An artificial neural network (ANN) approach for early cost estimation of concrete bridge systems in developing countries: the case of Sri Lanka

Nirodha Fernando
School of Computing, Engineering and the Built Environment, Edinburgh Napier University – Merchiston Campus, Edinburgh, UK

Kasun Dilshan T.A.
Tudawe Brothers (Private) Limited, Colombo, Sri Lanka, and

Hexin (Johnson) Zhang
School of Computing, Engineering and the Built Environment, Edinburgh Napier University – Merchiston Campus, Edinburgh, UK

Abstract

Purpose – The Government's investment in infrastructure projects is considerably high, especially in bridge construction projects. Government authorities must establish an initial forecasted budget to have transparency in transactions. Early cost estimating is challenging for Quantity Surveyors due to incomplete project details at the initial stage and the unavailability of standard cost estimating techniques for bridge projects. To mitigate the difficulties in the traditional preliminary cost estimating methods, there is a requirement to develop a new initial cost estimating model which is accurate, user friendly and straightforward. The research was carried out in Sri Lanka, and this paper aims to develop the artificial neural network (ANN) model for an early cost estimate of concrete bridge systems.

Design/methodology/approach – The construction cost data of 30 concrete bridge projects which are in Sri Lanka constructed within the past ten years were trained and tested to develop an ANN cost model. Backpropagation technique was used to identify the number of hidden layers, iteration and momentum for optimum neural network architectures.

Findings – An ANN cost model was developed, furnishing the best result since it succeeded with around 90% validation accuracy. It created a cost estimation model for the public sector as an accurate, heuristic, flexible and efficient technique.

Originality/value – The research contributes to the current body of knowledge by providing the most accurate early-stage cost estimate for the concrete bridge systems in Sri Lanka. In addition, the research findings would be helpful for stakeholders and policymakers to propose policy recommendations that positively influence the prediction of the most accurate cost estimate for concrete bridge construction projects in Sri Lanka and other developing countries.

Keywords Artificial neural network, Concrete bridge project, Early-stage cost estimating, Cost estimating models

Paper type Research paper

1. Introduction

Bridge structures, railways and urban roads play essential roles in the economy, politics, culture and national defence (Weiwei and Yoda, 2017). Bridges are also one of the imperative public infrastructure projects in any country (Ongkowijoyo et al., 2021). According to the Oxford Dictionary, "a bridge structure is built over a road, railway, river, etc., so that people, vehicles, etc. can cross from one side to the other". Accordingly, the bridge is essential to enable, sustain and improve community living conditions and economic stability in any country (Ongkowijoyo et al., 2021). Building bridges in various sectors is rapid in every country, whether public or private institutions fund it (Ongkowijoyo et al., 2021). All major infrastructure bridges are built with the public's money (Ketterer and Powell, 2018). Hence, the bridge's design must best serve the public interest regarding efficiency, economics and elegance (Billington et al., 2023).

Sri Lanka is a developing, lower-middle-income country with a dynamic economy (OCED, 2023). Despite challenges relating to the availability of labour and importation of construction materials caused by the COVID-19 pandemic, the Government of Sri Lanka persistently continued to reinforce the road and infrastructure projects of the country to ensure improved urban–rural linkages and thereby reinforce inclusive growth (Central Bank of Sri Lanka, 2021). There is uncertainty about the success of large-scale bridge construction projects in terms of project aspects such as cost, time and quality (Mahamid, 2013; Gohar et al., 2012). Furthermore, public sector transportation funding is limited, and cost increases on one project lead to reduced funding for other projects (Odeck, 2014). Hence, completing the infrastructure project on the allocated budget is vital. Bridge construction often substantially overruns the estimated cost (Fragkakis et al., 2010) due to a longer life span and is subject to a certain level of uncertainty regarding demand forecasting and cost estimations (Bruzelius et al., 2002) and their cost, a high level of public attention or political interest is also involved (Greiman, 2013), increased complexity and a considerable impact on the economy, society and the environment (Locatelli et al., 2017). Furthermore, the main problem in the estimation of infrastructure project costs is a significant deviation between the estimated costs and the actual construction cost due to intentional underestimation in the initial project phases, when the costs are evaluated to decide whether the transport infrastructure should be built (Kovacevic et al., 2021). In most projects, actual costs were significantly higher than initially estimated, e.g. 34% higher on average for bridges and tunnels (Flyvbjerg et al., 2002). Although this underestimation is not an error, it is prone to subjectivity and may introduce biases in decision-making (Flyvbjerg et al., 2002). Therefore, being able to forecast these costs objectively is highly desirable. Because most of the major bridges are funded by the Sri Lankan government, the Cabinet of Parliament in Sri Lanka should approve the budget allocation for infrastructure projects. To overcome this problem, professionals must prepare an early estimate of the final cost based on previous experience (Fragkakis et al., 2010). Accordingly, predicting construction costs is one of the most important preliminary steps in any construction project because cost prediction is crucial to avoid construction delays and ensuring successful project completion (Elfaki et al., 2014).

Literature shows that many studies focused on cost prediction models for building (Ji S-H et al .2019; Qian and Ben-Arieh,2008; Hegazy and Ayed,1998; Elfaki et al., 2014; Jiang, 2019; Khalaf et al., 2020; Chandanshive and Kambekar, 2019) and a few studies conducted to predict the cost on infrastructure projects in early stage (Wang,2017; Du Z, Li B (2017); Amin M (2017); El-Sawalhi and Shehatto,2014)). However, a few studies have been conducted on estimating bridge maintenance and repair costs using ANN techniques and not the initial cost of the bridge (Bouabaz and Hamami, 2008). Also, Kim and Kim (2010) researched to estimate the bridge's cost. They applied case-based reasoning (CBR)and genetic algorithms (GA) for cost estimation of bridge construction projects rather than ANN. Also, he conducted another research to investigate the effect of GA on optimising CBR attribute weights for estimating the cost of railway bridge projects (Kim, 2011). However, research still needs to concentrate on the cost prediction of bridge construction projects using the ANN model. The current practice to estimate the early-stage cost of the bridge in Sri Lanka is to determine the initial cost based on the Per running meter of span depending upon the structure, type, and foundation depth (Ranasinghe, 2019). This technique's accuracy is limited due to unpredictable, unforeseen situations at the construction stage (Oladokun et al., 2013). Accordingly, this research aims to develop the ANN prediction model to predict the estimated cost of a bridge construction project at an early stage in Sri Lanka. The study assesses the most accurate cost of the concrete structure bridge project in Sri Lanka at the early stage. In addition, the research findings would benefit policymakers and government organisations in arriving at the most accurate cost estimate at the early stage of the bridge construction project, which helps apply for funding approval through the parliaments of Sri Lanka. In return, the public would benefit from having completed the bridge construction project due to utilising accurately allocated funding for the project and to minimise halting the project due to exceeding the approved budget. The research findings would be helpful for stakeholders and policymakers to propose policy recommendations that positively influence the prediction of the most accurate cost estimate for concrete bridge construction projects in Sri Lanka and other developing countries.

