional measures such as spot speed or space mean speed are not suitable for mixed traffic due to the significant speed disparities between vehicle types. To address the challenge of mixed traffic flows, Cao et al. (2009) introduced an adjusted formula for computing the mean stream speed (V_m) to represent the collective dynamics of mixed traffic flows within these environments, which is represented by Equation (5.4). This equation calculates a weighted average that accounts for the speed of each vehicle type k (v_k) and the number of vehicles of each type (n_k), across all vehicle categories present within the traffic stream (N).

$$V_m = \frac{\sum_{k=1}^{N} n_k \cdot v_k}{\sum_{k=1}^{N} n_k} \tag{5.4}$$

To further refine the model and capture the variability of speeds across different segments of the traffic network, Equation (5.5) is employed. This equation calculates the weighted speed for each vehicle type (v_k) across various segments of the road network, where v_{ik} indicates the mean speed of vehicle type k at link i while l_i is the length of that link i.

$$v_k = \frac{\sum_i v_{ik} \cdot l_i}{\sum_i l_i} \tag{5.5}$$

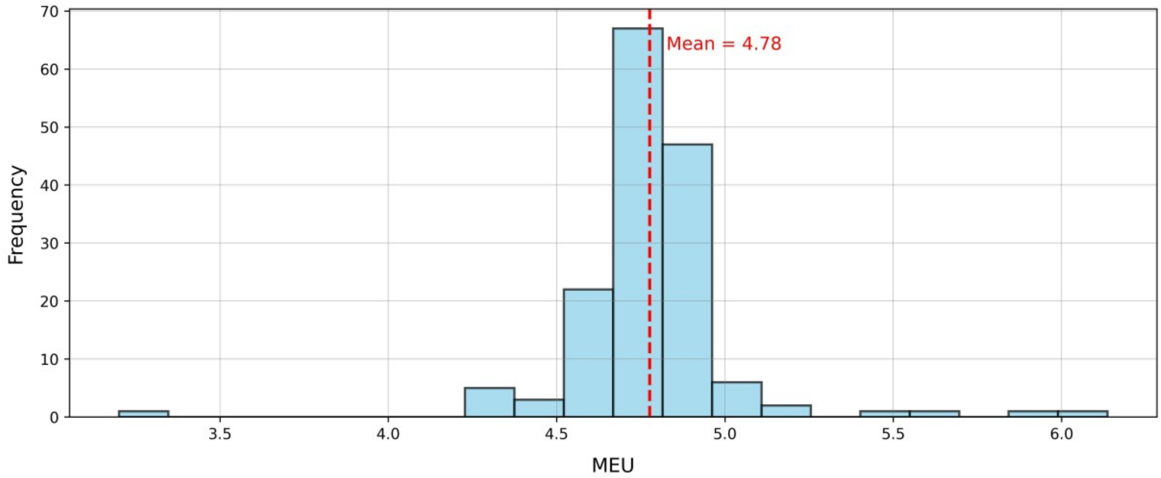
In the MEU computation, average dimensions and projected areas for each vehicle category were sourced from Chandra and Kumar (2003), as detailed in Table 5-1.

Table 5-1 Classification of vehicle types and rectangular area projection size.

No	Type	Vehicles included	Average dimensions (m)	Rectangular area (m^2)
1	Motorcycle	Scooter, motorbike, mopeds	1.87 x 0.64	1.20
2	Car	Car, jeep, van	3.72 x 1.44	5.36

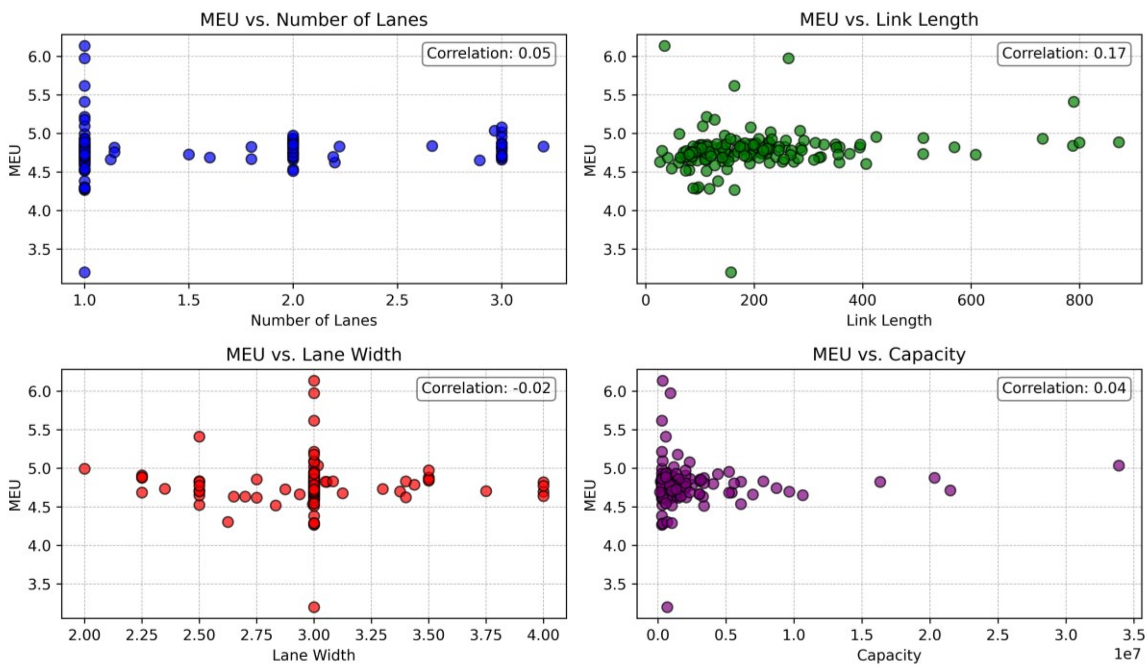
With motorcycles being predominant, their MEU is standardized at 1, serving as a baseline for their network influence. For cars, MEUs are computed for each individual road segment using Equation (5.3) to evaluate their relative impact on traffic flow, with their distribution shown in Figure 5-2.

Figure 5-2 Distribution of MEU values across road sections in Ninh Kiều District.



The histogram presented in Figure 5-2 from the micro-simulation model for Ninh Kiều District displays the MEU metric for cars across 1,533 road segments. The MEU values ranging from 3.20 to 6.14 with an average of 4.78 suggest that the road space occupied by a single car is nearly equivalent to five motorcycles. This metric, essential for accurate traffic analysis and modeling in regions with a high prevalence of motorcycles, helps to create a more balanced and realistic representation of mixed traffic conditions. The concentrated range between 4.5 and 5.5 MEUs and the scarcity of values below 4.3 or above 5.2 illustrate relatively stable traffic conditions with infrequent extremes, reflecting a moderate impact by most cars on the overall traffic flow. This information is essential in motorcycle-dependent cities where the sheer volume and dynamics of motorcycle traffic can significantly differ from that of cars, allowing for the development of traffic models and management strategies that more effectively accommodate the unique composition and behavior of traffic in such environments.

Figure 5-3 Correlation analysis of MEU values with road geometry attributes.



Moreover, the study further investigates the relationship of MEU values with road geometry properties, including length, width, capacity, and lane count of each link. Figure 5-3 shows scatter plots that measure the correlation between MEU and these geometric factors, as denoted by the correlation coefficient. The strength and direction of these relationships are then quantified using Pearson's correlation coefficient, as defined in Equation (5.6). This analysis evaluates the role of the MEU in macroscopic traffic analysis and assesses its effectiveness in representing mixed traffic dynamics.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{5.6}$$

where,

r : the correlation coefficient
x_i : the width/length of the road section i
$\bar{x}$: the mean width/length of the road sections
y_i : the MEU value for the road section i
$\bar{y}$: the mean MEU values

In the first plot, a correlation coefficient of 0.05 suggests an almost nonexistent linear relationship between MEU values and the number of lanes, implying that changes in one variable do not consistently affect changes in MEU values. The second plot shows a positive relationship with a correlation coefficient of 0.17 between MEU and link length, suggesting that increases in one tend to be accompanied by minor decreases in the other, though the relationship is not strong or particularly significant to suggest significant influence. The third plot, depicting a correlation of -0.02 between MEU and lane width, implies an almost negligible relationship. This conclusion contradicts the findings of a study by Chandra and Kumar (2003), which linked PCU to the carriageway width. The last plot presents a very weak positive correlation of 0.04 between MEU and road capacity, evidenced by a dispersed data set that suggests significant variability not explained by a linear relationship. Overall, these low correlation values indicate that the relationship of the MEU with the road network attributes examined is not strongly linear. These findings indicate a general independence of MEU from these particular geometric characteristics within Ninh Kiều District. Nevertheless, further research is required to determine whether this conclusion about the applicability of the MEU metric extends beyond the scope of this case study area. External factors, for instance, local driving behaviors, infrastructure conditions, and regional differences may impact the relevance and utility of MEU in other contexts.

In conclusion, the MEU metric, as detailed above, is utilized in macroscopic evaluation and analysis in the subsequent section, enabling the aggregation of heterogeneous traffic flows effectively.

5.3.2 Accounting for Spatial Utilization: The Role of Area Occupancy

In heterogeneous traffic systems where diverse vehicle types share the road, standard density metrics, such as the number of vehicles per unit length of road and lane, fall short. Unlike homogeneous settings with similar vehicle dimensions and strict lane discipline, heterogeneous traffic complicates spatial dynamics of road use. In motorcycle-dependent environments, where traffic interactions extend beyond the longitudinal to include lateral dimensions and motorcycles engage in filtering through traffic, weaving, and maintaining shorter headways by aligning laterally close to preceding vehicles, unique abilities not commonly seen in car-dominated traffic emerge (Lee, 2007). These behaviors allow for the simultaneous occupation of lane space by multiple vehicles, particularly near intersections, challenging the applicability of lane density measurements in capturing the true nature of traffic flows.

The concept of 'area occupancy' has become essential as a substitute for density measures, offering a more accurate assessment of traffic concentration and spatial utilization in environments with irregular or absent lane discipline. Introduced by Mallikarjuna and Rao (2006) and building on the work of Chandra and Sikdar (2000), this metric accounts for the actual space occupied by vehicles, considering both length and width. It provides a detailed view of traffic flow in mixed traffic conditions where various vehicle types, from motorcycles to larger vehicles, occupy road space differently and influence traffic flow in distinct ways. As traffic complexity heightens with an increase in non-lane-based vehicles (Trinh et al., 2021), area occupancy emerges as a comprehensive measure of space usage, capturing the true essence of motorcycle-dependent traffic. A specific formula was developed to calculate area occupancy (ρ_A) (Mallikarjuna & Rao, 2006), expressed in Equation (5.7) below.

$$\rho_A = \frac{1}{T \cdot W \cdot L} \cdot \sum_{k=1}^{N} (O_k \cdot w_k \cdot l_k) \tag{5.7}$$

where,

T : observation period (in seconds),
N : the set of vehicles.
O_k : occupancy time of vehicle type k (in seconds),
W, L : width and length of the study area, and
w_k , l_k : width and length of vehicle type k.

The formula integrates the dimensional and operational characteristics of different vehicle types, providing a detailed view of their spatial impact in mixed conditions. Introducing area occupancy as a measure signifies a shift in analyzing heterogeneous traffic, particularly in motorcycle-dependent settings, enabling a more realistic assessment of how various vehicles utilize road space. For the specific case of Ninh Kiều District, area occupancy at the link i (ρ_{A_i}) is determined using Equation (5.8).

$$\rho_{A_i} = \frac{1}{T_i \cdot W_i \cdot L_i} \cdot \sum_t \sum_{k \in N_t} (w_k \cdot l_k) \tag{5.8}$$

where,

T_i : observation period (set to 600 seconds),
N_t : index of the set of vehicles that appeared at time t,
W_i , L_i : width and length of the link i, and
w_k , l_k : width and length of vehicle type k.

5.3.3 Adapting Macroscopic Traffic Analysis for Motorcycle-Dependent Traffic

In the context of mixed motorcycle traffic, comprehensive macroscopic analysis is essential to assess the impact of traffic strategies across the interconnected network, where changes in one section can affect congestion elsewhere. Traditional MFD, which relies on aggregate measures of traffic flow and density, need refinement to effectively capture these dynamics. Therefore, integrating adjustments into the macroscopic traffic analysis is crucial to ensure the MFD accurately reflects the traffic system, highlighting the need for adapted approaches in these complex traffic environments.

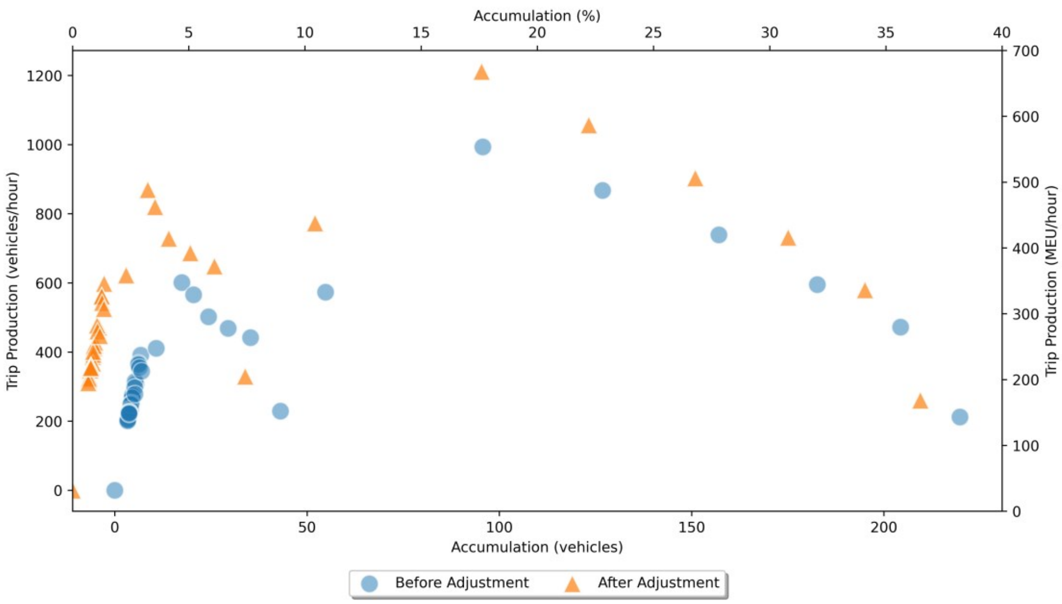
The standard MFD equations, as presented in Equations (5.1) and (5.2), undergo transformations to include MEU-based traffic properties and replace density metrics with area occupancy. This adjustment, which converts counts of larger vehicles into motorcycle-equivalent numbers and measures spatial utilization, provides a more accurate depiction of network performance. Consequently, these modifications enhance the utility of the MFD as a tool for assessing and managing traffic in motorcycle-dependent regions, delivering a holistic view of the traffic dynamics and accurately portraying transition points between free-flowing and congested states. The resulting new equations, outlined in Equations (5.9) and (5.10), where q_{MFD_t} represent the network-scale traffic flow, weighted by the traffic flow of cars ($q_{pc_{it}}$) and motorcycles ($q_{mc_{it}}$) on link l_i during time interval t, further adjusted by MEU factors. Similarly, traffic concentration is measured by area occupancy ($\rho_{A_{MFD_t}}$), which is also weighted across the network to provide a macroscopic perspective on traffic performance.

$$q_{MFD_t} = \frac{\sum_i \left[\left(q_{pc_{it}} \cdot MEU_{car} \right) + q_{mc_{it}} \right] \cdot l_i}{\sum_i l_i} \tag{5.9}$$

$$\rho_{A_{MFD_t}} = \left(\sum_i \left(\frac{1}{T_i \cdot W_i \cdot L_i} \cdot \sum_t \sum_{k \in N_t} (w_k \cdot l_k) \cdot l_i\right)\right) / \sum_i l_i \tag{5.10}$$

Following the aforementioned elaboration, Figure 5-4 compares traffic performance evaluations from a macroscopic perspective using two distinct metrics for measuring vehicle accumulation: density and area occupancy. The blue data plot, labeled as 'before adjustment' MFDs, utilizes traffic density in accordance with the standard MFD approach suited to homogeneous traffic scenarios. However, this metric is less effective in reflecting mixed traffic contexts. In contrast, the orange data plot, representing the 'after adjustment' MFDs, employs area occupancy. This metric has been refined in the dissertation to better align with the unique properties of mixed traffic systems predominantly composed of motorcycles. Although the trends in these comparative metrics of accumulation appear similar, area occupancy proves to be a more suitable metric for analyzing traffic in motorcycle-dependent cities.

Figure 5-4 Comparative analysis of MFD using traffic density and area occupancy.



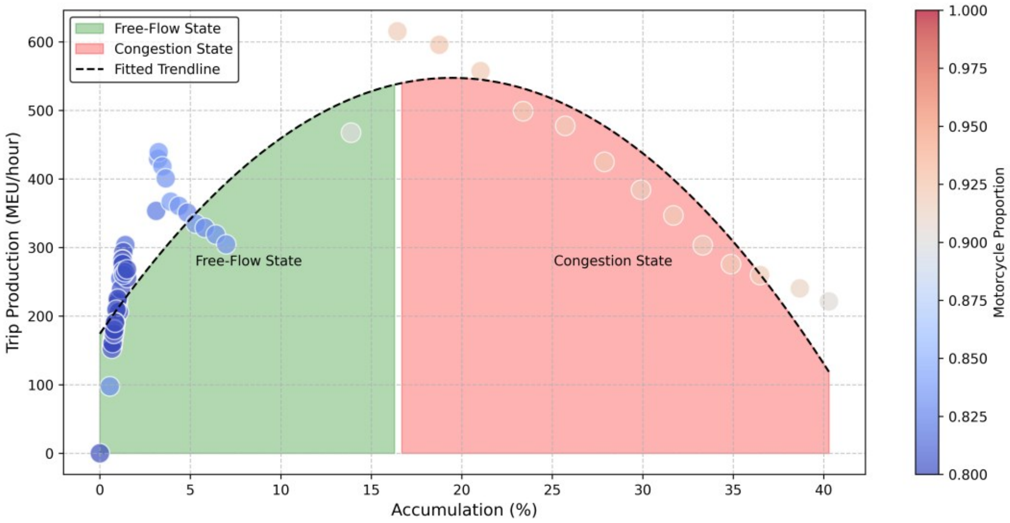
5.4 Network Performance Evaluation

This section presents a thorough evaluation of network performance in Ninh Kiều District. It focuses on leveraging this redefined MFD to reveal intricate traffic behavior in a motorcycle-dominated setting, highlighting empirical results that demonstrate substantial improvements central to the study.

5.4.1 Scenario without Traffic Control Strategies: Existing Traffic Condition

Figure 5-5 showcases the network performance evaluation in Ninh Kiều District using a redefined three-dimensional MFD that incorporates motorcycle proportions. Under Scenario 0, representing existing conditions without traffic reports, route choices are made pre-trip and lack the real-time traffic updates that could optimize flow. The AIMSUN software captures trip production and accumulation in 5-minute intervals over 10 hours. Initially, the MFD shows a positive trend where increased trip production correlates with rising accumulation, indicating efficient use of the network or the free-flow state.

Figure 5-5 Three-dimensional recalibrated MFD for mixed traffic with motorcycle dominance.



Furthermore, a hysteresis loop phenomenon is observed in the MFD of Ninh Kiều District before peak hour, likely caused by several factors. The unbalanced spatial distribution of traffic density within the network plays a significant role—while some areas may function relatively well, others become heavily congested, creating bottlenecks that hinder overall traffic flow. This imbalance causes a delay in returning to normal traffic conditions even as accumulation decreases. High traffic density, limited road capacity, inadequate infrastructure, changes in traffic patterns during peak hours, and driver behavior all exacerbate this effect by slowing down recovery times. This phenomenon underscores the need to address spatial density variations and other contributing factors to mitigate congestion. More detailed analysis is needed in future work to fully understand the hysteresis phenomenon.

As vehicle accumulation grows, the MFD reaches a critical peak—this point marks where additional vehicles no longer contribute to efficient flow, reflecting the network's capacity limit. The peak of trip production, occurring at 614.99 MEU per hour at 07:10 a.m., marks the maximum volume manageable before the onset of congestion. Secondary data analysis indicates that the network's throughput capacity is reached early due to notable morning commuter trends, with a sharp increase of 146.37% in traffic volume from 6 a.m. to 7 a.m. Consequently, the capacity threshold is reached when 16.39% of the network is occupied by vehicles, leading to a transition to a congested state as further accumulation causes decreased trip production and potential gridlock. The relatively low accumulation threshold is also due to 74.65% of the roads in Ninh Kiều District being local and residential types. Integrating a third dimension via a color gradient, the MFD quantifies the motorcycle share in the network. Motorcycles are shown to enhance trip production at low to moderate accumulation levels, due to their compact size, allowing for more efficient space utilization. Nonetheless, as traffic volume approaches and surpasses the network's capacity, the efficiency of a higher motorcycle presence diminishes, aligning with a decrease in the overall performance of the traffic system.

The simulation results for Ninh Kiều District provide a comprehensive view of existing traffic conditions across various metrics. Figure 5-6 shows the volume-to-capacity ratio, indicating the extent to which road segments are utilized, from underutilized to near or at full capacity. Figure 5-7 displays average speeds along different road segments, identifying areas where traffic flow is smooth versus those where delays are prevalent. Figure 5-8 demonstrates the traffic density, revealing how vehicles are distributed throughout the area. Notably, bottlenecks are consistently observed along major roads such as Cầu Rạch Ngỗng, Nguyễn Văn Cừ, Trần Hưng Đạo, Hoà Bình, and 30 Tháng 4 streets.

Figure 5-6 Simulation results: Mean flow of existing traffic conditions in Ninh Kiều District.

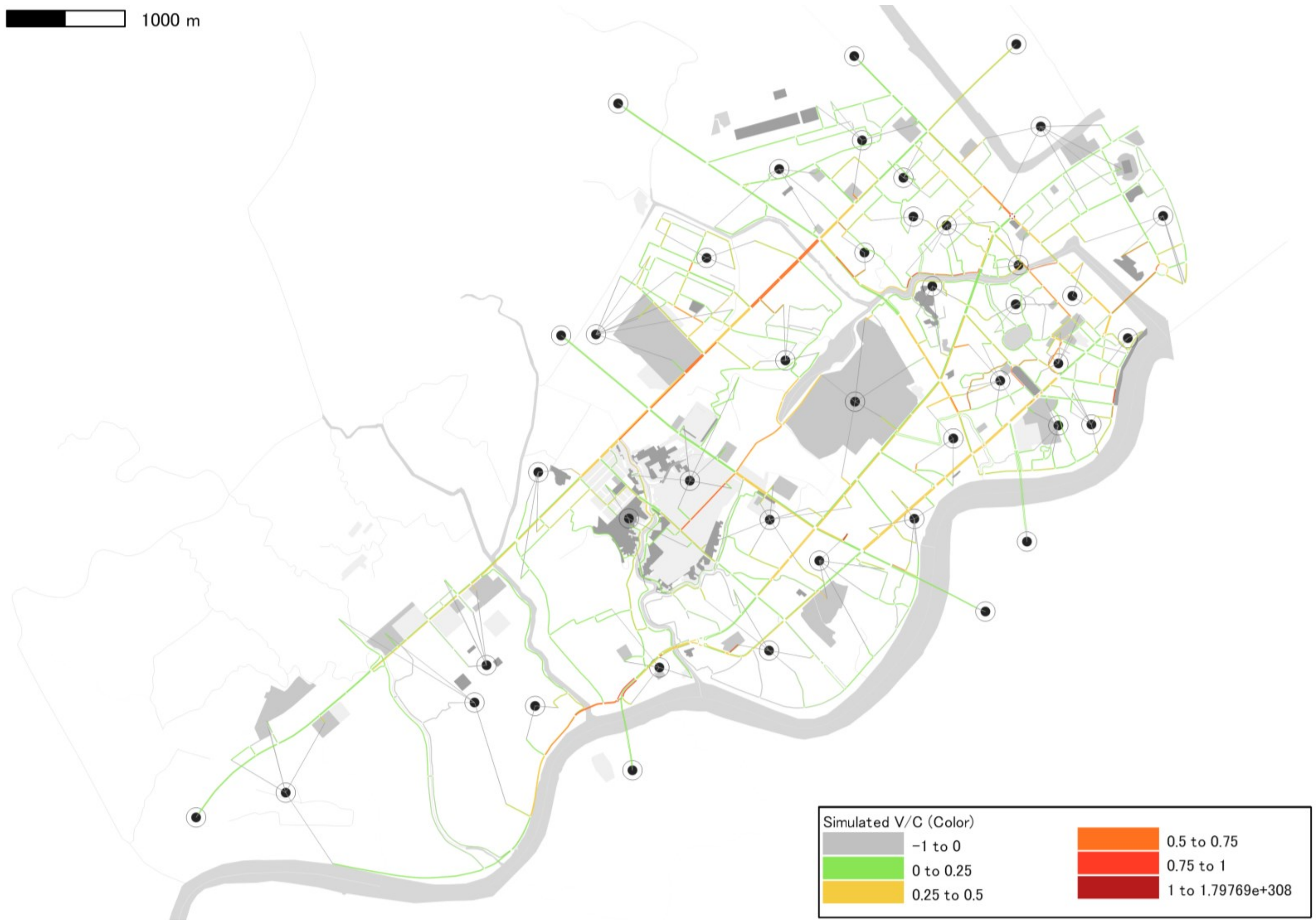


Figure 5-7 Simulation results: Mean speed of existing traffic conditions in Ninh Kiều District.

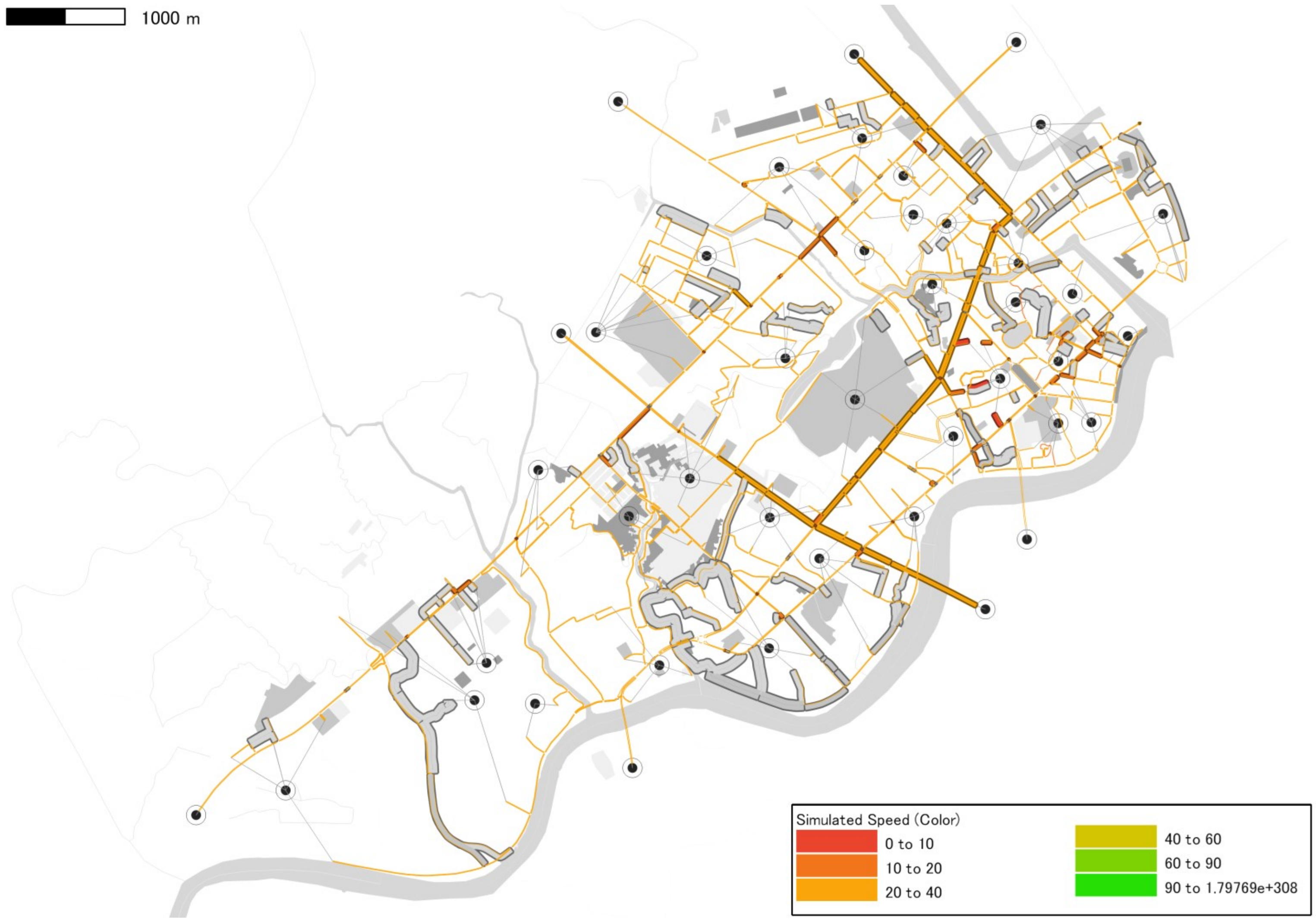
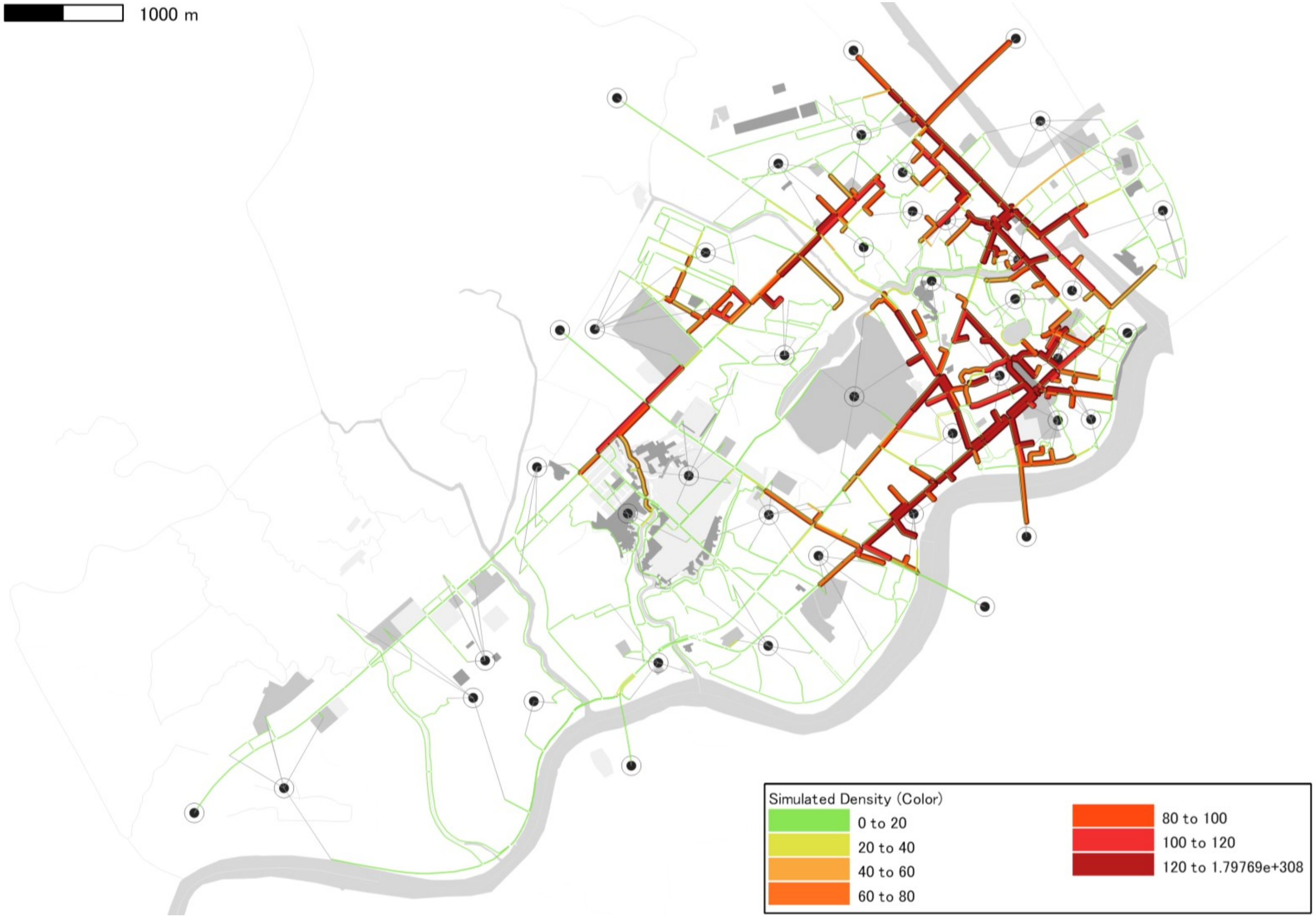


Figure 5-8 Simulation results: Mean density of existing traffic conditions in Ninh Kiều District.



5.4.2 Scenario with Traffic Control Strategies

This segment evaluates the potential of traffic information schemes in motorcycle-dependent regions, representing a concentrated effort beyond mere technological progress to enhance traffic efficiency. Building on Chapter 3 insights, the adaptation of VMS for urban roads is introduced, making them accessible and informative for motorcycles, who comprise the majority of traffic. The rationale behind this strategic deployment is rooted in empirical evidence derived from route choice analysis and further substantiated by simulation modeling. The customization of VMS for motorcycle accessibility not only highlights the novel aspects of this dissertation but also showcases a systematic traffic management approach that is sensitive to local commuting patterns and the widespread use of two-wheeled vehicles.

5.4.2.1 Scenario Definitions

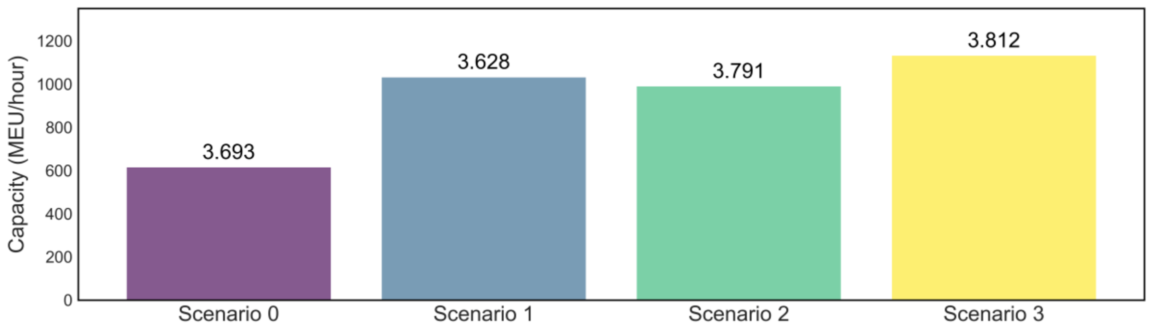
A series of scenarios, varying in presentation and coverage from no intervention to comprehensive VMS integration across the network, are outlined below. These scenarios are then incorporated into the AIMSUN model to perform simulations and generate detailed traffic performance at each time step.

1. **Scenario 0 (Without Traffic Control)**: This scenario represents the existing condition and serves as the baseline. It reflects the current situation without interventions from any control schemes.
2. **Scenario 1 (With Traffic Information Accessed from Major Roads)**: Traffic reports are provided on trunk and secondary roads and can only be accessed from these locations.
3. **Scenario 2 (With Selective Reports but Network-Wide Access)**: While traffic information specifically covers key arterial routes, they are accessible to all road users across the entire network.
4. **Scenario 3 (With Comprehensive Network-Wide Information Provision)**: This scenario presents a fully informed system where traffic report is accessible and available across the network.

5.4.2.2 Impact Assessment of VMS Strategies

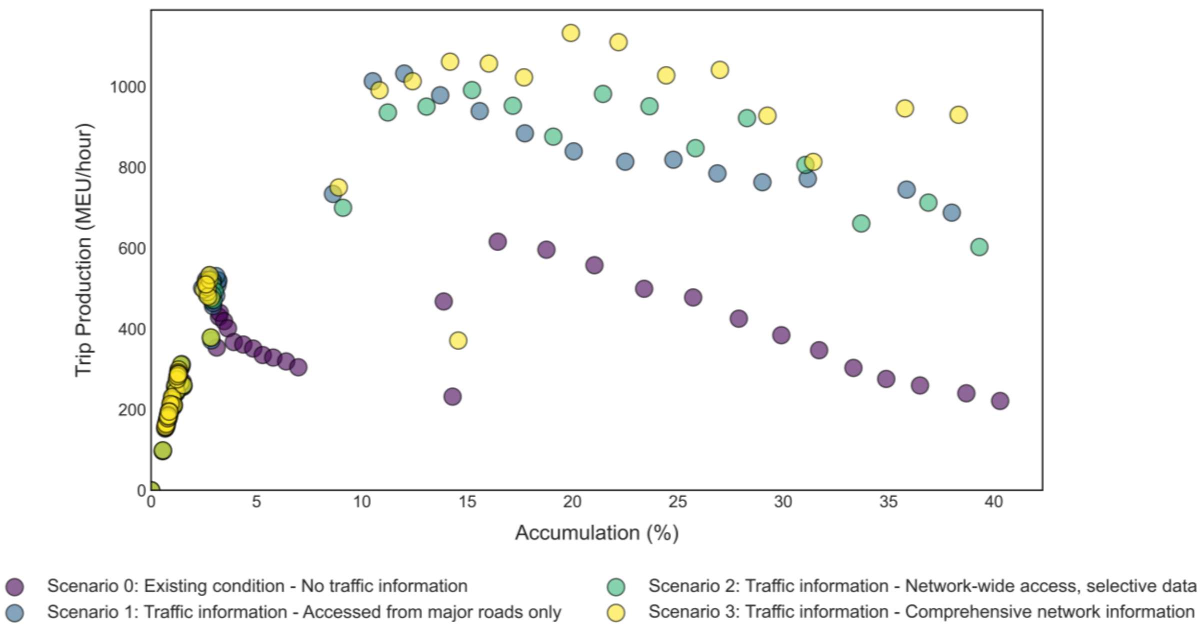
This section evaluates the impact of each control strategy using redefined MFDs. The micro-simulation model serves as a critical tool, synthesizing all traffic characteristics such as flow, vehicle count, speed, and density from the AIMSUN model. To ensure the accuracy and relevance of the findings, each scenario is simulated under identical parameters and time periods, maintaining conditions that mirror those of the established existing conditions. Figure 5-9 summarizes the MEU values for cars across various traffic management scenarios, laying the groundwork for the subsequent MFD analysis.

Figure 5-9 Comparison of MEU metrics across all scenarios.



In evaluating each scenario, Figure 5-10 presents a comparative MFD analysis that aggregates the relationship between weighted traffic flow and accumulation for each link, demonstrating how real-time traffic information with varying coverage and scope affects network performance. The scatter of data points along each curve, collected every five minutes from the AIMSUN model, shows the variability in traffic conditions at different times of the day. In general, the MFD for scenarios with traffic control shows that trip production remains stable as accumulation increases, indicating that the network is maintained to operate at a capacity level. Notably, the hysteresis loop observed under existing conditions disappears with the provision of traffic information, suggesting a more balanced spatial distribution of traffic density across the networks. This improvement highlights the effectiveness of real-time traffic updates in preventing localized congestion and promoting a smoother, more consistent traffic flow across the network. Overall, the shape, trajectory, and stability of these MFD curves are significantly influenced by traffic management strategies, as in line with Ambühl et al. (2018) and Ji et al. (2010).

Figure 5-10 MFD comparison across all scenarios.



