Prediction and estimation of civil construction cost using linear regression and neural network

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Abstract: Adequate construction cost estimation is a main factor for any type of construction projects. Forecasting cost of construction projects can be considered as a difficult task. In order to forecast the cost of the civil construction projects, we have used the ordinary least square regression (OLSR) model and multilayer perceptron (MLP) in our proposed model. The performance of the proposed model is analysed on the data of the 12 years of schedule rates of construction projects in Pune region of India. The experiment shows 91% to 97% of accuracy in prediction using ordinary least square regression model. Similarly, we have conducted series of experiments on multilayer perceptron model with different activation functions. It was observed that the multilayer perceptron model with 'softplus' activation function can be able to predict the project cost of the civil constructions with accuracy of 91% to 98%. Thus, it shows that the prediction of cost using multilayer perceptron model gives higher accuracy than the ordinary least square regression model.

Keywords: construction cost estimation; ordinary least square regression; OLSR; multilayer perceptron; MLP; activation functions; root mean square error; RMSE; mean absolute percentage error; MAPE.

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1 Introduction

The estimation of cost is the basic component of all project-related engineering fields, which greatly affects planning, bidding, design and implementation. Hence, cost estimation is used to plan and execute the entire project. Such estimates can be used by planner owners to find out feasibility of a project. According to given schedule, further estimation of civil construction cost with automated mechanism is the need of recent smart city plans. Because of the less availability of information related to project during the early stages of a project, construction managers can use this knowledge, experience to estimate project costs (Hong, 2011). Cost estimation includes estimating the materials, overhead and quantity of labour, floor space, utilities, sales, time and other costs for a set series of time periods. Such construction costs estimates should be reliable so that it can be used for justifying a project on economic ground. The economic impact of a construction cost overrun is the possible loss in the economy for the project. A cost overrun can also be critical issue for sustainable development on the basis of economic costs.

Such issues of cost overrun, less availability of information motivated researchers to develop cost estimators that can maximise the practical value of less information related to project available in order to improve cost estimate accuracy and reliability, which should improve the suitability of resultant designs and subsequent project execution work.

In this paper, we have proposed a construction cost estimation model which is applicable for predicting the construction cost of any type of work like building, road, bridges, cross drainage work, etc. at its early phases. Earlier cost estimation helps to manage the budget of a project. Though any construction site suffers from any type of delay, we are able to find out construction cost in early stages. This will be very helpful to the contractor to be ready for the budget.

The paper is arranged as following. Section 2 gives description about earlier work related to cost estimation. Section 3 describes proposed models of ordinary least square regression (OLSR) and multilayer perceptron (MLP). Section 4 gives idea about experimental design, model construction. Comparison of proposed models of OLSR and MLP is done in Section 5. This section also compares the proposed model with earlier models. At last, conclusion and future research directions are addressed in Section 6.

2 Literature review

In 2004, Kim et al. compared an efficiency of three cost estimation models. Those three models were case-based reasoning (CBR), neural network (NN) and multiple regression analysis (MRA). Experiments were performed on 530 projects of residential buildings from Seoul, Korea. The data sample was divided into two parts as training part and testing part. Training part included 490 data samples, while remaining 40 data samples was used as testing part. Those three models were evaluated on the basis of values of mean absolute error rate (MAER). MAER for CBR, NN and MRA were 4.81, 2.97 and 6.95, respectively. From these results, conclusions were drawn as NN performed better than CBR and MRA.

In 2004, Gunaydin and Dogan proposed novel method for cost estimation method based on NN theory. Experiments were performed on thirty projects. Performance of proposed method were measured in terms of mean square error (MSE) and cost percentage error (CPE). Proposed method gave better performance with 93% accuracy and 0.038 MSE.

In 2010, in order to increase reliability in estimation of cost, Shi and Li proposed a hybrid model by combining artificial neural network (ANN), rough sets (RS) theory and fuzzy logic (FL). Experiments were performed on 54 projects from Beijing City. The average variance and training time proved that integration ANN, RS theory and FL can forecast more reliable construction cost.

In 2010, Cheng et al. proposed a hybrid model by combining ANN and FL. Hybrid model of NN and high-order NN was combined with FL to create fuzzy hybrid NN. At last, addition of genetic algorithm was done to complete the model called evolutionary fuzzy hybrid NN. Experiments were performed on 28 data samples. The data samples were divided into two parts as training part and testing part. Training part included 23 data samples, while remaining five data samples was used as testing part. Overall error of a proposed model was less as compared to earlier model. The experiment had shown that proposed model of evolutionary fuzzy hybrid NN gave better performance.

In 2013, Mahamid designed regression models to forecast future construction cost. Experiments were performed on 52 projects from Saudi Arabia. Performance of those models was evaluated upon the basis of a coefficient of determination and mean absolute percentage error (MAPE). MAPE of the proposed model was lies between 17% to 42%, which showed that the relationship between the dependent and independent variables of the proposed model was good forecasted values from a proposed model fit near real-time data.