2. Literature review

Public expenditure on infrastructure development in Sri Lanka on roads and bridges accounted for US$1,906.1m in 2021, 23.9% of the total infrastructure allocation (Ministry of Finance, 2020). The Ministry of Finance aims to maintain public investment at an average of 5%–6% of the GDP annually till 2025. Around 24% of the foreign financing is expected to be disbursed during the next two to five years for the road and bridges sector in Sri Lanka (Ministry of Finance, 2021). According to the National Road Master Plan (NRMP), 2018–2027, published by the Road Development Authority (2018), a total of 37 weak and narrow bridges have been selected for reconstruction under the NRMP with the final assistance of The Japan International Cooperation Agency. According to Public Finance (2021), LKR 27.1bn was allocated in the 2021 Sri Lankan government budget to the construction of new bridges, including the new Kelani Bridge (LKR 15.5bn), design and construction of flyover and bridge Kohuwala and Gatambe (LKR 4.4bn) and construction of flyovers for over railway line (LKR 3.2bn). Accordingly, Sri Lankan government investments in public sector infrastructure projects are at a considerable level. Also, estimating bridge construction costs is an increasing necessity for accurate budgeting and effective funding allocation (Markiz and Jrade, 2022). The success of any construction project is evaluated based on the level of closeness between the actual and estimated costs (Markiz and Jrade, 2022). Hence, the government needs an effective cost-estimating process before the cabinet approval because most infrastructure projects are done with foreign funds in developing countries (Raymond, 2008). According to the literature, the government must estimate the cost of getting funds from foreign funding sources. An accurate early-stage cost estimate is vital to get more done with existing resources, use taxpayers' money more efficiently and make infrastructure projects more attractive to private investors (Bisbey et al., 2020). Construction costs and time involved in bridge construction are high (Lee et al., 2004); transactions should be transparent due to their taxpayers' money (Bisbey et al., 2020). The lack of adequate project preparation budget and skills is widespread in developing countries (Hurley et al., 2019). Therefore, there is the possibility of cost overrun during construction. To avoid the effect of cost overrun, an accurate early-stage cost estimate should be established before construction (Flyvbjerg et al.,2004; Elmousalami, 2020). It shall prevent the suspension or termination of the project during its construction (Elmousalami, 2020). Concerning bridge construction, the preliminary cost estimation technique is paramount for project success (Kim et al., 2004; Markiz and Jrade, 2022). Previous researchers made many attempts to predict the early-stage cost estimate for infrastructure projects, which includes bridge construction, and different approaches were used to indicate the cost estimate. Table 1 illustrates various studies that used different approaches to predict the early cost estimate for infrastructure projects.

Table 1: Summary of previous studies on cost prediction in infrastructure projects

Source	Area of cost prediction	Methods used
Hegazy, T., & Ayed, A. (1998)	Highway construction costs	ANN Backpropagation, simplex optimisation and Genetic Algorithm (GA)
Marcous, G., Bakhoum, M.M., Taha, M.A., El-Said, M.(2001)	Prediction of the volume of concrete and the weight of prestressing steel in the bridge superstructure	ANN with a backpropagation learning algorithm
Mostafa, E.M. (2003)	Estimation of the costs of bridges and culverts	Multiple Regression Analysis
Cheng, M.Y., & Wu, Y.W. (2005)	Prediction of building cost	Support Vector Machines (SVM)
Sodikov J (2005)	Cost estimation of highway projects	ANN
Wilmot CG, & Mei B (2005)	Forecasting highway construction cost	Neural Network Model and regression-based model
Bouabaz M, & Hamami M (2008)	A cost estimation model for repairing bridges	ANN
Kim, K.Y., & Kim, K.(2010)	Preliminary cost estimations for the bridge project	Case-Based Reasoning (CBR) and GA
Fragkakis, N., Lambropoulos, S., Tsiambaos, G. (2011)	Prediction model for bridge foundation costs that predicted material quantities for various types of foundations and estimated the total foundation costs	Backward Stepwise Regression
Kim B.S. (2011)	The approximate cost estimation model for the railway bridge project	CBR method
Cirilovic, J., Vajdic, N., Mladenovic, G., Queiroz, C.(2013)	Prediction models for the unit costs of road reconstruction work	Multiple Regression Analysis and ANNs
Pesko, I., Trivunic, M., Cirovic, G., Mucenski, V.(2013)	Estimation of traffic infrastructure reconstruction costs	ANN
Hollar, D.A., Rasdorf, W., Liu, M., Hummer, J.E., Arocho, I.M. (2013)	The preliminary cost of engineering bridges	Multiple Regression Analysis
Elfaki, A.O., Alatawi, S., Abushandi, E.(2014)	Estimation of construction costs of buildings	Machine Learning, Rule-based Systems, Evolutionary Systems,

		Agent-based systems, and Hybrid Systems
Chou, J.S., Lin, C.W., Pham, A.D., Shao, J.Y.(2015)	Prediction of bid prices for bridge construction projects	Multiple Regression Analysis, CBR and ANNs
Gunduz M, & Sahin H.B. (2015)	An early cost estimation model for hydroelectric power plant projects	ANN
Marinelli, M., Dimitriou, L., Fragkakis, N., Lambropoulos, S(2015)	Estimation of concrete road bridges' Superstructure	ANN
Mahalakshmi G, & Rajasekaran C (2019)	Early cost estimation of highway projects	ANN
Tijanić K, Car-Pušić D, Šperac M (2020)	Cost estimation in road construction	ANN Multi-Layer Perceptron (MLP), General Regression Neural Network (GRNN)
Nizar Markiz & Ahmad Jrade (2022)	Cost estimation and linear scheduling at the conceptual design stage of bridge projects	Expert system with Bridge Information Management System (BrIMS)

Source: Hegazy and Ayed (1998); Marcous et al., (2001); Mostafa (2003) ;Cheng and Wu (2005); Sodikov (2005); Wilmot and Mei (2005); Bouabaz and Hamami (2008); Kim and Kim (2010); Fragkakis et al., (2011); Kim (2011); Cirilovic (2013); Pesko et al., (2013); Hollar et al., (2013); Elfaki et al., (2014); Chou et al., (2015); Gunduz and Sahin (2015); Marinelli et al., (2015); Mahalakshmi and Rajasekaran (2019); Tijanic et al., (2020) and Markiz and Jrade (2022)

Previous studies have adopted ANN, linear regression and hybrid models for anticipating the early-stage cost estimate of infrastructure projects. On the other hand, artificial intelligence and machine learning tools offer capabilities, such as learning from experience and knowledge generalisation, which make them applicable for early cost estimation models (Juszczyk, 2019). Furthermore, Al-Zwainy and Aidan (2017) highlighted that to develop the most accurate early-stage cost estimate applying artificial intelligence such as ANN and support vector machine is an effective tool to use. Especially for bridge projects, developing such models is supposed to accurately provide early estimates or forecasts of the final cost (Juszczyk, 2019). According to Wegener et al. (2016) and Karasu et al. (2017), neural networks could generate high accuracy across various forecasting circumstances. Also, the latest studies conducted by Xu and Zhang (2022a), Xu and Zhang (2022b) and Xu and Zhang (2022c) used a neural network approach to predict not only building cost but also to predict Canola and soybean oil price, the high-frequency CSI300 first distant futures trading volume and Steel price index forecasting. Neural network prediction model benefit from neural networks' capabilities of self-learning for forecasts and capturing non-linear characteristics data (Xu and Zhang (2022b). Hence, using ANN techniques for the cost prediction methods would provide the most accurate prediction among other techniques. However, although some previous studies used ANN to predict the early-stage cost of infrastructure projects, there are still limited studies to predict the cost of bridge construction projects at the early stage in a developing country like Sri Lanka. Therefore, the current research adopting ANN to develop the early cost estimation prediction model for bridge projects in Sri Lanka was carried out to address the identified literature gap.

3. Research design

To achieve the aim of the study, the research was designed sequentially, as depicted in Figure 1. The research followed three steps: The first step: this step aimed at identifying the most cost-significant items in the concrete bridge construction projects.

	Methodology	The Purpose of Use Method	Analysis
Step 1	Semi-structured Interviews	To identify the most cost-significant items in Bridge Construction.	Content analysis to further confirmation of literature findings.
		↓	
Step 2	Document Review	To develop a cost model for a concrete bridge in Sri Lanka	Statistical data analysis to develop a cost model
		↓	
Step 3	Validate the ANN model		

Figure 1:Research process

The second step: in this step, past concrete bridge cost data was collected, and statistical analysis was done to develop the ANN model. Such adaptations are proposed by Elbeltagi et al. (2014). Finally, the third step is to validate the ANN model using completed concrete bridge cost data to estimate the cost deviation based on the actual and prediction.

3.1 Interviews

The interviewees' selection was conducted using the purposive sampling technique. This technique allows researchers to choose interviewees based on their judgements to address research questions (Saunders et al., 2011). As a result, seven professionals having experience in bridge construction projects in Sri Lanka were selected to participate in interviews to identify the costliest components in the bridge construction projects. The profiles of the interviewees are presented in Table 2.

