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An Artificial Intelligence Approach to Objective Health Monitoring and Damage Detection in Concrete Bridge Girders

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ABSTRACT: The purpose of this study is to facilitate damage detection and health monitoring in concrete bridge girders without the need for visual inspection while minimizing field measurements. Simple span beams with different geometry, material and cracking parameters were modeled using Abaqus finite element analysis software to obtain stiffness values at specified nodes. The resulting databases were used to train two Artificial Neural Networks (ANNs). The first network (ANN1) solves the forward problem of providing a health index parameter based on predicted stiffness values. The second network (ANN2) solves the inverse problem of predicting the most probable cracking pattern. For the forward problem, ANN1 had the geometric, material and cracking parameters as inputs and stiffness values as outputs. This network provided excellent prediction accuracy measures ($R^2 > 99\%$). ANN2 had the geometric and material parameters as well as stiffness values as inputs and cracking parameters as outputs. This network provided less accurate predictions compared to ANN1, however, ANN2 results were reasonable considering the non-uniqueness of this problem's solution. An experimental verification program will be conducted to qualify the effectiveness of the method proposed.

1 INTRODUCTION

Damage detection and structural health monitoring are topics that have been receiving an increased attention from researchers around the world. A structure accumulates damage during its service life, which in turn can impair the structure's safety. Assuring the safety of aging infrastructure necessitates periodic assessments and maintenance. The currently used approach, visual evaluation, is performed by experienced personnel and is subject to their personal judgment. This approach is affected by the constraints of time and the availability of qualified personnel. Due to these drawbacks, many alternative approaches are being evaluated for possible application in the field.

Damage detection is achieved by obtaining specific features from the structure to be inspected, then analyzing these features using different processing techniques to obtain cracking parameters. Features include dynamic characteristics, wave response methods, visual features, and static properties. Artificial Neural Networks (ANNs) are commonly employed in analyzing the features obtained from the structure. An Artificial Neural Network (ANN) is a computational model inspired of human cognition and neural biology. ANNs are highly capable learning machines that are able to adapt to very complex relationships. ANNs learn by providing example observations of the phenomenon to be modeled. That and their robustness have contributed to the recent increase in their usage in many fields. Advantages of ANNs include their ability to adapt to complex relations and provide immediate predictions after training is complete (Basheer 1998). Multiple studies utilized ANNs for damage detection. Masri et al. (2000) proposed a method that relies on vibration measurements from a healthy system to train the neural network for identification purposes. This network is then fed comparable vibration measurements from the same structure under different episodes of response in order to monitor the health of the structure. The network then delivers an indicator of damage in the structure. It was concluded that ANNs are a robust tool to detect changes or damage in systems, however, the non-uniqueness of the optimal ANN structure prevents the attribution of changes in the system with the changes in the ANN's parameters. Xu and Humar (2006) combined the modal energy and ANN approaches to determine the location and extent or magnitude of the damage. The location is first determined from the plots of damage indices for the elements in the model, then the damage extent is predicted with an ANN trained on simulated damage in elements and their corresponding damage indices. Kazemi et al. (2011) applied a multi-stage procedure to determine the location and depth of two cracks in cantilever beams. First, the finite element method was used to obtain 3 natural frequencies for cantilevers with varying crack depths and locations. Four ANNs were then created and trained using the Particle Swarm Optimization (PSO) method. Each network predicted a single crack parameter. Finally, the networks were tested and the results demonstrated good agreement with the actual parameters.

The approach presented in this study involves the application of a defined static load at a specified number of equally spaced nodes in the structure and obtaining the deflection at the node under the load. The stiffness values can then be obtained at each node and the generated database can be used to train a static Artificial Neural Network (ANN) with back-propagation learning algorithm to inversely predict a cracks' depth, width and location in a simply supported concrete beam given the beam's geometric and material parameters and stiffness ratios associated with this specific cracking profile.

