A study of the use of artificial neural networks to estimate
dynamic displacements due to dynamic loads in bridges

S Ok¹, W Son² and Y M Lim²

¹ Hyundai Engineering & Construction, 75 Yulgok-ro, Jongno-gu, Seoul 110-920, Korea
² Department of Civil & Environment Engineering, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 120-749, Korea

E-mail: yunmook@yonsei.ac.kr

Abstract. Measurement of dynamic displacement is one of the most essential aspects of a structural behavior because it portrays history of the global behavior of structure. In general, structural engineers are accepted these response as reliable physical quantities to evaluate the conditions of a structure. The reason is that these physical quantities can easily generate strain as well as stress, velocity and acceleration at the measuring points. However, it is difficult to directly measure the displacement of the bridge due to problems such as test conditions and the limitations of equipment. Therefore, in this study, an artificial neural network (ANN) demonstrates how it could overcome such limitations and utilize the random dynamic load to obtain the reliable estimations. Numerical analysis is conducted to obtain learning data about the axial strain as well as vertical displacement with time frame at multi-points and then applied to the ANN. The scenario centered on a variety of dynamic loads from the analysis of an urban bridge that was selected based on its general volume of traffic. The analysis was performed to estimate its displacement, which corresponds to the strain on the bridge caused by arbitrary loads of leaning results from the ANN. Then, it is confirmed that the estimated displacements of ANN show well agreements with that of an independent set of traffic scenario.

1. Introduction
The displacement of dynamic responses of structures is closely related to the magnitude of damage experienced under ultimate loads. It is a long-term history expressing global behavior, and it is thus important to secure the data (Powell and Allahabadi 1988; Jang and Kim 2008). By measuring the responses of structures to vehicle loads, not only can the characteristics of loads on a bridge be predicted (Moses 1979), but the state of the structure can also be intuitionally judged. Also, measuring the deflection changes of a bridge would be the basis for the criteria of structural degradation (Cho and Kim, 2008). There are various ways and means to measure the physical quantity, yet it is hard to do in a real construction site. To overcome difficulties at the site, in this study, an ANN was used. A way to write more realistic dynamic load scenarios that will be applied to ANN is also suggested.

The ANN has an advantage in that the relationship between strain and displacement can be numerically decided without complicated assumptions and limits. Through the dynamic scenarios and the ANN, we suggest a way to fairly precisely estimate the real-time vertical displacements of a bridge, which are generated by arbitrary dynamic vehicle loads.
2. Numerical Analysis

This study does not offer particular results from a specific bridge, but proposes a way to estimate vertical displacements with time through strain values that are applicable to typical bridges we can see anywhere. Moreover, there are many problems with measuring strain on-site under all of the various load cases. Accordingly, testified numerical analysis needs to be conducted to provide the ANN with data for learning.

2.1. Vehicle Model

A bridge is affected by many factors, such as its weight, length, suspension system, and the natural frequencies of vehicles. There are sophisticated interactions among them, which makes it tough to practically consider every component when making a model. Thus, it was assumed there were only three kinds of vehicles: trucks, cars, and buses; these vehicles were driven at speeds of 40km/h, 60km/h, and 80km/h. As shown by Figure 1, the vehicle model used in the analysis was a three-axle truck consisting of two rigid bodies. To be applied to this numerical analysis, Zeng and Bert’s (2003) truck model was modified, and car and bus models were made by eliminating trailers from the truck. Each model’s specifications were from Li’s (2005) truck, Zuo and Nayfeh’s (2003) car, and Ahmed et al.’s (1997) bus.

2.2. Bridge model

A simply supported slab-girder bridge was selected for the analysis. Each slab had a 36-m span and was 15 m wide (four lanes). A type I steel girder was used. Verification of the model was carried out by experiment results. In modeling, the moment and design loads, as well as the spacing of girders and diaphragms, were calculated in accordance with AASHTO LRFD (AASHTO 2002; AASHTO 2007). Since we assumed that there were small effects by slippage in anchorage, relaxation, shrinkage, and so on, they were negligible in the analysis and only vehicle movement was considered as a load on a bridge. A 3D solid element (linear hexahedral element) was used as an element of the slab, and a 3D shell element (linear quadrilateral element) was used for the girder for the finite element method. The shell element was constrained from rotation around a vertical direction by a tie-constant at the boundary between solid and shell elements. An approach slab was deployed at both ends of the bridge in order to reduce measuring errors, which can occur if vehicles enter and exit.

![Figure 1. The truck model used in the numerical analysis](image)
2.3. Verifying numerical model
A comparison of the results of the numerical analysis and those of the experiment regarding the behavior of the bridge, the model of the static-state conditions, and the dynamic state was verified. Statically, the experimental values of the Woodruff Bridge in Michigan were used. Dynamically, those of high-speed highway bridges in Florida were used.

3. Dynamic Moving Load Scenario
Information about the kinds of vehicles and distances between them was gained at one bridge in Seoul, Korea. All of the vehicles using the bridge were classified according to three velocities for writing scenarios: 40km/h, 60km/h, and 80km/h. To apply vehicle distances to the scenarios, we introduced a distribution function of the Pearson Type III distribution of traffic theories (May 1990).

\[ f(t) = \frac{\lambda}{\Gamma(K)} [\lambda(t - \alpha)]^{K-1} e^{-\lambda(t-\alpha)} \]

In the equation above, \( f(t) \) represents probability density functions. Influencing a form of the distribution, \( K \)—ranging from 0 to \( \infty \)—is a coefficient determined by the user. If \( K \) is 1, the distribution becomes the negative exponential function. \( \alpha \) is nonnegative and affects the distribution location. If \( \alpha \) is zero, there is no movement. If \( \alpha \) becomes 0.5, it means that a time headway under 0.5 s is considered to be zero. \( \lambda \) is a coefficient of the function of vehicle distance as determined by \( K \) and \( \alpha \). \( t \) is a time (in seconds) difference of the distance. \( \Gamma(K) \) is a gamma function. The observed data being applied to the distribution, a theoretical distribution curve of vehicle movements on the bridge can be obtained, which can describe real traffic situations.