From above earlier work, we have observed that to calculate construction cost, different parameters were used. Those parameters were year, ground floor area, duration, earthwork, skilled worker, non-skilled worker, etc. But when the project is specifically a government construction project, standard rates from schedule rates are used to calculate total construction cost. Schedule rates are the standard rates of different construction components like excavation, plain cement concrete, reinforcement cement concrete, brick work, wood finish, etc. These standard rates are declared on each year by the government authority. By considering these rates total cost is calculated. So, prediction of schedule rates of construction components helps contractors for the long-term projects like dams, canals, bridges, etc.

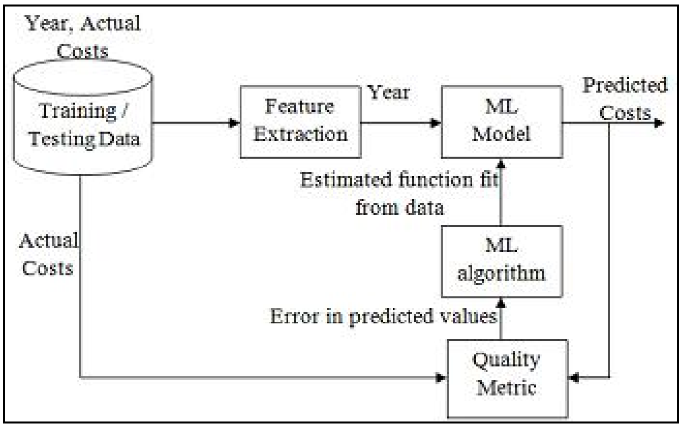
This problem of prediction of schedule rates of construction components not covered in earlier work. In 2017, Arage and Dharwadkar focused on this problem of calculating the cost based on predicted schedule rates by using OLSR model. Experiments are done on schedule rates of Pune region from India. OLSR model has given 91% to 97% accuracy. In this paper, we are extending this work by applying MLP model.

3 Proposed models

In this paper, we are predicting the future schedule rates from previous schedule rates. If these schedule rates can be predicted at earlier stage, it will be very helpful to contractors to find out the construction cost. Here, we have taken 12 years of schedule rates of Pune region from India. From these, we are able to predict schedule rates for next year.

To accomplish this paper, experiments are done using OLSR model and MLP model. The general framework of proposed models is shown in Figure 1.

Figure 1 General framework of proposed method



As shown in Figure 1, details of training and testing data are provided in Section 3.1. Training and testing data contain year and cost of construction materials. Next, from this training/testing dataset feature extraction takes out the input, i.e., independent variable. As the training dataset contains the costs of each item for 12 years, here the independent variable is a year. That is feature extraction provides input to machine learning (ML) model as a year. Quality metric contains output, i.e., dependent variable (actual cost of items) from training dataset. Quality metric also provides error in our predicted values that can be used further to reduce the error in prediction.

Here, we have used OLSR and MLP as a ML algorithm which provides the estimated functions which are discussed in Sections 3.2 and 3.4, respectively. Here, ML models are OLSR and MLP, which are discussed in Sections 4.2.1 and 4.2.2, respectively.

3.1 Linear regression

Linear regression is a popular statistical model as well as a ML model which is used to model data. Linear regression is a technique used to predict response/dependent variables on the basis of independent/predictor variables (Karanci, 2010). The important theme behind linear regression is to fit the curve for provided data points in such a way that the error should be at a minimum level. Linear regression is a relationship between several independent variable and dependent variable. Dependent variable may be continuous or binary (Yilmaz and Kaynar, 2011).

We have applied OLSR, which is a type of linear regression method to forecast future cost of construction materials. In our experiment, as defined above response/dependent variable is cost of construction materials and independent/predictor variable is a year. We have applied this linear model because the data sample is labelled. Second reason is that the dependent variable, i.e., cost is continuous one. And also, data sample shows the linearity trend. These reasons have motivated us to use a linear model.

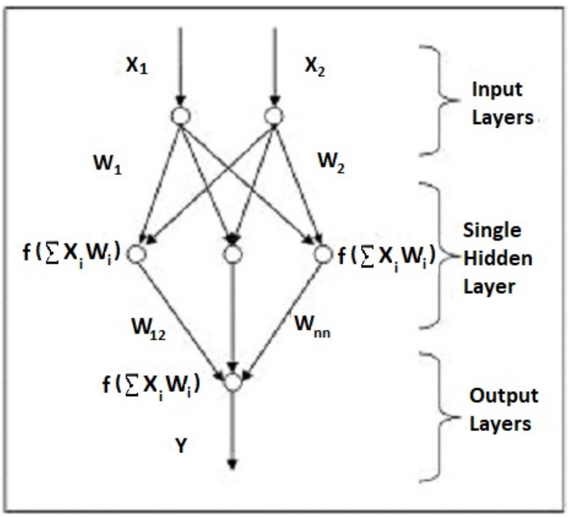
3.2 Ordinary least squares regression

OLSR is a common linear modelling method which used to predict a single dependent variable. Performance of a model can be calculated by comparing observed variable and predicted variable. Difference between observed variable and predicted variable is called as an error term or residual. Error term represents how a good model has predicted the response variable. To get performance of a model, if we add these error terms, it gives null error as half of the error terms are negative. So, we add squared error terms, which ignore an effect of negative error terms. Summation of all these squared error terms is called as a residual sum of square (RSS) which gives performance of OLSR (Hutcheson and Moutinho, 2011).

