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AN EARLY COST ESTIMATION MODEL FOR HYDROELECTRIC POWER PLANT PROJECTS USING NEURAL NETWORKS AND MULTIPLE REGRESSION ANALYSIS

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Abstract. Energy is increasingly becoming more important in today's world, whereas energy sources are drastically decreasing. One of the most valuable energy sources is hydro energy. Because of limited energy sources and excessive energy usage, cost of energy is rising. Among the electricity generation units, hydroelectric power plants are very important, since they are renewable energy sources and they have no fuel cost. To decide whether a hydroelectric power plant investment is feasible or not, project cost and amount of electricity generation of the investment should be precisely estimated. In this paper, fifty four hydroelectric power plant projects are analysed by using multiple regression and artificial neural network tools. As a result, two cost estimation models have been developed to estimate the hydroelectric power plant project cost in early stages of the project.

Keywords: artificial neural network, multiple regression analysis, early cost estimation, hydroelectric power plants.

Introduction

There is no doubt that electricity is crucial for daily life but green electricity is more crucial. In order to generate green electricity, renewable energy resources must be used. HEPP (hydroelectric power plant) projects are not only the most common way of generating green electricity but they also have one of the highest potential among the renewable resources.

There are numerous problems encountered in the delivery of construction projects worldwide that need urgent and drastic solutions because they have far reaching consequences on the industry (Idoro 2012). In this paper, HEPP projects are taken into account among the other electricity generation methods. Hydro power plants may have higher initial installed cost per KW, but they are insensitive to the variation in fuel cost and have low maintenance costs (Adhau *et al.* 2012). Every hydro potential should be investigated because of the limited water resources available to end users. In HEPP projects, two indicators should be considered; the amount of energy generation and the cost of investment which is studied in this paper.

In order to calculate the cost of a HEPP project accurately, a detailed hydrological study, site investigation, good basin planning, geotechnical survey and various tests about soil and environmental conditions are essential. Not only do these steps take a long time and consume financial resources, but also they might result in waste of time and money altogether. Since these design stages are too time consuming, other fast yet accurate methods are required (Verlinden *et al.* 2008). In order to develop the cost estimation model, multiple regression and neural network tools are used. These cost estimation models would enable the users to predict the investment cost of a HEPP project at early stages of the project such as bidding or pre-construction phases.

1. Literature review

1.1. Cost prediction techniques

In the construction business profit margins are narrow and certain levels of uncertainties must be dealt with (Chen, J. H., Chen, W. H. 2012). The construction industry is a sector having significant uncertainties (Jiang *et al.* 2011). Many authors listed cost overrun and delay are the major uncertainties in construction projects (Abdul-Rahman *et al.* 2011; Lin *et al.* 2011). An assessment method based on Artificial Intelligence which takes advantage of data-calculation from rough set theory, genetic algorithm and neural network algorithm was studied by Zheng and Lian-Guang (2012). Kim *et al.* (2012a) presented a practical hybrid conceptual cost estimating model for large building projects, including multiple mixed-use buildings. Petroutsatou *et al.*

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(2012) developed an early cost estimation model using two types of neural networks: (1) the multilayer feed-forward network; and (2) the general regression neural network. In Wang *et al.* (2012) and Okmen and Oztas (2010), the efficiency and effectiveness of the model is evaluated through an application of CCRAM and Monte Carlo simulation (MCS) based method using the same hypothetical data. The findings show that CCRAM operates well and produces more consistent results compatible with the theoretical expectancies. (2012) proposed a novel model for quickly making a bid-price estimation that integrates a probabilistic cost sub-model and a multi-factor evaluation sub-model. In Espinoza (2011), an attempt to bridge the gap between theory and practice was made by proposing an equivalent linear stochastic process to model the complex non-linear random variation with time of the technical and market uncertainty for projects. Kim *et al.* (2012b) proposed an approximate cost estimating model for irrigation-type river facility construction at the planning stage, based on Case-Based Reasoning (CBR) with Genetic Algorithms (GA). In Choi and Kwak (2012), an innovative, reliable tool called Construction Analysis for Pavement Rehabilitation Strategies (CA4PRS) was used for the simulation. In Yuan (2011), the significance of the correlation is investigated through a multivariate competitive bidding model. Two time series models were built by analyzing time series index data and comparing them with existing methods in Hwang (2011). Kim, K. J. and Kim, K. (2010) proposed a preliminary cost estimation model using case-based reasoning (CBR) and genetic algorithm (GA). According to the study, it is expected that a more reliable construction cost estimation model could be designed in the early stages by using a weight estimation technique in the development of a construction cost estimation model.

