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Cost estimation for electric light and power elements during building design: A neural network approach

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A neural network approach

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Abstract

Purpose – The study reported in this paper proposed the use of artificial neural networks (ANN) as viable alternative to regression for predicting the cost of building services elements at the early stage of design. The purpose of this paper is to develop, test and validate ANN models for predicting the costs of electrical services components.

Design/Methodology/Approach – The research is based on data mining of over 200 building projects in the office of a medium size electrical contractor. Of the over 200 projects examined, 71 usable data were found and used for the ANN modeling. Regression models were also explored using IBM Statistical Package for Social Sciences Statistics Software 21, for the purpose of comparison with the ANN models.

Findings – The findings show that the cost forecasting models based on ANN algorithm are more viable alternative to regression models for predicting the costs of light wiring, power wiring and cable pathways. The ANN prediction errors achieved are 6.4, 4.5 and 4.5 per cent for the three models developed whereas the regression models were insignificant. They did not fit any of the known regression distributions.

Practical implications – The validated ANN models were converted to a desktop application (user interface) package – "Intelligent Estimator." The application is important because it can be used by construction professionals to reliably and quickly forecast the costs of power wiring, light wiring and cable pathways using building variables that are readily available or measurable during design stage, i.e. fully enclosed covered area, unenclosed covered area, internal perimeter length and number of floors.

Originality/value – Previous studies have concluded that the methods of estimating the budget for building structure and fabric work are inappropriate for use with mechanical and electrical services. Thus, this study is unique because it applied the ANN modeling technique, for the first time, to cost modeling of electrical services components for building using real world data. The analysis shows that ANN is a better alternative to regression models for predicting cost of services elements because the relationship between cost and the cost drivers are non-linear and distribution types are unknown.

Keywords Multiple regression analysis, Prediction, Modelling, Estimating, Cost estimates, Neural net

Paper type Research paper

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1. Introduction

Engineering services are important elements of a building. They include electric light and power, gas services, space heating, ventilation systems, evaporative cooling, air-conditioning, water supply, fire protection, communication systems, transportation systems (e.g. lift and escalators), sanitary plumbing, sanitary fixtures and special services (which may include lighting protection and security systems). They can rate between 30 and 40 per cent of the total costs of a building (Rawlinsons, 2012). Services elements can also impact the operational costs of a building. Thus they are important elements to consider during project planning and design stage when finding ways to prevent cost overrun and when seeking to achieve an energy efficient building. However, the cost of services elements are the most difficult to forecast at the early stage of building design process. The problem with services elements is that their design, choice of system and so their costs often depend on the architectural and structural design or layout and orientation of a building. The costs may also be influenced by a large number of design variables which are often difficult to understand and unravel by visual inspection of design documents. The impacts of the variables can also be difficult to quantity on the basis of estimator's experience. On top of that, a large number of variables can greatly affect the actual production cost on site. Cost forecasting for services elements for the purpose of cost planning and control as well as for evaluating alternative designs proposals is a critical activity at the design stage. Quick method of forecasting and checking of costs as design options are produced should facilitate evaluation of alternative design options. It should facilitate comparison of costs with the cost of a previous design and with the total money available for the project without the need to wait until the whole design for the building is completed. It should allow the design team to compare the costs with other known and similar design schemes in order to see whether the amount of money allocated to each part of the design is reasonable in itself and whether or not it is a reasonable proportion of total money available for a project. Broadly speaking, design decisions need to be based on a reliable cost estimate. However, accurate and reliable estimation of costs would depend on the technique of estimating and on the level of development and design information available. On another hand, the level of design development would vary as design progresses from conceptual, outline proposal, sketch design, detailed design to tender documentation. Thus at any stage of the design process, an effective design cost control process should allow estimates of costs for different components/elements to be prepared using a suitable cost estimating techniques depending on the level of development available for each components/elements. The objective of the study reported was to develop and test model for forecasting the cost of light wiring, power wiring and cable pathways at the early stages of design when information about the scope of a building work is limited. The model make use of artificial intelligent (AI) learning algorithm – artificial neural network (ANN), technique. Light wiring, power wiring and cable pathways are cost components of electric light and power for building. The specific objectives of the study are:

(1) to develop a learning model that can be used to reliably forecast and benchmark the costs of light wiring, power wiring, and cable pathways during the early stage of design when limited information is available about project scope;

(2) to show that learning model based on ANN are more viable alternative to regression technique when modelling the costs of services elements; and

(3) to develop a user-friendly interface established to talk to the best ANN models developed for light wiring, power wiring and cable pathways.

The study is important because the model developed can be used to reliably and quickly forecast costs when design information is incomplete and uncertain, and detailed designs are not yet developed. The model could be extended to other services elements and other building elements and could be linked to receive inputs from 3D building information model (BIM).

2. Cost estimation and the use of cost models during design stages

The Australian Institute of Quantity Surveyors (AIQS) – the peak body representing construction cost managers in Australia, advises that at every stage of the design costs planning process (brief, outline proposal, sketch design and tender documentation), input should be obtained from respective engineering services discipline regarding the cost implications of various services element proposals (Australian Institute of Quantity Surveyors (AIQS), 2000, pp. 2-12 to 2-13), and from contractors or tenderers (pp. 4-9). Due to insufficient information at the early stage of design process, estimates provided by contractors or sub-contractors are often unreliable depending on assumed scope of services work. Early design process would benefit from quick, reliable and on-demand cost estimation for different building elements so that alternative design decision can be evaluated from financial perspective. At the early stage of design, the use of cost models could support the design process. According to Kirkham (2007) cost modelling is a symbolic representation of a system, expressing the content of that system in terms of factors which influence its cost. Cost models are also techniques of estimating costs. There are three main categories of estimating techniques, namely: analytical/detailed method, analogous estimating and feature-based estimating. Of the three, analogous and feature-based estimating methods are very useful for forecasting cost at the early stage of design.

Analogous estimating is the use of costs of a similar past project to estimate the cost of a current project. It is based on the supposition that the current project being estimated is similar to the past project(s) forming the basis of the estimate (Challal and Tkiouat, 2012). All single-price-rate estimating methods, namely, functional unit, superficial method, cube method and functional area method belong to this category. Analogous estimating are the least accurate and are often used where there is limited information regarding a project; especially at the conceptual design stage. The assumption that the current project being estimated is similar to the past is often incorrect because site production rate of the past project and the current project may not be the same for various reasons. However, the estimates are useful at the feasibility stage.

Feature-based estimating uses the relationship between cost and cost drivers to calculate the cost (Staub-French *et al.*, 2003). They make use of cost models developed based on historical project data but in scalable manner to accurately estimate cost. Large number of historical information can be modeled statistically and mathematically to produce a model for predicting cost. Feature-based estimating models include parametric estimating with regression and artificial intelligence models (based on pattern recognition principle). This can be used to forecast cost when the scope or specifications of a component or a building is not yet developed. They are useful at the early stage of design.

During the early stage of project development, the use of feature-based estimating methods are viable alternative to analogous estimating where historical data are available for modelling the costs.

Researchers have developed cost models for forecasting the total cost of a building based on known characteristics of buildings (Emsley *et al.*, 2002; Kim *et al.*, 2004). Such models assume that the cost influencing characteristics will influence the cost of various components of buildings in the same way. The assumption that all costs are influenced by the same factors and in the same way is simplistic and can be a source of estimating error. This is because the variables influencing costs of various elements may differ. The impact of the variables may also differ across the various elements. Thus there is need for separate cost estimation system for the various elements or components of a building. With regards to services elements, Swaffield and Pasquire (1996) assert that the methods of estimating the budget for building structure and fabric work are inappropriate for use with mechanical and electrical services.

Researchers have also developed featured-based estimating models for forecasting cost per m^2 for structural systems of building (Gunaydin and Dogan, 2004), and concrete slab and beam (Singh, 1990).