3.3 Artificial neural network

ANN is a computational technique which is used to solve many real time ML problems like pattern classification, clustering, forecasting, etc. (Basheer and Hajmeer, 2000). ANN is composed of processing elements or artificial nodes (Nassif et al., 2013). These nodes are arranged into some layers and they are connected to each other by a link. Each node has its input and output. Output is generated by the applying different activation functions on input vector. This output works as input for the next layered node (Gaudart et al., 2004).

Figure 2 Architecture of single hidden layer feed forward network



Mainly, there are three types of layers. First one is an input layer, where external information is collected. Last layer is an output layer, which provides the required outputs like numerical value or class, etc. The intermediate layer is called as a hidden layer (Zhang et al., 1998). These layers greatly affect on performance of ANN.

We have applied NN to model the data sample because NNs are preferable for time series prediction as the network itself learns from observations and there is no need for additional information required to do prediction.

3.4 Multilayer perceptron

A MLP is a type of feed forward ANN. Architecture of single hidden layered MLP is given in Figure 2 (Kalogirou and Bojic, 2000).

Our study is focused on MLP. In MLP, data always travels in single direction, it never flows backward, i.e., information goes from layer i to layer i + 1, it never goes through any loops (Nassif et al., 2013).

4 Experimentation designs

The experimental data is schedule rates and it is collected on Pune region from India. The total numbers of data samples are 831 construction materials.

4.1 Data preparation

These data samples include a name of each construction material, price of each construction material for 12 years (i.e., from 2005 to 2016). These materials belong to 20 different categories like excavation, plain cement concrete, reinforcement cement concrete, brick work, roofing and ceiling, structural steel work, stone masonry, cement concrete block masonry, water proofing, expansion joint, white washing, plastering and pointing, sanitary fitting and water supply, doors and windows, paving, flooring and dado, wood finish, distempering, oil painting, colour, wood work, iron work and miscellaneous. Out of this data sample, year and construction material cost for these years are used as an input for both model. Output will be the construction material cost for the upcoming/next year, i.e., if data sample contains construction material cost from year 2005 to 2016 as an input then output will be construction material cost for year 2017. From this data sample, 19 samples are taken randomly for testing the model.

4.2 Model building

Two models are developed using OLSR and MLP techniques on schedule rates of construction material.

4.3 Ordinary least square regression

To build model based on linear regression, OLSR technique is applied. OLSR can be shown using equation (1) (Karanci, 2010).

$$y = B_0 + B_1 * x \tag{1}$$

where y = response variable, B_0 and B_1 = regression coefficients and x = predictor variable. In this experiment, y is predicted cost or schedule rate of construction material and x is a year. B_1 is a regression coefficient also called as a slope that represents an amount of response variable y changes with respect to 1 unit change on a predictor variable x. B_0 is a regression coefficient also called as intercept that represents an amount of response variable y when a predictor variable is 0.

Algorithm 1 OLSR algorithm

Input: year wise cost of each construction material
Output: predicted cost of each construction material
1 Extract year[i], cost[i] from available dataset
2 mean_year sum_year = number_of_samples
3 mean_cost sum_cost = number_of_samples
4 for i = 1 to number_of_samples
do
variance_year + ← (year[i] – mean_year) ∨ (year[i] – mean_year)
variance_cost + ← (cost[i] – mean_cost) _ (cost_[i] – mean_cost)
variance_year_cost + ← (year[i] – mean_year) _ (cost[i] – mean_cost)
end
5 slope ← variance_year_cost / variance_year
6 intercept ← mean_cost – slope ∗ mean_year
7 predicted_cost ← slope ∗ year[number_of_samples + 1] + intercept
8 for i = 1 to number_of_samples do
predicted_cost[i] ← slope ⇑ year[i] + intercept
error ← cost[i] – predicted_cost[i]
temp ← abs(error) / cost[i] end
9 R ← variance_year_cost / sqrt(variance_year ∗ variance_cost)
R^2 ← square(R)
RMSE ← sqrt($(error)^2$ / number_of_samples)
MAPE ← temp / number_of_samples ∗ 100

From the observation of this algorithm with respect to equation (1), predicted cost, intercepts, slope from the algorithm are y, B0, B1 from equation (1). Slope and intercepts are the regression coefficient that can be used to find out the future cost which is calculated in Step 7. Coefficient of regression (R), coefficient of determination, root mean square error (RMSE) and MAPE is calculated in Step 9. RMSE and MAPE are explained in Section 4.5.