1.2. Cost prediction techniques for HEPP

Brauers *et al.* (2012) presented the process of effective selection of building elements for renovation important for energy saving in buildings. The areas studied by Bieksa *et al.* (2011) include the currently applied mechanisms for identifying and evaluating energy efficiency measures, data analysis of measuring actual energy efficiency and determination of the economic feasibility of the renovation process. Ji *et al.* (2012) develops a case adaptation method that is balanced for both methods. To validate the method, a CBR cost model was developed that has an adaptation function using 129 military barrack projects in Korea, and then the method was tested by using 13 test cases. Furthermore, an applicability test was conducted based on 164 Korean public apartment projects. Ogayar and Vidal (2009) studied the electromechanical equipment cost of small HEPP projects. They developed cost estimation functions for different regions. They applied the best fit analysis to determine the most significant parameters. The factor they took into consideration while determining the cost of the turbine were power, net head and typology of turbine. They divided turbines into three groups as pelton, francis and kaplan turbines and they formed three cost determination functions for each group. Singal and Saini (2008) analysed the cost of small low-head dam-toe hydropower plant projects based on the number of generating units. They classified them as micro-hydro, mini-hydro and small hydro HEPPs according to their station and unit capacities. Signal and Saini (2008) categorized HEPPs according to their heads as low head, medium head and high head HEPPs. Additionally, a method was developed by regression analysis based on the head and installed capacity of a HEPP. This method was applied to develop correlations between number of turbines and layout characteristics of a power house. Moreover, they divided the cost of HEPP projects into three categories as civil works cost, electro-mechanical cost and other miscellaneous items and indirect cost. They took the miscellaneous items and indirect cost as 13% of the total cost of civil and electro-mechanical works.

From the above literature review, it can be easily seen that many researchers used regression analysis and neural networks to build a prediction model in various fields of construction business. Some made comparisons between the results obtained from the application of each method. It can be seen from the literature that determining the HEPPs cost is quite difficult in early stages not only due to many cost dependent parameters but also due to the availability of various types of HEPP projects. In order to overcome this problem, researchers either limit the types of HEPPs or they generalize or lessen the cost dependent parameters while developing the cost estimation models.

2. Scope

The main aim of this paper is to develop cost predictive models for HEPPs in early stages by the help of the MRA (Multiple regression analysis) and NNA (Neural network analysis) tools. Since these tools rely on the use of historic data, the data were gathered from fifty four HEPPs and analysed with regression and neural network tools. The costs of these fifty four sample projects from 2005 to 2009 were determined. All costs of sample projects were transformed to 2009 prices by using the official escalation coefficient of the related year. Cost escalation coefficient is calculated by considering changes in the cost or price of specific goods or services in a given economy over a period. These models can be applied to almost all types of HEPP projects, because basic parameters valid for all types of HEPPs are used in these models.

3. Data collection and identification

Developing the prediction models follows certain steps and the first step is data collection. A total of fifty-four HEPP projects were investigated and data from these projects were accumulated. While selecting the sample projects, the projects that contained almost all types

Table 1. Analysed data set

PC	Project cost
IC	Installed capacity
Qa	Average discharge
Qd	Project design discharge
Hd	Project design head
Lt	Length of tunnel
Lc	Length of channel
Letl	Length of energy transmission line
Dp	Diameter of penstock
Lp	Length of penstock
Q5	Five year occurrence flood discharge
Q100	Hundred year occurrence flood discharge
A	Catchment area of the basin

of HEPP projects were selected. Variables that best described the trackway cost were selected with special care. The list of variables and their definitions can be seen in Table 1. While selecting these variables, the views of the professionals working on this subject were taken into consideration through interviews. The project holders were promised confidentiality during the data collection phase. Forty nine out of fifty four projects were selected as sample projects in order to be analysed for developing prediction models. This sample of projects was composed of various projects located in fourteen different provinces of Turkey. Other five projects were selected to be used for validation purposes.