2 FINTIE ELEMENT MODELING OF AN RC BEAM WITH TWO CRACKS

For this study, the finite element mesh developed for models included two types of elements: healthy and cracked elements. Healthy elements, representing the healthy parts of the beam, had the same depth as the beam, while cracked elements had a reduced depth to represent the crack. A 2-node cubic beam in a plane element (B23) was chosen to model the beam segments in Abaqus FEA 6.10-2 software package ("Abaqus 6.10 Online Documentation" 2010). Concrete was also modeled using a linear elastic material model with a Poisson's ratio (ν) of 0.2 and a modulus of elasticity (E) calculated by equation 1:

$$E = 4723 \times \sqrt{f'_c} \quad (Both\ in\ MPa) \tag{1}$$

Additionally, a specified number of stiffness nodes was added to the mesh along the beam. A defined load (Pn) was applied to each stiffness node and the resulting displacement (Δn) was obtained. The local stiffness (kn) at that node could then be calculated according to equation 2:

$$kn = Pn\ /\ \Delta n \tag{2}$$

This was done for the healthy and the cracked beams to determine the stiffness ratios (kn%), which are obtained by dividing the cracked stiffness (kn_{cr}) by the healthy stiffness (kn_h) at each node for beams with the same geometry and material parameters, as shown in equation 3:

$$kn\% = kn_{cr} \;/\; kn_h \tag{3}$$

Stiffness ratios (kn%) serve as an indicator of the severity of the damage in the beam and can reveal where the crack could be located in the beam. Lower stiffness ratios are expected in beams with deeper and wider cracks. Stiffness ratios at nodes close to the location of the crack are expected to be lower compared to the ratios at nodes farther away.

3 DAMAGE DATABASE GENERATION

Concrete beams with different parameters were modeled in order to generate the damage databases. These parameters included geometric parameters such as the width of the cross-section (b), the depth of the cross-section (d) and the span length of the beam (L), a material parameter represented by the concrete compressive strength (f'_c), and cracking parameters including the depth (d_{cr}), width (w_{cr}) and location (b_{cr}) of the cracks. Most parameters were normalized so that the database could be generalized to beams that were not included in this study but are within the range of the modeled data. In this study, damage databases were generated for beams with two cracks. In order to regulate the possibilities for this case, beams' spans were divided into two regions. Only a single crack could exist in each region, thus a beam could have two, one or no cracks at all. Figure 1 shows an example of a beam with two cracking regions. The parameters and the associated values used to generate the aforementioned damage databases are given in Table 1.

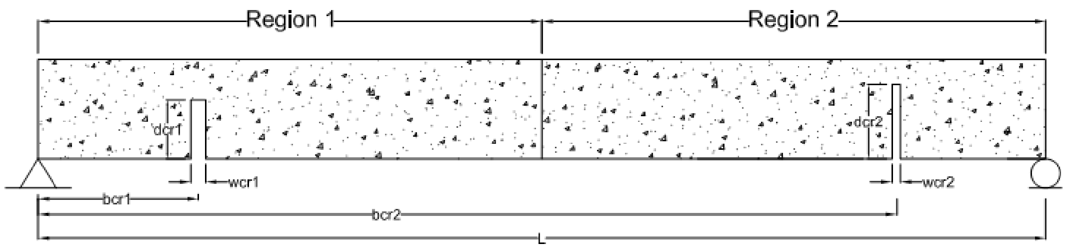

Figure 1. Elevation view of a sample concrete beam with two cracks.

Table 1. List of modeling parameters

b/h	L/h	f'_c (MPa)	Crack 1			Crack 2		
			d_{cr}/h	w_{cr} (mm)	b_{cr}/L	d_{cr}/h	w_{cr} (mm)	b_{cr}/L
0.5	7	21	0.25	0.5	0.167	0.25	0.5	0.667
0.7	10	3	0.5	2.5	0.333	0.5	2.5	0.833
0.9	13	41	0.75	5	0.5	0.75	5	-

Utilizing the results obtained from previous work (Al-Rahmani et al. 2013), databases were generated for the optimum at nine stiffness nodes. A Python script was written to generate the input files directly using Abaqus. The created input files were run in Abaqus and another Python script was written to extract the output deflections from Abaqus binary output databases (*.odb files), determine the stiffness values corresponding to the stiffness nodes, normalize them with the healthy beam stiffness values and store them in the stiffness database. The normalized stiffness values, or stiffness ratios (kn%), were calculated as the ratio of the stiffness at a node in the cracked beam to the stiffness at same node in the healthy beam.

