BRIDGE LIFE-CYCLE COST ANALYSIS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Life-Cycle Cost analysis can significantly assist in making investment decisions. Several recent studies have recognized the potential benefits of Life-Cycle Cost analysis and call for use of such analyses when making infrastructure investments, including investments in bridges. The Life-Cycle Cost of a bridge consists of the total investment throughout the life of the bridge. This includes the initial construction cost, repair and rehabilitation costs, and all maintenance costs. The ability to accurately determine the Life-Cycle Cost of a bridge will help agencies evaluate the asset value of existing bridges, make better decisions on the design and construction of new ones, and choose improved methods and approaches for rehabilitating existing structures. Research has shown that timely maintenance, repair, and rehabilitation can lower the Life-Cycle Cost of a bridge. However, this is a complex and nonlinear problem, and previous studies have failed to develop a satisfactory model.

One effective technique for solving nonlinear problems with complicated functions is an Artificial Neural Network. A neural network is a powerful data-modeling tool that captures and represents complex input/output relationships. Using a set of input and output data belonging to a particular problem, a neural system can be trained to predict outcomes for new versions of the same problem. Accordingly, an extensive set of data (bridge dimensions, age, initial cost, and Life-Cycle Cost) for 14 Chicago bridges was used to quantify the degree of success that could be achieved with this model. Sixty percent of the data was used as input to train the model and the remaining forty percent was used to assess the success of the model for predicting the Life-Cycle Cost. The results achieved were encouraging and suggest that the neural network model is a promising tool for predicting the Life-Cycle Cost of a bridge.

Keywords: life-cycle cost, artificial neural network, bridges, initial cost, repair and rehabilitation cost, maintenance cost

1. INTRODUCTION

The most critical decisions that significantly affect the Life-Cycle Cost (LCC) of infrastructure projects occur in the early stages. For example, it is more beneficial to correctly choose the optimum bridge type than to choose the optimum construction process or repair method. The ability of a bridge to provide service over time requires appropriate maintenance, repair, and rehabilitation (MRR). Therefore, the investment decision should consider not only the initial capital cost, but also all future activities that will be required to keep that investment serviceable for the public. In the final analysis, it is the cumulative value of the initial capital cost, the repair and rehabilitation costs, and the annual maintenance costs that is of interest. Our studies show that the maintenance and rehabilitation costs, as a percentage of the initial cost, are reasonably similar for many, but not all, types of bridges during approximately the first 65 years of their service life, after which these costs increase significantly. The challenge facing bridge managers and the purpose of LLC analysis is to specify a set of economical actions and their timing during the life of a bridge to achieve the 50- to100-year service life that many bridge management professionals feel is an appropriate target for this major public investment

(NCHRP 2003). A large amount of research has shown the success of Artificial Neural Networks (ANN) to solve complicated nonlinear mathematical construction and transportation problems, and this methodology will be employed here to illustrate its applicability to describe the complex relationship between input/output variables from a set of life cycle cost data for fourteen Chicago area bridges.

2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are extremely useful in such diverse fields as mathematics, chemistry, physics, engineering, economics, and finance, as well as infrastructure and construction management. In general, any field that poses complex problems of classification, prediction, or control may benefit from an ANN, and conversely, every application of an ANN provides an opportunity to further understand how it successfully solves very difficult problems (Principe 2000). In essence, a neural network is a data-modelling tool that performs intelligent tasks comparable to those performed by the human brain to formulate complex relationships between input and output data, as illustrated in Figure 1. The model is “trained” by using a set of input and output data belonging to a particular problem. Then, if new input data representative of the same problem, but not in the training set, are entered into the system, the ANN can predict outcomes without any specific programming relating to the category of events involved. The true power and advantage of neural networks lies in their ability to represent both linear and nonlinear relationships and in their ability to “learn” these relationships directly from the data being modelled.