Table 2: Profile of interviewees

Interviewee Code	**Designation**	**Experience (Years)**	**Currently working Organization (Consultant/ Contractor/ Employer)**
QS/01	Senior Quantity Surveyor	13 Years	Consultant Organization
QS/02	Senior Quantity Surveyor	21 Years	Consultant Organization
CE/01	Cost Estimator	20 Years	Consultant Organization
CMS/01	Contact Management Specialist	18 Years	Consultant Organization
QS/03	Senior Quantity Surveyor	20 Years	Consultant Organization

QS/04	Chief Quantity Surveyor	14 Years	Contractor Organization
SDE/01	Senior Design Engineer	15 Years	Employer (Bridge Design Team - Road Development Authority)

Table 2 shows that most interviewees hold essential roles in their organisations and have over ten years of experience in bridge projects. This ensures the reliability of interview data in identifying the costliest components in bridge construction. Qualitative data from interviews were analysed using content analysis to determine the expensive items that apply to the bridge construction in Sri Lanka. Accordingly, based on professionals' opinions, four expensive main components of sub-structure and superstructure were identified as listed in Table 3. This cost-significant component is used to development of the ANN model.

Table 3: Cost significant components in brides

Costly main components in the Substructure of the bridge	Expensive main features in the Superstructure of the bridge
• Piling work	• Concrete Slab
• Pire	• Bridge Paving
• Abutment	• Bridge Furniture
• Pre-stressed Beams	• Miscellaneous

3.2 Document reviews

The document review technique collects secondary data by referring to the existing documents. Accordingly, Creswell (2014) stated that document review records might be public or private, written or electronic-based copies. The utmost caution was taken to ensure the confidentiality of the records when reviewing documents related to the cost data, as evidenced by Creswell (2014). Required permission has been taken to review the cost data documents such as BOQ, final accounts, cost plans, cost analysis and drawings of past bridge construction projects. As a result, 30 project cost data have been collected. The 21 total vital parameters (i.e. independent variables of the bridge construction) for the input layer were selected from the analysis of documents review to evaluate the output data (i.e. the cost of the structural systems per linear meter), as shown in Table 4.

Table 4: Independent and Dependent Variables of the Cost Model

Element	**Independent Variable**	**Data Range**	**Dependent Variable**	**Data Range (LKR)**
Piling Work	Pile length (m)	167- 398 m	Cost of piling work	25,370,128 - 97,235,534

	No of Pile cap (nr)	3-4 nr		
Piers	Pier length (m)	7-9m	Cost of piers	3,262,976 - 4,872,751
	Pier width (m)	1-2m		
	Pier height (m)	6-10m		
	No of piers (nr)	1-2 nr		
Abutments	Abutment wall Centre line girth (m)	15-38m	Cost of abutments	4,635,544-14,576,857
	Abutment wall height (m)	4-8m		
	Abutment wall width (m)	0.5m-1m		
Pre-stressed Beams	Beam span (m)	10-20m	Cost of pre-stressed beams	3,798,301-26,159,352
	Beam height (mm)	380-850mm		
	Beam width (mm)	400mm		
	No of beams (nr)	30-57nr		
Concrete Slab	Slab length (m)	20-73m	Cost of concrete slab	3,282,737-16,076,240
	Slab width (m)	6-8m		
	Slab thickness (mm)	200-300mm		
Bridge Paving	Paving length (m)	20-73m	Cost of bridge paving	368,724-1,220,407
	Paving width (m)	6-8m		
Bridge Furniture	Bridge length (m)	20-73m	Cost of bridge furniture	618,339-2,277,383
Miscellaneous	Bridge length (m)	20-73m	Cost of miscellaneous	121,949-403,628
	Bridge width (m)	6-8m		

Develop Neural Network with Neuroph Studio – The model has been developed into six phases, as shown in Figure 2.

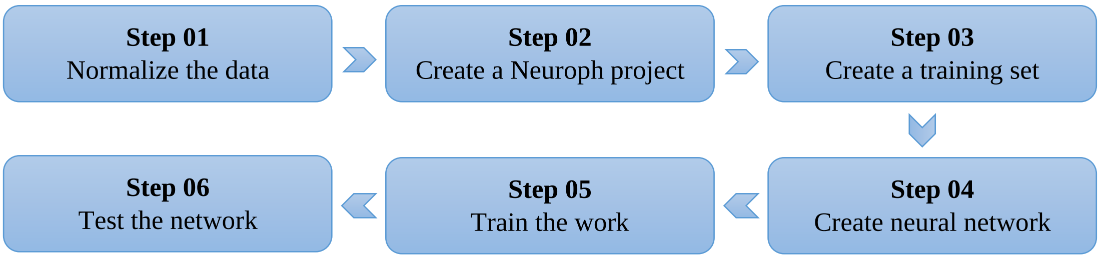


Figure 2: Steps to train Neural Network
Source: Gunaydin and Dogan (2004)

Step 01 – Data Normalisation

Data normalisation involves adjusting the data set depending on the location and time. According to the opinions, location only affects the cost of the selected projects in Sri Lanka; adjustment for the location was not required. Though bridge projects were initiated in different years during the ten years, time adjustment was essential for data normalisation. To normalise the collected da, the following equation has been used:

$$\mathbf{A_t = A\left[\frac{I_c - I_b}{I_b} + 1\right]}$$

A_t - Time adjusted sub-element amount.
A - Sub-element amount before time adjustment
I_c - Current index published by CIDA (Construction Industry Development Authority, Sri Lanka) (current index for first Quarter 2021)
I_b - Base index

To train a neural, The data set had to be normalised to train a neural network from 0 to 1. The following formula was used for normalising the data set.

$$\mathbf{X_n = \frac{X - X_{min}}{X_{max} - X_{min}}}$$

X_n - Normalized sub-element amount
X - Sub element amount before normalisation
X_{min} - Minimum value of X
X_{max} - Maximum value of X

Step 02 – Create a Neuroph project

A project name can be given (i.e. Piling Works), and select a suitable project location to save the file. Then, by clicking on the 'Finish' button, the new Neuroph project was created.

Step 03 – Create a Training set.

A new training data set can be created by clicking on the new project and selecting 'New' and 'Training set'. Then, the name for the data set and type was chosen as 'Supervised' training. Supervised training was selected to minimise error prediction through an iterative procedure and the most common way of data training in a neural network. Supervised training can succeed by giving sample data to the neural network and anticipating outputs from each data set. Then, that sample would be collected data using an MS Excel database. In the supervised training procedure, the neural network was taken through several iterations until the neural network matched the anticipated output with a low error rate.

Step 04 – Creating a Neural Network

To create a first neural network, right-click the project in the 'Projects' window and then click 'New' and 'Neural Network'. First, the project's name and network must be entered into the wizard. Multi-layer perceptron was used since it is the most widely used neural network classifier. It can model complex functions, is robust (ignore irrelevant inputs and noise), and adapt its weights and/or topology in response to environmental changes. As well as the multi-layer perceptron is easy to understand; it implements a black-box point of view and can be used with little knowledge about the relationship of the function to be modelled.

After selecting the network file type, click the 'Next' button, which is directed to a new window, where some more parameters must be set. The number of inputs and outputs is the

same in several inputs and the number of results in training the data set. After that, several hidden layers and the number of neurons had to be selected.
In the next window, tick ‘Use Bias Neurons’ and ‘Sigmoid’ as a transfer function. ‘Backpropagation with Momentum’ was chosen as a learning rule since it is the most commonly used technique and one of the more accurate techniques. Momentum is added to the backpropagation since it improves the algorithm’s efficiency.

Step 05 – Training the Neural Network
Once create a neural network, it needs to train with the training data set. First, select the training data set and click ‘Train’. Then a new window appeared, which had to set learning parameters. The maximum error was entered as 0.01, and several architectures were trained using different learning rates and momentums. The learning rate is the size of the ‘step’ the algorithm will take when minimising the error function in an iterative process, changing the error in respect of every iteration.

Step 06 – Testing the Neural Network
The same neural network has to be tested by clicking the test button. Every data set's Mean Square Error (MSE) will appear in the next window. The optimum neural network, which gives minimum MSE, must be selected from several neural networks.

4. Research findings

The main elements of a concrete bridge, dependent and independent variables, were identified during the interviews, as shown in Table 4. Separate neural networks were created for each bridge component, and the data set identified through document review was trained and tested within each neural network. Each aspect was introduced and experimented with different hidden layers, momentums and learning rates. Accordingly, the tested and trained results were presented and discussed for each element separately (Figure 3).

