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Iterative neural network strategy for static model identification of an FRP deck

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Abstract. This study proposes a system identification technique for a fiber-reinforced polymer deck with neural networks. Neural networks are trained for system identification and the identified structure gives training data in return. This process is repeated until the identified parameters converge. Hence, the proposed algorithm is called an iterative neural network scheme. The proposed algorithm also relies on recent developments in the experimental design of the response surface method. The proposed strategy is verified with known systems and applied to a fiber-reinforced polymer bridge deck with experimental data.

Keywords : fiber-reinforced polymer (FRP); system identification; neural network (NN); response surface method (RSM); iteration.

1. Introduction

The use of fiber-reinforced polymer (FRP) as a primary structural material is increasing rapidly in the construction industry. FRP has received significant attention for use in civil infrastructure due to their unique properties, such as the high strength-to-weight ratio and stiffness-to-weight ratio, corrosion and fatigue resistance. It had been used for reinforcement of bridges, columns and beams and several researches have been performed to investigate their structural behavior experimentally and numerically (Cheng, *et al*. 2002, Kim, *et al*. 2004, Naghipour and Mehrzadi 2007). Although FRP composites are increasingly being considered for use in civil engineering, their widespread use is constrained due to current consideration of their higher initial cost, lack of comprehensive design approaches and guidelines, and the predominant use of a one-to-one replacement method that often restricts the full utilization of the characteristics of the material. The development of such new FRP composite bridge systems raises concerns about dynamic responses to traffic loads and mass and stiffness characteristics, which differ significantly from those of conventional steel and the structural components of concrete bridges. Therefore, a technique of system identification (SI) is needed for the purpose of updating the finite element (FE) models of FRP decks.

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There are a number of SI techniques in which dynamic characteristics, the dynamic response as it is, or the static data are used in accordance with numerical schemes developed on the basis of algebraic relations or artificial intelligence. The scheme used in this study is a neural network (NN). Recently, the problem of identifying mathematical models of physical structures based on experimental measurements has been receiving considerable attention. Numerous publications and methods have focused on the SI of structures (Astrom and Eykoff 1971, Ljung 1987 and Billings 1980). The use of SI approaches for damage detection has been expanded in recent years owing to the improvement of structural modeling techniques, particularly in techniques that incorporate response measurements and advancements in signal analysis and information processing capabilities (Lee, *et al*. 2005). Structural health monitoring has become an important research topic in conjunction with damage assessment and safety evaluation of structures (Chassiakos and Masri 1996, Zou, *et al*. 2000). Feng, *et al*. (2004) proposed an NN-based method of building baseline models for monitoring the performance of bridges. Gupta and Sinha (1999) used NNs in their improved approach to nonlinear SI. Pepijn (2007) proposed an NN-augmented identification of underwater vehicle models: several NNs are used to identify different parts of the model separately. With regard to other aspects, Pavic, *et al*. (2007) proposed a combined experimental and analytical approach for the purpose of investigating modal properties of a lively open-plan office floor: this approach is based on state-of-the-art FE modeling, shaker modal testing, FE model correlation, manual model tuning, and sensitivity-based automatic model updating of a detailed FE model of the composite floor structure.

The prevalent technique for modeling highly nonlinear systems is a surrogate model technique, which is represented by the response surface method (RSM) (Hou, *et al*. 2007). The idea involves the use of some simple basis functions, typically the polynomials (Fang, *et al*. 2005 and Forsberg and Nilsson 2006), to approximate the complex response of a structure; this method obviates the need for FE-driven sensitivity analysis. The polynomial basis function generally provides a good approximation for modeling the energy absorption; however, the multi-quadratic and inverse multi-quadric basis functions are more precise for such highly nonlinear responses as peak acceleration in a full-scale vehicle model. Indeed, the suitability of the RSM for crashworthiness optimization has been exhaustively demonstrated in the literature for a range of design cases. Cylindrical tubes with uniform cross sections (Lee, *et al*. 2002) and tubular-tapered thin-walled structures (Avalle, *et al*. 2002 and Chiandussi and Avalle 2002) are some of the typical applications with regard to sectional columns. In general, the RSM most likely converges to a local optimum, even though it can yield a global optimum if the basis function is selected properly and the analysis domain is sufficiently large. The computing cost can also be improved by using such local refinement techniques as a successive RSM (Stander and Craig 2002 and Kurtaran, *et al*. 2002), a two-step RSM-enumeration algorithm (Xiang, *et al*. 2006) or a D-optimality criterion (Redhe, *et al*. 2002).

