STRUCTURAL HEALTH DIAGNOSIS/MONITORING USING NEURAL NETWORKS FOR CABLE-STAYED BRIDGE MANAGEMENT SYSTEM

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***ABSTRACT*:** The cable-stayed bridge is generally a highly statically indeterminate structure. The structural performance of the bridge is highly sensitive to the load distribution among major components of the bridge. Therefore, the stayed cables of the cable–stayed bridge should be monitored to prevent bridge damage due to earthquake, strong wind, differential settlement, fatigue/defect of the material or loose of tension within the cables. That makes the structure health monitoring and diagnosis of the cable forces for the optimum structural performance very important in a cable-stayed bridge maintenance procedure. This study proposes a structural health diagnosis/monitoring management system for cable-stayed bridges using Neural Networks and field measurement data. The neural networks were used to 1. Analyze reversely the corresponding axial forces of all the stayed cables using sets of rotation measured from the pylon and 2. Determine the type and degree (scope) of the damaged bridge with ease and efficiency. Based on the cable force evaluated, the structural behavior including the deformation and stress state of the bridge can be traced successfully. Also, the damage state of the cable-stayed bridge can be identified using neural networks through the measured cable forces within stayed-cables. A few cases were studied and the results obtained could be applied for Cable-Stayed Bridge Management System.

KEYWORDS: Neural Network, Structural Health Diagnosis, Monitoring, Bridge Management System

1. INTRODUCTION

One of the engineers' favorite types of bridges is the cable-stayed bridge since its special style and the need for long span bridge. The span length record for the cable-stayed bridge was extended since the progress of the design ability as well as the break-through of the construction technology recently. Since the structural performance of the cable-stayed bridge is very sensitive to the load distribution among major components of the bridge such as pylons, stayed cables and the girders, the cables of the bridge should be monitored to prevent bridge damage due to earthquake, strong wind, differential settlement, fatigue or defect of the material as well as loose of tension within the cables. The bridge authority in Taiwan works very hard in monitoring, maintenance, and retrofitting of the bridges to prevent any defects on the bridges and to assure the robustness and safety of the bridges since most of the cable-stayed bridges play important roles in the transportation network. Usually the monitoring and maintenance jobs cost lots of money and manpower in tradition ways, therefore, the structure health diagnosis and monitoring (SHD/M) of the post-tensioning cable forces is very important for the cable-stayed bridges. An automatic monitoring system is needed for the bridge life-cycle management to reduce the maintenance cost. New technologies such as soft computing tools were used in the bridge management system (BMS) and feasibility of such application was studied.

In order to prevent the unexpected bridge damage and its consequence including the repairing cost, the casualty, the traffic impact and indirect economic loss, the SHD/M techniques become very important recently. Four important factors were mentioned for a robust SHD/M system: (a) the instrumentation and data collection, (b) the transfer of the measured data (signal), (c) the data analysis and the characteristics recognition, and (d) the diagnosis of element damage and the bridge safety assessment. Several methods for SHD/M were developed by the International Association for Structural Control and ASCE; Grosso et al. (2002) also provided the experience of SHM on bridges at Europe. For diagnosis of structural damage, Rytter (1993) from Denmark proposed that five items should be evaluated: 1. the damage occurrence, 2. location, 3. type, 4. scope, and 5. its influence to structure safety.

The vibration-based method has been a common approach to detect the damage of bridges. The methods developed are mainly based on the premise that modal parameters, such as natural frequency and mode shape, would change as damage forms. Theoretically the measurement of the vibration data can provide the information about the damage occurrence and its location. From that, the dynamic characteristics such as mode, frequency and damping ratio of the structure can be recognized, if the structure is suffered from damage, its natural frequency and stiffness matrix will change so the structural damage can be diagnosed. In reality, modal parameters are, in general, not sensitive to damage. The temperature change can induce remarkable frequency shift in case of the analyzed data coming form girder vibration. In addition, when damage forms the major change of modal parameters often takes place in higher modes, which needs very precise measurement. Later, another vibration-base method, which is developed on the basis of cable vibration, is proposed to detect the damage of cable-stayed bridge. The reason to change the monitoring target from girder to stay cable is that in comparison with girder it is much easier to extract the model parameters of cable from the recorded ambient vibration data and the cable forces can be determined as its natural frequencies is obtained. Because the cable force dominates the stress condition of the bridge and also is sensitive to the loadings applied to the bridge, it can be an appropriate index for the detection of damage. Hence, the micro-vibration method is able to provide the information we need to evaluate the structure safety for cable-stayed bridge. The previous researches on recognition of structural dynamic characteristics for bridges using measured micro-vibration data including Farrar et al (1997), Qin et al (2001), Chen et al (2004), indicates the success of the micro-vibration method.