In terms of modelling methodology, there is lack of a featured-based cost estimation model utilizing artificial intelligence algorithm, for various components of engineering services. Previous research developed feature-based cost models using parametric methods such as regression analysis (RA) (Park and Kim, 2007; Singh, 1990). Parametric models have limitations in that the underlying relationship between the drivers of cost (input variables) and the cost (output variable) are straight forward and too simplistic when compare to the complexity of the real world relationship between those variables. Regression assumes that the relationships between cost and the drivers of the cost are linear whereas in construction projects the relationship between the cost of elements and the factors influencing those costs are non-linear and sometimes unknown. Parametric models also require normally distributed data for modelling. While the outcome of regression model is easier to analyse, understand, explained and implement, they may produce a less accurate result since the model is far from the real world (Smith and Mason, 1996).

Recent years have seen an increase in the use of AI learning algorithm (especially ANN) as technique for developing feature-based estimating models. ANN is based on the principles of biological neuron. ANNs feature-based cost models are non-linear and they eliminate the need to find a good cost estimating relationship that mathematically describes cost as a function of the variables that has the most significant effects on the cost (Kim *et al.*, 2004). Also, ANN can model subtle real word relationship between cost and the cost influencing variables even when the natures of those relationships are unknown. Kim *et al.* (2004) discovered that ANNs are viable and are better approach for estimating construction cost. The application of ANNs in construction is a relatively new research area (Kim *et al.*, 2004).

3. Literature review: cost estimation models using ANN algorithm

Potential applications of ANN in construction have been explored over the last two decades. ANN can be used to predict project cost overruns and thereby assist management in developing an appropriate contingency (Chen and Hartman, 2000). Studies applying ANN to predict cost performance often compares the accuracy of ANN with multiple linear regression and in most cases ANN produce more accurate predictions (e.g. Chen and Hartman, 2000; Sonmez, 2004; Kim *et al.*, 2004; Baccarini, 2005). Examples of the application of ANNs to predict the level of cost overrun/underrun include: Chen and Hartman (2000) used ANN to predict the final cost of completed oil and gas projects from one organization using 19 risk factors as the input data. It was found that 75 per cent of the predicted final cost aligned with the actual variance i.e. where the ANN model predicted an overrun/underrun, an overrun/underrun actually occurred.

The prediction accuracy of ANN outperformed multiple linear regression. Chua *et al.* (1997) used eight key project management factors to predict the final cost of construction projects. It was found that more than 70 per cent of the examples did not differ by more than one degree of deviation from the expected. Gunaydin and Dogan (2004) used eight design parameters to estimate the square metre cost of reinforced-concrete structure systems in low-rise residential buildings and found that the ANN provided an average cost estimation accuracy of 93 per cent. In a study (Kim *et al.*, 2004), neural networks (NN) resulted in much accurate cost estimates than multiple regression (MR) analysis and case-based reasoning. Similar results were obtained from Shehab *et al.* (2010) evaluation of NN against RA. Kim *et al.* (2013) also compared the accuracy of three estimating techniques (RA, NN, and support vector machine techniques (SVM) by performing estimations of construction costs for school buildings. Using historical cost data, it was found that ANN model is more accurate than the RA and SVM models for school building projects.

Adeli and Wu (1998) formulated a NN based decision-support system to estimate the cost of reinforced-concrete pavement. They identified that accuracy of the results is largely influenced by the input data used in training of the network. This emphasizes the need to identify most influencing training factors, i.e. cost significant variables. In the prediction of total construction cost (Emsley *et al.*, 2002) the error margin identified by mean absolute percentage error was at 16.6 per cent, in comparison with other methods value (between 20.8 and 27.9 per cent). Hola and Schabowicz (2010) presented a methodology for determining earthworks execution time and cost using ANN approach. The predicted time and cost values can be used as the basis for selecting a proper set of machine. Using NN, Pearce *et al.* (1996) developed a technique for calculating range estimates to evaluate the risk of cost escalation in building construction.

ANN is suitable for modelling the cost of engineering services elements because costs can be influenced by a large number of variables which are often difficult to evaluate by visual inspection of project documents; especially at the early stage of design when there is lack of details about the project. The impacts of project variables on costs are often difficult to quantity based on estimator's experience. ANN can help model the subtle relationship between the variables and the costs. To minimize estimation error, this study proposed cost models for light wiring, power wiring and cable pathways using ANN algorithms. The models will use real life project data based on sub-contractors breakdown of costs. The advantage is that the data can reflects the actual cost of work thereby improving the reliability of cost forecasts.

4. Research methodology

This aim of this study is to develop and test a feature-based cost models based on ANN for forecasting the cost of power wiring, light wiring and cable pathway. Six steps were followed in the development of the learning ANN models:

(1) define the ANN output variable;

(2) identify the ANN input variables;

(3) data collection from past project estimates;

(4) data processing: Train the learning ANN model;

(5) test the ANN model: i.e. predicting the accuracy of estimates using new data set; and

(6) evaluate the performance of the learning model and sensitivity analysis – Validation.

4.1 Output variable

The output variables for the three models are "Cost of Power Wiring" (PW), "Cost Of Light Wiring" (LW) and the "Cost of Cable Pathways" (CP). The costs exclude contractor's overheads and profits.

4.2 Input variables

In order to identify the input variables, the literature on factors influencing cost estimates and cost estimate accuracies was reviewed. Gunner and Skitmore (1999) summarized the factors influencing cost estimates as follows: building function, type of contract, conditions of contract, contract sum, price intensity, contract period, number of bidders, good/bad years, procurement basis, project sector (public, private or joint), number of priced items and number of drawings. Using data from 42 projects in Singapore Ling and Boo (2001) compared five variables against Gunner and Skitmore's (1999) work. Skitmore and Picken (2000) studied the effect that four independent factors (building type, project size, project sector and year) had on estimating accuracy. They tested the four factors using data from 217 projects in the USA. They found that estimates of the projects are influenced by project size and year. Cost drivers identified by Thalmann (1998) include: usable floor area, proportion of external wall areas underground, proportion of openings in external wall areas, year of construction. Wheaton and Simonton (2005) identified cost drivers such as number of stories, absolute size, number of units, frame type and year of construction. Emsley *et al.* (2002) identified gross internal floor area while Picken and Ilozor (2003) identified building height as a factors influencing cost. Volume 1 of the *Australian Cost Management Manual – ACMM* (AIQS, 2000) specified various factors that need to be considered when estimating the cost of engineering services during the design stages (pp. 4-1 to 4-21). The *ACMM* Volume 1, is a best practice guide document for cost planning and cost analysis published by the AIQS – the peak body regulating the practice of quantity surveying and cost estimation in Australia. Based on the literature and the *ACMM*, 25 variables that could influence the cost of engineering services were identified. The variables identified include: Building function, Type of contract, Contract sum, Price intensity, Contract start and completion dates, Number of bidders, Good/bad years, Procurement basis, Project sector, Number of priced items, Number of drawings, gross floor area (GFA), fully enclosed covered area (FECA), unenclosed covered area (UCA), Year of estimate, Floor to floor height (measured from top of structural floor to underside of structural floor), Total height/number of floors, Usable height, Useable volume, Plant room area, Plant room volume, Horizontal distribution volume, Vertical distribution volume, Glazed area and Internal perimeter length. Thereafter, Data mining of over 200 electrical light and power estimates was conducted. Information about many of the 25 variables identified was not available for majority of the projects and thus many missing data.