In this paper, the baseline model construction methodology for an FRP deck is presented by using SI through iterative training of NNs. The data for training and validating NNs are produced from the simulation of the mathematical model for the FRP deck test model. A multilayer perception network is selected for the model structure. To construct the baseline model for an FRP deck, we use static displacement as the input variable and stiffness as the output variable. Laboratory tests on static displacement are conducted on a real-sized structure. Initially, we use a sampling point method, which is an application of the RSM, to evaluate the effectiveness of the NN training data. We can determine the optimum training data. A numerical model is then performed to investigate the effectiveness of the proposed method. The simulation results confirm that the proposed method is effective and efficient in SI.

2. Theoretical background

2.1 Identification with NNs

SI usually consists of two stages: model selection and parameter estimation. In NN-based identification, the selection of the number of hidden modes corresponds to the model selection stage. The network can be trained in a supervised manner with a back-propagation algorithm that is based on an error-correction learning rule. The error signal is propagated backward through the network. The back-propagation algorithm utilizes a gradient descent to determine the weights of the network; thus, this process corresponds to the parameter estimation stage. The NNs are trained to approximate relations between variables regardless of their analytical dependence; they are usually referred to as model-free estimators.

Rumelhart, *et al*. (1986) and Kim and Park. (2005) reported the development of the back-propagation NN. The back-propagation NN is the most prevalent self-learning model of artificial NNs. The simple architecture of an NN consists of an input layer, a hidden layer, an output layer, and connections between the layers (Fig. 1). The sigmoid functions are utilized as nonlinear activation functions for all layers.

2.2 Response surface method (Myers and Montgomery 1995)

The RSM is utilized as a Meta model approach based on deterministic FE analyses to define the optimized value of the response or to examine the relation between the experimental responses and variations in the values of the input variables. In determining the optimized value of the design points, the RSM is designed to consider the uncertainty or variations in the values of the input variables.

The number of design points should be minimized to increase the computational efficiency. To construct performance functions that contain a second-order polynomial, we can divide the available procedures for experimental design into two categories: classical design and saturated design. In the classical design approach, responses are first calculated at specified design points and then a regression analysis is conducted to formulate the performance function. In this approach, one of the conceptually simpler designs is the factorial design, where the response values are estimated for each variable sampled at equal intervals (Fig. 2(c)). The saturated design consists of only as many design points as the total number of coefficients necessary to define a polynomial which represents the performance function. The design can be used for second-order polynomials with and without cross terms (Figs. 2(a) and 2(b)).

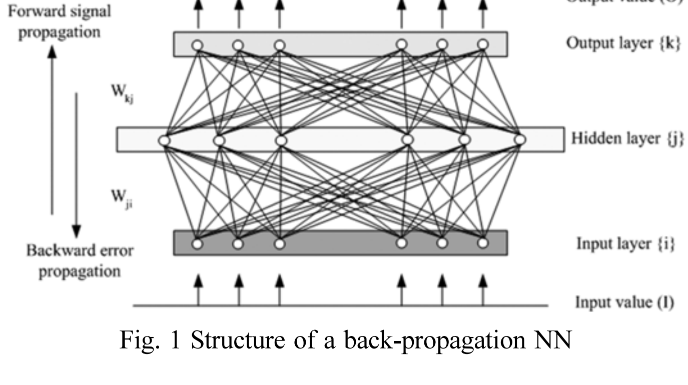


Fig. 1 Structure of a back-propagation NN

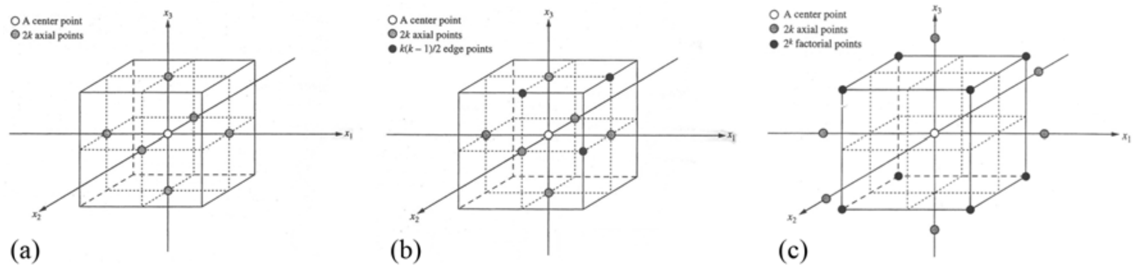


Fig. 2 Experimental design points of the RSM (Haldar and Mahadevan 2000)

