Loads on Shores and Slabs during Multistory Structure Construction: An Artificial Neural Network Approach

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Abstract

Neural computing is a relatively new field of artificial intelligence (AI), which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an Artificial Neural Network (ANN) on a computer. Artificial Neural Networks have the ability to be trained by example. Patterns in a series of input and output values of example cases are recognized. This acquired "knowledge" can then be used by the Artificial Neural Network to predict unknown output values for a given set of input values. This paper demonstrates the feasibility of using an Artificial Neural Network (ANN) back-propagation multi-layered model to estimate loads on shores and slabs during the construction phases of a multistory structure. It also determines the number of stories above the slab with the maximum load. This model permits, in an early planning stage, to establish the minimum cycle time for the erection of stories given the number of shores and reshores to be used.

I. Introduction

In the construction of a multistory structure, construction loads may exceed the design loads by an appreciable amount. Thus, shoring must be provided to support these loads without excessive stresses or deflection. The calculation of the loads imposed on these shores as well as on the structure must be calculated to determine the cycle time for the erection of the structure and for the design of the shoring proper. No single procedure for shoring and reshoring multistory structures is recommended in the literature[1]. The main objective of the research presented in this paper was to develop a prototype Artificial Neural Network (ANN)-based software – IntelliShores – to determine maximum loads on shores and slabs of a multistory structure. Further, it was determined that it would be useful to include a feature permitting the determination of the number of stories above the slab with the maximum load. This feature would permit, in an early planning stage, to establish the minimum cycle time for the erection of stories given the number of shores and reshores to be used.

ANN is one of the artificial intelligence algorithms that relates to the class of machine learning. It mimics a human brain process of acquiring and retrieving knowledge. It models the biological neuron, which consists of nodes (cells) and links (axon). It is defined as "A computing system made up of a number of simple, highly interconnected processing elements, which processes information by its dynamic state response to external input[2]. These ANNs are modeling

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techniques that are especially useful to address problems where solutions are not clearly formulated[3] or where the relationships between inputs and outputs are not sufficiently known. ANNs have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired "knowledge" can then be used by the ANN to predict unknown output values for a given set of input values.

ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections are on the input side correspond to the dendrites of the biological original and provide the input from other PEs while the connections on the output side correspond to the axon and transmit the output. Figure 1 illustrates a simple processing element of an ANN with three arbitrary numbers of inputs and outputs[4, 5]. The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive ($w_i > 0$) or inhibitory ones when negative ($w_i < 0$). The PEs output is computed by applying the transfer function to the activation. The type of transfer function to be used depends on the type of ANN to be designed.

