COST ESTIMATION OF HIGHWAY PROJECTS USING ARTIFICIAL NEURAL NETWORK COUPLED WITH BOOTSRAP & MONTE CARLO SIMULATION

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ABSTRACT

Some applications and mathematical models are limited in simulating the complex behavior of problems. However, various studies have shown how Artificial Neural Network (ANN) has significant benefits and makes it a practical tool for solving complex problems in the field of engineering and construction. Although ANN is a powerful computing system, it has its own limitations. For example, ANN is frequently criticized as being "black box". In addition, ANN does not sufficiently incorporate the effect of the learning curve and the time factor in predicting ongoing operations when objective data like historical data and/or information are at hand. This study aims at coupling ANN with bootstrap (BS) resampling to enhance its performance and prediction capability by taking highway project cost data as a case study. The accrued data were collected from Ethiopian Road Authority's (ERA) Procurement Compilation Report (PCR) and Engineering Report, which contain contract cost data and project related parameters. Monte Carlo Simulation is also utilized to assess the capability of ANN in detecting meaningful differences and thereby increase its ability to detect sensitivity in changes when it really exists. A range of parameters were set at different possible scenarios and the outputs were simulated. The study identified that neural network approach when coupled with bootstrap resampling and simulation provided better prediction. The enhanced models showed a far more consistent performance and produced smaller Mean Absolute Percentage Error (MAPE) of 0.18 in comparison with the standard models (0.20). This approach is crucial for addressing the several parameters that can influence construction project costs and in turn develop close-to-accurate cost models in which the developed model can be applicable in estimating costs for future projects.

Key Words: Artificial Neural Network (ANN), Bootstrap, Monte Carlo simulation, Cost Estimation, Road Project

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1 Introduction

In the construction industry, the successful application of Artificial Neural Network (ANN) can be observed through cost prediction, optimization and scheduling, risk assessment, claims and dispute resolution outcomes and decision making (Pathak, 2014). ANN's are tools of artificial intelligence which have the ability to model data relationships with no need to assume priori equations or formulas which bind the variables. The potential of ANN is shown especially when the relationship between dependent and independent variables are difficult to model using methods such as regression models, making them beneficial in construction where there are various parameters (MichaB et al., 2018). Although, neural networks overcome the main limitations of traditional regression methods, they have a few limitations of their own: lack of interpretability and the need for a strong signal in the data. The lack of interpretability is the basis for the well-known black box objection to neural networks.

Prior studies have shown how Bootstrap (BS) resampling can enhance the performance of neural networks (Ahiaga, 2014). The bootstrap method is a resampling technique used to estimate statistics on a population by iteratively resampling a dataset with replacement. Thus, this study will couple ANN with bootstrap (BS) resampling to enhance its performance and prediction capability by taking Ethiopian Road Authority (ERA) highway project cost data as case study and validating the model through a Monte Carlo simulation. Monte Carlo simulation is utilized to discover the cause and effect relationship between input and output cost variables of the network.

At early project stages, project characteristics might not be decided for certain as project scope is not well-defined. Therefore, the simulation enables a user to see various outcomes and probabilities associated with it, in which the developed model can be applicable in estimating costs for future projects.

1.1 Problem Statement

One of the challenges of using neural networks is the fact that there are no set rules on the nature of the network architecture, number of neurons or layers to use (Ahiaga, 2014). Unlike regression models, whose equation can be easily interpreted, the model exposes neither the algorithms used, nor the exact data sources. The network parameters (i.e. transfer functions, learning rules, network architecture, weights, etc.) do not show casual explanations, making it difficult to elucidate what is learnt from the neural network model. For that reason, it is frequently criticized as being "black box". The model's inner work is unknown to the user and is therefore subjected to suspicion (ISPA, 2008). This has contributed to the slow applicability in the construction industry (Ayed, 1997). In addition, ANN models do not sufficiently incorporate the effect of the learning curve and the time factor in predicting ongoing operations when the final model outputs are used to analyze the dynamic and stochastic behavior of construction (Kisi, 2015). Therefore, one potential means is to couple neural network with other mathematical procedures to maintain its credibility (Roxas, 2014).

1.2 Research objective

The objective of the study is to improve ANN method by coupling it with Bootstrap resam

pling and Mote Carlo Simulation using actual highway project data of ERA in estimating project costs.

