DEVELOPING AN ARTIFICIAL NEURAL NETWORK MODEL FOR LIFE CYCLE COSTING IN BUILDINGS

Olufolahan Oduyemi[1], Michael Okoroh[2] and Angela Dean[3]

[1 and 3] *College of Engineering and Technology, University of Derby, Derby, UK*

[2] *College of Engineering, Imam Muhammad ibn Saud Islamic University, Riyadh, Saudi Arabia*

Life-cycle costing is an economic assessment which considers all the significant initial, operating, maintenance and disposal costs of ownership over the economic life of a building. Particularly, the maintenance and operating costs associated with these buildings are diverse and reflect the effect buildings have on their owners, users and the environment. An Artificial Neural Networks (ANN) model is presented to estimate operating and maintenance costs of existing buildings. Historical data were gathered from an Office Block, Penllergaer Business Park. The resulting ANN model reasonably predicted the total cost of the building with favourable training and testing phase outcomes. The study can be used to improve the confidence in life cycle costing (LCC) modelling.

Keywords: artificial neural networks, life cycle costing, modelling.

INTRODUCTION

Life cycle costing is defined as the costs associated with acquiring, using, caring for and disposing of physical assets. This encompasses feasibility studies, research and development, design, production, maintenance, replacement and disposal of an asset. It also covers training and operations costs generated by the acquisition, use, maintenance, and replacement of permanent physical assets (British Standards Institute, 1998).

One can draw from this definition that LCC quantifies and forecasts choices which can be used to determine the ideal choice of assets. It allows the life cycle cost and the trade-off between cost elements, throughout the asset life stages to be understood.

Yet, there are immense doubts about the accuracy of LCC estimates as they are deemed to be imprecise, inexact, uncertain and vague (Kirkham *et al*. 2004). The above submission unmistakeably shows a variance in prevailing cost estimation techniques and underlines the necessity for re-assessment and potential re-evaluation of LCC methodologies (Doloi, 2011).

Consequently, the challenge among practitioners is to develop a framework for LCC that is not only universal, but more importantly dynamic as clients now want buildings that demonstrate value for money over the long term, and are not interested simply in the design solution which is the least expensive.

These changes have led to and highlighted the importance of LCC approaches to the design, construction and operation of buildings (HMSO, 2000). The purpose of this

[1] olufolahanoduyemi@yahoo.co.uk

Oduyemi, O, Okoroh, M and Dean, A (2015) Developing an artificial neural network model for life cycle costing in buildings *In:* Raidén, A B and Aboagye-Nimo, E (Eds) *Procs 31st Annual ARCOM Conference*, 7-9 September 2015, Lincoln, UK, Association of Researchers in Construction Management, 843-852.

work is to explore the ANN technique and predict the operating and maintenance cost of the building.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are non-linear mapping structures based on the function of the human brain. They are powerful tools for modelling especially when the underlying data relationship is unknown. The primary advantages of ANNs include their ability to learn by examples and are ideally suited for complex and non-linear data (Gallant, 1993) and to generalise solutions for forthcoming applications (Nikola, 1998).

ANNs do not require a prerequisite establishment of rules and reasoning which govern relationships between a desired output and its significant effective variables (Hornik, 1991). Neural network based modelling process which according to Ogunlana *et al*. (2001) involves five main aspects namely;

1) Data acquisition (variable selection) and analysis
2) Problem representation at architecture determination
3) Learning process determination
4) Training of the network
5) Testing of the trained network for generalisation evaluation.

A neural network is constructed by arranging several processing units in a number of layers. The output of a single layer provides the input to the subsequent layer and the strength of the output is determined by the connection weights between the processing units of two adjacent layers. A back-propagation neural network is utilised 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:

• A set of input factors are 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 (generalized-delta rule and extended delta-bar-delta rule) the errors are back propagated through the hidden layer(s) and the connection weights is adjusted and updated accordingly.

• A feed-forward process starts all over again. New output values are computed and the above cycle continues until a desired set of requirements are achieved.