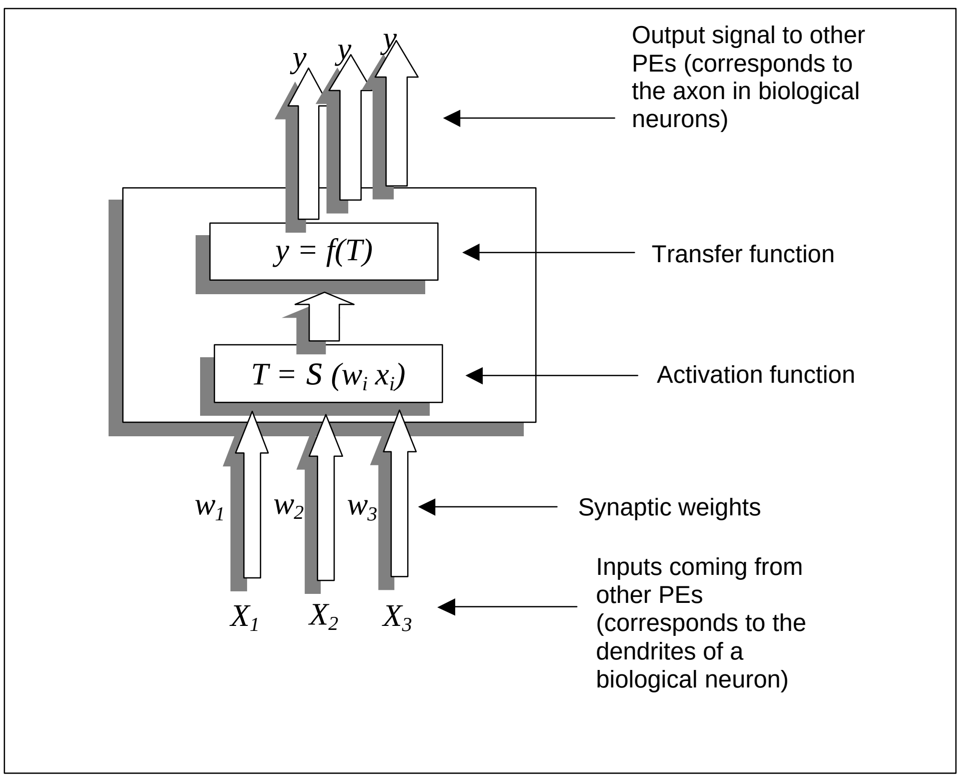

Figure 1. Processing element of an ANN model with three arbitrary numbers of inputs and outputs

Currently, back-propagation is the most popular, effective, and easy to learn model for complex networks[4, 5]. For the last few years, the first author has been using various ANN back-propagation Multi-layer Perceptron (MLP) modeling techniques in materials science and

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engineerin[4, 5], and construction management[6]. To develop a back-propagation neural network, a developer inputs known information, assigns weight to the connections within the network architecture, and runs in the networks repeatedly until the output is satisfactorily accurate. The weighted matrix of interconnections allows the neural networks to learn and remember[7]. In essence, back propagation training adapts a gradient-descent approach of adjusting the ANN weights. During training, an ANN is presented with the data thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge[8].

This paper describes an ANN back-propagation MLP model to determine maximum loads on shores and slabs of a multistory structure and to determine the number of stories above the slab with the maximum load.

II. *IntelliShores* Development Methodology

IntelliShores is an ANN-based prototype software, developed by the authors of this paper, for the simplified analysis of loads on shores and slabs of a multistory structure as presented by Hurd[1]. Figure 2 depicts the user interface. As can be seen, the sole input required is the number of shores and reshores to be used, and the number of stories of the structure. This data is fed as an input to a neural network developed for this purpose. The respective output is the maximum load on a shore and a slab as well as the number of stories above the slab with the maximum load.