2. Methodology: Quasi-Experimental design

The architectural layout of the ANN model followed a pre-experimental approach (a quasi-experimental research design (Thyer, 2016) through collection of specific cost data from Ethiopian Roads Authority (ERA). The accrued data came from ERA's Procurement Compilation Report (PCR) and Engineering Report, which contained contract cost and corresponding parameters. The PCR provided summarized information on a specific highway project, which includes project information, procurement selection method, process of the contract award and other relevant information of the procurement process. Likewise, the Engineering Report portrays key features of the road project. It gives a brief description of the project area, its intended scope of work, etc. The data were originally archived data that made the approach fast and low-cost to (Bärnighausen, 2017).

However, this approach is seriously limited in such a way, without any systematic assessment of the pre-existing data before the intervention, it makes it logically difficult to make any legitimate inferences regarding whether the training set receiving treatment actually had changed. Besides, the independent variables are selected from pre-existing values and not created through manipulation by the researcher, which is attributed for the lower levels of control over the study (Arthur, 2013).

To tackle this problem, Thyer (2016) has put forward some measures to strengthen the internal validity. The first suggestion is to use several different outcome measures that are

reliable and valid. However, one method that judges the best in a uni-dimension is not necessarily the best in terms of other dimensions (Guoqiang, 1998). Because of the limitations associated with each individual measure, multiple performance measures were implemented in this problem. Thus, six different performance measures were adopted to quantify the reliability and the validity of the trained model.

Thyer (2016) also recommends the incorporation of measures that are capable of detecting meaningful differences and changes in lieu of surveys or rating scales. To accommodate this, the use of larger sample sizes increases the ability to detect true differences or changes when they really exist. The mathematical procedure known as bootstrap resampling was one approach that facilitated this intention. Sensitivity analysis was also applied to calibrate the magnitude of each input parameters that were listed in the model using Monte Carlo Simulation technique.

3. Discussion of results

ERA's highway project from 2016-2019 (three years data) was used as objective data for training the model in predicting the cost estimates. To check and prove whether the models are good and the predicted values from the forecast models fit in forecasting future projects, a technique called bootstrap (BS) is used. In addition, in parametric cost estimating models, it is difficult to decide which parameters to measure and how to evaluate their significance to the model (Ayed, 1997). Such uncertainty can be accounted for by conducting a sensitivity analysis. Thus, this study adopted ANN to build a cost estimation model for highway projects

by combining it with Bootstrap and

Monte Carlo Simulation technique to enhance the estimation accuracy of a standard ANN cost model. The developed model evaluates several independent variables in highway projects to recognize the influential parameters in construction cost prediction of road projects.

The primary task in the respective model development was collecting all types of road construction project data. The PCR documents for highway projects, where summarized aspect of the road projects were presented, allowed for collecting 40 projects. After the actual data training stage, the results achieved were then evaluated and presented in a meaningful form to aid decision-making. To implement the study design, the data was first transformed into numerical values and stored in a data-list. The data pertaining to the input parameters for all projects were then entered into a spreadsheet program (Microsoft Excel) and further transformed into numerical values. Accordingly, a three-layer Neural Network was simulated on a spreadsheet format that was easy to use, transparent, and customary to many practitioners in construction

3.1 Training outcomes for the standard ANN model

As mentioned in the previous section, the study adopted six relative measures of accuracy dealing with percentage errors to compute forecasting results of the cost model. After several trials, a network structure with hyperbolic tangent (TANH) activation function on all layers (Model 1 :TANH-TANH) was found to be the best model to estimate the total cost of road projects having an excellent performance on both the training and test cases.

This model was trained using offline (Batch) training and consists of an input layer with 9 nodes, an output layer with 1 node and hidden layer with 8 nodes. "9 nodes" represents the road parameters identified from the sample case studies taken from ERA. These parameters are "Location", "Region", "Class", "Type of project", "Length", "Geometric design standard", "Duration" and "Base year". The remaining one node is the output node which represents "cost of a project" in Ethiopian Birr (ETB).

As shown in Table 1, "Model 1 :TANH-TANH" obtained a satisfactory correlation coefficient, R, values of 0.85 for testing phases. The resulting MAPE of the model is equal to 0.20, which is the smallest value among the entire model tested. It has been shown from the results that the model performs well and no significant difference could be discerned between the estimated output and the desired budget value. An average accuracy of 80% was achieved.