4. Multivariable regression analysis

The variables of a regression model can be tested statistically to select the best number of variables that fit best to the available data. A typical first step in determining the relative importance of numerous quantitative variables would involve a multivariate regression analysis of the data. However, multivariate regression analyses proved useless due to considerable multicollinearity in the data. Multicollinearity is a condition wherein one or more of the independent variables can be approximated by a linear combination of the other independent variables (Trost, Oberlender 2003). If some of the variables are interconnected, then multicollinearity occurs generating wrong cost equation relationships and resulting in inaccurate cost estimates.

The aim of correlation analysis is to reveal the linear relationship between each variable pairs. Correlation coefficients of two variables are calculated by using Pearson correlation values. Correlation coefficient is in the range of +1 and –1. If two variables are directly proportional, correlation coefficient is positive. Whereas, when a variable increases as another variable decreases, the correlation coefficient between two variables is negative. The equation of correlation coefficient can be calculated by Eqn (1).

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{(n-1)s_x s_y}. \quad (1)$$

In this paper, if the p-value between two parameters is higher than 0.80 (it was determined by statistical expert comments), these two parameters are assumed to be highly correlated with each other. Table 2 shows the correlated parameter pairs and the Pearson correlation values.

Regression is a data oriented technique because it deals directly with the collected data without considering the process behind these data. Regression is a mature technique that has been used in many scientific applications. Regression models can be linear or nonlinear, which represents a relation between dependent variable(s) and independent variable(s). Regression model for estimating the cost of HEPP projects in the early stages consider one dependent variable (cost), against several independent variables (design discharge, design head, length of tunnel, length of channel, etc.).

The final regression model is performed through a step by step procedure. In every step if there exists an unnecessary parameter with little significance on the model, it is dropped from the model and the analysis is repeated until all parameters become significant. This procedure is called 'parsimonious modelling'.

In parsimonious models, a backward elimination method is used for the initial regression model. According to this technique, variables that are not contributing to the model are eliminated one by one at each step. The regression statistic, significance level (p-value, which gives an indication of the significance of the variables included in the model) is used for determination of variables to be eliminated. In general, the variables corresponding to the coefficients with p-values close to or less than 0.10 are considered to have significant contribution to the model. This procedure is repeated until all predictor variables have p-values equal to or smaller than 0.1 in regression model.

Table 2. Highly correlated variable pairs and correlation coefficient

Correlated parameters	Pearson correlation values
Qd-Qave	0.991
Qd-IC	0.836
Qave-IC	0.84
Dp-Qave	0.847
Dp-IC	0.816
Dp-Qd	0.805
Q5-Qave	0.818
Q5-Qd	0.821
A-Qave	0.857
A-Qd	0.834

Above mentioned steps were followed to perform regression analysis by a software package called Minitab. At the end of each regression, results were analysed in order to find out the insignificant parameters. After removing the insignificant variable(s), a new regression analysis was performed until all predictors had p-values equal to or smaller than 0.1.

The final regression model was attained after three trials. In the first trial, because the length of channel had the highest p-value, which was 0.993, this parameter was disregarded in the next analysis. In the second trial, the length of penstock was disregarded because of having the second highest p-value. In the last trial, every parameter in the model had small p-values (around the value of 0.100). The best regression model result obtained through the aforementioned processes is given below.

$$\text{Cost} = -0.0169 + 1.21\text{Qd} + 0.0565\ \text{Hd} + 0.0369\ \text{Lt} + 0.0995\ \text{Letl} - 0.0249\ \text{Q100}. \quad (2)$$

5. Neural network analysis

As an alternative to regression techniques, artificial neural networks are used to generate cost estimates. They are applied in many fields such as financial services, biomedical applications, time-series prediction, text-mining, decision making and many others. Although the applications of ANNs (Artificial Neural Networks) are numerous, they all share an important common aspect: the processes to be predicted are correlated with a large number of explanatory variables and there may exist high-level non-linear relationships between those variables (Verlinden *et al.* 2008). Developing the best model by determining the high-level non-linear relationship between the predictors and predicted variables is the main objective of NNA. Artificial neural network analysis was performed by the software called Neural Power in this study.

