AN ARTIFICIAL NEURAL SYSTEM FOR COST ESTIMATION OF CONSTRUCTION PROJECTS

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Cost estimation is an experience-based task, which involves evaluations of unknown circumstances and complex relationships of cost-influencing factors. An artificial neural network (ANN) is an analogy-based process, which best suits the cost forecasting domain. The primary advantages of ANNs include their ability to learn by examples (past projects), and to generalise solutions for forthcoming applications (future projects). ANNs do not require a prerequisite establishment of rules and reasoning which govern relationships between a desired output and its significant effective variables. Two ANN models have been developed to predict the lowest tender price of primary and secondary school buildings. Thirty projects were involved in this study and their pertaining data was extracted from the BCIS database. Model I utilises 13 cost-determinant attributes, but in contrast only 4 input variables are involved in developing model II. The findings show that, the two ANN models effectively learned during training stage, and gained good generalisation capabilities in testing session. The ANN model I and II managed to achieve average accuracy percentages of 79.3% and 82.2% respectively.

Keywords: Artificial neural network, back-propagation algorithm, cost forecasting techniques, cost influencing factors, lowest tender price.

INTRODUCTION

Reliable predictions of cost and duration are amongst the highest determinants of success of construction projects. Construction practitioners are aware of uncertainty, incompleteness, unknown circumstances and complex relationships of factors affecting cost and duration of construction projects.

A wide range of cost forecasting methods has been exploited in the construction industry. It is found that these techniques do not take into account most of the significant factors affecting project costs, such as site conditions, contract procedures and market characteristics.

A methodology utilising artificial neural networks (ANNs) is seen to be competent to traditional techniques, which are used for cost forecasting of construction projects. They have the ability to learn from past incomplete and hazardous data as well as to generalise solutions for future practices (Hecht-Nielsen 1990).

Several researchers have addressed potential applications of artificial neural networks in construction (Boussabaine 1996). Khosrowshahi and Elhag (1995) developed a neural network model for bankruptcy prediction of contracting organisations. Hegazy and Moselhi (1994) used a back-propagation neural network for bidding strategy appraisal and markup estimation. Boussabaine and Elhag (1997) developed a neuro-fuzzy system for forecasting cost and duration of construction projects.

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In this study, two models for cost estimation of school buildings are developed using artificial neural networks. For the first model 13 influencing factors are used, whereas in the second model only 4 determinant variables are provided. These models achieved overall average accuracy of 82.2% and 79.3% respectively.

COST FORECASTING TECHNIQUES: A REVIEW

The primary function of cost estimation is to produce an accurate and reliable cost forecast of a construction project. However, which cost should be forecasted depends on the requirements of a client and also upon the information and data available to develop the model. For instance, a client or a contractor may need to know the lowest tender price at one stage and/or the final project cost at completion stage.

There are different techniques currently used for project cost estimation at different stages of the project development process, and even within the same stage. The attractiveness of each of these methods includes its ease of application, familiarity and speed, together with a tolerable level of accuracy and reliability (Ashworth 1995).

A Literature survey has elicited the following estimating methods (Brandon 1994, Raftery 1994, Seeley 1996):

- Functional unit
- Cube method
- Superficial area
- Superficial-perimeter
- Storey-enclosure
- Approximate quantities
- Elemental analysis
- Interpolation
- Resource analysis
- Cost engineering

These methods suffer the major disadvantages of lack of precision and uncertainty. Their weaknesses also lie in the difficulty of making allowance for a whole range of factors such as:

- Client characteristics
- Consultant and design characteristics
- Contractor characteristics
- Project characteristics
- Contract procedures and procurement methods
- External factors and market characteristics

Other cost modelling techniques include: Linear / Dynamic Programming, Regression Analysis, Simulation / Risk Analysis, and Expert Systems (ES). These models lack the ability to deal with problems such as:

- Imprecision and uncertainty of data and variables affecting costs of construction projects.
- Unknown combined effects and inter-relationships of cost-influencing factors.
- Complex and vagueness of input – output relationships which cannot fit nicely and successfully into a quantitative description.

ARTIFICIAL NEURAL NETWORKS (ANNs): BACKGROUND

Neural computation is one of the inductive machines learning methodologies, It is most often used to learn, generalise and represent general knowledge. It extracts information from existing data by inductive learning. It is a fundamentally different approach to other information processing approaches. Algorithmic computing is used in cases where the processing can be described as a known procedure or a set of known rules. Neural computation allows the development of information processing for which the rules and relationships knowledge are not available (Hecht-Nielson 1990).

