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Artificial Neural Networks for Cost Estimation of Road Projects in Nepal

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Abstract

The success of any Construction Project relies on the accuracy of the cost estimated at the early stage of the Project. Estimating such cost in Road Projects with high accuracy is challenging, as only limited information is available at the early stage. However, past data collected from the completed Road projects can be used to estimate the Construction cost of Road Projects using Artificial Neural Networks. In this study, feed forward artificial neural networks with different numbers of Hidden layers were modeled. Dataset from 70 Road projects of Nepal were collected and models were trained and validated using 10 Folds cross validation. ANN model with structure of (14-6-6-9-1) produced the best result with MAPE of 13.90%. The application of Neural Network in the cost estimation of Road Projects can yield much more quick and accurate results.

Keywords

Cost Estimation, Road Construction Project, Artificial Neural Network, Multi-layer Perceptron, Prediction Modeling

1. Introduction

Road construction is an essential component of development, and it has been a priority sector for decades. Road Transportation is the primary mode of transportation in Nepal, outnumbering all other modes of transportation. The development of a sufficient road network has been prioritized[1]. Feasibility is essential before starting any project. Cost Estimation is a key step to determine the feasibility of the Project. Construction project success relies on the accuracy of cost estimates produced at the early stage of the Project[2].

Cost estimating is a very experience-oriented procedure in which numerous aspects, such as relative influencing factors and their interrelationships, must be examined based on suitable data and expertise[3]. Traditional cost estimation methods in the construction sector have long been recognized as methodologies riddled with uncertainty, requiring significant improvements in forecast accuracy[4]. Construction project cost estimation is a complicated task to perform since it is influenced by numerous variables[5]. Due to the number of significant variables and relationships between them, all traditional approaches have limitations in accurately project cost prediction[6]. The construction cost prediction is a multi-variable problem, and approaches like regression[7], artificial neural networks[8], and support vector machines[9] have been used for it. These estimating approaches take historical cost data and identify a relationship between cost change and the elements that influence cost[6]. Traditional methods of project cost prediction are known to have several flaws, such as the inability to diagnose complex interrelationships between a number of existing variables, the failure to account for inevitable uncertainties, and thus the inability to arrive at a reliable predicted final cost[10].

Discrepancies are very often observed in the estimated and the actual cost of the Road projects in Nepal. Public organizations, particularly those owned by the government, frequently project cost estimates while positioning themselves on the higher side to minimize cost variation[11]. Cost overruns cause a sub-optimal number of projects to be approved and executed[12], perhaps leaving inadequate cash for other vital projects[13]. Cost overruns occur in road construction projects as well, with the main issues being a lack of information, an absence of a road cost database, a failure to use appropriate cost estimation methods, and the inclusion of uncertainty[14].This research aims to develop an cost prediction model using the past data of completed Road projects in Nepal. And, several study shows that ANN outperforms standard estimating techniques and can forecast the future in the absence of data and information[15]. The use of artificial neural networks to provide preliminary estimates would considerably cut the time and cost of data processing[16]. So, this research is oriented towards developing a cost estimation model for Road Projects in Nepal using Artificial Neural Network and historical data of completed Road Projects in Nepal.

2. Literature Review

2.1 Cost Estimation methods

The estimation of construction costs at early stage requires a variety of multivariate statistical methodologies. In construction projects such as apartments [17], buildings [18, 19, 8, 20, 5, 21, 22, 7, 23, 24, 25, 26], hydropower [27, 28] and road projects [15, 29, 16, 14, 30, 31, 9, 32, 33, 34] regression models, support vector machines, fuzzy logic, Case Based Reasoning (CBR) and Artificial Neural Network (ANN) models were employed to estimate cost.

Neural network was used to determine highway construction costs, utilizing the following input variables: project scope, project type, year, construction season, location, duration, size, capacity, water body, and soil condition[32]. Backpropagation training, simplex optimization, and genetic algorithms were then used to determine the best neural network weights. Based on this experimentation, the simplex optimization produced the best neural network. Similarly, another ANN model was developed to forecast the rise in highway building costs over time[30]. They established a network that links total highway building costs, as measured by a highway construction cost index, to the costs of construction materials, labor, and equipment, contract specifications, and the contractual environment at the time of contracting. The results showed that the model was capable of accurately replicating previous highway project cost patterns.