This study is further developed using micro-vibration measured data combined with grouped neural networks for SHD/M. Using neural networks with supervised learning (ex. back-propagation neural network), the type of the damage as well as its scope and influence to structure safety can be evaluated. In this paper, the applications of neural networks on SHD/M for cable-stayed bridges are introduced. This study demonstrates two SHD/M cases for cable-stayed bridges using neural networks combined with field measurement data. The neural networks were used to analyze the corresponding axial forces of all the stayed cables using sets of rotation measured from the pylon of Mau-Lo-Hsi Cable-Stayed Bridge, and also to determine the damage type and scope of the Chi-Lu Cable-Stayed Bridge using field measured data with ease and efficiency. In the case of Mau-Lo-Hsi Cable-Stayed Bridge, the neural networks show their potentials to evaluate the cable force and trace the structural behavior successfully from the rotation angles of the pylon while the direct measurement of the cable force was in difficulty. Besides, a concept of so-called expert group neural networks was proposed to mimic the behavior of experts from a committee. Furthermore, in the case of Chi-Lu Bridge, the neural networks are able to identify the damage state of the bridge through the measured forces within stayed-cables. The validity of the proposed method is confirmed by the numerical studies using SAP2000 on several bridge models. The results obtained from these cases can be very helpful to the SHD/M for cable-stayed bridges in the BMS.

2. NEURAL NETWORKS

Neural networks are known as a biologically inspired soft computing tool that possesses a massively parallel structure. The unique structure of neural networks provides their learning capabilities, which differs them from other mathematically formulated methods, and allow the development of neural network based methods for certain mathematically intractable problems. The neurons of the neural network were able to process the signals from the neurons of the previous layer and send signals to the neurons at next layers. The knowledge learned from the training data was stored in the connected weights among the neurons. The whole network works as a highly nonlinear system capable of dealing problems with imprecise data as well as acceptable prediction ability (generalization). Therefore, neural network is very suitable for SHD/M applications. Since 1989 (Venkatasubramanian and Chan), numerous researchers had applied neural networks on SHD/M related issues. Pandey and Barai (1995), Chan et al (1999), Liu and Sun (1997), Barai and Pandey (1997), Huang and Loh (2001), Zhu and Qian (2005), had some excellent researches in this area. In this paper, the authors proposed solutions using grouped neural networks for SHD/M and BMS.

2.1 Grouped neural networks

There are several ways to group neural networks in applications. The first one used in this study is called Expert Group Neural Network (EGNN). EGNN is proposed by Lin and Sung (2006) to determine the appropriate axial force combination within the cables of the cable stayed bridge. Many neural networks trained by different inputs constituted the expert group as a committee of experts. Each expert with individual expertise could provide the appropriate comment (answer) when meeting together, and the solution among the comments can be chosen based on the optimization methodology.

Besides the EGNN, the Auto Associative Neural Network and Probability Neural Network were used in a group for SHM at Tsing-Ma Bridge, as Sun et al (2003, 2004) proposed. Therefore, the authors used a bunch of neural networks in BMS to monitor the structural health of cable-stayed bridge. The method is applied using the field measurement and analysis result from Chi-Lu Cable-Stayed Bridge. Several feed-forward back-propagation neural networks trained by different types of inputs constituted the Grouped Neural Network. The architecture of each neural network among the group is set to be different. Among them, one neural network is with the training data set of uniform loading plus differential settlements, while another neural network having training datasets of other type of loading change such as earthquake, wind, etc. Each of the neural networks was used to analyze reversely the relationship between the cable force and damage scope of the bridge.

3. CASE STUDY

3.1 Mau-Lo-Hsi Cable-Stayed Bridge

The superstructure of the Mau-Lo-Hsi Cable-Stayed Bridge reveals an asymmetric two-span layout to minimize the detrimental influence on hydraulics of pylon setting in the central part of the river. Besides, the concrete grouting is employed inside the girders of the short span as a counter-weight to reduce the unbalanced loading arising from the asymmetry of the superstructure. A parabolic shape was adopted as the geometric skeleton of the pylon for anti-buckling performance as well as its aesthetic appearance. It is 85 m between the two sides of the pylon base and a tie-beam arranged at the pylon waist links two girders to enhance the lateral stiffness of the decks. In addition, an underground steel tie-beam connecting the bottoms of the pylon was pre-stressed to eliminate the influence of the horizontal shear forces due to the dead load on the piles (Fig. 1).