4.4 Multilayer perceptron

In the second model of MLP dataset is divided into two parts as training part and testing part. Training part consists of 70% of the data sample while testing part consists of remaining 30% of the data sample. Next to this, time-series data is converted into a supervised ML problem, i.e., extraction of data is performed in such a way that previous data acted as an input and current data acted as an output. In this model, three layers are used. They are one input layer, one output layer and one hidden layer. Input layer has one neuron and output layer also has one neuron. Hidden layer contains eight neurons.

In this model, to get better performance, experiments are done by varying number of epochs as well as activation functions. Experiments are done with 50, 100, 200, 300, 400, 500, 1,000 and 2,000 epoch size. For this experiment, we have used rectified linear unit as an activation function because it is used as default activation function. To get best epoch size, we have used two evaluation metrics as given in Section 4.5. We have used RMSE and MAPE metrics to find out accuracy. Epoch size that is giving less RMSE and MAPE can be considered as best epoch size. After finding best epoch size, different activation functions like rectified linear unit, linear, tanh, softmax, exponential linear unit, softplus, softsign, sigmoid was used to get better efficiency.

In this model, within its all variations, adaptive moment estimation (ADAM) is used as an optimiser. ADAM is one of the gradient descent-based optimisation algorithms (Kingma and Ba, 2015). This algorithm calculates adaptive learning rates of every parameter.

4.5 Metrics used to evaluate performance

To measure the performance of above proposed models, two accuracy measures are used. They are RMSE and MAPE. RMSE and MAPE can be calculated by equations (2) and (3) (Wang et al., 2011):

$$RSME = \sqrt{\frac{\sum_{i=0}^{No.\,of\ samples} (Actual\_cost - Predicted\_cost)^2}{No.\,of\ samples}} \tag{2}$$

$$MAPE = \frac{\sum_{i=0}^{No.\,of\ samples} \frac{(Actual\_cost - Predicted\_cost)}{Actual\_cost}}{No.\,of\ samples} * 100 \tag{3}$$

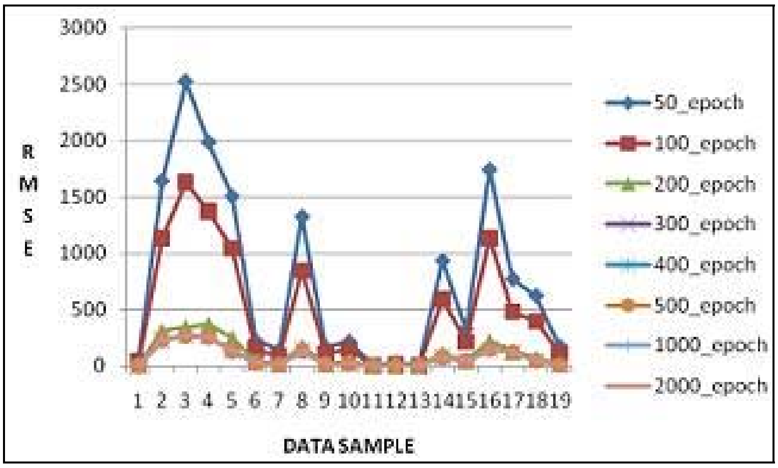
Lesser the values of accuracy measures show that greater accuracy and more the values accuracy measures show that lesser accuracy.

5 Results discussions

In MLP, to get best model fitting, we have conducted series of experiments by varying number of epochs and activation functions. In this experiment, firstly, we observe each model of MLP with epoch variations and then with different activation functions for 19 randomly taken test data sample.

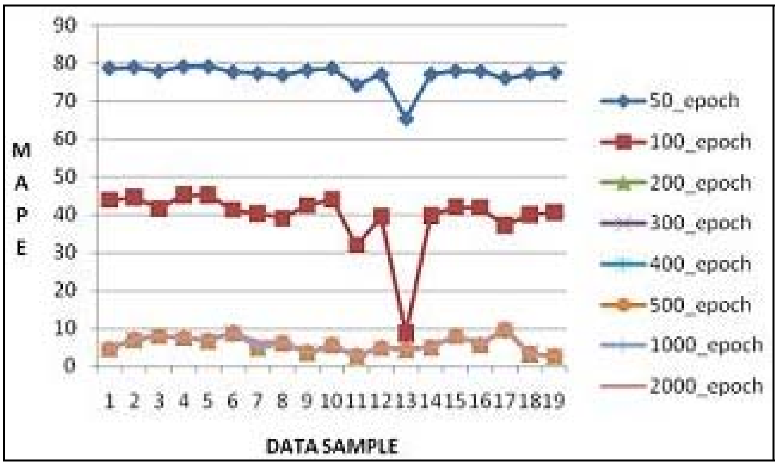
In first experiment, we have calculated values of RMSE and MAPE for MLP model with different epoch sizes by using equations (2) and (3). Then, to compare the performance of each epoch size, graphs are plotted for RMSE values as well as MAPE values. RMSE and MAPE values of these eight MLP models are presented graphically in Figures 3 and 4, respectively.