Expert systems require rules or instructions, which are executed one at a time to arrive at an answer. By contrast, artificial neural networks take in a great amount of information at once, and then draw a conclusion. Once taught, an ANN looks at new input data and produces an answer instantaneously.

A back-propagation neural network consists of a number of layers; each layer synthesised of different number of neurons (processing elements) as depicted in Figure 1. The input layer represents influencing factors of a specific problem. The output layer in which the solution of the problem takes place, e.g. prediction, classification, etc. The hidden layer through which the information is processed. The numbers of hidden layers and hidden neurons are usually determined by trial and error according to the complexity of the problem.

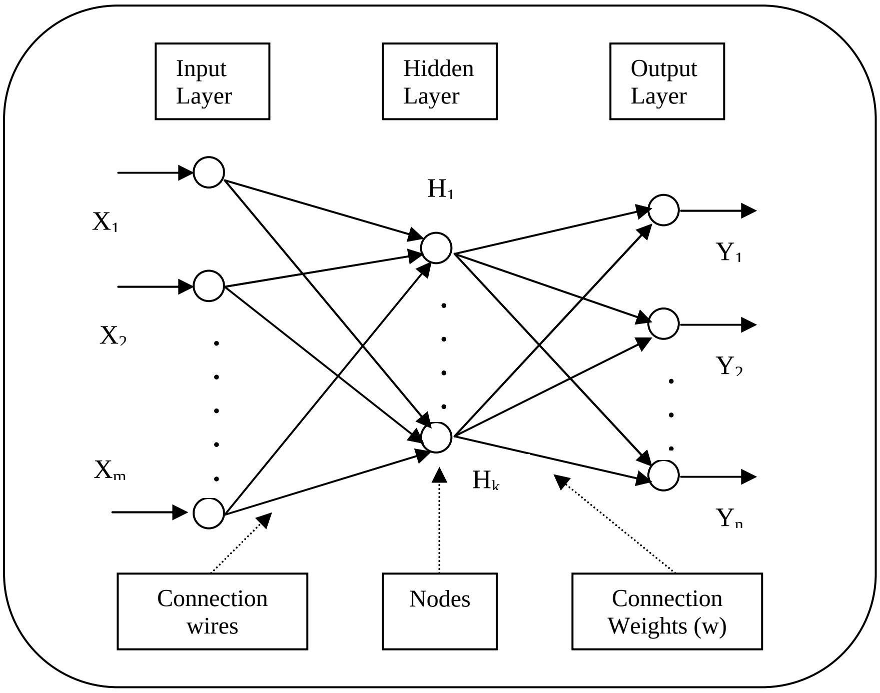

Figure 1: A Simple Artificial Neural Network Structure

Each neuron receives input(s), processes the input(s), and delivers an output as delineated in Figure 2. The processing element computes a weighted sum, S (x), of its input signals, x_i (i = 1, 2, ….. , m) and their corresponding weights (w_i), as illustrated in Equation 1. The neuron generates an output through an activation function, F(s). Different types of activation functions are portrayed in Figure 3, (Jain, et al 1996).

