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A Cost Estimation Model for Repair Bridges Based on Artificial Neural Network

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Abstract: Estimating the total cost of bridges repair and maintenance with high accuracy is an important components, and points to a need for a cost estimation model. This paper focuses on the development of a more accurate estimation model for repair and maintenance of bridges in developing countries using artificial neural networks. Cost and design data for two categories of repair bridges were used for training and testing our neural network model, with only three main parameters used in estimating the total cost of repairing bridges. An accuracy of 96% was achieved.

Keywords: Bridge repair; cost model; neural networks.

INTRODUCTION

Estimating the cost of bridges repair and maintenance with high accuracy is crucial and needed to provide an accurate estimate to assist project managers to choose adequate alternatives. Practice shows that current artificial neural network models are based solely on elementals and parametric[1, 4, 9] models which relies on more details, complexity, design and time consuming.

The objective of this paper is to develop and test a cost estimation model to estimate the total cost of repairing bridges based on items packaged by the application of artificial neural networks. This model can help the estimator to save time and to make a more realistic decision, on which to choose between replacing and repairing a bridge. It should be pointed out that with items packaged, it is possible to obtain a fairly accurate estimate.

The data employed for cost estimation in this paper comes from a research report of bridges repair and maintenance cost analyses from, bills of quantities in Uk. As a developing country. Uk experiences account for bridges repair and maintenance more than 50% of the construction industry's turnover. The cost of repair and maintenance of bridges becomes increasingly important during the life cycle of bridges.

METHODOLOGY

A research methodology was carried out to achieve the objective of the study approach. In the first step, other theory of artificial neural network based on cost estimation models were investicated. In the second step an artificial neural network model was designed for estimating the cost of repair and maintenance of bridges for two categories. Then the model was tested on separate data for best-possible architecture. These steps will be examined in the following sections.

Cost Estimation Model Based On Neural Network: Artificial neural network is applied for complex problems such as cost estimation .They are inspired from the biological structure of the human brain, which acquires knowledge through a learning process. A neural network is constructed by arranging several units in a number of layers. The output of a single layer provides the input of a subsequent layer and the strength of the output is determined by the connection weights between the processing units of two adjacent layer. The ability of neural network is to learn from examples to detect by themselves the relationships that link inputs to outputs. Artificial neural network are used in solving problems, where numerical solutions are hard to obtain.

Several researchers have used neural networks as a tool for estimating costs for the earlier stage of project development .Hegazy T, and Amr Ayed[1] used

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a neural network approach to manage construction cost data and developped a parametric cost estimating for highway projects. They introduced two alternative techniques to train network's weights: simplex optimization (Excel's inherent solver function), and genetic algorithms, which is a flexible and adaptable model for estimating highways projects by using a spreadsheet simulation. Adeli et al.[2] formulated a regularization neural network to estimate highway construction costs and indicated that the model were very noisy and this noise results from many umpredictable factors related to human judgement, such as random market fluctuations, and weather conditions.They concluded that the model is successful in introducing a number of attributes to make it more reliable and predictable. Also Gwang et al.[3] examined different methods of cost estimation models in the early stage of building construction projects such as multiple regression analysis and neural networks. They concluded that neural networks performed best prediction accuracy. Murat et al.[4] developed a cost estimation model for building based on the structural system for the early design process. They suggested that their model establishes a methodology that can provide an economical and rapid means of cost estimating for the structural system of future building design process. They argued that neural networks are capable to reduce the uncertainties of estimate for a structural system of building and the accuracy of the model developed was 93% level. Setyawati et al.[5] developed a neural networks for cost estimation and suggested regression analysis with combined methods based on percentage errors for obtaining the appropriate linear regression which describe the artificial neural network models for cost estimating. Emsley et al.[6] suggested that procurement routes cannot be isolated from cost significant variables in a building project. Therefore, Al Tabtabai et al[7] developed a neural network model that could be used to estimate the percentage increase in the cost of a typical highway project from a baseline reference estimate such as environmental and project specific factors. Their model generates a mean absolute percentage error of 8.1%. Shtub and versano[8] developed a system to estimate the cost of steel pipe bending that was a comparison between neural network and regression analysis They found that neural networks outperform linear regression analysis. Recently Jamshid[9] also examined a cost estimation for highway projects by artificial neural network and argues that neural network approach might cope even with noisy data or imprecise data. They reported that artificial neural network could be an appropriate tool to help solve problems which comes from a number of incertainties such as cost estimation at the conceptual phase. Because backpropagation neural network has good non linear approach ability and higher prediction accuracy [10] it has been used for cost prediction.