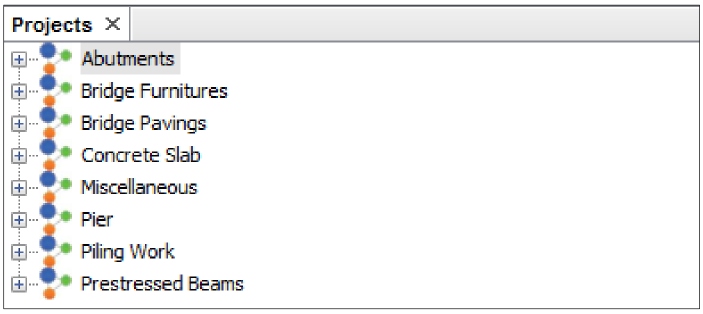


Figure 3: Neuroph Project for Data Analysis

Piling Work
The preliminary cost estimate for piling works includes the cost of the following items in the concrete bridge construction.

- Auguring for in-situ bored piles.
- Reinforcement for bored piles.
- Concrete for bored piles.
- Pile hacking.

- Pile testing.
- Concrete for pile caps.
- Reinforcement for pile caps.
- Formwork for pile caps.
- Additional borehole testing.
- Concrete screed for pile caps.

Seven NN architectures were created and trained to obtain optimum NN for piling works, as shown in Table . One to four hidden layers were tested, while the number of inputs and outputs of the NN was two and one, respectively. All the training attempt's learning rates were between 0.1 to 0.3, and momentum was 0.6 to 0.8. Training attempt 5 was successful, as shown in Table 5, with three hidden layers, 0.2 learning rate, 0.7 momentum and 0.0246 minimum MSE.

Table 5: Neural Network Training Result for Piling Work

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	2	1	1	0.2	0.7	10000	0.0499
02	2	1	2	0.1	0.6	10000	0.0310
03	2	1	2	0.2	0.7	10000	0.0289
04	2	1	3	0.1	0.6	10000	0.0301
05	2	1	3	0.2	0.7	10000	0.0246
06	2	1	4	0.1	0.6	10000	0.0287
07	2	1	3	0.3	0.8	10000	0.0334

The selected data set that was trained had only pile foundations and identified two bridges that bared higher cost than the other bridges. Therefore, those two projects were disregarded to gain the accuracy of the cost model. Accordingly, it is recommended that this cost model be used for the concrete pile foundation. With time, more than 50% of the total cost of most bridges was apportioned to the piling work construction, according to the data set. The cost of piling works in a concrete bridge covers nearly ten sub-items mentioned above. Therefore, it took time to identify the relationship between the inputs and the output and challenging to create the optimum neural network architecture for the piling works. For example, a pile foundation's length was drastically changed according to the site conditions. Most bridges constructed to create the neural network cost model were across the rivers. Therefore, there was a high possibility of changing the soil condition location. Most of the time superstructure of the bridges was altered according to the site condition. Hence, it was tough to identify the relationship between the parameters of the piling works. Though 30 project data were trained and tested, insufficient data affected the accurate output of the cost model. Cost of constriction of cofferdams and cost of detraining was excluded from the trained data, and output shall give accordingly. Because the construction of cofferdams and dewatering were allocated lump sum prices in the estimates, those costs were highly unpredictable. To avoid the inaccurate output of the cost model, those items were excluded from the calculation. The independent parameters selected showed a clear relationship between the pile length and the number of pile caps. Nevertheless, the iteration of the pile work's optimum architecture was increased due to insufficient data and cost changes due to the site condition's unpredictability. However, optimum neural network architecture was created with satisfactory hidden layers, learning rate, momentum and MSE, as shown in Figure 4.

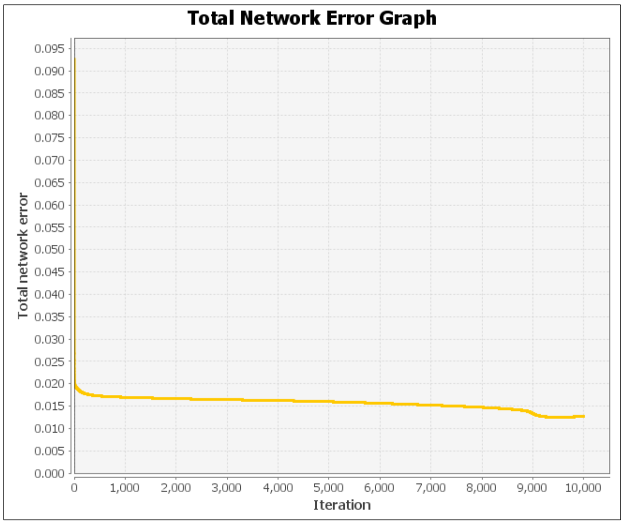


Figure 4: Total Network Error Graph for Optimum Neural Network for Piling Works-

Piers

The preliminary cost estimate for piers includes the cost of the following items in the concrete bridge construction.

- Concrete for piers.
- Formwork for piers.
- Reinforcement for piers.
- Excavation, backfilling and compaction.

Ten NN architectures were created and trained to obtain optimum NN for piers. One to three hidden layers were tested, while the number of inputs and outputs of the NN was four and one, respectively. In addition, a strong relationship was built between independent and dependent variables by creating an NN architecture, indicated in Table 6. Ultimately, identified optimum neural network architecture details were used to develop a cost model for piers.

Table 6: Neural Network Training Result for Piers

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	4	1	1	0.2	0.7	50.000	0.0174
02	4	1	1	0.1	0.6	10.000	0.0187
03	4	1	2	0.2	0.7	34.000	0.0158
04	4	1	2	0.1	0.6	8.000	0.0182
05	4	1	3	0.2	0.7	15.000	0.0168
06	4	1	2	0.3	0.8	12.000	0.0155
07	4	1	2	0.4	0.8	160.000	0.0130
08	4	1	2	0.5	0.7	38.000	0.0141
09	4	1	2	0.4	0.7	18.000	0.0151
10	4	1	2	0.4	0.9	2.000	0.0101

All the training attempt's learning rates were between 0.1 and 0.5, and momentum was 0.6–0.9. Training attempt 10 was successful, as shown in Table 6, having two number of hidden layers, 0.4 learning rate, 0.9 momentum and 0.0101 minimum MSE. The training of the Piers data set was successful, as evidenced by the decreasing iterations shown in Table 6 and the total network error shown in Figure 5. The low level of iteration indicates that the optimum neural network was decisive in output. This may be generated due to a strong relationship between the selected parameters for inputs and output. However, the number of trained data was insufficient to create an optimum neural network. Because the training data set must be taught several times and has top several neural network architectures to get the optimum neural network for piling works in concrete bridges. The selected data set contained piers. The length of the piers was approximately equal to a two-lane road between 6.67 and 8.55 m. Therefore, it shall be effective to use a developed cost model for two-lane bridges, which will be estimated accurately. The concrete piers bore approximately 5%–10% of the total cost. The cost of constructing piers in a concrete bridge covers nearly four sub-items in the abovementioned cost model. To determine the relationship between the piers' inputs and output, optimum neural network architectures for the piers were created. Sometimes, it was challenging to identify the relationships between inputs and outputs because the design was changed according to the location. For example, the pier was altered according to the site conditions because all the construction projects were river bridges. Hence, a pier's height must be changed according to the river's water level. There was a high possibility of changing the river's water level from location to location. The bridges' superstructure and piers were mainly altered according to the site condition. Consequently, it was tough to identify the relationship between the parameters of the piers, the same as piling works. However, 30 project data were trained and tested, and insufficient data affected the cost model's accurate output. The accuracy of the estimation through the cost model shall depend on the number of trained data. However, the cost of piers is more related to the pier length, height, width and the number of piers. Low iteration in the tenth training attempt, as shown in Table 6, indicated strong relationships between parameters. Several hidden layers, learning rate, iteration, momentum and MSE, were used to develop a cost model for piers.