In a detailed analysis of traffic management strategies, Scenario 1 raises the network capacity to 1031.66 MEU/hour by 07:15 a.m., demonstrating the effectiveness of providing timely traffic information on congested routes. This enables road users to make better-informed route choices, thereby minimizing congestion and balancing traffic distribution. Scenario 2 extends the delivery of traffic information across the entire network, focusing reports on major roads, resulting in an adequate network capacity of 989.53 MEU/hour by 07:20 a.m. Despite the broader reach, the network performance under this scenario is slightly lower than in Scenario 1. This illustrates that, particularly in motorcycle-dependent cities, as examined in this dissertation context, the extent of information coverage is more critical than merely providing access to all road users. If only major road information is available, drivers may not switch to lower-hierarchy roads, which are more prevalent. In Ninh Kiều District, only 25.35% of the roads are major roads, while the majority are tertiary and residential streets. The finding highlights the need for a comprehensive dissemination of traffic information across all road types to ensure optimal traffic management and to encourage the use of less congested routes. In Scenario 3, the fully informed system, by 07:35 a.m., significantly enhances traffic management, boosting network capacity to 1132.03 MEU/hour. This highlights the profound impact of widespread guidance, showing how broad access to traffic information can balance vehicle distribution and encourage drivers to avoid congested routes.

The comparative analysis of MFDs in Figure 5-10, therefore, not only illustrates the impact of traffic management strategies on network capacities, which is summarized in Figure 5-11 but also emphasizes the need for comprehensive traffic information dissemination to optimize traffic management. Among all the assessed traffic management scenarios, Scenario 3 emerges as the most effective, suggesting a shift towards a more intelligent traffic ecosystem, where information is disseminated not just through VMS but also via a range of ATIS devices, including mobile apps. Leveraging technological advancements in smartphone integration, this approach broadens the reach and effectiveness of traffic systems to accommodate diverse users and scenarios. The redefined MFD analysis reveals that effective traffic management goes beyond preventing congestion; it requires precise adjustments to maintain operations near the network's capacity, minimizing delays and improving flow. Collectively, findings highlight the transformative potential of VMS and other ATIS tools in revolutionizing traffic systems in motorcycle-dependent areas, providing a framework for data-driven policymaking to enhance traffic efficiency and reduce congestion in such environments.

Figure 5-11 Network capacity across all scenarios.

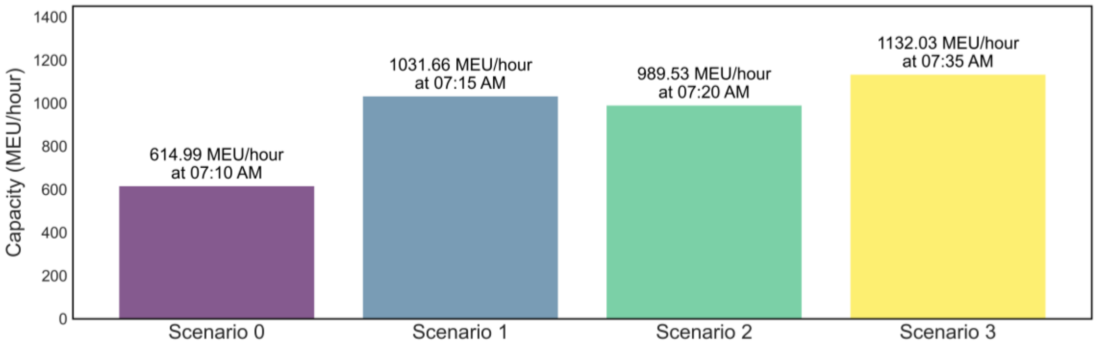
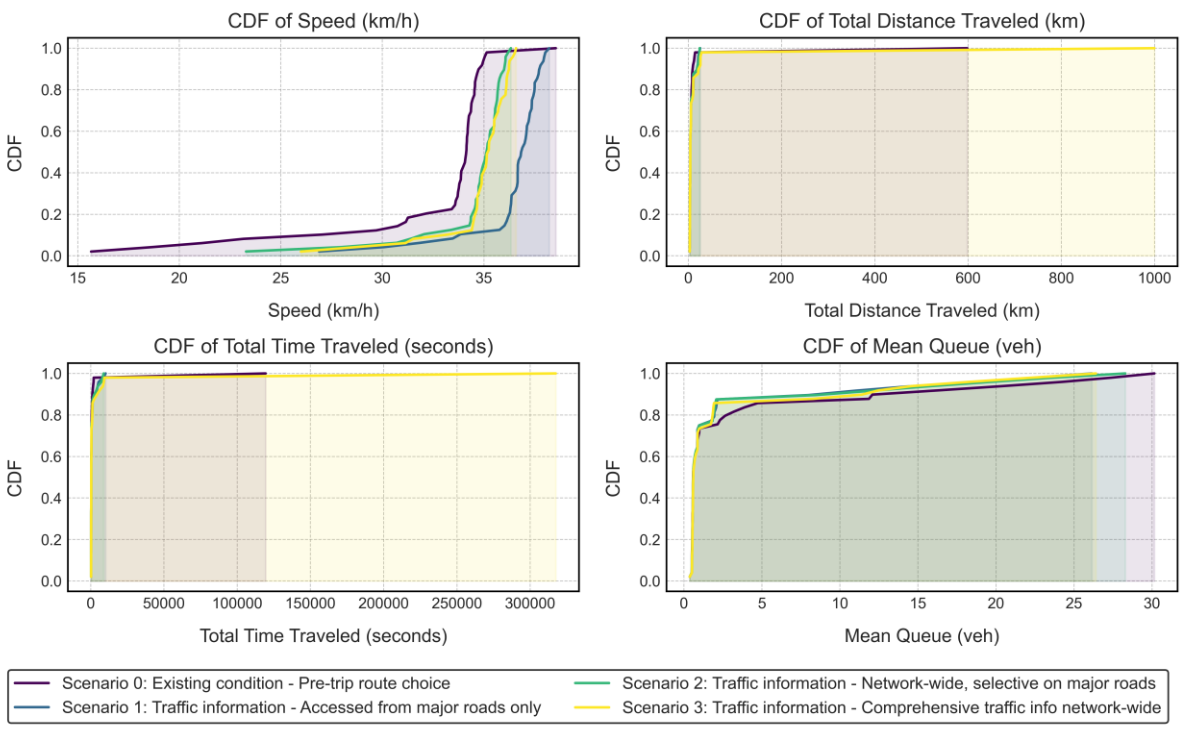


Figure 5-12 shows the Cumulative Distribution Functions (CDFs) to illustrate the impact of different traffic information provision scenarios on various traffic indicators over time.

Figure 5-12 Simulation results - CDF analysis across all scenarios.



The CDF graphs reveal that higher speeds are maintained more consistently in scenarios with comprehensive, network-wide traffic reports, suggesting that real-time data enables drivers to adapt more effectively. Vehicles in these scenarios also tend to travel farther, as shown by the CDF for total distance traveled, indicating that traffic information boosts driver confidence and efficiency, leading to longer trips that help evenly distribute traffic. The CDF for total time traveled shows that Scenario 3 results in shorter travel times, affirming the significant reduction in time on the road due to efficient data dissemination. Lastly, the mean queue length CDF indicates shorter queues, reflecting smoother traffic flow and more effective management. Collectively, these results underscore the substantial benefits of widespread, detailed traffic information in enhancing network performance, with the greatest improvements observed when traffic data covers all road types and is accessible throughout the network.

One of the notable strengths of utilizing a microscopic simulation model in traffic analysis is its ability to provide comprehensive visual representations of traffic evolvement. Figure 5-13 presents a color-coded map depicting speed variations during peak hours across four distinct scenarios. The map highlights traffic bottlenecks consistently appearing along key routes, such as Cầu Rạch Ngổng, Nguyễn Văn Cừ, Trần Hưng Đạo, Hoà Bình, and 30 Tháng 4 streets. It can be observed that in Scenario 0, speeds are relatively low, particularly in the district's central areas. Scenarios 1 and 2 demonstrate slight improvements in speed, though congestion remains on some major roads. Scenario 3, however, exhibits the most significant enhancements, where comprehensive traffic information provision leads to a substantial increase in speeds and a marked reduction in bottlenecks, particularly in the busiest areas, underscoring the benefits of a fully informed traffic system.

Figure 5-13 Visualization of speed changes during peak hours across four traffic scenarios.

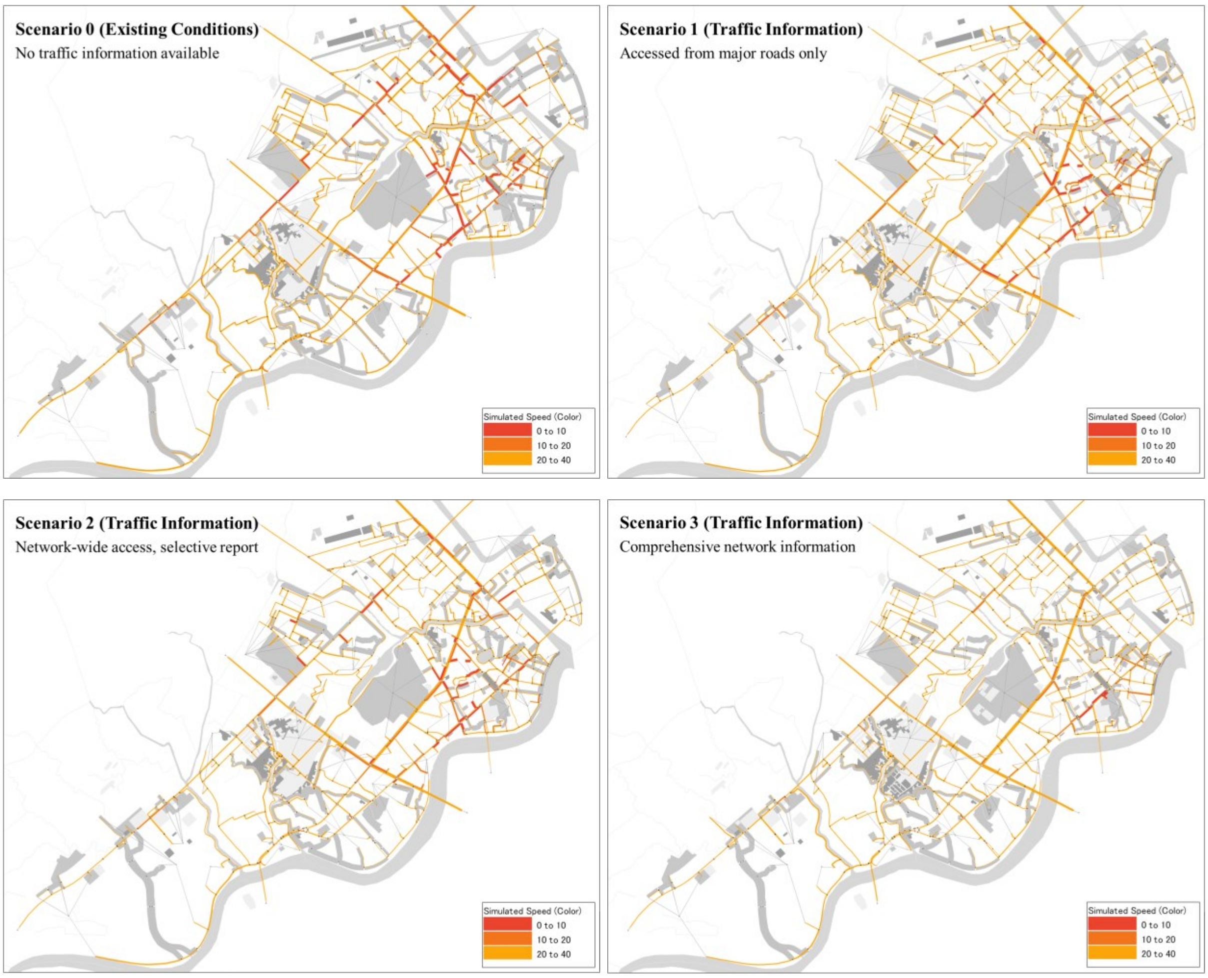


Figure 5-14 Performance changes of different control scenarios over existing conditions.

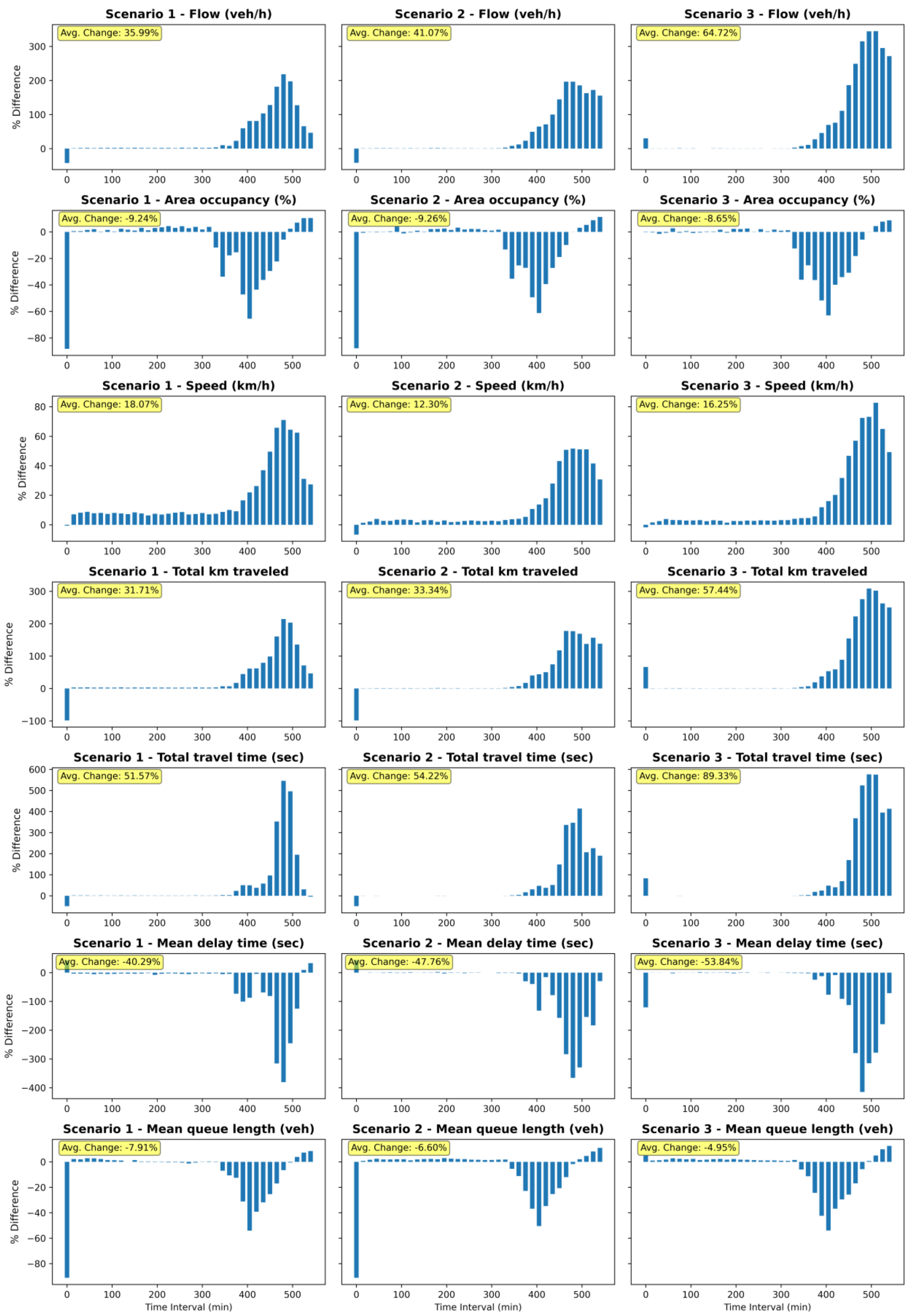


Figure 5-14 illustrates the performance changes of each scenario compared to the baseline (Scenario 0) across key indicators like traffic flow, area occupancy, speed, total distance traveled, total travel time, delay time, and queue length, with percentage differences evaluated at 15-minute intervals. A notable initial difference is observed at minute 0, attributed to the inherent randomness within the micro-simulation model, such as variations in vehicle arrival times and distribution patterns. As time progresses, the graph shows how traffic conditions respond to varying levels of traffic information provision. Scenario 1 demonstrates a quicker adaptation to evolving traffic, leading to more efficient traffic flow and improved performance metrics. Scenario 2, meanwhile, shows slower gains, indicating that while widespread information is valuable, the precision and relevance of data in Scenario 1 may have a more immediate impact on trip efficiency. Scenario 3 initially experiences fluctuations as drivers adjust to new data but eventually shows improvements as drivers become accustomed to using real-time information, highlighting the impact of thorough data on driver behavior and network performance.

Overall, the trends in Figure 5-14 indicate increases in both total distance traveled and total travel time, suggesting that while routes may be longer, they are faster, resulting in more efficient traffic flow. The reduction in delay times points to a shift towards a system optimum, where the network optimizes collective travel time, potentially at the cost of increased individual travel times. The baseline scenario likely represents a user equilibrium state, where drivers select routes that minimize personal travel times, leading to congestion on popular routes. Both Scenarios 1 and 2 aim to influence drivers' route choices through targeted and extensive traffic information, pushing the system towards a more balanced traffic distribution and system optimum. Scenario 3, after initial fluctuations, gradually stabilizes as drivers adjust to the extensive traffic information, demonstrating how comprehensive data dissemination can significantly improve traffic management by guiding the network toward a system optimum.

5.5 Discussion

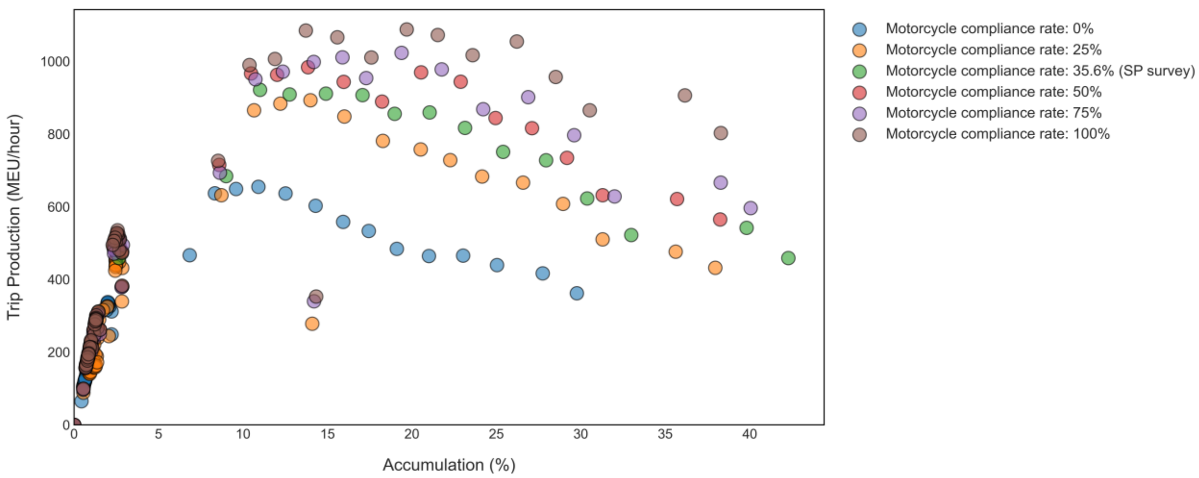
This section explores the broad effects of traffic control strategies examined within Ninh Kiều District, specifically focusing on how different scenarios of traffic information dissemination and compliance rates affect network performance and reshape traffic dynamics. The findings from these analyses underpin the strategic policy recommendations proposed to enhance traffic flow and reduce congestion.

5.5.1 Scenarios Evaluation: Macroscopic Impact of Compliance Rates

The effectiveness of traffic control measures proposed here is largely determined by how drivers respond to traffic reports and their willingness to adjust their routes. Figure 5-15 presents the MFD curves from Scenario 3, which showed the most significant improvements while factoring in varying compliance rate scenarios among road users, ranging from 0% to 100%. This underscores how different levels of adherence can impact overall network performance. It is worth mentioning that compliance refers to the context where drivers, all over the network follow the route choice function defined in the simulation model to calculate and maximize their utility, rather than merely following a single route suggestion.

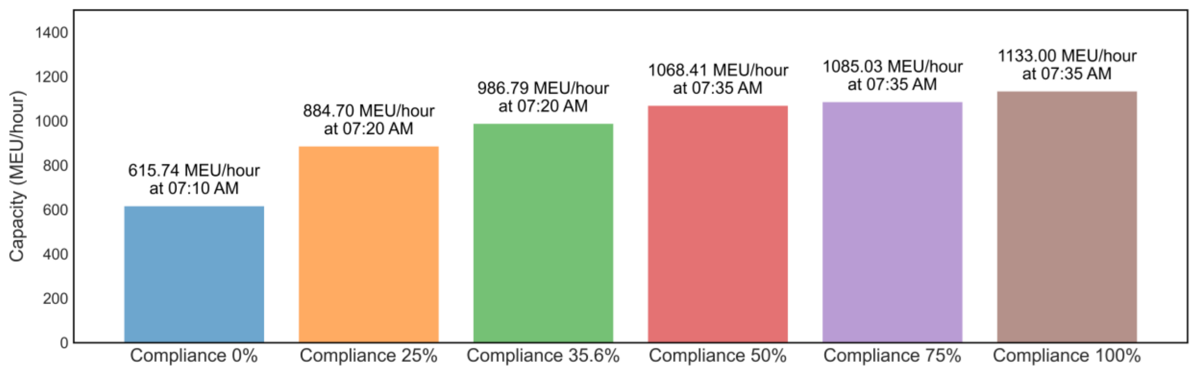
At a 0% compliance rate, trip production is tightly clustered at lower accumulation levels, indicating limited traffic flow and potentially inefficient network utilization. Without adherence to traffic information, vehicles tend to concentrate on popular routes, which subsequently become congested areas, degrading overall performance. As compliance rates increase to 25% and 35.6%—the latter from an SP survey discussed in Chapter 3—the data points begin to spread across higher trip productions and accumulations, suggesting that even partial compliance can significantly improve traffic flow and capacity by helping drivers adjust their routes and alleviate bottlenecks. It is noteworthy that the SP survey was conducted in the absence of ATIS devices like VMS to distribute traffic reports in urban roads, highlighting the potential for even higher compliance rates with increased socialization and education about such tools. Higher compliance rates of 50% and 75% correspond with increases in trip production at varied accumulation levels, reflecting more evenly distributed traffic.

Figure 5-15 Impact of compliance rates on network performance: An MFD comparative analysis.



At a 100% compliance rate toward traffic information, the MFD shows the highest trip production levels across a wide range of accumulations. This state, where all drivers adhere to traffic advisories, leads to optimal traffic distribution and network utilization. The consistently high trip production across various accumulation levels, even in congested states, suggests a well-managed flow that maintains network efficiency by operating close to its capacity. Despite increases in area occupancy, the system effectively sustains vehicle throughput by maximizing infrastructure utilization, highlighting the critical role of compliance in enhancing traffic management and network performance. In summary, network capacity increased by 84% as compliance rates grew from 0% to 100%, illustrating the profound impact of full compliance. Figure 5-16 details these changes across various compliance rate scenarios.

Figure 5-16 Summary of network capacity by compliance rate scenarios.



5.5.2 Impact of Motorcycle Compliance on Network Performance

In evaluating proposed traffic management, it becomes crucial to account for the distinct behaviors of varying vehicle types, particularly motorcycles. Motorcycles, due to their size and agility, may interact differently with traffic control measures, such as their reception and response to traffic information, compared to larger vehicles in mixed traffic settings. This assesses the impact of motorcycle behavior on network performance across scenarios, maintaining car compliance at a constant 30%, derived from a range of documented findings in the literature. For instance, Zhong et al. (2012) noted car route change rates did not exceed 40%, while Ramsay and Luk (1997) observed a 30% compliance rate, matching the 6-41% range reported by Davidsson and Taylor (2003). This rate accommodates both higher compliance rates like the 50% (Kattan et al., 2011) and the conditional 100% rates during road closures (Erke et al., 2007). It also considers lower observed ranges, such as Zhou and Wu (2006), where 16.9% would change paths and 65.4% might consider it, and Erke et al. (2007), where generally 20% follow VMS.

Figure 5-17 Network capacity comparison across compliance scenarios for motorcycles and cars.

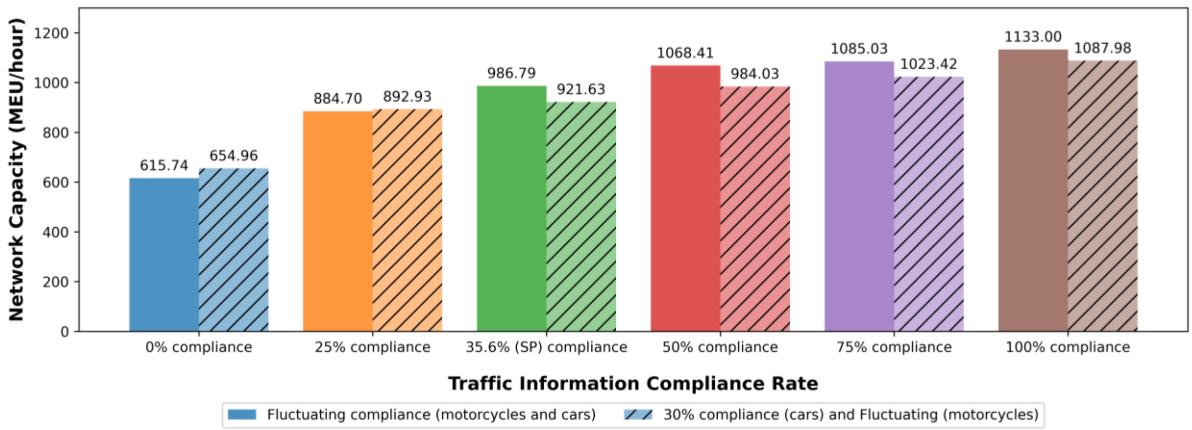


Figure 5-17 presents a comparison of network capacities under different compliance scenarios: (1) fluctuating compliance for both motorcycles and cars, and (2) a scenario where cars maintain a constant 30% compliance while motorcycle compliance fluctuates. This methodological focus provides a clearer understanding of how specific adaptations in motorcycle management can lead to more efficient network usage and supports the development of motorcycle-specific interventions. The graph reveals that at lower compliance levels of 0% and 25%, network capacity tends to be higher when car compliance is constant, suggesting that optimizing network performance may still be achieved not by altering the established car compliance but rather by focusing on managing motorcycle behaviors. In comparison, as expected, higher compliance rates lead to greater capacities when both vehicle types have fluctuating compliance, but the overall improvement is modest, averaging around 5.24% (see Table 5-2). These findings demonstrate the effectiveness of managing motorcycle compliance dynamically, which significantly influences overall traffic conditions without requiring changes to car behavior.

In conclusion, while improving compliance among both motorcycles and cars significantly boosts network efficiency, strategically managing motorcycle behavior alone can enhance traffic conditions without needing to alter car behavior. These findings confirm earlier hypotheses and results from previous chapters, highlighting the crucial role of motorcycles in mixed traffic and the importance of route choice behaviors in shaping traffic dynamics. Using traffic information, especially in developing countries and on non-toll roads where it is often limited, emerges as a highly effective strategy.

Table 5-2 Network capacities and compliance differences for various scenarios.

Compliance Rate	Network capacity (MEU/hour)		Absolute Differences (%)
	Fluctuating compliance (cars and motorcycles)	30% compliance (cars) and fluctuating (motorcycles)	
0%	615.7	655.0	6.37
25%	884.7	892.9	0.93
35.6% (SP survey)	986.8	921.6	6.60
50%	1068.4	984.0	7.89
75%	1085.0	1023.4	5.68
100%	1133.0	1088.0	3.97

5.5.3 Policy Development

This section draws on macroscopic analysis to identify the role of traffic information in managing motorcycle-dependent networks, leading to strategic policy recommendations as follows.

1. **Comprehensive Information Distribution**: Develop a unified traffic information system that delivers real-time updates accessible to all network users. Incorporate IoT devices, sensors, and mobile apps to facilitate seamless data sharing and route planning. By extending coverage from major arteries to smaller streets, the system not only ensures comprehensive utility but also bridges technological gaps in developing countries, promoting the adoption of ATIS across all road types.
2. **Enhanced Driver Compliance and Education**: Given the effect of compliance rates on network performance (see Figure 5-15), increase driver compliance through targeted educational campaigns that highlight the benefits of adhering to traffic advisories, thereby promoting efficiency and safety.
3. **Real-Time Adaptive Traffic Control Measures**: Adopt adaptive traffic control measures that dynamically adjust to real-time data, including rerouting suggestions, adjusted signal timings, and modified road usage rules, to optimize traffic flow continuously.
4. **Regular Monitoring and Feedback Incorporation**: Establish mechanisms for regular monitoring of traffic conditions and the effectiveness of information dissemination. Use this feedback to adjust strategies continually, ensuring they address evolving urban mobility challenges effectively.

5.6 Summary

This chapter critically evaluates traffic dynamics in Ninh Kiều District, assessing both existing conditions and proposed improvements through hypothetical scenarios. The study highlights the challenges of analyzing motorcycle-dependent traffic and introduces a redefined MFD that incorporates MEU and area occupancy metrics, surpassing the limitations of traditional density-based metrics.

The findings reveal that network capacity remains low without traffic interventions but improves markedly with targeted information, especially when made universally accessible, suggesting that comprehensive and real-time traffic data is essential for optimal network performance and congestion reduction. Analysis across scenarios shows that while targeted information on major roads quickly boosts traffic flow, broader dissemination of information takes longer to show benefits yet eventually leads to substantial improvements as the system stabilizes and drivers adapt. Moreover, higher compliance rates greatly enhance network performance, with the most notable improvements observed at full compliance, where trip production and network utilization reach their optimal states. These results highlight the importance of precise, relevant traffic information and high compliance rates in driving efficient traffic management, advocating for strategic education and integration of advanced traffic systems are critical for maximizing network efficiency.

The novelty of this chapter lies in its substantial advancements in applying the MFD for motorcycle-dependent traffic contexts, providing a more accurate representation of such systems by shifting from traditional density measures to area occupancy. The recalibrated MFD proves effective in identifying key operational patterns and potential bottlenecks, representing a major step forward in adapting the MFD for mixed traffic conditions typical in Southeast Asia. This approach not only enhances the analytical capabilities for traffic studies but also contributes substantially to developing the MFD frameworks for regions with a high prevalence of motorcycles. As the prominence of motorcycles in transport persists, the findings provide a vital foundation for performance evaluation, as well as shaping future transportation planning and policy-making in similar contexts.

Chapter 6

Conclusion

6.1 Introduction

The final chapter summarizes the key findings, highlights the research's contributions to academic knowledge and practical applications, addresses the study's limitations, and proposes future directions.

6.2 Summary of Research Findings

The dissertation primarily focuses on evaluating the performance of mixed motorcycle traffic conditions and introducing traffic control measures tailored to influence driver behavior based on route selection considerations. This section provides a summary of the findings from each phase of analysis.

A major contribution of this study is its focus on the route choice behavior of motorcycle riders, contrasting with existing literature that primarily examines passenger cars. It is particularly relevant to Asian countries, where motorcycles dominate transportation. Behavioral reactions were collected through a Stated Preference (SP) experiment, which utilized a hypothetical network designed to mirror the distinctive characteristics of motorcycles and the typical road topology in such context, including prevalent shortcut roads and railway crossing gate closures. Methodologically, the mixed-PSL model outperformed other discrete choice models, such as MNL and basic PSL models, due to its ability to account for unobserved random terms. The mixed-PSL model particularly excels in handling route choice analysis as it addresses the serial correlation and the inevitable overlap of links within routes. The dynamic route choice model, which focuses on a link-based framework, proved highly effective in capturing en-route routing decisions under traffic information systems environment. This model accommodates sequences of link choices, maximizing utility at each node, which aligns well with the flexibility required for motorcycle navigation as traffic updates are received.

As a novel aspect, the study underscores the potential of expanding VMS to urban roads, which is crucial in many developing countries where such systems are either absent or limited to higher-tier roads, providing only qualitative rather than real-time traffic updates. The study shows that integrating VMS with real-time data, including travel times and a color-coded map of volume-capacity ratios, offers a complete view of traffic conditions, enabling riders to make informed route decisions and eventually achieve more balanced traffic distribution. Sensitivity and probability change analyses further confirm the significant impact of traffic information provision on shaping travel choices, emphasizing its crucial role in traffic management strategies. The survey revealed that 35.6% of motorcycle riders comply with VMS guidance and are willing to switch routes, while about 6% of participants, mostly older riders, consistently take the same routes regardless of traffic conditions. Model estimation shows that traffic flow significantly influences their route choices, with a strong tendency to avoid heavily congested, longer, or time-consuming roads. The behavior reflects the disutility of denser traffic, highlighting riders' preferences, akin to those of all vehicle types, for more efficient routes. While travel time has the least effect on link choice probabilities, traffic flow conditions display substantial sensitivity; preference for a link increases with better traffic conditions. Additionally, link length is highly elastic; a 1% increase in link length reduces the likelihood of a motorcycle rider choosing that link by about 1.28%.

Incorporating socioeconomic and riding characteristics into the model, both as main or interaction effects, highlighted the taste of heterogeneity among individuals. Factors such as gender, age, occupation, travel purpose, and driving frequency influence routing decisions. Service-related jobs, conservative riding styles, and socioeconomic factors like education level, employment status, and driving experience notably shape route preferences, highlighting a complex interaction between personal characteristics and travel behaviors. The study further found that while most riders prefer wider roads, those in service professions, like motorcycle taxi drivers or delivery couriers, often choose shortcuts to save time. In comparison, riders over 50 tend to avoid shortcuts, likely due to the increased hazards from narrow roads and high-disruption areas featuring residences and small stalls, which can compromise safety. In developing countries, these shortcut roads are typically accessible only to motorcycles, non-motorized vehicles, and pedestrians because of their narrow width. The dissertation also introduces ramp metering on non-highway roads heavily trafficked by motorcycles, a novel adaptation of a system typically used on toll roads but not yet implemented in developing countries. This strategy aims to regulate motorcycle entry onto arterial roads, maintaining flow within capacity limits to prevent congestion. The analysis indicates that ramp metering on arterial roads effectively redirects riders to alternative routes. When ramp metering is active, motorcycles avoid longer waits at these controls, prompting some riders to opt for less congested roads over major arteries.

In contrast to its counterpart, most existing studies on route choice models for cars identify travel time as a more significant factor than distance. This emphasis on time reflects the substantial impact that travel duration tends to have on perceived travel costs for car drivers. However, this dissertation finds that motorcycle route choice behavior deviates from this pattern, with distance emerging as the most important attribute influencing their route preferences. This difference likely stems from motorcycles' ability to navigate through traffic, often bypassing congestion more effectively than cars, which could explain why distance remains a more prominent role in their decision-making process. The study highlights the importance of traffic information and the effectiveness of ramp metering in managing motorcycle proportions in mixed traffic. By directing traffic via VMS, ramp metering prompts riders to consider alternative routes, catering to the diverse preferences of different rider demographics.

The outputs from the route choice analysis were then integrated into a microscopic simulation model for Ninh Kiều District, Cần Thơ City, Vietnam. Known for having the highest number of motorcycles worldwide for nearly 90% of all vehicles, Vietnam presents an ideal subject for studying mixed traffic. Particularly in Ninh Kiều District—the city's activity hub and most densely populated area—traffic reaches its peak on Mondays, marking the start of the workweek, and experiences the lowest volumes over the weekends. The majority of recorded trips are short, typically under 15 minutes and less than 5 kilometers, mainly for daily commutes. Significant congestion occurs during morning peak hours, driven by high trip generation linked to schools and workplaces. Notably, about 41% of workers begin their commute before 6 a.m., influenced by local economic activities such as early morning markets and the fishing industry, contributing to a 146.37% spike in the early morning traffic.

The model, developed on the AIMSUN software, was meticulously fine-tuned to represent the unique characteristics of motorcycles and reflect observed mixed traffic behaviors. During calibration, iterative adjustments were made to configure the road network configuration, vehicle demand, and driver behavior, all of which impact overall traffic flow. A critical component of this process involved integrating a pre-defined discrete choice function that defined route choice mechanisms by estimating factors that influence drivers' decisions and their responses to dynamic road conditions. The dissertation shows that motorcycle riders do not strictly adhere to the shortest path principle; instead, they adapt their routes in response to real-time traffic conditions. This adaptability led to a 27.59% improvement in accuracy during the model's validation, underscoring the importance of accurately modeling route choice behavior. As a result, the model effectively captures the decision-making processes of motorcycle riders, marking a significant step forward in simulating and understanding motorcycle-dependent traffic. The literature review, citing Elesawey and Sayed (2011), notes that calibrated and validated micro-simulations on large networks—those with over 100 intersections—are exceedingly rare, particularly in the context of mixed traffic patterns typical in Asia. This dissertation bridges these gaps by addressing both the large network scale and the specific traffic compositions prevalent in these settings.

The traffic patterns of Ninh Kiều District were simulated in AIMSUN to assess network performance under existing conditions by analyzing traffic flow, density, vehicle count, and speed. This research pioneers the adaptation of the MFD to motorcycle-mixed traffic, as previous studies have mainly focused on unimodal scenarios using standard MFD metrics. In contrast, this study delves into the complex dynamics of mixed motorcycle traffic, marking a significant advancement in macroscopic analysis by redefining the MFD through the integration of MEU and area occupancy metrics to better capture such conditions. The strong presence of motorcycles introduces complexities in data utilization and analysis, as conventional traffic flow models, designed for homogenous, lane-disciplined environments, fail to account for the nuances of heterogeneous traffic, particularly the tendency of motorcycles to ignore lane markings. Previous studies (e.g., Gani et al., 2017; Kov & Yai, 2010; Tan et al., 2018) have showed the inadequacy of the PCU metric in describing motorcycle-dependent traffic landscapes. Motorcycles, due to their smaller size and greater maneuverability, require less road space and can navigate traffic more freely than larger vehicles, making the MEU a more appropriate standard for assessing their impact in cities reliant on motorcycles. The MEU acknowledges motorcycles' distinctive behaviors compared to other vehicle types and underscores the need to adapt traffic measurement tools in such systems. Therefore, regions with a significant prevalence of motorcycles should consider adopting the MEU to improve the accuracy of traffic performance evaluation. Another novelty of this dissertation lies in its progress in adapting the MFD to mixed motorcycle traffic, providing a close representation of such systems, and proposing a shift from traditional density measures to area occupancy. This approach fills a critical gap and enhances the analytical tools available for traffic studies. Moreover, alongside the development of an MFD tailored for mixed motorcycle traffic, this study also marks a seminal contribution to establishing the MFD framework for traffic patterns in Southeast Asia. The redefined MFD proves effective in highlighting key operational patterns in traffic networks, essential insights for future transportation planning and policymaking in similar contexts.

This research integrates route choice analysis into a traffic simulation model for motorcycle-dependent areas, revealing that network capacity remains limited without targeted interventions but improves significantly with widespread access to traffic information. Scenario analysis shows that immediate improvements on major roads can quickly boost vehicle throughput, while broader information dissemination leads to systemic gains as drivers adjust their behaviors. It is important to note that the success of traffic control schemes depends on driver compliance. The analysis shows that higher compliance rates significantly boost traffic performance, with peak efficiency achieved at full compliance, leading to an 84% increase in network capacity. Partial compliance still yields notable benefits, while full compliance ensures optimal traffic distribution and utilization. A fully informed system is achievable, as the 35.6% compliance rate observed in the SP survey during the route choice analysis phase of this dissertation was reached without existing information systems. With increased awareness and education, compliance could be further boosted, enhancing traffic management and network efficiency. The study also examines the impact of motorcycle behavior on traffic systems, finding that higher capacities are achieved at increased compliance rates when both motorcycles and cars exhibit fluctuating compliance. However, the difference in overall performance improvement between adjusting both vehicle types or only motorcycles is modest, averaging 5.24%. This suggests that effectively managing motorcycle behavior alone can significantly enhance network performance, even without altering car compliance rates. In summary, the strategic integration of advanced traffic systems, focusing on dynamic control and behavioral adjustments, can substantially improve motorcycle-dependent traffic, with accurate, timely traffic reports and strong compliance rates being crucial for efficient traffic management..