3. Experimental tests

A test model of an FRP composite deck that is adjoined to several FRP deck units as shown in Fig. 3 is instrumented. For the static displacement tests of the FRP composite deck, two steel girders along the longitudinal direction, two smaller steel girders along the transverse direction, and four bracings between the girders are utilized to bind the test model. Fig. 4 shows a photograph of the test model and

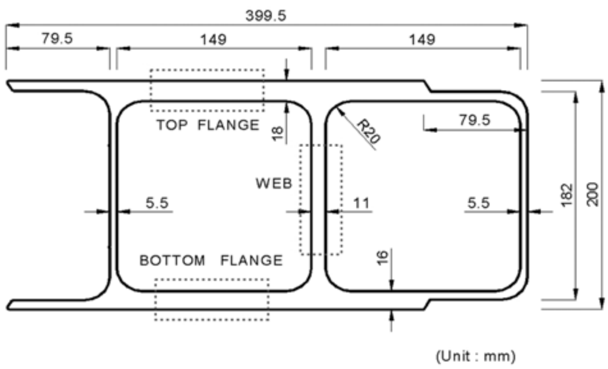


Fig. 3 Unit module section

Fig. 4 FRP test model

Fig. 5 shows a schematic representation. The two longitudinal steel girders are supported by four base blocks at each end of the bottom flanges; the unsupported lengths are about a quarter of the length of the steel girders. For these two girders, we use H100 × 100 × 6 × 8 and C75 × 40 × 5 × 7 I-shaped sections. Two tires are used to exert a load of 50 kN at the center of the deck. The static displacement experiments are performed three times so that we can measure the displacements at the six points shown in Fig. 6. The experimental results are shown in Table 1.