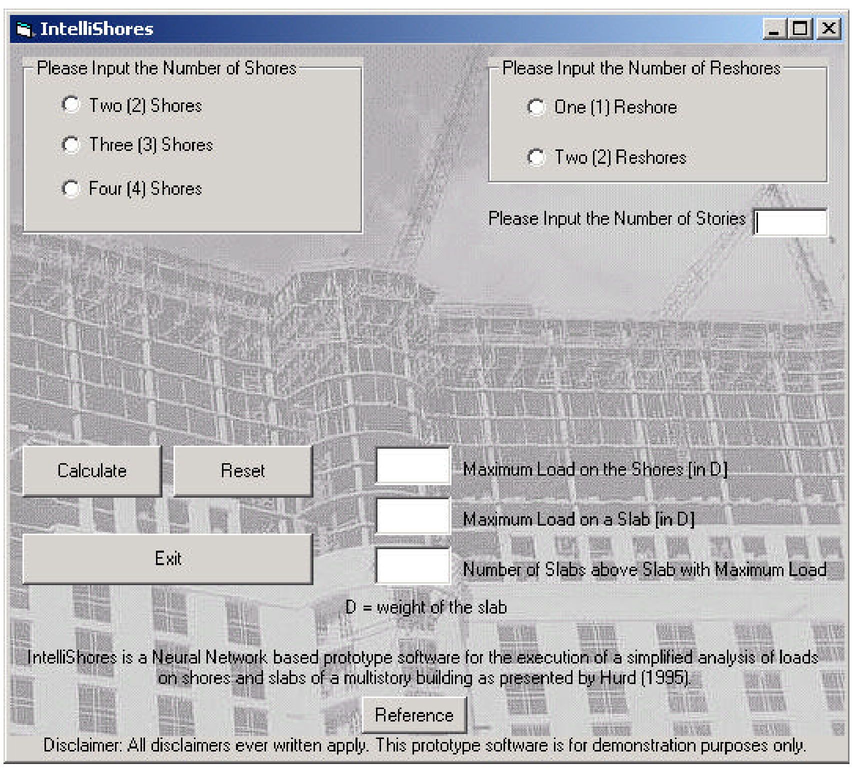

Figure 2. *IntelliShores* User Interface

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ANN Training Data

Training data for the development of the neural network was developed by manually performing the simplified analysis of loads on shores and slabs of a multistory structure as described above. This was done for various combinations of numbers of stories, shores and reshores and resulted in the development of a total of 84 training cases. Another set of 15 cases was not used during training the model. These 15 cases were used during evaluation of the trained model. The combinations of number of stories, shores and reshores are designated through out the paper using alpha-numeric characters, such as, N8S3R1 represents an 8 story building with 3 shores and 1 reshore construction sequence. The training data included three inputs – the number of shores to be used, the number of reshores to be used, and the number of stories of the structure – and three outputs – the maximum load on a shore, the maximum load on a slab, and the number of stories above the slab with the maximum load.

Neural Network Architecture Implemented

The neural network used for *IntelliShores* was, as mentioned above, a MLP with two hidden layers developed with NeuroShell 2 software by Ward Systems Group, Inc. The number of processing elements, for which standard sigmoidal (logistic) transfer functions were used, was determined according to the following formula[9]:

Number of hidden neurons = 0.5(Inputs + Outputs) + Ö(Number of training patterns)

Given the properties of the training data used – 3 inputs, 3 outputs, and 84 training examples – the number of processing elements was determined to be 12 (actual 12.165). These were equally distributed between the two hidden layers.

III. ANN Training Model Performance

In the present research, several different ANN back-propagation trial models with different layers/slabs connections, weights and activation functions (including linear, Logistic, Gaussian, etc.) were trained. The presented ANN back-propagation MLP model with logistic activation function was the best one among all ANNs tested as it converges rapidly to reach the excellent statistical performance (as illustrated below in *Statistical Performance*). Figure 3 depicts the graphical comparisons between the actual and the ANN predicted maximum shore and slab load during training phase of the ANN model. Figure 4 represents the graphical comparison between the actual and ANN predicted number of stories above the slab with the maximum load. The figures clearly demonstrate very good agreement between the actual loads and predicted loads. In addition the trained model was evaluated by a set of 15 cases that were not used during training phase. Table 1 shows an excellent agreement between the actual and the ANN predicted maximum shore load, maximum slab load, and number of stories above the slab with the maximum load during the evaluation phase.

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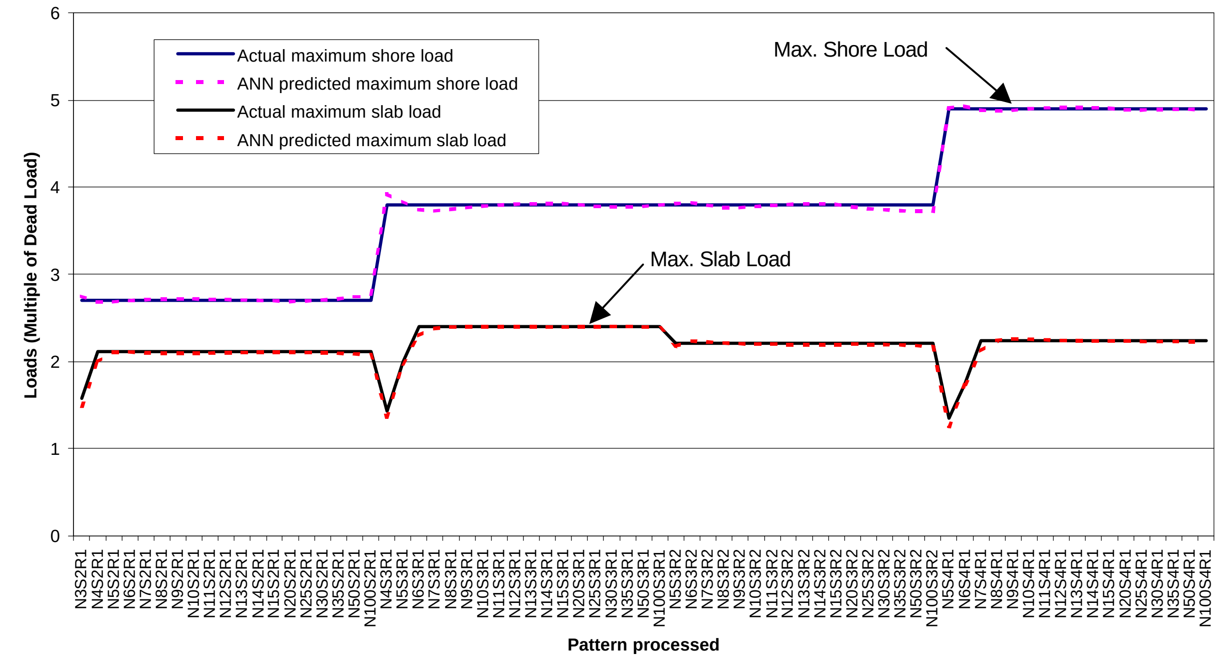