6.3 Research Limitations

Some limitations are acknowledged, arising from the assumptions made, the data collected, the methodologies applied, and the analytical approaches employed. Each of them is broken down below.

6.3.1 Chapter 3 – Route Choice Analysis

Initially, in terms of the data collection, the route choice model of motorcycle riders was estimated using behavioral responses exclusively from an SP survey, without integrating RP data. This experiment relied on hypothetical choices from a single O-D pair within a confined area over a short period, which may limit the research scope. The study assumed that all riders possessed uniform baseline knowledge of the road networks, alternate routes, and specific route attributes like distance and free-flow travel time. However, this assumption might not fully represent the diversity in their familiarity with road topologies or traffic conditions, which can vary due to individual knowledge and driving experiences.

Regarding the stated choices provided, the adoption of the VMS pictogram in the hypothetical scenarios used to gather route choice behavior was directly influenced by prior research. This approach was selected despite the possibility of varied preferences among road users in Indonesia toward different forms of VMS content. This could lead to an oversight in accounting for the diversity in how these messages are perceived and interpreted across various user groups. Furthermore, the study did not consider the varying levels of exposure and awareness among motorcycle riders to the VMS messages. Expanding the model to include more attributes related to VMS interaction could deepen understanding of riders' tendencies to divert routes. Additionally, the study overlooked the reliability of real-time traffic information and did not account for the heterogeneity in the degree of trust and risk acceptance of riders about VMS messages, which may influence their decision-making processes in actual conditions.

6.3.2 Chapter 4 – Traffic Microscopic Simulation Model

In terms of the secondary data employed, sourced from traffic counts and activity diary surveys, presents certain limitations in scope and comprehensiveness. The activity diary data encompasses a seven-day period and captures 1.08% of the population. While this sample size is relatively robust for developing regions where automatic data recording tools may be scarce, it nonetheless provides only a snapshot and may not fully encapsulate the wider variations and behaviors observed over extended periods. The approach to handling this data simplifies the complexity of actual travel behaviors by treating each recorded trip as distinct, potentially missing nuanced travel patterns, especially in dense areas where short, multiple trips are common. This simplification may lead to an incomplete understanding of activity-based travel, where trips are often interconnected by common purposes or part of a multi-stop journey, affecting the accuracy of traffic volume and congestion analysis. On the other hand, the traffic count surveys were conducted over three days at 12 major intersections, potentially overlooking variations in traffic patterns that occur outside these specific times and locations. The need to interpolate data and make assumptions to create O-D matrices for micro-simulation analysis and evaluations can introduce additional uncertainties and potential inaccuracies in modeling traffic dynamics.

In developing the microscopic simulation model, several assumptions were necessary due to limitations in available data and network configurations. The research focused on Cần Thơ City, a location not covered by Google Street View—a platform typically used to fill gaps in network data by providing detailed geometries and land-use patterns to complement OSM data. The absence of this resource made it difficult to obtain comprehensive data, which is crucial for ensuring the accuracy and validity of the model. Gathering extensive data on road width, road length, number of lanes, and traffic signal specifics for the entire network proved challenging. Furthermore, the traffic signal settings in the simulation were based on direct observations from a single time period, assuming uniform signal timing across different days and times, which omits potential variations and may impact the realism.

In terms of the calibration of parameters and the testing of scenarios, the micro-simulation model's setup for detailed driving behaviors—specifically reaction times, lane changing, car following, and gap acceptance—primarily utilized established results from previous studies. However, another oversight in the analysis is the exclusion of the lateral movement behavior of motorcycles, a critical aspect of traffic flow and safety analysis in regions where motorcycles are prevalent. Such behaviors, which include lane changes and maneuvering around obstacles, are essential for accurately modeling traffic interactions and congestion in motorcycle-dependent environments. Omitting these dynamics can lead to an incomplete representation of actual traffic conditions, potentially affecting the effectiveness of congestion analysis and traffic management strategies. This reliance may limit the model's capacity to adapt to locale-specific driving patterns that are distinct from those documented in prior studies, although the parameters adopted were chosen to closely align with the specific characteristics of the current study case, which is motorcycle-dependent areas. Lastly, the model does not incorporate scenarios involving traffic incidents, roadworks, or non-recurring congestion. These situations may impact network performance differently, as they significantly influence traffic behavior and require tailored management strategies. This omission highlights a gap in the model's ability to comprehensively analyze and address diverse traffic situations effectively.

In addition, the model concentrates exclusively on trips made by cars and motorcycles, omitting other transportation modes such as bus, cycling, or walking. This limitation could potentially skew the understanding of overall traffic interactions between modes. Additionally, by excluding pedestrian movements and non-motorized vehicles, the model may neglect critical aspects of mixed traffic mobility. This is particularly relevant in motorcycle-dependent cities, especially in developing countries, where jaywalking is commonplace, highlighting a gap in simulating the complete traffic ecosystem.

6.3.3 Chapter 5 – Evaluation of Traffic Control Strategies

This dissertation employs the MFD to evaluate traffic performance in Ninh Kiều District, drawing from traffic data captured over a single day. While this methodology yields valuable insights, its narrow temporal scope limits the comprehensiveness of the findings. The dataset's constraints—limited temporal range and a lack of diverse traffic conditions—hinder the depth and breadth of the analysis. Additionally, the study faces limitations in its methodological approach; it uses administrative boundaries to segment traffic within a specific district of Cần Thơ City, rather than employing network partitioning based on homogeneous traffic characteristics. Adopting a partitioning strategy that divides the larger, heterogeneous network into smaller, more homogeneous regions could reveal more detailed key traffic properties and effectively manage flow heterogeneity, thus establishing a well-defined MFD.

The focus on a specific network within Ninh Kiều District provides useful data on macroscopic traffic dynamics of mixed traffic, particularly where non-lane-based vehicles dominate, through the use of MEU metrics and area occupancy. However, the applicability of these findings to areas with different traffic behaviors and infrastructural configurations may be constrained, potentially not capturing the heterogeneity and complexity of motorcycle traffic patterns beyond the studied area. Despite its significant contributions, the generalizability of these conclusions to other contexts is limited. The relevance of the findings requires careful consideration and adaptation for application in different geographical and traffic contexts, highlighting the need for broader data collection and analysis to enhance the universality and utility of the research outcomes.

6.4 Future Work

Given the limitations identified in the dissertation, a number of worthwhile directions for future research are recommended for further exploration in this field.

6.4.1 Chapter 3 – Route Choice Analysis

In terms of data collection, efforts should focus on refining SP surveys to better represent diverse traffic behaviors by developing hypothetical network structures and offering a variety of stated choices that reflect a broad range of road characteristics. Such enhancements may improve the heterogeneity of the data, thereby capturing motorcycle riders' route preferences more thoroughly. Combining SP and RP data could be one of the solutions, enhancing predictions of route preferences by integrating crucial variables like past experiences and familiarity with road networks. Additionally, expanding the sample size would allow for a more comprehensive representation of perceived utility. Observing the day-to-day dynamics of routing decision-making is equally important, as it enables the collection of varied route patterns through panel data and helps capture individuals' unique urgencies and characteristics.

In terms of methodology, it is essential to broaden the scope to include a wide array of variables that influence both traffic performance and driver perspectives. This expansion should cover aspects such as the occurrences of traffic incidents or roadworks, the economic impacts of time and congestion, and driver-specific factors like habits, familiarity, learning effects, and the awareness and reliability of VMS information. Integrating variables, such as departure times, work schedule flexibility, and lateness tolerance, will further enrich the comprehension of individual travel behaviors. Such an approach allows for a deeper analysis of the factors influencing route choice, including investigating the thresholds at which motorcycle riders opt to switch routes. Future studies should also focus on how interactions between motorcycles and automobiles in mixed traffic settings impact routing decisions and explore the distinct spatial networks in developing countries characterized by diverse road types and conditions.

In terms of analytical tools, exploring various formats of VMS could determine the most effective displays for road users in specific regions. Adding cost-related variables associated with vehicle operation or delays could enhance the analysis of economic factors influencing travel decisions and aid in formulating traffic management strategies. In addition, extending the study on motorcycle route choice behavior to investigate the thresholds of attributes that influence riders to switch routes can provide valuable insights. Understanding the specific thresholds that motivate changes in route choices among motorcycle riders can enrich the practical implementation of traffic management solutions. In terms of expanding the research's applicability and validity, this research could be extended to other motorcycle-dense countries in Southeast Asia, such as Thailand, Malaysia, and Taiwan. Investigating how the high proportion of motorcycles impacts network performance and congestion levels in mixed traffic could provide a broader understanding of the dynamics in motorcycle-dependent cities.

6.4.2 Chapter 4 – Traffic Microscopic Simulation Model

The behavior of road users forms a fundamental element of any microscopic simulation model, yet drivers' behavior varies significantly depending on driving conditions and geographical contexts. Future studies should, therefore, aim to diversify the types of data collected, capturing not just traffic demand but also detailed driving behaviors, allowing for a more precise alignment of behavioral parameters with local traffic characteristics. Accordingly, expanding data collection methods is essential; incorporating more comprehensive activity-diary surveys that cover a larger portion of the population and span longer observation periods would be beneficial. In addition, extending traffic count surveys beyond their current scope to include a wider range of intersections and days—encompassing special event days and different seasons—will provide a more thorough understanding of traffic patterns. Videotaping traffic, moreover, may offer essential insights, capturing vehicle trajectories and enabling a detailed analysis of behaviors such as car following, lane changing, and gap acceptance. It is also important for future research to integrate the lateral movement behaviors of motorcycles into simulation models. This is particularly vital in regions with a high prevalence of motorcycles, as accurate modeling of these behaviors is essential for understanding their impact on traffic flow and safety dynamics. These enhancements in data collection and analysis are vital for refining simulation models and improving their accuracy and relevance in depicting real-world traffic dynamics.

Enhanced methodological approaches are also necessary, such as developing methods to account for multi-trip journeys within activity-diary data, which could provide a clearer picture of actual trip chains and their impact on network congestion. Recognizing that individuals may engage in multiple connected trips throughout a single day is crucial for understanding the complexity of travel behaviors and their consequent effects on traffic systems. Additionally, an inclusive approach that incorporates all modes of transportation, such as buses, trucks, and pedestrian movements, can significantly enhance the comprehensiveness of the analysis. The latter is particularly crucial in this context, where jaywalking is prevalent. This method aims to capture the complete range of interactions among different traffic components within mixed traffic environments. By exploring the varied movements of people and vehicles in mixed traffic scenarios, researchers can gain a deeper understanding of traffic flow patterns, identify potential bottlenecks, and develop targeted strategies to improve safety and efficiency throughout the network. Such an approach not only aids in the accurate modeling of current traffic conditions but also enhances the ability to predict and mitigate potential traffic issues.

6.4.3 Chapter 5 – Evaluation of Traffic Control Strategies

This dissertation evaluates network performance in mixed traffic settings under high motorcycle usage, and assesses the effectiveness of proposed control measures using the MFD. The MFD provides a valuable framework for understanding the relationship between traffic flow and concentration on a network-wide level. Building upon the findings, there is considerable scope for research in the future to enhance its applicability, particularly in the context of regions heavily dependent on motorcycle traffic.

One critical area for further work is the heterogeneity in traffic composition. Although this dissertation has successfully applied and modified the MFD for mixed traffic of cars and motorcycles, it remains important to explore the impacts of a more diverse array of vehicle types, such as buses, trucks, and bicycles—though they may represent a smaller portion compared to motorcycles in such settings—on the MFD. Since these vehicles exhibit varying operational characteristics, their differing effects on traffic flow and congestion could modify the dynamics typically represented by a standard MFD. Understanding these variations can enable a more detailed evaluation of the overall traffic system.

Another promising direction for future research is the examination of spatial variability of MFDs. The assumption that a single MFD can closely represent an entire area often falls short due to spatial variations in infrastructure and traffic patterns. To address this, there is a need to develop localized MFDs that mirror the specific characteristics of different sectors. Implementing network partitioning based on the distinct traffic characteristics of each area is essential, as a well-defined MFD can only be developed within a homogeneous network. This process could involve dividing a region into multiple areas, each equipped with its own MFD, to provide a more accurate tool for traffic management and planning. Such an approach would not only enhance the granularity of traffic analyses but also improve the effectiveness of interventions aimed at alleviating congestion across varied urban landscapes.

Moreover, there is considerable potential to apply these findings to real-world situations, particularly in Vietnam, which serves as the case study for this dissertation. Should the opportunity arise, implementing the results from this study into actual traffic management strategies is expected to significantly benefit urban areas facing similar challenges. Collaborating with local governments or transportation authorities to test the proposed MFD-based control measures in a live setting could validate the model's effectiveness and lead to practical solutions for enhancing traffic system performance and reducing congestion in motorcycle-dominated environments. Such an application could act as a pilot project, providing valuable insights and lessons that could be replicated in other cities or regions experiencing comparable traffic conditions. In summary, future studies could extend to different regions, cities, or countries with high motorcycle usage, employing larger sample sizes to assess the validity and transferability of these findings across diverse contexts.

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Appendix-A

Activity Diary Survey Data

Motorcycle origin-destination movement patterns on Monday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0	5	0	0	3	0	2	2	0	0	1	0	0	0	0
12	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0
13	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	4	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0
21	2	2	0	0	0	0	0	23	22	1	3	4	2	6	17	0	4	0	2	6	6	10	0	7	14	3	8	6	11	20	1	2	0	2	5
22	0	0	0	0	0	0	0	24	0	0	0	3	0	0	6	0	0	0	0	0	3	10	0	1	2	0	1	1	0	2	0	0	0	0	0
31	0	0	0	0	0	0	0	1	0	0	0	9	0	0	1	2	0	0	0	0	3	3	0	3	4	1	1	0	4	1	0	0	0	0	0
32	0	0	0	0	0	0	0	2	0	0	2	15	1	0	2	0	0	0	0	0	0	3	0	14	10	0	0	1	0	6	4	0	0	0	0
33	0	0	0	0	0	0	0	4	3	9	13	19	12	4	12	6	1	4	5	1	2	2	2	15	2	2	2	4	5	6	8	4	3	5	4
34	0	0	0	0	0	0	0	2	0	0	0	12	0	0	0	0	0	0	0	0	0	2	1	1	0	0	0	5	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	6	0	2	1	3	0	1	4	0	1	6	0	0	0	2	0	2	3	0	2	6	0	0	0	0	0	0	1
41	0	0	0	0	0	0	0	17	3	1	4	10	0	3	26	1	1	0	0	2	3	17	1	4	7	0	1	9	5	11	1	1	2	5	7
51	0	0	0	0	0	0	0	0	0	0	0	6	0	2	1	0	0	28	1	0	4	6	0	4	2	1	0	1	0	0	0	0	0	1	0
52	0	0	0	0	0	0	0	2	0	0	0	1	0	1	1	0	4	4	1	0	3	5	0	2	0	0	2	1	0	1	0	0	0	0	0
53	2	0	0	0	0	0	0	0	0	0	0	4	0	6	0	28	4	18	8	6	1	2	0	1	8	1	3	4	1	21	0	2	4	1	1
54	0	0	0	0	0	0	0	2	0	0	0	4	0	1	0	1	1	8	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	1	0
61	0	0	0	0	0	0	0	6	0	0	0	1	0	0	2	0	0	6	0	0	6	9	0	1	0	0	3	1	0	0	0	0	0	1	0
71	0	0	0	0	0	0	0	8	3	2	1	2	0	0	3	2	3	1	1	6	49	12	1	0	5	0	0	6	0	5	1	0	0	8	0
81	5	0	0	0	0	1	0	10	9	4	2	2	4	2	18	7	5	2	1	10	10	142	4	10	13	12	18	10	19	32	6	0	5	9	29
91	0	0	1	0	0	0	0	1	0	1	1	2	1	0	1	0	0	1	0	0	1	4	0	5	2	0	2	0	0	0	0	2	0	1	0
92	0	0	0	0	1	0	0	8	2	3	14	16	2	1	5	4	2	1	1	1	0	11	6	13	20	2	2	2	3	2	2	1	2	1	2
93	3	2	1	0	0	0	0	15	6	4	8	3	0	3	8	2	0	9	0	0	6	13	2	20	10	4	7	5	2	4	2	7	1	4	1
101	0	0	0	0	0	0	0	3	0	1	0	2	0	0	0	1	0	1	0	0	0	12	0	2	5	0	4	3	0	1	0	0	0	2	0
102	2	1	4	0	0	0	2	8	0	0	0	2	0	2	1	0	2	3	0	2	0	18	2	2	8	4	0	2	3	3	0	0	6	3	11
103	3	0	1	0	1	0	0	6	2	0	1	5	3	5	9	2	1	4	2	0	7	12	0	2	4	5	4	13	2	1	2	3	2	5	3
111	0	0	0	0	0	0	0	10	0	4	0	4	0	0	4	0	0	1	0	0	0	19	0	3	2	0	3	2	0	6	0	0	1	0	0
112	0	0	0	0	0	0	0	20	1	0	6	5	0	2	9	0	1	21	0	0	5	32	0	2	5	2	4	1	5	23	4	0	5	9	1
121	0	0	0	0	0	0	0	0	0	0	4	7	0	0	1	0	0	0	0	0	2	6	0	2	4	0	0	2	0	3	7	0	0	1	0
122	0	0	0	0	0	0	0	2	0	0	0	5	0	0	0	0	1	2	0	0	0	0	2	2	9	0	1	2	0	0	0	0	0	2	0
131	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	0	0	4	0	0	0	4	1	2	1	0	6	2	0	5	0	0	1	3	1
132	1	0	0	0	0	0	0	1	1	1	0	6	0	1	4	0	0	0	0	1	7	8	3	2	5	0	1	10	0	9	0	1	1	5	0
133	0	0	0	0	0	0	0	5	0	1	0	4	0	0	6	0	0	1	0	0	0	30	0	3	1	0	10	3	1	1	0	0	0	0	0

Car origin-destination movement patterns on Monday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0

Motorcycle origin-destination movement patterns on Tuesday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	8	0	0	1	1	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	1	1	0	3	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	1	0	1	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	3	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	3	0	0	2	0	0	0	0	0
17	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	1	0	0	0	5	0	0	1	1	1	0	0	0	5	8	0	1	0	0	6	0	0	0	0	0
22	0	0	0	0	0	0	0	0	1	4	0	0	0	0	2	0	1	0	0	0	0	0	0	0	2	0	0	1	1	0	0	0	0	0	0
31	0	0	0	0	2	0	1	1	2	3	16	2	6	27	4	4	0	1	1	6	8	9	0	0	10	6	1	6	5	8	3	2	0	12	7
32	0	0	0	0	0	0	0	0	0	12	1	0	1	1	1	3	3	0	0	2	0	1	0	5	2	0	0	0	0	1	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	1	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	8	0	0	0	0	4	0	1	0	2	0	0	1	0	2	1	1	0	3	0	0	0	0	0	0	0
35	0	0	0	0	1	0	1	0	0	21	0	0	4	2	0	0	2	0	0	0	1	0	0	0	1	1	2	4	0	1	0	0	1	2	0
41	0	0	0	0	0	0	0	4	3	5	0	0	3	0	28	0	0	0	0	4	1	2	0	11	9	1	3	9	2	9	4	1	1	2	3
51	0	0	0	0	0	0	0	0	0	6	0	0	0	0	1	2	8	2	2	0	0	1	0	1	0	0	0	1	0	0	0	0	0	1	1
52	0	0	2	0	0	3	0	0	1	0	3	0	1	2	0	12	18	1	4	2	0	1	0	0	2	1	5	1	0	6	0	0	0	3	0
53	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	2	4	0	0	0	0	0	1	1
54	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	6	0	0	0	1	0	0	2	0	0	1	0	0	0	0	0	0	0	0
61	1	0	0	0	0	0	0	1	0	5	0	0	0	1	3	0	2	0	0	0	0	1	0	0	3	0	5	3	0	2	0	1	0	1	1
71	0	0	0	0	0	0	0	0	0	10	0	0	0	1	1	0	0	0	2	1	2	0	0	1	0	0	0	5	1	2	7	0	0	2	0
81	0	0	0	0	0	0	0	0	1	3	0	0	1	1	2	0	2	0	0	0	2	2	0	0	2	1	1	1	1	0	1	0	0	2	1
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
92	0	0	0	0	1	0	0	5	0	0	6	4	2	0	8	1	0	0	1	0	1	0	0	12	13	4	0	1	0	0	2	0	3	0	0
93	0	0	0	0	0	0	0	9	1	14	3	0	0	0	9	0	2	0	0	2	0	1	0	9	51	1	4	3	0	9	3	0	1	4	0
101	1	0	0	0	0	0	1	0	0	5	0	0	0	0	1	0	1	0	0	0	0	0	0	4	0	1	2	7	1	4	0	0	0	1	0
102	1	4	1	0	3	2	2	0	0	1	2	0	0	3	3	0	5	3	1	4	0	2	0	1	1	3	3	12	1	9	0	0	7	9	7
103	0	0	2	0	0	0	0	0	2	7	0	1	3	6	9	2	1	2	0	2	5	1	0	1	2	6	13	8	0	5	2	0	2	12	1
111	0	0	0	0	0	0	0	0	1	4	0	0	0	0	2	0	0	0	0	0	0	2	0	0	2	0	2	1	1	12	0	0	0	0	0
112	8	0	3	0	2	2	0	8	0	7	1	0	0	1	11	0	6	0	0	3	3	0	0	0	10	2	9	5	12	14	0	0	2	3	6
121	0	0	0	0	0	0	0	0	0	4	0	0	1	0	4	0	0	0	0	0	8	1	0	3	1	0	0	2	0	0	5	1	0	0	0
122	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0
131	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	3	1	0	5	1	0	3	0	0	1	0	2
132	1	1	0	0	0	0	0	0	0	15	0	0	0	1	1	0	3	1	0	1	2	1	0	0	4	0	7	14	1	4	0	0	0	2	0
133	0	0	0	0	1	0	0	0	0	7	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	7	3	0	7	0	0	0	0	0

Car origin-destination movement patterns on Tuesday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	2	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
132	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Motorcycle origin-destination movement patterns on Wednesday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	9	16	10	1	0	1	1	0	1	0	0	1	1	0	0	4	3	0	12	2	1	0	0	0	4	7	6	0	0	1	0	1	2	2
12	10	0	5	2	0	0	0	1	0	0	1	0	1	2	0	1	0	3	0	1	3	4	0	2	1	4	3	5	3	1	2	1	0	1	0
13	15	5	7	6	15	1	4	0	0	2	3	0	2	1	0	3	0	4	1	0	0	0	0	0	1	1	4	1	1	0	0	0	1	1	0
14	8	2	6	17	2	1	2	0	0	0	0	0	0	0	0	0	0	2	1	1	0	0	0	0	0	4	7	1	0	1	0	0	0	0	2
15	1	0	18	2	0	0	0	0	0	2	2	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
16	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	2	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0
21	1	2	0	0	0	0	0	1	0	4	8	0	22	0	3	0	0	0	1	2	1	1	0	2	3	0	0	1	0	1	0	0	0	1	0
22	0	0	0	0	0	0	0	0	1	1	0	0	12	0	2	0	0	0	0	7	7	0	0	0	3	0	1	0	1	0	1	0	0	0	1
31	0	0	1	0	2	0	0	3	0	10	9	3	17	12	6	2	3	4	9	8	1	5	0	5	6	2	1	1	8	4	1	4	0	10	5
32	0	1	1	0	2	0	0	8	0	12	50	4	19	2	2	4	0	2	0	1	0	0	0	2	21	0	4	2	5	2	5	2	6	0	0
33	0	0	0	0	0	0	0	0	0	2	4	0	5	1	1	0	0	0	0	5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
34	2	0	2	0	0	0	0	22	11	18	19	5	6	30	8	4	2	2	3	2	4	0	0	1	15	10	0	8	5	13	9	12	1	4	8
35	1	2	0	0	0	0	0	0	0	17	3	0	29	3	2	2	0	0	0	3	3	0	0	0	0	0	1	0	0	1	0	0	0	0	0
41	0	0	0	0	0	0	0	2	3	4	3	1	8	2	34	1	0	9	0	18	3	2	0	5	13	0	3	10	6	6	2	4	0	6	3
51	0	0	3	0	1	0	0	0	0	2	4	0	4	2	1	7	0	3	3	0	0	0	0	0	2	0	4	1	0	1	0	0	0	0	0
52	2	1	0	0	2	0	1	0	0	0	0	0	2	0	0	1	0	1	0	0	0	1	0	2	1	0	3	0	0	0	0	0	0	0	0
53	4	2	3	2	0	0	0	0	0	4	2	0	2	0	9	2	1	0	1	2	0	0	0	0	0	3	2	0	0	0	2	0	0	0	0
54	0	0	1	1	0	0	0	0	0	9	0	0	4	0	0	3	0	0	0	2	1	0	0	0	0	0	2	2	0	0	1	0	1	0	0
61	12	1	0	1	1	2	0	4	7	8	1	5	3	3	17	0	0	2	2	83	3	6	4	4	8	2	7	3	18	39	2	3	10	1	4
71	2	2	0	0	0	0	0	1	9	1	0	1	4	3	3	0	0	0	1	3	10	3	1	2	0	0	2	3	1	2	2	0	0	0	0
81	1	2	0	0	0	0	0	0	0	7	0	0	1	0	2	0	0	0	0	7	3	0	0	4	1	0	2	1	0	1	1	1	0	3	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	0	1	2	0	0	2	1	0	0	0	0	0	0	0
92	0	2	0	0	0	1	0	2	0	6	2	0	1	0	5	0	2	0	0	4	3	3	2	6	4	1	2	0	0	0	0	0	3	0	0
93	0	2	0	0	0	0	1	3	4	4	19	0	17	0	12	0	1	0	0	8	0	1	0	5	7	0	1	2	1	1	5	1	0	8	0
101	6	5	1	2	0	0	0	0	0	1	0	0	10	0	0	0	0	2	0	2	0	0	0	0	0	0	2	7	0	0	0	0	0	2	1
102	7	3	5	7	1	0	1	1	1	1	4	0	0	0	3	4	3	1	2	7	4	3	2	2	0	1	5	7	0	3	0	0	4	3	6
103	6	7	1	1	0	0	0	1	0	1	2	0	8	1	10	1	0	0	2	3	2	1	1	0	4	8	4	0	2	3	2	2	2	1	2
111	1	3	1	0	0	0	0	0	0	5	5	0	6	0	6	0	0	0	0	18	1	0	0	1	0	0	1	4	1	3	0	0	0	0	0
112	0	0	0	1	0	0	0	1	0	7	2	0	11	1	7	1	0	0	0	39	1	0	0	0	1	0	8	2	2	2	2	0	1	3	0
121	1	1	0	0	0	0	0	1	0	1	6	0	9	0	2	0	0	2	1	1	3	1	0	0	5	0	0	3	0	2	11	4	0	0	2
122	0	2	0	0	0	0	0	0	0	3	1	0	12	2	4	0	0	0	0	3	0	0	0	0	0	0	0	2	0	1	5	0	0	0	0
131	1	0	1	0	0	0	0	1	0	0	7	0	0	1	0	0	0	0	1	8	0	1	0	4	0	0	4	1	0	0	1	0	0	0	0
132	3	3	1	0	0	0	0	2	0	11	0	0	3	1	6	0	0	0	0	2	0	2	0	0	6	3	3	3	0	1	0	0	0	1	1
133	2	0	0	2	1	0	0	0	0	1	0	0	8	0	3	0	0	0	0	4	0	1	0	0	1	0	5	2	0	1	2	0	0	2	0

Car origin-destination movement patterns on Wednesday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	2	0	0	1	0	0
52	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
132	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Motorcycle origin-destination movement patterns on Thursday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	0	0	1	0	0	0	2	4	0	0	1	0	0	2	0	7	0	2	0	0	0	0	2	7	0	2	0	0	1	0	3	0
12	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	1	0	0	1	1	0	1	0	2	1	0
13	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	1	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	2
16	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
21	0	0	0	0	0	0	0	2	17	7	10	0	0	0	0	0	0	0	0	0	1	0	0	7	0	0	0	0	0	0	0	0	2	11	2
22	0	0	0	0	0	0	2	18	40	1	0	1	1	0	10	3	0	0	0	1	4	3	0	0	9	0	1	1	3	6	2	0	0	9	3
31	2	0	0	0	1	0	2	5	2	4	2	2	3	31	0	3	3	1	0	2	0	7	0	0	9	9	0	4	10	11	2	0	2	8	11
32	4	0	0	0	0	0	2	10	1	4	33	4	0	2	0	4	11	3	0	1	4	0	0	3	18	0	4	0	5	0	8	0	1	2	6
33	0	0	0	0	0	0	0	0	1	2	4	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	2	0
34	0	0	0	0	0	0	0	0	1	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
35	2	0	0	0	0	0	0	0	0	27	4	0	0	6	1	1	0	0	10	0	1	0	0	2	0	0	1	0	0	1	1	1	2	7	2
41	0	0	1	0	0	0	0	0	9	1	0	0	0	3	8	0	0	1	4	1	0	0	0	6	2	0	0	4	0	0	5	2	0	5	4
51	0	0	0	0	0	0	0	0	4	5	4	0	0	0	0	2	0	1	19	1	1	0	0	0	0	0	0	4	0	0	0	0	0	1	0
52	2	0	0	0	0	0	0	0	0	3	11	0	0	0	0	0	1	0	4	0	0	0	0	1	0	0	2	4	0	0	0	0	0	4	0
53	0	0	0	0	0	0	0	0	0	1	3	0	1	0	1	2	0	0	7	0	0	0	0	0	0	1	5	8	0	0	6	1	1	4	0
54	7	1	0	0	0	0	0	0	0	0	0	1	0	11	4	19	4	8	34	0	5	1	0	2	3	1	2	1	2	12	0	0	0	0	10
61	0	0	1	0	0	0	0	0	2	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	7	1	0	0	0	0	0	12	1
71	2	0	0	0	0	0	0	0	4	1	4	0	0	0	0	0	0	0	6	1	0	0	0	0	0	1	1	0	0	0	4	12	1	10	2
81	0	0	0	0	0	0	0	1	2	3	1	0	0	2	1	0	0	1	2	0	0	0	0	2	0	0	0	0	0	3	0	3	1	23	1
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
92	0	2	0	0	0	0	0	7	0	0	3	2	0	2	6	0	1	0	2	0	0	2	0	0	3	3	0	1	0	0	0	4	1	4	1
93	0	1	0	0	0	0	0	0	7	9	18	0	0	0	6	0	0	0	3	0	0	0	0	3	1	1	0	2	0	0	1	4	0	6	0
101	2	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	1	0	1	0	0	4	0	0	5	0	0	0	0	0	1	3	1
102	6	0	2	1	0	2	0	0	1	0	3	0	0	2	0	0	2	5	2	7	0	0	0	0	0	5	2	3	0	1	1	2	2	17	4
103	0	1	0	0	0	0	0	0	1	2	0	0	0	0	4	4	4	8	1	1	0	0	0	1	2	1	3	8	3	1	0	1	5	4	4
111	2	0	0	0	0	0	0	0	2	11	5	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	3	0	0	4	2	4	10	0
112	0	0	0	0	0	0	0	0	6	13	0	0	0	1	0	0	0	0	13	0	0	0	0	0	0	0	1	1	0	0	1	4	0	8	3
121	0	1	0	0	0	0	0	1	1	3	7	0	0	0	3	0	0	6	0	0	4	0	0	0	5	0	1	0	4	1	0	6	0	0	3
122	1	0	0	0	3	0	0	1	0	0	0	0	1	1	2	0	0	1	0	0	11	3	0	4	2	0	2	1	2	4	8	16	0	2	0
131	0	2	1	0	0	0	0	2	0	2	1	0	0	2	0	0	0	1	0	0	0	0	0	1	1	1	2	5	3	0	0	0	4	30	7
132	4	2	1	1	1	0	0	12	9	8	2	2	1	4	5	1	4	5	0	11	12	27	2	4	7	2	18	4	9	8	0	2	28	47	19
133	0	0	0	0	2	0	1	2	3	11	6	0	1	1	4	0	0	0	11	1	3	1	0	1	0	0	3	3	0	3	3	0	8	20	6

Car origin-destination movement patterns on Thursday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
71	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
102	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	1	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Motorcycle origin-destination movement patterns on Friday

Zone	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	1	3	0	1	1	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	4	0	0	0	0	2	0
12	1	0	2	0	2	4	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	2	2	1	2	0	0	0	1	4	3	0
13	1	2	0	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0	0	0	0	0
14	0	0	0	0	4	5	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	1	3	0	5	0	3	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	2	1	3	2	0	0	0	0	1	0
16	3	4	1	4	3	0	2	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0
17	4	0	4	5	0	2	8	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
21	0	0	1	0	0	0	0	0	0	0	4	0	0	1	0	0	0	0	0	0	1	0	0	4	0	6	1	0	0	28	2	0	2	0	0
22	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	2	0	2	1	0	1	1	2
31	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	0	0	0	2	1	0	5	0	0	1	0	2	0
32	0	2	0	0	0	0	2	4	2	0	21	3	0	1	0	2	4	1	0	0	6	0	0	9	12	1	4	1	5	4	9	0	0	6	1
33	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	1	0	0	3	5	3	0	0	1	0	0	0	1	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	2	0	0	1	0	0	2	1	1
35	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	1	0	2	7	0	0	0	0	1
41	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	7	0	0	7	8	3	2	0	1	5	3	1	0	4	1
51	0	0	0	0	1	1	0	0	0	0	2	0	1	0	1	0	0	0	0	0	2	1	0	1	6	1	0	0	2	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	1	0	0	0	0	0
53	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	10	2	3	3	1	1	0	1	0	0
54	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0	2	0
61	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	4	2	1	0	1	2	1
71	0	0	0	0	0	0	0	1	0	5	7	0	1	0	5	3	0	2	0	0	30	15	3	0	0	5	4	0	4	6	1	0	1	3	2
81	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	13	1	0	0	2	4	1	0	4	1	0	0	1	4	2
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	4	0	0	0	2	0	0	0	0	0	0
92	0	0	0	0	0	0	1	2	2	0	10	3	0	0	7	1	0	1	0	0	0	0	0	16	13	4	4	1	2	0	1	0	4	5	0
93	0	2	0	0	0	0	0	2	0	0	12	5	3	3	8	7	0	0	0	0	0	2	4	8	23	12	1	0	2	6	7	2	1	7	1
101	3	0	0	0	3	2	0	6	2	2	1	2	3	9	4	1	0	10	2	1	6	3	0	4	11	60	29	25	14	1	3	2	8	11	5
102	1	1	1	0	1	2	0	1	0	1	4	0	3	0	2	0	1	2	0	0	3	1	0	4	1	29	0	5	4	2	0	0	3	6	9
103	0	3	0	0	3	0	0	0	2	0	1	0	0	0	0	0	0	3	0	0	1	0	0	1	1	23	3	0	0	2	1	0	1	0	0
111	4	0	0	0	2	0	0	0	0	5	5	1	0	0	1	2	2	3	0	5	4	6	2	2	3	14	5	0	21	11	1	0	4	5	5
112	0	0	3	0	0	0	0	27	2	0	4	0	0	7	5	0	1	1	0	2	8	0	0	0	6	1	2	2	13	24	2	0	6	11	0
121	0	0	0	0	0	0	0	2	1	0	9	0	0	0	3	0	0	1	1	1	1	0	0	1	7	3	0	1	1	2	8	1	1	0	2
122	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	2	0	0	0	0	1	0	2	0	3
131	0	2	0	0	0	0	0	2	1	0	0	1	2	0	0	0	0	1	1	1	1	0	0	4	1	8	4	0	5	6	1	2	1	14	6
132	2	2	0	0	1	0	0	0	1	2	6	0	0	0	4	0	0	0	2	2	3	4	0	5	7	10	6	1	5	12	0	0	14	41	18
133	0	0	0	0	0	0	0	0	2	0	1	0	2	1	1	0	0	0	0	1	2	2	0	0	1	5	9	0	5	0	2	3	4	18	14

Car origin-destination movement patterns on Friday

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
81	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
132	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0

Motorcycle origin-destination movement patterns on Saturday

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
32	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	2	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	1	0	1	0	0	1	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
111	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
131	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	4	4	0
132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	0	1	0	1	0	0	0	4	6	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	2	0	1	1	3

Car origin-destination movement patterns on Saturday

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
81	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
132	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0

Motorcycle origin-destination movement patterns on Sunday

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Car origin-destination movement patterns on Sunday

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix-B

Traffic Count Survey Data: Vehicle Volume

Intersection 01: Nút công viên Lưu Hữu Phước

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	248	34	511	122	487	180	206	34
01:00:00	02:00:00	178	15	375	69	379	146	133	21
02:00:00	03:00:00	170	12	297	40	379	106	132	13
03:00:00	04:00:00	251	14	271	44	452	132	137	10
04:00:00	05:00:00	421	18	368	50	784	135	261	29
05:00:00	06:00:00	598	42	661	66	1232	203	744	70
06:00:00	07:00:00	1073	128	1654	137	3750	307	2473	148
07:00:00	08:00:00	1620	208	3378	273	6982	661	4788	219
08:00:00	09:00:00	2215	250	3725	402	6944	610	3868	282
09:00:00	10:00:00	2318	236	3941	462	5231	611	3269	289
10:00:00	11:00:00	2408	263	4098	445	4360	554	3200	295
11:00:00	12:00:00	2334	214	4144	431	3797	505	3089	264
12:00:00	13:00:00	1357	187	2128	306	2809	465	2374	215
13:00:00	14:00:00	1527	205	2402	301	4402	568	3596	264
14:00:00	15:00:00	1837	217	2890	373	4232	521	3031	264
15:00:00	16:00:00	2123	252	3228	408	4053	562	3171	291
16:00:00	17:00:00	2383	250	4301	459	5164	549	3966	270
17:00:00	18:00:00	3094	255	5230	452	5854	613	4438	262
18:00:00	19:00:00	2134	211	4414	367	5622	608	3767	238
19:00:00	20:00:00	1887	203	4155	377	5396	562	3621	217
20:00:00	21:00:00	1604	198	3911	361	4186	448	3021	208
21:00:00	22:00:00	1330	174	3672	389	2761	497	2161	169
22:00:00	23:00:00	956	101	2148	178	1604	442	1042	69
23:00:00	00:00:00	572	74	849	97	810	336	464	51
Total		34638	3761	62751	6609	81670	10321	56952	4192

Intersection 02: 30 Tháng 4 - Nguyễn Văn Linh

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	108	26	241	76	177	29	627	12
01:00:00	02:00:00	147	23	168	57	177	18	626	21
02:00:00	03:00:00	162	26	203	58	269	22	690	34
03:00:00	04:00:00	314	61	303	53	547	48	829	31
04:00:00	05:00:00	590	95	638	62	1094	82	1199	53
05:00:00	06:00:00	1302	150	1112	99	2201	167	1776	83
06:00:00	07:00:00	2472	209	2203	190	4172	259	2359	147
07:00:00	08:00:00	3211	298	3778	324	5361	320	2367	224
08:00:00	09:00:00	2573	293	3716	335	4370	376	2500	230
09:00:00	10:00:00	2223	270	3076	323	3787	254	2415	192
10:00:00	11:00:00	1832	237	2821	280	3142	222	2386	227
11:00:00	12:00:00	1812	196	2646	257	3021	198	2275	252
12:00:00	13:00:00	1673	153	2636	246	2833	149	2316	227
13:00:00	14:00:00	1933	163	3039	242	3239	154	2134	197
14:00:00	15:00:00	1788	176	2912	227	3049	169	2235	227
15:00:00	16:00:00	2120	210	2824	215	3540	167	2462	202
16:00:00	17:00:00	2926	245	3735	234	5108	222	2299	234
17:00:00	18:00:00	3182	233	3954	226	5704	235	3182	258
18:00:00	19:00:00	2522	315	3567	203	5126	229	3375	261
19:00:00	20:00:00	1972	249	3950	241	3732	171	3187	194
20:00:00	21:00:00	1552	175	2740	207	2503	144	2224	177
21:00:00	22:00:00	1094	97	2167	133	1259	77	1667	108
22:00:00	23:00:00	480	71	618	96	672	49	660	73
23:00:00	00:00:00	241	40	314	80	331	38	394	39
Total		38229	4011	53361	4464	65414	3799	46184	3703