4 ANN MODEL DEVELOPMENT

First, in order to validate the databases obtained from Abaqus, an ANN with the beams' geometric, material and crack parameters (b/h, L/h, f'$_c$, d_{cr}/h, w_{cr} and b_{cr}/L) as inputs and stiffness ratios (kn%) as outputs was created. This is a forward problem that is expected to yield a unique solution for each database. Obtaining good results from this type of networks should verify the datasets and show that the ANN can nicely understand the logic behind them. Additionally, a second forward ANN was created. This ANN had the same inputs, but had the health index (ki%) as its sole output. The health index was calculated by normalizing the total area under the stiffness ratios profile by the beam's span length, and can be obtained by equation 4:

$$Health\ Index\ (ki\%) = \left(\frac{l_n}{L}\right)\left[1 + \sum_{m=1}^{n} km\%\right] \quad (4)$$

$where\ l_n = distance\ between\ two\ consecutive\ stiffness\ nodes.$

$L = beam's\ span\ length.$

$n = number\ of\ stiffness\ nodes.$

$km\% = \ stiffness\ ratio\ at\ node\ m.$

The second type of ANN, in which the stiffness ratios (kn%) and the beam parameters (b/h, L/h and f'$_c$) are the inputs and the crack parameters (d_{cr}/h, w_{cr} and b_{cr}/L) are the outputs, is the main objective of this study. This ANN solves an inverse problem for which no unique solution exists. Each damage database contained 14364 datasets that correspond to the generated Abaqus beam models. The datasets included 27 healthy beams, in addition to the damaged beams obtained by varying the previously mentioned modeling parameters. Following the ANN modeling methodology discussed in the work reported by Najjar and his Co-workers (2003; 2007), several ANN models were included in the evaluation. These ANNs were trained and tested on 7188 and 3588 datasets, respectively, to obtain the optimal number of hidden nodes and iterations. The best 3 ANN models were then chosen based on statistical measures such as the Averaged-Squared-Error (ASE), coefficient of determination (R^2), and Mean Absolute Relative Error (MARE). To determine the best model, validation was performed on the remaining 3588 datasets. Finally, after deciding on the best model of the three, the ANN is retrained at this optimal structure on all the available 14364 datasets to improve the prediction accuracy (Najjar and Huang 2007).

5 RESULTS AND DISCUSSION

Multiple ANN models were created and evaluated for the forward and inverse problems. The convention (# of Inputs_# of Hidden Nodes_# of Outputs) will be used to identify the models. Also, unless noted otherwise, the statistics reported were obtained from training the ANN on all datasets.

As previously mentioned, two ANNs were trained on the generated 9 stiffness nodes damage database using the prescribed procedure. The first ANN had 9 inputs (b/h, L/h, f'$_c$, d_{cr}/h^1, w_{cr}^1, b_{cr}/L^1, d_{cr}/h^2, w_{cr}^2 and b_{cr}/L^2), 9 outputs (k1%, k2%, k3%, k4%, k5%, k6%, k7%, k8% and k9%) %). From training, testing, and validation, the optimal network structure was obtained at 19 hidden nodes (Model 9-19-9) with 19600 iterations. This network provided the following statistics when trained on all datasets: ASE = 0.000016, R^2 = 0.99817 and MARE = 0.169%. The second ANN had the same inputs but a single output, which was the health index (ki%). From training, testing, and validation, the optimal network structure was obtained at 18 hidden nodes (Model 9-18-1) with 18100 iterations. This network provided the following statistics when trained on all datasets: ASE = 0.000003, R^2 = 0.99959 and MARE = 0.062%. The statistics for training, testing, validation, and training on all datasets are summarized in Table 2.

Table 2. Forward problem ANNs' detailed results.

Output		kn%	ki%
Model		9-19-9	9-18-1
Iterations		19600	18100
Training	MARE	0.171	0.066
	R^2	0.99832	0.99957
	ASE	0.000016	0.000003
Testing	MARE	0.173	0.066
	R2	0.99825	0.99955
	ASE	0.000016	0.000003
Validation	MARE	0.172	0.068
	R^2	0.9983	0.99953
	ASE	0.000016	0.000004
All Data	MARE	0.169	0.062
	R^2	0.99817	0.99959
	ASE	0.000016	0.000003

These ANNs provided excellent prediction accuracy. The statistics were very close for both ANNs in all modeling stages due to the large size of the databases and the diversity of the datasets used for training, testing and validation. The very low errors and high coefficient of determination obtained indicate that the databases are accurate and that this type of ANNs is capable of understanding the logic within them. The high degree of prediction accuracy is very evident in this network as shown in Figure 2, where the actual vs. predicted values for k1% and ki% are plotted.