Several researchers in the construction industry have addressed potential applications of ANN. De Silva *et al*, (2013) discussed the use of ANNs in complex risk analysis applications. Ahiaga-Dagbui and Smith (2014) used ANN for estimating final cost of water infrastructure projects while Lin and Mohan (2011) used ANN for the mass appraisal of the real estate by the municipalities in the USA. Although a substantial amount of research presently exists in ANN forecasting, none explicitly emphasise on commercial offices despite the fact that the costs of running and maintaining these buildings make up a significant portion of their entire outlay (Barlow and Fiala, 2007).

DATA COLLECTION

In order to develop an ANN cost model, historical cost data was gathered from the BCIS for a sustainable commercial office building case study. Data from the building cost information services (BCIS) was chosen because they give early cost advice to budget and benchmark projects and to prepare life cycle cost plans.

Similarly, BCIS data are used by consultants, clients and contractors to produce specific estimates for option appraisals, early cost advice, cost planning, reinstatement costs, benchmarking, whole life costing, facilities and maintenance budgeting.

The BCIS case study is a two storey office Block, Penllergaer Business Park built in November, 2004. It is a new build; steel framed with a floor area of 2,681m. It has a building cost of £3,007,373 and has an excellent BREEAM rating. The forecasted period was put at ten years.

The following four steps discussed below are used in this paper to develop ANN conceptual framework.

i. Identification of project objectives, and project constraints
ii. Determine the length of the study period
iii. Cost breakdown structure
iv. Forecasting using ANN (Variable selection, Training and Validation)

i.) Identification of project objectives and project constraints.

The LCC analysis is used in this paper to provide an accepted methodology by facilitating a more accurate, consistent application of LCC estimations thereby creating a more effective and standardised basis for life cycle cost analysis.

ii.) Determine the length of the study period.

The study period commenced at time zero which was previously defined.

iii.) Cost breakdown structure

For each LCC project, cost centre was identified and information gathered from historic data and building surveys of the BCIS and subsequently a cost breakdown structure (CBS) is developed for the building.

The cost breakdown structure helps to organise the different costs so it can be distinctly defined and estimated. The BCIS standard form of cost analysis was adopted in this research because it is more elements oriented (see table 1).

Table 1: Historical cost breakdown structure of the operating and maintenance costs of office block, Penllergaer Business Park, Swansea, West Glamorgan

Costs (in £)	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Fuel	21094	23098	27490	29874	31983	37894	41094	43098	47652	49847
Cleaning	12764	15097	17645	19836	20739	21735	23984	25408	27498	30763
Admin costs	6590	6945	7630	7953	8506	8943	9583	10984	11473	11847

iv.) Forecasting using ANN

The historical maintenance and operational cost data were forecasted using the Neural Networks fitting toolbox in MATLAB R2015a. ANNs are constructed with layers of units, and thus are termed multilayer ANNs. First layer of a multilayer ANN consists of input units known as independent variables, as well as output units known as dependent or response variables.

All other units are called hidden units. A multilayer perceptron (MLP) learned by back propagation algorithm is used for forecasting because it is a powerful system capable of modelling complex relationships between variables. It also allows prediction of an output object for a given input object and uses sigmoid and linear activation function for hidden and output layers and are universal approximates.

ANALYSIS AND DISCUSSION OF RESULTS

A training set of 30 values, a testing set of 20 target time steps while validation and testing target time steps of 5 values each were used for the ten year forecasting period (data acquisition). Training was set at 70% while cross validation was at 15% and testing was also at 15%.

The objective of the training is to establish weights that minimise errors as the output neurons first give a set of values that differ greatly from the correct results while the objective of cross validation and testing is to learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to learn.

During training, both the inputs (representing problem parameters) and outputs (representing the solutions) are presented to the network normally for thousands of cycles. At the end of each cycle, or iteration, the network was used to evaluate the error between the desired output and actual output. This error was used to modify the connection weights according to the training algorithms used.

The determination of the number of hidden layers and nodes are crucial since if there are too many hidden layers the neural network will not learn the underlying pattern, while with too few the neural network will not pick up the full details of the underlying patterns in the data.