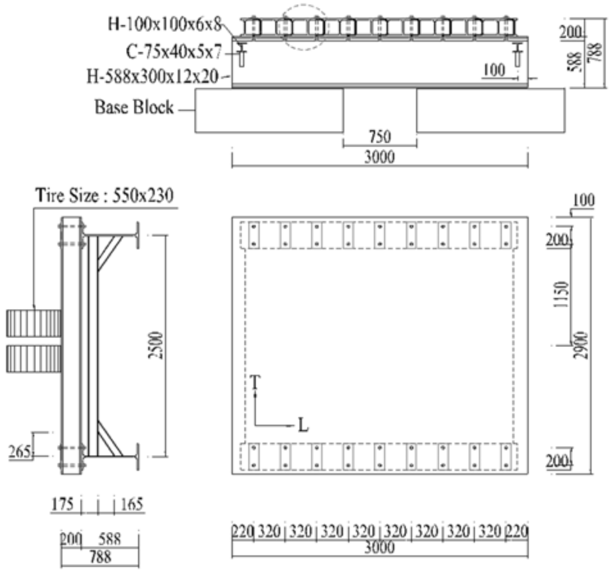


Fig. 5 Schematic of the FRP test mode

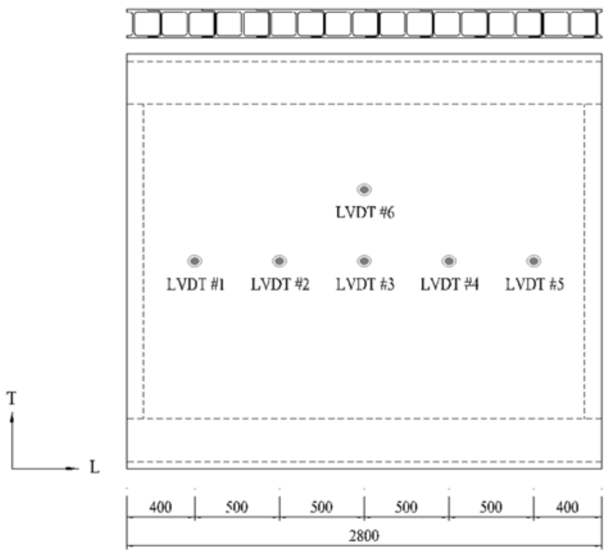


Fig. 6 Schematic of measured points

Table 1 Static displacement through experiments

No. of points	Displacements (mm)			
	Test 1	Test 2	Test 3	Mean
P1	0.16	0.15	0.15	0.1533
P2	0.51	0.48	0.48	0.4900
P3	2.33	2.29	2.23	2.2833
P4	0.92	0.91	0.88	0.9033
P5	0.22	0.23	0.23	0.2267
P6	1.76	1.75	1.70	1.7367

4. Preliminary FE model

The development of the first FE model in this analysis is based on the best engineering judgment. That means we rely solely on information that is typically available in the design, such as construction and architectural drawings and specifications of the various construction materials. Strand7 (R2.4 2005), which is a general-purpose FE analysis program for static and dynamic analysis of structures, is used as our FE analysis tool. To build the test model, which is shown in Fig. 7, we used a total of 172 beam elements, 19,836 plate elements and 19,261 nodes. Plate elements are extensively used because the deck is made up of FRP laminates. Table 2 shows the theoretical values of the material properties and geometric parameters used to build the FE model.

5. SI process

During the SI process, displacements at six different points are chosen as input values, whereas the stiffness (E_X and E_Y) of the flanges and the web, respectively, are chosen as output values. The use of these values means that there are six input parameters and six output parameters in total. As shown in

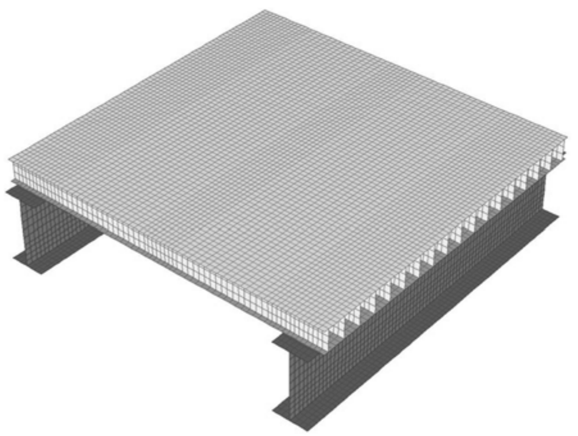


Fig. 7 FE model of the test model

Table 2 Material properties and geometric parameters

Properties of material		Top flange	Web	Bottom flange
Elastic modulus	Transverse ($E_X(GPa)$)	15.83	17.61	15.21
	Longitudinal ($E_Y(GPa)$)	14.86	14.27	15.80
Poisson ratio (V_{XY})		0.253	0.287	0.230
In-plane shear strength ($G_{XY}(GPa)$)		4.457	4.953	4.310
Mass density ($\rho(g/cm^3)$)		1.9	1.9	1.9
Geometry	Thickness (mm)	18	11	16

Table 3 Numerical displacements by static analysis of the preliminary FE model

Items	P1	P2	P3	P4	P5	P6
Displacements (mm)	0.2065	0.7221	2.7915	1.1832	0.3749	1.9797

Fig. 8, the SI with iterative NN training is a process of optimization.

An experimental design based on recent developments of the RSM is used here to find the optimized value of the design points. First, in the design range of stiffness, only a first-order approximation to g(X) is used for the sampling, resulting in 13 ($6 \times 2 + 1$) evenly distributed design points. Six stiffness parameters are then changed simultaneously to form the upper and lower boundaries. Finally, two kinds of second-order polynomials (Figs. 2(b) and 2(c)) are added in succession to find the most effective and efficient model.