This paper focuses on the development of a more accurate cost estimation model. The method has been applied to work packages derived from bills of quantities to estimate the cost of repair and maintenance bridges using artificial neural network.

The Design Of Artificial Neural Network : The choice of artificial neural network in this study is based on optimum design and prediction using a feed-forward neural network architecture and back-propagation learning technique. Neurosolution software[11], were used for analysis. The proposed model has been developed in three phases: the modeling phase, the traing phase and the testing phase. The modeling phase involves the identification of the main parameters and the adoption of the network architecture with its internal rules. The training phase were used to train the network in order to choose its parameters (weights). The testing phase were used for generalisation, that is to produce better output for unseen examples.

The Modeling Phase: The modeling phase consist of the design of the neural network architecture. The choice of the neural network structure and rules depends on a number of factors such as the nature of the problem, data characteristics , complexity of data and the number of sample data. A three-steps procedures was developed to enhance the target. Firstly, a set of data for two categories of repair bridges, based on the principle of cost-significance work packages (Cswp's), were used to identify the main parameters as a neural network inputs. In the second stage, an artificial neural network was designed. Then, the model was tested on separate data for best neural network architecture.

The current model has been designed to include an input layer of three processing elements (neurons) corresponding to the three input parameters and one output layer of one processing element as the target. The hidden layer with four processing elements was selected after several trials during the training phase. The number of processing element for the hidden layer is determined by trials, since there is no rule to determine it[5, 11] . Figure. 1.

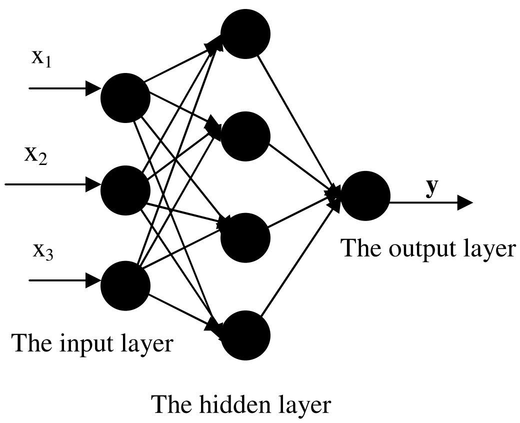

Fig. 1: The architecture of the neural network model

Data Description: Cost-significance work packages models were used for this research.This database contains bridge repair works for two categories. For this reason, they were chosen in this study to investigate the relationship between work packages cost and other variables such as cost model factor and the type of repair work to estimate the total project by artificial neural network. The work packaging concept involves combining similar items into packages that are similar in nature and correspond more closely to site operation than to the individual items[12]. These work packages models based on the principle of cost-significance items. It has been known for many years that 80% of the value of a bill of quantities is contained within only 20% of the items; those which are cost-significant.

A data analysis has revealed the main parameters to be used in modelling and training the network. These parameters are the master key of the cost drivers for the case example. They defined the value of cost-significant work packages, the cost model factors which are the ratio of the cost significant work packages value to the bill value and the type of bridge work. The value of cost work packages bears a significant relation which in turn defines the cost of repair bridges. The records of forty projects for two types of bridge repair work and maintenance from a research report [13], with data on all of the selected parameters were used.

Identification Of The Design Parameters: The cost and design related from 40 projects were divided into two sets; one set for training the neural network; and the second set for validating the performance of the neural network.

As suggested[4, 5, 11], 20% of the observation (data) were selected at random for the validation set. So, this provided thirty two projects for training and a set of eight projects for testing. However, the training sample covered all spectrums of data (lower bill value to higher bill value). Data were normalised between -1 and 1, for effective training of the model being developed in order to guarantee network learning precision and avoid that weight step-change. The real coding of training data is recognised to improve the performance of trained networks[14, 16]. The input and output values were normalised for training and testing purposes.