The training set was used to train the network in order to choose its parameters (weights) while the cross validation set was used for generalization that is to produce better output for unseen examples.

The best ANN model to estimate the operating and maintenance cost of buildings was determined by defining the number of neurons (nodes) in the input and output layers, number of hidden layers and the number of neurons in each hidden layer. The model generated utilizes six input variables (factors affecting operating and maintenance costs) namely engineering services, building materials, budget and finance, skilled labour, building user behaviour, management and administration.

There is no specific rule in determining the number of hidden layers and the number of neurons in each hidden layer (Shtub and Versanob, 1999). For simplicity of the current problem, one hidden layer was used and the following rules were employed to determine the optimum number of neurons for a network (Oreta 2012):

- A network with n-input and m-output units requires a hidden layer with at most 2n+1 units (Hecht-Nielson, 1998) is (13 neurons)
- Should be between the average and the sum of nodes on the input and output layers is (4-7 neurons)
- Seventy-five percent (75%) of the input nodes is (5 neurons)

After several trials, ANN Structure 6-7-1 (6- input variables, 7-nodes in the hidden layer, 1- output) was found to be the best model to estimate the total operating and maintenance costs of the building (see figure one).

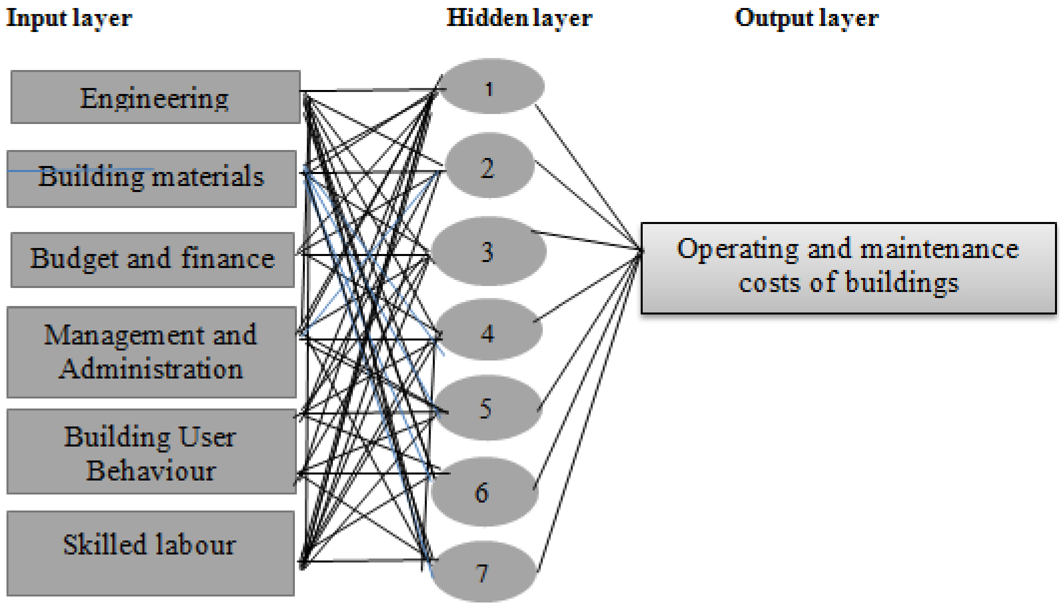

Figure one. 1. ANN Structure 6-7-1

The resulting coefficients and parameters are given in Table two along with the R squared value which indicates how close the relationship is between the dependent and independent variables. The backpropagation algorithm gradually reduces the error between the model output and the target output by minimizing the mean square error (MSE) over a set of training set (Gunaydin and Dogan 2004).

The MSE is a good overall measure of the success of the training process (Al-Tabtaba, et.al., 1999). The weights and bias values were updated according to the Levenberg-Marquardt network training function. This is often the fastest backpropagation algorithm and highly recommended, though it requires more memory that other algorithms (Neural Network Toolbox).

The Table two results show a strong linear relationship between the variables. The accuracy of the costs is favourable but it is important to take cognisance of the fact that a larger amount of data will produce better forecasted values.