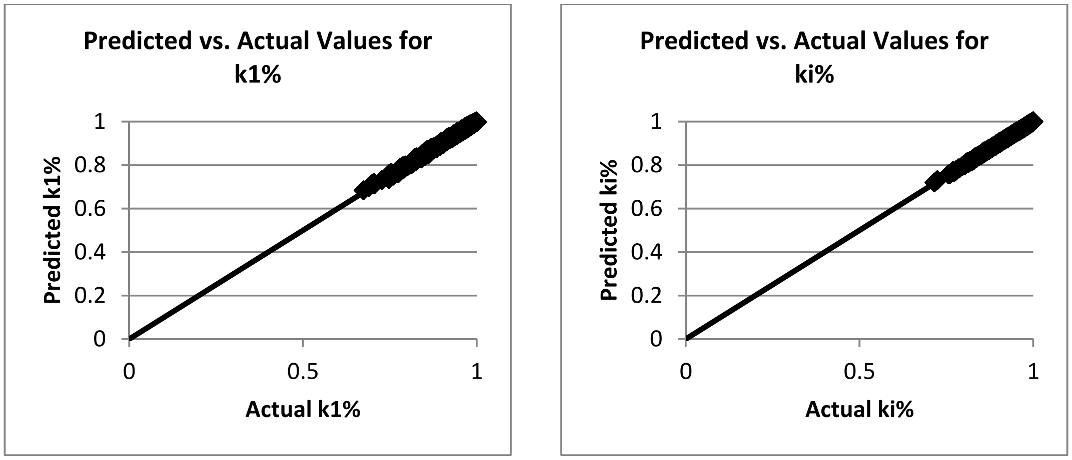

Figure 2. Forward problem's predicted vs. actual values for (a) k1% (b) ki%.

Moving to the inverse problem, ANNs were created to solve the damage detection problem for beams with two cracks modeled using Abaqus following the previously described methodology. These ANNs were trained, tested and validated on the generated 9 stiffness nodes database. For this problem, the inputs were the beams' geometric and material parameters (b/h, L/h and f'_c) in addition to the stiffness ratios (kn%), while the outputs were the two cracks' parameters (d_{cr}/h^1, $w_{cr}{}^1$, b_{cr}/L^1, d_{cr}/h^2, $w_{cr}{}^2$ and b_{cr}/L^2). The results for this ANN are shown in Table 3.

Table 3. Inverse problem ANNs' detailed results.

Model@Iterations		12_18_6@20000
Training	MARE	88.174
	R^2	0.6092
	ASE	0.022252
Testing	MARE	87.913
	R^2	0.60742
	ASE	0.02237
Validation	MARE	85.971
	R^2	0.60304
	ASE	0.022614
All Data	MARE	84.568
	R^2	0.65207
	ASE	0.018121

A slight decrease is observed in the accuracy of the inverse problem's ANN (ANN2-2C) compared to previously developed ANN model (ANN2-1C) for beams with a single crack (Al-Rahmani et al. 2013). Statistical measures for ANN2-2C were: MARE = 84.568%, R^2 = 0.65207, ASE = 0.01812, compared to ANN2-1C, where MARE = 52.338%, R^2 = 0.67834, ASE = 0.012113. The percentage differences from ANN2-1C to ANN2-2C were 61.58%, -

3.87%, and 49.59%, for MARE, R^2, and ASE, respectively. This decrease was expected as the ANN is trying to predict three additional outputs for beams with two cracks. Even though the obtained errors were relatively high, the predictions of this ANN could still be considered reasonable for practical applications. This is due to the fact that the cracking parameters (especially the crack width) are very small in magnitude, so even a large error value can only cause a variation of fractions of millimeters. Figure 3 plots the predicted values provided by ANN2-2C vs. the actual values for the first crack's parameters. It is also perceived that the most accurately predicted parameter is the location of the crack.