Intersection 03: Ba Tháng Hai - Nguyễn Văn Linh

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	233	71	138	37	489	10	306	85
01:00:00	02:00:00	186	44	116	27	490	20	329	54
02:00:00	03:00:00	105	34	115	12	475	10	269	60
03:00:00	04:00:00	209	40	161	26	431	30	362	46
04:00:00	05:00:00	330	66	325	42	503	27	492	70
05:00:00	06:00:00	448	112	750	75	766	38	1127	86
06:00:00	07:00:00	992	119	1302	74	1674	45	1926	148
07:00:00	08:00:00	1896	191	2326	134	2865	194	3122	308
08:00:00	09:00:00	2276	362	2728	204	3068	197	3571	394
09:00:00	10:00:00	2058	225	2665	210	3137	232	3312	436
10:00:00	11:00:00	1857	187	3220	189	3526	239	3122	378
11:00:00	12:00:00	1590	133	2610	188	3965	259	2799	307
12:00:00	13:00:00	1288	170	1553	182	2520	170	2560	263
13:00:00	14:00:00	1478	171	1620	157	2633	189	2639	326
14:00:00	15:00:00	1603	170	2069	186	2786	215	3414	302
15:00:00	16:00:00	1789	227	2515	210	3036	283	4085	320
16:00:00	17:00:00	1885	211	2972	211	3482	213	3480	290
17:00:00	18:00:00	2784	293	3936	215	5956	245	3208	365
18:00:00	19:00:00	2820	255	4385	221	4055	195	3362	346
19:00:00	20:00:00	2606	228	4046	208	3754	184	3220	299
20:00:00	21:00:00	2170	210	3196	155	3060	171	3078	238
21:00:00	22:00:00	1581	168	1198	89	2863	159	2246	239
22:00:00	23:00:00	1025	103	569	47	2584	94	1807	250
23:00:00	00:00:00	452	57	494	24	804	49	552	137
Total		33661	3847	45009	3123	58922	3468	54388	5747

Intersection 04: 30 Tháng 4 - Nguyễn Văn Linh

Time period		Traffic volume (veh)					
From	To	East		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	203	25	147	13	187	27
01:00:00	02:00:00	147	14	79	3	136	6
02:00:00	03:00:00	113	12	81	5	170	14
03:00:00	04:00:00	133	23	126	10	250	29
04:00:00	05:00:00	281	33	234	15	661	44
05:00:00	06:00:00	668	103	438	41	1399	84
06:00:00	07:00:00	1939	103	1284	68	4915	227
07:00:00	08:00:00	2696	157	1765	108	6045	337
08:00:00	09:00:00	2182	192	1630	116	4305	354
09:00:00	10:00:00	2152	223	1622	120	3691	323
10:00:00	11:00:00	2007	199	1582	135	3098	295
11:00:00	12:00:00	1887	206	1574	127	3431	269
12:00:00	13:00:00	1501	141	1258	87	2717	237
13:00:00	14:00:00	1518	167	1312	99	2859	267.5
14:00:00	15:00:00	1521	173	1355	93	2992	279
15:00:00	16:00:00	2025	207	1601	111	3772	283.5
16:00:00	17:00:00	2515	217	1837	115	4567	271
17:00:00	18:00:00	3460	178	2566	124	5004	307
18:00:00	19:00:00	2485	138	1975	56	4481	205
19:00:00	20:00:00	1931	111	1665	92	3765	258
20:00:00	21:00:00	1623	124	1437	74	2240	128
21:00:00	22:00:00	1357	86	1186	67	1374	114
22:00:00	23:00:00	976	47	325	18	1276	58
23:00:00	00:00:00	461	24	180	14	465	15
Total		35781	2903	27259	1711	63800	4432

Intersection 05: CMT8 - Nguyễn Văn Cừ

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	266	49	77	16	98	14	145	22
01:00:00	02:00:00	178	37	61	17	57	12	144	27
02:00:00	03:00:00	146	14	61	16	47	4	115	12
03:00:00	04:00:00	170	17	72	16	70	8	109	10
04:00:00	05:00:00	266	26	193	11	198	12	483	16
05:00:00	06:00:00	680	69	493	42	463	27	1054	29
06:00:00	07:00:00	1911	112	1332	80	1674	69	3154	113
07:00:00	08:00:00	2100	190	1516	61	2113	110	4792	227
08:00:00	09:00:00	2382	275	1618	82	1862	119	3655	212
09:00:00	10:00:00	2521	225	1204	60	1820	137	2980	235
10:00:00	11:00:00	2900	233	1566	51	1666	128	3228	175
11:00:00	12:00:00	3150	198	1463	57	1605	117	2629	153
12:00:00	13:00:00	1664	167	1138	44	1168	115	2155	138
13:00:00	14:00:00	2027	222	1311	52	1425	168	3158	216
14:00:00	15:00:00	2163	287	1206	50	1699	160	2738	188
15:00:00	16:00:00	2604	267	1166	45	1706	191	3149	221
16:00:00	17:00:00	2877	221	1270	49	2156	217	4075	218
17:00:00	18:00:00	4426	293	1624	65	2396	167	3884	244
18:00:00	19:00:00	2954	232	1431	69	1803	239	3318	203
19:00:00	20:00:00	2405	216	1169	73	1459	226	3269	167
20:00:00	21:00:00	2373	207	1089	74	1465	227	2059	184
21:00:00	22:00:00	2120	202	970	39	1342	174	1117	104
22:00:00	23:00:00	673	87	829	34	1207	169	595	79
23:00:00	00:00:00	1115	124	370	21	494	80	244	42
Total		44071	3970	23229	1124	29993	2890	52249	3235

Intersection 06: Nút giao Hùng Vương

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	630	88	412	91	434	93	599	51
01:00:00	02:00:00	463	60	375	56	291	74	433	30
02:00:00	03:00:00	380	69	357	44	237	59	343	23
03:00:00	04:00:00	345	47	379	54	231	55	279	14
04:00:00	05:00:00	396	70	638	79	328	51	262	14
05:00:00	06:00:00	697	80	1287	121	576	84	434	27
06:00:00	07:00:00	1548	189	1941	126	1088	76	829	65
07:00:00	08:00:00	2238	271	4313	336	2504	246	1396	135
08:00:00	09:00:00	2185	276	4101	309	2185	224	1607	193
09:00:00	10:00:00	2922	289	3285	304	2056	245	1856	204
10:00:00	11:00:00	2935	331	3349	294	2010	232	2040	196
11:00:00	12:00:00	2896	275	3203	294	2057	248	1906	204
12:00:00	13:00:00	1972	256	2456	178	1500	210	1156	134
13:00:00	14:00:00	2466	323	3697	271	1893	214	1383	167
14:00:00	15:00:00	2642	296	3045	264	1701	242	1468	183
15:00:00	16:00:00	2886	307	3133	283	1972	231	1660	176
16:00:00	17:00:00	3280	281	3945	334	2280	211	2255	239
17:00:00	18:00:00	3843	280	4156	335	2768	234	2366	178
18:00:00	19:00:00	3518	333	3914	306	2579	210	1986	161
19:00:00	20:00:00	3667	343	3526	260	2216	215	1728	162
20:00:00	21:00:00	3509	316	2570	204	1828	175	1574	153
21:00:00	22:00:00	2424	284	2692	196	1839	214	1368	148
22:00:00	23:00:00	1648	199	1492	146	1266	180	971	146
23:00:00	00:00:00	1150	171	656	115	639	149	723	153
Total		50640	5434	58922	5000	36478	4172	30622	3156

Intersection 07: Mậu Thân - Ba Tháng Hai

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	176	20	494	64	366	49	238	26
01:00:00	02:00:00	114	22	321	45	240	23	134	20
02:00:00	03:00:00	66	10	248	40	171	15	120	12
03:00:00	04:00:00	106	18	208	32	138	21	172	20
04:00:00	05:00:00	197	39	317	39	204	24	316	37
05:00:00	06:00:00	446	49	479	68	543	53	871	83
06:00:00	07:00:00	2036	100	1389	98	1828	78	2964	152
07:00:00	08:00:00	3073	175	2289	131	4628	194	4931	206
08:00:00	09:00:00	2905	180	2604	189	3656	212	3083	145
09:00:00	10:00:00	2522	182	2812	233	3433	276	2713	146
10:00:00	11:00:00	2633	156	3227	228	3432	241	3058	159
11:00:00	12:00:00	2346	128	3320	221	3196	222	4094	188
12:00:00	13:00:00	2408	186	2043	122	2471	161	3311	144
13:00:00	14:00:00	2379	161	2486	167	3262	221	3372	147
14:00:00	15:00:00	2423	170	2469	183	2884	198	2851	135
15:00:00	16:00:00	2741	204	2949	209	2963	246	2284	117
16:00:00	17:00:00	2583	149	3265	248	3987	227	3100	129
17:00:00	18:00:00	2993	178	4372	216	4645	199	4094	168
18:00:00	19:00:00	2758	149	3521	138	4430	169	3695	158
19:00:00	20:00:00	2681	169	3362	134	4086	184	3217	131
20:00:00	21:00:00	2251	111	3024	131	1807	115	2648	99
21:00:00	22:00:00	1772	65	2634	125	1264	92	1853	64
22:00:00	23:00:00	981	45	2270	123	937	75	971	19
23:00:00	00:00:00	339	15	863	100	399	49	422	10
Total		42929	2681	50966	3284	54970	3344	54512	2515

Intersection 08: Nguyễn Trãi - Cầu Ninh Kiều

Time period		Traffic volume (veh)					
From	To	East		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	93	18	311	68	214	43
01:00:00	02:00:00	99	10	221	49	155	43
02:00:00	03:00:00	75	8	131	18	118	18
03:00:00	04:00:00	83	2	172	14	183	11
04:00:00	05:00:00	139	5	295	26	301	20
05:00:00	06:00:00	220	15	699	74	435	53
06:00:00	07:00:00	390	35	1279	156	1138	93
07:00:00	08:00:00	410	112	1918	382	1904	135
08:00:00	09:00:00	473	162	2082	434	1995	183
09:00:00	10:00:00	589	259	2234	440	2054	187
10:00:00	11:00:00	747	256	2679	520	1949	177
11:00:00	12:00:00	876	229	3174	512	1654	196
12:00:00	13:00:00	955	242	3183	543	1086	123
13:00:00	14:00:00	827	245	2358	488	1540	125
14:00:00	15:00:00	690	271	2493	556	1502	136
15:00:00	16:00:00	896	198	2960	581	1702	167
16:00:00	17:00:00	945	193	3358	545	1702	163
17:00:00	18:00:00	1195	243	3488	612	1775	170
18:00:00	19:00:00	1091	309	2807	555	1677	159
19:00:00	20:00:00	1018	225	2476	557	1690	142
20:00:00	21:00:00	712	204	2354	535	1558	147
21:00:00	22:00:00	429	163	1822	394	1150	149
22:00:00	23:00:00	223	83	1194	219	736	80
23:00:00	00:00:00	127	53	620	188	322	69
Total		13302	3540	44308	8466	28540	2789

Intersection 09: Nguyễn Văn Linh - Nguyễn Văn Cừ

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	1082	94	359	49	118	20	298	53
01:00:00	02:00:00	1223	79	198	42	78	20	273	49
02:00:00	03:00:00	1287	75	148	31	68	9	238	45
03:00:00	04:00:00	1051	78	202	48	87	14	248	50
04:00:00	05:00:00	984	80	346	45	259	23	536	70
05:00:00	06:00:00	827	79	886	72	728	57	1039	207
06:00:00	07:00:00	1350	102	2917	108	2376	137	2755	193
07:00:00	08:00:00	1609	107	3753	223	2639	194	3663	263
08:00:00	09:00:00	1479	112	2914	222	2275	232	3163	272
09:00:00	10:00:00	1810	135	2980	246	2564	215	3000	296
10:00:00	11:00:00	1940	136	3099	198	2537	186	3122	287
11:00:00	12:00:00	1852	151	3593	209	2629	199	2767	301
12:00:00	13:00:00	1552	131	2584	154	1738	165	2528	276
13:00:00	14:00:00	1473	116	2697	171	2150	169	2421	268
14:00:00	15:00:00	1492	137	2688	197	2094	219	2290	255
15:00:00	16:00:00	1638	164	2614	162	2230	275	2504	268
16:00:00	17:00:00	2026	160	2821	135	3063	309	3773	304
17:00:00	18:00:00	2769	167	2999	133	3548	311	4280	292
18:00:00	19:00:00	2903	175	3480	174	2826	218	3370	309
19:00:00	20:00:00	1782	172	2586	172	2224	166	2493	282
20:00:00	21:00:00	1650	128	1586	247	1276	136	2052	282
21:00:00	22:00:00	873	103	999	302	797	108	1793	287
22:00:00	23:00:00	543	73	617	191	534	72	1296	204
23:00:00	00:00:00	344	51	256	92	224	29	842	102
Total		35539	2805	47322	3623	39062	3483	50744	5215

Intersection 10: Nút giao Quang Trung

Time period		Traffic volume (veh)					
From	To	East		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	453	108	166	71	226	68
01:00:00	02:00:00	329	52	167	40	184	53
02:00:00	03:00:00	216	47	128	32	169	26
03:00:00	04:00:00	185	36	166	41	168	19
04:00:00	05:00:00	365	62	542	46	431	51
05:00:00	06:00:00	729	126	1130	95	981	95
06:00:00	07:00:00	2411	197	4072	258	2965	201
07:00:00	08:00:00	3853	378	5323	440	5057	320
08:00:00	09:00:00	4493	590	4482	492	3840	294
09:00:00	10:00:00	4121	553	3859	531	3365	363
10:00:00	11:00:00	5280	606	3729	456	3153	329
11:00:00	12:00:00	5292	574	4009	437	2621	300
12:00:00	13:00:00	3336	416	2731	371	2456	249
13:00:00	14:00:00	3884	445	4080	477	3139	295
14:00:00	15:00:00	4077	479	3576	467	3042	340
15:00:00	16:00:00	4450	476	3641	431	3185	243
16:00:00	17:00:00	6773	555	4613	490	3402	362
17:00:00	18:00:00	8161	574	7111	549	4199	312
18:00:00	19:00:00	7372	515	4799	456	3951	319
19:00:00	20:00:00	6102	459	3963	416	4014	304
20:00:00	21:00:00	5326	407	2283	270	3541	430
21:00:00	22:00:00	3854	312	1503	216	2584	292
22:00:00	23:00:00	1971	178	717	110	1424	148
23:00:00	00:00:00	1066	106	314	72	341	48
Total		84099	8251	67104	7264	58438	5461

Intersection 11: Võ Văn Kiệt - Mậu Thân

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	373	23	332	34	339	18	201	34
01:00:00	02:00:00	211	19	191	27	202	17	269	28
02:00:00	03:00:00	163	14	118	24	134	15	165	40
03:00:00	04:00:00	153	21	137	10	158	13	196	60
04:00:00	05:00:00	270	25	250	32	381	27	262	59
05:00:00	06:00:00	718	62	461	52	889	43	272	65
06:00:00	07:00:00	3151	122	672	40	3064	130	536	159
07:00:00	08:00:00	4335	270	2858	161	4000	250	2945	270
08:00:00	09:00:00	3577	265	2773	180	3094	198	2692	259
09:00:00	10:00:00	3363	277	2864	174	2720	177	2633	281
10:00:00	11:00:00	4155	300	2389	144	2522	255	1721	207
11:00:00	12:00:00	4433	266	2358	136	2710	227	1678	246
12:00:00	13:00:00	2799	207	2051	129	2617	148	1460	194
13:00:00	14:00:00	3206	262	2244	168	2740	209	2100	214
14:00:00	15:00:00	3172	231	2489	145	2784	196	1279	234
15:00:00	16:00:00	3592	278	2499	145	2657	191	1622	239
16:00:00	17:00:00	4771	261	3121	173	2314	213	1593	228
17:00:00	18:00:00	6903	361	4902	213	3857	277	2511	252
18:00:00	19:00:00	4861	253	3762	153	3494	195	1526	199
19:00:00	20:00:00	4209	282	2693	143	3194	174	2457	181
20:00:00	21:00:00	3528	206	2608	127	2564	171	1647	238
21:00:00	22:00:00	2963	173	1874	84.2	2135	121	1315	166
22:00:00	23:00:00	2018	95	1443	67	1042	57	961	96
23:00:00	00:00:00	790	87	658	51	317	40	388	75
Total		67714	4360	45747	2612.2	49928	3362	32429	4024

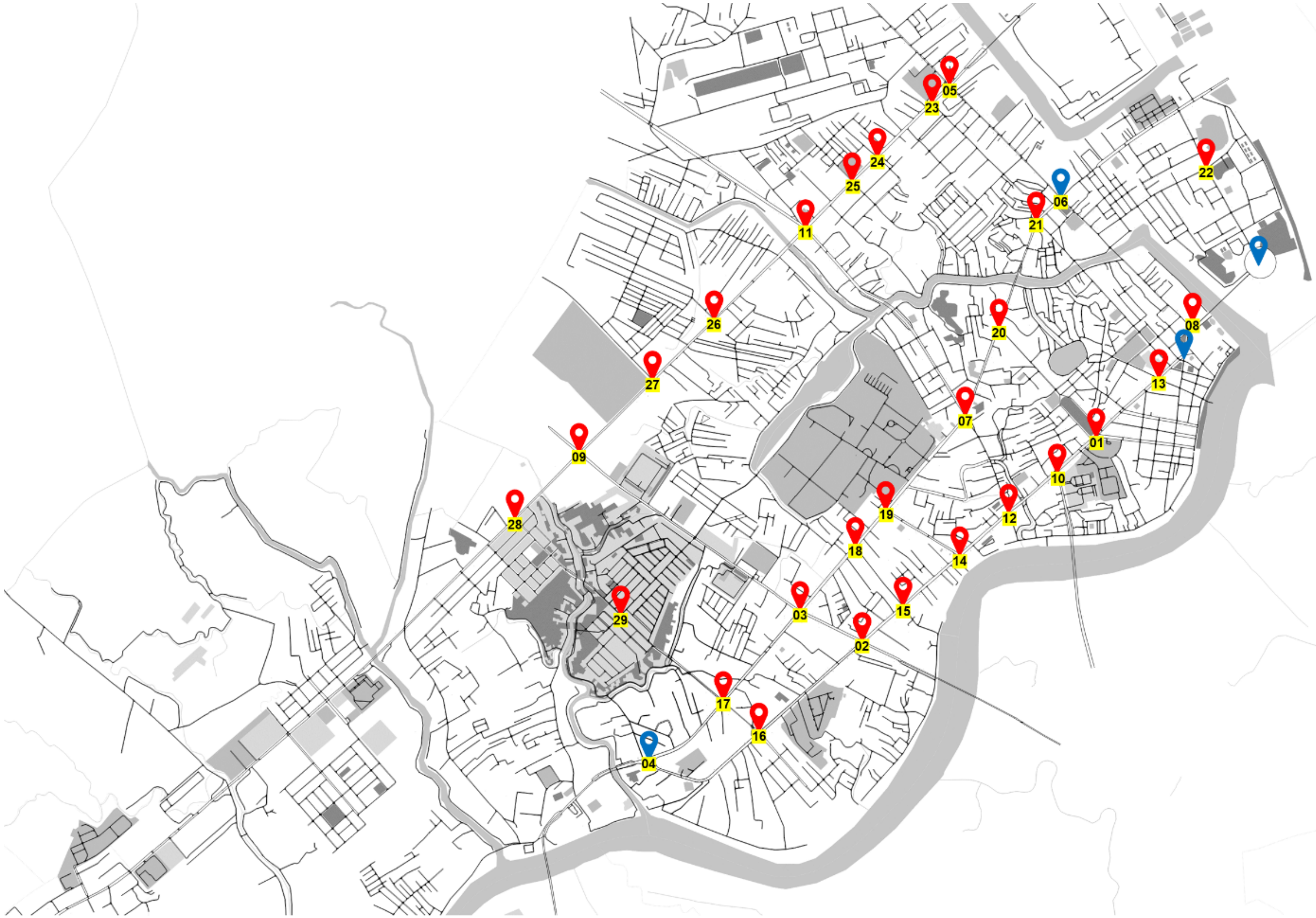
Intersection 12: Mậu Thân - 30 Tháng 4

Time period		Traffic volume (veh)							
From	To	East		North		South		West	
		Motorcycle	Car	Motorcycle	Car	Motorcycle	Car	Motorcycle	Car
00:00:00	01:00:00	274	39	162	50	58.57	6	229	25
01:00:00	02:00:00	261	34	138	21	59.89	8	301	28
02:00:00	03:00:00	221	37	127	17	73.93	4	261	35
03:00:00	04:00:00	256	39	97	10	153.05	1	279	29
04:00:00	05:00:00	374	45	199	27	362.85	11	599	60
05:00:00	06:00:00	886	73	503	54	561.03	8	998	87
06:00:00	07:00:00	1794	161	1738	105	991.46	9	2456.5	151
07:00:00	08:00:00	1851	96	2936	153	1132	15	3465.5	195
08:00:00	09:00:00	1849	116	2367	173	1299	16	2934.5	232
09:00:00	10:00:00	2046	120	2172	230	1281	15	2738	249
10:00:00	11:00:00	2040	107	2103	170	1176	24	2228.5	195
11:00:00	12:00:00	1420	74	2091	148	1023	10	1908.5	162
12:00:00	13:00:00	1692	77	1533	117	613	20	1804.5	141
13:00:00	14:00:00	2433	79	2113	182	589	10	2156.5	194
14:00:00	15:00:00	1053	63	1811	160	604	21	2515.5	207
15:00:00	16:00:00	1242	73	1982	167	723	19	2507	194
16:00:00	17:00:00	1457	65	2364	227	886	18	2690	190
17:00:00	18:00:00	2806	75	3466	185	1500	15	3521.5	258
18:00:00	19:00:00	2852	108	2477	147	871	10	3668	234
19:00:00	20:00:00	1698	83	2659	133	605	12	2717	98
20:00:00	21:00:00	2462	81	2073	127	369	10	1655.5	179
21:00:00	22:00:00	2317	50	1407	105	372.54	23	1087	132
22:00:00	23:00:00	1643	53	937	64	131.11	3	1192	69
23:00:00	00:00:00	852	27	317	29	67.05	3	467	34
Total		35779	1775	37772	2801	15502.48	291	44380	3378

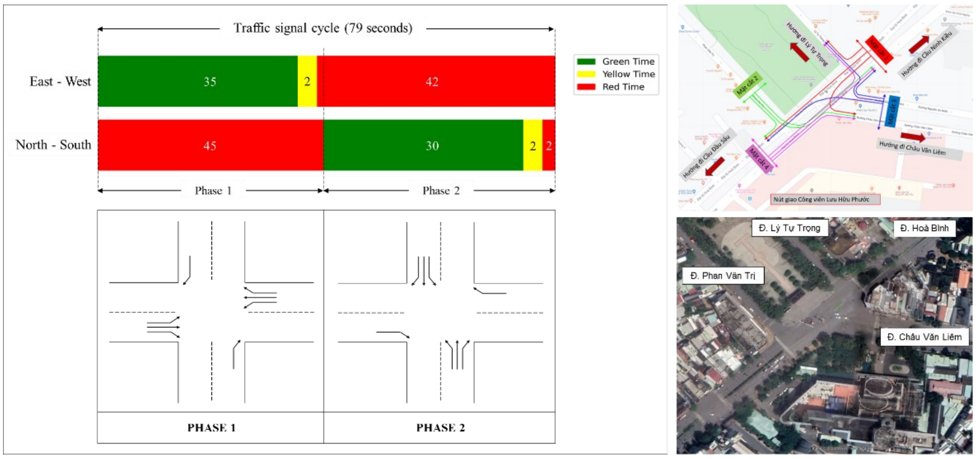
Appendix-C

Traffic Signal Configurations from Field Survey

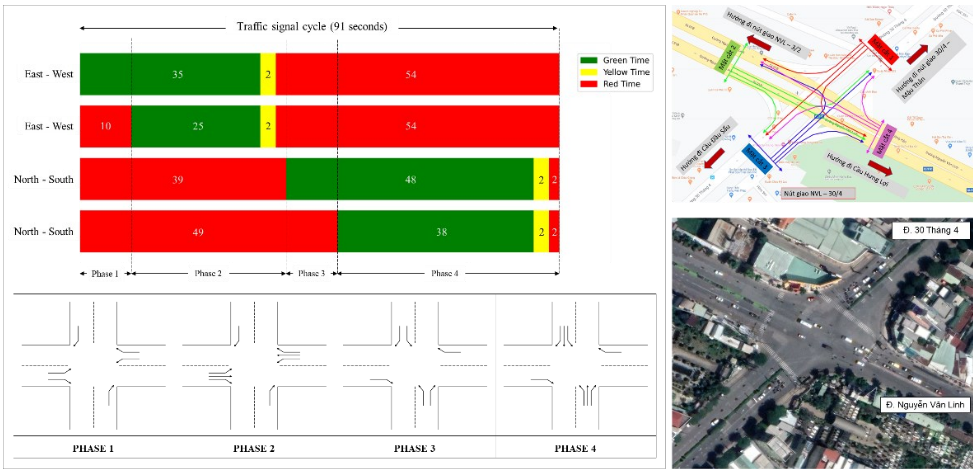
Distribution of traffic signal survey locations in Ninh Kiều District.



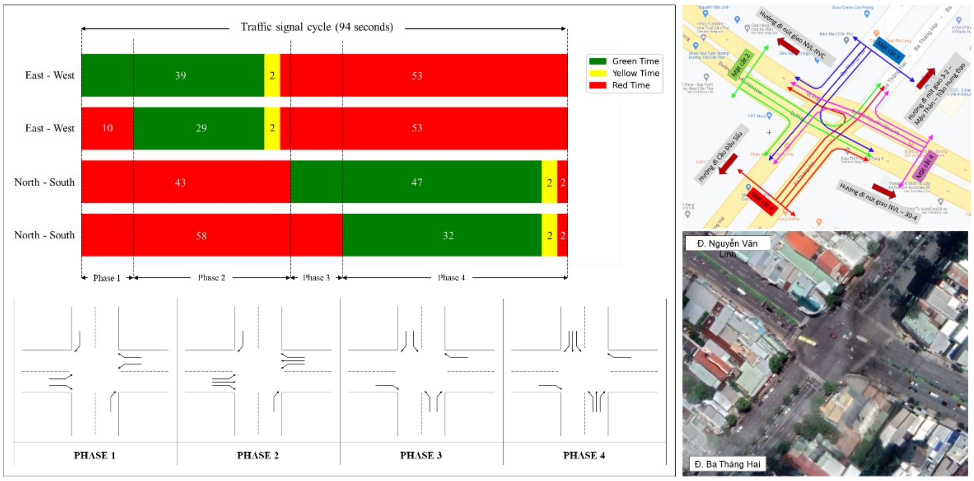
Four-phase traffic signal system at Intersection 01: Nút công viên Lưu Hữu Phước.



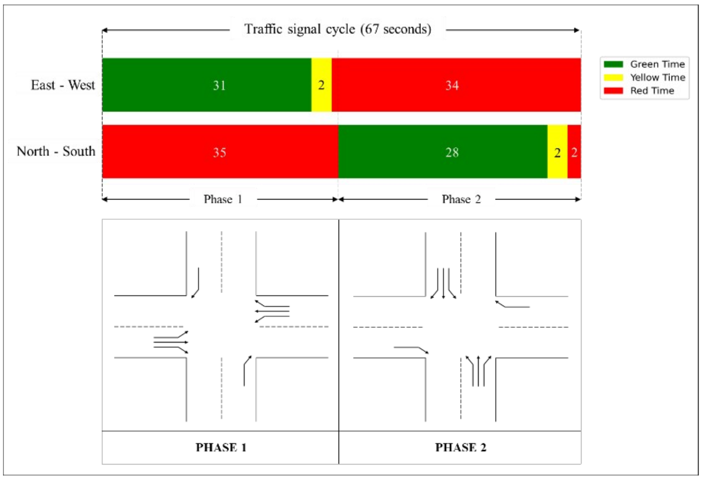
Four-phase traffic signal system at Intersection 02: 30 Tháng 4- Nguyễn Văn Linh.



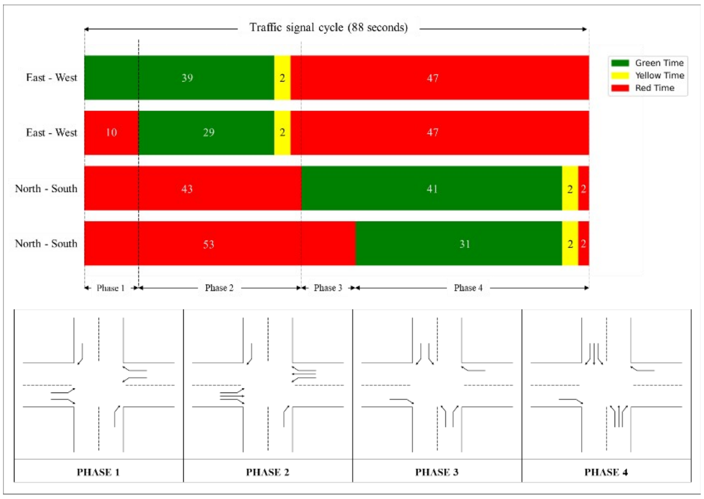
Four-phase traffic signal system at Intersection 03: Ba Tháng Hai - Nguyễn Văn Linh.



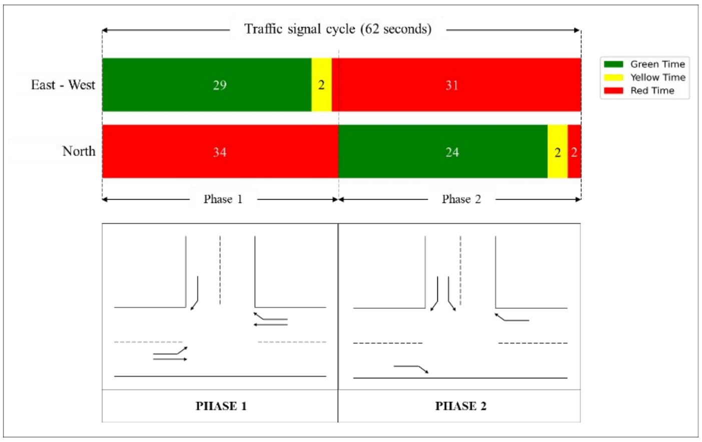
Two-phase traffic signal system at Intersection 05: CMT8 - Nguyễn Văn Cừ.



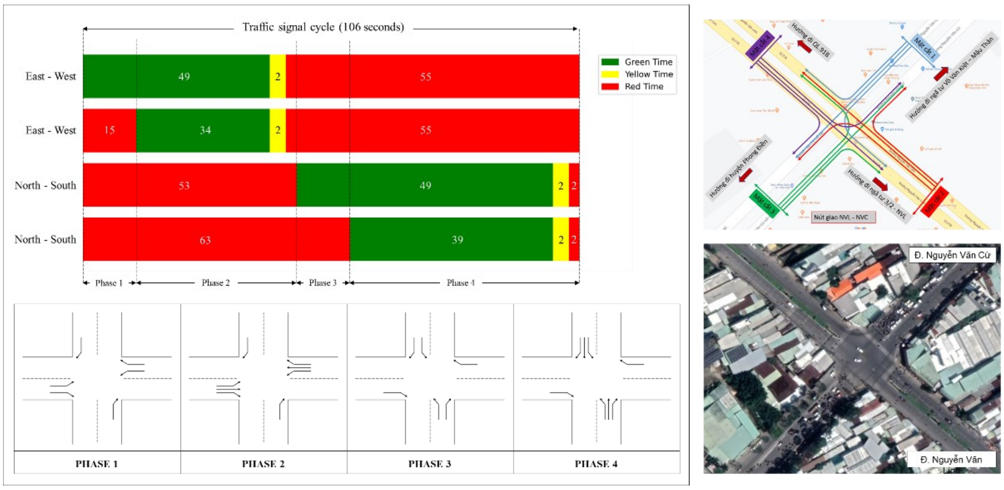
Four-phase traffic signal system at Intersection 07: Mậu Thân - Ba Tháng Hai.



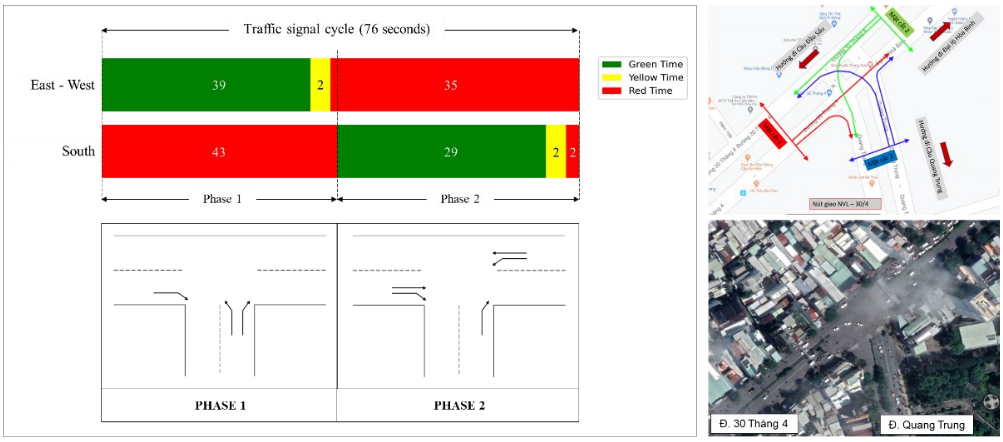
Two-phase traffic signal system at Intersection 08: Nguyễn Trãi - Cầu Ninh Kiều.



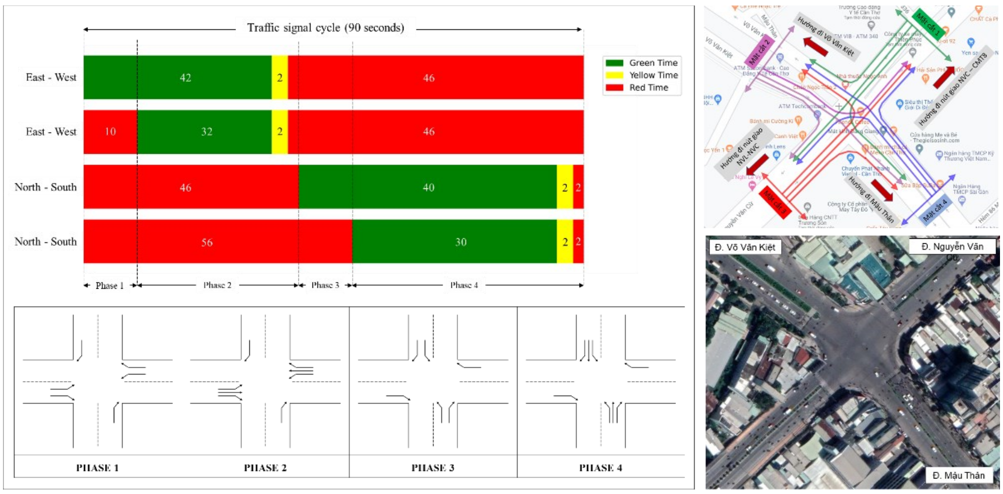
Four-phase traffic signal system at Intersection 09: Nguyễn Văn Linh - Nguyễn Văn Cừ.



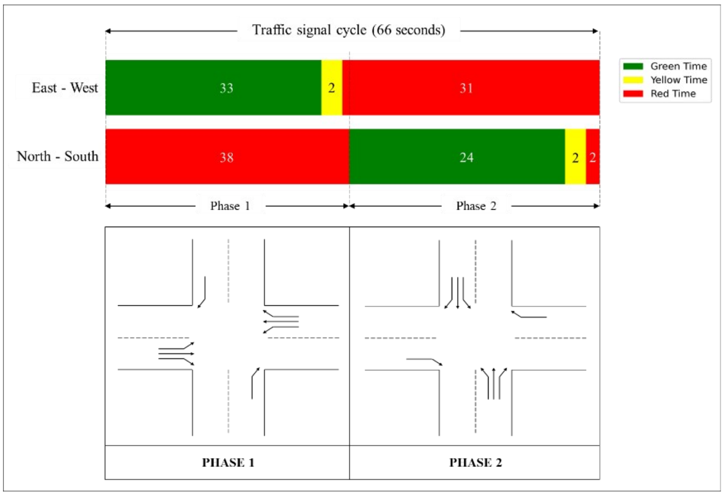
Two-phase traffic signal system at Intersection 10: Nút giao Quang Trung.



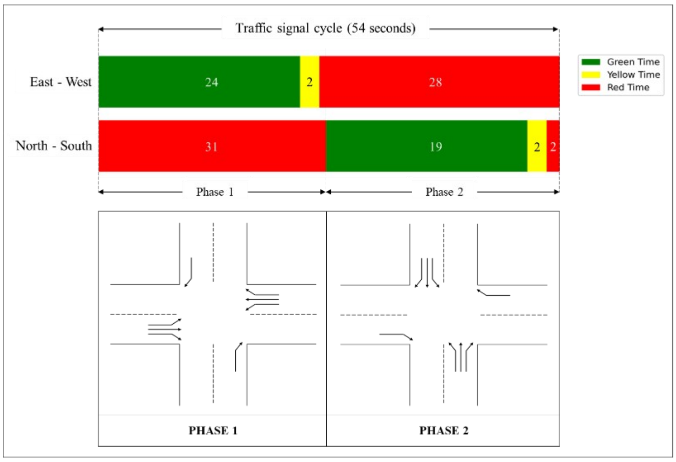
Four-phase traffic signal system at Intersection 11: Võ Văn Kiệt - Mậu Thân.



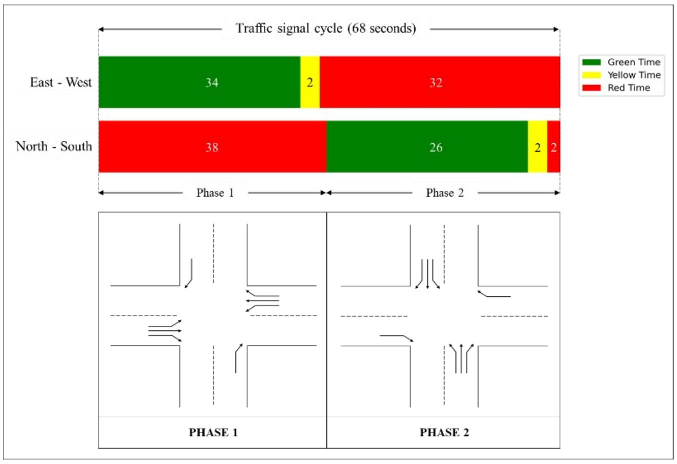
Two-phase traffic signal system at Intersection 12: Mậu Thân - 30 Tháng 4.