Table 2: Regression and Mean Squared Error Analysis

	Regression	Mean Squared Error
Training	0.99985	2.41633
Training	0.99264	1.29839
Validation	0.99259	1.83725
Testing	0.99224	1.49321

Regression values measure the correlation between outputs and targets. An R value of 1 implies that there is a close relationship, 0 means there is a random relationship. The smaller the value of the regression is, the smaller the difference between the predicted time series and the actual one. The mean squared error on the other hand is the average squared difference between outputs and targets. Lower values are better while zero means no error. The values were close to zero thus exhibiting better performance results

For the case study, the training data indicated a good fit. The validation and test results also show R values that greater than 0.99. The next step in validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets (see figure two). If the training was perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice.

The following regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. For this problem, the fit is reasonably good for all data sets, with R values in each case of 0.993 or above.

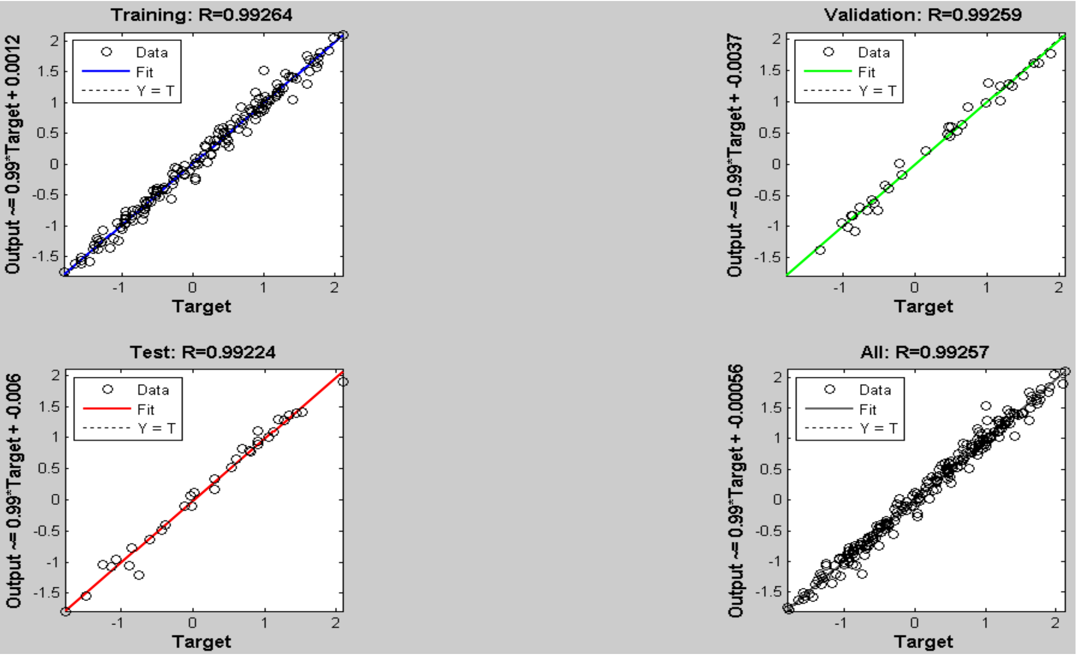

Figure two: Regression result

ERROR AUTOCORRELATION TEST

The following plot (see figure three) shows the error autocorrelation function. It defines how the forecast errors are interrelated in time. For a faultless prediction model, there must only be one non-zero value of the autocorrelation function, and it ought to occur at zero lag.

This implies that the forecast errors were entirely uncorrelated with each other. If there was substantial relationship in the forecast errors, then it would improve the forecast possibly by increasing the number of delays in the tapped delay lines. For the case study, the correlations, but for the one at zero lag, fall roughly within the 95% confidence limits about zero, so the model is satisfactory.