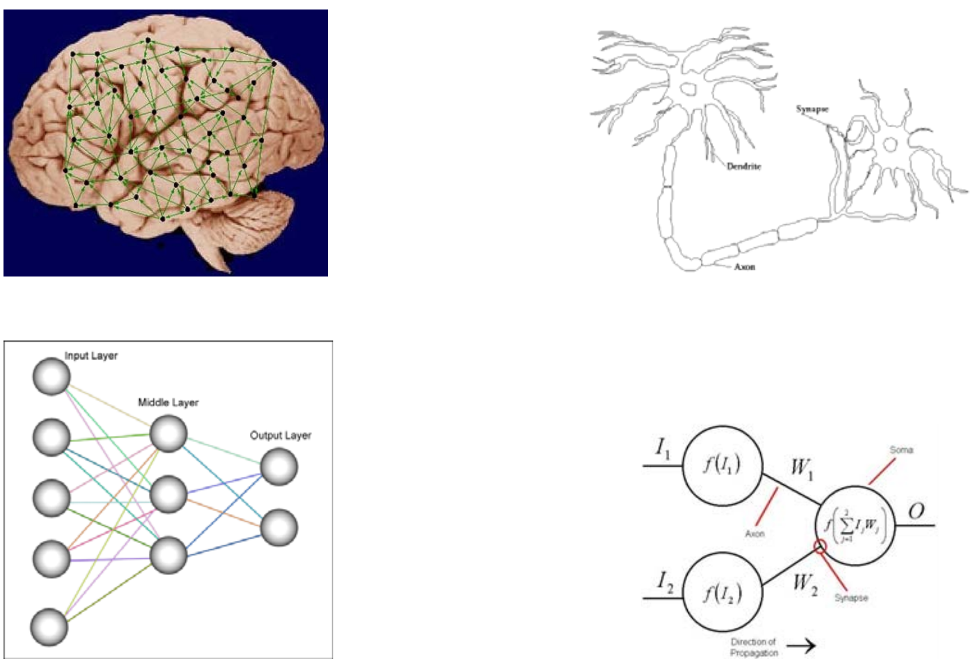

Figure 1: Analogue for architecture of a biological and ANN neuron (Principe 2000).

Since traditional linear models are inadequate for modeling nonlinear responses, the most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. The MLP and many other neural networks learn by using an algorithm called back propagation. With back propagation, the input data are repeatedly presented to the model and with each presentation the output is compared to the desired output and an error is computed. This error is then fed back (back propagated) to the model and used to adjust the weights such that the error decreases with each iteration. This process is known as "training" the model. The back propagation algorithm is a gradient descent method that minimizes the Mean Square Error (MSE) between the actual and target output of a multiplayer perceptron. The nonlinear activation functions used in the network are the Sigmoid function, sigmoid(x) = $(1-e^{-x})^{-1}$, and the Hyperbolic Tangent function, tanh(x) = $(e^{x} - e^{-x}) / (e^{x} + e^{-x})$ (Ham 2001).

3. GOALS AND OBJECTIVES

The total Life-Cycle Cost (LCC) of a bridge is the cost required to build, maintain, repair, and rehabilitate the structure during its useful life. Historical cost data for a variety of geographically distributed bridges were collected and analyzed to determine the total LCC for these bridges, and it was determined that, for the same useful life, the LCC can be quite different for different types of bridges. Hence, only bridges of one specific type will be included in this study and ANN will be used to determine their LCC. A multilayer perceptron (MLP) is a neural network that has more than two layers (input layer and output layer), termed "hidden layers," which are between the input layer and the output layer (Ham 2001). Each hidden layer contains several neurons with structures as shown in Figure 2. It is common for different layers to have different numbers of neurons, and MLP is used to solve nonlinear problems in the neural networks. In some complicated problems, it is possible that a network will need more than one hidden layer. Figure 3 illustrates a typical example of a trained neural network in which the input parameters are the length, width, age, and the initial cost of various bridges and the output is the LCC. A random number generator is used to randomize the order of the data points for training and testing the neural network so that it learns the input/output mapping independent of a specific pattern of input samples.