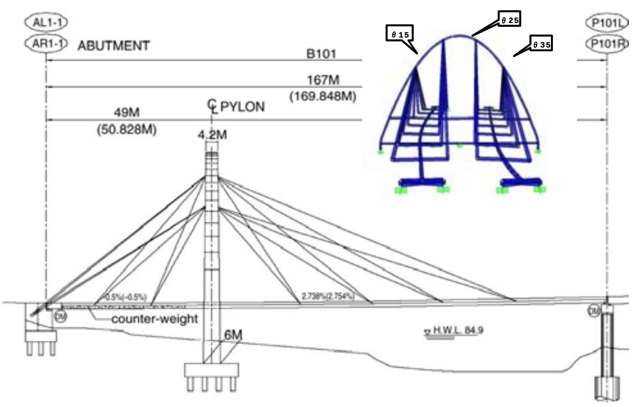

Fig. 1. Elevation of the Mau-Lo-Hsi Cable-Stayed Bridge.

The EGNN was applied for Mau-Lo-Hsi Cable-Stayed Bridge with field measurement data. Each of the EGNN were used to predict the corresponding axial forces of nearly all the stayed cables using 3 sets of rotation angles measured from the pylon. Based on the cable force evaluated, the structural behavior including the deformation and stress state of the bridge can be successfully traced. 36 cables of Mau-Lo-Hsi Cable-Stayed Bridge were grouped into 18 pairs with 9 actual pairs of cables attached along the edges of the bridge decks and connected to the pylon at two different concentrated zones. Because of the relatively short distance between the uppermost two pairs of cables above the short span, they were simply simulated as one single pair with twice the cross sectional area in the structure model. The element numbers of eight pairs of model cables attached along the left bridge deck from short span to long span are indicated as 501–508, and 511–518 respectively while the numbers of the other cables along the right bridge deck are indicated as 521–528 and 531–538. As a result, the cable forces were regarded as the variables for SHM/D of this bridge.

Table 1. The structures of Expert Group Neural Network (EGNN)

No.	Structure	No.	Structure
EGNN-1	3-75-32	EGNN-11	3-60-60-32
EGNN-2	3-80-32	EGNN-12	3-60-65-32
EGNN-3	3-85-32	EGNN-13	3-65-65-32
EGNN-4	3-90-32	EGNN-14	3-65-75-32
EGNN-5	3-95-32	EGNN-15	3-70-75-32
EGNN-6	3-100-32	EGNN-16	3-75-75-32
EGNN-7	3-105-32	EGNN-17	3-75-85-32
EGNN-8	3-110-32	EGNN-18	3-80-85-32
EGNN-9	3-115-32	EGNN-19	3-85-85-32
EGNN-10	3-120-32	EGNN-20	3-85-90-32

20 feed forward back-propagation neural networks trained by different inputs constituted the EGNN as a committee of experts in this case. The architecture of each neural network among EGNN is set to be different as described in Table 1. It consisted of one input layer with 3 neurons, one or two hidden layers and one output layer with 32 neurons. The huge amount of training and testing data are evenly and exclusively divided into 20 groups to train and test 20 neural networks in order to form the expert group.

The EGNN behaved like a group of experts, who grew up from different backgrounds with individual expertise, and were able to provide the appropriate comment when working together as a committee. The optimal solution among the comments will be chosen with easiness and efficiency.

Table 2. The sample of the input data to the EGNN (rotation angles of the pylon, rad.)

	θ15	θ25	θ35
Day 1	0.000671	0.001097	0.001049
Day 2	0.000586	0.001073	0.001051
Day 3	0.000765	0.001086	0.00086
Day 4	0.000558	0.001005	0.001247
Day 5	0.001035	0.001288	0.000909

When preparing the training and testing data for EGNN, different sets of the rotation angles from the top of the pylon were calculated with different combination of the axial force within the stayed cables of the bridge using SAP2000. Then the proposed EGNN were trained to learn the reverse relationship between the rotation angles and the cable forces. Later, the trained EGNN will be able to determine the current axial force within the stayed cables of Mau-Lo-Hsi Cable-Stayed Bridge through the measured rotation angles from the pylon, and the results were verified by the design analysis. Among the EGNN, 10 neural networks are with one hidden layer of 75-120 neurons while another 10 neural networks having two hidden layers with 60-90 neurons. Using a set of 3 rotation angles from the pylon as input (Table 2), the neural networks were able to provide the corresponding axial forces of stayed cables as their outputs (Table 3). The trained neural networks were tested using the measured data from the bridge in the field. Several structural statuses were provided through these EGNN, and the optimal solution among these results will be chosen based on the theory of minimum potential energy. Based on the cable force evaluated, the structural behavior including the deformation and stress state of the bridge can be traced successfully.