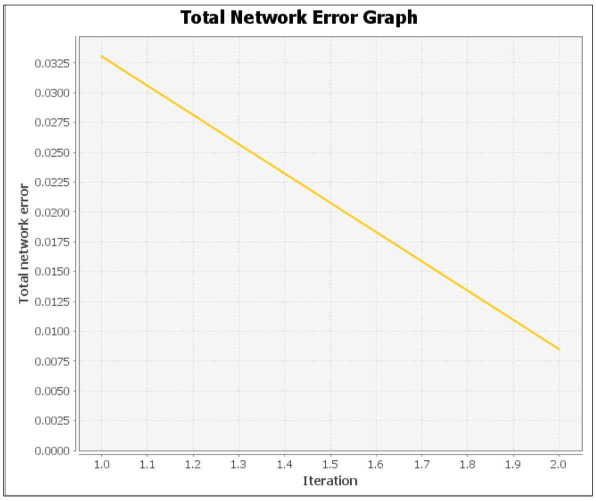


Figure 5: Total Network Error Graph for Optimum Neural Network for pier

Abutments

The preliminary cost estimate for abutments includes the cost of the following items in the concrete bridge construction.

- Concrete for abutments.
- Reinforcement for abutments.
- Excavation, backfilling, and compaction.
- Weep holes
- Clay puddled.
- Formwork for abutments.
- Excavation and backfilling.
- Granular filter medium.
- Aggregate backfilling for wing walls.
- End plastic in concrete.
- Geotextiles.

Eight NN architectures were created and trained to obtain optimum NN for abutments. One to three hidden layers were tested, while the number of inputs and outputs of the NN were three and one, respectively. All the training attempt's learning rates were between 0.1 to 0.4, and momentum was 0.6 to 0.9. Training attempt 06 was successful, as shown in table 7, having two no of hidden layers, 0.4 learning rate, 0.9 momentum and 0.0072 minimum MSE.

Table 7: Neural Network Training Result for Abutments-'Source: Author's own creation'

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	3	1	1	0.2	0.7	50.000	0.0168
02	3	1	1	0.1	0.6	108.000	0.0186
03	3	1	1	0.3	0.8	30.000	0.0140
04	3	1	2	0.2	0.7	18.000	0.0170
05	3	1	2	0.3	0.8	18.000	0.0152
06	3	1	2	0.4	0.9	9.000	0.0072
07	3	1	3	0.2	0.7	10.500	0.0171
08	3	1	3	0.4	0.9	17.000	0.0121

Similarly, as in piers, the length of abutments is approximately equal to two-lane roads. But abutments are comprised of wing walls beside the abutments. Therefore, the length of the abutments was calculated and incorporated with the length of the wing walls. Consequently, it shall be effective to use a developed cost model for two-lane bridges, which will be estimated accurately. The concrete abutments bore approximately 5% to 15% of the total cost. As mentioned above, the cost of abutments in a concrete bridge covered nearly eleven sub-items in the cost model. Therefore, it was required to identify the relationships between those eleven cost elements and the abutment’s parameters. The optimum neural network architecture for the abutments was created in the 6th training attempt to recognise the relationship between the abutments' inputs and output. Sometimes it was challenging to identify the relationships between inputs and outputs because the design was changed according to the location. For example, abutment height was altered according to the site conditions and wing wall designs were adjusted according to the water level of the river and soil condition of the embankments. Hence, abutment height and wing wall designs must be changed according to the river's water level and the embankments' soil conditions. Most loads imposed on the beam bridge were transferred to the rock strata through abutments. Therefore, there was a high possibility of changing the design of the abutments and wing walls. Most of the time, the bridges' superstructure, including abutments and wing walls, were altered according to the site condition. Accordingly, it was tough to identify the relationship between the parameters of the abutments. Insufficient data affected the accurate output of the cost model through 30 project data were trained and tested in the cost model. The estimation accuracy through the cost depended on the number of trained data. However, abutment cost was more related to the centre abutment wall's centre line girth, height, and width iteration in the 06th training attempt, as shown in Figure 6, indicating strong relationships between parameters in abutments.

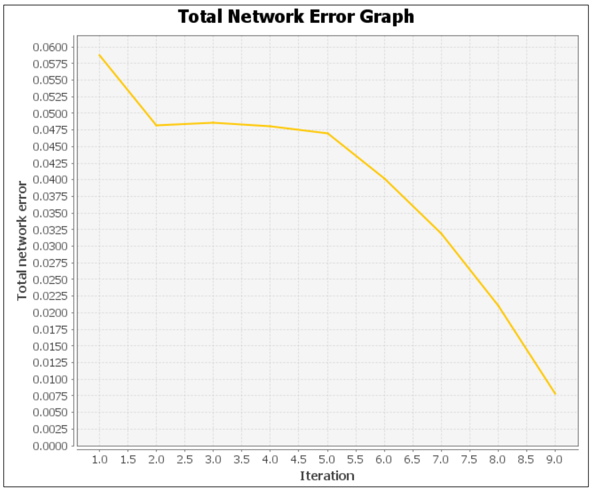


Figure 6: Total Network Error Graph for Optimum Neural Network for Abutments

Pre-stressed Beams

The preliminary cost estimate for pre-stressed beams includes the cost of the following items in the concrete bridge construction.

- Pre-stressed beams supply to the site.
- Pre-stressed beams launched to the position.
- Cost of bearing strips.
- Bituminous sealing felt under capping beams of abutments.

Table 8: Neural Network Training Result for Pre-stressed Beams

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	3	1	1	0.2	0.7	3.000	0.0156
02	3	1	1	0.1	0.6	80.000	0.0189
03	3	1	1	0.3	0.8	4.000	0.0185
04	3	1	2	0.2	0.7	6.000	0.0188
05	3	1	2	0.1	0.6	42.000	0.0188
06	3	1	2	0.3	0.8	3.000	0.0060
07	3	1	3	0.2	0.7	9.000	0.0166
08	3	1	2	0.4	0.9	6.000	0.0035
09	3	1	2	0.4	0.8	13.000	0.0140
10	3	1	2	0.5	0.9	33.500	0.0119

Ten NN architectures were created and trained to obtain optimum NN for pre-stressed beams. One to three hidden layers were tested, while the number of inputs and outputs of the NN were three and one, respectively. All the training attempt's learning rates were between 0.1 to 0.5, and momentum was 0.6 to 0.9. Training attempt 08 was successful, as shown in Table 8, having two no of hidden layers, 0.4 learning rate, 0.9 momentum and 0.0035 minimum MSE. The selected data set, which was trained, had only pre-stressed concrete beams constructed according to the standard sizes of the UK pre-stressed concrete Association (PCA). Therefore, using a developed cost model of pre-stressed concrete beams shall be effective and estimated accurately. The pre-stressed concrete forms bore approximately 10% to 20% of the total cost. The cost of pre-stressed concrete beams in a concrete bridge covered nearly four sub-items in the cost model. As mentioned above, pre-stressed concrete beams were a significant portion of the total cost. Therefore, it was required to identify the relationships between those four cost elements and the pre-stressed concrete beam's parameters. To recognise the relationship between the inputs and the output of the pre-stressed concrete beams, the optimum neural network architecture for the abutments was created in the 08th training attempt. Pre-stressed concrete beam span significantly affects the bridge's cost because the number of piers has to be improved when the beam's span is increased. Therefore, it was essential to define the cost model for the range of the selected beam. Trained and tested data sets were between 10m to 20m approximately. Hence, this cost model shall be effective for such a span. Identifying the relationships between parameters and the cost of the pre-stressed beams was not tricky because the beams were designed according to the standards. However, insufficient data affected the accurate output of the cost model through project data that were trained and tested in the cost model. Nevertheless, the cost of pre-stressed concrete beams was more related to the beam span, height, and width. Low iteration in the 8th training attempt, as shown in figure 7, indicated strong relationships between parameters in pre-stressed. Concrete beams. Training and testing were carried out to identify the strong relationship between variables.