Considering the potential use of the model, i.e. for cost evaluation at early design stage, preference was given to a few variables that could be practically used at the early design stage to predict cost of electrical services elements, especially variables that are often known at the early stage design as well as variables that are available for the majority of the projects in the data set. It was also considered that fewer input variables would enhance the efficiency and the ease of use of the model. Four variables were selected as discussed below. We also conducted a discussion with the managing director of an electrical services company, who has prepared numerous electrical services estimates in the past and has managed the execution of numerous electrical services projects. He is from an electrical trade as well as a quantity surveying background. Based on the examination of the data set in the database, the four variables selected as the input variables are as follows:

(1) FECA – defined by the AIQS as "The sum of all such areas at all building floor levels, including basements (except unexcavated portions), floored roof spaces and attics, garages, penthouses, enclosed porches and attached enclosed covered ways alongside buildings, equipment rooms, lift shafts, vertical ducts, staircases and any other fully enclosed spaces and usable areas of the building, computed by measuring from the normal inside face of exterior walls but ignoring any projections such as plinths, columns, piers and the like which project from the normal inside face of exterior walls. It shall not include open courts, light wells, connecting or isolated covered ways and net open areas of upper portions of rooms, lobbies, halls, interstitial spaces and the like which extend through the storey being computed." This was measured in square metres based on the architectural drawings for each project, and from the cost plan.

(2) UCA – defined by the AIQS as "The sum of all such areas at all building floor levels, including roofed balconies, open verandahs, porches and porticos, attached open covered ways alongside buildings, undercrofts and usable space under buildings, unenclosed access galleries (including ground floor) and any other trafficable covered areas of the building which are not totally enclosed by full height walls, computed by measuring the areas between the enclosing walls or balustrade (i.e. from the inside face of the UCA excluding the wall or balustrade thickness)". When the covering element (i.e. roof or upper floor) is supported by columns, is cantilevered or is suspended, or any combination of these, the measurements shall be taken to the edge of the paving or to the edge of the cover, whichever is the lesser. UCA shall not include eaves overhangs, sun shading, awnings and the like where these do not relate to clearly defined trafficable covered areas, nor shall it include connecting or isolated covered ways. This was also measured in square metres based on the architectural drawings for each project.

(3) Number of floors and total height: the number of floors and total building height can be used to measure the vertical scale of a building. The number of floors is the total identifiable number of levels including the basement, ground floor, and all upper floors but excluding the roof element. The total building height can be measured in metres as the sum of all floor to floor heights. In this study, data on floor to floor height was unavailable and was excluded from the analysis. It is reasonable to assume that total number of floors and the total building height provides similar information about the vertical scale of a building. Of course the total height would provide more accurate information. In the absence of data on total height, the number of floors is a good measure of the vertical scale of a building. Thus this study uses the number of floors as a variable in the model.

(4) Internal perimeter length: measured in metres as perimeter of building measured on the internal face of the enclosing structural walls.

4.3 The data

After an examination of over 200 projects in the database of an electrical contractor, 71 projects comprising of 28 residential and 43 educational projects were extracted for the modelling. The minimum FECA is 200 m^2 and the maximum is 110,001 m^2. Minimum UCA is 0 m^2 while the maximum UCA is 2,763 m^2. The minimum number of floor is 1 and maximum is 30.

The partitioning of the data into training, cross-validation and testing is shown in Table I.

Training means that a set of input and output data were used to adjust the weights in the ANN, so that the ANN could give the same outputs as seen in the training data. Thus training involves optimization whereby the mean square error (MSE) of the entire set of training data is minimized. Cross-validation was used to assess how the results of the ANN will generalize when independent data set not used in the training is used. Cross-validation gives insight into how the model would perform in practice. Model testing means feeding the model with a new sample (data) never seen before, and no corrections are made. If the results of a testing process are acceptable in terms of error margin, the model is suitable for use. The acceptable level of the result of the model qcan be evaluated based on the value of the correlation between the predicted values and actual values in the new sample as well as the MSE. If the result is inappropriate, the model may need to be re-specified and re-designed.

4.4 Network architecture and training of the learning ANN model

Figure 1 shows an example of the network structure. A single biological neuron is not intelligent. A collection of those neurons is made intelligent by making cooperate actions. Collection as a network creates a pattern of inputs to a NN and processed as a pattern and results as a pattern. ANN, is a mathematical model that was developed based on the phenomenon of error minimization. A processing element (PE) in ANN, was arranged as a simple model of biological neuron. ANN learning occurs as given in Equation (1), which simply represents the cost function of a desired (actual) and ANN output:

$$\delta_i^p = d_i^p - y_i^p \tag{1}$$

where d_i^p is the desired ith output of the pattern p and y_i^p is the network's ith output received from the neuron system. The error for all patterns in Equation (1) is measured using MSE, which is a major performance measurement in ANN learning shown in Equation (2). Lower MSE indicates higher learning of the set of input pattern:

$$MSE = \frac{\sum_p \sum_i \left(d_i^p - y_i^p\right)^2}{N \times P} \tag{2}$$

where N is number of input data sets and P is number of PEs.

Network	Training set	Cross-validation set	Testing set	Total
Cable pathways	48 samples	15 samples	8 samples	71
Light wire	48 samples	15 samples (simulated)	8 samples	71
Power wiring	48 samples	15 samples (simulated)	8 samples	71

Table I. Partitioning of sample data

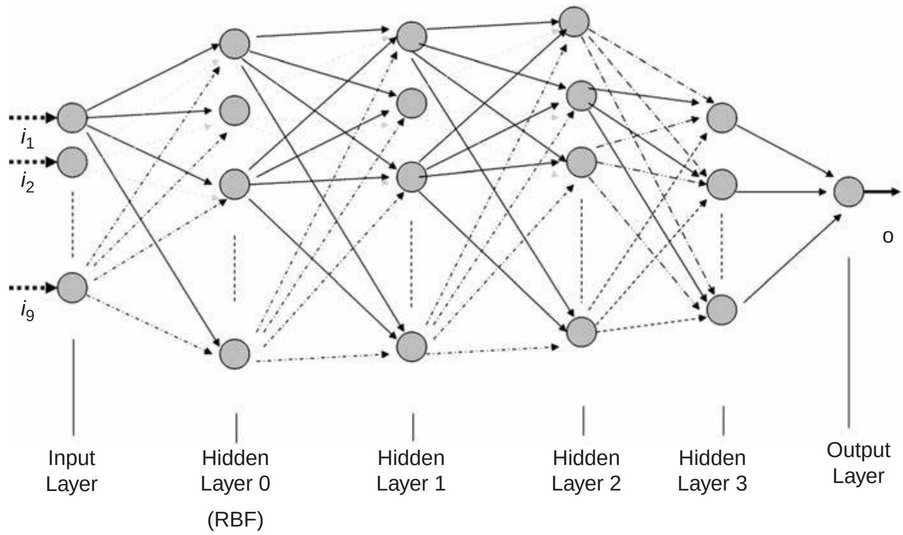


Figure 1.
Structure of a typical network trained

The learning (training) of ANN model from given inputs and outputs occurs through the iterations. Equation (3) shows the network output y of an ANN calculated from n elements of an input pattern x through a summation of weighted inputs and a transfer function:

$$y = F\left(\sum_{i=1}^{n} w_i x_i + \theta\right) \tag{3}$$

where x_i denotes ith element of the input pattern x, w_i is the weight for the input $_{xi}$, θ is the offset and F is a transfer function, which is a smoothing function.

Table II shows the network found for each of the three models. The models consist of different numbers of hidden layers (HL). The HL determines the number of layers in the ANN architecture. For instance, a one-HL implies a three-layer NN model with one input layer, one output layer and one-HL. The HL sieves the distinct pattern structure present in the data and it captures any non-linearity present in the data. It provides the network the ability to generalize (Ramlall, 2010). With each HL are PEs or neurons which determines how well a problem can be learned. Too many PEs can lead to the NN memorizing the problem and not generalize well while too few PEs can lead to the NN learning well but lacking the power to learn the pattern well (El-Abbasy *et al.*, 2014). Iteration is needed to generate the optimum numbers of PEs.