The author created different Multiple Regression (MR) and ANN models using datasets of Poland and Thailand highway projects to estimate the cost of highway projects at the early stage[34]. The author used 4 and 8 input variables in the Thailand and Poland models respectively. The author developed the models with MMRE of 24 for ANN and 36 for MR model for the Poland dataset and 26 and 30 for ANN and MR model for the Thailand dataset. This demonstrates that, ANN models performs better than regression models in cost estimation problems. The author[35]) created a highway engineering cost estimation model using a back-propagation neural network. Their study employs an artificial neural network to extract the relationship between the project's attributes and the estimation of fabrication cost from a large number of previous estimation materials and establishes the neural network model for the estimation. They demonstrated that the estimation accuracy matches the standards and concluded that utilizing a neural network to estimate highway project investment is a viable and useful strategy. Similarly, ANN was employed to calculate the duration and cost of highway road building[16]. In this study, the Neural Network Fitting tool (Nftool) and Neural Network/Data Manager (Nntool) techniques are employed, and statistical analysis is performed on the created models. The difference of the output data from the real values is less than 8%, which is acceptable for estimating task duration and cost.

The author[36] provided a parametric approach for estimating the conceptual cost of highway improvements. For the estimation of characteristics substantially influencing the cost of highway construction, a supervised neural network model with one hidden layer optimized using evolutionary algorithms was developed. The findings demonstrated that the created model is dependable and suitable for use in the early phases of highway development. Similarly, varieties of artificial neural networks (Multi Layer Perceptron (MLP), Generalized Regression Neural Network (GRNN), and Radial Basis Function Neural Network (RBFNN)) were modeled using 57 road sections in the territory of Republic of Croatia for estimating Road Construction Costs where, GRNN has obtained the best accuracy with MAPE of 13% and coefficient of determination of 0.9595 [14].

From above study, it can be concluded that the artificial neural network is a promising alternative to be utilized in the early stages of road projects, when only a limited data is available for cost analysis. The use of a neural network to estimate cost in road projects is thought to be completely feasible and capable of producing a sufficiently accurate result.

2.2 Factors affecting Cost of Road Projects

Numerous factors affecting the cost of Road Projects have been identified from thorough Literature review and they are presented in Table (1).

Table 1: Factors affecting cost of Road Construction Projects

Group	Factors
Project	Project scope [37, 38, 39, 36]
	Project duration [38, 40, 39, 36]
	Year of Construction [38, 40, 39, 36]
	Project Contract Type [40, 39, 36]
Environment	Project Location [38]
	Terrain Type [39, 39, 41, 40, 29]
	Construction Season [39]
Engineering	Mainline Length [38, 41, 29, 39, 36]
	Mainline Width [38, 41, 29, 39, 36]
	Mainline Classification [41, 39, 36]
	Bridges' Length [38, 42]
	Tunnels' length [38, 43]
	Design Speed [41, 43, 37]
	Average Daily Traffic [37, 44]
	No. of interchanges [45, 39]
	Pavement Material [45]
	Maximum grade [41]

2.3 Artificial Neural Network

ANNs are biomimetic models that are used to replicate the human brain system for information processing and computing. A neural network (ANN) is a machine learning (ML) technology that can learn from previous data. There are three types of learning: supervised, unsupervised, and reinforcement learning. ANN models, unlike conventional modeling approaches such as linear regression analysis, may estimate nonlinear functions to a defined accuracy. Warren McCulloch presented the original model of ANNs to simulate the human brain system. The model is based on the idea of electrical circuits, with outputs of zero or one. This is known as a perceptron or neuron, and it is the unit of the ANN[46]. Generally, ANNs can be categorized into two main categories: feedforward networks and recurrent networks. The problem in this study i.e. estimating cost based on past data of completed projects, is based on feed-forward neural network architecture and back-propagation technique. In a feedforward network, all neurons are connected together. The feedforward network consists of the input vector (x), a weight matrix (W), a bias vector (b), and an output

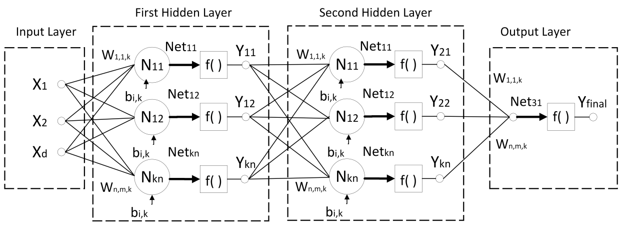

Figure 1: Multi-Layer Perceptron Architecture [49]

vector (Y) that can be formulated as Eq (1).

$$y = f(W.x + b) \quad (1)$$

where f() refers to a nonlinear activation function. Neural Network is composed of three major layers: input, hidden, and output. Except for the output layer, which has one neuron that represents the output of the training process, each layer may contain several neurons. A cost estimating model based on an artificial neural network that adapts to cost estimation is utilized in a construction project[47].