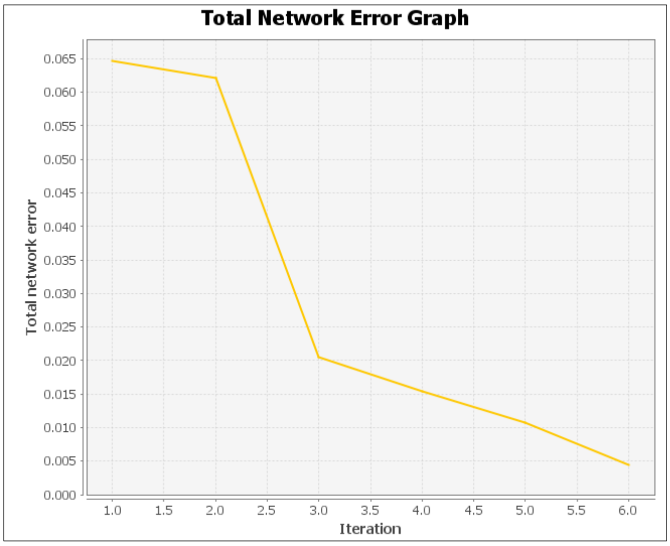


Figure 7: Total Network Error Graph for Optimum Neural Network for Pre-stressed Beams- 'Source: Author's own creation'

Concrete Slab

The preliminary cost estimate for the concrete slab includes the cost of the following items in the concrete bridge construction.

- Concrete for a concrete slab.
- Reinforcement for a concrete slab.
- Stainless steel dowel bars.

- Formwork for approach slab.
- Formwork for a concrete slab.
- Cost for expansion joints.
- Concrete for approach slab.
- Reinforcement for approach slab.

Fourteen NN architectures were created and trained to obtain the optimum NN for a concrete slab. One to three hidden layers were tested, while the number of inputs and outputs of the NN were three and one, respectively. All the training attempt's learning rates were between 0.1 to 0.5, and momentum was 0.6 to 0.9.

Table 9: Neural Network Training Result for Concrete Slab

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	3	1	1	0.2	0.7	11.000	0.0172
02	3	1	1	0.1	0.6	600.000	0.0188
03	3	1	1	0.3	0.8	7.000	0.0127
04	3	1	1	0.4	0.9	10000	0.0676
05	3	1	2	0.2	0.7	7.000	0.0138
06	3	1	2	0.3	0.8	11.000	0.0128
07	3	1	2	0.4	0.9	4.000	0.0062
08	3	1	2	0.5	0.9	5.000	0.0109
09	3	1	2	0.5	0.8	5.000	0.0069
10	3	1	2	0.5	0.7	3.000	0.0128
11	3	1	3	0.2	0.7	9.000	0.0164
12	3	1	2	0.4	0.8	9.000	0.0096
13	3	1	2	0.4	0.7	9.000	0.0142
14	3	1	2	0.4	0.6	12.000	0.0145

Attempt 09 was successful, as shown in Table 9, having two no of hidden layers, 0.5 learning rate, 0.8 momentum and 0.0069 minimum MSE. Optimum neural network architect data were used to develop a cost model for a concrete slab. The data set that was trained and tested had only precast concrete panels, and concrete slabs were constructed on top of the pre-stressed concrete beams. Therefore, a developed cost model for bridges with precast concrete panels and concrete slabs will be effective. The concrete slab bore approximately 5% to 10% of the total cost. Therefore, the cost of the concrete slab in a concrete bridge construction covered nearly sub-item in the abovementioned cost model. Consequently, it was required to identify the relationships between those eight cost elements and the concrete slab's parameters. To recognise the relationship between the inputs and the output of the concrete slab, optimum neural network architecture for the abutments was created in the 09th training attempt—low iteration, obtained during the training data set, and strong relationships between parameters, as shown in figure 8. The design of the concrete slab was not much affected by the cost model, and it was given accurate figures according to the strong connections between parameters. However, there was insufficient data concerning the cost model's accuracy, though 30 project data were trained and tested in the cost model. According to selected and trained data, it was proved that the cost of concrete slab was more related to the slab length, width, and thickness.

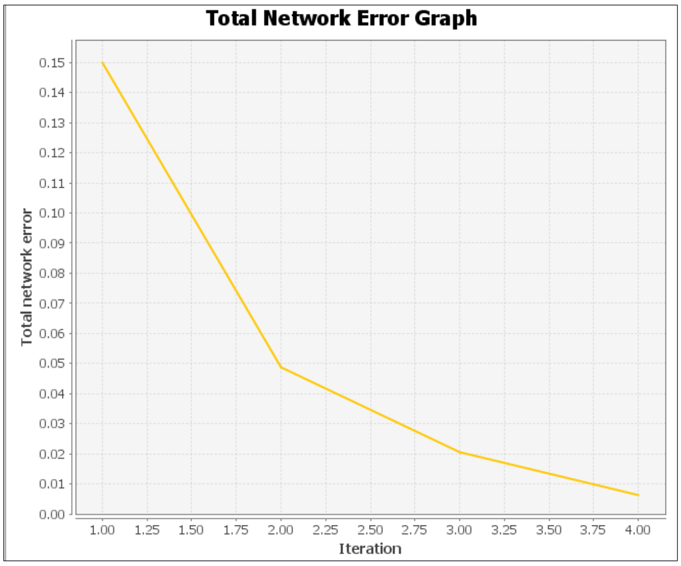


Figure 8: Total Network Error Graph for Optimum Neural Network for Concrete Slab- 'Source: Author's own creation'

Bridge Paving

The preliminary cost estimate for bridge paving includes the cost of the following items in the concrete bridge construction.

- Bituminous emulsion tack coat
- Asphaltic surfacing

Table 10: Neural Network Training Result for Bridge Paving

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	2	1	1	0.2	0.7	16.000	0.0161
02	2	1	1	0.3	0.8	11.000	0.0120
03	2	1	1	0.4	0.9	22.000	0.0113
04	2	1	1	0.5	0.9	15.000	0.0083
05	2	1	1	0.6	0.9	17.000	0.0218
06	2	1	1	0.5	0.8	8.000	0.0136
07	2	1	1	0.5	0.7	7.000	0.0098
08	2	1	1	0.5	0.6	14.000	0.0134
09	2	1	2	0.2	0.7	17.000	0.0151
10	2	1	2	0.3	0.8	5.000	0.0124
11	2	1	2	0.5	0.9	10000	0.1172
12	2	1	2	0.4	0.9	2.000	0.0177
13	2	1	3	0.2	0.7	9.000	0.0143
14	2	1	3	0.3	0.8	6.000	0.0077
15	2	1	3	0.4	0.9	11.000	0.0145
16	2	1	3	0.3	0.7	7.000	0.0152
17	2	1	3	0.3	0.9	4.000	0.0091

18	2	1	3	0.4	0.8	3.000	0.0067
19	2	1	3	0.5	0.8	6.000	0.0079

Nineteen NN architectures were created and trained to obtain optimum NN for bridge paving. One to three hidden layers were tested, while the number of inputs and outputs of the NN was two and one, respectively. All the training attempt's learning rates were between 0.2 to 0.5, and momentum was 0.6 to 0.9. Training attempt 18 was successful, having three no of hidden layers, 0.4 learning rate, 0.8 momentum and 0.0067 minimum MSE. The cost of bridge paving in a concrete bridge construction covered nearly two sub-items in the cost model mentioned above, and bridge paving was borne less from the total cost. However, this portion was not much affected by the total cost; it was required to identify the relationships between those two cost elements and the bridge paving parameters. To determine the relationship between the bridge's inputs and output, paving optimum neural network architectures for the abutments were created in the 18th training attempt. The cost model development did not affect bridge paving design because standard mix designs were used. However, insufficient data involved the cost model's accurate output through several project data that were trained and tested in the cost model. 19 training attempts were carried out to get the optimum neural network for the cost model, as shown in Figure 9. However, the cost of bridge paving was more related to the paving length and paving width. Low iteration in the 18th training attempt, as shown in Table 10, indicated strong relationships between parameters in bridge paving.