The model was developed in three phases: the modelling phase, the training phase, and the testing phase. The modelling phase involves the analysis of data, the identification of cost estimation parameters and the selection of the network architecture of the internal rules. The training phase requires the preparation of the data and the adoption of the learning law for the training. The testing phase evaluates the prediction accuracy of the model. The actual costs are compared with the estimated costs and the cost percentage error is calculated (Gunaydin, Dogan 2004).

Typical neural network architecture is composed of three types of layers which are the input layer, hidden layer and output layer (Kim *et al.* 2004). All layers include various number of neurons by which layers are connected with each other with a weighed function called transfer function.

In the modelling phase independent variables were carefully selected because the selection of input variables affects the accuracy of the neural network predictions significantly. In this paper, the neural network model was developed depending on twelve parameters as explained previously. Similar to regression modelling, forty nine projects were utilized in the training phase and five projects were used to evaluate the accuracy of the model that was used in the rest of the projects.

In the training phase, the best model was developed by a trial and error procedure, because in a trial and error procedure, each step includes changes in learning and momentum rates, and thus the best estimation model is constructed.

One of the critical points in developing a neural predicting model is determining the number of hidden layers and neurons in these hidden layers. The function of the hidden layers is to extract and remember the useful features and sub features from the input patterns to predict the outcome of the network (values of the output layer). One hidden layer and 0.75 m, m, or 2 m + 1 number of hidden neurons, where m is the number of input variables, were used in the neural network model developed in this study. That is, three models each having different number of hidden neurons and one hidden layer were developed. The models are described below and the structures of the models are given in Figure 1.

a) The First Model (M1): This model was constructed with 0.75 m (0.75 × 12 = 9) hidden neurons. After the trial and error procedure, the best model was obtained. The learning rate was 0.550 and momentum rate was 0.325.
b) The Second Model (M2): This model was constructed with m (1 × 12 = 12) hidden neurons. After the trial and error procedure, the best model was obtained. The learning rate was 0.550 and momentum rate was 0.225.
c) The Third Model (M3): This model was constructed with 2 m + 1 (2 × 12 + 1 = 25) hidden neurons. After the trial and error procedure the best model was obtained. The learning rate was 0.550 and rate was 0.225.

After constructing the structure of the model (the number of hidden layers and hidden neurons), the next step was the arrangement of the settlements to decide on the learning rate, momentum rate, stopping criteria and other options. Although the learning and momentum rates were determined by a trial and error procedure, the stopping criteria could be assigned at the beginning of the neural network analysis. Firstly, an analysis of the learning and momentum rates was performed, then the learning and momentum rates were changed accordingly to find the most suitable values in each trial.

In Neural Power software, stopping criteria are various which can be the root of the mean square error (RMSE), number of iterations, correlation coefficient and determination coefficient. RMSE was taken as stopping criteria in this study and the value was decided as 0.001. The RMSE behaviour during the analysis is given in Figure 2.