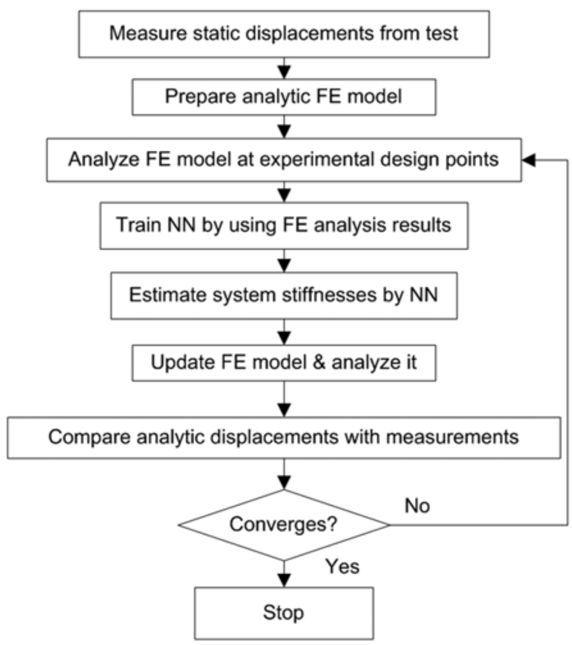


Fig. 8 Flow chart of iterative NN training for SI

5.1. Numerical verification

Three cases of stiffness and displacements, which are shown in Table 4, are used for NN test patterns with regard to the numerical verification; the values are obtained by linear static analysis of the FE model in Strand7. Cases I, II and III refer to the three cases of target stiffness, which are set through certain percent changes of theoretical stiffness.

5.2 Example studies

The experimental displacements shown in Table 1 are used as inputs; the stiffness can be estimated by the NNs. All three tests and average displacements are used to investigate the effectiveness of the proposed method. The construction of the model is based on a simulation of the tested FRP deck and is described in the section on the preliminary FE model. The results are compared and discussed in the next section.

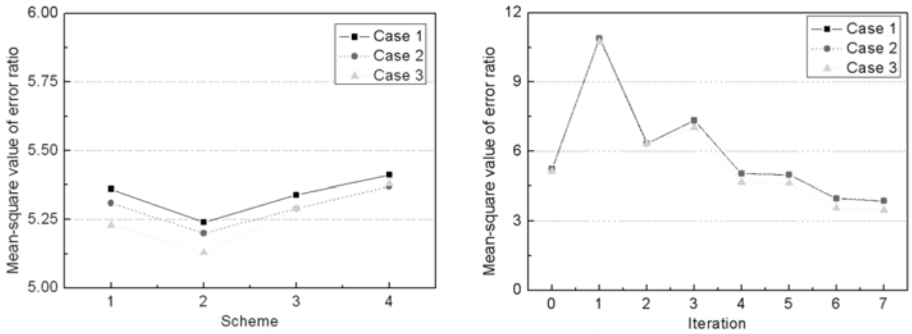
6. Results and discussion

As shown in Fig. 9, the results of the numerical verification are compared in terms of the mean square value of errors of the estimated stiffness and the target stiffness. Four training database schemes are coordinated with the four types of sampling points shown in Fig. 9(a). As shown in Fig. 2, four experimental design schemes for selecting the design points are considered in this section: scheme 1 is a saturated design with a second-order polymer and no cross terms; scheme 2 is a central composite design with a second-order polymer and cross terms; scheme 3 is a saturated design with a second-order polymer and cross term I; and scheme 4 is a saturated design with a second-order polymer and cross term II. The four schemes use 13, 15, 27, and 43 cases of the training database, respectively. Fig. 9(b) shows the results when iterations are performed.

As we can see from the comparison in Fig. 9(a) and Fig. 10(a), scheme 2 is the most effective for estimating stiffness; that means 15 cases of the training database can be used to obtain the optimum value. There appears to be no improvement in accuracy as the number of cases from the training data

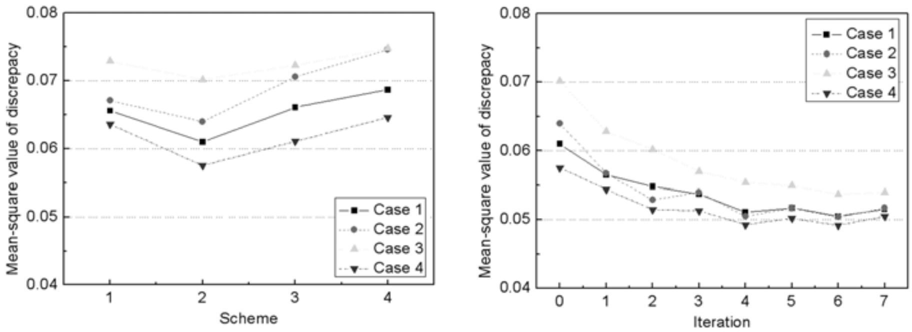
Table 4 Test pattern for the numerical verification