In each model, the input data were normalized and arranged in three sets:

(1) training – 48 data sets (67.6 per cent);

(2) cross-validation – 15 data sets (21.12 per cent); and

(3) testing – eight data sets (11.26 per cent).

The training data set was used to train networks whilst cross-validation data set was used to evaluate the training. Once a network has learnt, the test data set was used to forecast the output variables, i.e. "Cost of Power Wiring," Cost of Light Wiring' (LW)

Model	Type of network	Number of hidden layers (HL)	Number of processing elements (PEs) in hidden layers (HL)	Number of network runs
Model 1: Cost of Power Wiring (CPW)	Radial basis function (RBF)	5	RBF Layer: 20 HL-1: 50 HL-2: 20 HL-4: 16 HL-4: 10 HL-5: 6	3
Model 2: Cost of Light Wiring (CLW)	Multilayer perceptron	5	HL-1: 20 HL-2: 30 HL-3: 20 HL-4: 15 HL-5: 10	3
Model 3: Cost of Cable Pathway (CCP)	Multilayer perceptron	4	HL-1: 50 HL-2: 20 HL-3: 16 HL-4: 10	1

Table II.
Models trained and network found

and the "Cost of Cable Pathway" (CP) from the network; and comparison could be made against actual values of the output variables. Normalized data set was useful in training as each parameter is mapped into a radius of 1 in order to setup a unique boundary. The ANN was considered to be well trained when (Hola and Schabowicz, 2010):

- the training error values and the testing error values were similar;
- the numbers of epoch was the smallest for the adopted error value;
- the correlation coefficient for the data mapping was close to 1; and
- the relative training and the testing errors were the smallest, and in this case tending to zero.

The MSE was used as the criteria for ending the training. This defines the degree of learning of each ANN. The error was calculated concurrently for the training and the test data in the training of each ANN model.

Model 1 consists of five HL and the radial basis function (RBF) layer. The number of PEs in the HL were 20 (RBF layer), 50 (HL-1), 20 (HL-2), 16 (HL-3), 10 (HL-4), and 6 (HL-5) inputs that produced "Cost of Power Wiring" in single output. Gaussian transfer function was used in the aforementioned RBF layer, Tanh transfer functions were used in all other GFF layers.

Model 2 consists of five HL using multilayer perceptron network where HL were 20 (HL-1), 30 (HL-2), 20 (HL-3), 15 (HL-4), and 10 (HL-5) inputs that produced "Cost of Light Wiring" in single output.

Model 3 consists of four HL using multilayer perceptron network where HL were 50 (HL-1), 20 (HL-2), 16 (HL-3), and 10 (HL-4) inputs that produced "Cost of Cable Pathways" in single output.

5. Results: training performance

5.1 Cost of Power Wiring (CPW)

In the case of power wiring, the best network was found after one run and 4,899 iterations using RBF and cross-validation data sets, Figure 2 shows the performance of

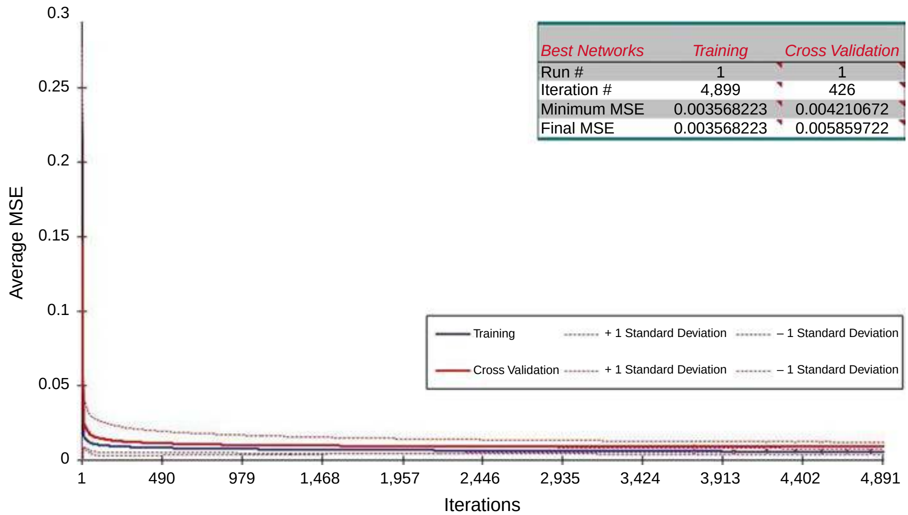


Figure 2.
Best network predicting the Cost of Power Wiring

the best network found. It shows that the MSE of the training and cross-validation are almost zero (0.0035 and 0.0.0058).

5.2 Cost of Light Wiring (CLW)

For Light wiring, the best network was found after two runs and 33,358 iterations using multilayer perceptron and cross-validation data sets. Figure 3 shows the performance of the best network found. The MSE for the training and cross-validation are almost zero (0.0029 and 0.0026).

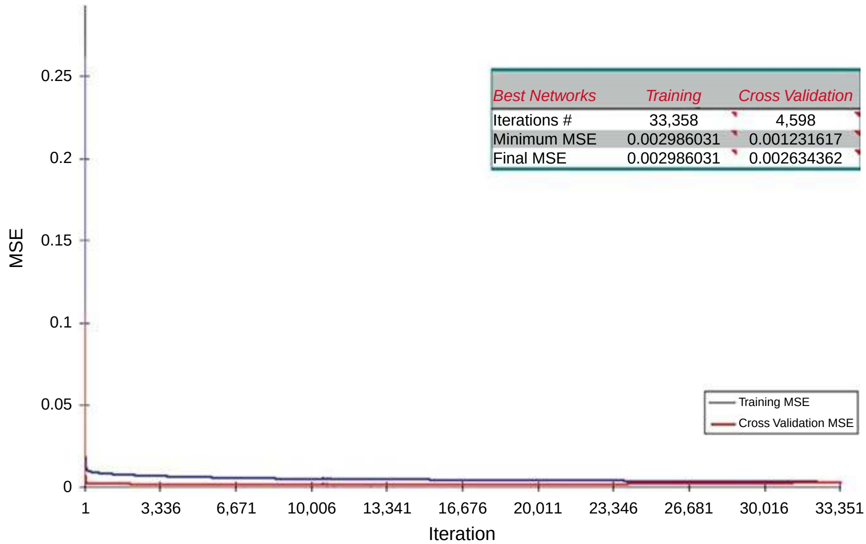


Figure 3.
Best network predicting the Cost of Light Wiring

5.3 *Cost of Cable Pathway (CCP)*

The best network for cable pathways was found after 1 run and 50,000 iterations using Multilayer Perceptron and cross-validation data sets. Figure 4 shows the performance of the best network. The MSE for the training and cross-validation are almost zero (0.00012 and 0.075).

6. Results: test performance (with entire data set)

6.1 *Cost of Power Wiring (CPW)*

Figure 5 shows the scatter plot of actual and predicated values of "Cost of Power Wiring" for the entire data set. It shows that the forecast values are very close to the actual values.