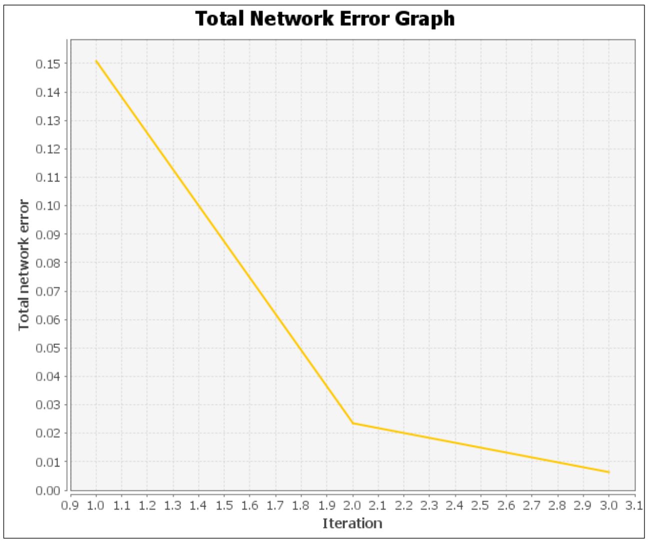


Figure 9: Total Network Error Graph for Optimum Neural Network for Bridge Paving

Bridge Furniture

The preliminary cost estimate for bridge furniture includes the cost of the following items in the concrete bridge construction.

- Cost of precast kerbs
- Railings
- Guard stones

- Light posts

Fifteen NN architectures were created and trained to obtain optimum NN for bridge furniture. One to three hidden layers were tested, while several inputs and outputs of the NN were one. All the training attempt's learning rates were between 0.2 to 0.5, and momentum was 0.6 to 0.8. Training attempt 12 was successful, as shown in Table 11, having three no of hidden layers, 0.4 learning rate, 0.7 momentum and 0.0023 minimum MSE.

Table 51: Neural Network Training Result for Bridge Furniture

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	1	1	1	0.2	0.7	9.000	0.0148
02	1	1	1	0.3	0.8	78.000	0.0175
03	1	1	1	0.2	0.6	18.000	0.0160
04	1	1	1	0.3	0.7	18.000	0.0117
05	1	1	1	0.4	0.7	28.000	0.0106
06	1	1	1	0.5	0.7	10000	0.0832
07	1	1	2	0.4	0.7	35.000	0.0148
08	1	1	2	0.3	0.7	3.000	0.0078
09	1	1	2	0.2	0.7	26.000	0.0144
10	1	1	3	0.3	0.7	8.000	0.0115
11	1	1	3	0.2	0.7	7.000	0.0045
12	1	1	3	0.4	0.7	2.000	0.0023
13	1	1	3	0.5	0.7	2.000	0.0034
14	1	1	3	0.4	0.6	7.000	0.0122
15	1	1	3	0.4	0.8	2.000	0.0148

The bridge furniture bared approximately 1% to 2% of the total cost. This portion was less percentage compared with the concrete bridge's total cost. The cost of bridge furniture in a concrete bridge construction covered nearly four sub-items in the cost model mentioned above, and bridge furniture was borne less from the total cost. To recognise the relationship between the inputs and the output of the bridge furniture, the optimum neural network architecture for the abutments was created in the 12th training attempt. Bridge furniture design was not much affected by the cost model development. However, insufficient data concerning the cost model's accurate output through 30 project data were trained and tested in the cost model. 15 training attempts were carried out to get the optimum neural network for the Cost model. However, the cost of bridge paving was more related to the bridge length. Most of the sub-items in the bridge furniture created a relationship between the bridge's span. Therefore, there was less possibility of deviating the estimated cost from the actual cost other than insufficient trained and tested data. Low iteration in the 12th training attempt, as shown in Figure 10, indicated strong relationships between parameters in bridge furniture.

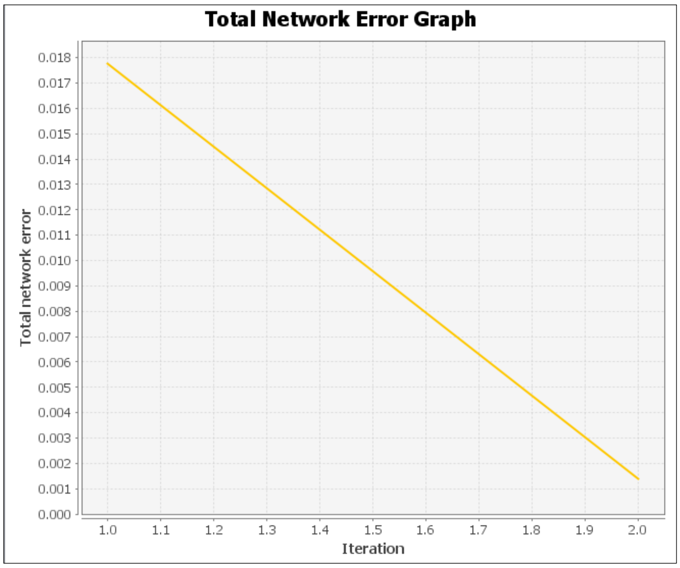


Figure 10: Total Network Error Graph for Optimum Neural Network for Bridge Furniture

Miscellaneous

The preliminary cost estimate for miscellaneous includes the cost of the following items in the concrete bridge construction. Most of the items listed below were related to the services of the bridge.

- Rainwater outlets.
- Dowel bars to abutments and wing walls.
- Drainpipes.
- Service ducts.

Ten NN architectures were created and trained to obtain optimum NN for miscellaneous. One to three hidden layers were tested, while the number of inputs and outputs of the NN was two and one, respectively. All the training attempt's learning rates were between 0.2 to 0.4, and momentum was 0.7 to 0.9. Training attempt 04 was successful, as shown in Table 12, having one no of hidden layers, 0.3 learning rate, 0.9 momentum and 0.0083 minimum MSE.

Table 6: Neural Network Training Result for Miscellaneous

Training Attempts	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
01	2	1	1	0.2	0.7	18.000	0.0147
02	2	1	1	0.3	0.8	10.000	0.0132
03	2	1	1	0.4	0.9	10000	0.0535
04	2	1	1	0.3	0.9	41.000	0.0083
05	2	1	1	0.3	0.7	34.000	0.0148
06	2	1	2	0.3	0.9	5.000	0.0107

07	2	1	2	0.2	0.7	12.000	0.0136
08	2	1	3	0.3	0.9	28.500	0.0124
09	2	1	3	0.2	0.7	4.000	0.0168
10	2	1	3	0.3	0.8	5.000	0.0094

According to the selected data set, approximately less than 1% of the total cost was borne by the miscellaneous. Miscellaneous expenses in a concrete bridge construction covered nearly four sub-items in the cost model mentioned above, and miscellaneous were delivered less than the total cost. However, this portion was relatively unaffected by the total cost; it was required to identify the relationships between those four cost elements and the various parameters. To recognise the relationship between the inputs and the output of the different optimum neural network architectures for the abutments were created in the 04^{th} training attempt. However, insufficient data affected the accurate output of the cost model through several projects. Data were trained and tested in the cost model. 10 training attempts were carried out to get the optimum neural network for the cost model. However, the cost of miscellaneous was more related to the paving length. Low iteration in the 04^{th} training attempt shall indicate strong relationships between parameters in Figure 11.