A neuron computes the sum of their weighted inputs, substract its threshold from the sum and transfers these results by a function

y_i

$$y_i = f_i \left(\sum_{j=1}^{n} w_{ij} x_j - \Theta_i \right) \quad (1)$$

where y_i is the output of a neuron, w_{ij} is the connection weight with the input j, Θ_i is the threshold value of the neuron, n is the number of samples evaluated in the training phase (n = 32 projects) , and f_i is the transform function of hidden layer node. All neurons are independent on each other via weighted connections. The function adopted for the current model, was the hyperbolic tangent sigmoid transfer function which generates output values between -1 to 1 and defines the behavior of the network model.

$$Tansig\,(x) = 2/(1+\exp(-2x))-1 \quad (2)$$

where x is the model output related to the sample

The Training Phase: The training dataset was used to train the network, in order to select its parameters. Artificial neural networks have been applied to almost every application area, where a data set is available and a good solution is sought. The most important criterions when applying artificial neural network, is to define which training parameters to adopt for similar problem. Backpropagation algorithm was used to train the network since it is recommended and simple to code. Gradient descent momentum and learning rate parameters were set at the start of the training cycle.

They determine the speed and the stability of the network [17].The learning rate determines the amount of weight modification among the neurons during each training iteration. This value range between 0 and 1. A learning rate of 0.1 was adopted since larger learning rates have been found to lead to oscillations in weights changes, which results in an increase in error. The momentum coefficient was set to 0.1 found to fit well after several trials.

The back-propagation algorithm involves the gradual reduction of the error between model output and the target output. It develops the input to output, by minimizing a mean square error cost function measured over a set of training examples. The mean square error is as follow.

$$Mse = \frac{\sqrt{\sum_{i=1}^{n}(xi - E(i))^2}}{n} \tag{3}$$

Where n is the number of projects to be evaluated in the training phase, x_i is the model output related to the sample, and E is the target output. The mean square error is a good overall measure whether a training run was successful[7, 17].The mean square error evaluate the performance of the model during the training process. The error was measured for each run of the epoch number selected and a mean error of 0.029 was indicated. Training should be stopped when the mean square error remains unchanged for a given number of epochs. This is done in order to avoid overtraining, in which case the network memories the training values and is unable to make good predictions when unseen example is presented to it.

The Testing Phase: The testing dataset was used for generalisation, that is to produce better output for unseen examples. Data from eight projects, for two categories of bridge repair which had been excluded from the development of the training phase were used for testing purposes. A spreadsheet simulation program on Microsoft excel was used for testing our model accordingly to the weights adopted. Evaluation of cost estimation accuracy is carried out by comparing actual cost and estimated neural network cost, the common approaches being to deter;ine the cost percentage error (CPE) and the mean estimated error (ME) which can be expressed by Equations 4 and 5.

$$Cpe = \frac{Enn - Bv}{Bv} \times 100\% \tag{4}$$

$$Me = \frac{1}{n}\sum_{i=1}^{i=n} Cpe_{(i)} \tag{5}$$

RESULTS AND DISCUSSION

The accuracy of the cost model developed by artificial neural network sound very favourably with data based from work packaged. It has been shown from the results that the model perform well and no significant difference could be discerned between the estimated and the actual bill value. An average accuracy of 96% was achieved. Results are shown in Table. 1.

Table 1: Results of neural network model at testing phase

Proj N°	Estimated value (nn) (£)	Bill value (£)	Cpe (%)
1	24 018	23 621	1.68
2	21 095	22 595	-6.63
3	18 726	18 152	3.16
4	87 514	82 841	5.52
5	53 208	54 570	-2.49
6	63 673	62 029	2.65
7	24 705	25 625	-3.58
8	37 833	38 728	-2.30

Mean error = -0.25

The mean error of the model developed is calculated from the test cases. Combined errors with their accuracies are presented in Table. 2.

Table 2: Expected accuracy at tested phase

Cost model	Maxi positi error (%)	Maxi negat error (%)	Mean error (%)	Stand deviat (%)	Accuracy range (%)
Ann	+5.52	-6.63	-0.25	$\pm$ 4.10	+3.85 -4.35

Regression analysis was used to ascertain the relationship between the estimated cost and the bill value. The results of analysis is illustrated graphically. The statistics can be interpreted that the correlation coefficient is 0. 998, indicating that, there is a good linear correlation between the actual value and the estimated neural network cost at tested phase. The results of linearly regressing, is shown graphically in Fig. 2.