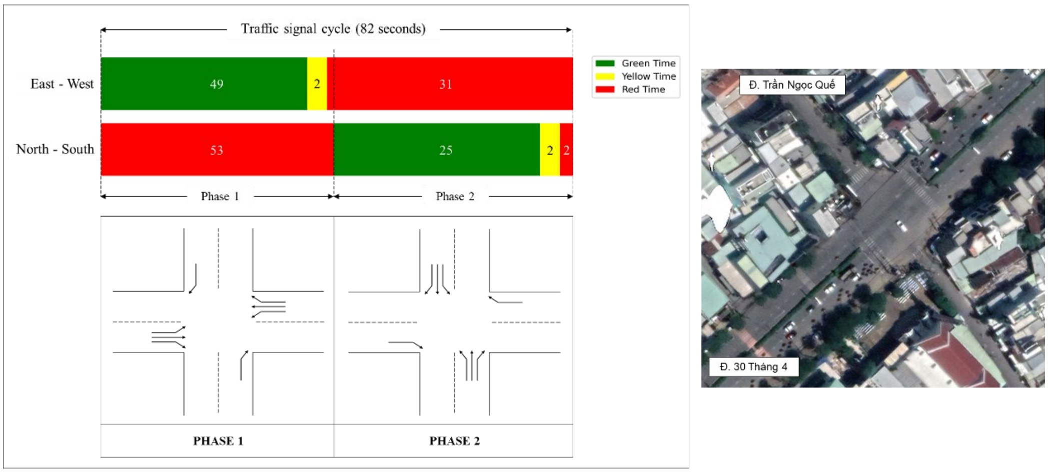
Two-phase traffic signal system at Intersection 13: Ngô Quyền - Hoà Bình.



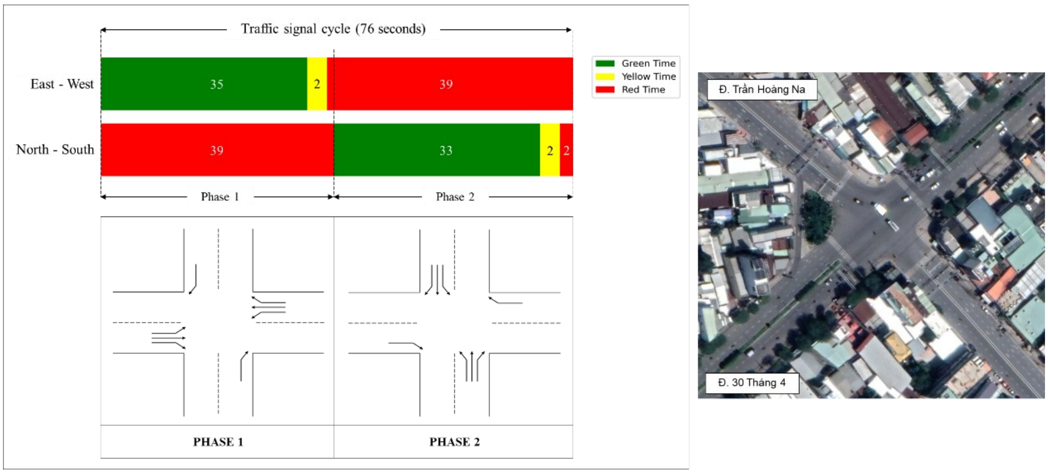
Two-phase traffic signal system at Intersection 14: Trần Văn Hoài - 30 Tháng 4.



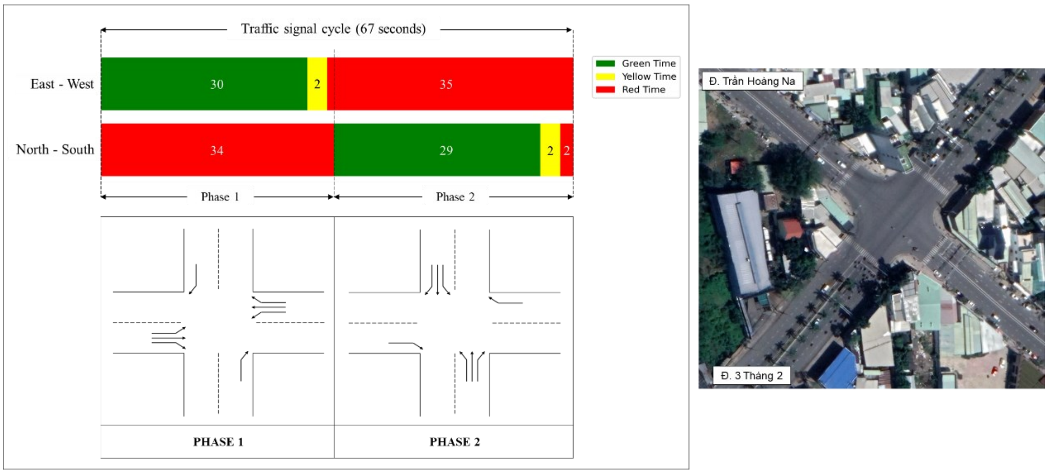
Two-phase traffic signal system at Intersection 15: Trần Ngọc Quế - 30 Tháng 44.



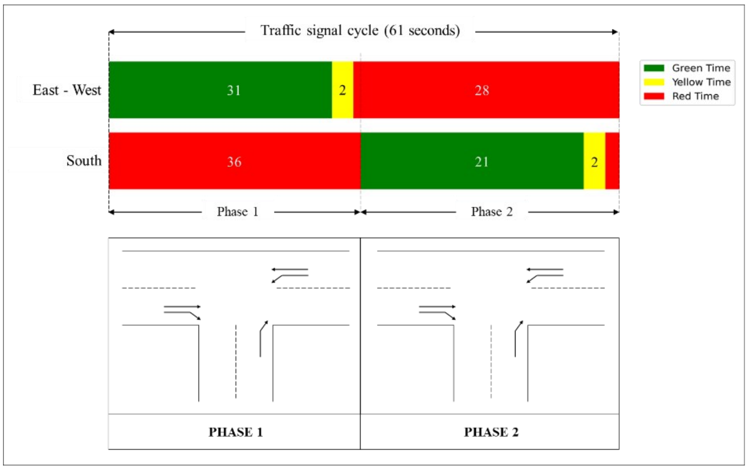
Two-phase traffic signal system at Intersection 16: Trần Hoàng Na - 30 Tháng 4.

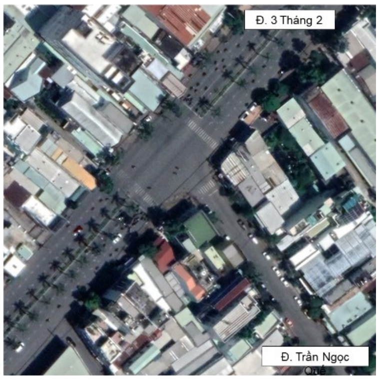


Two-phase traffic signal system at Intersection 17: Trần Hoàng Na - 3 Tháng 2.

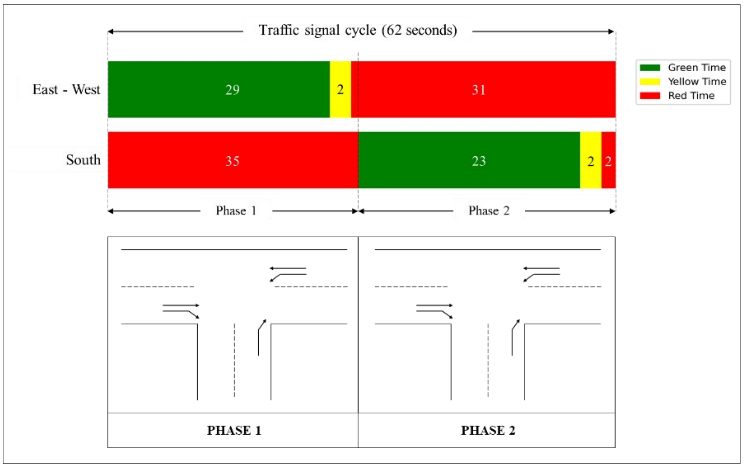


Two-phase traffic signal system at Intersection 18: Trần Ngọc Quế - 3 Tháng 2.

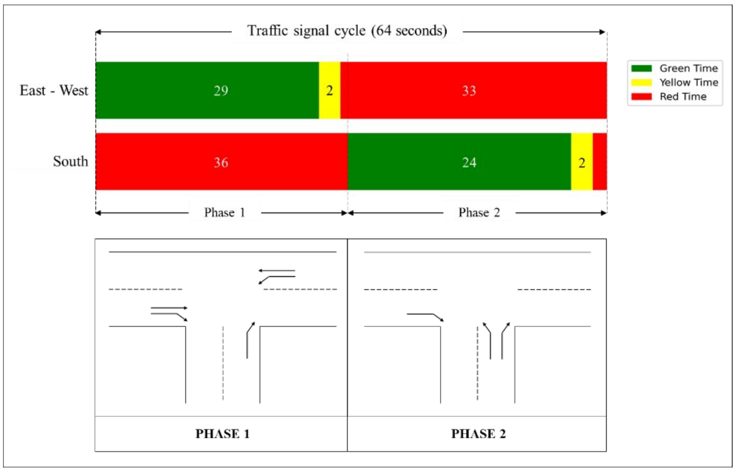


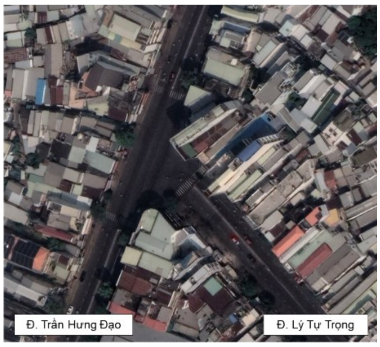


Two-phase traffic signal system at Intersection 19: Trần Văn Hoài - 3 Tháng 2.

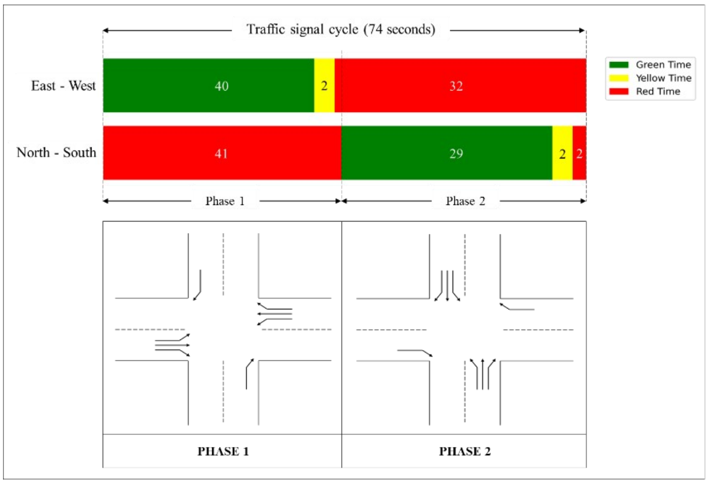


Two-phase traffic signal system at Intersection 20: Lý Tự Trọng - Trần Hưng Đạo.

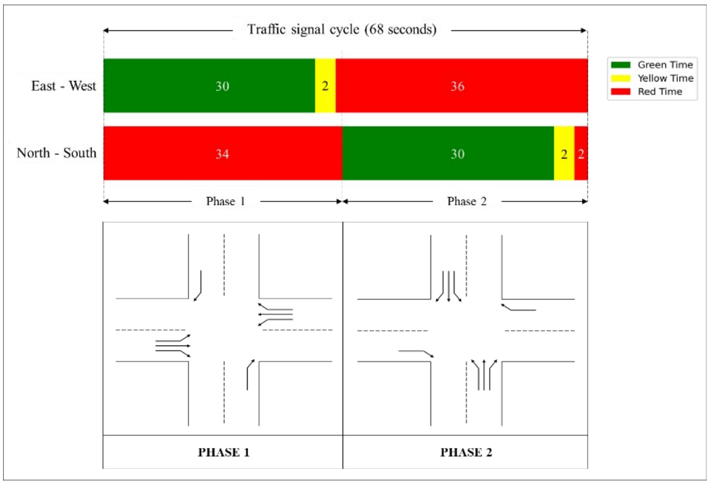




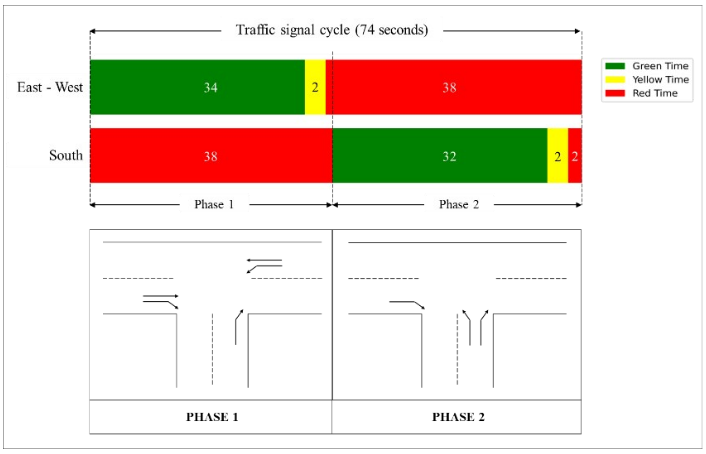
Two-phase traffic signal system at Intersection 21: Hùng Vương - Đinh Tiên Hoàng.



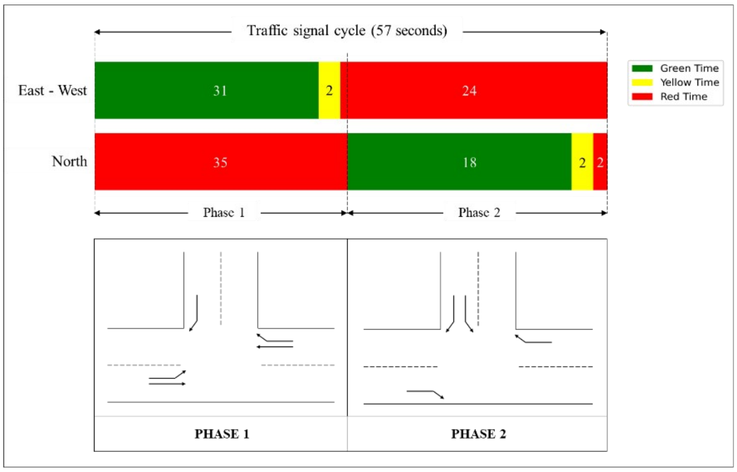
Two-phase traffic signal system at Intersection 22: Trần Văn Khéo - Lê Lợi.



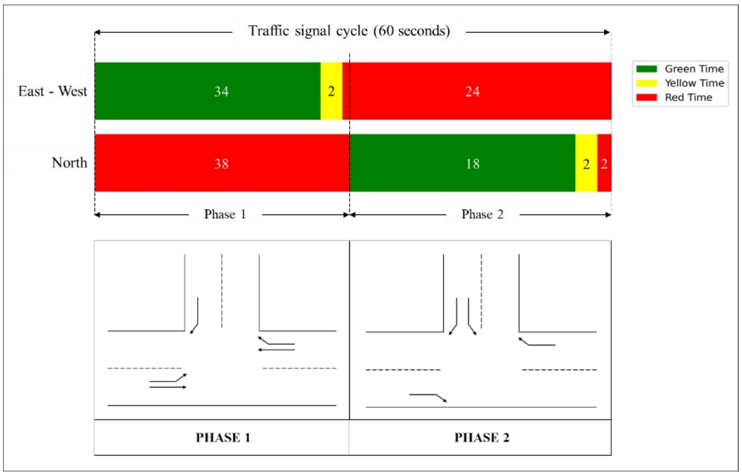
Two-phase traffic signal system at Intersection 23: Nguyễn Văn Cừ - Trần Việt Châu.



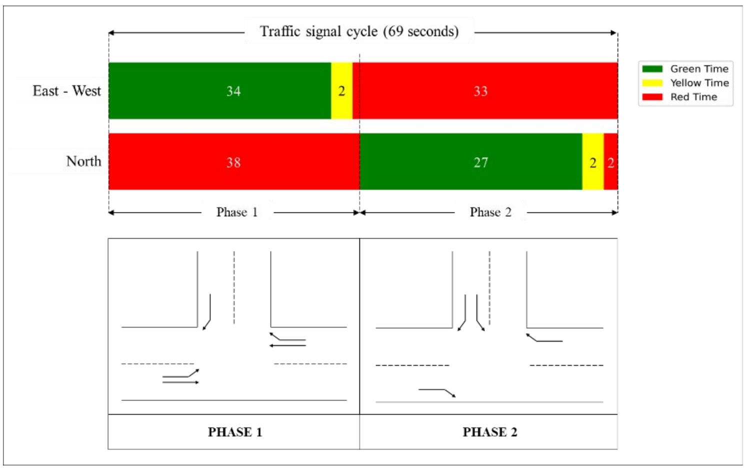
Two-phase traffic signal system at Intersection 24: Nguyễn Văn Cừ - Hẻm 188 Đ. Nguyễn Văn Cừ.



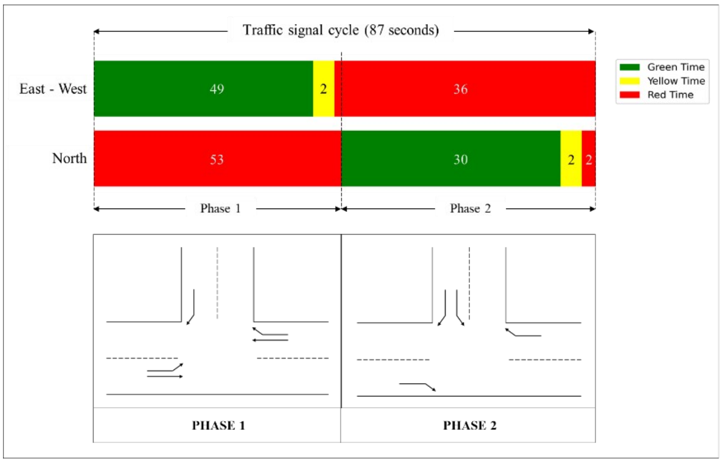
Two-phase traffic signal system at Intersection 25: Nguyễn Văn Cừ - Đ. Võ Trường Toản.



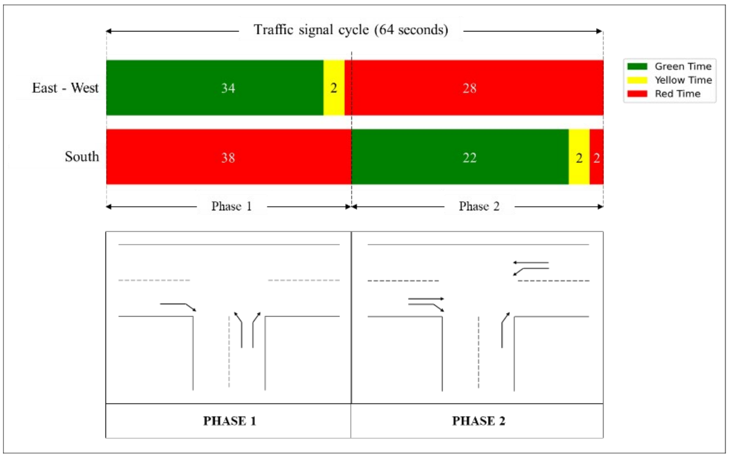
Two-phase traffic signal system at Intersection 26: Nguyễn Tri Phương - Nguyễn Văn Cừ Nối Dài.



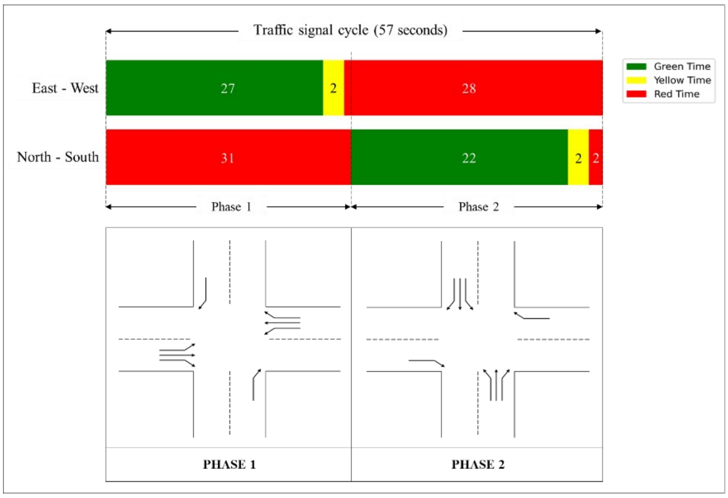
Two-phase traffic signal system at Intersection 27: Trần Bạch Đằng - Nguyễn Văn Cừ Nối Dài.



Two-phase traffic signal system at Intersection 28: Trần Hoàng Na - Nguyễn Văn Cừ Nối Dài.



Two-phase traffic signal system at Intersection 29: Trần Hoàng Na - Nguyễn Hiền.



Appendix-D

Origin – Destination Matrices

Motorcycle origin-destination movement patterns on Monday at 12:00 a.m. – 01:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	3	3	3	3	3	4	4	4	4	4	5	5	1	1	2	2	2	2	2	1	1	1	1	2	23	23	2	2	1	1	5	4	4	4
12	3	0	3	3	4	4	4	4	5	5	5	5	5	1	1	2	19	27	19	2	1	1	1	1	2	2	2	8	2	1	1	5	5	4	4
13	3	3	0	3	4	4	4	5	5	5	5	5	5	1	1	2	2	2	2	2	1	1	1	1	2	2	2	2	2	1	1	5	5	5	4
14	3	3	3	0	4	4	5	5	5	5	5	5	6	1	1	2	2	2	2	2	1	1	1	1	2	2	2	2	2	1	1	5	5	5	5
15	3	3	4	4	0	1	1	1	1	1	1	3	2	3	3	4	7	8	11	11	11	12	12	8	8	3	3	5	3	5	10	10	11	11	9
16	3	3	4	4	4	0	1	2	2	2	2	4	4	4	3	3	7	7	10	10	10	13	13	9	9	4	4	7	5	7	11	11	13	12	10
17	3	4	4	4	5	1	0	2	3	3	3	6	7	9	8	9	12	12	15	13	11	14	13	9	9	4	4	7	5	7	12	12	13	13	10
21	3	4	4	4	5	1	1	0	23	5	5	7	9	10	84	9	12	12	15	175	23	254	13	10	94	4	4	7	10	33	84	12	89	232	10
22	3	4	4	4	5	1	1	3	0	5	33	7	9	10	45	9	12	12	15	13	12	15	13	10	45	4	5	7	5	7	45	33	14	14	11
31	4	4	4	5	5	1	1	3	5	0	33	18	31	9	11	80	76	14	68	15	13	16	2	2	9	4	5	7	5	7	12	15	14	14	11
32	2	2	2	2	2	2	2	4	5	21	0	22	21	16	14	15	17	16	19	16	15	17	10	10	10	5	5	7	5	7	12	12	14	14	11
33	2	2	2	2	3	3	3	5	6	8	5	0	13	14	12	13	11	11	11	8	7	8	6	6	4	3	4	4	4	4	4	5	5	4	3
34	4	6	6	6	7	6	4	6	6	8	29	29	0	54	13	13	39	11	13	9	27	7	4	4	3	2	3	2	2	2	2	3	4	3	3
35	4	6	54	6	7	6	4	6	6	30	10	9	50	0	11	74	9	8	54	8	7	6	5	30	3	2	3	2	2	2	2	4	5	4	4
41	4	6	6	6	7	6	4	70	5	6	9	8	10	11	0	10	9	8	9	7	7	70	4	5	1	3	4	3	2	70	3	5	7	6	6
51	5	63	63	8	63	8	5	7	6	7	9	8	10	12	13	0	36	36	12	9	8	6	4	5	5	4	5	5	5	5	4	5	6	5	36
52	5	6	7	8	9	8	5	6	5	6	31	31	8	97	10	16	0	8	11	9	52	6	5	6	6	5	7	6	6	7	6	7	7	5	52
53	4	5	6	7	8	7	5	5	5	4	6	5	6	8	9	9	9	0	9	9	6	4	4	6	6	4	26	30	6	9	11	15	21	21	21
54	4	5	37	7	7	37	37	4	4	3	6	5	6	8	10	27	27	61	0	11	8	6	6	5	6	7	36	36	10	15	19	23	21	18	18
61	1	1	2	3	3	3	3	3	4	3	7	6	7	8	9	8	10	9	10	0	8	55	6	5	6	7	10	10	40	40	19	22	16	16	17
71	1	1	2	3	3	3	3	3	3	2	3	3	3	46	6	6	46	7	9	8	0	8	5	4	6	7	10	10	11	15	19	21	102	109	147
81	1	1	2	3	4	5	4	20	6	6	7	7	7	33	7	7	9	11	11	120	51	0	11	9	7	10	12	61	101	110	25	27	84	112	63
91	2	2	2	3	3	4	4	6	6	11	7	7	11	11	5	5	7	9	9	10	11	11	0	9	6	8	11	12	15	19	25	28	25	22	19
92	2	2	2	3	3	4	4	6	6	3	6	7	6	7	5	5	8	10	8	9	10	10	3	0	6	9	10	11	14	19	26	6	27	25	22
93	3	3	3	4	4	5	5	30	35	6	97	6	6	6	65	11	13	16	15	16	132	13	44	97	0	11	13	14	30	21	167	132	27	25	23
101	43	3	3	43	4	5	43	6	6	5	5	5	5	5	7	10	10	6	11	12	14	10	8	9	7	0	7	6	11	14	17	19	21	21	17
102	3	3	3	4	7	10	10	11	11	10	9	8	5	5	7	11	11	22	14	15	17	12	11	12	10	15	0	36	12	15	18	20	55	55	51
103	8	3	13	8	13	13	8	11	10	10	9	8	5	5	7	13	13	177	165	15	17	12	11	12	10	68	68	0	12	15	18	20	129	129	105
111	3	3	3	4	6	10	10	9	8	8	7	5	2	2	6	10	10	10	13	13	13	10	9	10	11	7	7	9	0	10	13	15	15	15	13
112	1	1	2	2	5	9	9	146	107	9	9	7	3	3	40	11	12	13	19	15	20	121	16	17	17	10	11	12	40	0	15	18	17	15	15
121	1	1	2	2	6	12	12	12	12	11	12	8	3	3	7	10	12	13	21	20	21	18	17	18	17	10	11	12	11	11	0	16	15	13	12
122	4	4	5	5	5	12	12	12	67	12	13	9	2	2	3	3	4	7	15	15	16	67	18	39	67	8	9	11	9	9	94	0	8	7	5
131	4	4	4	5	7	13	14	14	59	14	15	10	4	45	4	4	5	10	15	55	104	145	19	19	18	46	46	57	10	37	9	9	0	51	78
132	4	4	4	5	4	9	9	80	56	9	10	8	3	3	9	3	4	6	13	13	8	63	17	17	16	5	5	10	17	22	8	8	5	0	8
133	3	4	4	4	4	9	9	9	36	9	10	8	3	3	4	3	5	8	13	13	36	49	17	17	16	6	10	41	9	8	9	8	18	31	0

Motorcycle origin-destination movement patterns on Monday at 01:00 a.m. – 02:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	2	3	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	1	1	18	18	1	1	1	1	4	3	3	3
12	2	0	2	3	3	3	3	3	3	4	4	4	4	1	1	1	12	18	12	1	1	1	1	1	1	1	1	7	1	1	1	4	4	3	3
13	2	2	0	3	3	3	3	3	4	4	4	4	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	4	4	3
14	2	2	3	0	3	3	4	4	4	4	4	4	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	4	4	4
15	2	3	3	3	0	1	1	1	1	1	1	2	2	2	2	2	5	6	8	8	8	9	9	6	6	2	3	4	3	4	7	7	8	8	7
16	2	3	3	3	3	0	1	1	1	1	1	3	3	3	2	2	5	5	7	7	7	9	9	7	6	3	3	5	4	5	8	8	10	9	8
17	2	3	3	3	4	1	0	2	2	3	3	5	5	6	5	5	7	8	9	9	8	10	10	7	6	3	3	5	4	5	9	9	10	10	8
21	3	3	3	3	4	1	1	0	15	4	4	6	7	7	57	6	7	8	9	133	15	182	10	7	66	3	3	5	9	26	57	9	62	167	8
22	3	3	3	3	4	1	1	2	0	4	22	6	7	7	37	6	7	8	9	9	8	10	10	7	37	3	3	5	4	5	37	22	11	11	9
31	3	3	3	4	4	1	1	3	4	0	33	20	30	8	10	39	37	10	29	11	10	12	2	2	7	3	3	5	4	5	9	13	11	11	9
32	1	1	1	1	1	1	2	3	5	20	0	20	20	13	11	11	13	12	14	12	11	13	6	6	7	4	4	5	4	5	9	9	11	11	9
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34	2	3	3	3	4	3	3	4	5	7	33	33	0	66	10	25	58	8	25	7	35	5	3	3	2	1	2	2	2	2	2	2	4	3	3
35	2	3	33	3	4	3	3	4	5	20	8	7	30	0	9	42	8	7	33	6	5	5	4	20	2	1	2	2	2	2	2	3	4	3	3
41	2	3	3	3	4	3	3	51	4	5	7	6	8	9	0	8	8	7	8	6	5	51	3	4	1	2	3	2	1	51	3	4	5	5	5
51	3	31	31	5	31	6	4	5	6	5	7	6	8	10	10	0	20	20	10	8	6	4	3	4	4	3	4	4	4	4	3	4	5	4	20
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53	3	3	4	5	6	5	4	4	4	3	4	3	4	5	6	6	6	0	7	6	5	3	3	4	5	2	22	23	5	7	9	11	19	19	19
54	3	3	38	5	5	38	38	3	3	2	4	3	4	6	7	25	25	54	0	8	7	5	5	4	5	6	30	30	9	12	16	18	16	14	14
61	1	1	2	3	3	3	3	3	3	3	4	4	5	5	6	6	8	7	8	0	6	56	5	4	5	6	9	9	39	39	16	17	17	17	13
71	1	1	2	3	3	3	3	3	3	2	2	2	3	26	4	4	26	6	7	7	0	5	5	4	5	6	9	9	9	12	16	17	73	77	97
81	1	1	2	3	4	5	4	13	3	5	5	6	6	22	6	6	8	10	9	92	39	0	9	8	6	8	10	56	76	83	21	22	74	94	48
91	2	2	2	2	2	3	4	5	5	9	5	6	9	9	4	4	6	8	7	8	9	9	0	7	5	7	9	11	13	17	21	23	21	18	16
92	2	2	2	2	2	3	4	5	5	3	5	6	5	5	5	5	6	8	7	8	8	8	3	0	5	7	8	10	12	17	22	5	23	21	19
93	2	2	3	3	4	4	4	33	42	5	67	5	5	5	74	12	14	16	15	15	112	11	30	67	0	9	11	12	33	20	154	112	26	25	22
101	26	2	3	26	3	4	26	5	5	5	4	5	4	4	8	12	12	6	12	13	14	9	6	7	6	0	6	6	10	14	17	20	22	22	18
102	2	2	3	3	6	8	8	9	9	8	8	7	4	5	8	12	12	29	15	15	16	11	9	9	8	15	0	43	11	14	18	20	58	58	54
103	6	2	15	6	15	15	6	9	8	8	7	7	4	5	8	15	15	202	188	15	16	11	9	9	8	56	56	0	11	14	18	20	146	146	118
111	2	2	3	3	5	8	7	7	6	6	5	4	1	2	7	10	11	11	13	13	13	9	7	8	9	6	6	7	0	9	13	16	15	16	14
112	1	1	2	2	4	7	7	113	85	6	7	5	2	2	29	11	12	13	19	13	19	98	13	13	14	8	9	10	29	0	15	19	19	13	17
121	1	1	2	2	5	9	9	9	9	8	9	6	2	2	7	11	12	13	19	19	19	16	14	15	14	8	9	9	8	10	0	16	15	14	13
122	3	4	4	4	4	9	9	9	43	9	9	6	2	2	2	2	4	5	12	12	12	43	14	28	51	6	7	8	7	6	67	0	8	7	5
131	3	3	4	4	5	10	10	10	39	11	11	8	3	30	3	3	4	8	12	49	68	147	15	15	14	35	35	41	7	38	8	8	0	73	89
132	3	3	4	4	4	6	7	60	42	7	8	5	3	3	7	2	4	5	10	10	10	52	13	13	13	4	4	8	12	15	7	8	4	0	10
133	3	3	3	4	4	6	7	7	13	7	8	6	3	3	3	3	4	5	10	10	13	25	14	14	13	7	9	30	7	7	7	8	10	22	0

Motorcycle origin-destination movement patterns on Monday at 02:00 a.m. – 03:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	2	2	2	2	2	2	2	2	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	30	30	2	2	1	1	3	3	3	3
12	2	0	2	2	2	2	2	3	3	3	3	3	3	1	1	1	8	14	8	1	1	1	1	2	2	2	2	6	2	1	1	3	3	3	3
13	2	2	0	2	2	2	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	3	3	3	3
14	2	2	2	0	2	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	3	3	3	3
15	2	2	2	2	0	1	1	1	1	1	1	1	1	1	2	2	4	4	6	6	6	7	7	4	4	2	2	2	2	3	5	5	6	6	6
16	2	2	2	2	3	0	1	1	1	1	1	2	2	2	2	2	4	4	6	6	6	7	7	5	5	2	2	4	3	3	6	6	7	7	6
17	2	2	2	3	3	1	0	1	2	2	2	3	4	4	4	4	6	6	7	7	6	8	7	5	5	2	2	4	3	4	6	6	8	8	6
21	2	2	2	3	3	1	1	0	10	3	3	4	5	5	33	4	6	6	7	103	10	140	7	5	39	2	2	4	6	16	33	6	44	132	7
22	2	2	2	3	3	1	1	2	0	3	15	4	5	5	33	4	6	6	7	7	6	8	7	5	33	2	2	4	3	4	33	15	8	8	7
31	2	3	3	3	3	1	1	2	3	0	24	11	15	4	6	29	29	8	25	8	7	9	2	2	5	2	2	4	3	4	6	13	8	8	7
32	1	1	1	1	1	1	1	2	3	14	0	14	14	9	7	8	9	9	10	9	8	9	4	4	5	3	3	4	3	4	6	6	8	9	7
33	1	1	1	1	2	2	2	3	4	5	3	0	7	8	7	7	6	6	6	5	4	4	2	2	2	2	2	3	3	3	3	3	4	3	2
34	2	2	2	2	3	3	2	3	4	5	20	20	0	42	7	13	37	6	13	5	24	4	2	2	2	1	2	1	2	2	2	2	3	2	2
35	2	2	27	2	3	3	2	3	4	12	6	5	20	0	6	35	5	5	27	4	4	3	3	12	2	1	2	1	1	1	1	2	3	3	3
41	2	2	2	2	3	3	2	40	3	3	5	4	5	6	0	6	5	5	5	4	3	40	2	3	1	1	2	2	1	40	2	3	4	3	3
51	3	22	22	4	22	5	3	4	4	4	5	4	6	7	8	0	16	16	7	6	4	3	2	3	3	2	3	3	3	3	2	3	3	3	16
52	3	3	4	4	5	5	3	4	3	3	16	16	4	38	5	8	0	5	7	5	15	3	3	3	4	3	4	4	4	5	4	4	4	3	15
53	2	2	3	4	4	4	3	3	3	3	3	2	3	4	5	5	5	0	6	5	4	3	3	3	4	2	11	13	4	6	7	8	11	11	11
54	2	2	32	4	4	32	32	3	3	2	3	3	3	4	5	25	25	48	0	7	5	4	4	3	4	5	25	25	8	10	13	14	12	10	10
61	1	1	2	2	3	3	2	3	3	2	3	3	4	5	5	5	7	6	7	0	5	43	4	3	4	5	8	8	34	34	13	14	10	10	10
71	1	1	2	2	3	3	2	2	2	2	2	2	2	20	4	4	20	5	6	6	0	3	4	3	4	5	8	8	8	11	13	14	57	60	77
81	1	1	2	2	3	4	3	13	2	4	5	5	5	16	5	5	7	9	8	88	27	0	8	7	5	7	9	53	73	81	18	19	62	81	31
91	2	2	2	2	2	3	3	4	4	9	5	5	9	9	3	3	5	7	7	7	8	8	0	6	5	6	8	10	12	15	19	20	18	16	14
92	2	2	2	2	2	3	3	4	4	2	5	5	4	4	4	4	6	7	6	7	8	7	2	0	5	7	8	9	11	15	20	5	20	19	16
93	2	2	2	3	3	4	4	25	32	4	60	5	4	4	55	12	14	16	15	15	106	11	32	60	0	9	10	11	25	18	136	106	24	22	20
101	27	2	2	27	3	3	27	4	4	4	4	4	4	4	8	12	12	6	13	13	14	9	6	7	6	0	6	6	9	13	16	18	35	35	16
102	2	2	2	3	5	8	7	8	8	8	7	6	4	4	8	12	12	34	15	15	16	11	8	9	8	9	0	42	10	13	17	19	48	48	42
103	2	2	13	2	13	13	2	8	8	8	7	6	4	4	8	13	13	212	201	15	16	11	8	9	8	53	53	0	10	13	17	19	132	132	106
111	2	2	2	3	5	7	7	6	6	6	5	4	1	2	7	11	11	11	13	13	13	9	6	7	8	6	6	6	0	9	12	14	14	14	13
112	1	1	1	1	4	7	6	116	85	6	6	5	2	2	32	12	13	13	17	10	17	95	11	12	13	8	9	10	32	0	14	16	16	10	14
121	1	1	1	1	5	9	8	8	8	8	8	6	2	2	7	11	12	13	18	18	18	15	12	13	13	8	9	9	9	9	0	14	14	13	12
122	3	3	4	4	4	8	8	8	36	8	9	6	2	2	2	2	3	4	10	10	10	36	12	23	41	7	7	8	7	6	53	0	6	5	5
131	3	3	3	4	5	9	9	10	25	10	10	7	3	26	3	3	4	8	10	40	48	113	13	13	13	42	42	50	8	32	7	7	0	59	75
132	3	3	3	4	3	6	6	56	42	6	7	5	2	2	6	2	3	4	8	9	14	55	11	12	12	7	7	8	10	13	6	6	7	0	14
133	3	3	3	4	3	6	6	6	13	6	7	5	2	2	3	2	3	3	9	8	13	25	12	12	12	10	8	26	7	6	6	7	6	17	0