Figure 3 RMSE values of MLP models with different epoch size (see online version for colours)



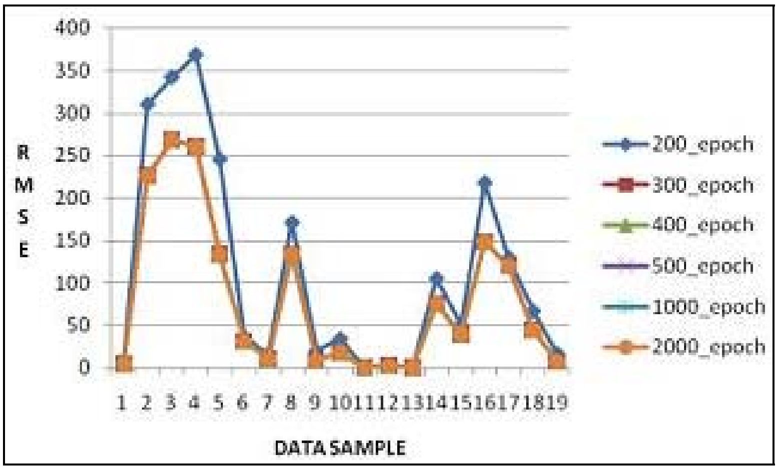
As shown in Figures 3 and 4, it is observed that MLP models with epoch sizes 200, 300, 400, 500, 1,000 and 2,000 works better than other epoch sizes like 50 and 100. The basic reason behind poor performance of MLP models with epoch sizes like 50 and 100 is that the under fitting of the models, i.e., such fewer numbers of epochs are not enough to train the models

Figure 4 MAPE values of MLP models with different epoch size (see online version for colours)



As shown in Figures 3 and 4, it is also observed that MLP models with epoch sizes like 200, 300, 400, 500, 1,000 and 2,000 gives equal performance. So to simplify this, graphs are plotted for RMSE values as well as MAPE values for these epoch sizes. The detailed comparison for RMSE and MAPE values of epoch size like 200, 300, 400, 500, 1,000 and 2,000 epoch sizes is shown in Figures 5 and 6.

Figure 5 RMSE values of MLP model with epoch sizes 200, 300, 400, 500, 1,000 and 2,000 (see online version for colours)



As shown in Figures 5 and 6, it is again observed that MLP models with 200, 300, 400, 500, 1,000 and 2,000 gives equal performance. From these epochs, we have taken 300 as the best number of epoch. Because of taking epoch size 400, 500, 1,000 and 2,000 needs unnecessarily extra training time and extra training iterations/computations. And also, epoch size 200 performs lower than 300 as observed in Figure 5. That is, MLP models with 300 epoch size outperformed among all other epoch sizes. MAPE learning convergence curve and RMSE learning convergence curve of MLP model is shown in Figures 7 and 8.

Figure 6 MAPE values of MLP model with epoch sizes 200, 300, 400, 500, 1,000 and 2,000 (see online version for colours)

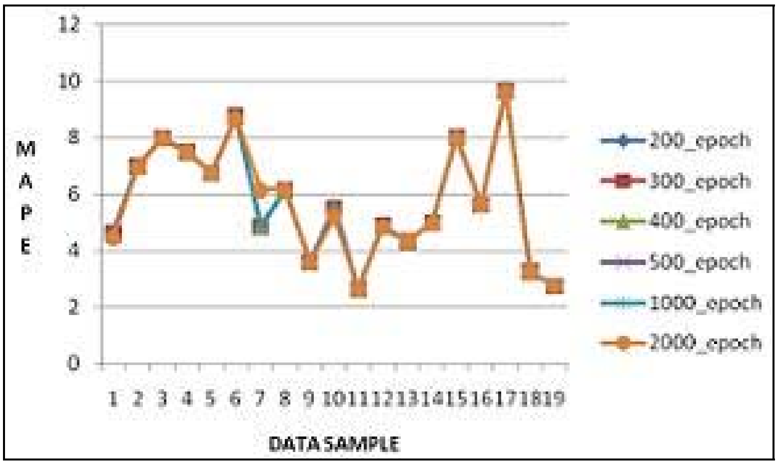


Figure 7 RMSE learning convergence curve of MLP model (see online version for colours)

