System Identification 기법을 이용한 복합소재 바닥판 해석모델의 최적강성추정

Optimal Stiffness Estimation of Composite Decks Model using System Identification

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ABSTRACT

Fiber reinforced polymer(FRP) composite decks are new to bridge applications and hence not much literature exists on their structural mechanical behavior. As there are many differences between numerical displacements through static analysis of the primary model and experimental displacements through static load tests, system identification (SI)techniques such as Neural Networks (NN) and support vector machines (SVM) utilized in the optimization of the FE model. During the process of identification, displacements were used as input while stiffness as outputs. Through the comparison of numerical displacements after SI and experimental displacements, it can note that NN and SVM would be effective SI methods in modeling an FRP deck. Moreover, two methods such as response surface method and iteration were proposed to optimize the estimated stiffness. Finally, the results were compared through the mean square error (MSE) of the differences between numerical displacements and experimental displacements at 6 points.

Keywords: fiber reinforced polymer (FRP), finite element model (FEM), neural networks (NN), support vector machines (SVM), system identification (SI)

1. Introduction

The use of Fiber Reinforced Polymer (FRP) as a primary structural material is developing rapidly in the construction industry. FRP materials have considerable advantages in terms of weight, strength and corrosion resistance. They have been used for several decades in the aerospace, automobile and marine industries, where they have developed a good record of accomplishment in very adverse environmental conditions. Although FRP composites are increasingly beingconsidered for use in civil engineering, their widespread use is constrained due to current consideration of higher initial cost, lack of comprehensive design approaches and guidelines, and the predominant use of a one-to-one replacement methodology that often restricts the full utilization of the characteristics of the material. The development of such new FRP

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composite bridge systems raises concerns related to the dynamic response, including under traffic loads, due to the mass and stiffness characteristics which are significantly different from those of conventional steel and structural concrete bridge structural components. Therefore, the technique of system identification is needed to update the finite element models of FRP decks.

The identification of mathematical models of physical structures based onexperimental measurements is a problem that has been receiving increasing attention in the recent past. Numerous publications are available on the subject of system identification of structures(Astrom & Eykoff, Ljung, Billings). The most familiar approaches for system identification are Neural Networks and Support Vector Machine. NN has been used in identification for health monitoring and damage detection(Chassiakos & Masri). Feng *et al* proposed a method to build baseline models for bridge performance monitoring using Neural Networks. An improved approach for nonlinear system identification using neural networks was proposed by Gupta and Sinha. Tang *et al* proposed an online sequential weighted Least Squares Support Vector Machine (LS-SVM) technique to identify the structural parameters and their changes when vibration data involve damage events that can be used for structural health monitoring. Support vector machines framework for linear signal processing was posted by R-Alvarez *et al*.

The paper is organized as follows: Section 2 expounds the theory of Neural Networks and Support Vector Machine used for system identification.In Section 3, static displacement tests are performed and primary finite element model is built, while the identifications of stiffness are discussed. Among which, the response surface method (RSM, Hou *et al*) was utilized to optimize the results. Section 4 Compares experimental displacements with numerical displacements before system identification and identified by NN and SVM. Conclusions are drawn in Section 5.

2. Technique of system identification

Identification is the determination, based on input and output, of a system within a specified class of systems, to which the system under test is equivalent. System identification usually consists of two stages--model selection, and parameter estimation. In neural network based identification, the selection of the number of hidden nodes corresponds to the model selection stage. The network can be trained in a supervised manner with a back-propagation algorithm, which is based on an error-correction learning rule. The error signal is propagated backward through the network. The back-propagation algorithm utilizes gradient descent to determine the weights of the network and thus corresponds to the parameter estimation stage. Neural networks are trained to approximate relations between variables regardless of their analytical dependency, they are usually referred to as model-free estimators.

2.1 Neural Networks

Rumelhart *et al* reported the development of the back-propagation neural network (NN).NN is the most prevalent of the self-learning model of artificial neural networks. A simple architecture of NN consistsof an input layer, a hidden layer, an output layer, and connections between them (Fig. 1). Sigmoid functions are utilized as non-linear activation functions for all layers.

The corresponding architecture for back- propagation learning is incorporating both the forward and the backward phases of the computations involved in learning process. The learning mechanism of this back-propagation network is a generalized delta rule that performs a gradient descent on the error space to minimize the total error between the actual calculated values and the desired ones of an output layer during modification of connection strengths. In other words, a least mean square procedure is carried out which finds the values of the connecting weights that minimize the error function by using a gradient descent method.

In the back-propagation network, the error at output neurons is propagated backward to hidden layer neurons, and then to input layer neurons modifying the connection weights and the biases between them by a generalized delta rule. The modification of the weights and the biases in a generalized delta rule is used through a gradient descent of the error.