Motorcycle origin-destination movement patterns on Monday at 03:00 a.m. – 04:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	2	2	2	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	43	43	2	2	2	1	3	3	3	3
12	2	0	2	2	2	2	3	3	3	3	3	3	3	1	1	1	12	19	12	1	1	1	1	2	2	2	2	8	2	2	1	3	3	3	3
13	2	2	0	2	2	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	1	3	3	3	3
14	2	2	2	0	3	3	3	3	3	3	3	4	4	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	1	4	4	3	3
15	2	2	2	3	0	1	1	1	1	1	1	2	1	2	2	2	4	4	6	6	6	6	6	4	4	2	2	3	2	3	5	5	6	6	6
16	2	2	2	3	3	0	1	1	1	1	1	2	2	2	2	2	4	4	5	5	5	7	7	5	5	2	2	4	3	4	6	6	7	7	6
17	2	2	3	3	3	1	0	1	2	2	2	4	4	5	4	4	6	6	7	6	6	7	7	5	5	2	3	4	3	4	6	6	8	8	6
21	2	2	3	3	3	1	1	0	9	3	3	4	5	5	42	4	6	6	7	92	9	128	7	5	49	2	3	4	9	13	42	6	42	120	6
22	2	2	3	3	3	1	1	2	0	3	18	4	5	5	28	4	6	6	7	7	6	8	7	5	28	3	3	4	3	4	28	18	8	8	7
31	2	3	3	3	3	1	1	2	3	0	24	13	18	5	7	33	32	8	28	9	7	9	2	2	5	3	3	4	3	4	6	12	8	9	7
32	1	1	1	1	1	1	1	2	3	10	0	10	10	9	8	9	10	9	11	9	8	9	4	4	5	3	3	4	3	4	6	6	8	9	7
33	1	1	1	1	2	2	2	3	4	5	3	0	7	8	7	8	7	6	7	6	4	5	3	3	3	2	3	3	3	3	3	3	4	3	3
34	2	3	3	3	4	4	3	4	4	5	18	18	0	46	7	20	48	7	20	6	29	4	3	3	2	1	2	2	2	2	2	2	4	3	3
35	2	3	22	3	4	4	3	4	4	15	7	6	23	0	7	30	6	5	22	5	4	4	3	15	2	1	2	2	2	2	2	2	4	3	3
41	2	3	3	3	4	4	3	60	4	4	6	5	6	7	0	7	6	5	6	5	4	60	3	3	1	2	3	3	1	60	3	4	5	4	4
51	3	35	35	5	35	5	4	5	5	5	6	5	7	8	9	0	20	20	9	7	5	4	3	4	4	3	4	4	4	4	4	4	5	4	20
52	3	4	4	5	6	5	4	4	4	4	28	28	5	45	6	9	0	5	7	6	10	4	3	5	6	4	6	6	6	6	6	6	6	4	10
53	2	3	4	4	5	5	4	4	4	3	4	3	4	5	6	5	5	0	7	6	5	3	3	4	5	3	23	26	6	7	8	9	20	20	20
54	2	3	26	4	4	26	26	3	3	2	4	3	4	5	6	26	26	57	0	7	6	4	5	4	5	6	33	33	9	12	14	15	13	11	11
61	1	1	2	2	2	2	2	3	3	3	4	4	5	5	6	5	7	6	7	0	6	55	5	4	5	6	9	9	42	42	14	14	13	13	10
71	1	1	2	2	2	2	2	2	2	2	2	2	3	16	4	4	16	6	7	6	0	4	4	4	5	6	9	9	9	12	14	14	46	51	62
81	1	1	2	2	3	3	3	15	3	4	5	5	5	24	5	5	7	9	9	83	42	0	8	7	6	8	10	49	72	81	18	18	59	75	46
91	2	2	2	3	3	3	4	4	4	10	5	5	10	10	3	3	5	7	7	8	9	8	0	7	5	7	8	10	12	16	20	21	19	17	15
92	2	2	2	3	3	3	4	4	4	2	6	5	4	4	4	4	6	8	7	7	9	7	2	0	5	7	8	10	12	17	22	6	22	21	19
93	3	3	3	4	4	5	5	27	22	5	68	5	4	4	48	11	13	15	14	14	101	11	33	68	0	10	11	12	27	20	123	101	27	25	23
101	42	3	3	42	4	4	42	5	4	4	4	4	4	4	7	11	10	8	11	12	13	8	6	7	7	0	7	8	10	14	19	21	70	70	19
102	3	3	3	4	7	9	9	9	9	9	8	6	4	5	8	11	11	51	14	14	15	10	8	9	9	16	0	66	11	15	20	22	72	72	63
103	3	3	17	3	17	17	3	9	9	9	8	6	4	4	8	13	13	172	160	14	15	10	8	9	9	56	56	0	11	15	20	22	133	133	105
111	3	3	3	4	6	9	8	7	7	7	6	4	2	2	7	10	10	10	12	12	12	8	6	7	8	7	7	7	0	11	15	17	17	17	16
112	1	1	2	2	5	7	7	139	91	6	7	5	2	2	49	11	12	12	16	11	16	102	11	13	15	11	12	12	49	0	16	18	17	11	16
121	1	1	2	2	6	10	10	10	9	9	9	6	2	3	6	10	11	12	18	17	17	14	14	15	16	10	12	12	11	12	0	15	14	13	12
122	3	3	4	4	5	9	9	9	22	9	10	6	2	2	2	2	4	5	11	11	12	22	14	21	37	9	11	11	10	9	38	0	7	6	5
131	3	3	4	4	6	10	11	11	25	11	11	7	3	16	4	3	5	14	12	42	40	118	15	16	16	68	68	82	11	36	9	8	0	59	67
132	3	3	4	4	4	6	6	82	51	7	7	5	2	2	12	2	4	5	9	18	26	77	13	14	15	15	15	10	20	27	8	7	15	0	26
133	3	3	3	4	4	6	6	6	13	7	7	5	2	2	3	2	4	4	10	9	13	34	14	14	15	12	13	32	10	8	8	7	4	25	0

Motorcycle origin-destination movement patterns on Monday at 04:00 a.m. – 05:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	3	3	3	3	3	4	4	4	4	4	5	5	1	2	3	3	3	3	3	2	1	2	4	5	95	95	5	5	3	1	5	5	4	4
12	3	0	3	3	4	4	4	4	5	5	5	5	5	1	2	3	39	57	39	3	2	1	2	4	5	5	5	20	5	3	1	5	5	5	4
13	3	3	0	4	4	4	4	5	5	5	5	5	6	1	2	3	3	3	3	3	2	1	2	4	5	5	5	5	5	3	1	5	5	5	5
14	3	4	4	0	4	5	5	5	5	6	6	6	6	1	2	3	3	3	3	3	2	1	2	4	5	5	5	5	5	3	1	6	6	5	5
15	3	4	4	4	0	1	1	1	1	1	1	2	2	3	4	5	8	8	10	10	9	10	9	6	6	3	4	5	3	5	8	8	10	10	8
16	3	4	4	4	5	0	1	1	1	1	1	4	3	3	3	3	6	6	7	7	7	10	10	7	7	3	4	6	4	6	9	9	11	11	9
17	3	4	4	5	5	1	0	3	4	5	5	8	8	10	7	7	9	9	10	9	8	11	10	7	7	4	4	6	5	7	10	10	12	12	10
21	4	4	5	5	5	1	1	0	13	6	6	8	9	10	80	8	9	9	10	137	12	172	10	7	89	4	4	6	10	37	80	10	60	161	10
22	4	4	5	5	6	1	1	4	0	6	25	8	9	10	38	8	9	9	10	10	9	12	11	8	38	4	5	6	6	7	38	25	13	14	11
31	4	5	5	5	6	1	1	4	6	0	95	40	49	11	11	54	55	12	44	12	10	13	6	6	8	4	5	6	6	7	10	56	14	14	11
32	1	1	1	1	1	2	1	5	6	12	0	12	12	16	13	14	15	14	15	13	12	14	9	9	8	5	5	6	6	7	10	10	14	14	12
33	1	1	1	1	3	3	3	6	8	10	6	0	13	15	11	12	10	10	11	8	7	8	11	11	5	3	4	4	5	5	5	6	7	6	5
34	4	5	5	5	7	6	4	7	7	9	25	24	0	55	12	33	65	10	33	10	32	7	5	5	4	2	4	3	4	4	4	4	7	5	5
35	4	5	38	5	7	6	4	6	7	23	12	10	39	0	12	52	10	8	38	8	7	7	5	23	4	2	3	3	3	3	3	4	6	5	5
41	4	5	5	5	7	6	4	97	7	7	11	9	11	12	0	11	10	8	10	8	7	97	5	6	2	3	5	4	2	97	5	6	8	7	7
51	5	62	62	8	62	9	6	8	8	8	11	9	12	16	17	0	33	33	16	12	9	6	4	6	7	5	7	6	6	7	6	5	7	5	33
52	5	6	7	8	10	9	6	7	7	7	62	62	10	110	14	18	0	11	17	13	32	8	7	9	11	8	13	12	12	13	13	13	12	7	32
53	4	5	6	7	9	8	6	7	7	6	8	6	8	11	13	12	12	0	15	13	10	7	7	9	10	5	39	43	12	15	16	18	26	26	26
54	4	5	46	7	8	46	46	6	6	5	7	7	9	12	14	81	81	132	0	17	14	10	10	8	10	12	52	52	18	23	26	28	23	17	17
61	1	1	2	3	4	4	4	5	6	6	9	8	10	12	14	12	16	13	17	0	13	180	10	8	10	12	18	18	138	138	26	28	42	42	17
71	1	1	2	3	4	4	4	4	4	4	5	4	6	26	10	10	26	12	16	15	0	6	10	8	10	12	18	18	18	23	26	27	70	76	95
81	1	1	2	3	5	6	6	27	8	7	8	9	9	41	12	12	15	17	19	183	75	0	16	13	11	14	19	62	157	169	32	34	79	118	78
91	4	4	4	5	5	6	7	7	7	28	8	9	28	28	6	6	9	12	14	15	16	16	0	12	9	12	17	19	23	29	37	39	33	27	24
92	4	4	4	5	5	6	7	7	7	6	14	9	8	8	8	8	11	14	12	13	14	12	6	0	8	12	14	16	20	27	35	15	34	31	28
93	5	5	6	8	7	9	9	46	46	8	90	8	7	7	92	13	16	20	18	19	144	15	47	90	0	16	18	20	46	31	190	144	39	36	33
101	76	5	6	76	7	8	76	8	8	8	6	7	7	6	9	12	12	15	12	13	15	9	9	11	10	0	10	15	15	21	27	29	127	127	27
102	5	5	6	8	12	16	16	16	15	15	13	11	7	7	10	13	13	94	16	17	19	14	13	14	14	19	0	112	17	23	29	31	91	91	64
103	11	5	31	11	31	31	11	16	15	14	13	10	6	6	10	12	12	154	143	17	19	13	13	14	14	90	91	0	17	23	29	31	170	170	126
111	5	5	6	8	11	15	15	13	12	12	10	6	2	3	8	11	11	11	14	14	14	9	8	10	13	10	10	11	0	16	23	24	23	23	22
112	2	2	3	3	8	13	12	242	162	11	11	8	3	3	81	12	14	15	22	19	22	180	19	22	27	19	20	21	81	0	24	25	24	18	22
121	2	2	3	3	10	17	16	16	15	15	15	10	3	4	7	10	13	15	25	25	25	22	24	27	28	18	21	22	22	20	0	24	22	19	18
122	5	6	6	7	8	15	15	15	46	15	16	10	3	3	4	4	7	9	20	20	21	46	25	9	22	17	20	21	20	17	59	0	13	11	10
131	5	5	6	6	10	17	18	18	41	19	19	12	5	19	6	5	8	26	21	83	58	233	26	28	30	145	145	169	21	74	17	16	0	122	129
132	5	5	6	6	6	10	10	127	64	11	12	7	4	4	28	4	6	9	17	46	60	123	23	25	27	36	36	20	39	58	15	14	36	0	60
133	5	5	5	6	6	10	10	10	26	11	12	8	4	4	5	4	7	6	18	17	26	56	24	26	28	27	24	74	20	17	16	15	20	50	0

Motorcycle origin-destination movement patterns on Monday at 05:00 a.m. – 06:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	5	5	6	6	6	7	7	8	8	8	9	9	3	6	9	9	9	9	9	6	3	4	8	9	173	173	9	9	5	1	9	8	8	7
12	5	0	6	7	7	7	8	8	9	9	9	10	10	3	6	9	117	159	117	9	6	3	4	8	9	9	9	44	9	5	1	9	9	8	8
13	5	6	0	7	7	8	8	9	9	9	10	10	10	3	6	9	9	9	9	9	6	3	4	8	9	9	9	9	9	5	1	10	9	9	8
14	6	6	7	0	8	9	9	10	10	11	11	11	12	3	6	9	9	9	9	9	6	3	4	8	9	9	9	9	9	5	1	11	11	10	9
15	6	7	7	8	0	1	1	1	1	1	1	5	5	7	10	13	18	18	21	21	19	20	18	12	13	6	8	12	7	10	16	15	19	19	15
16	6	7	8	8	9	0	1	2	2	2	2	7	7	7	6	6	11	12	13	13	13	19	19	14	13	7	8	13	9	11	17	17	21	21	16
17	6	7	8	9	10	1	0	6	8	10	10	16	17	19	14	14	18	18	19	18	16	21	20	14	14	7	8	13	11	13	20	20	24	24	19
21	7	8	8	9	10	1	2	0	31	12	12	18	19	21	194	15	18	18	19	248	31	332	20	15	213	8	9	13	20	65	194	20	119	303	19
22	7	8	9	10	11	1	2	7	0	12	44	18	19	21	67	15	18	18	19	18	17	23	21	16	67	9	9	13	11	14	67	44	26	27	22
31	8	9	10	10	11	1	2	8	11	0	201	81	94	23	19	97	108	21	85	21	19	24	15	15	16	9	9	13	11	14	20	120	26	27	22
32	2	2	2	2	2	3	3	9	12	30	0	30	30	30	24	25	26	25	27	23	21	27	19	19	17	10	10	13	11	14	20	20	27	27	22
33	2	2	2	2	5	5	5	11	14	19	18	0	25	26	20	21	16	15	17	13	12	13	24	24	8	6	7	6	9	9	9	18	13	10	9
34	7	10	10	10	13	10	8	13	13	18	32	32	0	58	24	33	60	19	33	17	28	12	8	8	7	4	6	4	6	6	6	9	13	10	11
35	7	10	80	10	13	10	8	12	13	60	22	19	110	0	24	129	20	15	80	14	13	10	8	60	6	4	6	4	4	4	4	7	11	9	10
41	7	10	10	10	13	10	7	137	12	14	20	18	22	24	0	22	20	15	18	14	12	137	7	9	5	6	8	6	5	137	6	8	13	11	12
51	9	123	123	15	123	16	11	14	15	16	20	17	24	29	33	0	115	115	28	21	16	9	7	11	13	10	13	12	12	12	8	8	11	9	115
52	9	12	14	15	18	16	11	14	14	14	137	137	21	242	29	52	0	22	33	26	55	15	14	18	21	15	23	22	22	25	24	24	22	15	55
53	7	10	12	14	17	14	10	12	13	11	15	12	15	21	26	23	23	0	29	26	20	13	13	17	20	8	58	66	22	27	29	31	20	20	20
54	7	10	90	14	16	90	90	12	12	10	16	14	17	23	28	119	119	254	0	34	29	21	21	17	20	24	136	136	37	45	53	56	45	35	35
61	2	2	4	6	8	8	8	11	13	13	20	18	21	23	26	23	30	25	33	0	26	374	21	17	20	24	37	37	239	239	53	54	135	135	33
71	2	2	4	6	8	8	8	9	9	8	10	8	10	33	17	17	33	23	31	29	0	12	21	16	20	24	37	37	37	46	54	53	105	117	137
81	2	2	4	6	9	11	11	94	16	16	18	17	18	93	20	20	27	31	36	394	158	0	33	28	25	30	40	138	350	374	65	66	194	306	167
91	6	6	6	9	10	12	13	15	15	62	18	17	62	62	10	10	17	22	27	30	34	33	0	25	20	25	35	38	43	57	74	76	65	53	48
92	6	6	6	9	10	12	13	15	15	21	32	17	16	14	15	15	22	26	24	27	30	25	22	0	17	26	31	33	39	53	71	32	66	59	54
93	8	9	11	14	14	16	16	72	80	17	209	17	15	14	152	19	26	31	28	31	258	27	136	209	0	33	37	40	72	59	339	259	71	64	59
101	136	9	11	136	12	14	136	16	15	15	13	15	13	12	15	17	16	35	17	19	23	15	17	21	21	0	20	35	28	38	47	47	246	246	44
102	8	9	11	14	20	26	25	27	26	25	21	18	12	12	15	17	18	217	24	27	30	23	25	27	27	26	0	241	31	40	50	51	194	194	129
103	18	9	61	18	61	61	18	26	25	24	20	17	11	11	15	26	26	120	94	26	30	22	24	27	27	166	166	0	30	40	50	50	211	211	165
111	8	9	11	14	18	24	23	20	18	17	14	9	3	4	12	14	15	15	20	19	19	12	14	17	22	17	17	19	0	27	38	39	38	38	36
112	2	4	5	5	12	20	19	355	240	16	17	12	5	5	115	15	21	23	36	54	35	294	36	40	47	35	39	40	115	0	40	38	37	54	32
121	2	4	5	5	17	27	26	25	24	23	24	15	6	6	10	12	19	23	39	38	38	36	43	45	48	33	38	39	38	33	0	33	30	24	23
122	9	10	11	12	12	24	24	24	53	24	25	17	5	5	6	6	14	19	38	38	39	53	46	22	47	32	37	38	37	31	78	0	21	16	15
131	9	9	10	11	16	28	29	29	83	30	32	21	9	56	10	9	17	41	40	237	139	407	49	50	54	279	279	319	39	196	30	25	0	129	142
132	8	9	10	11	11	18	18	217	105	20	21	14	7	7	63	7	14	19	33	84	79	182	44	45	50	47	47	38	51	73	27	21	47	0	79
133	8	8	9	10	11	18	18	18	84	20	22	14	7	7	9	7	14	10	34	33	84	161	45	47	51	66	51	175	37	31	28	22	51	128	0

Motorcycle origin-destination movement patterns on Monday at 06:00 a.m. – 07:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	13	14	16	17	18	19	20	21	22	22	23	24	9	21	30	30	30	30	30	21	9	12	24	26	551	551	26	26	15	3	22	21	19	18
12	14	0	17	18	20	21	22	23	24	25	26	27	27	9	21	30	428	562	428	30	21	9	12	24	26	26	26	135	26	15	3	24	22	21	19
13	15	16	0	19	21	22	24	24	25	26	27	28	29	9	21	30	30	30	30	30	21	9	12	24	26	26	26	26	26	15	3	25	24	22	21
14	16	18	20	0	24	25	27	27	28	29	30	32	33	9	21	30	30	30	30	30	21	9	12	24	26	26	26	26	26	15	3	29	27	25	23
15	17	19	21	23	0	2	2	2	2	2	2	10	8	17	29	37	52	53	62	62	54	50	41	27	29	12	18	26	17	23	38	36	46	44	37
16	18	20	22	24	25	0	2	3	3	3	3	13	12	12	10	10	25	26	34	34	34	43	43	29	28	11	16	26	18	24	39	39	49	48	38
17	19	21	23	25	28	2	0	16	21	27	27	37	38	41	27	25	34	35	41	39	37	47	45	31	29	13	17	26	25	31	46	46	58	57	47
21	20	22	24	26	29	2	4	0	61	32	33	41	43	44	381	26	34	35	41	718	61	813	47	33	402	15	19	26	22	264	381	46	297	752	48
22	20	22	25	27	30	2	4	19	0	34	81	43	44	46	77	26	34	35	41	42	43	53	51	37	77	19	20	26	27	33	77	81	64	64	54
31	22	24	26	29	32	2	4	21	30	0	598	245	268	32	37	138	145	39	114	46	45	55	44	44	35	19	20	26	27	33	48	354	65	64	55
32	7	7	7	7	7	8	8	26	34	87	0	87	87	76	59	60	58	57	64	52	56	66	57	56	39	24	25	26	27	33	48	48	65	65	56
33	7	7	7	7	15	15	15	32	40	57	72	0	70	69	51	52	36	34	39	28	32	33	92	92	23	15	19	12	20	20	20	72	32	25	24
34	30	40	40	40	48	37	26	41	38	56	87	87	0	120	62	58	91	43	58	39	35	32	22	22	21	13	17	8	17	17	17	23	34	28	28
35	30	40	313	40	48	37	26	37	37	225	69	61	476	0	74	563	58	44	313	38	38	33	25	225	19	11	16	8	10	10	10	21	31	26	27
41	30	40	40	40	48	37	24	370	35	44	64	56	73	75	0	68	58	44	52	37	36	370	23	26	3	15	21	14	4	370	14	23	35	31	31
51	36	538	538	60	538	56	37	47	46	49	62	54	76	84	92	0	290	290	74	53	44	27	19	29	33	25	33	28	28	28	20	22	30	24	290
52	36	47	53	60	68	56	37	45	42	45	399	399	69	831	85	180	0	62	97	76	254	52	46	55	60	43	70	66	66	74	74	76	65	40	254
53	30	40	47	54	61	50	33	40	37	32	43	37	45	58	68	60	60	0	81	73	60	41	42	51	56	20	127	145	66	80	87	98	38	38	38
54	30	40	323	54	58	323	323	39	37	30	50	46	53	67	76	262	262	586	0	106	93	75	75	55	54	68	324	324	112	137	161	178	139	98	98
61	7	7	14	21	25	27	23	32	39	37	60	56	64	68	72	63	89	75	104	0	87	1339	75	55	54	68	112	112	924	924	161	172	418	417	92
71	7	7	14	21	25	27	25	26	26	23	30	26	30	100	42	42	100	67	95	90	0	32	72	51	55	70	112	112	114	139	162	168	299	330	398
81	7	7	14	21	28	32	30	212	77	37	44	42	43	411	48	48	74	78	101	1428	580	0	91	69	63	79	117	291	1144	1255	177	185	455	839	610
91	16	16	16	24	23	28	32	35	35	164	44	42	164	163	27	27	53	58	80	86	93	91	0	62	52	69	107	108	115	149	191	204	165	124	118
92	16	16	16	24	23	28	32	35	35	58	82	42	38	36	35	35	61	66	61	67	74	64	58	0	36	61	80	81	89	118	156	82	146	123	117
93	22	25	28	37	35	38	40	120	137	39	425	40	40	39	260	45	72	78	73	75	325	65	252	425	0	75	95	96	120	126	465	324	147	124	118
101	377	25	28	377	30	33	377	36	33	34	28	31	32	32	37	37	34	91	32	35	38	24	32	39	44	0	40	92	49	63	77	75	476	476	77
102	22	25	28	37	49	67	65	67	64	61	52	40	27	30	35	36	41	388	58	60	65	50	58	59	65	92	0	480	54	68	88	86	259	259	162
103	77	25	131	77	131	131	77	64	61	58	49	37	24	28	35	203	203	259	57	59	64	48	57	58	63	359	358	0	52	66	86	84	367	367	313
111	22	25	28	37	47	64	62	52	49	47	37	23	10	14	29	30	36	36	54	50	46	33	40	42	54	36	36	38	0	51	72	70	69	69	65
112	6	9	12	13	32	55	53	953	720	46	47	33	13	17	234	33	53	60	103	282	95	1001	101	98	111	68	80	83	234	0	80	74	72	282	57
121	6	9	12	13	39	67	64	62	60	57	59	39	16	20	27	28	53	62	106	102	98	93	111	106	107	61	76	79	78	68	0	68	63	47	44
122	24	26	28	30	29	62	62	62	131	62	65	45	12	12	14	14	39	54	109	109	110	131	124	22	73	59	74	77	75	67	181	0	53	38	37
131	22	24	26	28	38	73	74	74	324	77	81	56	22	154	24	21	46	61	112	739	476	1184	132	122	125	536	536	596	79	613	74	61	0	250	278
132	21	23	25	27	23	42	44	399	147	49	52	37	18	18	160	17	37	51	88	217	100	245	110	106	109	71	71	77	94	151	64	50	71	0	100
133	19	21	22	24	23	42	44	44	304	49	53	37	19	18	22	18	37	27	89	88	304	541	114	110	113	109	82	412	74	68	66	53	198	436	0

Motorcycle origin-destination movement patterns on Monday at 07:00 a.m. – 08:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	22	24	26	29	31	34	35	36	37	38	39	40	10	22	31	31	31	31	31	22	10	16	31	35	735	734	35	35	19	4	37	34	32	29
12	22	0	27	30	33	35	38	39	40	41	43	44	45	10	22	31	434	601	434	31	22	10	16	31	35	35	35	168	35	19	4	40	37	34	32
13	23	26	0	31	34	36	39	40	42	43	44	46	47	10	22	31	31	31	31	31	22	10	16	31	35	35	35	35	35	19	4	42	39	37	34
14	25	29	32	0	38	40	43	44	46	47	49	51	52	10	22	31	31	31	31	31	22	10	16	31	35	35	35	35	35	19	4	47	43	40	37
15	26	30	33	36	0	4	4	4	4	4	4	16	12	21	34	42	69	72	92	92	83	83	74	49	48	17	26	37	25	36	65	61	77	74	63
16	27	31	34	37	40	0	4	8	8	8	8	23	19	19	15	15	41	45	63	63	63	77	77	51	48	17	25	39	28	39	68	68	84	82	68
17	29	33	36	40	45	4	0	27	34	41	44	59	68	80	58	62	79	80	98	87	74	90	79	53	50	19	26	39	40	51	79	79	99	97	82
21	30	34	38	41	47	4	6	0	170	48	51	66	74	85	569	64	79	80	98	1273	170	1571	82	56	600	21	27	39	33	403	569	79	534	1403	83
22	31	35	39	42	48	4	6	32	0	50	194	68	76	87	141	64	79	80	98	91	81	97	86	61	141	26	30	39	42	53	141	194	108	108	93
31	33	37	41	45	51	4	6	37	51	0	907	330	395	154	103	568	657	112	503	119	96	111	47	47	57	26	30	39	42	53	81	578	109	109	94
32	11	11	11	11	11	14	14	44	59	111	0	112	111	161	131	141	144	138	155	129	113	128	69	68	65	33	37	39	42	53	81	81	110	110	96
33	11	11	11	11	23	23	23	53	68	91	107	0	132	149	120	129	106	97	107	80	64	68	109	109	33	21	29	19	35	35	35	107	52	41	39
34	37	51	51	51	64	50	37	63	64	87	270	270	0	769	132	200	698	110	200	95	500	65	40	40	30	18	26	14	28	28	28	36	52	41	42
35	37	51	483	51	64	50	37	54	59	362	112	100	653	0	126	773	107	87	483	78	68	60	46	362	28	16	25	14	16	16	16	32	46	39	39
41	37	51	51	51	64	50	35	615	54	68	106	93	117	132	0	120	107	87	99	77	65	615	44	49	7	24	35	25	7	615	25	37	54	47	48
51	47	657	657	80	657	79	53	69	72	74	104	91	121	143	149	0	375	375	127	96	75	53	39	53	49	37	49	41	41	42	31	35	47	37	375
52	47	61	71	80	92	79	53	64	60	64	492	492	91	1094	110	222	0	82	130	104	381	74	66	78	84	62	101	93	93	104	103	106	92	56	381
53	37	51	61	70	82	70	46	56	53	43	60	47	58	76	89	79	79	0	110	99	80	58	59	72	78	44	227	271	93	113	122	139	84	84	84
54	37	51	474	70	80	474	474	57	54	44	73	62	70	88	101	323	323	731	0	152	134	111	112	75	73	106	410	410	178	211	248	272	210	143	144
61	10	10	20	30	40	43	37	47	58	52	84	73	82	88	93	83	130	111	147	0	126	1750	112	75	73	106	178	178	1271	1271	248	264	479	479	136
71	10	10	20	30	40	43	38	40	40	35	45	35	38	195	56	56	195	99	136	130	0	53	106	69	74	107	178	178	180	213	250	258	454	507	648
81	10	10	20	30	42	52	47	519	138	59	70	66	63	572	66	66	111	122	150	2458	767	0	145	103	89	123	184	407	2080	2262	279	292	669	1384	795
91	22	22	22	33	35	44	49	56	56	193	70	66	193	193	40	40	86	97	125	136	147	145	0	94	75	110	170	176	192	237	297	316	256	187	174
92	22	22	22	33	35	44	49	56	56	58	97	66	56	55	50	50	96	107	99	110	121	109	58	0	58	102	137	143	159	197	256	97	235	194	180
93	31	35	39	52	52	62	62	115	326	62	752	62	57	56	450	58	104	118	110	115	711	109	488	752	0	121	156	162	115	210	1046	711	236	194	180
101	513	35	39	513	41	48	513	54	49	49	40	47	45	44	45	46	42	134	43	50	61	42	56	66	68	0	59	134	81	99	121	120	596	596	119
102	31	35	39	52	80	116	113	118	114	110	97	73	41	45	45	46	55	467	91	97	108	90	103	105	107	213	0	678	90	108	138	137	397	397	279
103	104	35	216	104	216	216	104	115	110	107	94	71	38	43	45	233	233	274	42	96	107	89	102	104	106	485	485	0	88	106	136	135	562	562	472
111	31	35	39	52	77	112	108	95	91	86	74	43	14	19	37	37	45	45	80	75	72	56	70	72	88	53	53	59	0	73	104	103	100	101	94
112	9	14	18	20	57	107	103	1882	1483	92	99	69	23	28	401	46	78	94	172	413	163	1895	178	172	181	103	120	125	401	0	123	118	115	413	93
121	9	14	18	20	69	123	119	117	112	109	114	76	26	31	38	39	76	95	177	172	168	162	189	181	173	91	112	118	116	101	0	108	98	77	72
122	38	41	44	47	51	114	114	114	217	114	123	84	21	21	25	25	62	88	187	187	187	217	208	29	122	93	114	120	118	105	311	0	88	67	65
131	35	37	40	43	67	132	134	135	770	140	149	101	37	427	41	37	74	128	193	1167	1196	2111	221	209	209	817	817	944	123	840	120	100	0	503	602
132	34	36	39	42	36	70	73	564	239	79	89	65	31	30	170	30	59	84	149	239	117	355	181	176	176	87	87	120	157	226	105	84	87	0	117
133	31	33	36	38	36	70	73	73	398	79	90	65	32	31	37	31	60	60	149	149	398	836	187	183	183	167	158	730	115	105	107	88	347	786	0

Motorcycle origin-destination movement patterns on Monday at 08:00 a.m. – 09:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	19	21	24	26	28	32	32	34	35	36	37	38	8	18	25	25	25	25	25	18	8	11	22	25	511	511	25	25	14	4	36	33	31	29
12	19	0	24	27	29	31	35	36	37	38	39	41	41	8	18	25	340	496	340	25	18	8	11	22	25	25	25	156	25	14	4	39	36	34	31
13	20	23	0	28	30	32	36	37	38	40	41	42	43	8	18	25	25	25	25	25	18	8	11	22	25	25	25	25	25	14	4	41	38	36	33
14	22	25	28	0	34	36	40	41	42	44	45	46	48	8	18	25	25	25	25	25	18	8	11	22	25	25	25	25	25	14	4	45	42	39	36
15	23	26	29	32	0	6	6	6	6	6	6	19	13	20	31	37	65	70	94	94	87	90	83	56	54	18	27	39	27	39	72	69	83	79	68
16	24	27	30	33	36	0	6	9	9	9	9	25	20	20	17	17	44	49	71	71	71	87	87	60	54	18	27	43	30	43	75	75	91	87	72
17	25	29	32	35	40	6	0	24	30	37	38	55	62	74	57	63	83	85	107	95	82	99	88	61	56	20	28	43	38	52	84	84	102	98	82
21	27	30	33	37	42	6	9	0	252	46	48	64	72	81	614	66	83	85	107	1342	252	1809	92	65	649	23	30	43	37	444	614	84	661	1560	83
22	27	31	34	38	43	6	9	29	0	47	168	66	73	83	162	66	83	85	107	99	90	107	96	69	162	27	32	43	40	54	162	168	110	109	92
31	30	34	37	40	46	6	9	35	48	0	697	275	340	128	100	592	655	113	528	124	103	119	41	41	64	27	32	43	40	54	86	424	110	109	93
32	10	10	10	10	10	16	16	41	55	157	0	157	157	148	123	133	140	137	158	134	119	136	86	86	71	34	38	43	40	54	86	86	110	110	95
33	10	10	10	10	24	24	24	49	63	83	90	0	120	136	111	120	100	92	102	77	63	66	97	97	34	21	29	21	32	32	32	90	47	37	34
34	29	37	37	37	51	41	33	54	60	80	266	266	0	723	120	162	618	102	162	90	457	63	39	39	30	17	26	14	25	25	25	31	46	36	36
35	29	37	470	37	51	41	33	48	55	332	102	88	518	0	109	656	91	74	470	72	63	57	44	332	29	15	25	14	16	16	16	29	42	35	36
41	29	37	37	37	51	41	30	636	49	60	92	78	99	110	0	102	91	74	88	70	60	636	41	47	10	25	37	28	10	636	27	36	52	43	44
51	37	444	444	62	444	66	46	59	64	66	90	77	103	121	127	0	312	312	112	87	69	49	37	50	48	36	48	41	41	42	32	34	45	35	312
52	37	45	54	62	74	66	46	54	52	55	384	384	74	858	91	159	0	72	114	92	318	67	58	71	78	56	90	83	83	94	92	93	83	52	318
53	27	37	44	52	65	56	39	47	45	37	52	39	48	66	77	70	70	0	98	88	71	52	53	66	73	46	278	323	83	104	113	130	105	105	105
54	27	37	396	52	61	396	396	44	43	36	61	53	60	77	89	294	294	643	0	130	112	93	94	67	69	94	349	349	153	187	221	245	193	139	139
61	9	9	17	25	34	36	33	40	48	44	74	67	73	80	85	77	113	96	127	0	107	1470	94	67	69	94	153	153	1022	1022	221	238	449	449	133
71	9	9	17	25	34	36	33	36	36	32	44	37	40	253	57	57	253	86	117	112	0	56	89	61	70	95	153	153	155	190	223	234	492	547	744
81	9	9	17	25	37	44	41	404	115	54	67	65	63	557	65	65	101	110	132	1968	715	0	126	93	79	108	157	438	1745	1899	252	266	696	1168	767
91	21	21	21	31	32	39	45	51	51	221	67	65	221	221	41	41	77	86	110	119	128	126	0	86	67	95	145	151	169	213	266	287	237	182	167
92	21	21	21	31	32	39	45	51	51	45	111	65	57	57	51	51	87	96	88	99	108	96	45	0	57	95	123	130	147	183	235	111	219	184	170
93	28	32	36	47	46	54	56	136	267	58	697	60	55	54	412	54	90	104	96	102	751	96	444	697	0	112	142	148	136	194	1027	751	218	183	169
101	485	32	36	485	38	44	485	50	46	47	40	45	44	42	42	43	38	89	41	47	58	41	55	64	65	0	58	89	82	97	116	115	493	493	112
102	28	32	36	47	77	111	109	113	110	106	94	71	40	43	42	43	52	464	85	92	102	86	100	101	102	265	0	728	92	107	135	133	332	332	236
103	73	32	198	73	198	198	73	110	106	102	91	68	37	40	42	184	184	236	53	91	102	85	99	100	101	442	442	0	90	105	132	130	594	594	494
111	28	32	36	47	74	109	104	93	89	85	73	44	14	18	35	36	43	43	75	72	69	55	69	70	86	54	54	61	0	73	101	99	94	95	87
112	8	12	16	17	54	101	97	1888	1410	87	92	63	21	25	478	42	71	82	150	391	144	1799	159	158	174	106	119	126	478	0	122	112	108	391	88
121	8	12	16	17	70	123	119	117	113	110	114	74	25	29	37	37	71	85	159	155	152	147	174	169	167	94	114	120	117	104	0	110	97	77	71
122	35	37	40	43	55	111	111	111	253	111	117	77	21	21	25	25	58	76	160	160	161	253	183	33	139	97	116	123	120	103	359	0	75	57	53
131	33	35	38	40	70	127	129	130	599	135	142	93	36	312	40	36	70	139	166	954	910	1749	195	186	195	831	831	969	125	665	110	91	0	487	509
132	32	34	37	39	37	67	69	756	338	75	82	56	28	27	196	28	53	71	124	280	140	477	156	155	164	92	92	121	223	306	94	73	92	0	140
133	30	31	34	36	37	67	69	69	160	75	83	56	28	28	35	28	54	66	125	124	160	496	162	162	170	196	188	627	116	101	96	77	180	516	0

Motorcycle origin-destination movement patterns on Monday at 09:00 a.m. – 10:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	19	21	23	26	27	31	32	33	34	35	36	37	8	20	27	27	27	27	27	20	8	9	18	22	420	420	22	22	13	4	35	33	31	28
12	18	0	23	26	28	30	34	35	36	38	38	39	40	8	20	27	363	550	363	27	20	8	9	18	22	22	22	188	22	13	4	37	35	33	30
13	19	22	0	27	30	32	35	36	37	39	40	41	42	8	20	27	27	27	27	27	20	8	9	18	22	22	22	22	22	13	4	40	37	35	32
14	21	24	27	0	33	35	38	40	41	42	43	45	46	8	20	27	27	27	27	27	20	8	9	18	22	22	22	22	22	13	4	43	40	38	35
15	22	25	28	31	0	6	6	6	6	6	6	20	14	22	34	40	68	73	98	98	90	93	86	59	57	20	28	41	28	40	72	68	81	78	65
16	23	26	29	32	35	0	6	10	10	10	10	27	21	21	18	18	45	51	72	72	72	89	89	62	56	19	28	44	31	43	74	74	89	86	69
17	24	28	31	34	38	6	0	22	26	33	36	53	58	71	56	61	81	84	105	94	82	100	90	63	57	21	28	44	37	50	81	81	98	95	77
21	25	29	32	35	40	6	10	0	282	41	44	62	67	76	666	64	81	84	105	1341	282	1837	94	67	699	24	30	44	35	404	666	81	619	1556	79
22	26	30	33	36	41	6	10	27	0	43	162	64	69	78	169	64	81	84	105	98	89	107	98	70	169	28	32	44	39	52	169	162	106	105	87
31	28	32	35	38	43	6	10	32	44	0	570	223	303	162	97	539	621	112	461	123	102	119	32	32	65	28	32	44	39	52	83	348	107	105	88
32	10	10	10	10	10	16	15	37	49	150	0	150	150	141	119	129	137	135	155	132	116	135	82	82	71	34	37	44	39	52	83	83	107	106	89
33	10	10	10	10	24	24	23	45	57	76	89	0	110	128	106	115	96	88	98	75	60	63	89	89	32	19	28	22	31	31	31	89	45	34	31
34	28	36	36	36	50	41	33	51	54	72	241	241	0	712	116	153	625	98	153	89	472	60	38	38	29	15	25	15	24	24	24	31	44	33	34
35	28	36	443	36	50	41	33	47	53	285	96	82	472	0	105	632	88	72	443	71	61	54	41	285	28	14	24	15	16	16	16	28	40	32	33
41	28	36	36	36	50	41	30	662	47	57	87	73	92	106	0	98	88	72	86	69	57	662	39	44	6	23	35	27	6	662	26	34	49	40	40
51	36	441	441	60	441	65	44	57	61	63	85	72	96	115	122	0	335	335	109	85	66	47	36	47	46	33	46	40	40	41	31	32	42	32	335
52	36	44	52	60	73	65	44	52	51	53	380	380	69	748	87	144	0	68	107	86	227	60	52	64	72	50	80	75	74	84	82	83	76	48	227
53	27	36	43	51	65	55	38	46	45	37	51	37	46	64	75	68	68	0	92	83	66	46	47	59	67	46	248	292	74	95	106	122	93	93	93
54	27	36	376	51	57	376	376	40	39	32	55	49	56	74	86	278	278	609	0	117	99	80	81	59	64	80	331	331	127	162	198	219	180	138	138
61	8	8	16	24	30	32	27	35	42	37	65	59	66	74	78	71	102	85	112	0	92	1266	81	59	64	80	127	127	854	854	198	213	413	413	131
71	8	8	16	24	30	32	28	30	30	25	36	31	35	275	53	53	275	77	105	100	0	60	77	55	65	81	127	127	129	164	199	210	532	590	805
81	8	8	16	24	33	39	36	272	86	46	58	57	56	515	61	61	92	100	119	1675	641	0	110	82	72	93	132	494	1305	1439	226	241	724	1232	698
91	20	20	20	30	30	36	39	45	45	156	58	57	156	156	39	39	71	78	97	105	112	110	0	75	61	81	121	126	143	184	239	257	218	176	162
92	20	20	20	30	30	36	39	45	45	42	79	57	50	52	47	47	78	87	79	87	95	84	42	0	52	81	104	108	125	161	214	79	207	180	168
93	26	30	35	44	43	49	49	177	218	49	654	51	47	44	403	48	79	93	85	90	705	86	307	654	0	99	121	127	177	172	930	705	201	176	163
101	477	30	35	477	37	42	477	46	42	41	35	38	36	35	35	37	35	96	37	42	54	39	49	58	59	0	55	96	76	91	108	109	411	411	106
102	26	30	35	44	67	92	88	93	89	85	74	59	36	36	37	40	46	412	70	74	86	71	81	84	85	220	0	631	86	100	123	124	343	343	260
103	45	30	194	45	194	194	45	90	86	82	72	56	34	36	37	90	90	246	156	73	85	70	80	83	84	442	442	0	84	98	122	122	584	584	483
111	26	30	35	44	64	90	86	75	72	68	57	36	12	13	29	32	37	37	61	59	58	46	56	60	74	51	51	59	0	70	94	94	89	90	81
112	6	10	15	15	44	82	78	1434	995	70	74	54	18	20	441	38	62	73	130	282	127	1276	139	139	149	93	106	113	441	0	112	108	104	282	84
121	6	10	15	15	60	105	101	100	96	92	97	65	22	24	31	34	63	77	140	138	137	133	155	150	145	84	104	111	108	97	0	106	93	74	67
122	32	33	36	39	46	94	94	94	297	94	100	68	20	20	23	23	53	71	142	142	143	297	162	36	157	85	105	112	109	94	417	0	71	52	46
131	29	31	34	36	60	108	110	111	577	116	123	82	34	295	37	33	63	98	147	880	872	1638	174	165	170	677	677	775	113	625	101	85	0	437	477
132	28	30	33	35	36	65	67	771	345	73	80	54	26	25	187	26	49	67	118	276	140	483	147	144	149	96	96	110	241	328	86	71	96	0	140
133	26	28	30	32	36	65	67	68	143	73	81	55	27	26	32	26	50	76	118	118	143	449	153	150	155	208	156	575	106	92	88	74	138	443	0