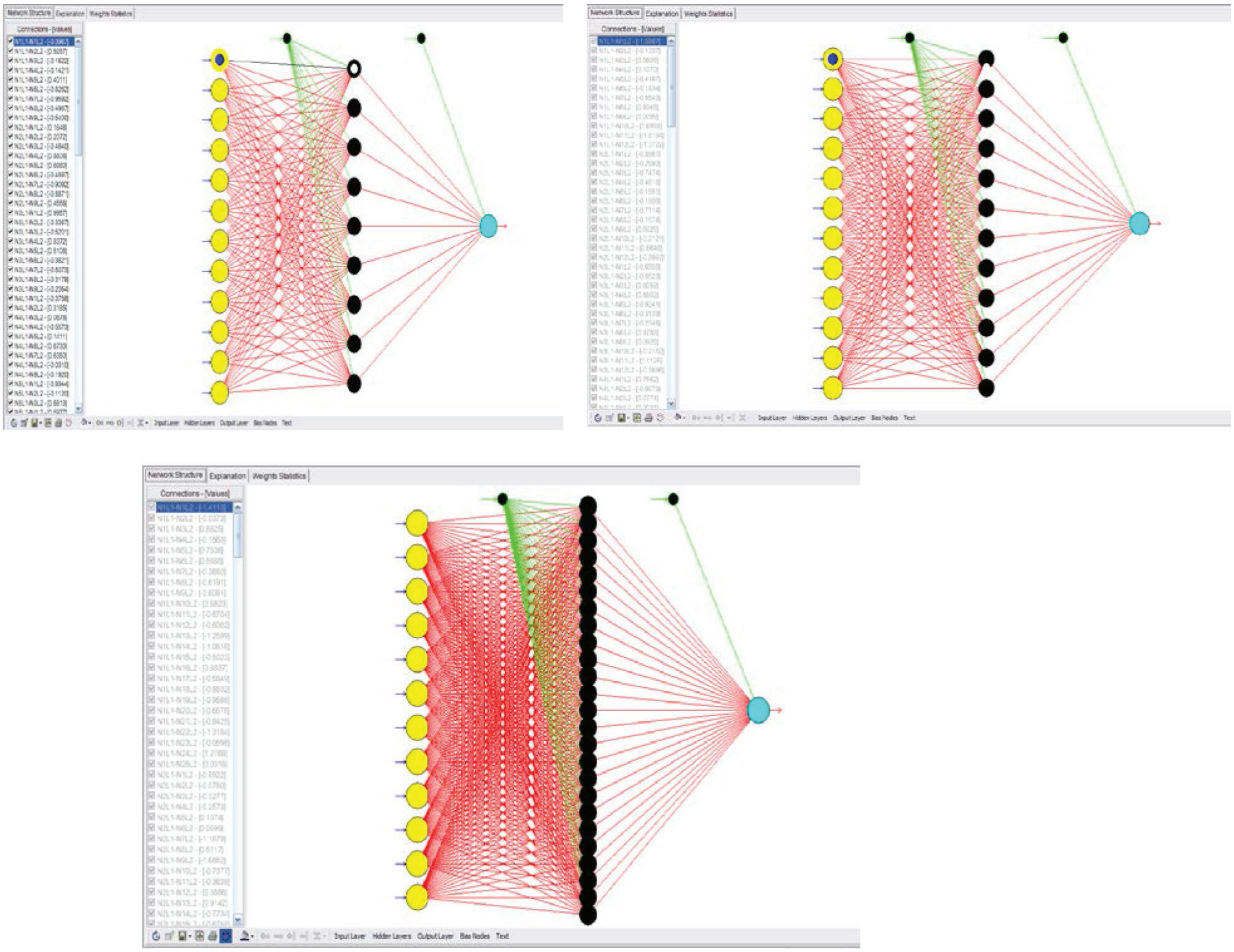

Fig. 1. Hidden layer structures of neural network models

6. Validation

Developed models are validated through comparing their results to the collected validation data points. If these results do not match; then, the model should be improved to produce better results (Zayed, Halpin 2005).

In order to check the accuracy of developed models, five HEPP projects were selected as testing projects. The costs of HEPP projects were determined by multiplying the quantity take-off with unit prices of each project. Reliability of each model can be checked by comparing the estimated costs from developed predicting models. This model is effective, because of the newly introduced data which was never used in the analysis section.

The performances of models were tested by using the mean absolute percentage error (MAPE) of which equation is given in Eqn (3).

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|\text{actual}_i\text{-predicated}_i\right|}{\left|\text{predicted}_i\right|}\times 100, \qquad (3)$$

where: “i” is the number of the project, actual is the real cost of that project; and “predicted” is the predicted cost of that project calculated by means of estimation models.

First of all, the regression model was checked by comparing the actual cost of testing projects with their predicted costs from the developed model. Table 3 shows the predicted costs of testing projects, percent error and MAPE.

Different from the regression model, three neural network models were developed with different numbers of hidden neurons in each model. The testing results of all three models are given in Table 4. In model 1 the mean absolute percentage error is about 0.05 and this is acceptable and this model provides a highly accurate result.

The weight distribution of the best neural network model is given in Figure 3. The effect of each parameter is given in the importance chart which is represented in Figure 4.