Table 1: Performance Result of Different ANN Models

Model Name	Stopping Iteration Point	Mean Absolute Error (MAE)	Mean Square Error (MSE)	Mean Percentage Error (MPE)	Mean Absolute Perc. Error (MAPE)	Total Accuracy Performance (TAP)	Pearson Correlation
Model 1 :TANH-TANH	14,710	0.242	0.111	-0.085	0.201	0.799	0.850
Model: Mini-Batch 1	1,712	0.408	0.278	-0.103	0.391	0.609	0.577
Model Mini-Batch 2	20,575	0.325	0.215	-0.077	0.369	0.631	0.703
Model Mini-Batch 3	13,450	0.308	0.163	-0.026	0.258	0.742	0.796
Model Mini-Batch 4	48,162	0.886	1.089	0.014	0.886	0.114	0.091
Model Mini-Batch 5	32,045	0.882	1.135	0.379	0.664	0.336	0.050
Model: Mini-Batch 6	48,162	0.505	0.342	-0.016	0.456	0.544	0.571
Model: Mini-Batch 7	19,593	0.879	1.093	0.480	0.606	0.394	0.214
Model 2: Random	304	0.173	-0.202	0.367	0.633	0.701	

3.2 Coupling Bootstrap with the standard ANN model

In this study, the introduction of BS method in the standard ANN cost estimating model has shown to improve the model performance. This involved designating the original dataset to act as the population, then randomly re-sampling it a specific number of times to generate a large number of new samples. A different combination of new sub-samples was then used each time for making simulation on the model before averaging the model performance across the samples. This helped to glean as much information as possible from the entire dataset. 2000 different training, BS sample sets were generated by perturbing the entire dataset for each model using sampling with replacement over a uniform probability distribution. This should ensure that as many information as possible get excavated from the available data.

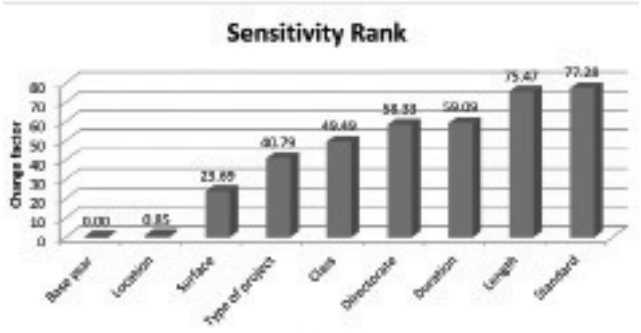
The bootstrapped models showed a far more consistent performance and produced smaller MAPE (0.18) in comparison with the standard models (0.20). It becomes obvious then that the bootstrapped models outperform the standard models. This performance improvement can be attributed to the fact that by using the 2000 bootstrapped sub samples afforded the models a wider learning space than the standard models. Thus, developing a stochastic and point estimating model with the same set of data has become apparent that: the integration of ANN with other soft computing method can indicate a better result when compared with conventional ANNs. Likewise, bootstrap sampling combined with-artificial neural networks is proven as a suitable method to produce a range estimate for highway Projects (Table 2).

Table 2: Range Estimates (Confidence Interval for 2000 BS) in thousand ETB

Test Project Cases	Standard ANN Output	MAX	Confidence Interval				MIN	Actual
			95%	80%	10%	5%		
1	1,462.90	1,669.98	1,483.36	1,479.80	1,442.62	1,439.06	1,268.02	1,193.16
2	473.86	680.95	494.33	490.77	453.59	450.03	278.99	449.72
3	1,462.89	1,669.98	1,483.36	1,479.79	1,442.62	1,439.06	1,268.02	1,580.65
4	473.72	680.80	494.18	490.62	453.44	449.88	278.84	1,159.85
5	1,463.24	1,670.33	1,483.71	1,480.14	1,442.97	1,439.41	1,268.37	1,578.62
6	473.72	680.80	494.18	490.62	453.44	449.88	278.84	421.63
7	473.72	680.80	494.18	490.62	453.44	449.88	278.84	542.49
8	1,462.89	1,669.98	1,483.36	1,479.79	1,442.62	1,439.06	1,268.02	1,835.77
9	1,462.89	1,669.98	1,483.36	1,479.79	1,442.62	1,439.06	1,268.02	1,325.19
10	1,462.89	1,669.98	1,483.36	1,479.79	1,442.62	1,439.06	1,268.02	1,615.64
11	1,462.90	1,669.98	1,483.36	1,479.80	1,442.62	1,439.06	1,268.02	1,593.43
12	1,462.90	1,669.98	1,483.36	1,479.80	1,442.62	1,439.06	1,268.02	2,142.00