Motorcycle origin-destination movement patterns on Monday at 10:00 a.m. – 11:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	19	21	23	26	27	31	32	33	35	36	37	37	8	20	27	27	27	27	27	20	8	9	17	21	400	400	21	21	13	4	37	34	32	30
12	19	0	23	26	29	30	34	35	37	38	39	40	41	8	20	27	370	544	370	27	20	8	9	17	21	21	21	175	21	13	4	39	36	34	32
13	20	22	0	27	30	32	36	37	38	40	40	42	43	8	20	27	27	27	27	27	20	8	9	17	21	21	21	21	21	13	4	41	38	36	34
14	22	25	27	0	33	35	39	40	41	43	44	46	47	8	20	27	27	27	27	27	20	8	9	17	21	21	21	21	21	13	4	45	42	39	36
15	23	26	28	31	0	7	7	7	7	7	7	23	17	24	35	43	71	78	107	107	100	105	98	69	67	23	32	47	31	49	88	85	98	95	78
16	24	27	30	33	36	0	7	10	10	10	10	29	23	23	20	20	49	55	81	81	81	101	101	72	66	22	31	49	33	52	91	91	105	102	82
17	25	29	31	34	39	7	0	23	30	36	39	58	62	71	55	57	78	82	108	100	90	109	103	73	68	23	32	49	40	59	98	98	114	110	92
21	26	30	33	36	41	7	11	0	295	49	52	70	73	79	775	61	78	82	108	1421	295	2213	105	76	828	27	33	49	52	431	775	98	929	1920	93
22	27	31	34	37	42	7	11	29	0	50	153	71	75	81	149	61	78	82	108	103	97	116	108	80	149	30	35	49	41	61	149	153	121	119	101
31	29	33	36	39	44	7	11	34	48	0	646	294	368	133	86	447	504	97	372	116	104	123	31	31	73	30	35	49	41	61	100	353	122	120	102
32	13	13	13	13	13	19	18	40	56	199	0	199	199	137	114	121	127	125	151	128	122	141	84	84	81	36	41	49	41	61	100	100	122	121	103
33	13	13	13	13	26	26	25	47	63	85	72	0	115	121	99	105	82	74	84	61	55	58	81	81	32	19	28	20	29	29	29	72	43	33	31
34	32	40	40	40	54	44	35	54	59	82	239	239	0	473	109	92	327	86	92	75	235	55	34	34	29	16	25	14	23	23	23	30	44	33	34
35	32	40	584	40	54	44	35	48	56	341	95	82	560	0	99	803	80	65	584	60	57	49	35	341	28	15	24	14	15	15	15	26	39	31	32
41	32	40	40	40	54	44	30	630	47	59	82	70	91	98	0	92	80	65	78	59	53	630	34	37	5	22	33	25	5	630	25	32	47	39	39
51	40	457	457	68	457	70	48	61	64	67	81	69	95	107	113	0	351	351	101	74	62	43	30	41	44	32	44	37	37	38	30	31	41	31	351
52	40	50	59	68	80	70	48	56	54	57	381	381	73	690	91	138	0	72	110	86	174	61	50	61	70	47	76	70	70	79	79	80	74	49	174
53	29	37	46	56	69	59	41	49	47	38	50	37	45	65	76	69	69	0	91	82	63	44	44	56	64	42	217	258	70	91	105	124	96	96	96
54	29	37	435	56	61	435	435	43	41	33	55	49	56	75	87	268	268	590	0	115	96	77	77	56	61	77	323	323	122	160	198	221	184	143	144
61	10	10	19	28	34	35	31	38	46	41	69	63	70	77	81	73	102	83	109	0	89	1222	77	56	61	77	122	122	776	776	198	214	448	448	137
71	10	10	19	28	34	35	32	34	34	30	42	36	39	334	57	57	334	76	103	99	0	70	75	53	62	78	122	122	124	162	200	213	586	656	918
81	10	10	19	28	37	44	40	272	99	52	65	64	63	502	66	66	94	101	117	1607	647	0	109	83	72	93	130	494	1299	1430	229	245	757	1206	714
91	20	20	20	30	31	36	41	48	48	218	65	64	218	218	45	45	73	80	97	105	112	109	0	77	62	82	119	124	141	183	237	257	218	177	165
92	20	20	20	30	31	36	41	48	48	40	109	64	57	59	52	52	80	87	79	87	94	85	40	0	53	82	104	108	126	160	209	109	203	177	165
93	26	31	35	45	44	51	52	231	204	54	683	57	52	48	441	51	79	92	83	90	716	87	349	683	0	99	120	125	231	169	926	716	194	169	156
101	469	31	35	469	39	43	469	50	46	46	40	44	42	38	37	40	36	121	37	43	56	41	50	59	58	0	55	121	76	87	103	103	291	290	99
102	26	31	35	45	63	83	80	85	81	77	67	55	36	37	35	39	44	341	65	70	83	69	77	80	79	221	0	560	84	95	115	116	269	269	194
103	52	31	198	52	198	198	52	82	78	74	64	52	33	35	35	85	85	262	178	70	82	68	76	79	78	408	408	0	81	93	113	113	600	600	511
111	26	31	35	45	58	80	76	66	62	58	47	31	10	12	27	31	35	35	56	55	54	42	52	55	69	48	48	57	0	64	84	85	82	82	73
112	7	11	15	16	38	72	69	1161	795	60	65	49	17	18	367	36	57	69	118	269	116	1063	126	126	134	83	93	102	367	0	103	102	99	269	80
121	7	11	15	16	55	97	93	92	88	84	89	60	20	22	30	33	59	72	130	128	127	123	141	138	131	75	93	102	98	90	0	103	91	75	67
122	32	34	36	39	41	87	87	87	317	87	94	65	19	19	22	22	48	66	133	133	134	317	154	33	177	83	101	109	105	91	461	0	70	54	47
131	29	31	34	36	55	102	104	105	553	109	116	79	33	319	36	32	58	95	139	747	872	1462	166	159	164	587	587	680	109	493	100	83	0	418	482
132	29	30	33	35	37	68	70	811	376	76	83	57	26	26	183	25	46	64	113	264	121	496	143	142	147	83	83	108	254	335	88	70	83	0	121
133	26	28	30	32	37	68	70	70	211	76	84	57	27	26	32	26	47	56	114	113	211	511	149	148	153	297	178	720	103	91	90	74	192	492	0

Motorcycle origin-destination movement patterns on Monday at 11:00 a.m. – 12:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	19	21	24	27	28	32	33	34	36	37	38	38	10	22	31	31	31	31	31	22	10	9	17	20	395	395	20	20	12	4	38	35	33	31
12	19	0	24	27	29	31	35	36	37	39	40	41	42	10	22	31	432	593	432	31	22	10	9	17	20	20	20	163	20	12	4	40	37	35	32
13	20	23	0	28	30	32	36	37	38	40	41	42	43	10	22	31	31	31	31	31	22	10	9	17	20	20	20	20	20	12	4	42	39	37	34
14	22	25	28	0	33	35	39	40	42	44	45	46	47	10	22	31	31	31	31	31	22	10	9	17	20	20	20	20	20	12	4	45	42	40	37
15	23	26	29	32	0	6	6	6	6	6	6	25	20	29	40	49	78	84	112	112	103	111	103	74	71	26	34	52	32	53	95	92	104	102	83
16	24	27	30	33	36	0	6	10	10	10	10	32	26	26	23	23	51	57	83	83	83	105	105	77	71	25	33	54	35	56	98	98	111	108	87
17	25	28	31	35	39	6	0	21	26	33	35	56	60	70	57	60	82	86	112	103	93	115	106	78	72	26	34	54	40	62	103	103	118	116	95
21	26	30	33	36	41	6	10	0	279	43	46	68	71	78	909	64	82	86	112	1408	279	2333	110	82	975	30	35	54	67	380	909	103	1026	2054	96
22	27	31	34	37	42	6	10	26	0	45	157	69	72	79	144	64	82	86	112	106	100	123	114	86	144	34	37	54	41	63	144	157	126	125	103
31	29	33	36	40	44	6	10	32	47	0	531	248	319	109	87	485	522	97	413	116	104	128	26	26	80	34	37	54	41	63	104	284	126	126	103
32	13	13	13	13	13	19	18	39	55	188	0	188	188	138	116	123	129	126	152	128	124	147	99	99	87	41	44	54	41	63	104	104	127	126	105
33	13	13	13	13	24	24	23	45	60	83	63	0	115	119	98	104	81	72	81	57	53	56	86	86	31	20	27	18	25	25	25	63	39	31	29
34	33	43	43	43	54	44	34	52	57	80	312	312	0	485	112	66	239	87	66	74	174	53	32	32	28	17	24	12	19	19	19	28	41	33	34
35	33	43	587	43	54	44	34	48	56	373	97	86	620	0	103	833	83	66	587	58	56	47	34	373	27	16	24	12	13	13	13	26	38	32	33
41	33	43	43	43	54	44	30	536	48	61	85	74	97	103	0	96	83	66	76	56	52	536	31	35	4	21	30	21	4	536	22	32	47	40	41
51	40	489	489	66	489	67	44	59	62	68	84	73	101	111	117	0	428	428	98	70	60	39	27	36	39	29	39	32	32	34	26	31	41	33	428
52	40	50	58	66	76	67	44	52	49	55	364	364	76	712	95	178	0	76	113	88	171	62	50	60	67	45	73	67	67	77	79	84	77	51	171
53	29	38	46	54	65	55	37	44	42	35	48	37	46	68	79	71	71	0	93	84	63	43	44	53	60	33	178	210	67	90	106	131	103	103	103
54	29	38	373	54	59	373	373	40	37	30	54	49	57	77	90	262	262	536	0	115	94	74	75	56	55	66	275	274	106	140	177	208	174	137	137
61	8	8	16	24	29	31	27	35	41	38	67	62	69	77	81	73	98	78	106	0	85	1314	75	56	55	66	106	106	845	845	177	200	472	471	129
71	8	8	16	24	29	31	28	30	30	26	40	35	39	340	55	55	340	71	100	95	0	66	72	53	56	67	106	106	108	142	179	198	621	686	960
81	8	8	16	24	35	39	37	236	83	50	65	64	64	515	65	65	90	94	112	1410	637	0	106	84	69	86	118	308	1053	1165	206	227	505	984	646
91	20	20	20	29	30	35	40	48	48	205	65	64	205	205	45	45	69	74	93	102	108	106	0	78	61	76	109	111	126	165	215	239	204	167	155
92	20	20	20	29	30	35	40	48	48	41	99	64	58	60	53	53	77	81	73	81	89	80	41	0	47	72	88	90	105	137	184	99	187	168	156
93	26	30	34	44	44	50	51	273	199	53	717	57	54	52	478	53	77	89	79	85	631	81	380	717	0	88	103	106	273	147	837	631	183	163	152
101	461	30	34	461	39	43	461	50	46	46	40	44	43	41	39	42	38	95	37	43	55	39	48	56	55	0	52	95	69	85	104	109	307	307	105
102	26	30	34	44	59	77	74	80	76	72	62	52	37	39	37	40	46	359	62	68	79	64	72	74	74	149	0	508	75	92	116	121	303	303	234
103	46	30	198	46	198	198	46	77	73	69	59	49	35	37	37	144	144	277	135	67	78	64	71	74	73	383	383	0	73	90	113	119	700	700	614
111	26	30	34	44	54	73	69	60	56	51	41	28	10	13	28	31	36	36	55	52	50	38	46	49	61	42	42	50	0	63	87	92	91	91	82
112	7	11	15	16	35	66	62	985	677	53	58	44	17	20	309	37	56	66	111	261	106	936	113	114	120	75	83	92	309	0	102	105	103	261	87
121	7	11	15	16	51	89	85	84	80	76	82	55	20	23	31	34	56	69	121	118	116	111	129	126	120	69	84	93	90	85	0	103	93	79	70
122	31	33	35	37	36	80	80	80	307	80	87	61	17	17	20	20	42	61	127	127	128	307	145	26	160	76	91	100	97	86	443	0	70	57	51
131	28	30	33	35	50	96	98	98	515	103	109	74	31	322	34	30	53	96	132	633	836	1294	157	151	154	540	540	634	101	422	99	83	0	358	469
132	27	29	32	34	35	68	69	777	377	75	83	56	26	25	155	24	42	60	110	226	115	492	137	137	140	68	68	101	246	318	88	71	68	0	116
133	25	27	29	31	35	68	69	69	273	75	83	57	26	26	31	25	43	39	110	110	273	670	143	142	145	257	135	701	95	86	90	75	274	673	0

Car origin-destination movement patterns on Monday at 12:00 a.m. – 01:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	5	3	1	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1
16	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1
17	1	1	1	1	1	1	0	1	1	1	1	1	1	3	3	3	2	2	6	6	11	7	6	3	3	3	2	1	2	5	5	6	9	9	8
21	1	1	1	1	1	1	1	0	2	2	1	1	1	5	15	5	2	2	6	35	2	42	6	5	16	5	2	1	2	7	15	9	13	41	8
22	1	1	1	1	1	1	1	1	0	2	5	3	1	6	11	6	2	1	6	6	11	7	7	5	11	5	2	1	2	7	11	5	10	9	8
31	1	1	1	1	1	1	1	1	1	0	2	1	2	2	4	4	4	1	3	1	2	1	1	1	3	3	2	2	2	4	5	2	2	2	1
32	1	1	1	1	1	1	1	1	1	3	0	3	3	2	1	2	2	1	1	1	2	1	2	2	1	2	2	2	2	2	1	1	1	2	2
33	1	1	1	1	1	1	1	1	1	3	2	0	6	3	2	2	2	1	1	1	1	2	2	2	1	2	2	2	2	2	1	2	1	2	2
34	1	1	1	1	1	1	1	1	1	2	5	5	0	8	3	2	5	2	2	1	4	1	1	1	1	2	2	2	2	2	1	1	1	2	1
35	1	1	3	1	1	1	2	2	2	2	3	4	2	0	3	4	2	2	3	1	2	2	2	2	1	2	2	2	2	2	2	2	2	2	1
41	1	2	2	2	1	1	2	11	2	1	1	1	1	1	0	2	3	2	1	1	2	11	2	1	1	2	2	2	2	11	2	2	2	1	2
51	1	5	5	2	5	1	2	2	2	1	1	1	1	1	1	0	5	5	1	1	2	2	2	3	3	3	3	2	2	2	2	2	2	2	5
52	1	2	2	2	1	1	2	2	2	1	3	3	1	6	1	1	0	2	1	1	3	1	3	3	1	3	4	4	2	2	2	1	2	4	3
53	1	1	1	1	1	2	2	1	2	1	1	1	1	1	2	2	4	0	2	1	1	1	3	3	1	2	7	8	4	3	2	1	4	4	4
54	1	1	5	1	1	5	5	1	2	2	2	2	2	2	1	4	4	9	0	3	3	3	3	3	1	4	6	6	6	3	2	2	4	4	4
61	1	1	1	1	1	2	2	1	2	2	2	2	1	1	2	2	4	3	2	0	3	12	3	3	3	2	4	5	9	9	2	5	5	5	15
71	1	1	1	1	2	2	1	1	1	1	2	2	2	4	2	1	4	1	4	5	0	2	3	3	3	3	2	6	8	7	4	6	10	11	13
81	1	1	1	1	2	2	1	3	2	1	1	1	2	3	2	1	1	1	4	18	5	0	1	3	3	3	2	7	14	15	3	6	8	13	4
91	1	1	1	1	2	2	1	1	2	2	1	1	2	2	1	3	3	3	4	5	5	2	0	1	3	3	2	4	6	5	3	2	6	7	6
92	1	1	1	1	2	2	1	2	3	2	2	3	1	2	2	2	3	3	3	3	3	4	2	0	3	3	3	1	1	5	8	2	5	2	2
93	1	1	1	1	1	1	1	5	6	4	11	3	2	2	10	2	1	1	1	3	17	4	5	11	0	3	1	1	5	5	22	17	6	2	3
101	3	1	1	3	1	1	3	2	2	3	2	2	2	2	2	2	2	2	2	3	3	4	4	4	4	0	4	2	4	5	8	11	4	4	15
102	1	1	1	2	2	2	1	1	2	2	2	2	2	2	1	1	5	7	6	2	3	3	3	3	2	4	0	9	3	2	2	5	10	10	9
103	1	1	4	1	4	4	1	1	2	2	2	2	2	2	1	3	3	11	8	2	3	3	3	3	2	4	4	0	3	2	2	4	2	2	2
111	1	1	1	2	2	2	7	12	12	6	2	2	2	2	2	3	4	5	5	3	6	6	6	2	1	2	2	4	0	3	2	1	2	2	2
112	1	1	1	1	1	1	7	44	34	6	2	2	2	2	11	2	2	2	1	6	6	38	6	2	2	2	2	3	11	0	2	2	1	6	1
121	1	1	1	1	1	1	7	12	12	6	2	2	2	2	2	2	2	2	1	1	7	6	6	1	1	1	2	3	3	4	0	2	1	1	1
122	1	1	1	1	1	1	2	3	6	3	2	2	1	1	1	2	1	1	2	6	11	6	5	1	4	6	8	6	4	3	8	0	2	2	2
131	1	1	1	1	1	1	2	5	8	4	2	2	1	4	1	1	1	5	3	6	10	13	6	1	4	11	11	14	6	5	4	2	0	4	4
132	1	1	1	1	1	1	2	7	5	4	2	2	1	1	1	1	1	1	3	3	2	6	6	2	4	2	2	10	4	5	2	1	2	0	2
133	1	1	1	1	1	1	4	6	3	3	1	1	1	1	1	1	1	1	2	3	3	4	4	2	3	3	3	6	4	2	1	1	2	2	0

Car origin-destination movement patterns on Monday at 01:00 a.m. – 02:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	5	4	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	0	1	1	1	1	1	1	2	2	2	1	1	3	4	7	5	5	2	2	2	2	1	1	4	3	4	5	5	5
21	1	1	1	1	1	1	1	0	4	2	1	1	1	4	11	4	1	1	3	17	4	25	5	4	11	4	2	1	2	4	11	6	8	22	5
22	1	1	1	1	1	1	1	1	0	3	4	3	1	4	9	5	1	1	4	4	7	5	5	4	9	4	2	1	1	6	9	4	6	5	6
31	1	1	1	1	1	1	1	1	1	0	3	2	2	1	3	4	3	1	3	1	2	1	1	2	2	2	2	2	2	3	4	2	2	1	1
32	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	2	1	1	1	1	2	2	2	2	2	1	1	1	2	1
33	1	1	1	1	1	1	1	1	1	1	1	0	3	2	2	2	2	2	1	1	1	1	1	1	1	2	2	2	2	2	1	1	1	2	1
34	1	1	1	1	1	1	1	1	1	1	2	2	0	5	2	4	6	2	4	1	4	1	1	1	1	2	2	2	2	2	1	1	1	2	1
35	1	1	1	1	1	1	2	2	2	2	2	2	3	0	2	2	2	2	1	1	2	2	2	2	1	1	2	1	2	2	2	2	2	2	1
41	1	1	1	1	1	1	2	9	2	1	1	1	1	1	0	3	4	3	2	1	2	9	2	1	1	1	2	1	1	9	2	2	2	2	2
51	1	2	2	1	2	1	2	2	2	1	1	1	1	1	1	0	7	7	2	1	2	2	2	1	1	1	2	1	2	2	2	2	2	2	7
52	1	1	1	1	1	1	1	2	2	1	2	2	1	5	1	2	0	3	2	1	2	1	2	2	1	2	3	3	2	2	2	1	1	3	2
53	1	1	1	1	1	2	2	1	2	1	1	1	1	1	2	2	4	0	2	1	1	1	2	2	1	2	5	6	3	2	2	1	2	2	2
54	1	1	4	1	1	4	4	1	2	2	2	2	2	2	1	4	4	9	0	2	2	2	2	2	1	3	6	6	5	2	1	1	2	3	2
61	1	1	1	1	1	2	2	1	2	2	2	2	1	1	2	2	4	4	2	0	2	9	2	2	2	2	3	4	6	6	1	2	4	4	7
71	1	1	1	1	1	1	1	1	1	1	2	2	2	5	2	1	5	1	3	4	0	1	2	2	2	2	1	5	7	6	3	4	4	5	7
81	1	1	1	1	1	1	1	5	1	1	1	1	2	5	2	1	1	1	3	12	6	0	1	2	2	2	1	6	13	13	3	3	6	9	6
91	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	3	4	4	2	0	1	2	2	1	4	6	5	3	2	5	6	6
92	1	1	1	1	1	1	1	2	2	1	3	2	1	1	1	1	2	2	2	2	2	3	1	0	3	2	2	1	1	4	6	3	3	2	1
93	1	1	1	1	1	1	1	4	4	3	8	2	2	1	6	1	2	2	2	2	12	3	3	8	0	2	2	1	4	4	15	12	4	1	2
101	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	1	1	1	1	2	2	3	3	3	3	0	2	2	2	4	6	9	2	2	15
102	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1	1	4	4	5	2	2	2	2	2	1	2	0	5	1	2	2	5	11	11	9
103	1	1	2	1	2	2	1	1	2	2	2	2	2	2	1	3	3	10	8	2	2	2	2	2	1	4	4	0	1	2	2	5	3	3	2
111	1	1	1	1	1	1	6	11	11	6	2	2	2	1	1	2	3	4	4	2	6	6	6	2	1	2	2	2	0	1	2	1	2	3	3
112	1	1	1	1	1	1	6	36	32	6	2	2	2	1	5	1	2	2	1	6	6	36	6	2	2	2	2	1	5	0	2	2	1	6	1
121	1	1	1	1	1	1	6	11	11	6	2	2	2	1	1	1	2	2	1	1	6	6	6	1	1	1	2	1	1	2	0	1	1	1	1
122	1	1	1	1	1	1	1	1	3	1	1	2	1	1	1	2	1	1	2	4	6	3	3	1	2	5	7	5	4	2	4	0	2	3	3
131	1	1	1	1	1	1	1	2	4	2	1	1	1	4	1	1	1	4	2	6	6	9	4	1	3	9	9	11	5	5	2	1	0	4	6
132	1	1	1	1	1	1	1	5	2	2	1	1	1	1	2	1	1	1	2	2	1	3	4	2	3	1	1	8	2	3	2	1	1	0	1
133	1	1	1	1	1	1	3	4	1	2	1	1	1	1	1	1	1	1	1	2	1	2	2	2	2	2	3	6	3	1	1	1	2	3	0

Car origin-destination movement patterns on Monday at 02:00 a.m. – 03:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	2	3	5	4	3	1	1	1	1	1	1	2	2	3	4	4	4
21	1	1	1	1	1	1	1	0	3	1	1	1	1	2	5	2	1	1	2	12	3	17	3	2	6	2	1	1	1	4	5	5	7	16	4
22	1	1	1	1	1	1	1	1	0	2	3	1	1	3	6	3	1	1	3	3	5	4	3	2	6	2	1	1	1	4	6	3	5	4	4
31	1	1	1	1	1	1	1	1	1	0	2	1	1	2	2	3	4	1	3	1	2	1	1	2	1	1	1	1	1	2	3	2	1	1	1
32	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	2	1	1	1	1	2	2	2	2	1	1	1	1	1	1
33	1	1	1	1	1	1	1	1	1	1	1	0	4	2	3	2	2	2	1	1	1	1	1	1	1	2	2	2	2	2	1	1	1	1	1
34	1	1	1	1	1	1	1	1	1	3	6	6	0	7	3	4	6	2	4	2	3	1	1	1	1	2	2	2	2	2	1	1	1	1	1
35	1	1	2	1	1	1	1	1	1	1	4	4	2	0	3	3	3	2	2	2	1	1	1	1	1	1	2	1	1	1	1	2	2	1	1
41	1	2	2	2	1	1	1	5	1	1	1	1	1	1	0	2	2	2	1	1	1	5	1	1	1	1	2	1	1	5	1	2	2	1	2
51	1	4	4	1	4	1	1	1	1	1	1	1	1	1	1	0	4	4	1	1	1	1	1	1	1	1	2	1	1	1	1	2	2	1	4
52	1	2	2	1	1	1	1	1	1	1	3	3	1	5	1	1	0	2	1	1	2	1	2	2	1	2	2	2	1	2	2	1	1	3	2
53	1	1	1	1	1	2	2	1	1	1	1	1	1	1	2	2	4	0	2	1	1	1	2	2	1	2	4	5	3	2	2	1	3	3	3
54	1	1	5	1	1	5	5	1	1	2	2	2	2	2	1	4	4	8	0	2	2	2	2	2	1	3	6	6	5	2	1	1	3	3	3
61	1	1	1	1	1	2	2	1	1	2	2	2	1	1	2	2	4	3	2	0	2	6	2	2	2	2	4	1	5	5	1	2	4	4	7
71	1	1	1	1	1	1	1	1	1	1	2	2	1	5	1	1	5	1	2	3	0	1	2	2	2	2	1	3	5	4	2	3	4	5	7
81	1	1	1	1	1	1	1	2	1	1	2	2	1	2	1	1	1	1	2	8	4	0	1	2	2	2	1	5	7	7	2	3	6	7	4
91	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	3	3	1	0	1	2	2	1	2	3	3	2	2	4	5	4
92	1	1	1	1	1	1	1	1	1	1	3	2	2	1	1	1	2	2	2	3	3	3	1	0	2	2	2	1	1	5	7	3	4	2	1
93	1	1	1	1	1	1	1	3	4	3	6	2	2	1	6	1	1	1	1	3	15	3	3	6	0	2	1	1	3	1	17	15	5	1	2
101	2	1	1	2	1	1	2	1	1	2	2	2	2	1	1	1	2	2	2	3	3	3	3	3	3	0	3	2	3	5	7	10	2	2	13
102	1	1	1	1	1	1	1	1	1	2	2	2	2	2	1	1	5	6	5	2	2	2	2	2	2	2	0	6	2	2	2	5	10	10	8
103	1	1	3	1	3	3	1	1	1	1	2	2	2	2	1	3	3	10	8	2	2	2	2	2	2	4	4	0	2	2	2	4	3	3	2
111	1	1	1	1	1	1	5	8	7	4	1	2	2	1	1	1	3	4	5	3	5	5	5	2	1	2	2	2	0	1	2	1	2	3	3
112	1	1	1	1	1	1	5	25	24	4	1	2	2	1	1	1	2	2	1	6	5	28	5	2	2	2	2	1	1	0	2	2	1	6	1
121	1	1	1	1	1	1	5	8	8	5	1	1	2	1	1	1	2	2	1	1	6	5	5	1	1	1	2	1	1	1	0	1	1	1	1
122	1	1	1	1	1	1	1	1	3	1	1	1	1	1	1	2	1	1	2	2	4	3	3	1	2	6	8	6	4	2	5	0	1	2	2
131	1	1	1	1	1	1	1	3	3	2	1	1	1	2	1	1	1	4	2	5	4	9	3	1	4	11	11	13	5	5	2	1	0	4	4
132	1	1	1	1	1	1	1	5	3	2	1	1	1	1	2	1	1	1	2	2	5	3	3	2	3	1	1	7	2	3	2	1	1	0	2
133	1	1	1	1	1	1	3	3	1	2	1	1	1	1	1	1	1	1	1	1	1	2	2	1	2	2	2	3	2	1	1	1	1	2	0

Car origin-destination movement patterns on Monday at 03:00 a.m. – 04:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	3	1	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	3	3	6	4	4	1	1	1	1	1	1	2	2	2	5	5	5
21	1	1	1	1	1	1	1	0	1	1	1	1	1	2	3	2	1	1	3	16	1	19	4	2	4	2	1	1	1	3	3	4	6	18	5
22	1	1	1	1	1	1	1	1	0	2	3	2	1	2	5	2	1	1	3	3	6	4	4	2	5	2	1	1	1	3	5	3	5	5	5
31	1	1	1	1	1	1	1	1	1	0	2	1	1	1	2	2	3	1	2	1	2	2	2	1	1	1	1	1	1	2	3	2	1	1	1
32	1	1	1	1	1	1	1	1	1	2	0	2	2	1	1	1	1	1	1	1	2	1	1	1	1	2	2	2	2	1	1	1	1	1	1
33	1	1	1	1	1	1	1	1	1	3	1	0	6	3	4	3	3	3	1	2	1	1	1	1	1	2	2	2	2	2	1	1	1	1	1
34	1	1	1	1	1	1	1	1	1	3	6	6	0	11	5	6	10	3	6	2	5	1	1	1	1	2	2	2	2	2	1	1	1	1	1
35	1	1	2	1	1	1	1	1	1	1	5	5	2	0	5	4	4	3	2	2	2	2	1	1	1	2	2	2	1	1	1	2	2	1	1
41	1	2	2	2	1	1	1	4	1	1	1	1	1	1	0	2	3	2	1	1	1	4	1	1	1	2	2	2	1	4	1	2	2	1	2
51	1	6	6	2	6	1	1	1	1	1	1	1	1	1	1	0	4	4	1	1	1	1	1	2	2	2	2	2	1	1	1	2	2	2	4
52	1	2	2	2	1	1	1	1	2	1	2	2	1	4	1	1	0	2	1	1	2	1	2	2	1	2	3	3	1	2	2	1	1	3	2
53	1	2	2	2	2	3	3	2	2	1	1	1	1	1	1	2	3	0	2	1	1	1	2	2	1	1	5	5	3	2	2	1	2	2	2
54	1	2	8	2	2	8	8	2	2	2	2	2	2	2	1	3	3	7	0	2	2	2	2	2	1	3	5	5	4	2	1	1	3	3	3
61	1	2	2	2	2	3	3	2	2	2	2	2	1	1	2	2	4	3	2	0	2	8	2	2	2	2	3	4	5	5	1	2	4	4	5
71	1	1	1	1	1	1	1	1	1	1	2	2	2	6	2	1	6	1	2	3	0	1	2	2	2	2	1	2	4	3	2	3	2	2	6
81	1	1	1	1	1	1	1	1	1	1	1	1	2	4	2	1	1	1	2	6	5	0	1	2	2	2	1	4	4	5	1	2	5	6	5
91	1	1	1	1	1	1	1	1	1	2	1	1	2	2	1	2	2	2	2	3	3	2	0	1	2	2	1	2	2	2	1	2	4	5	5
92	1	1	1	1	1	1	1	1	1	1	2	2	1	1	1	1	2	2	2	3	3	3	1	0	2	2	2	1	1	4	6	2	4	2	1
93	1	1	1	1	1	1	1	1	1	2	6	2	2	1	2	1	1	1	1	3	16	3	3	6	0	2	1	1	1	4	16	16	6	2	2
101	3	1	1	3	1	1	3	1	1	2	2	2	2	1	1	1	2	2	2	3	3	3	3	3	2	0	2	2	2	4	6	11	4	4	19
102	1	1	1	2	2	2	1	1	2	2	2	2	2	2	1	1	4	5	5	2	2	2	2	2	1	1	0	5	2	2	2	6	14	14	8
103	1	1	3	1	3	3	1	1	2	2	2	2	2	2	1	2	2	9	8	2	2	2	2	2	1	4	4	0	2	2	2	6	4	4	4
111	1	1	1	1	1	1	6	10	10	5	2	2	2	1	1	1	3	4	5	3	6	6	6	2	1	2	2	2	0	1	2	1	3	4	4
112	1	1	1	1	1	1	6	33	29	5	2	2	2	1	5	1	2	2	1	6	6	35	6	2	2	2	2	1	5	0	2	2	1	6	1
121	1	1	1	1	1	1	6	10	10	5	1	2	2	1	1	1	2	2	1	1	6	6	6	1	1	1	2	1	1	2	0	1	1	1	1
122	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	2	2	4	2	2	1	2	5	7	5	4	2	2	0	1	2	2
131	1	1	1	1	1	1	1	2	2	2	1	1	1	3	1	2	1	4	2	5	4	8	3	1	3	9	9	11	4	4	2	1	0	4	5
132	1	1	1	1	1	1	1	4	4	2	1	1	1	1	1	2	1	1	2	1	6	4	4	2	3	1	1	8	1	2	1	1	1	0	3
133	1	1	1	1	1	1	3	4	2	2	1	1	1	1	1	1	1	1	1	1	2	4	3	2	2	1	4	4	2	1	1	1	1	3	0

Car origin-destination movement patterns on Monday at 04:00 a.m. – 05:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	4	4	2	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	4	2	1	1	1	1	1	1	3	3	3	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	3	4	6	4	4	1	1	1	2	1	1	3	3	3	5	5	5
21	1	1	1	1	1	1	1	0	2	1	1	1	1	3	6	3	1	1	3	17	2	21	4	2	6	2	2	1	1	5	6	5	7	20	5
22	1	1	1	1	1	1	1	1	0	2	3	3	2	3	6	4	2	1	4	4	6	4	4	2	6	2	2	1	1	4	6	3	6	5	5
31	1	1	1	1	1	1	1	1	1	0	3	2	2	2	3	4	5	1	4	1	2	1	1	2	2	1	2	2	2	2	3	2	1	2	1
32	1	1	1	1	1	1	1	1	1	2	0	2	2	2	1	2	2	1	1	1	2	1	1	1	1	2	2	2	2	2	1	1	1	2	1
33	1	1	1	1	1	1	1	1	1	3	2	0	6	4	4	3	3	2	1	2	1	2	1	1	1	2	2	2	2	2	1	2	1	2	1
34	1	1	1	1	1	1	1	1	1	3	8	8	0	13	4	4	9	3	4	2	6	1	1	1	1	2	2	2	2	2	1	1	1	2	1
35	1	1	2	1	1	1	1	1	1	2	5	5	3	0	4	4	3	3	2	2	2	2	1	2	2	2	2	2	1	1	1	2	2	2	1
41	1	2	2	2	1	1	1	5	1	2	2	1	1	1	0	2	3	2	1	1	1	5	1	2	2	2	2	2	1	5	1	2	2	1	2
51	1	4	4	1	4	1	1	1	1	1	1	1	2	1	2	0	5	5	1	1	2	2	1	2	2	2	2	2	1	1	1	2	2	3	5
52	1	2	2	1	1	1	2	2	2	1	2	2	2	7	2	2	0	2	1	1	6	1	2	2	1	3	4	4	2	2	2	1	1	4	6
53	1	1	1	1	2	3	3	2	2	1	1	1	2	1	2	2	5	0	3	1	1	1	3	2	1	2	7	8	4	2	2	1	2	2	2
54	1	1	7	1	2	7	7	2	2	2	2	2	2	2	1	5	5	13	0	3	2	2	2	3	1	5	9	9	6	3	2	1	3	3	3
61	1	1	1	1	2	3	3	2	2	2	2	2	1	1	2	3	5	5	3	0	3	11	3	3	3	3	5	6	8	8	2	2	4	4	6
71	1	1	1	1	1	2	1	1	1	2	2	2	3	5	3	1	5	1	3	6	0	2	3	3	3	3	1	5	7	6	4	3	3	4	6
81	1	1	1	1	1	2	1	4	1	1	1	1	3	8	3	1	1	1	3	16	10	0	1	3	3	3	1	6	12	12	2	3	6	12	10
91	1	1	1	1	1	2	1	1	1	2	1	1	2	2	2	2	2	3	3	6	6	3	0	1	3	3	1	3	5	5	3	2	6	8	7
92	1	1	1	1	1	2	1	1	2	1	2	3	1	1	1	1	2	2	3	3	3	4	1	0	3	3	3	1	1	5	8	2	5	2	2
93	1	1	1	1	1	1	1	2	3	3	10	2	2	1	4	1	1	1	1	3	19	4	6	10	0	2	1	1	2	5	21	19	7	4	3
101	5	1	1	5	1	1	5	2	1	3	2	2	2	1	1	1	3	3	3	3	3	4	4	4	4	0	4	3	4	5	8	14	6	6	21
102	1	2	1	2	2	2	2	1	2	2	2	2	2	2	1	1	6	8	6	2	3	3	3	3	2	3	0	10	4	2	2	7	15	15	10
103	1	1	3	1	3	3	1	1	2	2	2	2	2	2	1	3	3	10	7	2	3	3	3	2	2	6	6	0	3	2	2	6	4	4	3
111	1	1	1	1	1	1	6	10	10	5	2	2	2	1	1	2	3	4	4	2	6	5	5	2	2	4	4	3	0	1	2	1	3	3	3
112	1	1	1	1	1	1	6	33	30	5	2	2	2	1	5	1	2	2	1	4	6	32	5	2	2	2	2	1	5	0	2	2	1	4	1
121	1	1	1	1	1	1	6	10	10	6	2	2	2	1	1	1	2	2	1	1	6	5	5	1	1	1	2	1	1	2	0	1	1	1	1
122	1	1	1	1	1	1	1	2	2	2	2	2	1	1	1	2	1	1	3	5	8	2	5	1	1	8	11	7	6	3	3	0	2	3	3
131	1	1	1	1	1	1	2	3	5	2	2	2	1	3	1	1	1	3	3	9	6	14	6	1	5	15	15	16	6	9	3	1	0	4	5
132	1	1	1	1	1	1	2	6	4	3	2	2	1	1	1	1	1	1	3	2	1	5	6	2	6	2	2	12	3	3	3	1	2	0	1
133	1	1	1	1	1	1	4	5	3	3	1	1	1	1	1	1	1	1	1	3	3	6	4	2	3	3	4	7	4	1	1	2	2	5	0

