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Detailed load rating analyses of bridge populations using nonlinear finite element models and artificial neural networks

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ABSTRACT

For assessing load rating capacity of bridges, American Association of State Highway and Transportation Officials Manual (AASHTO) recommends a simple method, where distribution of the forces in transverse direction is estimated by axle-load distribution factors on a simply supported beam. Although the method is practical in the sense that it allows for rapid evaluation of bridge populations, it leads to over-conservative load ratings. A finite element (FE) based load rating analysis is conceived as a more accurate strategy, yet the need for constructing and analyzing a FE model for every single bridge in the population makes it impractical for load rating analyses of a bridge population. In this study an efficient method is developed for detailed load rating analyses of bridge populations through nonlinear FE models and artificial neural networks (ANNs). In this method, geometric-replica 3D FE models are used for nonlinear response analyses and load rating calculations for a sample bridge set. ANNs are then trained to learn implicit relationships between the governing bridge parameters and the resulting load ratings using this sample bridge set, and to make cost-free load rating estimations for other bridges that are not included in the set. The single-span reinforced concrete T-beam bridge population in Pennsylvania State is used to demonstrate a practical case study for application of the method. The results indicate that FE based load rating calculation procedure integrated with ANNs can be used as efficient tools for in-depth condition assessment of bridge populations.

1. Introduction

Load rating is a component of the bridge inspection process and is used to determine safe-load carrying capacity of a bridge. Visual inspection can only provide qualitative information about the as-is condition of a bridge to a limited extent. It cannot quantify the actual intrinsic load capacity, and therefore it should be complimented with other practical tools. To this end, American Association of State Highway and Transportation Officials Manual (AASHTO) [1] recommends the use of a simple and practical method for a rapid evaluation of load rating capacity of T-beam bridges. In this method, an individual beam is taken out as a free-body, idealized as simply-supported, and the continuity of the bridge in the transverse direction is indirectly accounted for by means of axle-load distribution factors. It has been shown that this approach significantly underestimate the contribution of deck slab to lateral load distribution for many bridge geometries [2]. A more accurate evaluation of load rating capacities of T-beam bridges is possible through a properly constructed, geometric replica 3D finite element (FE) model since the contribution of slab can properly be simulated by such a complete FE model. In addition, the contributions of the secondary components such as parapets and diagrams can also be accounted for in the latter approach. A FE based load rating analysis may be deemed as a reasonable strategy for accurate and detailed condition assessment of a single bridge. However, the problem can easily grow into an unmanageable size when it is required to achieve load rating analysis of a bridge population, rather than a single bridge. Apparently an inordinate amount of time and effort is needed to construct and analyze 3D FE models for all the bridges in the population.

Artificial neural networks (ANNs) are a group of powerful computing units that employ a simulation of biological nerve systems to recognize patterns, learn tasks, and solve problems. They have proved to be particularly suitable for problems that incorporate erroneous, incomplete or fuzzy data, which cannot be easily handled with classical methods [3]. The ability of ANNs to learn from experience and then generalizing these learning to solve new problems make them a popular and unique tool for modeling some of the challenging engineering problems encountered in the field of structural engineering, such as structural response approximation and system identification.

A review of the literature reveals that ANNs have been successfully used in structural system identification and response approximation of bridges. Barai and Pandey [4] presents an ANN based

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approach for damage identification in steel bridges. In the study the vertical displacements resulting from moving truck loads are used as inputs to the networks, and the outputs are cross-sectional areas of the bridge members used as a measure of loss of stiffness in damage state. Consolazio [5] presents a method based on coupling of ANNs with a preconditioned conjugate gradient iterative equation-solving algorithm for enhancing finite-element analysis. The method is applied to flat-slab highway bridges to encode the load–displacement relationships for these systems. Chang et al. [6] proposes a model updating scheme with an adaptive neural network for developing viable structural health assessment methodologies. An iterative procedure is followed, where the task of model updating and network training is repeated until a good agreement is achieved between the calculated and measured modal responses of a steel bridge. Çevik et al. [7] applies ANNs to predict natural frequencies of suspension type bridges. Five physical parameters related to mass, stiffness and geometry of the bridges are specified as inputs, whereas the first three natural frequencies are the output variables. It is shown that ANNs can predict frequencies to a very good degree of accuracy within a trivial computation time. Mehrjoo et al. [8] proposes a method for estimating structural damage intensities in truss bridges using ANNs. A substructuring technique is employed to reduce the number of unknown damage parameters to be estimated. The numerical analyses performed on a real truss bridge demonstrate the suitability of the method for online or real-time damage diagnosis of structures. In Hasançebi and Dumplupınar [9], ANNs are employed to achieve rapid structural response analyses of a bridge population that have identical structural and architectural characteristics. In Gonzalez-Perez and Valdes-Gonzalez [10], an application of ANNs is presented for damage detection caused by bending in the girders of a vehicular bridge. The model strain energy differences are used as inputs to the network, and the outputs are flexural stiffness of the members. It is stated that location and severity of damage can be predicted by ANNs with a high accuracy. Finally, Hasançebi and Dumlupınar [11] investigates the use of ANNs for model updating of reinforced concrete (RC) bridges. In the study a real RC bridge is calibrated using ANNs trained according to datasets generated from linear and non-linear analyses separately. The simulated responses obtained from calibrated FE models are compared to the field-measured responses of the bridge to quantify accuracy of parameter estimation and success of the model updating process.