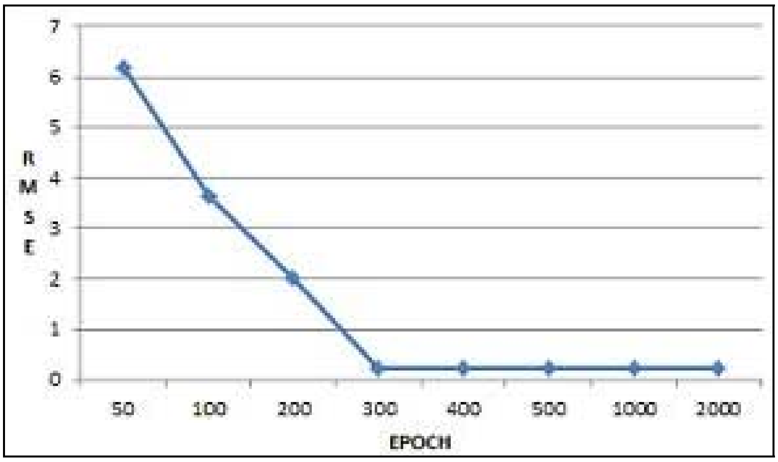
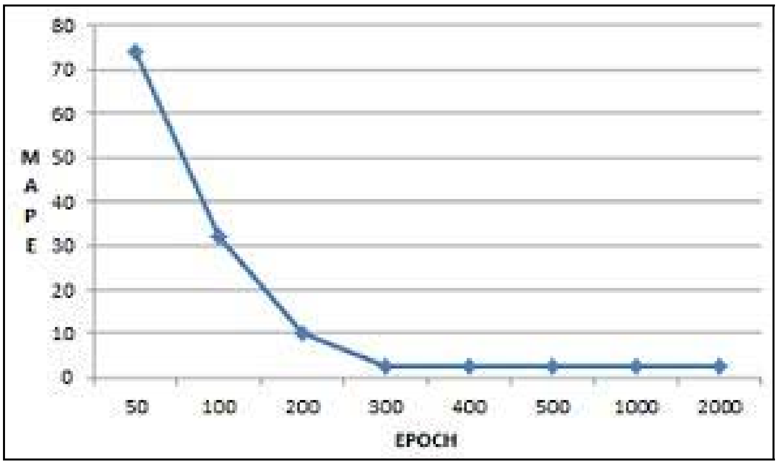


Figure 8 MAPE learning convergence curve of MLP model (see online version for colours)



As shown in Figures 7 and 8, MLP model get saturated at epoch size 300. So, it is concluded that MLP model get best result with epoch size 300.

In second experiment, we have calculated values of RMSE and MAPE for MLP models with different activation functions by using equations (2) and (3). Then, to compare the performance of each activation function, graphs are plotted for RMSE values as well as MAPE values. RMSE and MAPE values of these eight MLP models are presented graphically in Figure 9 and Figure 10, respectively.

As shown in Figure 9 and Figure 10, it is observed that MLP models with activation functions like rectified linear unit, linear, exponential linear unit and softplus activation function work better than activation functions like tanh, softmax, softsign and sigmoid. There are basically two reasons behind poor performance of MLP models with activation functions like tanh, softmax, softsign and sigmoid function. First one is the data sample is having a linear trend. And second one is that these activation functions are nonlinear functions. So, dealing of linear data sample with nonlinear function gives poor performance as compare to linear function.

Figure 9 RMSE values of MLP models with different activation functions (see online version for colours)

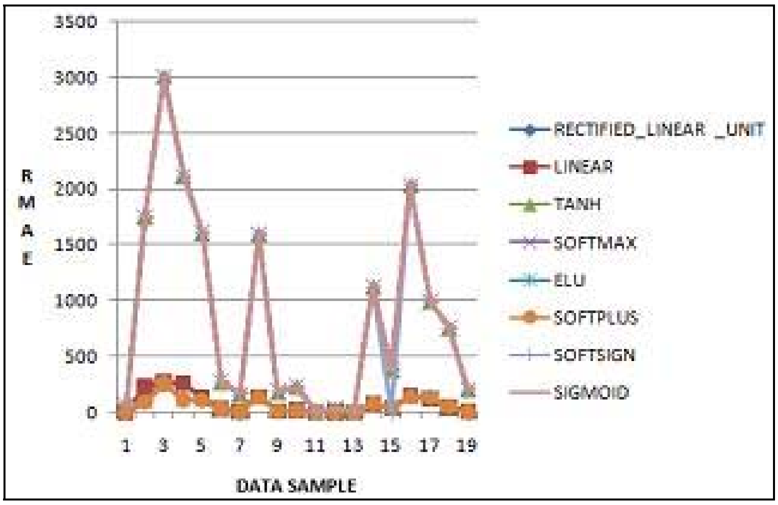
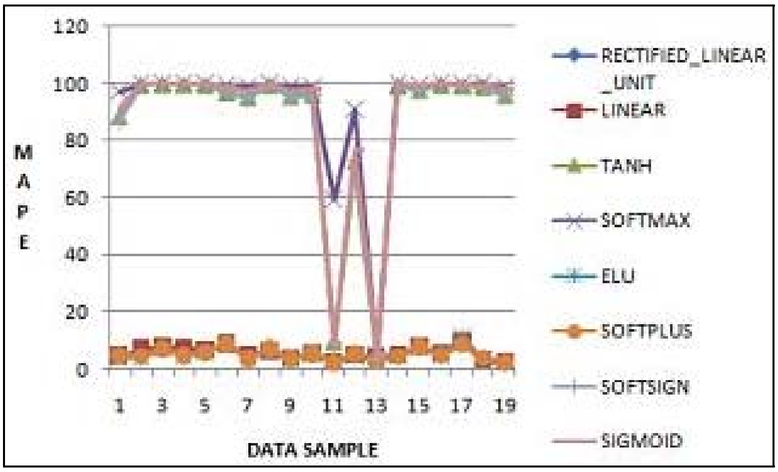


Figure 10 MAPE values of MLP models with different activation functions (see online version for colours)



As shown in Figures 9 and 10, it is also observed that MLP models with activation functions like rectified linear unit, linear, exponential linear unit and softplus give equal performance. So to simplify this, graphs are plotted for RMSE values as well as MAPE values for these activation functions. The detailed comparison for RMSE and MAPE values of rectified linear unit, linear, exponential linear unit and softplus activation functions is shown in Figures 11 and 12.