Table 3. The example of the output data to the EGNN (axial force of the stayed cable, ton)

	Day 1	**Day 2**	**Day 3**
Cable501	821.13	733.39	726.27
Cable502	413.97	417.47	277.53
Cable503	266.75	420.00	446.64
Cable504	236.54	96.01	219.11
Cable505	178.35	250.03	237.67
Cable506	362.61	340.35	321.37
Cable507	359.90	328.03	379.47
Cable508	325.76	310.69	268.01
Cable511	746.81	744.51	761.26
Cable512	302.42	302.85	248.0
Cable513	196.24	239.51	258.32
Cable514	168.09	98.09	147.35
Cable515	348.15	389.60	214.73
Cable516	334.71	302.31	418.02
Cable517	408.55	410.96	389.35
Cable518	171.59	142.08	147.49
Cable521	861.21	817.32	712.52
Cable522	456.41	293.78	471.94
Cable523	151.79	212.72	113.31
Cable524	211.19	161.07	214.66
Cable525	193.80	207.77	185.49
Cable526	392.80	298.14	470.39
Cable527	377.01	452.97	309.88
Cable528	221.48	188.08	186.09
Cable531	607.66	599.08	759.9
Cable532	334.80	406.15	352.35
Cable533	263.73	402.58	315.0
Cable534	116.64	105.65	126.39
Cable535	285.90	335.87	332.71
Cable536	458.12	428.70	334.95
Cable537	267.22	370.01	404.36
Cable538	251.93	218.33	237.86

3.2 Chi-Lu Cable-Stayed Bridge

Since the stayed-cable is the main path for load distribution on cable-stayed bridges, the change of the stress condition within the bridge can be detected from the stayed-cables. Besides, the modal parameters, such as natural frequency and mode shape, can also be evaluated. Hence, the vibration-base method developed is proposed to detect the damage of cable-stayed bridge. From analysis result, when the pylon or the pier of the bridge is suffered from damage, the variation of the cable force is not as obvious as the variation of the modal frequency. However, if the girder suffered from the damage, the variation of the cable force is much more obvious than the modal frequency. Therefore, the monitoring of the cable force plus modal frequency is very helpful for us to discover the damaged elements as well as the type and the scope of the damage to the cable-stayed bridge.

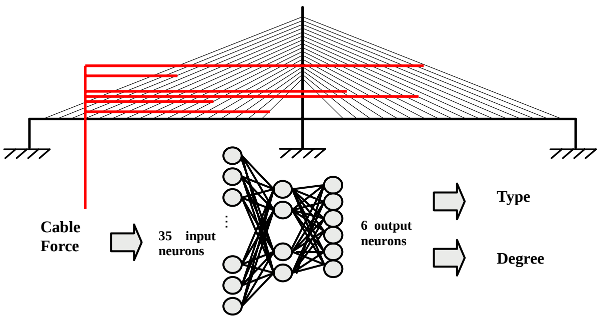

Fig. 2. SHM/D for BMS using neural networks for cable-stayed bridge.

In the case of Chi-Lu Cable-Stayed Bridge, the cause (type) and the scope (degree and location) of the un-usual loading condition including differential settlement, earthquake, strong wind, distributed loading (over layered AC, overweight truck, and traffic jam, etc.) were recognized through the in-situ measured cable forces of the stayed-cables using neural networks. The influence of temperature and noise on measurement data is also considered (Fig. 2). The neural networks were divided into several groups for different type of loading. For example, one neural network is trained to monitor the differential settlement and uniform over-loading, while the other neural network is trained to monitor the damage caused by the earthquake and the strong wind. As for the influence of earthquake, the main concern is the re-distribution of the cable force and the change of the modal frequency of the bridge. The damages on the pylon, the girder, and the pier with different location and scope were considered.