A feed-forward neural network with many hidden layers is known as a Multilayer Perceptron (MLP) network. The single layer perceptron can handle problems that are linearly separable. Multilayer perceptron are developed when many layers are added to a single layer perceptron to tackle a difficult problem that is not linearly separable[48]. An MLP neural network is made up of a number of interconnected artificial neurons that form layers. Artificial neurons are the basic processing element of a neural network. It is made up of a linear combiner and a transfer or activation function.

3. Research Methodology

First of all, the factors affecting the cost of the Road / Highway Construction Projects were identified through thorough literature review. The identified variable were validated using Expert Opinion. Moreover, others factors affecting the cost of Road Construction Projects were also identified from the Expert Opinion. Within the scope of the research, data collection and analysis were carried out, followed by data preparation for the purposes of model construction, as well as final model formation. The survey's purpose was to collect data for road projects in order to develop a model for predicting construction costs. The acquired data were sent into the neural network as input.

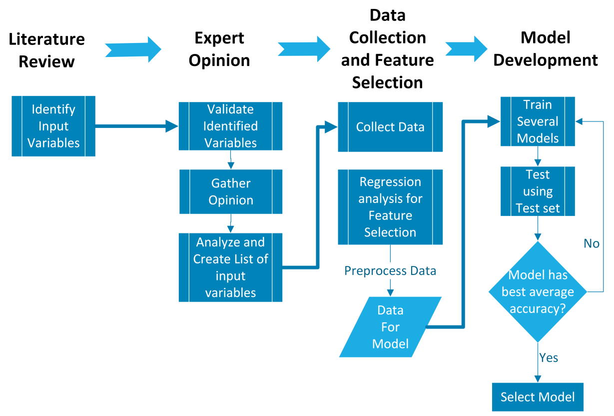

Figure 2: Research Flow Chart

3.1 Expert Opinion

When obtaining research evidence, the expert opinion technique ensures the validity and reliability of the research. As a consequence, the outcomes of expertise, i.e., the evaluation and opinion of qualified and experienced experts on the subject area, serve as the foundation for making important decisions[50]. For this research, the factors affecting the Construction cost of Road Projects were identified from vigorous literature review. The factors obtained from Literature Review were validated through Expert opinion. In addition to this, other factors affecting the cost Road projects in Nepal were also identified from the Expert opinion.The response of the experts were analyzed to obtain the list of features/factors affecting the cost of the Road projects in Nepal.

3.2 Data Collection and Feature Selection

The data required i.e. the values of identified features and actual realized cost of the Project were collected from the database maintained by Department of Roads and renowned Road Contractors, and the cost data published by World Bank for Road Sector Development Project.The ratio of sample size to the number of variables is suggested to be between 5 and 10 times per number of variables[51]. So, Regression analysis with forward selection method was performed for feature selection using SPSS to reduce the number of variables and select statistically relevant variables. Forward selection with F-criterion was used and only the effects with p-values less than 0.05 were used for further process. Forward selection begins with no variables in the model and tests each additional variable against a comparison criteria to enhance model performance [52]. If the independent variable considerably improves the model's ability to predict the dependent variable, it is kept in the model and the technique looks for a second independent variable[53].

The data was processed before feeding to the ANN model. The model does not handle the Categorical and textual values. So the following steps were done to pre-process the data before feeding to the model:

1. The location data was converted into accessibility factor from the following table:

Table 2: Value for Vehicle accessibility and Construction Environment [54]

Vehicle Accesibility	Grade	Coefficient / Value
Very Difficuly	A	1.20
Difficult	B	1.1
Medium	C	1.05
Easy	D	1

2. The actual construction cost was transformed into Base year cost 2014/15 AD using CPI index provided by Nepal Rastra Bank (NRB). The averaged CPI value over the Construction period was used and the transformed cost was obtained as followed:

$$Basecost = (ActualCost/AveragedCPI) * 100 \quad (2)$$

3. The Binary parameters (i.e. the parameters with values Yes or No) is transformed into numerical by mapping Yes to 1 and No to 0

4. The rest of the Categorical values are transformed to numerical variables using one hot encoding.

3.3 Model Development

Neural networks with 1,2 and 3 hidden layers with varying number of neurons in the layer were generated. Ten fold cross validation was used for model training and validation. The models were trained for 500 epochs and with a default learning rate of 0.001. The model with architecture that gave the least Mean Absolute Percentage Error (MAPE) over training and validation set was selected as the best model. The Neural network model was developed in Python using Tensorflow 2.0 for model development. TensorFlow is a free and open-sourced AI and machine learning library.