Items			CASE I	CASE II	CASE III
Stiffness (Units: GPa)	Top flange	E_X	17.41	15.83	15.83
		E_Y	14.86	14.86	14.86
	Web	E_X	17.61	17.61	19.37
		E_Y	14.27	14.27	14.27
	Bottom flange	E_X	15.21	15.21	15.21
		E_Y	15.80	15.80	15.80
Displacements (Units: mm)	P1		0.2093	0.2081	0.2128
	P2		0.7237	0.7229	0.7238
	P3		2.7786	2.7835	2.7584
	P4		1.1864	1.1853	1.1808
	P5		0.3777	0.3766	0.3821
	P6		1.9700	1.9735	1.9537



(a) Results of the RSM (b) Results of iterations

Fig. 9 Results of numerical verification



(a) Results of the RSM (b) Results of iterations

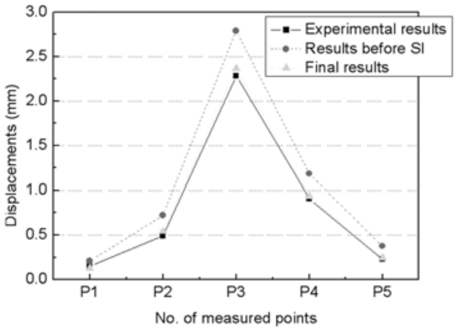
Fig. 10 Results of example studies

increases. To interpret this trend, we assume there is a target line in the coordinate and we endeavor to find an approximation line that is close to the target line. The sampling points are linked so that they represent the approximation line. This process improves the precision at the sampling points, though the precision of the point at the median area (that is, between the sampling points) may be decreased.

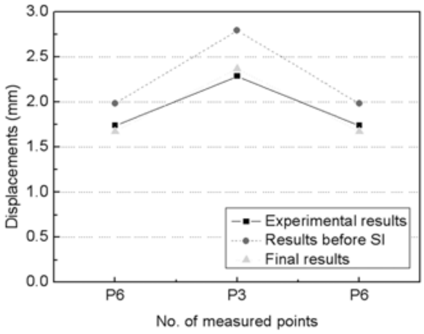
To verify the accuracy of the proposed method, we compare the mean square value of the discrepancies between the numerical displacements and the experimental displacements at six points. The comparison is shown in Fig. 10. The horizontal axis represents the cases of numerical and experimental displacements. A comparison of the iteration results confirms that the mean-square error ratio between the simulated and measured displacements shows a decreasing trend (albeit with slight fluctuations) as the iterations are performed. As shown in Fig. 11, the results of the numerical displacements obtained with the final estimated stiffness are compared with experimental displacements and there is good convergence between the experimental displacements and the final numerical displacements. Thus, the proposed method of iterative NN training is promising for the SI of an FRP deck.

The following conclusions can be drawn from the above discussions:

(1) An increase in the number of cases from the training data does not guarantee any improvement in the accuracy of the method. However, we can obtain a very close approximation of the target accuracy by linking the sampling points. In this way, the precision is improved at the sampling points, though the precision of the point at the intermediate area (that is, between the sampling points) may be decreased.



(a) Longitudinal direction



(b) Transverse direction

Fig. 11 Comparison of numerical and experimental results

(2) In spite of the fluctuations, discrepancies in the numerical and experimental displacements show a decreasing trend. Hence, the proposed method is generally an effective procedure in SI.

7. Conclusions

In this paper, we propose iterative training of NNs for the SI of an FE modeled FRP deck. Static displacements are used as the input to the NNs to estimate the stiffness of the FRP composite material and to reduce the effect of modeling errors in the baseline FE model, from which the training patterns are to be generated. In addition, the RSM is incorporated to make the proposed method more effective and efficient in the preparation of training data. Example analysis with simulated data demonstrates the effectiveness and applicability of the proposed method, which seems to have significant potential for identification of real structures.

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