A comparison of regression and selected neural network validation models are provided in Table 5.

If three models are compared, the Model 1 is the best model which gives the high accurate results in cost prediction for HEPP projects. Therefore Model 1 was selected as neural network cost estimation model is compared with the regression model.

Conclusions

Important points of early cost estimation models are easy to use, applicable to different types of projects and can be used to estimate the cost within an acceptable error

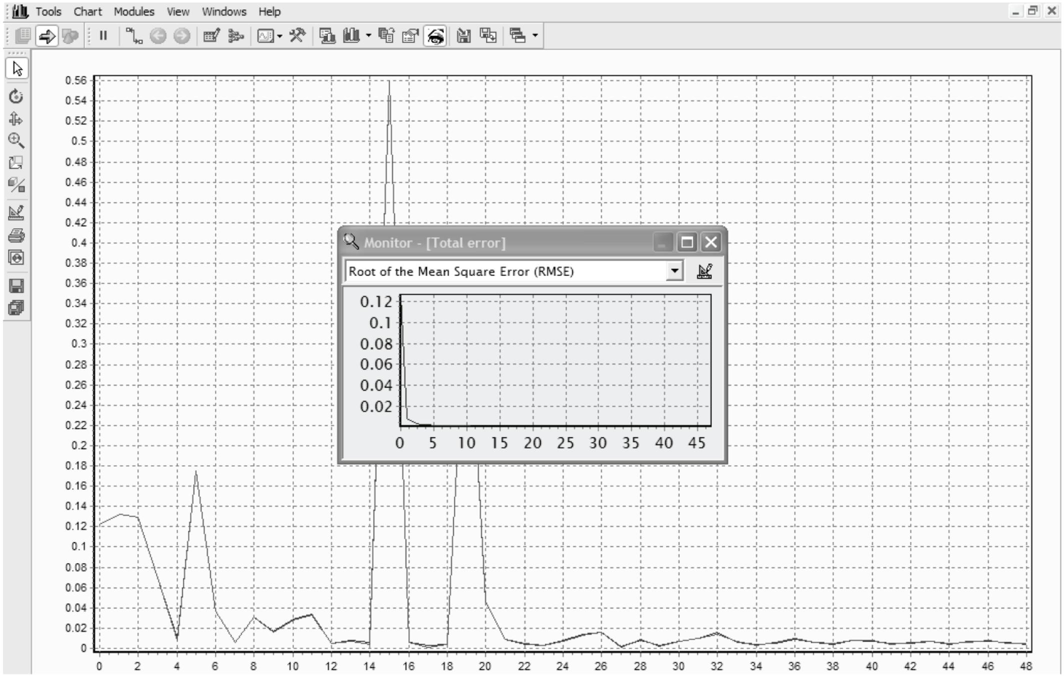

Fig. 2. RMSE behavior during analysis

Table 3. Results of regression model cost estimations and MAPE

Project	Real cost million $	Estimated cost million $	Percent error	MAPE
1	8.799	7.840	–10.90%	9.94%
2	3.604	3.283	–8.91%	
3	8.545	9.478	10.93%	
4	50.313	55.176	9.67%	
5	146.712	160.364	9.31%	