Figure 3. Actual and ANN predicted shore and slab loads for the training pattern processed

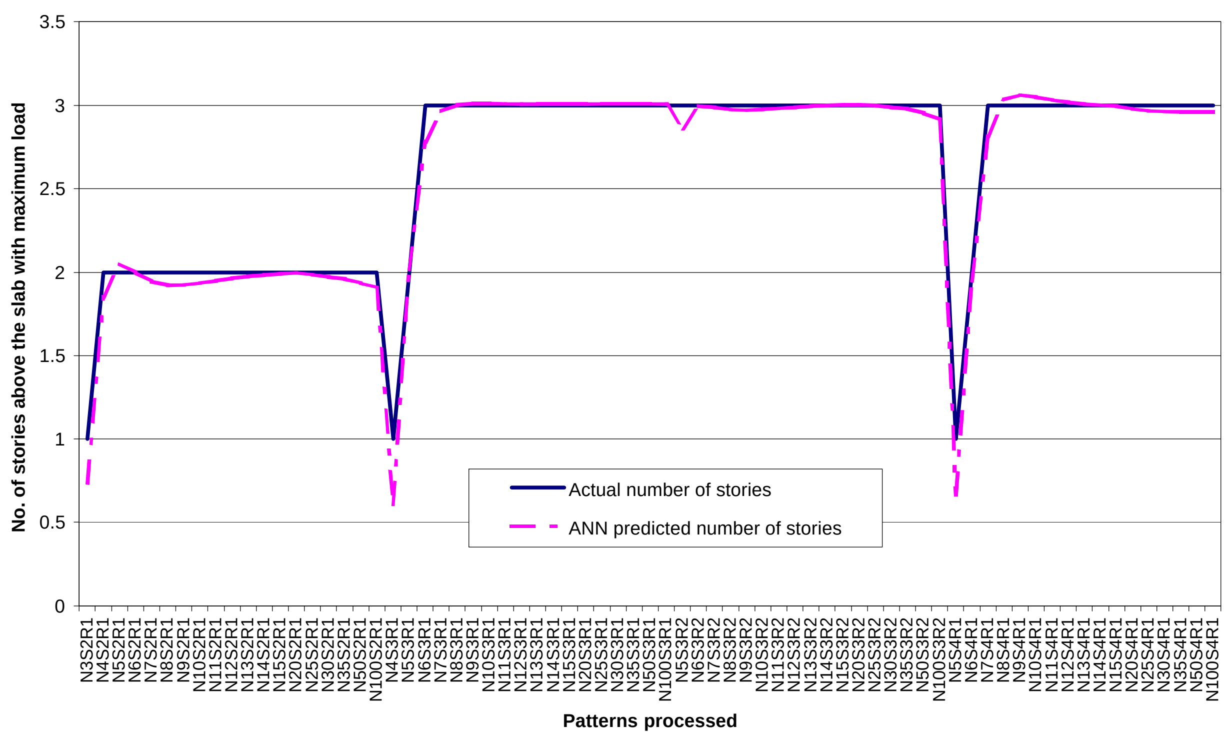

Figure 4. Actual and ANN predicted number of stories above the slab with the maximum load for the training patterns processed