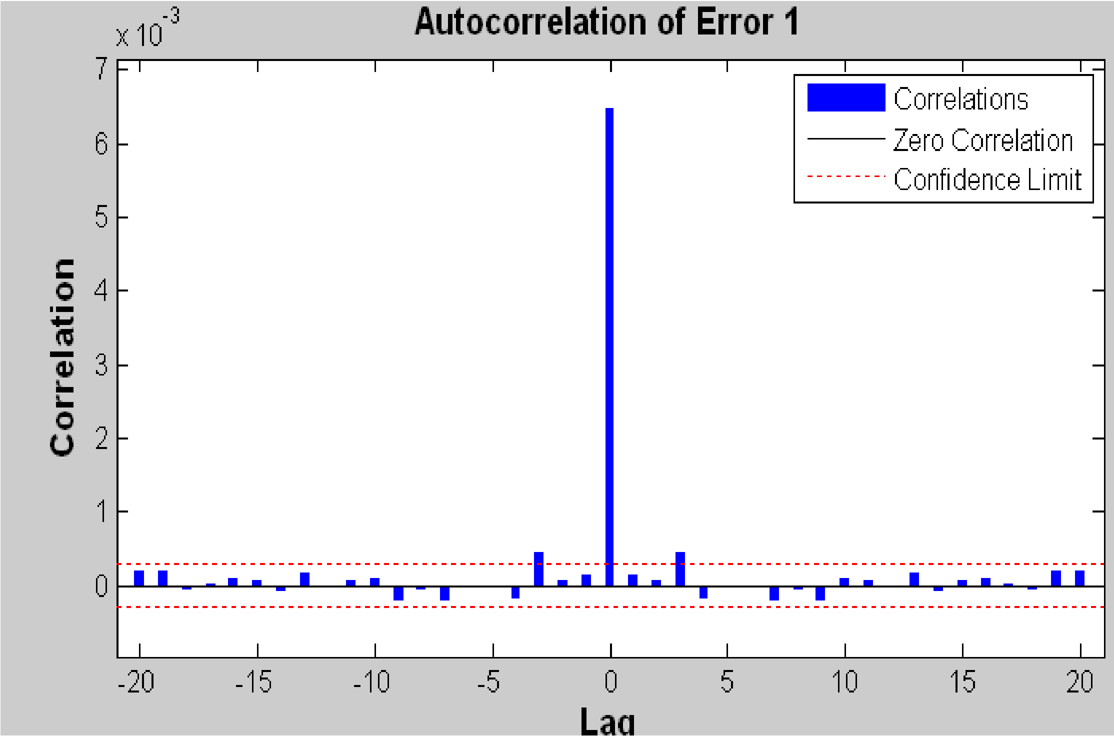

Figure three: Autocorrelation result

PERFORMANCE TEST

When the training was completed, the network performance was checked to determine if any changes needed to be made to the training process, the network architecture, or the data sets. First, the training record, tr, returned from the training function.

Then the cost tr.best epoch indicated the iteration at which the validation performance reached a minimum. The training for case study one continued for 6 more iterations before the training stopped. This result did not indicate any major problems with the training as seen in figure four.

Similarly, the validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some over fitting might have occurred. This is however not the case in this model.