Figure 11 RMSE values of MLP models with rectified linear unit, linear, exponential linear unit and softplus as an activation functions (see online version for colours)

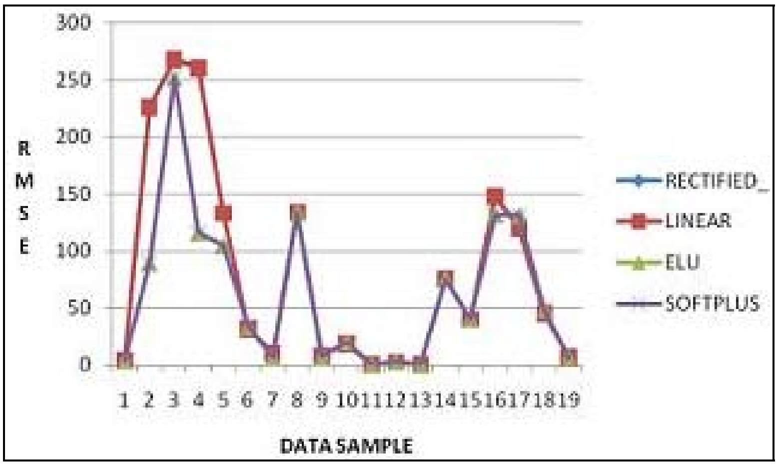
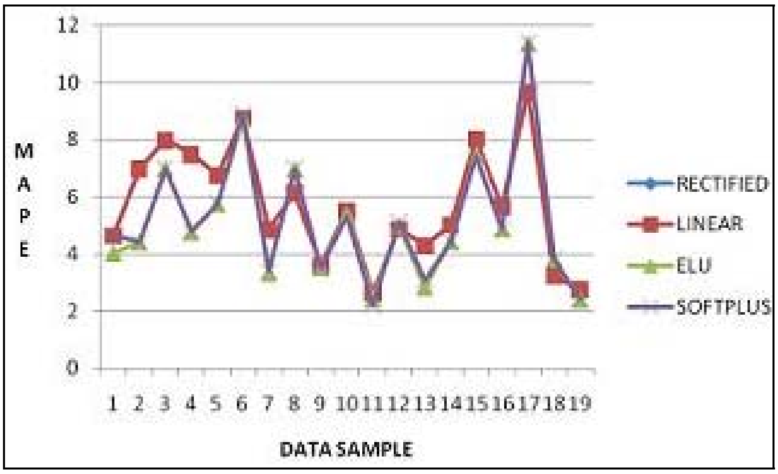


Figure 12 MAPE values of MLP models with rectified linear unit, linear, exponential linear unit and softplus as an activation functions (see online version for colours)



As shown in Figures 11 and 12, it is also observed that MLP models with softplus activation function work better than rectified linear unit, linear and exponential linear unit. That is, MLP models with softplus activation function outperformed among all other activation functions.

Finally, we have compared values of RMSE as well as MAPE for OLSR model with MLP model having softplus as an activation function and epoch size is 300 for 19 randomly taken test data sample. RMSE and MAPE values of these models are presented graphically in Figures 13 and 14, respectively.

As shown in Figures 13 and 14, MAPE values of OLSR model show that the accuracy of the model lies between 91% to 97%, while MAPE values of MLP model show that the accuracy of the model lies between 91% to 98%. But the frequency of RMSE and MAPE values of MLP model is lesser than the frequency of RMSE and MAPE values of OLSR model. This proves that MLP model with softplus activation function and epoch size 300 works well than OLSR model.