2.2 Support Vector Machine

SVM can be applied to regression problem by introducing an alternative loss function. The basic idea of the SVM is to map the input data $\mathbf{x}_i$ into a higher dimensional feature space Φ (Aizerman *et al.*). That is, the SVMis to find the regression function that can best approximate the output and an error tolerance from input data (Fig. 2).

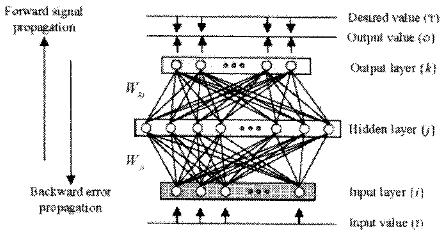


Fig. 1. Structure of back-propagation neural network (Kim *et al.*)

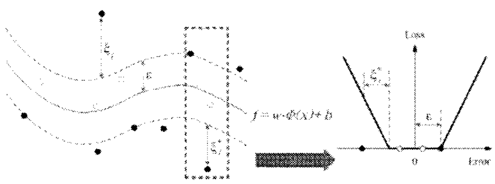


Fig. 2. Nonlinear SVM with ε- insensitive loss function (Yu *et al.*)

3. Case studies

3.1 Experimental test

Two steel girders along the longitudinal direction, two smaller steel girders along the transverse direction bound the test model for static displacement tests of the FRP composite deck between vertical girders as shown in Fig. 3. Several FRP deck units as shown in Fig. 4 adjoin the FRP composite deck. All steel girders are using I-shaped. The static displacement experiment was performed for three times, in which displacements at 6 points were measured. The measured points and experimental results are as shown in Fig. 5 and Table 1.

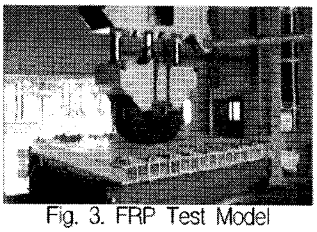


Fig. 3. FRP Test Model

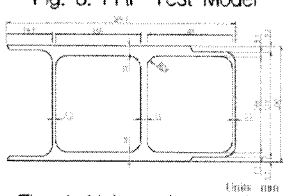


Fig. 4. Unit module section

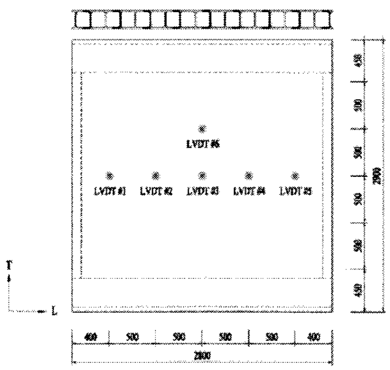


Fig. 5. Schematic of measured points

Table 1 Experimental displacements at 6 points (mm)

	LVDT #1	LVDT #2	LVDT #3	LVDT #4	LVDT #5	LVDT #6
Test 1	0.1600	0.5100	2.3300	0.9200	0.2200	1.7600
Test 2	0.1500	0.4800	2.2900	0.9100	0.2300	1.7500
Test 3	0.1500	0.4800	2.2300	0.8800	0.2300	1.7000
mean	0.1533	0.4900	2.2833	0.9033	0.2267	1.7367

3.2 Primary finite element model

We selected Strand7 as the finite element analysis tool, and a total of 172 beam elements, 19,836 plate element and 19,261 nodes were used to model the test model as shown in Fig. 6. Plate element is extensively used, since the deck was made of FRP laminates. Table 2 shows material properties and geometric parameters that are their theory values used to build finite element model.

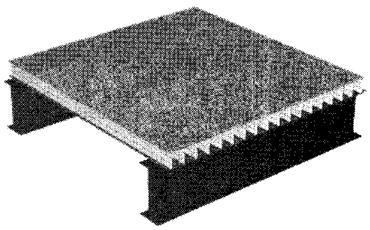


Fig. 6. Finite element model

Table 2 Material properties and geometric parameters

Item	Thickness (mm)	E_X (GPa)	E_Y (GPa)	ν_{XY}	G_{XY} (GPa)	ρ (g/cm3)
Top Flange	18	15.83	14.86	0.253	4.457	1.9
Web	11	17.61	14.27	0.287	4.953	1.9
Bottom Flange	16	15.21	15.80	0.230	4.310	1.9

3.3 System identification

During the process of system identification, displacements at 6 different points was selected as input while stiffness (EX and EY)of flanges and web as output. It means that there are totally 6 input parameters and 6 output parameters. Here NN and SVM that work in the MATLAB are utilized with collaboration of Strand7. The processing of SI was as following: Firstly, establishing training database by static analysis using the primary finite element model. Secondly, Training NN or SVM to obtain the estimated stiffness. Thirdly, inputting the estimated stiffness to the finite element model.