4. Result and Discussion

4.1 Expert Opinion

After analyzing the response from three experts with experience over 10 years in the Road Projects, different input variables were identified. The input features were classified into three categories: Categorical, Binary and Numerical variables. Categorical variable have pre-defined categories as values, while Binary variables has either Yes or No as values. The values in the Binary refers to inclusion of works in the Project cost.

Table 3: Categorical Variables

S.No	Identified Variables
1	Project Scope
2	Administrative Classification
3	Functional Classification
4	Project Location
5	Terrain Type
6	Pavement Type

Table 4: Binary Variables

S.No	Identified Variables
1	Sub-grade Works
2	Sub-base Course Works
3	Base Course Works
4	Surface Course Works
5	Surface Drainage Works
6	Cross Drainage Works
7	Road Furniture Works
8	Utility Relocation Works
9	River Bank Protection Works
10	Check Dams Works
11	Retaining or Breast Walls Works
12	Slope Protection Works
13	Bio Engineering Works
14	Footpath Works

4.2 Data Collection and Feature Selection

Data from 70 Road project contracts were collected from the relevant sources out of which 34 were Feeder Roads, 28 were National Highway, 4 were District Road, 3 were Rural Road and 1 was Urban Road. According to Terrain Type, 19 were Mountainous, 16 were Plain, 23 were Rolling and 12 were Steep Terrain. According to Pavement type, 2 were Earthen, 37 were Flexible, 29 were Gravelling, 2 were Partly

Table 5: Numerical Variables

S.No	Identified Parameters	Values
1	Length of Road	in km
2	Width of Carriage Way	in m
3	Flexible Pavement percentage	in %
4	Sub-base Course Thickness	in mm
5	Base Course Thickness	in mm
6	Surface Course Thickness	in mm
8	Year of Construction	in B.S.
9	Construction Duration	in months

Rigid and Partly Flexible. And according to Surface type, 14 were DBSD, 26 were Asphalt Concrete, 21 were Otta Seal and 9 were None.

Table 6: Percentage Wise distribution of data according to Binary Variables

Works in Contract Cost	No	Yes
Sub-grade Works	27.5	72.5
Sub-base Course Works	26.1	73.9
Base Course Works	18.8	81.2
Surface Works	43.5	56.5
Sub Surface Works	91.3	8.7
Cross Drainage Works	33.3	66.7
Road Furniture Works	30.4	69.6
Utility Relocation Works	44.9	55.1

After data collection, feature selection was performed with forward selection Regression method and the results are shown in Fig (3) and (4). As a result, Length, Terrain, Bio-engineering Works, Bank Protection Works, Width, Duration, Utility Relocation Works, Scope of Works and Retaining Wall Works were selected for further modeling process.

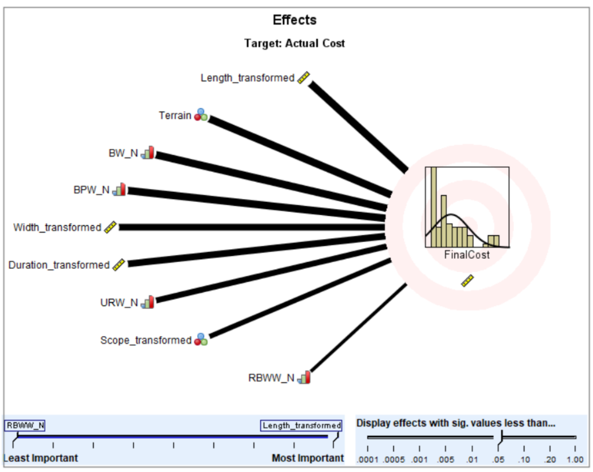

Figure 3: Effects with p-value less than 0.05

		Step									
		2	3	4	5	6	7	8	9	10	11
Significance of F Value		.000	.000	.000	.001	.002	.006	.000	.283	.018	.003
Effect	Duration_transformed	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	RBWW_N	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Length_transformed		✓	✓	✓	✓	✓	✓	✓	✓	✓
	Terrain			✓	✓	✓	✓	✓	✓	✓	✓
	SDW_N				✓	✓	✓	✓			
	Width_transformed					✓	✓	✓	✓	✓	✓
	BW_N						✓	✓	✓	✓	✓
	BPW_N							✓	✓	✓	✓
	URW_N									✓	✓
	Scope_transformed										✓