Figure 13 RMSE values of OLSR model and MLP model with softplus as an activation function (see online version for colours)

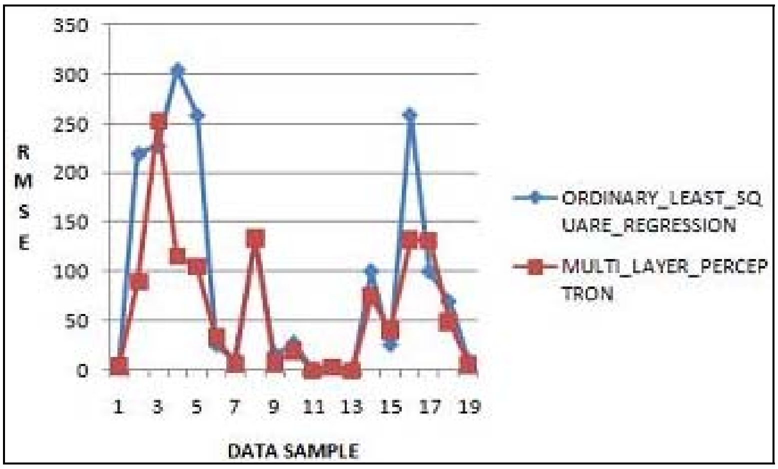
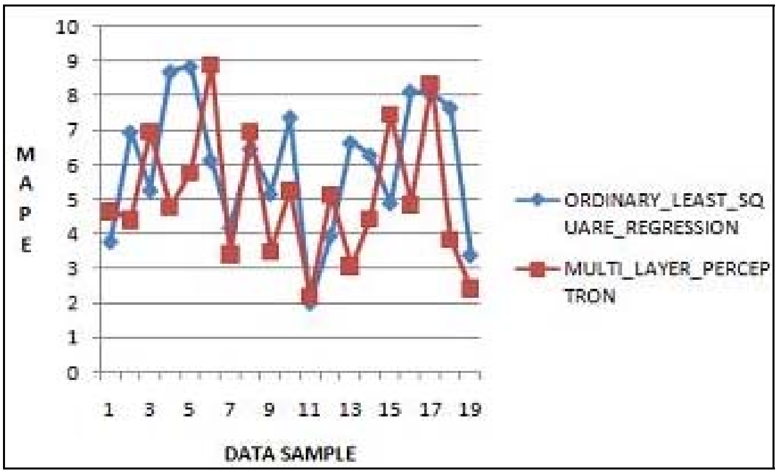


Figure 14 MAPE values of OLSR model and MLP model with softplus as an activation function (see online version for colours)



We have compared our proposed model with earlier implemented models. Comparison with earlier implemented models is given in Table 1. From Table 1, we can conclude that the proposed model of MLP works efficiently than earlier implemented models as well as

OLSR model. Hence, experiment has proven a better fitting of proposed MLP model. Thus, we can use this model to predict the future cost of any type of civil construction projects

Table 1 Comparison of the proposed model

Models prepared by	*Input data type*	*Machine learning models*	*Performance analysis of models*
Kim et al.(2004)	Year, duration, roof types, gross floor area, storey, finishing grades, total unit and usage of basement	MRA, NN, CBR	MAER NN (2.97) < CBR (4.81) < RA (6.95)
Shi and Li (2010)	Type of structure, period, total height, project management level, basement area and standard layer area	Fuzzy logic + set theory + NN	EPNN > BPNN
Arafa and Alequdra (2011)	No. of column, type of footing, no. of elevator, typical floor area, no. of rooms and ground floor area	NN	Accuracy 97%
Gunaydin and Dogan (2004)	Ratio of ground floor area to total area of building, total area, ratio of typical floor area to total area of building, no. of floors, foundation system of building and console direction of building	NN	Accuracy 93%
Kim et al. (2013)	Year, budget, school level, land acquisition, class number, building area, gross floor area, storey, basement floor and floor height	RA, NN, SVM	MAER NN (5.27) < RA (5.68) < SVM (7.48)
Karanci (2010)	Total site area, project duration, type of insulation, construction year, category of site topography, total number of apartments, earthquake region and no. of elevator stops	RA, NN, CBR	Accuracy RA > NN > CBR
Mahamid (2013)	Earth work, basework, asphalt work, road length and road width	RA	$0.65 < R^2 < 0.97$, 17% < MAPE < 42%
Yadav et al. (2016)	Cost of cement, sand, steel, aggregates, mason, skilled worker, non-skilled worker and the contractor per square feet	ANN	R = 0.9960, $R^2 = 0.9905$, MAPE = 21.43%
Proposed model	Cost of excavation, plain cement concrete, reinforcement cement concrete, expansion joint, oil painting, wood work, wood finish, etc.	OLSR, MLP	Accuracy OLSR (91% to 97%) < MLP (91% to 98%)

6 Conclusions

We have done experiments with the data sample of cost of different construction materials for last 12 years. By considering these data samples, we are predicting future cost for these construction materials. When we have plotted a graph for this data sample, it shows linear relationship between year and cost. As the input dataset shows linear nature, we firstly proposed OLSR model. This OLSR model has given 91% to 97% accuracy.

Later on to get better performance, we proposed a deep learning model called MLP model. We have experimented with MLP for different activation functions and different epoch sizes. Results have shown that MLP model with activation function softplus and epoch size 300 outperforms than all other activation functions and epoch sizes. This MLP model has given 91% to 98% accuracy. Comparison of this model to the OLSR model shows that the MLP model with softplus activation function and epoch size 300 works well than OLSR model.

This experiment shows that a deep learning model can work better than traditional ML models. Finding out and tuning other deep learning models like long short-term memory that can outperform MLP model could be a feature research topic.

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