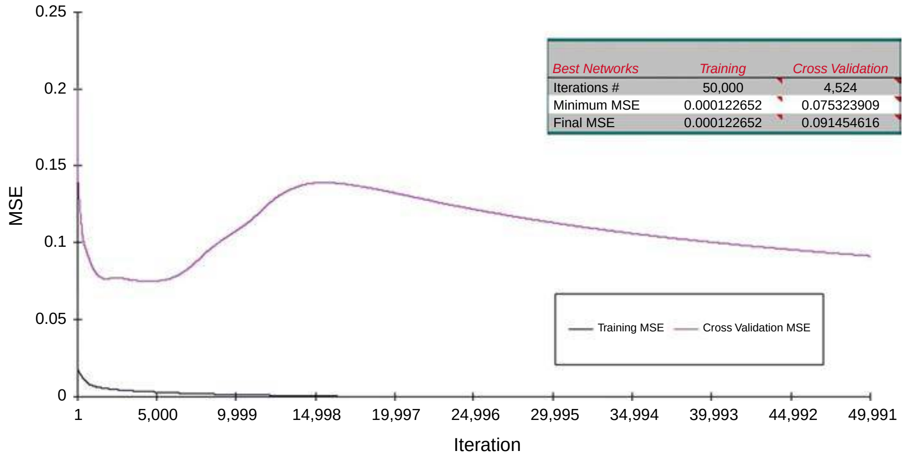


Figure 4.
Best network predicting the Cost of Cable Pathway

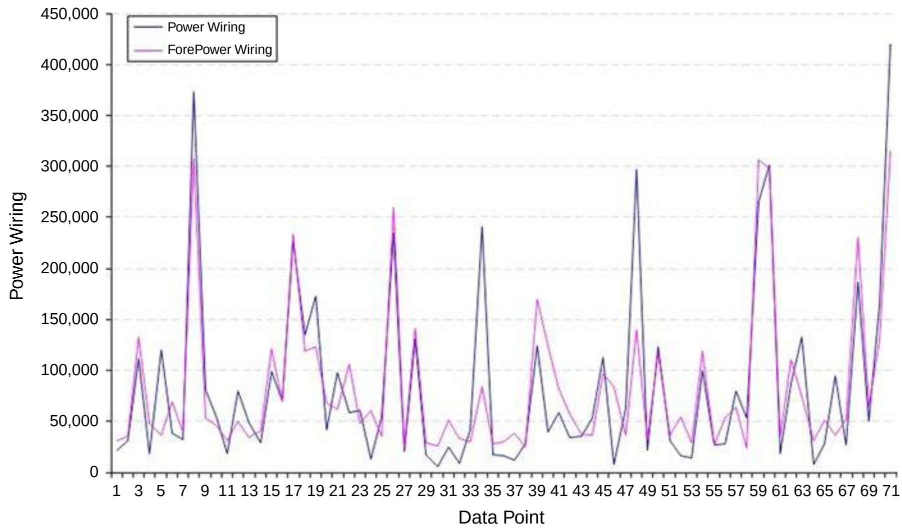


Figure 5.
Scatter plot of "Cost of Power Wiring"– actual vs forecast (entire data set)

6.2 Cost of Light Wiring (CLW)

Figure 6 shows the scatter plot of actual and predicated values of "Cost of Light Wiring" for the entire data set. It shows that the forecast values are very close to the actual values.

6.3 Cost of Cable Pathways (CCP)

Figure 7 shows the scatter plot of actual and predicated values of "Cost of Cable Pathways" for the entire data set. It shows that the forecast values are very close to the actual values.

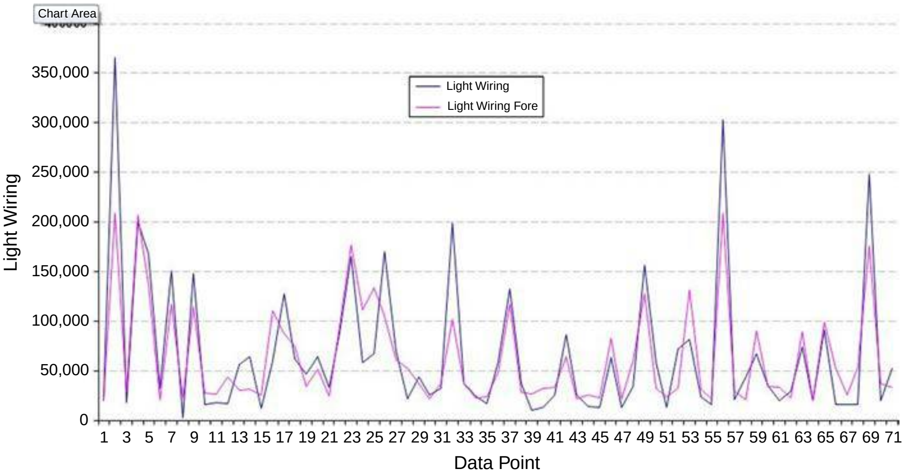


Figure 6.
Scatter plot of "Cost of Light Wiring" – actual vs forecast (entire data set)

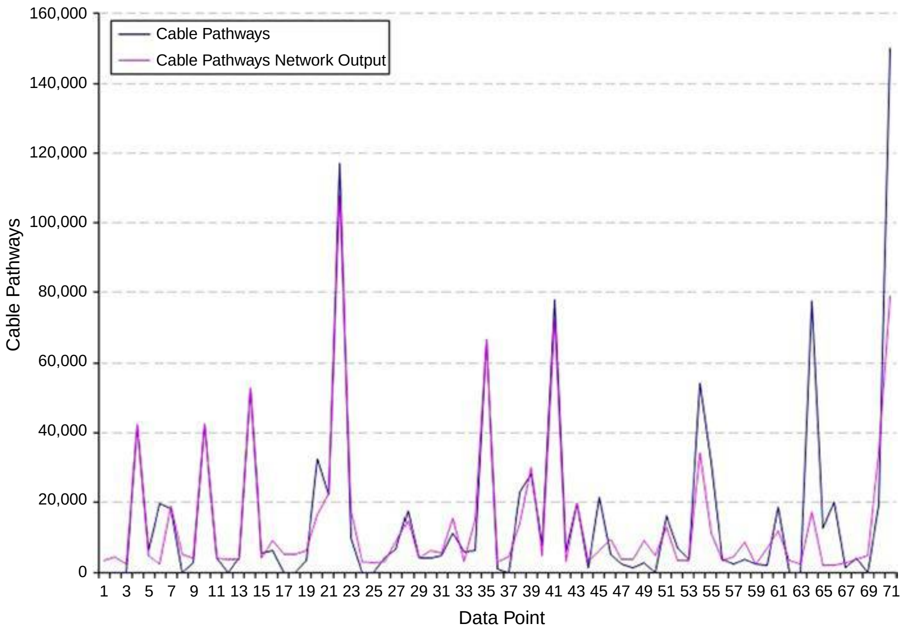


Figure 7.
Scatter plot of "Cost of Cable Pathways" – actual vs forecast (entire data set)

7. Results: model validation and performance (with test data set)

7.1 Cost of Power Wiring (CPW)

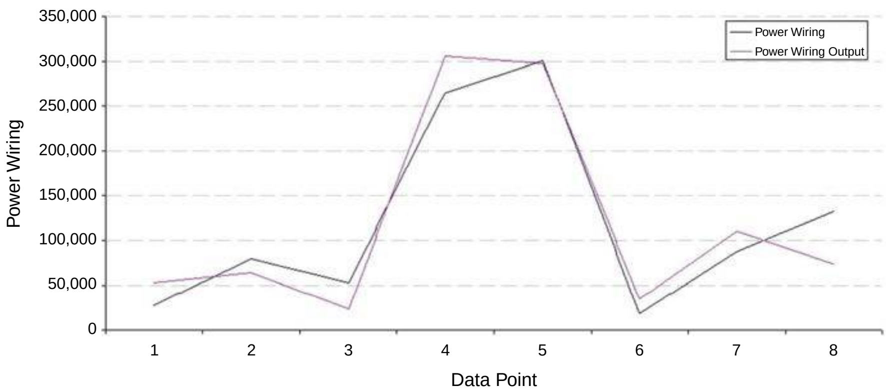
Figure 8 shows the actual and predicated values of "Cost of Power Wiring" for the test data set. The trained network forecast progressively on test data set. The major performance measures were MSE, correlation coefficient (*r*) and the mean absolute error (MAE). The MSE is 0.006 while the correlation coefficient (based on the normalized input data set) was found to be 96 per cent (0.96). The MAE is 0.064 (Figure 8). This means that in 96 per cent of the test cases, the predicted "Cost of Power Wiring" did not differ by more than 6.4 per cent from the expected. Based on this performance measures the trained network is suitable forecasting the "Cost of Power Wiring" in practice.