Car origin-destination movement patterns on Monday at 05:00 a.m. – 06:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	4	3	1	1	1	1	1	2	6	6	3	1	1	1	1	1	1	1
12	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	6	9	6	1	1	1	1	1	2	3	4	4	1	1	1	1	1	1	1
13	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	3	4	3	1	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1
15	1	1	1	1	0	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1
16	1	1	1	1	1	0	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
17	1	1	1	1	1	1	0	1	1	1	2	2	2	3	3	3	2	2	5	5	8	5	5	3	3	3	2	1	3	6	6	5	6	6	6
21	1	1	1	1	1	1	2	0	4	2	1	1	2	4	13	4	2	2	5	25	4	27	5	4	14	4	2	1	2	11	13	7	10	24	6
22	1	1	1	1	1	1	2	1	0	3	5	4	2	5	7	6	3	2	5	6	8	5	5	4	7	4	2	1	3	7	7	5	7	6	6
31	1	1	1	1	1	2	2	2	1	0	4	2	3	3	4	6	8	2	6	1	3	1	1	1	2	2	3	3	2	2	4	3	2	2	1
32	1	1	1	1	1	2	2	2	1	3	0	3	3	2	2	3	3	2	1	1	3	1	2	2	1	3	3	3	3	3	1	1	1	2	2
33	1	1	1	1	2	2	2	2	1	4	3	0	8	4	4	3	3	3	1	2	2	2	1	1	1	3	3	3	3	3	1	3	1	2	2
34	1	1	1	1	2	2	2	2	1	3	6	6	0	13	5	3	10	3	3	2	8	2	1	1	1	3	3	3	3	3	1	1	1	2	2
35	1	1	4	1	2	2	2	2	2	2	5	6	6	0	5	7	4	3	4	2	3	3	2	2	1	3	3	3	2	2	2	3	3	2	2
41	1	2	2	2	1	1	2	12	2	1	1	2	2	2	0	3	4	3	2	1	2	12	2	1	1	3	3	3	2	12	2	3	3	2	3
51	1	5	5	2	5	1	2	2	2	1	2	2	2	2	2	0	6	6	1	1	3	3	2	3	3	3	3	3	2	2	2	3	3	4	6
52	1	2	2	2	1	1	2	2	2	1	4	4	2	11	2	3	0	3	1	1	6	1	3	3	1	4	6	6	3	3	3	1	1	5	6
53	1	2	2	2	2	4	4	2	2	1	2	2	2	2	4	5	12	0	8	1	1	1	4	4	1	3	11	13	10	3	3	1	3	3	3
54	1	2	11	2	2	11	11	2	2	2	3	3	3	3	2	12	12	38	0	4	4	4	4	4	1	10	27	27	14	5	3	2	4	4	4
61	1	2	2	2	2	4	4	2	2	3	3	3	1	1	3	6	12	11	8	0	4	20	4	4	4	7	14	16	15	15	3	4	6	6	13
71	2	2	2	2	2	2	1	2	2	1	3	3	3	6	3	1	6	1	6	8	0	2	4	4	4	4	2	7	11	11	6	6	7	8	12
81	2	2	2	2	2	2	1	6	2	2	2	1	5	9	4	1	1	1	6	27	11	0	1	4	4	4	2	8	19	20	4	6	12	25	11
91	2	2	2	2	2	2	1	2	3	6	2	2	6	6	3	3	3	4	6	8	8	4	0	1	4	4	2	5	7	6	4	4	11	14	13
92	2	2	2	2	2	2	1	2	3	2	3	4	2	3	2	2	3	3	4	4	4	6	2	0	4	4	4	1	1	6	10	3	6	3	2
93	2	2	2	2	2	2	2	5	4	4	13	3	3	2	8	2	1	1	1	4	22	6	9	13	0	3	2	2	5	6	25	22	11	6	6
101	8	2	2	8	2	2	8	3	2	3	3	3	3	2	2	2	5	6	5	4	4	6	6	6	4	0	6	6	6	6	9	18	12	12	26
102	3	3	2	3	3	3	3	2	2	2	3	3	3	3	1	2	7	13	7	2	4	4	4	4	4	2	0	14	5	3	3	10	18	18	9
103	3	1	4	3	4	4	3	1	2	2	2	3	3	3	1	4	4	10	6	2	4	4	4	3	4	14	14	0	4	3	3	7	4	4	4
111	1	1	1	2	2	2	9	14	14	6	2	3	3	2	2	3	4	4	4	2	7	6	6	3	4	8	8	6	0	2	3	1	3	4	3
112	1	1	2	2	2	2	8	50	42	6	2	3	3	2	10	2	3	3	1	5	7	45	6	3	3	3	3	2	10	0	3	3	1	5	1
121	1	1	2	2	2	2	8	14	14	7	2	2	3	2	2	2	3	3	1	1	7	6	7	1	1	1	3	2	2	3	0	1	1	1	1
122	1	1	2	2	2	2	2	2	3	2	2	2	1	1	1	3	1	1	4	7	13	3	6	2	2	11	14	10	7	4	4	0	3	6	6
131	1	1	1	2	2	2	3	6	6	4	2	2	1	4	1	1	1	4	4	12	9	22	9	1	6	19	19	22	8	11	4	1	0	8	10
132	1	1	1	1	2	2	3	11	9	6	2	2	1	1	2	1	1	1	4	3	1	9	11	3	7	2	2	16	3	5	4	2	2	0	1
133	1	1	1	1	1	2	6	9	6	5	2	1	1	2	2	2	1	2	2	5	6	11	7	3	5	6	6	12	6	2	1	2	4	8	0

Car origin-destination movement patterns on Monday at 06:00 a.m. – 07:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	1	1	1	1	1	2	2	2	2	2	2	2	2	2	3	6	8	6	3	2	2	2	2	4	11	11	6	2	2	2	2	2	2	2
12	1	0	1	1	1	2	2	2	2	2	2	2	2	2	2	3	13	22	13	3	2	2	2	2	4	7	8	10	2	2	2	2	2	2	2
13	1	1	0	1	2	2	2	2	2	2	2	2	2	2	2	3	6	8	6	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
14	1	1	1	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2
15	1	1	1	2	0	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2
16	1	1	2	2	2	0	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2
17	1	1	2	2	2	2	0	2	2	2	2	2	3	5	5	5	3	3	7	8	16	10	9	5	5	5	4	1	4	9	8	8	11	11	11
21	1	1	2	2	2	2	2	0	7	2	1	1	3	5	25	5	3	3	7	46	7	55	9	6	28	6	4	1	4	15	25	10	18	49	11
22	1	2	2	2	2	2	2	2	0	9	4	11	4	6	4	6	3	2	8	9	16	10	9	6	4	6	4	1	4	10	4	4	13	11	12
31	1	2	2	2	2	2	2	3	2	0	15	5	5	2	3	7	7	2	6	1	4	1	3	3	2	1	4	4	4	1	4	11	3	3	2
32	2	2	2	2	2	2	3	3	2	6	0	6	6	4	2	3	3	2	1	1	4	2	2	2	2	4	4	4	4	4	3	3	3	3	3
33	2	2	2	2	2	2	3	3	2	9	6	0	19	9	8	6	6	6	1	4	3	4	3	3	1	5	4	4	4	4	1	6	1	4	3
34	2	1	1	1	2	3	3	3	1	7	15	15	0	33	11	6	23	6	6	5	18	4	2	2	2	5	5	5	4	4	1	1	1	4	3
35	2	1	5	1	2	3	3	3	4	5	10	12	12	0	11	13	8	6	5	5	6	6	4	5	1	1	5	1	4	4	4	4	4	4	3
41	2	3	3	3	1	1	3	19	4	1	1	4	4	4	0	6	9	6	4	1	3	19	4	1	2	1	5	1	2	19	4	4	4	4	5
51	2	7	7	2	7	1	3	3	3	2	3	3	6	4	5	0	14	14	3	2	5	5	3	1	1	1	5	1	4	4	4	4	4	8	14
52	2	3	3	2	1	1	3	3	3	2	10	10	6	27	5	6	0	6	3	2	14	2	5	5	1	4	6	6	3	5	5	1	2	10	14
53	2	2	2	2	3	5	5	3	4	2	3	3	6	4	6	6	11	0	6	2	2	2	6	6	1	4	10	13	6	5	5	1	5	5	5
54	2	2	14	2	3	14	14	3	4	4	4	4	4	4	3	14	14	28	0	6	11	11	11	6	1	7	15	15	20	14	7	5	10	11	8
61	2	2	2	2	3	5	5	3	4	4	4	4	2	2	4	6	11	10	6	0	11	59	11	6	6	5	8	15	43	43	7	9	17	17	26
71	2	2	2	3	3	3	2	3	3	1	4	4	4	8	4	2	8	2	12	17	0	1	11	6	6	6	3	20	34	33	16	12	15	15	21
81	2	2	3	3	3	3	2	12	2	2	2	2	6	13	6	2	2	2	12	71	20	0	1	6	6	6	3	15	60	63	10	9	17	36	20
91	2	2	3	3	3	3	2	3	5	8	4	3	8	8	5	5	5	6	12	17	17	6	0	1	6	6	3	12	22	20	11	5	17	21	19
92	2	2	3	3	3	3	2	4	6	4	5	6	3	6	4	3	5	5	6	3	3	6	4	0	6	6	5	2	2	6	10	5	6	5	3
93	3	3	2	2	2	3	4	9	8	7	23	6	4	3	17	3	1	1	1	3	20	6	11	23	0	5	1	3	9	6	28	20	16	11	9
101	13	3	2	13	2	3	13	6	4	6	5	5	4	3	3	3	6	5	6	3	3	6	8	8	7	0	8	5	9	6	9	22	22	22	35
102	4	5	4	5	5	5	4	3	4	4	4	4	4	5	2	3	11	22	10	2	6	6	6	6	4	4	0	24	7	5	5	14	22	22	13
103	5	2	6	5	6	6	5	1	4	4	4	4	4	4	2	7	7	13	7	2	6	6	6	5	4	13	13	0	6	5	5	9	6	6	5
111	1	2	2	3	3	3	12	19	19	9	4	4	4	3	4	5	6	6	6	3	10	9	9	5	3	7	7	7	0	4	5	2	5	6	5
112	2	2	2	2	2	3	11	71	56	9	3	4	4	3	17	3	5	5	2	10	10	65	9	5	5	5	5	4	17	0	5	5	2	10	2
121	2	2	2	2	2	3	11	19	19	9	3	3	4	3	3	3	5	5	2	2	11	10	10	2	2	2	5	4	4	5	0	2	2	2	2
122	2	2	2	2	2	3	3	3	5	3	3	3	1	1	1	4	2	2	6	11	22	5	11	3	6	17	22	16	12	6	8	0	5	7	7
131	2	2	2	2	2	2	6	11	9	6	3	3	1	5	1	1	2	9	8	25	12	40	17	2	10	30	30	38	18	23	10	3	0	11	13
132	2	2	2	2	2	2	6	25	15	9	3	3	1	1	1	1	2	2	8	7	1	15	20	5	10	2	2	27	11	17	8	3	2	0	1
133	2	2	2	2	2	2	10	17	11	8	3	2	2	2	3	2	2	2	4	8	11	20	13	5	6	5	6	17	11	6	4	3	8	17	0

Car origin-destination movement patterns on Monday at 07:00 a.m. – 08:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	2	2	2	3	3	3	3	3	3	3	3	3	4	10	13	10	4	4	4	4	4	6	20	20	8	2	3	3	3	3	3	2
12	2	0	2	2	2	3	3	3	3	3	3	3	3	3	3	4	24	32	24	4	4	4	4	4	6	12	13	10	2	3	3	3	3	3	3
13	2	2	0	2	2	3	3	3	3	3	3	3	3	3	3	4	10	13	10	4	4	4	4	4	4	4	2	2	2	4	3	3	3	3	3
14	2	2	2	0	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4	5	5	4	4	4	4	4	4	4	4	3	3	3	3
15	2	2	2	3	0	3	3	3	3	4	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4	4	3
16	2	2	2	3	3	0	3	3	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4
17	2	2	3	3	3	3	0	3	3	3	4	4	4	11	11	11	5	5	13	15	30	17	16	12	12	12	6	1	7	22	21	22	20	20	21
21	2	2	3	3	3	3	4	0	11	5	3	3	4	13	75	13	5	6	13	87	11	105	16	13	78	13	6	1	5	28	75	26	35	94	22
22	2	2	3	3	3	3	4	3	0	19	11	24	9	17	10	20	7	6	16	17	30	18	16	14	10	13	6	1	7	24	10	11	26	20	22
31	2	3	3	3	3	4	4	4	4	0	30	10	13	6	7	22	22	6	18	3	7	2	2	2	3	2	7	7	6	3	9	22	6	5	3
32	2	3	3	3	4	4	4	4	4	11	0	11	11	8	6	7	7	6	3	3	7	2	3	3	2	7	7	7	7	7	5	5	5	6	5
33	3	3	3	3	4	4	4	5	4	12	7	0	33	16	13	8	8	8	1	6	6	6	3	3	2	8	7	7	7	7	1	7	1	6	5
34	3	2	2	2	4	4	4	5	2	11	23	23	0	58	19	6	39	10	6	7	35	6	3	3	3	8	8	7	7	7	1	1	1	6	4
35	3	2	13	2	4	4	5	5	6	11	16	21	27	0	19	30	14	10	13	7	9	9	6	11	2	1	8	1	6	6	5	7	6	6	4
41	4	9	9	8	4	4	5	30	6	2	2	7	7	7	0	11	15	11	6	3	5	30	6	2	1	1	8	1	1	30	5	7	7	5	8
51	4	23	23	6	23	4	5	5	5	4	6	6	11	7	9	0	21	21	4	4	7	7	5	1	1	1	8	1	6	6	5	7	7	12	21
52	4	7	7	6	4	4	5	6	6	4	21	21	11	53	9	10	0	9	4	4	24	4	9	9	1	6	10	9	5	8	8	1	2	15	24
53	3	2	2	2	3	5	5	3	6	4	6	6	11	7	12	11	19	0	9	4	4	4	10	9	1	4	17	21	9	8	8	1	5	5	5
54	3	2	14	2	3	14	14	3	6	6	7	7	7	8	5	25	25	42	0	10	17	17	17	10	1	10	18	18	29	22	11	8	18	19	14
61	4	2	2	2	3	5	5	3	6	7	7	7	2	2	6	10	18	15	9	0	18	102	18	10	10	6	10	21	67	67	11	14	36	36	36
71	4	4	4	4	5	5	3	4	4	1	7	7	9	9	9	2	9	2	18	27	0	2	18	10	10	10	2	28	51	49	24	16	18	19	26
81	4	4	4	4	5	5	3	16	4	2	2	2	11	34	10	2	2	2	18	104	38	0	1	10	10	10	2	10	91	96	15	10	16	39	39
91	4	4	4	4	5	5	3	4	5	6	3	2	6	6	8	9	9	9	18	27	27	11	0	1	10	10	2	17	31	29	15	4	16	26	27
92	4	4	4	4	5	5	5	7	9	3	4	9	3	7	6	6	9	9	9	7	7	11	3	0	11	9	9	5	5	15	22	4	11	7	6
93	5	5	3	3	3	4	8	25	16	11	40	8	7	6	41	6	1	1	1	7	48	11	22	40	0	9	1	5	25	15	64	48	22	12	11
101	21	5	3	21	3	4	21	11	7	10	7	7	7	6	6	6	9	5	9	7	7	11	15	15	13	0	13	5	15	15	21	39	24	24	55
102	6	7	6	6	6	6	6	5	6	6	6	6	7	7	1	3	13	32	12	2	9	9	9	9	6	10	0	40	11	8	8	22	38	38	21
103	9	3	6	9	6	6	9	2	6	6	6	6	7	7	1	6	6	12	8	2	9	9	9	9	6	18	18	0	11	8	7	16	16	16	12
111	2	3	3	4	4	4	24	39	38	17	6	6	6	5	6	6	5	6	7	5	21	18	18	8	5	10	10	11	0	6	7	4	11	16	13
112	3	3	3	4	4	4	22	145	115	17	6	6	6	5	32	5	8	8	4	22	21	136	18	8	8	8	8	6	32	0	7	7	4	22	4
121	3	3	3	3	4	4	22	40	40	19	5	6	6	5	5	5	7	8	4	4	23	20	21	2	2	2	8	6	6	10	0	5	4	4	4
122	3	3	3	3	4	4	4	7	15	7	5	5	3	3	3	7	2	2	10	28	48	15	20	2	9	25	34	23	19	12	22	0	5	11	11
131	3	3	3	3	3	4	11	22	23	12	5	5	3	18	4	1	2	12	11	39	41	68	28	2	14	46	46	57	29	36	16	6	0	11	25
132	3	3	3	3	3	4	11	48	24	13	5	5	3	4	2	1	2	2	11	6	2	25	32	7	15	2	2	43	23	27	12	4	2	0	2
133	2	3	3	3	3	3	18	27	10	11	5	4	3	4	4	4	3	3	5	8	10	24	20	7	10	7	9	27	20	11	6	5	11	25	0

Car origin-destination movement patterns on Monday at 08:00 a.m. – 09:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	2	2	3	3	3	3	3	3	3	3	3	4	4	9	11	9	4	4	4	4	4	6	22	22	10	3	4	4	3	3	3	3
12	2	0	2	2	3	3	3	3	3	3	3	3	4	4	4	4	20	32	20	4	5	5	5	5	6	13	15	13	3	4	4	4	3	3	3
13	2	2	0	2	3	3	3	3	3	3	4	4	4	4	4	4	9	11	9	4	5	5	5	5	5	5	3	3	3	4	4	4	4	3	3
14	2	2	2	0	3	3	3	3	3	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4	4
15	2	2	2	3	0	3	4	4	4	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6	6	6	6	5	5	5	5	5	4	4	4
16	2	2	2	3	3	0	4	4	4	4	4	4	4	5	5	5	5	6	6	6	6	6	6	6	6	6	6	6	6	6	5	5	5	5	4
17	2	2	3	3	3	3	0	4	4	4	4	5	5	12	12	12	6	6	18	22	44	27	24	13	13	13	7	1	9	25	24	27	32	32	29
21	2	2	3	3	3	4	4	0	18	6	3	3	5	14	80	14	6	6	18	123	18	162	24	15	85	15	7	1	6	39	80	32	60	145	30
22	2	2	3	3	3	4	4	4	0	20	11	24	9	18	11	22	9	7	22	24	44	27	25	15	11	15	7	1	9	27	11	11	37	32	31
31	2	3	3	3	4	4	4	5	6	0	29	10	13	6	8	27	27	7	23	4	8	3	2	2	5	3	8	8	7	4	9	21	6	6	3
32	3	3	3	3	4	4	5	5	6	18	0	18	18	11	6	9	9	7	4	4	8	4	7	7	4	8	8	8	8	7	6	6	6	6	6
33	3	3	3	3	4	4	5	5	6	15	10	0	42	17	12	8	8	8	1	6	5	7	4	4	4	9	8	8	8	8	2	10	2	7	5
34	3	3	3	3	4	4	5	5	2	11	22	22	0	55	19	6	38	10	6	8	34	6	3	3	3	9	9	8	8	8	2	2	2	7	5
35	3	3	16	3	4	4	6	6	7	11	15	20	27	0	19	32	14	10	16	8	10	10	7	11	2	1	9	1	6	6	6	8	7	7	5
41	4	9	9	8	4	4	6	40	7	2	2	7	7	7	0	11	15	11	6	3	6	40	7	2	1	1	9	1	1	40	6	8	8	5	7
51	4	22	22	6	22	4	6	6	6	3	6	6	8	6	7	0	19	19	4	3	8	8	6	1	1	1	9	1	6	6	6	8	8	10	19
52	4	7	7	6	4	4	6	6	6	3	16	16	8	40	7	10	0	8	4	3	16	3	10	10	2	9	16	16	8	9	9	2	5	16	16
53	3	2	2	2	3	5	5	3	6	3	6	6	8	6	11	10	19	0	10	3	3	3	11	10	2	6	31	37	14	9	9	2	12	12	12
54	4	2	13	2	3	13	13	3	7	7	7	7	8	8	4	22	22	46	0	11	19	19	19	11	2	16	25	25	38	25	12	9	19	22	16
61	4	2	2	2	3	5	5	3	7	7	7	8	3	3	6	10	19	16	10	0	20	110	20	11	11	7	13	26	78	78	12	15	32	32	47
71	4	4	4	5	5	6	4	4	4	1	7	8	8	15	8	3	15	3	18	27	0	3	20	11	11	11	2	31	56	54	26	19	25	27	38
81	4	4	4	5	5	6	4	22	3	2	2	2	11	29	10	3	3	3	18	107	34	0	1	11	11	11	2	11	94	99	15	12	19	48	36
91	4	4	4	5	5	6	4	4	6	7	4	2	7	7	7	10	10	10	18	27	27	10	0	2	11	11	2	18	32	31	16	5	21	29	30
92	4	4	4	5	5	5	6	9	11	5	4	10	3	9	8	6	9	10	10	7	7	12	5	0	11	10	10	6	6	16	21	4	11	8	6
93	6	6	4	4	4	4	10	34	14	11	43	9	7	6	48	6	1	1	1	7	48	12	23	43	0	9	2	6	34	16	61	48	27	17	14
101	24	6	4	24	4	4	24	12	9	10	8	8	7	6	6	6	10	6	10	7	7	11	16	16	15	0	16	6	18	16	21	43	34	34	68
102	7	8	6	7	7	7	6	6	6	6	6	7	7	8	2	4	16	35	13	1	10	10	10	10	8	13	0	47	13	9	8	27	43	43	27
103	8	3	7	8	7	7	8	2	6	6	6	7	7	8	2	11	11	15	5	1	10	10	10	9	8	22	22	0	12	8	8	19	20	20	16
111	2	3	3	4	4	4	22	35	33	15	6	6	7	5	6	8	7	6	7	4	18	16	16	9	6	12	12	14	0	6	8	5	14	19	16
112	3	3	3	4	4	4	20	132	99	15	6	6	7	5	34	5	8	8	4	22	18	120	16	9	9	9	9	6	34	0	8	8	4	22	4
121	3	3	3	4	4	4	20	36	36	17	6	6	6	5	5	5	8	8	4	4	22	19	19	4	4	3	8	6	6	11	0	6	4	4	4
122	3	3	3	3	4	4	5	8	18	8	5	6	4	4	4	7	2	2	12	32	54	18	24	6	13	25	35	23	22	15	25	0	4	10	10
131	3	3	3	3	4	4	13	26	25	14	5	5	4	19	4	1	2	13	13	50	43	80	34	4	15	46	46	58	33	46	20	6	0	11	24
132	3	3	3	3	3	4	13	61	32	12	5	5	4	4	2	1	3	3	14	6	2	32	33	8	15	2	2	51	29	32	15	6	2	0	2
133	3	3	3	3	3	4	22	29	2	10	5	4	4	4	5	4	4	5	5	4	2	10	20	8	11	8	14	40	27	13	6	6	16	24	0

Car origin-destination movement patterns on Monday at 09:00 a.m. – 10:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	2	2	2	2	3	3	3	3	3	3	3	3	3	4	4	9	11	9	4	4	4	4	4	6	18	18	9	3	4	4	3	3	3	3
12	2	0	2	2	2	3	3	3	3	3	3	3	3	4	4	4	20	34	20	4	4	4	4	4	6	11	13	16	3	4	4	4	3	3	3
13	2	2	0	2	3	3	3	3	3	3	4	4	4	4	4	4	9	11	9	4	5	5	5	5	5	5	3	3	3	4	4	4	3	3	3
14	2	2	2	0	3	3	3	3	4	4	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4	4	3
15	2	2	2	3	0	3	4	4	4	4	4	4	4	4	5	5	5	5	5	5	6	6	6	6	6	6	5	5	5	5	5	5	4	4	4
16	2	2	3	3	3	0	4	4	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6	6	6	6	6	6	6	5	5	5	5	5	4
17	2	2	3	3	3	3	0	5	5	5	4	5	5	11	11	11	6	6	20	23	46	27	23	12	12	12	7	2	11	24	22	22	27	27	27
21	2	2	3	3	3	4	4	0	22	6	3	3	5	13	70	13	6	6	20	134	22	157	23	14	79	14	7	2	10	42	70	27	43	135	28
22	2	3	3	3	3	4	4	5	0	21	11	25	11	17	11	20	8	6	22	26	46	27	24	15	11	14	7	2	11	27	11	11	33	27	29
31	2	3	3	3	4	4	5	5	4	0	29	11	14	8	8	22	25	6	18	3	8	3	4	4	6	3	8	7	7	4	9	20	6	6	3
32	3	3	3	3	4	4	5	5	4	14	0	14	14	10	6	8	8	6	3	3	8	4	6	6	4	8	8	8	8	7	5	5	5	6	6
33	3	3	3	4	4	4	5	5	4	13	9	0	36	17	13	9	9	8	1	6	6	8	5	5	4	8	8	8	8	8	2	9	2	7	5
34	3	3	3	3	4	4	5	5	3	11	21	21	0	58	19	6	43	11	6	8	38	6	4	4	3	9	9	8	8	8	2	2	2	7	5
35	3	3	17	3	4	5	6	6	8	13	14	19	27	0	19	31	15	11	17	8	11	11	8	13	3	1	9	1	7	7	6	8	7	7	5
41	4	9	9	8	4	4	6	42	8	3	3	7	7	7	0	11	15	11	6	3	6	42	8	3	1	1	9	1	1	42	6	8	8	5	8
51	4	22	22	6	22	4	6	6	6	3	6	6	7	6	6	0	21	21	4	2	7	7	6	1	1	1	9	1	7	7	6	8	8	9	21
52	4	6	6	6	4	4	6	6	6	3	17	17	7	36	6	8	0	9	4	2	13	2	10	10	1	6	10	9	5	9	9	2	4	14	13
53	4	3	3	3	4	6	6	4	7	3	6	6	7	6	10	11	19	0	10	2	2	2	11	11	1	6	17	22	10	9	9	2	10	10	10
54	4	3	20	3	4	20	20	4	7	7	7	7	8	8	5	25	25	44	0	11	19	19	19	11	1	11	20	20	36	27	13	7	16	18	15
61	4	3	3	3	4	6	6	4	7	7	7	8	4	4	7	11	20	17	10	0	20	111	20	11	11	6	11	24	85	85	13	16	27	27	53
71	4	4	4	5	5	6	4	4	4	1	8	8	8	19	8	3	19	3	22	28	0	4	20	11	11	11	2	33	60	59	28	18	29	31	47
81	4	4	4	5	5	6	4	22	3	2	2	2	10	26	9	3	3	3	22	124	29	0	1	12	11	11	2	9	102	108	17	13	15	53	30
91	4	4	4	5	5	6	4	4	6	6	3	2	6	6	6	10	10	11	22	28	28	9	0	1	11	11	2	19	34	33	17	4	22	28	30
92	4	4	4	5	5	6	10	11	12	3	4	9	3	11	10	9	10	10	10	8	8	12	3	0	11	10	10	9	9	19	23	4	12	8	6
93	6	6	4	4	4	4	13	54	9	10	39	8	7	9	62	9	1	1	1	8	57	12	20	39	0	10	1	9	54	19	65	57	22	11	11
101	22	6	4	22	4	4	22	14	11	9	7	7	7	9	9	9	10	5	10	8	8	11	14	14	15	0	18	5	22	19	22	41	22	22	60
102	7	8	6	7	7	7	6	6	6	6	7	7	7	8	1	2	14	35	14	2	10	10	10	10	10	18	0	52	14	9	8	24	41	41	25
103	10	4	8	10	8	8	10	2	6	6	7	7	7	8	1	6	6	15	11	2	10	10	10	10	10	25	25	0	14	9	8	19	25	25	21
111	3	4	3	5	5	5	22	35	33	15	6	6	7	5	6	6	5	6	8	6	19	16	16	9	6	14	14	14	0	6	8	6	17	23	19
112	3	3	4	4	4	5	19	130	99	15	6	6	7	5	33	5	8	9	4	23	19	122	16	9	9	9	9	6	33	0	8	8	4	23	4
121	3	3	3	4	4	4	19	36	36	17	6	6	6	5	5	5	8	8	4	4	22	19	20	4	4	3	8	6	6	11	0	6	4	4	4
122	3	3	3	3	4	4	5	8	17	8	6	6	6	6	6	8	3	3	13	38	61	17	25	6	15	23	31	22	20	15	27	0	6	16	17
131	3	3	3	3	4	4	12	25	25	14	5	6	6	31	6	1	3	15	14	52	54	84	35	4	14	40	40	54	31	43	19	6	0	18	38
132	3	3	3	3	4	4	12	57	31	12	5	5	6	6	3	1	3	3	15	6	2	31	34	8	15	2	2	46	25	29	14	6	2	0	2
133	3	3	3	3	3	4	21	28	3	11	5	4	4	5	5	5	4	4	5	5	3	10	19	8	11	12	11	40	25	11	6	6	17	23	0

Car origin-destination movement patterns on Monday at 10:00 a.m. – 11:00 a.m.

	11	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**	**31**	**32**	**33**	**34**	**35**	**41**	**51**	**52**	**53**	**54**	**61**	**71**	**81**	**91**	**92**	**93**	**101**	**102**	**103**	**111**	**112**	**121**	**122**	**131**	**132**	**133**
11	0	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	8	11	8	3	4	4	4	4	6	19	19	8	2	4	4	3	3	3	3
12	2	0	2	2	2	3	3	3	3	3	3	3	3	3	4	3	18	29	18	3	4	5	5	4	6	11	13	12	2	4	4	4	3	3	3
13	2	2	0	2	3	3	3	3	3	3	3	4	4	4	4	3	8	11	8	3	5	5	5	5	5	5	2	2	2	4	4	4	4	3	3
14	2	2	2	0	3	3	3	3	3	4	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4	4	4
15	2	2	2	3	0	3	3	4	4	4	4	4	4	4	5	5	5	5	5	5	6	6	6	6	6	6	5	5	5	5	5	5	4	4	4
16	2	2	2	3	3	0	4	4	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6	6	6	6	6	6	6	5	5	5	5	5	4
17	2	2	3	3	3	3	0	4	4	4	4	4	5	12	12	12	6	6	20	22	47	28	25	14	14	14	6	3	11	26	24	27	32	32	30
21	2	2	3	3	3	3	4	0	19	6	3	3	5	14	80	14	6	6	20	134	19	171	25	16	91	16	7	3	13	39	80	31	60	154	31
22	2	2	3	3	3	4	4	4	0	16	10	18	7	17	11	19	6	5	22	24	47	28	26	16	11	16	7	3	11	28	11	10	38	32	32
31	2	3	3	3	4	4	4	5	5	0	22	7	10	6	6	17	18	5	14	2	8	3	2	2	5	3	7	7	7	4	8	16	6	6	3
32	3	3	3	3	4	4	5	5	5	16	0	16	16	9	5	6	6	5	2	2	8	4	6	6	4	8	8	8	8	7	5	5	5	6	6
33	3	3	3	3	4	4	5	5	5	12	9	0	34	14	10	6	6	6	1	5	4	6	6	6	4	8	8	8	8	8	2	9	2	7	5
34	3	3	3	3	4	4	5	5	3	11	18	18	0	43	16	6	30	9	6	7	26	5	5	5	4	8	8	8	8	8	2	2	2	7	5
35	3	3	18	3	4	4	6	6	8	16	13	18	31	0	16	33	13	9	18	7	9	9	8	16	3	1	9	1	6	6	6	7	7	7	5
41	3	8	8	8	3	3	6	39	8	3	3	8	8	8	0	12	16	11	6	3	6	39	8	3	1	1	9	1	1	39	6	8	7	5	8
51	3	18	18	6	18	3	6	6	6	4	7	7	11	7	9	0	20	20	4	3	8	8	6	1	1	1	9	1	6	6	6	8	8	11	20
52	3	6	6	6	3	3	6	6	6	4	23	23	11	52	9	11	0	9	4	3	20	3	10	10	1	6	9	8	5	9	8	2	3	15	20
53	3	3	3	3	4	6	6	4	6	4	7	7	11	7	12	11	19	0	10	3	3	3	11	10	1	4	16	20	10	9	9	2	7	7	7
54	4	3	21	3	4	21	21	4	7	7	7	7	7	8	4	23	23	43	0	11	18	18	18	10	1	11	22	22	31	22	11	8	18	19	15
61	4	3	3	3	4	6	6	4	7	7	7	7	3	3	6	11	19	16	10	0	18	102	18	11	10	6	11	22	69	69	11	19	34	34	61
71	4	4	4	4	5	6	4	4	4	1	7	8	7	14	7	2	14	2	19	27	0	3	18	11	11	11	2	27	50	49	23	21	35	37	48
81	4	4	4	5	5	6	4	19	3	2	2	2	9	22	8	2	2	2	19	112	29	0	1	11	11	11	2	7	86	91	14	15	12	51	28
91	4	4	4	5	5	6	4	4	6	6	3	2	6	6	6	9	10	10	19	27	27	8	0	1	11	10	2	16	29	28	14	4	20	27	29
92	4	4	4	4	5	5	10	11	12	2	3	9	3	11	10	9	9	9	10	7	7	11	2	0	11	9	9	9	9	19	22	3	11	8	6
93	5	5	4	4	4	4	13	55	9	10	41	8	7	9	63	9	1	1	1	7	53	11	19	41	0	9	1	9	55	19	61	53	19	9	10
101	22	5	4	22	4	4	22	14	11	9	7	7	7	9	9	9	7	3	7	7	7	11	15	15	15	0	16	3	19	19	22	38	16	16	56
102	6	7	6	6	6	7	6	5	6	6	6	7	7	8	1	2	11	25	11	3	10	10	10	9	10	18	0	43	11	8	8	23	39	39	22
103	10	4	6	10	6	6	10	2	6	6	6	6	7	7	1	6	6	16	11	3	10	10	10	9	10	22	22	0	11	8	8	19	29	29	25
111	3	4	3	4	4	4	19	31	29	13	6	6	7	5	5	6	6	6	9	6	17	15	15	9	5	12	12	12	0	6	8	6	19	27	22
112	3	3	4	4	4	4	17	114	86	13	6	6	6	5	30	5	8	8	4	26	17	110	15	9	8	8	8	6	30	0	8	7	4	26	4
121	3	3	3	4	4	4	17	32	32	16	6	6	6	5	5	5	8	8	4	4	21	18	18	4	4	3	8	6	6	11	0	6	4	4	5
122	3	3	3	3	4	4	5	8	21	8	5	6	5	5	5	7	2	2	11	34	56	21	23	5	13	18	26	17	17	14	29	0	6	14	14
131	3	3	3	3	4	4	13	27	24	15	5	5	5	27	5	1	2	14	13	45	49	75	35	4	12	32	32	45	28	38	19	7	0	16	34
132	3	3	3	3	3	4	13	60	33	13	5	5	5	5	4	1	3	3	13	9	2	35	33	8	12	3	3	43	26	31	13	6	3	0	2
133	3	3	3	3	3	4	22	30	4	11	5	4	4	5	5	5	3	3	5	6	4	11	20	7	11	10	11	38	25	12	6	6	17	24	0

Car origin-destination movement patterns on Monday at 11:00 a.m. – 12:00 a.m.

	11	12	13	14	15	16	17	21	22	31	32	33	34	35	41	51	52	53	54	61	71	81	91	92	93	101	102	103	111	112	121	122	131	132	133
11	0	2	2	2	2	2	3	3	3	3	3	3	3	3	3	5	11	14	11	5	4	4	4	4	5	17	17	8	2	4	4	3	3	3	3
12	2	0	2	2	2	3	3	3	3	3	3	3	3	3	4	5	26	36	26	5	4	4	4	4	5	11	12	11	2	4	4	4	3	3	3
13	2	2	0	2	2	3	3	3	3	3	3	3	4	4	4	5	11	14	11	5	5	5	5	5	5	4	2	2	2	4	4	4	3	3	3
14	2	2	2	0	3	3	3	3	3	4	4	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	4	4	4	4	4	3
15	2	2	2	3	0	3	3	4	4	4	4	4	4	4	5	5	5	5	5	5	5	6	5	5	5	5	5	5	5	5	5	4	4	4	4
16	2	2	2	3	3	0	4	4	4	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6	6	6	6	6	6	5	5	5	5	4	4
17	2	2	3	3	3	3	0	4	4	4	4	4	4	11	11	11	6	6	18	22	45	27	24	13	13	13	6	3	10	24	22	25	32	32	29
21	2	2	3	3	3	3	4	0	19	6	3	3	5	14	73	14	6	6	18	122	19	165	24	15	86	15	7	3	14	36	73	31	59	146	29
22	2	2	3	3	3	4	4	4	0	15	11	16	6	16	13	18	6	5	20	22	45	27	25	16	13	15	7	3	10	27	13	11	36	32	30
31	2	3	3	3	3	4	4	4	4	0	19	6	8	6	6	13	17	5	11	2	7	2	2	2	5	3	7	7	7	4	9	14	6	6	3
32	3	3	3	3	4	4	5	5	4	11	0	11	11	7	4	6	6	5	2	2	8	4	6	6	4	8	8	7	7	7	4	4	4	6	6
33	3	3	3	3	4	4	5	5	4	11	6	0	31	14	11	8	8	8	2	6	5	7	6	6	3	8	8	8	8	7	1	6	1	6	5
34	3	3	3	3	4	4	5	5	2	10	18	18	0	50	18	7	39	11	7	8	32	6	4	4	3	8	8	8	8	7	1	1	1	6	5
35	3	3	17	3	4	4	6	6	7	11	12	17	27	0	18	32	15	11	17	8	10	10	7	11	2	1	8	1	7	7	7	7	7	7	5
41	4	8	8	8	3	3	6	43	7	2	2	7	7	7	0	12	15	11	6	3	6	43	7	2	1	1	9	1	1	43	7	7	7	5	8
51	4	21	21	6	21	3	6	6	6	4	6	6	9	6	8	0	20	20	4	3	9	9	6	1	1	1	9	1	7	7	7	8	7	11	20
52	4	6	6	6	3	3	6	6	6	4	20	20	9	47	8	9	0	9	4	3	20	3	10	9	1	4	6	6	4	8	8	1	2	13	20
53	3	3	3	3	4	6	6	4	6	4	6	6	9	6	11	11	20	0	10	3	3	3	10	10	1	3	12	15	9	9	8	1	5	5	5
54	3	3	21	3	4	21	21	4	6	7	7	7	7	8	5	25	25	47	0	10	17	17	17	10	1	10	23	23	31	22	11	7	15	16	13
61	3	3	3	3	4	6	6	4	6	7	7	7	4	4	7	11	21	17	10	0	17	99	17	10	10	6	12	23	70	70	11	16	30	30	52
71	4	4	4	4	5	5	3	4	4	1	7	7	8	20	8	3	20	3	17	23	0	2	17	10	10	10	1	27	48	48	23	17	28	30	48
81	4	4	4	4	5	5	3	18	2	2	2	2	10	22	9	3	3	3	17	101	24	0	1	11	10	10	1	6	80	85	13	11	10	42	24
91	4	4	4	4	5	5	3	4	6	7	3	2	7	7	6	9	9	10	17	23	23	7	0	1	10	10	1	15	27	27	13	3	16	22	25
92	4	4	4	4	5	5	9	11	12	3	3	9	3	10	9	8	9	9	9	7	7	11	3	0	11	9	9	8	8	17	20	3	11	7	6
93	6	6	4	4	4	5	12	50	9	10	41	8	7	8	58	8	1	1	1	7	48	11	22	41	0	9	1	8	50	17	56	48	17	8	9
101	26	6	4	26	4	5	26	14	11	9	7	7	7	8	8	8	6	4	6	7	7	11	16	16	13	0	11	4	16	17	20	36	15	15	57
102	7	8	6	7	7	8	6	6	6	6	6	6	7	7	1	3	11	22	11	3	9	9	9	9	8	11	0	32	9	8	8	23	39	39	25
103	10	4	7	10	7	7	10	2	6	6	6	6	7	7	1	6	6	16	12	3	9	9	9	9	8	23	23	0	9	8	8	20	32	32	27
111	3	4	3	4	5	4	18	28	27	12	6	6	6	4	5	6	6	7	9	6	17	14	14	8	6	12	12	12	0	5	7	7	21	30	24
112	3	3	3	4	4	4	16	105	81	12	6	6	6	4	25	4	8	8	4	26	17	106	14	8	8	8	8	5	25	0	7	7	4	26	4
121	3	3	3	3	4	4	16	30	30	15	5	6	6	4	4	4	7	8	4	4	20	17	17	4	4	3	8	5	5	11	0	6	4	4	5
122	3	3	3	3	4	4	4	7	19	7	5	5	5	5	5	7	2	2	11	31	50	19	21	6	14	18	24	16	16	13	28	0	5	11	12
131	3	3	3	3	3	4	11	22	21	13	5	5	5	25	5	1	2	13	11	40	45	65	30	4	11	31	31	43	25	34	17	6	0	12	30
132	3	3	3	3	3	4	11	48	28	11	5	5	5	5	2	1	3	3	12	6	1	28	29	7	11	2	2	42	22	26	11	6	2	0	1
133	2	3	3	3	3	3	19	26	2	9	5	4	4	4	5	4	3	3	5	4	2	13	19	7	11	10	12	41	24	10	6	6	20	31	0