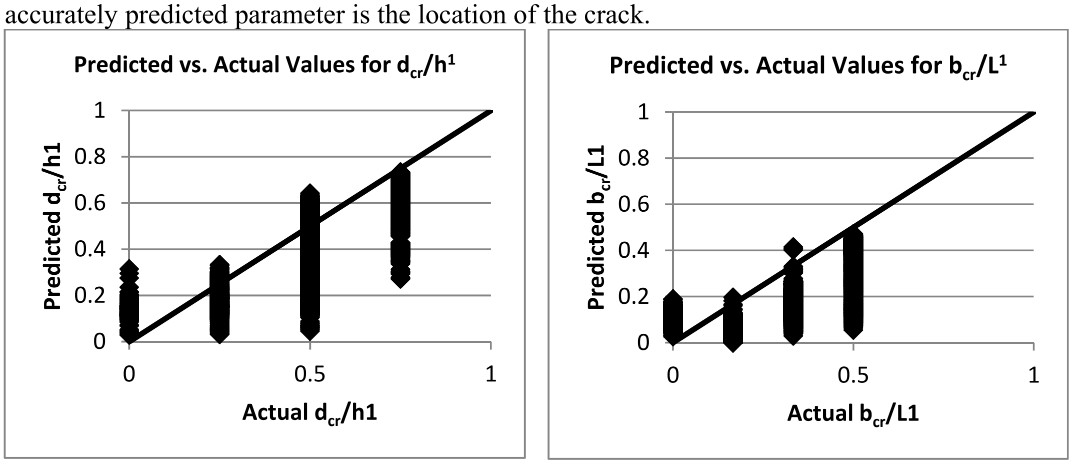

Figure 3. Inverse problem crack 1 predicted vs. actual values for (a) d_{cr}/h (b) b_{cr}/L.

6 CONCLUSION

In this study, a damage database for beams with different parameters was generated using finite element modeling software Abaqus for beams with up to two flexural cracks. The generated database was used to train a static Artificial Neural Network (ANN) with back-propagation learning algorithm to predict the cracks' depth, width and location in a simply supported concrete beam given the beam's geometric and material parameters. The forward problem ANN, where the beam's geometric (b/h, L/h), material (f'_c) and cracking parameters (d_{cr}/h^n, w_{cr}^n and b_{cr}/L^n) are inputs and the stiffness ratios (kn%) are outputs, provided excellent results in all phases (R^2 > 99%). The inverse problem's ANN had the beam's geometric and material parameters as well as the stiffness ratios as inputs and the cracking parameters as outputs. Although the accuracy of the ANN decreased when detecting two cracks compared to when a single crack is to be detected, the accuracy (R^2 = 65%) is still good enough for practical applications, as the cracking parameters are very small in magnitude, so even a large error value can only cause a variation of fractions of millimeters. Further investigation is required to determine the viability of using ANN approach to obtain the, analytically unattainable, solution of this inverse problem.

7 ACKNOWLEDGEMENTS

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8 REFERENCES

Abaqus 6.10 Online Documentation. (2010). Dassault Systèmes.

Al-Rahmani, A., Rasheed, H., and Najjar, Y. (2013). "Intelligent Damage Detection in Bridge Girders: A Hybrid Approach." *J.Eng.Mech*., 139(3). doi:10.1061/(ASCE)EM.1943-7889.0000536

Basheer, I.A. (1998). "Neuromechanistic-based modeling and simulation of constitutive behavior of fine-grained soils." Ph.D. dissertation, Manhattan, KS.

Kazemi, M. A.; Nazari, F. ; Karimi, M. ; Baghalian, S. ; Rahbarikahjogh, M.A. ; Khodabandelou, A.M. (2011). "Detection of multiple cracks in beams using particle swarm optimization and artificial neural network." *2011 Fourth International Conference on Modeling, Simulation and Applied Optimization (ICMSAO 2011),* 5.

Masri, S. F., Smyth, A. W., Chassiakos, A. G., Caughey, T. K., and Hunter, N. F. (2000). "Application of neural networks for detection of changes in nonlinear systems." *J.Eng.Mech*., 126(7), 666-676.

Najjar, Y. M. and Huang, C. (2007). "Simulating the Stress-Strain Behavior of Georgia Kaolin via Recurrent Neuronet Approach," *Computers and Geotechnics*, 34, 364-361.

Najjar, Y. M. and McRyenold, R. (2003). "Modeling the Joint Deterioration Behavior of PCC Kansas Pavements via Dynamic ANN Approach" *ASCE Geotechnical Special Publication # 123*, 209-222.

Xu, H., and Humar, J. (2006). "Damage Detection in a Girder Bridge by Artificial Neural Network Technique." *Computer-Aided Civil and Infrastructure Engineering,* 21(6), 450-464.