Table 1. Comparison between the actual and ANN prediction
During the Evaluation Phase of the Trained ANN model

Cases	**Max Shore Load**		**Max Slab Load**		**Stories above Slab**	
	Actual	**ANN**	**Actual**	**ANN**	**Actual**	**ANN**
N8S2R1	2.70	2.72	2.11	2.09	2	1.92
N9S2R1	2.70	2.72	2.11	2.09	2	1.92
N14S2R1	2.70	2.70	2.11	2.10	2	1.98
N15S2R1	2.70	2.70	2.11	2.11	2	1.99
N50S2R1	2.70	2.74	2.11	2.09	2	1.93
N100S2R1	2.70	2.77	2.11	2.08	2	1.91
N9S3R1	3.80	3.77	2.40	2.40	3	3.01
N11S3R1	3.80	3.80	2.40	2.40	3	3.01
N12S3R1	3.80	3.80	2.40	2.40	3	3.01
N9S4R1	4.90	4.88	2.24	2.26	3	3.06
N11S4R1	4.90	4.91	2.24	2.25	3	3.03
N25S4R1	4.90	4.89	2.24	2.23	3	2.97
N25S3R2	3.80	3.75	2.21	2.20	3	3.00
N30S3R2	3.80	3.74	2.21	2.19	3	2.99
N50S3R2	3.80	3.72	2.21	2.18	3	2.95

Statistical Performance

The neural network used for the presented model demonstrated an excellent statistical performance[9] as shown in Table 2. The coefficient of multiple determination, *R squared*, and correlation coefficient *r* were very close to 1, which indicated good agreement between the actual and the ANN predicted results. *R squared* is a statistical indicator usually applied to multiple regression analysis, and was calculated using the following formulae[9]:

$$R^2 = 1 - (SSE/SS_{yy})$$

Where $SSE = S\ (y - \hat{y})^2$, $SS_{yy} = S\ (y - \bar{y})^2$, y is the actual value, $\hat{y}$ is the predicted value of y, and $\bar{y}$ is the mean of the y values.

IV. Educational Significance

It is increasingly important to go beyond traditional departmental course curriculum boundaries for some areas of science and engineering education. ANN is one such field, because although electrical/computer engineers developed it largely, its contemporary applications are very extensive and interdisciplinary. A major part of this research was done by the second author as part of a class project for a graduate course – CMD 633 *Design of Construction Systems,* taught by the first author. This paper is an example of ANN's interdisciplinary application in the fields of construction science/engineering.

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Table 2. Statistical Performance of *IntelliShores*

Items	Network Training for			Network Evaluation for		
	Max Shore Load	Max Slab Load	Stories above Slab	Max Shore Load	Max Slab Load	Stories above Slab
Patterns Processed	84			15		
R squared	0.9630	0.9880	0.9871	0.9979	0.9768	0.9906
Correlation coefficient, r	0.9818	0.9955	0.9945	0.9992	0.9947	0.9982
Mean squared error	0.029	0.002	0.015	0.001	0	0.002
Mean absolute error	0.063	0.026	0.063	0.028	0.013	0.037
Minimum absolute error	0	0	0	0.002	0	0.003
Maximum absolute error	1.120	0.245	0.669	0.076	0.032	0.093

V. Conclusions

This paper demonstrated an ANN-based MLP back-propagation model that was applied to predict loads on shores and slabs during the construction phase of a multistory structure. The neural network for the *IntelliShores* established an excellent statistical performance in network training as well as in the evaluation of the trained network. The application of an ANN model certainly minimizes the extensive calculations for estimating the loads imposed on the shores and reshores as well as on the structural floors to determine the cycle time for the erection of the structure and for the design of the shores. This study also reveals the feasibility of using neural networks in the fields of construction science and engineering to minimize extensive calculation for obtaining a good/preliminary prediction in design.

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