We computed time headway by taking advantage of the above distribution and the data measured at the bridge. Figure 3 shows the measured percentage of vehicles with time headway and the calculated percentage of vehicles with time headway by the distribution in the first and second lanes. Acquiring this theoretical probability of headway, we could portray the simulated traffic situations as being closer to reality. Applying the headway information based on the Pearson Type III distribution, we composed 25 scenarios covering vehicle ratios of headway and arbitrary vehicle distances.
4. The Artificial Neural Network

There are two steps—Feedforward and Feedback—in an ANN error back-propagation learning algorithm. In the Feedback step, the output adjusts the synaptic strength between a hidden layer and an output layer to minimize errors related to target values. It repeatedly arranges the strengths between an input layer and the hidden layer through output from the hidden layer. This is called a generalized delta rule. In the Feedforward step, errors between the computed values of each unit are found; the errors are reduced by feedback calculation. The generalized delta rule can obtain the synaptic strength, which minimizes the error through the least mean square (LMS) learning rule. This is a way to yield the change volume of the synaptic strength proportional to the value resulting from differentiating the synaptic strength. The process repeats until the sum of the generated errors converges on a threshold of the error being previously determined until the system is stable.

The dynamic strain and dynamic displacement data of a bridge were obtained at 11 points on the bottom of each flange of each girder. The spacing between each point was 3.6m. There was a total of 55 points on five girders. Through the numerical analysis, the strain and displacement by dynamic vehicle loads from the scenarios were measured in 0.01-second process. There were 25 cases depending on each velocity that were arbitrarily made following the traffic theory. Twenty-four cases were used for learning data, and the remainder was used for test data to verify the ANN. The test data
were randomly extracted. Fifty-five input-layer elements, 40 hidden layer 1 elements, 40 hidden layer 2 elements, and 55 output-layer elements constituted an ANN structure. The learning ratio was set to 0.1 and the momentum term to 0.9. Non-linear functions, such as sigmoid or tan-sigmoid functions, were suitable for transfer functions since the ranges of the input and output data had upper load limits through a combination of dynamic vehicle loads.

5. Analyses of the Dynamic Load Scenarios and the ANN
The learning by the ANN through the 24 cases converged after 4,962 iterations. The correlation of the ANN after learning was 99.98%, so we can confidently state that the learning worked well. The result of inputting the extracted test data into the learned ANN was 0.0018 mm of the mean square error (MSE). Figure 4 shows the output from the ANN and the test values at a point in the middle of the second, third, and fifth girders. It represents the vertical displacements with time by dynamic vehicle loads. A blue line represents results from the ANN, and a red line represents results from the FEM.

Figure 4. The Dynamic Displacements due to the Dynamic Loading
Both lines mostly match up. It can be confirmed that a time-displacement curve from the numerical analysis using a finite element method fairly corresponds with that from the ANN through the MSE and the figures.

6. Conclusions
The ANN was used to estimate the dynamic vertical displacements of a bridge. There were plenty of constraints to directly measure its strain value. This means that only limitary information about the behavior of the bridge can be gained in the field.

This study proposed how to understand the global behavior of bridges through the limited information on specific points of girders. A bridge model was made to obtain the bridge’s data on strain and displacement through the numerical analysis, and dynamic vehicle load scenarios by the Pearson Type III distribution of traffic theory were written to reflect real traffic situations. Finally, we could fairly accurately estimate the vertical dynamic displacement through the ANN, which had been leaned upon by FEM results from loads based on real situations.

As we are going to widen the study ranges from bridges to other structures with difficulties in estimating overall displacement with time due to various load cases and complicated structures, only the measuring strain and displacement at a few points will make it possible to get precise displacement data and maintain sophisticated structures such as LNG tanks and more complex bridges than one we previously considered.

Acknowledgements
This research was supported by a grant from the Korea Gas Corporation.

References
[1] Powell G.H and Allahabadi R 1988 Seismic Damage Prediction By Deterministic Methods : Concept And Procedure Earthquake Engineering And Structural Dynamics 16 719-734
[2] Cho N and Kim N 2008 Prediction of the Static Deflection Profiles on Suspension Bridge by Using FBG strain Sensors Ksce Journal of Civil Engineering 28 5A 699-707
[3] Moses F 1979 Weigh-in-Motion System Using instrumented Bridges Transportation Engineering Journal 105 3 233-249
[4] Zeng H and Bert C.W 2003 Dynamic Amplification Of Bridge/Vehicle Interaction: A Parametric Study For A Skewed Bridge Journal of Structural Stability and Dynamics 3 1 71-90
[5] Li H 2005 Dynamic response of highway bridges subjected to heavy vehicles (Ph.D. diss) The Florida State University
[6] Zuo L and Nayfeh S.A 2003 Structured H2 Optimization of Vehicle Suspensions Based on Multi-Wheel Models Vehicle system dynamics 40 5 351-371
[7] AASHTO 2002 AASHTO Standard Specifications for Highway Bridges 17th Edition Washington, D.C.
[8] AASHTO 2007 AASHTO LRFD Bridge Design Specifications 4th Edition Washington, D.C.
[9] Chun P 2010 Skewed bridge behaviors: Experimental, analytical, and numerical analysis (Ph.D. diss.) Wayne state University