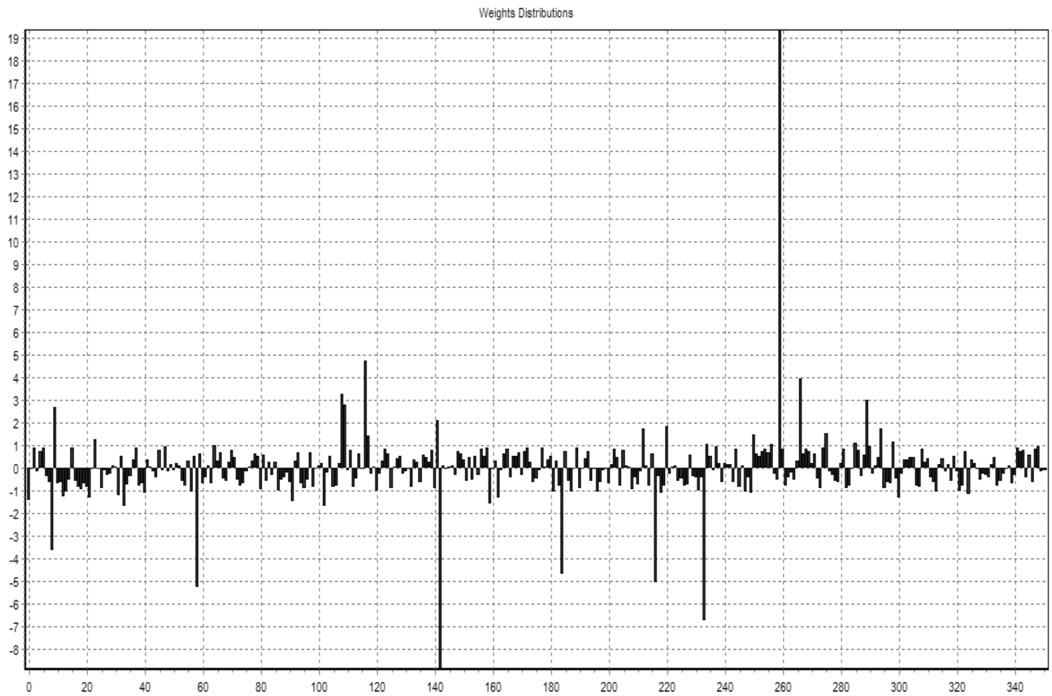

Fig. 3. Weight distribution of neural network Model-3 (M3)

Table 4. Results of neural network models cost estimations and MAPEs

Project	Real cost million $	Model 1			Model 2			Model 3		
		Estimated cost million $	Percent error	MAPE	Estimated cost million $	Percent error	MAPE	Estimated cost million $	Percent error	MAPE
1	8.799	9.111	3.55%	5.04%	8.055	–8.45%	8.71%	8.608	–2.17%	10.23%
2	3.604	3.496	–2.99%		3.206	–11.05%		2.863	–20.57%	
3	8.545	8.919	4.38%		8.419	–1.47%		7.658	–10.38%	
4	50.313	46.701	–7.18%		57.456	14.20%		44.781	–10.99%	
5	146.712	136.286	–7.11%		134.419	–8.38%		156.999	7.01%	

Table 5. Results of NNM and RM cost estimations

Project	Real cost million $	Estimated cost by NNM million $	Estimated cost by RM million $	Percent error in NNM	Percent error in RM	MAPE in NNM	MAPE in RM
1	13.199	8.799	8.608	3.55%	–10.90%	5.04%	9.94%
2	5.406	3.604	2.863	–2.99%	–8.91%		
3	12.817	8.545	7.658	4.38%	10.93%		
4	75.469	50.313	44.781	–7.18%	9.67%		
5	220.068	146.712	156.999	–7.11%	9.31%		

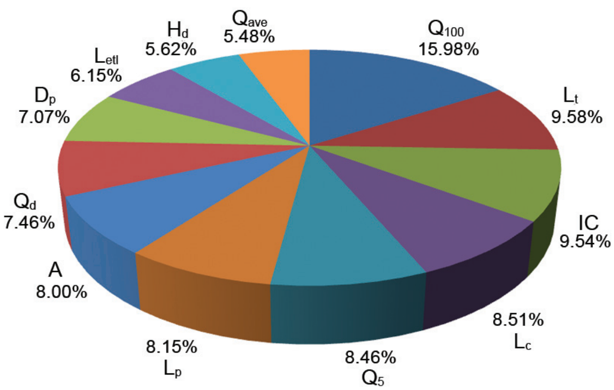

Fig. 4. Importance chart of the parameters in NNM-3 (M3)

range. The products of this paper are two cost estimation models which have been developed as based on multiple regression and artificial neural networks. These models have been developed depending on the data obtained from forty nine HEPP projects and validated by five projects. Comparisons of validation results revealed that the regression model had a 9.94%, and neural network model had 5.04% prediction accuracy. It can be seen that the neural network model yielded more accurate results. The estimation models presented in this paper are applicable to different types of HEPP projects. These models may help estimate the hydroelectric power plant project costs in early stages of a project. Moreover, the analyses carried out in this paper could be repeated for parts of HEPP projects.

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