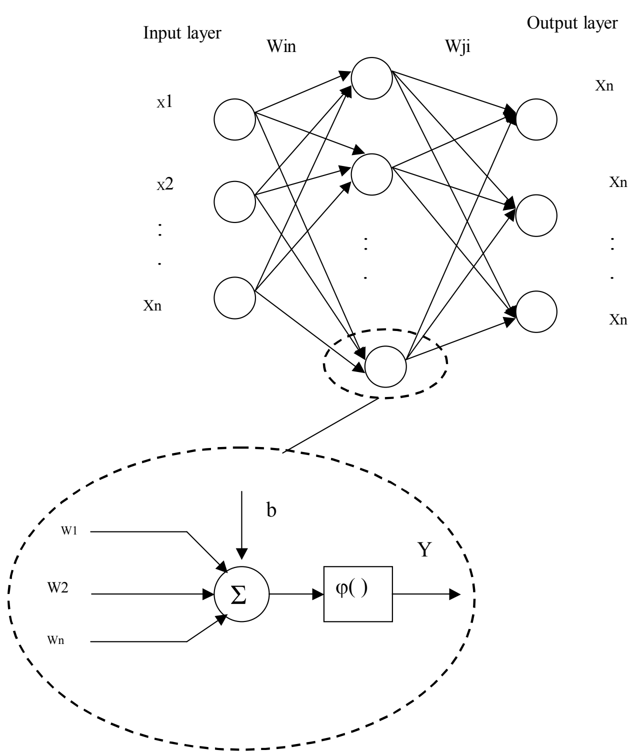

Figure 2: Multi-layer neural network and architecture of a neuron.

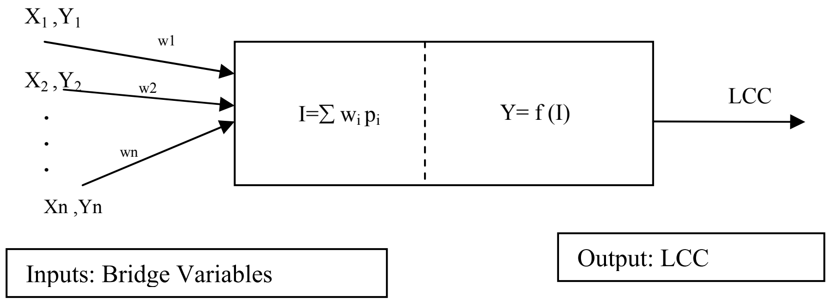

Figure 3: Conceptual architecture of the neural network for evaluating the Life-Cycle Costs of bridges.

4. CHICAGO MOVABLE BRIDGES

Compared to other big cities in the world, Chicago has an unusually large number of movable bridges. One of the most popular types, the double-leaf trunnion bascule bridge, evolved from earlier types of movable bridges, including swing bridges and rolling lift bridges. Alexander Von Babo, a city bridge engineer, patented the internal rack in 1911 and thereby eliminated the need for through-trusses by placing the rack below the bridge deck. In 1913 Edward H. Bennett, a consulting architect to the Chicago Plan Commission, started to work with engineers to improve the artistic quality of Chicago bridges. These efforts resulted in extensive revisions to the shape of the trusses, the configuration of the operator houses and pit walls, and the ornamental detailing of sidewalk railings, light fixtures, and other decorative metal elements. This new design was heavily influenced by Parisian architecture, which, at the time, was considered the model for urban design. These innovations defined the second generation Chicago-type bascule bridges, which are those built between 1910 and 1930. Although Hopson (1994) classified the Chicago-type trunnion bascule bridges into four generations that are characterized by the evolution of their design and construction, only the 14 second generation bridges given in Table 1 are included in this study. In the description of these bridges, the deck widths given are current values, which may be different from those of the original bridges due to reconstructions.