$$S(x) = \sum_{i=1}^{m} x_i * w_i \cdots\cdots (1)$$

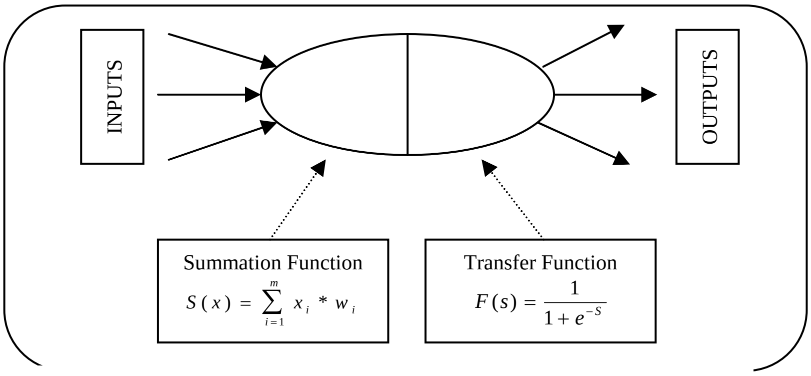

Figure 2: A simple artificial neuron model

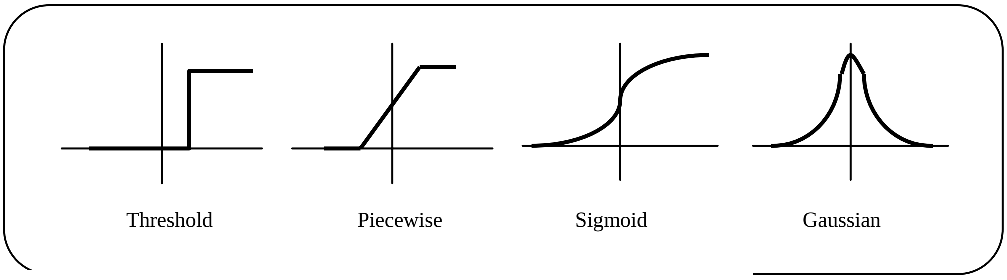

Figure 3: Different types of activation function

A back-propagation neural network is utilized in this study to develop the cost estimation models. The back-propagation algorithm is the most popular ANN paradigm used for adjusting the weights of a multi-layer neural network, that is because of its simplicity and good generalization capability (Rumelhart et al 1986). It is based on a gradient descent approach to minimize the output error with respect to the connection weights in the network. A summary of the process of a standard back-propagation algorithm can be illustrated as follows: (Figures 1 and 2).

- A set of input factors is presented to the ANN as well as their desired outputs.
- A training stage starts by arbitrary selecting a set of connection weights for each layer. Each neuron calculates its summation function value and accordingly computes its transfer function value, which represents its output. This process is held in a feed-forward manner.
- A set of computed outputs is delivered in the output layer. For each processing element in the output layer an error is calculated, each represents a deviation of the computed output from the desired output.
- Using a learning rule (e.g. generalized-delta rule, extended delta-bar-delta rule, etc.) the errors are back propagated through the hidden layer(s) and the connection weights will be adjusted and updated accordingly.
- A feed-forward process starts all over again. New output values will be computed and the above cycle continues until a desired set of requirements is achieved.

- To validate the model a testing session is undertaken using a new set of data, which has never been exposed to the network. The accuracy of the model and its generalization capability could then be examined.

DATA COLLECTION

The data was extracted from the Building Cost Information Service (BCIS) database. Thirty school projects were involved in the study, comprising 19 primary schools and 11 secondary schools. Fourteen factors were gathered for each school project. These factors represent the whole range of cost variables compiled for each project in the BCIS database. Table 1 shows details of these variables and their variations.

Table 1: Cost-Influencing Factors Used as Model's Attributes

Factor	Category One	Category Two	Category Three
Type of project	**PRIMARY SCHOOL**	secondary school	
Type of contract	JCT local authority	JCT intermediate	JCT private contract
Market conditions	extremely competitive	very competitive	competitive
Number of tenderers			
Site slope	leveled	gentle slope	steep slope
Start conditions	green site	demolition site	
Ground conditions	good	moderate	poor
Excavation conditions	above water table	below water table	
Site access	unrestricted	restricted	
Work space in site	unrestricted	restricted	
Number of stories			
Gross floor area (m^2)			
Duration (months)			
Lowest tender price (£)			

The lowest tender price for each project was adjusted for a base year (1995), and it was also adjusted for a base location using the mean location factor for UK according to the BCIS database. Equation 2 illustrates the adjustment of the lowest tender price.

$$C_{adjusted} = C_{actual} * \frac{TPI_{1995}}{TPI_{actual}} * \frac{M.L.F.}{C.L.F.} \quad \text{..(2)}$$

Where:

$C_{adjusted}$	= adjusted lowest tender price
C_{actual}	= actual lowest tender price
TPI_{1995}	= average tender price index for year 1995 = 130
TPI_{actual}	= tender price index at tender date of a specific project
M.L.F.	= mean location factor of UK for year 1995 = 1
C.L.F.	= county location factor of a specific project

TENDER PRICE ESTIMATION MODELS

Using back-propagation algorithm two models were developed for predicting the lowest tender price of school projects, (model I and model II). Model I comprises four cost-influencing factors as input attributes. They represent type of building, gross floor area, number of stories and project duration. Model II consists of 13 input cost variables, which are listed in Table 1. Architectures of the neural networks for models I and II are depicted in Table 2.

Table 2: Neuron Constituents of Models I & II

Model ID	Input buffer	Hidden layer	Output layer
Model I	4	3	1
Model II	13	13	1

The numbers of processing elements in the input layer for each model represent the cost-influencing factors. The output layer in each model contains one neuron, which stands for the lowest tender price.

The numbers of processing elements in the hidden layers were determined by trial and error. The findings show that selecting 3 and 13 neurons in model I and II respectively, assisted to achieve the lowest root mean squared error, as it will be demonstrated in the following section.

The main back-propagation parameters, which were also selected by trial and error and managed to achieve the best results, were stated in Table 3. These parameters were applied for both models.