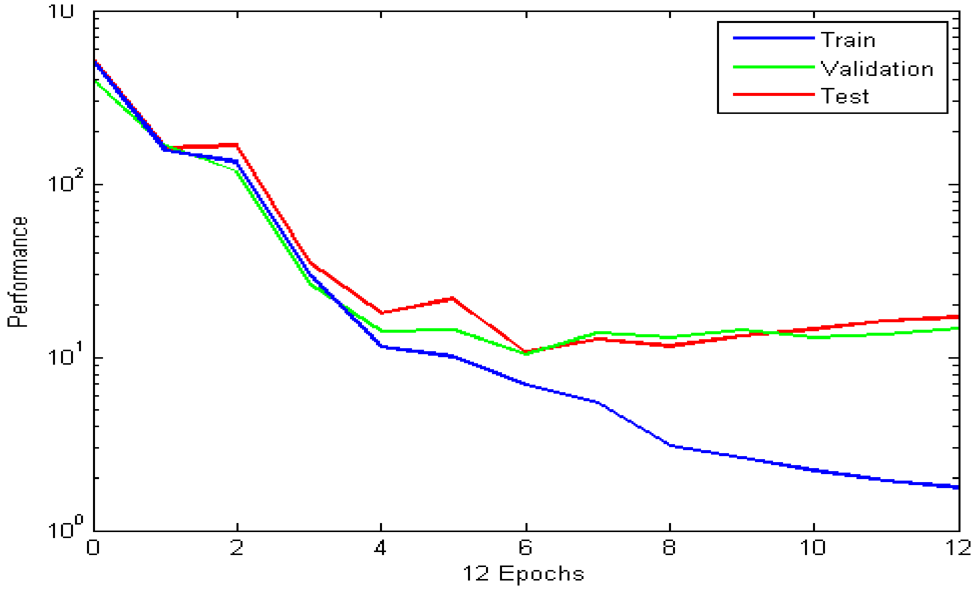

Figure four: Performance test.

Finally, a sensitivity analysis was carried out to study the influence of each input parameter on the performance of the ANN model to predict the cost of buildings (see figure five). The performed sensitivity analysis showed that the engineering services, building materials, budget and finance in the buildings are the most effective parameters influencing the cost estimates of buildings.

The remaining parameters had small effect on the estimated value but it is believed that their existence could be important to enhance the ability of the model to learn and generalize the results.

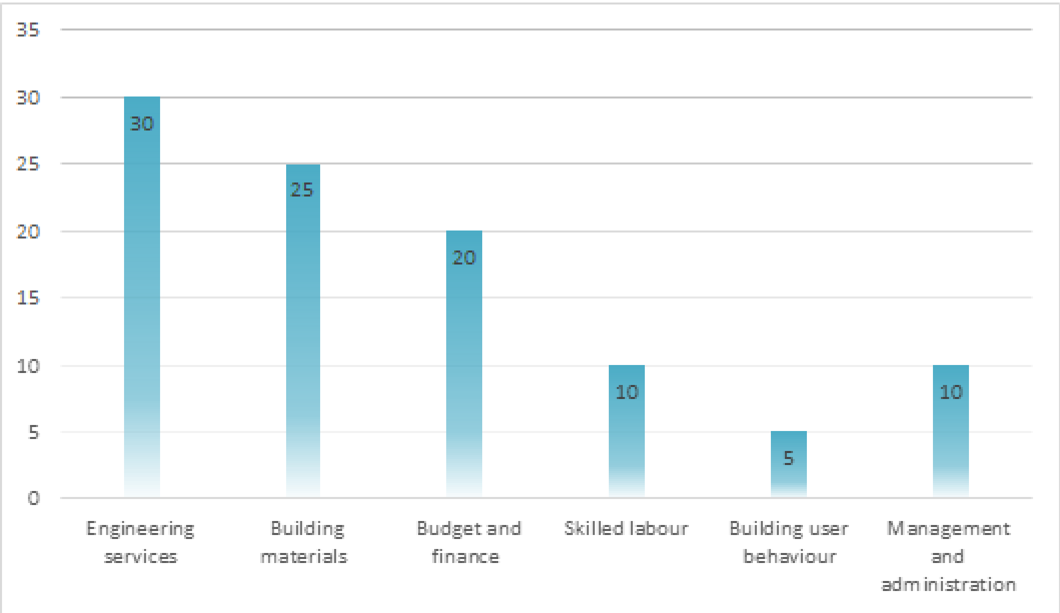

Figure five: Sensitivity measures of the input parameters on the output of the NN model

CONCLUSION

The value of LCC is its ability to provide more comprehensive and accurate cost predictions as there is an increasing realisation of the importance of considering operation and maintenance costs as opposed to capital costs throughout the life of an asset. In addition, new initiatives such as Public Private Partnership (PPP) schemes are becoming more popular.

It is therefore vital to embed life cycle forecasting of a building during conceptual design assessment stage. The use of modelling in predicting costs should be used not only in the context described here but also as a tool for reducing future costs accumulation in buildings.

Occupants and facilities managers need to be made aware of how their actions can in the long term have a significant impact on operating and future costs. The results obtained from this exercise provide the researcher with a great deal of information about forecasting costs when modelling inputs into life cycle costing exercises.