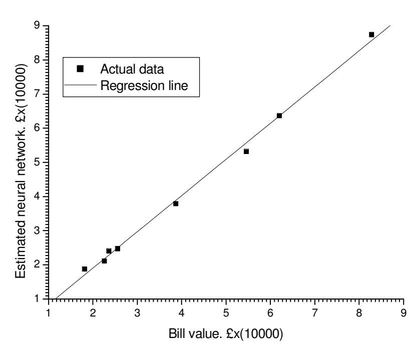

Fig. 2: Estimated neural network versus actual bill value

Sensitivity Analysis: Once the artificial neural network was built and tested, the next step is to evaluate the influence of each input parameters to output variable. This serves as a feedback, indicating which input chanel has a significant effect. It is a method for extracting the cause and effect relationship between the inputs and outputs of the network. One might decide to remove input variables with less significance to reduce the complexity of the artificial neural network model and to save time on training. However, the usage only of the value of cost significance reduce the accuracy from 96% to79%. In this model the value of cost- significance work packages found to be the most significant parameter.

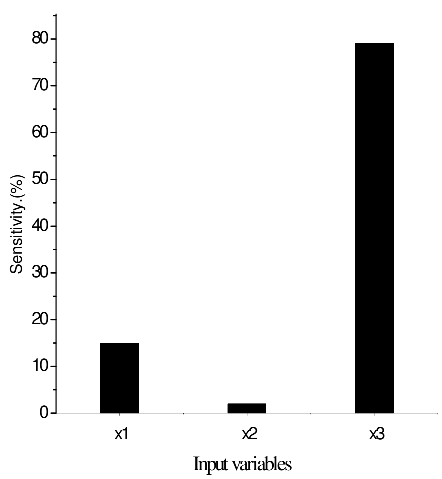

Fig. 3: Sensitivity about the mean

Furthermore, Table 3, is a comparison of two models including artificial neural network and estimated cost-significance work packages(Ecswp's), which is expressed by, Equation. 6, In the case of estimated neural network the accuracy of the model developed is ranging between +3.85% and -4.35%, compared to that produced by the cost model factor, is relatively within 11%. Eventually, estimated neural network model is more accurate and revealed as superior than that produced by cost model factor (Cmf).

$$Ecswp's = \frac{Vcswp's}{Cmf} \tag{6}$$

Table 3: Comparison of models results

N°	Value of Cswp's (£)	Estimated cswp's (£)	Estimated network (£)	Bill value (£)
1	21 016	27 118	24 018	23 621
2	18 509	23 883	21 095	22 595
3	15 388	19 855	18 726	18 152
4	69 536	84 800	87 415	82 841
5	48 020	58 560	53 208	54 570
6	54 589	66 572	63 673	62 029
7	18 828	22 961	24 705	25 625
8	27 950	34 085	37 833	38 728

Estimated neural network costs versus bill value were then plotted against estimated cost-significance work packages, that produced by cost model factors. It seems clearly that estimated neural network costs are more closer to the bill value than the estimated cost-significant work packages by cost factors. Results are illustrated graphically in Figure 4.

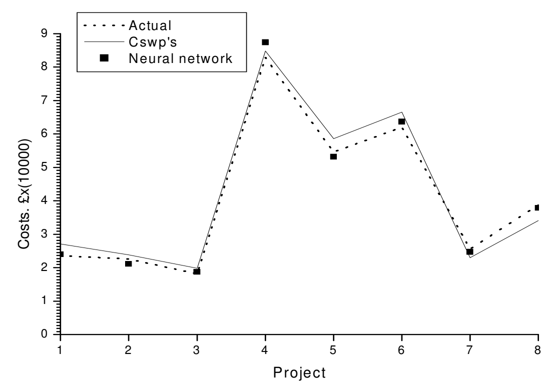

Fig. 4: Actual value versus estimated neural network and cswp's costs.

CONCLUSION

The study demonstrates the benefits of this technique into models based on work packaged for estimating repair and maintenance costs of bridges. The model developed for repair work therefore represent an improvement in the accuracy compared to that produced by the cost factors. Results are successfully and proofed that neural network provide a high level accuracy to the case studied. It is recognised that the results obtained from the model developed, is as good as the quality of the data input which is based from work packaged. It is believed that the relationship between the bill value and the estimated artificial neural network cost provide the basis of the model developed.

In conclusion, the model developed is more accurate and simple to use, with much time saving compared to elementals and parametrics models. This neural network model could be an appropriate tool to help solve problems which come from a number of uncertainties such as cost estimation at the early stage. So, the results are encouraging for further research of projects management by incorporating other methods including fuzzy logic, and other up to date techniques.

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