Table 3: Parameters of Back-Propagation Algorithm

Parameter	Description
Learning rule	**EXTENDED DELTA-BAR-DELTA**
Transfer function	Hyperbolic tangent
Learning coefficient ratio	0.5
Momentum coefficient	0.4
Number of epochs	50,000

ANALYSIS OF RESULTS

For validation of the neural network models, the original data set was split into two portions. A training data set comprises 14 primary schools and 9 secondary schools, and a test data set consists of 5 primary schools and 2 secondary schools. The selection of these sets was undertaken arbitrary.

Both models were trained using the save training data set for 50,000 cycles. In the training stage the back-propagation algorithm works to minimise the global output error. The root mean squared errors, expressed by Equation 3, were calculated as 0.0398 and 0.0001 for model I and II respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n}} \qquad (3)$$

Where:

RMSE = root mean squared error

x_i = actual lowest tender price

$\hat{x}_i$ = predicted lowest tender price

n = total number of cases (23 for training session, 7 for test stage)

For the training stage, the mean absolute percentage errors (MAPE) were obtained as 8.87% and 0.01% for models I and II respectively, Equation 4. The average accuracy percentages achieved for models I and II were 91.3% and 99.99% respectively, Equation 5.

These results show that model I demonstrates better learning ability, probably because it exploits more input variables, which pertains to gaining better experience in the knowledge domain.

$$MAPE \quad = \quad (\sum_{i=1}^{n} \frac{|x_i - \hat{x}_i|}{x_i} * 100\%) / n \quad \text{..(4)}$$

Average Accuracy % = 100% – MAPE ……………………………………(5)

The generalisation ability of an artificial neural network can be validated during the test session. Both back-propagation models were tested using the test data set, which was mentioned earlier. Table 4 delineates the outcomes of the ANN models I and II during the testing stage. Despite the level of noise inherited in the data of these projects, according to the subjectivity of factors involved, these networks managed to exhibit reasonable generalisation level.

Table 4: Test Stage Results of ANN Models I & II

Project No.	Actual lowest Tender Price (£)	Model I		Model II	
		Predicted Lowest Price	Accuracy %	Predicted Lowest Price	Accuracy %
Project 1	1273244	1147202	90.1	1190966	93.5
Project 2	714559	862098.7	79.4	708079.5	99.1
Project 3	1735755	1432146	82.5	2087536	79.7
Project 4	1106790	1421331	71.6	1537522	61.1
Project 5	1223240	1105315	90.4	972262.1	79.5
Project 6	424707	490346.3	84.5	476163.3	87.9
Project 7	735588	414916.5	56.4	920902.9	74.8

Table 5 summarises the results obtained during training and testing of both models. It is obvious that the ANN models achieved better results during the training session compared to the test stage, because the desired outputs of the test data are always unknown to the models. It is also apparent from the findings, that model II obtained better results in contrast to model I in both sessions, Table 5. These outcomes could be pertained to the fact that model II was exposed to 13 different cost-influencing factors, while on the other hand model I utilised only 4 out of these 13 variables.

Table 5: Summary of Results

Description	Model I		Model II	
	Training	Testing	Training	Testing
Root mean squared error	0.0398	0.0669	0.0001	0.0626
Correlation	0.9943	0.9802	0.9999	0.9837
Mean absolute error %	8.87%	20.74%	0.01%	17.77%
Average accuracy %	91.13%	79.26%	99.99%	82.23%
Standard deviation	10.23	11.98	0.02	12.65

CONCLUSION

This paper demonstrates the development of a cost estimation model using artificial neural networks and a back-propagation algorithm. Determinants of building project cost were identified, and their pertaining data was extracted from the BCIS database.

Two ANN models were developed, model I & II, for predicting the lowest tender price of primary and secondary school projects. Thirteen cost-influencing factors were involved in model I, whereas only 4 input variables contributed to model II.

The findings show that the two ANN models are able to learn the cause-effect relationships between input and output patterns, during the training stage, and obtained average accuracy percentages of 91.1% and 99.9% for model I and II respectively. On the other hand, in the testing session the elicited knowledge was utilised, and good generalisation capabilities were gained by both models. In the validation stage, the ANN model I & II achieved average accuracy percentages of 79.3% and 82.2% respectively.

It is also apparent that, model II exhibits better results in acquiring knowledge and generalising ability. This can be attributed to the fact that, the more significant factors contributed in developing an ANN model the better the outcomes will be.

The ANN models were developed using 30 projects for each model. However, it is recognised that neural networks are data intensive techniques, and to enhance the accuracy and reliability of the models, it is recommended to exploit more projects for future developments.

The second stage of this research is embarked on; its main objective is to develop artificial neural networks for cost prediction of commercial, industrial and residential buildings, as well as combining these models to build a hybrid cost estimation system.

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