Other interesting applications of ANNs in structural engineering and mechanics are presented in a number of articles in the literature, such as Refs. [12–15]. Szewczyk and Hajela [13] presents an ANN integrated damage identification method for structural systems. Possible damage and its extent are detected by relating changes in structural response directly to reduction in the stiffness of structural components. ANN is used to learn the inverse relationship between static displacements and damage parameters on frame and truss structures. Topping et al. [14] proposes a parallel processing implementation for neural computing to improve the computational efficiency. A parallelization method is implemented using a multiple-instruction, multiple-data distributed memory architecture for the parallelized neural network. Parallelized neural networks are applied on a structural design problem concerned with finite element mesh generation, and a high performance in training speed is achieved. Kaveh et al. [15] proposes a hybrid method for domain decomposition of finite element meshes employing graph theoretical algorithms and neural network methods. In their study graph theoretical method is used for primary decomposition, and then a neural network approach is employed for the completion of the partitioning.

This study proposes a method for detailed load rating analyses of bridge populations through nonlinear FE models and ANNs. The method works on the basis of training ANNs to learn the subtle relationships between the bridge parameters and the resulting load ratings using a representative (sample) bridge set. The single-span reinforced concrete (RC) T-beam bridge population in Pennsylvania State is taken as a particular case study to test and exemplify the implementation of the method. First several databases, including National Bridge Inventory (NBI) [16] and Pennsylvania Department of Transportation records, are scrutinized for a statistical evaluation of the bridge population. The commonality of design parameters and the level of dependency between structural and geometrical properties of the T-beam bridges are investigated. The independent bridges parameters that govern load rating analyses of the bridges are identified along with their ranges of variation within the population. Then, a representative bridge set is generated using different combinations of the governing parameters selected at random within their predefined ranges of variation. Nonlinear structural analyses are carried out for each bridge in the set using a complete 3D geometric-replica FE model, and the maximum moment and shear responses in beams are obtained at critical locations under various combinations of standard truck loads. These responses are then used to compute the moment and shear load ratings for the bridges. ANNs are then trained to learn the relationship between the governing bridge parameters (inputs) and the load ratings (outputs) based on the sample set. Several network architectures that are composed of different number of hidden layers and outputs are tested and measured in terms of load rating prediction capabilities. The best ANN models are identified and their predictions for load ratings are compared with those obtained according to the current practice by AASHTO [1]. The results indicate that a FE based load rating analysis procedure integrated with ANNs can be used as an efficient tool for in-depth condition assessment of bridge populations.

2. Bridge population

According to NBI [16], the total RC T-beam bridge population in the United States (US) is 38,170. Pennsylvania has the third largest population with 2440 T-beam bridges following California and Kentucky. Out of these 2440 T-beam bridges, 1899 of them are of single-span type constructed mostly between the 1900s and 1960s by using a standard set of design drawings. Therefore, these bridges share geometry and design details, materials and similar cast-in-place construction.

2.1. Structural features

The structural features of a typical T-beam bridge are such that it is an integration of beams and slab along the span of the bridge ending in rigid diaphragm beams (Fig. 1). The orthotropically reinforced slab is bounded by stiff edge girders monolithic with parapets in addition to the diaphragm beams. While the girders predominantly transmit forces through uni-axial shear-flexure, the orthogonal flexural response of the slab as a plate and the axial membrane forces in the slab that arise due to the restraining of the diaphragms at the abutment interfaces are additional mechanisms that contribute to load capacity.

2.2. Governing parameters

Structural behavior of T-beam bridges is controlled by a large number of structural and geometrical parameters. However, not all these parameters are independent on account of the fact that majority of the T-beam bridges in the population have been constructed using a standard set of drawings. The commonality of design parameters as well as the level of dependency between