7.2 Cost of Light Wiring (CLW)

Figure 9 shows the actual and predicated values of "Cost of Light Wiring" for the test data set. The trained network forecast progressively on test data set. The major performance measures used in the training were MSE, correlation coefficient (*r*) and MAE. The MSE is 0.003 while the correlation coefficient (based on the normalized input data set) was found to be 94 per cent (0.94). The MAE is 0.045 (Figure 9). This means that in 94 per cent of the test cases, the predicted "Cost of Light Wiring" did not differ by more than 4.5 per cent from the expected. Based on this performance measures the trained network is suitable forecasting the "Cost of Light Wiring."

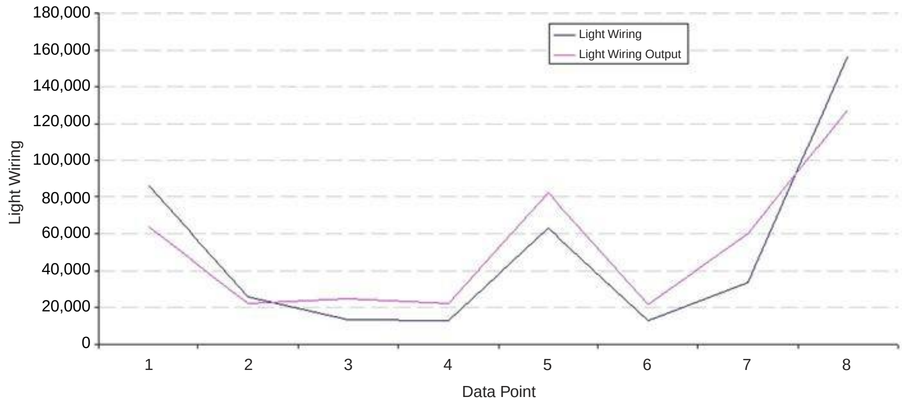
7.3 Cost of Cable Pathways (CCP)

Figure 10 shows the actual and predicated values of "Cost of Cable Pathways" for the test data set. The trained network forecast progressively on test data set. The major performance measures used in the training were MSE, correlation coefficient (*r*), and the MSE. Based on the results (Figure 10) the MSE is 0.004 while the correlation coefficient (based on the normalized input data set) is 0.94. The MAE is 0.045.



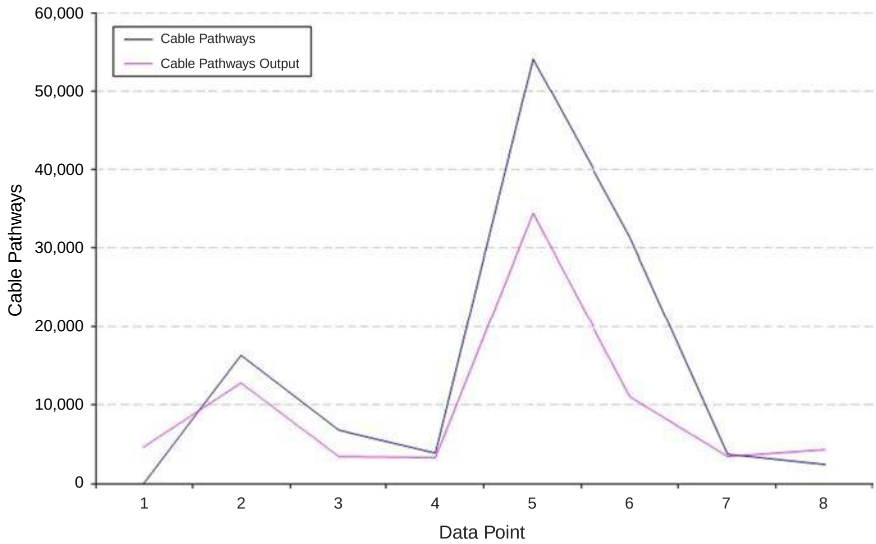
Performance	Power Writing
MSE	0.006
NMSE	0.095
MAE	0.064
Min Abs Error	0.007
Max Abs Error	0.141
r	0.96

Figure 8. "Cost of Power Wiring" – actual vs forecast (test data)



Performance	Light Wiring
MSE	0.003
NMSE	0.154
MAE	0.045
Min Abs Error	0.010
Max Abs Error	0.080
r	0.94

Figure 9.
"Cost of Light Wiring" – actual vs forecast (test data)



Performance	Cable Pathways
MSE	0.004725664
NMSE	0.339816818
MAE	0.045322297
Min Abs Error	0.002841129
Max Abs Error	0.135118287
r	0.942373548

Figure 10.
"Cost of Cable Pathways" – actual vs forecast (test data)

This means that in 94 per cent of the test cases, the predicted "Cost of Cable Pathways" did not differ by more than 4.5 per cent from the expected. Based on this performance measures, the trained network is suitable forecasting the "Cost of Cable Pathways."

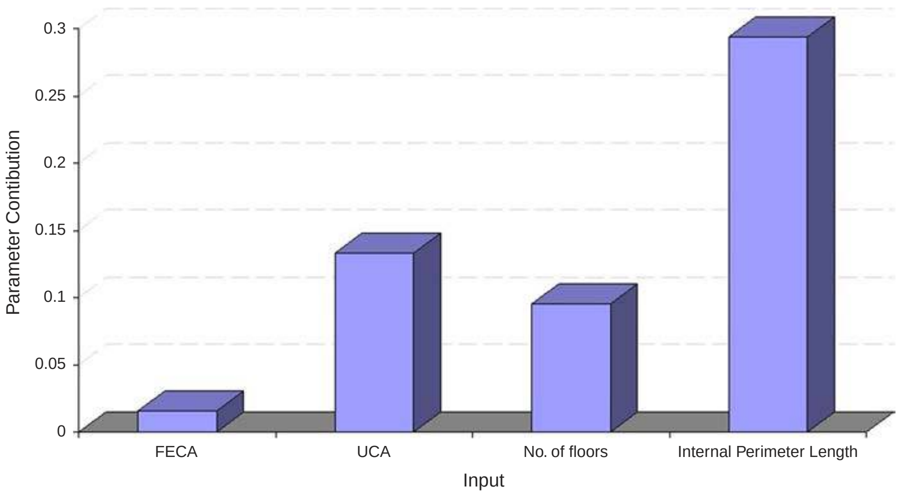
8. Results: parameters contribution

Some input variables are more effective than others in the models developed. In each of the models, the relative contribution (importance) of the four input parameters were generated by comparing the predictive error of the "full model" to that of a "reduced model" when each factor is removed from the NN. The variables were then arranged in order of importance according to the change in performance noticed when they were removed. Figures 11-13 show the results for the three models respectively.

First, the results for "power wiring" are shown in Figures 11. The parameter contributions (in per cent) show that internal perimeter length contributed the highest to predicting the "Cost of Power Wiring" (55 per cent) while UCA contributed 25 per cent. The contribution of "No. of Floors" is 18 per cent. FECA contributed the lowest (3 per cent). The dominance of internal perimeter length was not unexpected because power wiring involves cables to all power outlets on walls.