The architecture of the neural networks for Chi-Lu Cable-Stayed Bridge include 4 layers, which are one input layer with 35 neurons, one output layer with 6 neurons, and 2 hidden layers with adjustable number of neurons. The training data were prepared by SAP 2000 with models of Chi-Lu Cable-Stayed Bridge (Table 4). Several groups of simulated data with differential settlements and uniform loading are created using analytical models with different boundary conditions of Chi-Lu Cable-Stayed Bridge. There are 1200 sets of data in each group. 3/4 of the data sets were used for training the neural networks and the rest of the data were then used to test the generalization ability of the trained neural networks. The input data for the neural network is the cable forces within 34 stayed-cables of the Chi-Lu Cable-Stayed Bridge plus noise. The output of the neural network indicates the type of the abnormal loading, and the scope and the degree of the damage. For example, 0-0-1 in the first 3 neurons indicates differential settlement was happened and 0-0.10-0.01 in neurons means there are 10 cm settlement at the pylon and 1 cm settlement at the right pier (end of bridge). The neural networks were trained first by the numerical data, and then the measured field data lately for calibration. The results of the trained neural networks can successfully distinguish the damage type and scope from the measured cable force, even with insufficient measurement or error within 20%.

Table 4 The example of the training data to the NN in Chi-Lu Bridge case

		1	2	3
INPUT (CABLE FORCE)	Cable-01	0.00290	0.01775	0.36805
	Cable-02	-0.00472	-0.03050	0.36805
	Cable-03	0.00152	0.00903	0.41851
	Cable-04	-0.00336	-0.02192	0.41850
	Cable-05	0.00083	0.00460	0.51729
	Cable-06	-0.00289	-0.01901	0.51728
	Cable-07	0.00029	0.00123	0.50879
	Cable-08	-0.00205	-0.01355	0.50878
	Cable-09	0.00003	-0.00035	0.54766
	Cable-10	-0.00166	-0.01104	0.54763
	Cable-11	-0.00010	-0.00117	0.65601
	Cable-12	-0.00147	-0.00982	0.65596
	Cable-13	-0.00010	-0.00093	0.66282
	Cable-14	-0.00088	-0.00590	0.66274
	Cable-15	0.00004	0.00020	0.65411
	Cable-16	-0.00018	-0.00121	0.65400
	Cable-17	0.00029	0.00215	0.63103
	Cable-18	0.00064	0.00439	0.63087
	Cable-19	0.00065	0.00485	0.59448
	Cable-20	0.00162	0.01099	0.59428
	Cable-21	0.00109	0.00821	0.54541
	Cable-22	0.00274	0.01862	0.54517
	Cable-23	0.00202	0.01514	0.62245
	Cable-24	0.00498	0.03386	0.62209
	Cable-25	0.00223	0.01669	0.41507
	Cable-26	0.00542	0.03687	0.41474
	Cable-27	0.00360	0.02684	0.43223
	Cable-28	0.00862	0.05869	0.43178
	Cable-29	0.00447	0.03334	0.32275
	Cable-30	0.01062	0.07231	0.32368
	Cable-31	0.00536	0.03996	0.21107
	Cable-32	0.01267	0.08627	0.21119
	Cable-33	0.00503	0.03749	0.07592
	Cable-34	0.01184	0.08059	0.07659
OUTPUT	Type	0	0	0
		0	0	1
		1	1	0
	Damage Scope, Location	0	0	0.67333
		0.01	0.06	0.67333
		0.03	0.19	0.67333

4. CONCLUSIONS

This paper presents the new concept of structural health diagnosis/monitoring (SHM/D) with neural networks for cable-stayed bridges. Combined with the bridge safety index and alert or action level described in the bridge maintenance guideline, this technology can be integrated within the bridge management system and the safety of the cable-stayed bridge can be assured with the reduced maintenance cost. In the case of Mau-Lo-Hsi Cable-Stayed Bridge, the optimal determination of the post-tensioning cable forces for the best structural performance was considered as the main target in our SHM/D. The new concept of grouping the neural networks called Expert Group Neural Networks is proposed to assist conducting the SHM/D using field measurement data. The corresponding axial forces of all the stayed cables were evaluated reversely through EGNN from the rotation angles measured from the pylon. The structural behavior including the deformation and stress state of the bridge can be traced easily based on the cable force evaluated. In the case of Chi-Lu Cable-Stayed Bridge, the cause and the scope of the abnormal loading condition on the bridge including differential settlement, earthquake, strong wind, distributed loading can be recognized using grouped neural networks and measured cable forces. The field engineers can be assisted with the proposed methodologies to simplify the procedure while conducting the regular maintenance tasks for cable-stayed bridges. Meanwhile, the applications of neural networks on SHD/M of cable-stayed bridges show the feasibility and huge potential on implementing the next generation cable-stayed bridge management system.

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