Figure 4: Steps in Forward Selection

4.3 Model Development

During preprocessing One hot encoding was performed to convert categorical variables to numerical values. As a result, 9 variables were converted into 14 input features. After preprocessing, ANN models with different architecture were trained for 500 epochs. The number of hidden layers were varied from 1 to 3 and combinations of 3,6 and 9 were used for number of neurons in the Hidden layers. A fixed learning rate of 0.001 was used and Rectified Linear Unit (ReLU) function was used as activation function in the Hidden Layers. Ten fold cross validation was performed during training and validation of model. MAPE was used as the evaluation technique during modeling. If MAPE is less than 10%, it is an excellent predictor, and if it is between 10% and 20%, it is a decent predictor. Model produces acceptable forecasting with MAPE between 20% and 50%, however more beyond 50% produces erroneous prediction[55]. The models consist of 14 input features and one output neuron. The average MAPE for training and validation set for different Model Architecture(MA) has been shown in Table (7). The model with architecture 14-6-9-9-1 produced the best result with average validation and training MAPE of 13.90% and 12.24%.

5. Limitations

This research is intended to develop different ANN models by varying the Hyperparameters of the model. However, due to time and computing limitations, only the number of Hidden Layers and the numbers of neurons in the Hidden layers were varied in this research. The other Hyperparameters such as Learning rate was fixed to 0.001 and activation function was set to Rectified Linear Unit (ReLU) activation. In addition to this, the variation in the number of Hidden layers and number of neurons were also limited. Only upto 3 hidden layers and limited numbers of neurons in the Hidden layers were used. However, future researches may vary other hyperparameters as well and may use deeper networks with more number of Hidden layers and higher number of neurons in the layers which might increase the accuracy of the Model.

Table 7: Average Training and Validation MAPE for different Model Architecture

MA	Validation MAPE	Training MAPE
14-3-1	23.83799639	19.93822661
14-6-1	20.86452842	18.52046041
14-9-1	19.31083703	17.21649122
14-3-3-1	18.7248157	17.60396795
14-3-6-1	16.21118424	12.49380646
14-3-9-1	17.54627428	13.66226378
14-6-6-1	16.61516995	16.83851089
14-6-9-1	15.81517515	12.72706089
14-9-3-1	16.60593391	13.36341393
14-9-6-1	17.39669267	13.99976698
14-3-3-3-1	16.8920104	13.43551178
14-3-6-9-1	17.91851754	14.77164679
14-6-6-9-1	13.8976599	12.24083748
14-6-9-9-1	14.47731528	12.70277743
14-9-9-9-1	14.31424007	12.36532502

Due to limited data availability, data from only 70 Road Contracts were collected where the actual cost of Projects range from around NRs.30 million to 400 million. Moreover, the most Road contracts includes National highway with either gravelling type pavement or Repair and Maintenance type projects. So, the model's prediction may not be better suited to National Highway projects with other categories of Scope of Works and Pavement type. In addition to this, only few contracts with Scope of Works as New Construction works were available which limits capacity of this model to predict with this level of accuracy for New Construction Works.

6. Conclusion

In this study, a cost estimation model for Road Construction Projects in Nepal was developed using Artificial Neural Networks. The identified factors affecting the cost of Road Projects were validated from Expert opinion. After validation, data from 70 completed Road projects were collected accordingly. Regression Analysis with forward selection was performed on the collected data for feature selection which concluded that only 9 variables were significantly affecting the Cost of Road Projects projects in Nepal. The selected nine variables were used for model development. Different ANN models were generated by varying the number of Hidden layers and the numbers of neurons in the Hidden Layers. The models were trained and validated using 10 folds cross validation technique. The selected model with the architecture 14-6-6-9-1 produced least validation MAPE of 13.90% and training MAPE of 12.24%.

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