No.	***Bridge***	***Year Built***	***Structural Length (feet)***	***Deck Width (feet)***	***Initial Cost ($)***
1	Washington St. Bridge	1913	263	36	238,288
2	Grand Ave. Bridge	1913	270	60	195,141
3	Chicago Ave. Bridge	1914	291	37	255,583
4	Webster Ave. Bridge	1916	287	38	245,721
5	Monroe St. Bridge	1919	271	38	420,875
6	Franklin-Orleans Bridge	1920	320	38	827,487
7	Madison St. Bridge	1922	283	40	1,186,569
8	Adams St. Bridge	1926	250	64	1,065,644
9	100th St. Bridge	1926	326	40	930,948
10	106th St. Bridge	1928	349	38	907,144
11	LaSalle St. Bridge	1928	347	57	1,318,801
12	Clark St. Bridge	1929	346	38.5	1,331,020
13	Roosevelt Rd. Bridge	1929	257.5	90	1,195,449
14	Wabash Ave. Bridge	1930	345	60	1,568,499

Table 1: Second Generation Chicago-Type Bascules Bridges included in this study.

The data for these bridges were collected and itemized by year from the files of the Chicago Department of Transportation and the Chicago Public Library (Zhang et al 2008). The MRR costs for the years from 1900 to 1978 were quite complete except for a few years. For the years between 1978 and 2005, the major repair and rehabilitation costs were collected from the capital improvement reports. In many cases, no detailed maintenance costs were available for individual bridges, but lump sum data for all city bridges were available and "good faith" distributions were made based on the best historical information that could be determined.

5. IMPLEMENTATION

The length, width, age, and initial cost are considered as the inputs to the neural network and Life-Cycle Cost (LCC) is the output. A random number generator was used to enter the data with known amounts of LCC for training and testing the network. By so doing the training process will not follow a regular routine and thereby avoid any specific pattern. MATLAB programming, as illustrated in Figure 4, was used with the neural network toolbox to train and test the network. Several networks, each with a different number of neurons in their hidden layers were trained to find the optimal number of neurons in the hidden layer. As seen in Table 2, the network with 15 neurons in its hidden layer has the minimum amount of error and is thus the optimal network, as shown in Figure 5.

About 800 sets of data were available for the 14 bridges over a period of approximately 60 years. Sixty percent of the data were randomly used as input to train the model and the remaining forty percent were used to assess the success of the model for predicting the LCC. After running the networks with the various architectures, the following determinations have been made:

- A multi-layer network with one hidden layer using the back propagation with momentum method has the least probability of getting trapped in a local minimum and offers the best convergence speed. In other words, it minimizes the probability that the network will fall into a local minimum.
- A comparison of batch learning to online learning shows that online learning improves convergence speed (Principe 2000).
- The best activation function in the hidden layer and the output layer is the hyperbolic tangent.
- The optimal number of neurons in the hidden layer is 15, as shown in Figure 6.
- A stopping criterion of 100 epochs is satisfactory.
- Therefore, a network with a (10-15-1) topology and other previously mentioned specifications is the best network architecture and achieves the highest convergence speed.

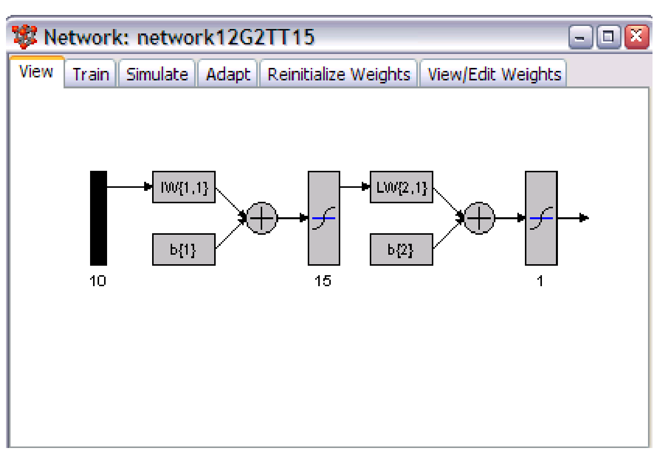

Figure 4: Architecture of the best neural network to train and test.