The conceptual framework is generic and can thus be applied to any sustainable building, at any level from sub-elemental to the whole cost scenario. This study is different from previous ones in terms of the input parameters used and a different case study.

This paper further demonstrates that the development of a cost estimation model using ANN methodology is feasible. There is a however the need to evaluate ANN with more projects for future developments

REFERENCES

Ahiaga-Dagbui, D D and Smith, S D (2014) Rethinking construction cost overruns: cognition, learning and estimation, *"Journal of Financial Management of Property and Construction*", **19**(1), 38 - 54.

AL-Tabtabai, H, and Alex, A P (1999). Using genetic algorithms to solve optimization problems in construction. "*Engineering Construction and Architectural Management*", **6**(2), 121-132

Barlow, S and Fiala, D (2007) Occupant comfort in UK offices - How adaptive comfort theories might influence future low energy office refurbishment strategies. *"Energy and Buildings*", **39**(7), 837-846.

Bouachera, T, Kishk, M and Power, L (2007) Towards A generic framework for whole life costing in the oil industry. In: Boyd, D (Ed.), *"23rd Annual ARCOM Conference"*, 3-5 September 2007, University of Belfast. Association of Researchers in Construction Management, 863-871.

BSI, (1998) "*ISO 15686 Buildings – Service Life Planning*", Part 1: General Principles.

De Silva, N, Ranasinghe, C and De Silva, (2013) Use of ANNs in complex risk analysis applications, *"Built Environment Project and Asset Management"*, **3**(1), 123 - 140.

Doloi, H (2011) Understanding stakeholders' perspective of cost estimation in project management, *"International Journal of Project Management"*, **29**(5), 622-635.

Edwards, P J and Bowen, P A (1998) Risk and Risk Management in construction: a review and future directions for research, *"Engineering Construction and Architectural Management*", **5**(4), 339-349

Gallant (1993) "*Neural Network and Learning and Expert Systems*", MIT Press, Cambridge.

Gunaydin, H and Dogan, S, (2004) *"A neural network approach for early cost estimation of structural systems of building"*, International Journal of Project Management, Volume (22): 595-602HMSO (2000) The new Treasury Procurement Guidance Note – No. 7; *"Whole Life Costs"*. The HM Treasury, HMSO, UK

Hecht-Nielsen, R (1998, October). "A Theory of the Cerebral Cortex. In "*ICONIP"* (pp. 1459-1464).

Hornik, K (1991) Approximation capabilities of multilayer feed-. forward networks. *"Neural Networks"*, **4**, 251–257.

Kirkham, R J, Alisa, M, Silva, A P, Grindley, T and Brondsted, J (2004) Rethinking whole life cycle cost based design decision-making. In: Khosrowshahi, F (Ed.), *"20th Annual ARCOM Conference*", 1-3 September 2004, Heriot Watt University. Association of Researchers in Construction Management, Vol. 1, 91-103.

Lin, C and Mohan, S (2011) Effectiveness comparison of the residential property mass appraisal methodologies in the USA, *"International Journal of Housing Markets and Analysis*", **4**(3), 224 - 243

Nikola K K (1998) *"Foundation of neural Networks, Fussy Systems, and Knowledge Engineering"*. The MIT Press Cambridge, Massachusetts.

Ogunlana, S O, Bhokha, S and Pinnemitr, N (2001) Application of artificial neural network (ANN) to forecast construction cost of buildings at the pre-design stage, *"Journal Financial Management of Property and Construction*", **6** (3), 179-192.

Oreta, A (2012) Artificial neural networks: Multilayer feedforward networks using back propagation, CIV578D Lecture Notes, De La Salle University – ManilaRumelhart, D, Hinton, G and Williams, R (1986) *"Learning internal representations by error propagation*", In: Parallel Distributed Processing, Rumelhart and McLelland, (eds),Massachusetts; MIT Press.

Shtub, A and Versanob, R, (1999) Estimating the cost of steel pipe bending, a comparison between neural networks and regression analysis, *"International Journal for Production Economics"*, **62** (3), 201– 207.