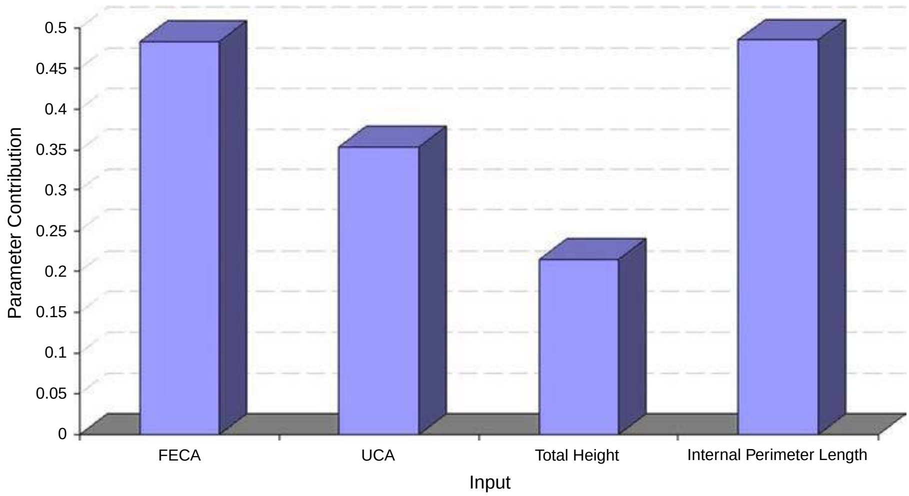
Second, the results for light wiring are shown in Figures 12. The parameter contributions (in per cent) show that internal perimeter length and FECA contributed the highest to predicting the "Cost of Power Wiring" (contributing 32 and 31 per cent, respectively). This was followed by UCA (23 per cent) and "No. of Floors" (14 per cent).

Third, the results for cable pathway are shown in Figure 13. The parameter contributions (in per cent) show that FECA contributed the highest to predicting the



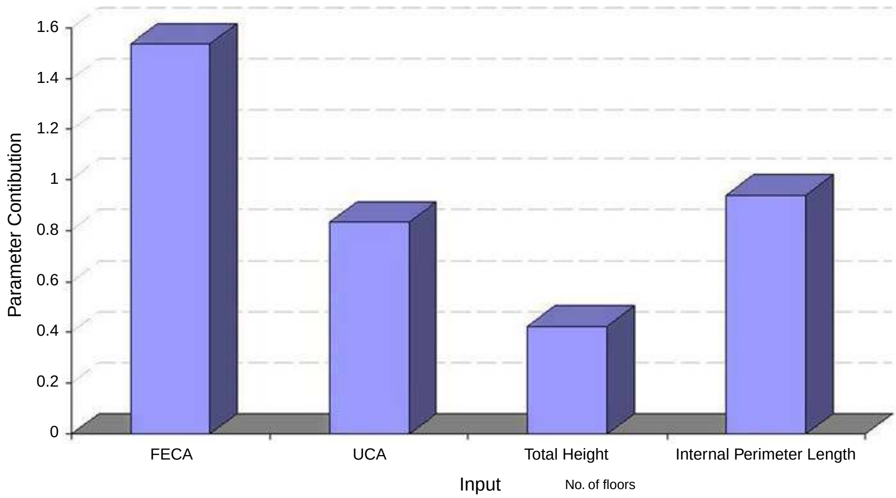
Parameter	Contribution %
Internal Perimeter Length	55
UCA	25
No. of floors	18
FECA	3

Figure 11. Parameter contribution – Cost of Power Wiring



Parameter	Contibution%
Internal Perimeter Length	32
FECA	31
UCA	23
No. of floors	14

Figure 12.
Parameter contribution – Cost of Light Wiring



Parameter	Contribution %
FECA	41
Length	25
UCA	22
No. of floors	11

Figure 13.
Parameter contribution – Cost of Cable Pathways

"Cost Light Wiring" (41 per cent) followed by internal perimeter length (25 per cent) and UCA (22 per cent). "No. of Floors" contributed the lowest (11 per cent).

9. Comparing ANN model with regression model

This study assumed that ANN models are more viable alternative to RA when modelling the cost of electrical services. It assumed that regression would be unsuitable for modelling cost of engineering services because the relationship between the cost influencing variables and cost of engineering services are subtle and may be unknown. After developing and validating ANN models, we tested our assumption by attempting to develop three MR models for predicting the Cost of Power Wiring' (PW), Cost of Light Wiring' (LW) and the "Cost of Cable Pathway" (CP). The performance of the three regression models and ANN can then be compared. We attempted using MR analysis with 50 samples for modelling and 21 test sample. MR is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The effect of independent variables on the dependent variable can be expressed mathematically as follows:

$$Y = f\left(X_1,\ X_2,\ X_3, \ldots\ldots X_n;\ \beta_1,\ \beta_2\ \beta_3 \ldots.\right)$$

where Y is the dependent variable; $X_1, X_2, X_3, \ldots\ldots X_n$ are independent variables; $\beta_1, \beta_2, \beta_3 \ldots\beta_n$ are regression parameters associated with independent variables X_1, X_2, X_3, …… X_n, respectively.

Different types of regression may be used for modelling the relationship between dependent and independent variables. Choice of regression modeling would depend of the character of the variation of the dependent variable around the regression function; and may be described by a probability function. Depending on the probability distribution, choice of regression methods may be linear, quadratic, exponential, cubic, power, logarithmic, logistic and inverse. Also regression modelling requires the need to find a significant correlation between the dependent variable (i.e. cost) and each of the input variables (i.e. FECA, UCA, number of floors and internal perimeter length). It also requires the need to choose a type of regression function that reflects the nature of the relationship between the dependent and the independent variables. Thus, we conducted a preliminary analysis to assess the characteristic of the data including the distribution of the data (test of normality) as well as the descriptive statistics particularly the bivariate correlation coefficients and their significance to test the linearity of the relationships. We used IBM Statistical Package for Social Sciences Statistics Software 21.

The correlation coefficients result is presented in Table III. The result shows that none of the input variables are significantly correlated to the three outputs (i.e. dependent) variables. Thus the input variables (i.e. FECA, UCA, number of floors and internal perimeter length) may not be suitable for predicting the output variables (i.e. Cost of Power Wiring, Cost of Light Wiring and the Cost of Cable Pathway) using a parametric linear model.

Next, we check if each of the output variables is approximately normally distributed for each of the input variables. We assessed the Shapiro-Wilk and Kolmogorov-Smirnov statistics generated from SPSS. Table IV shows the result. Both statistics shows that the Cost of Cable Pathways, Cost of Power Wiring, FECA, UCA, number of floors and internal perimeter length are significantly different from a normal distribution

		Cost of Cable pathways	Cost of Light wiring	Cost of Power wiring
Fully enclosed covered area	Pearson correlation	0.170	−0.202	−0.248
	Sig. (two-tailed)	0.237	0.159	0.083
	n	50	50	50
Unenclosed covered area	Pearson correlation	−0.011	−0.068	−0.108
	Sig. (two-tailed)	0.940	0.638	0.457
	n	50	50	50
Number of floors	Pearson correlation	0.074	−0.025	−0.083
	Sig. (two-tailed)	0.607	0.863	0.567
	n	50	50	50
Internal perimeter length	Pearson correlation	0.161	−0.195	−0.240
	Sig. (two-tailed)	0.264	0.174	0.093
	n	50	50	50

Table III.
Pearson correlation result

	Shapiro-Wilk			Kolmogorov-Smirnov		
	Statistic	df	Sig.	Statistic	df	Sig.
Cost of Cable Pathways	0.863	50	0.000	0.229	50	0.000
Cost of Power Wiring	0.950	50	0.034	0.132	50	0.029
Cost Light Wiring	0.974	50	0.321	0.120	50	0.070
Fully enclosed covered area	0.776	50	0.000	0.196	50	0.000
Unenclosed covered area	0.794	50	0.000	0.246	50	0.000
Number of floors	0.600	50	0.000	0.291	50	0.000
Internal perimeter length	0.803	50	0.000	0.201	50	0.000

Table IV.
Tests of normality

(significance value <0.05 in each case). Only the "Cost of Light Wiring" is normally distributed (significance value = 0.07).