3.4 Optimization methods

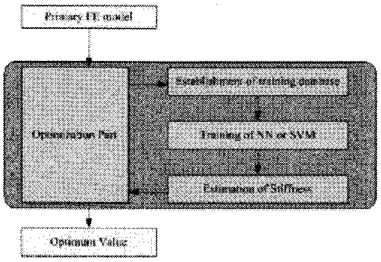


Fig. 7. Optimization process

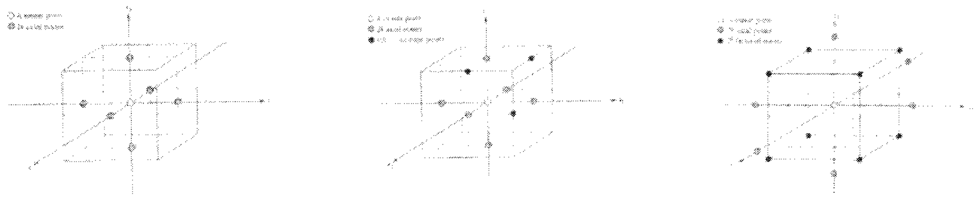
Response surface methodology (RSM) is a set of statistical techniques designed to find the optimized value of the response or toexamine the relationship between experimental responses and variations in the values of input variables. It is also used to optimize response quantities, which are influenced by several independent variables, because it provides simple models of complicated processes. Here two methods that are sampling point and iteration have been used to optimize the results. And the process of optimization was carried out as shown in Fig. 7.

(1) Sampling point : one of response surface methods. In the design range of stiffness, firstly, only first-order approximation to g(X) (Eq. (1)) was used for sampling, which resulted in 13 (6×2+1) evenly distributed design points. Secondly, six parameters of stiffness were changed simultaneously to form the upper and lower boundaries. Thirdly, tow kinds of second-order polynomial (Fig. 8 (b), (c)) were added in succession to find the most effective and efficient model, which can be described as Eq. (2).

$$g(X) = ax + b \quad (1)$$

$$g(X) = a + \sum_{i=1}^{n} b_i x_i + \sum_{i,j=1}^{n} c_i x_i x_j + \sum_{i,j,k=1}^{n} c_i x_i x_j x_k, \quad (n \geq 1) \quad (2)$$

(2) Iteration : In order to get results more accurate, the iteration method was utilized. Moreover, the staring training database was set to be 15 cases, which is more effective and efficient. Here 15 cases of training data mean the process of sampling point ending at the second step. The iteration was repeated for 5 times to obtain the trend of improvement.

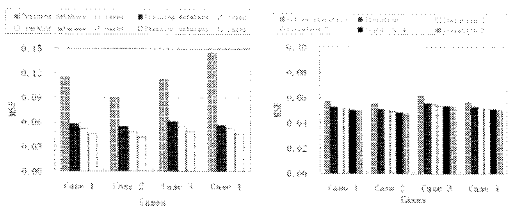


(a) without cross terms (b) saturated design with cross terms (c) central composite designok

Fig. 8. Design points for sampling

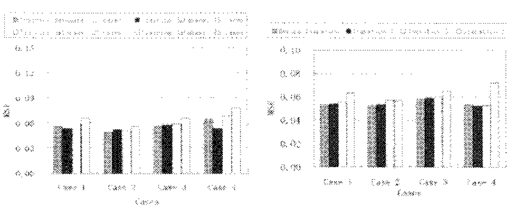
4. Results and discussion

The results were discussed separately, as two methods that are sampling point and iteration were performed independently. For the purpose of comparing their accurateness, the mean square error which is the mean square value of differences between numerical displacements and experimental displacements at 6 points was compared as shown in Fig. 9, 10.



(a) Training data added sampling point (b) Training data added iteration data

Fig. 9 Comparison of results obtained by SVM



(a) Training data added sampling point (b) Training data added iteration data

Fig. 10 Comparison of results obtained by NN

Here the horizontal axis is cases which means that comparing with experimental displacements. During the process of adding sampling point, there are four cases totally which are 13, 15, 27, 43 cases of training database. They are following the proceeding as described in the section of sampling point. In addition, the start-training database of iteration was selected as 15 cases. From the comparisons, we can note that results obtained by SVM have a trend of optimization either by adding sampling point or iteration. However, NN performs strangely since it has a different rule for making a decision response surface.

4. Conclusions

As FRP is new to be utilized in the field of civil engineering, their mechanical properties are not well discussed. This paper proposed two methodologies that are NN and SVM in system identification of modeling a FRP deck. From the comparison of results, we can note that they are both effective in improving finite element models. However, they may perform differently when applying the response surface method.

For further studies, we would like to perform researches on two aspects. Firstly, the method of sampling point will be applied in combination with iteration. Secondly, numerical verifications should be done to verify which one of NN and SVM is more effective in estimating stiffness of FRP

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