3.3 Monte Carlo Simulation Result

The basic concept in conducting the simulation is to capture a meaningful difference when the parameters in the model are shifted slightly by some factor and the corresponding change in the output is reported. The sensitivity of the best model predictions were assessed by variation in the project parameters. Random variations were introduced only in the parameters that the user selects and the sensitivity analysis was conducted by Monte Carlo Simulation. In order not to introduce impractical scenarios into the sensitivity analysis, random variations were limited to a range that is bounded by the maximum and minimum limits. The simulation result is presented in Figure 1.



The sensitivity analysis exhibits that the three independent variables, i.e. Duration, Geometric standard and Length with a change factor of 59.09, 77.27 and 75.46 respectively, represents the highest sensitivity in the analysis. Base year, with a change factor of 0, and location, with a change factor of 0.85, are less significant to actually bring an effect in the developed cost estimation model.

In summary, from prior literature reviews made (Jamous, 2013); Region, Functional class, Geometric design standard and road length are the most frequent parameters used for model development. As expected, these parameters are among the most five top influential parameters which brought a significant change in the performance of the model. Also, just like demonstrated in the Monte Carlo simulation result, project commencement year is seldom used in model development. Hence, the characteristics mentioned in the PCR and engineering report of ERA projects, they closely match with common descriptors of highway projects.

4 Conclusions

Although ANN is a powerful structure, it also comes with some limitations. To keep the internal validity of the experimental design intact, the incorporation of measures that are capable of detecting meaningful differences and changes are highly recommended. This study couples ANN with other mathematical procedures to improve the predictability using case study of highway project cost estimation.

In this study, Bootstrap method is used together with ANN to make project cost predictions especially when a desirable property of the results from estimating can be presented with confidence intervals, a feature not readily available within ANN its self (Table 3).

Table 3: Performance measure of the enhanced ANN model

Performance	MAE	MSE	MPE	MAPE	TAP	Angle difference
BS Model	0.25	0.119	-0.055	**0.189**	0.81	0.849
Standard ANN Model	0.242	0.11	-0.084	**0.201**	0.798	0.849

It is apparent that the point estimate results provide no rational means to assign an individual contingency for each project. Thus, the point estimate provides no improvement to the current state-of-the-practice for assigning contingency. Producing a stochastic estimate visually aided the comparison of expected construction costs for various projects. Hence, a certain contingency premium is added to the base estimate to increase the level of confidence developing a stochastic and point estimating model with the same set of data.

In addition, to evaluate highway project descriptors at inception stage where uncertainties are high, the probability associated with each input were easily outlined by powerful simulation technique. Monte Carlo simulation, in this perspective, helped to assess the risk of undesirable outcomes and the likelihood of desirable outcomes with a piece of historical information at hand (Table 4).

Table 4: Influence rank of input parameters

Rank(from Less sensitive to most sensitive	% Change	Input
1	0.000	Base year
2	0.854	Location
3	23.693	Surface
4	40.790	Type of project
5	49.493	Class
6	58.332	Region
7	59.094	Duration
8	75.468	Length
9	77.277	Standard

This procedure entails the arrangement and representation of the descriptive factors and their associated influence, as required by Neural Network modeling.

5 Recommendation for further studies

While tangible outcomes that indicated ANN based cost prediction can be improved by combining ANN with Bootstrap and Simulations have been achieved from this work, there are key issues that need to be addressed for application in real life context. The following points can be areas of study by which interested researchers could focus.

- The input parameters used in this work are not investigated for external risk that could arise from the dynamic construction environment. The reason is that ANNs is suitable to measure how well, rather than understand the why of a phenomenon. Further research in this area could focus on time-series prediction via ANN to incorporate and withstand the fluctuating nature of construction.
- The stochastic results produced for the standard ANN model was completed manually for 2000 iterations due to time constraint and operational capacity of the computer processer. Future research would conduct more than 2000 iterations of the stochastic estimating method to combine the ANN modeling with bootstrap sampling.

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