The histograms for each of the variables were also examined. The histograms show that the "Cost of Light Wiring" is the only variable that is approximately normally distributed. In order to meet the normality assumption for regression modelling, the data were transformed using the SPSS logarithm function so that they are normally distributed. MR analysis was conducted using the transformed data. All the multiple linear regression models were insignificant.

Next, it was assumed that since the majority of the variables are non-normally distributed, the relationships might be non-linear. The SPSS tool was used to explore a regression that fits the distribution of the data. SPSS allows different types of regression models to be explored. The best model that fits the data can be chosen based on the output of the model. Linear, quadratic, exponential, cubic, power, logarithmic, logistic and inverse regression functions were explored. All the models did not fit into any of the known regression functions. This means that regression is not suitable for modelling the Cost of Light Wiring, Power Wiring and Cable Pathways. This findings support the earlier assumption that ANN is a more viable alternative for modelling the cost of electrical services.

10. User interface: Intelligent Estimator

A user interface was established to talk to the best ANN models developed for light wiring, power wiring and cable pathways. This was performed by consolidating incoming and outgoing weights of the nodes in the network. These weights were bundled in a form of a software code (WSC) in Neurosolutions package. The UI has been arranged to capture inputs from the user as depicted in the Figure 14. The final application – Intelligent Estimator, is an easy to use tool that estimators can use when estimating the cost of power wiring, light wiring and cable pathways at the conceptual design stage of projects.

Once the data entered are confirmed by pressing "Confirm Data" button in the left panel, the user can press the "Forecast Now" button the right panel and is highlighted for the user to press it (Figure 15). Data are then combined with the weights by reading three networks from the aforementioned WSC to forecast the cost for light wiring, power wiring and cable pathways simultaneously, giving the values in the right hand panel.

11. Conclusion

This study proposed the use of ANN as viable alternative to regression for predicting the cost of building services elements at the early stage of design. The study applied ANN to develop cost models for predicting the costs of selected engineering services components of buildings, namely, power wiring, light wiring and cable pathways using information from 71 completed electrical services project, for building. By using FECA, UCA, number of floors and internal perimeter length as inputs, the results of the final models showed that the models can be used to realistically forecast costs at the early stage of design process. The ANN approach is promising for modeling the cost engineering services elements because the predictive error stands at 6.4, 4.5 and 4.5 per cent for power wiring, light wiring and cable pathways, respectively. This means that costs did not differ by more than 6.5, 4.5 and 4.5 per cent from the expected in 96, 94 and 94 per cent of the test cases in the respective models. Thus the predictive

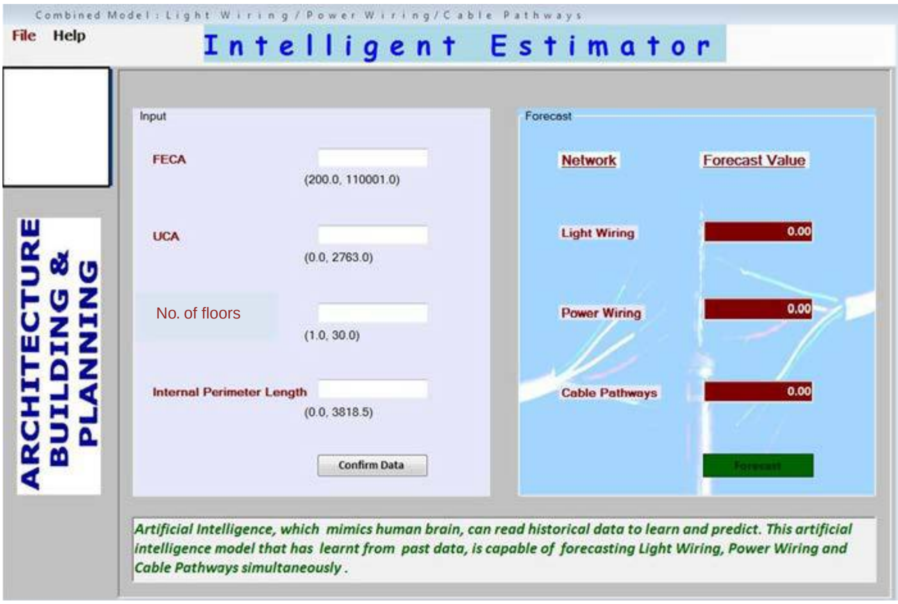


Figure 14. User interface of "Intelligent Estimator" (user needs to enter data in the left panel and press the "confirm data" button)

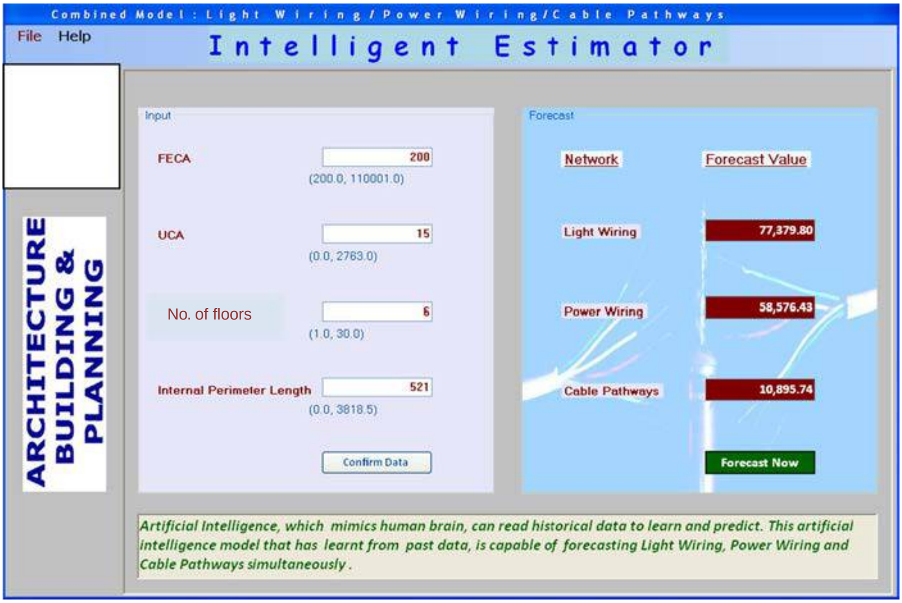


Figure 15. "Forecast now" button (reads the network weights and forecast light wiring, power wiring and cable pathways)

ability of the models is good especially for early stage estimate – when design is evolving. Attempt was made to compare the ANN modelling approach with parametric predictive modelling using RA. The preliminary data analysis shows that the relationships between the input variables and output variables are neither linear nor non-linear. This findings support the study's assumption that the ANN are more viable alternative for cost modelling because the distribution function of the relationship between the cost of engineering services and the cost influencing variables are of unknown distribution. They are stochastic in nature thereby making parametric modelling technique unsuitable. Different types of regression functions were explored but none of the outcome regression models were significant. The three ANN models developed were converted to a desktop application (user interface) package. The application is important because it can be used by construction professionals to predict the costs of power wiring, light wiring and cable pathways using factors that are readily available or measurable at the project planning stage, i.e. FECA, UCA, internal perimeter length and number of floors. The model would be very useful at the early design stage when information is incomplete and uncertain, and detailed designs are not available. Other potential advantage of the model is that it could greatly reduce the time and resources spent on cost estimation at the early stage of design as well as provide a benchmark to compare detailed cost estimates. In future research, the ANN procedure will be extended to other projects in the database of the research project partner as well as applied to other building elements. The potential is that it would allow the design team quickly and efficiently conduct economic evaluation of the costs of many alternative design solutions using "what if" analysis. The models can also be furnished with risk analysis module so that uncertainties associated with estimates generated by the model can be determined. This should provide useful information for making design decisions. In addition, future research would link the ANN models to 3D BIM so that the ANN model inputs can be automatically extracted.

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