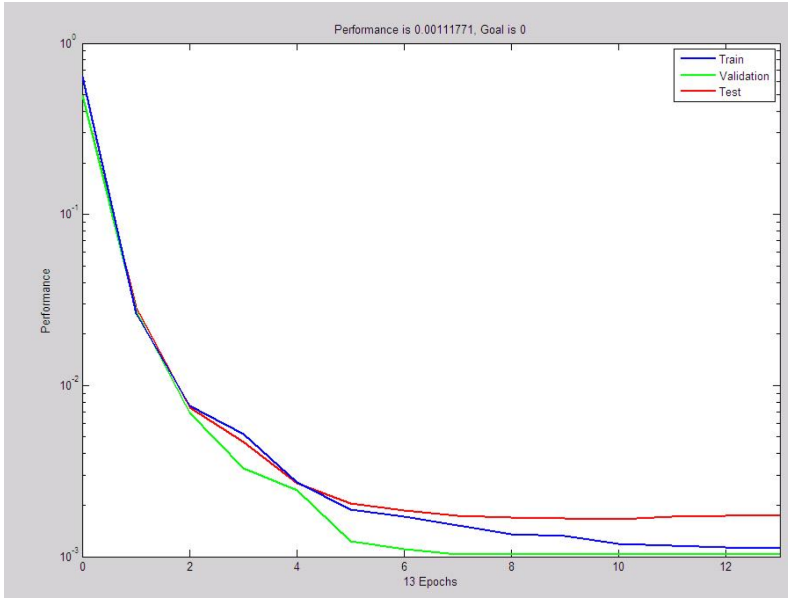

Figure 5: Graph illustrating the best neural network.

No.	***Number of Hidden nodes***	***MSE***
1	6	0.19647
2	8	0.08576
3	10	0.05359
4	12	0.00729
5	***15***	***0.00111***
6	18	0.05399
7	20	0.38576

Table 2: Training and testing results for different numbers of neurons.

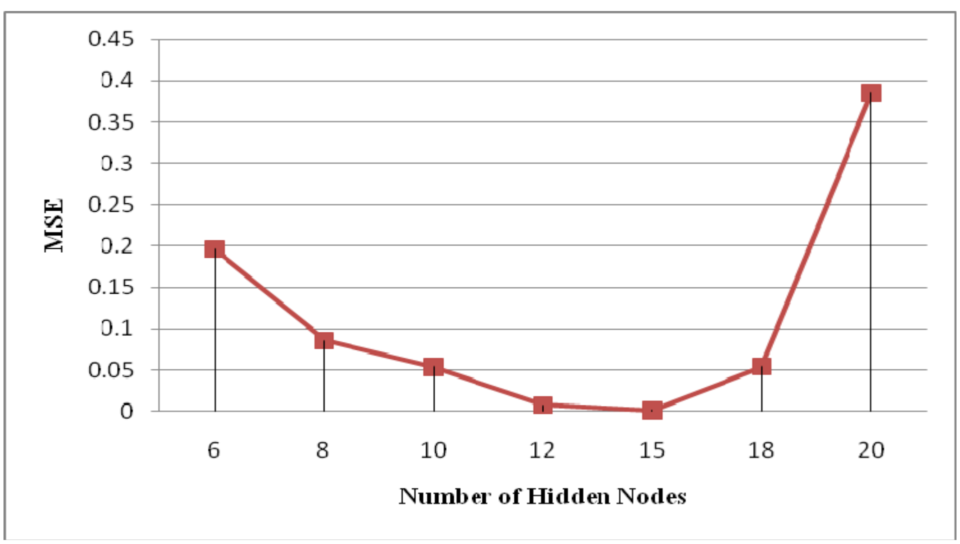

Figure 6: Chart used to determine the optimal number of neurons in the hidden layer.

6. CONCLUSION

The results achieved were encouraging and support the premise that the neural network model is a promising tool for predicting the Life-Cycle Cost of a bridge. The most important advantage of ANN is its innate ability to handle complex and nonlinear problems of the type characterized by most infrastructure facilities.

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