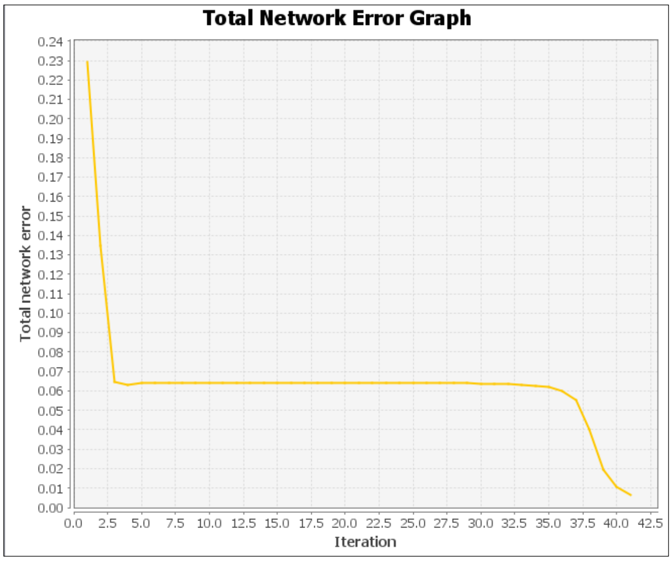


Figure 11: Total Network Error Graph for Optimum Neural Network for Miscellaneous

Development of a Cost Model

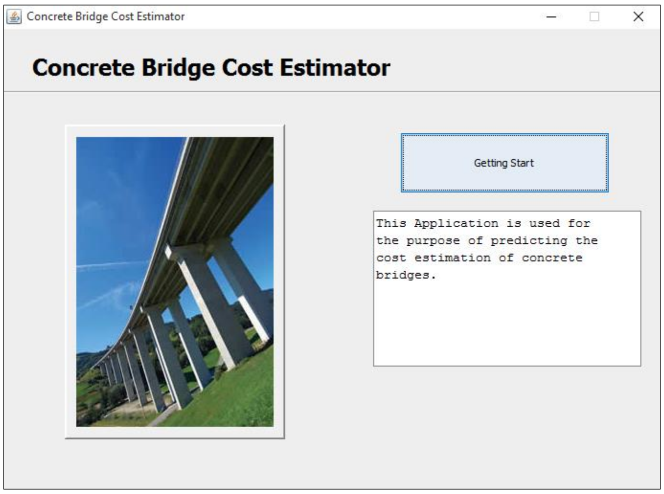
According to Table 13, eight optimum neural networks were created, which gives a more accurate estimate of the cost of each element. Most of the optimum neural networks comprised 2 or 3 hidden layers and a 0.4 learning rate. The momentum of those optimum neural networks was between 0.7 and 0.9. Other than high iteration in piling works, other elements were trained in low iterations, giving an accurate figure. Finally, the selected optimum neural network architectures were used to develop a cost model which offers minimum MSE.

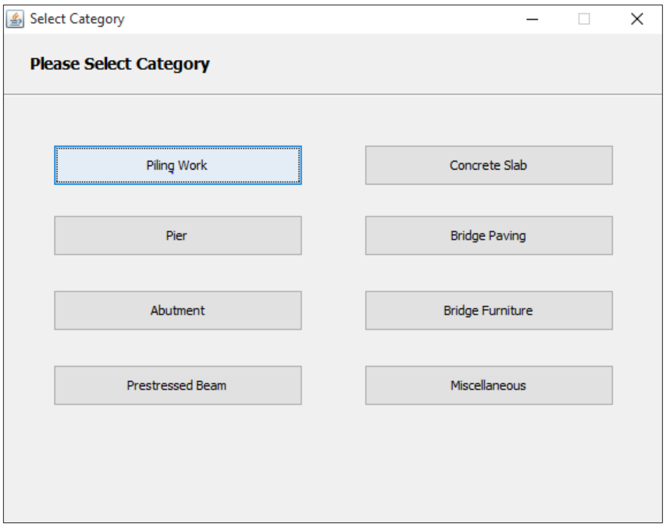
Table 7: Summary of the Optimum Neural Network Training Results for Elements

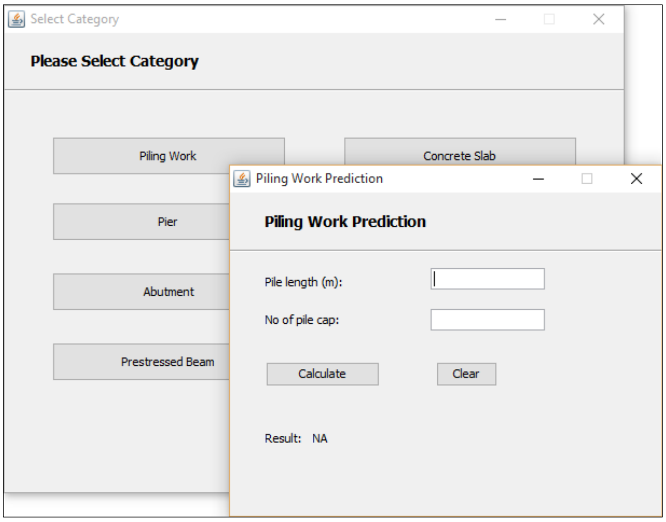
Element	Inputs	Outputs	Hidden Layers	Learning Rate	Momentum	Iterations	MSE
Piling Works	2	1	3	0.2	0.7	10000	0.0246
Piers	4	1	2	0.4	0.9	2.000	0.0101
Abutments	3	1	2	0.4	0.9	9.000	0.0072
Pre-stressed Beams	3	1	2	0.4	0.9	6.000	0.0035
Concrete Slab	3	1	2	0.4	0.9	5.000	0.0062
Bridge Paving	2	1	3	0.4	0.8	3.000	0.0067
Bridge Furniture	1	1	3	0.4	0.7	2.000	0.0023
Miscellaneous	2	1	1	0.3	0.9	41.000	0.0083

According to the optimum neural network architectures, several inputs, outputs and hidden layers were decided, and the value for learning rate, momentum and iteration was selected. Finally, the "Concrete Bridge Cost Estimator" was developed using the cost model's data and user interfaces, as shown in Figure 12.

Figure 12: User Interface for Developed Cost Model







Once clicking the "Getting Start" user interface, the cost mode category selection interface shall appear, as shown in Figure 12. Bridge elements for cost estimation can be selected in the following user interface. The required element button can enter parameters in the next user interface. For example, pile length and the number of pile caps should be included as element parameters to get an estimated value for piling works. This interface varies from element to element since different parts have different parameters. Once parameters are entered, the predicated cost for a particular element can be obtained by clicking the 'calculate' button. The cost model user interfaces were created using NetBeans (8.0 version) and the Java platform, which is user-friendly and most accessible among software developers.

Validation of Neural Network Cost Model

The developed cost model was validated using the basic project cost details to validate the neural network cost model. The cost model, developed based on optimum neural network architectures, was used to calculate the estimated cost for the selected project. According to the final accounts, almost all the optimum neural networks for bridge elements were compared with the actual construction cost. Nevertheless, it is noticed that the accumulation of the given element cost does not represent the total cost of the construction. As described, some expenditures were excluded from the cost model. Therefore, estimators should be aware of those expenditures and add the sum to the estimated construction cost.

When considering all the deviations as a percentage, most of the variations were in the range of 610.00%, as shown in Table 14. Therefore, this deviation was within the estimated cost deviation at the inception stage. Hence, it can be concluded that the developed neural network cost model has performed at the expected accuracy level in the research. Consequently, this cost model can be a more reliable preliminary cost-estimating tool than traditional techniques.

Table 8: Validation of Cost Model

Element	**Actual Cost (LKR)**	**Estimated Cost (LKR)**	**Deviation (LKR)**	**Deviation as a Percentage**
Project 01				
Piling Work	46,764,877.45	42,322,214.09	(4,442,663.36)	9.50%
Pier	4,575,017.48	4,834,420.97	259,403.49	-5.67%
Abutment	10,082,023.33	9,500,290.58	(581,732.75)	5.77%
Pre-stressed Beam	11,629,147.30	11,234,919.21	(394,228.09)	3.39%
Concrete Slab	5,362,897.47	5,923,320.26	560,442.79	-10.45%
Bridge Paving	602,372.21	564,904.66	(37,467.55)	6.22%
Bridge Furniture	1,139,044.99	1,084,484.73	(54,560.26)	4.79%
Miscellaneous	199,223.99	202,829.94	3,605.95	-1.81%
Project 02				
Piling Work	55,595,741.71	57,130,184.18	1,534,442.47	-2.76%
Pier	6,454,746.87	6,734,882.88	280,136.01	-4.34%
Abutment	8,685,887.52	8,306,314.24	(379,573.28)	4.37%
Pre-stressed Beam	16,521,695.70	17,863,257.39	1,341,561.69	-8.12%
Concrete Slab	8,536,857.20	8,300,386.26	(236,470.94)	2.77%
Bridge Paving	767,102.57	654,491.91	(112,610.66)	14.68%
Bridge Furniture	1,269,221.57	1,291,179.10	21,957.53	-1.73%
Miscellaneous	253,705.65	236,326.81	(17,378.84)	6.85%

5. Conclusions

The accurate data required to perform the neural network cost model was more significant. Therefore, the developed neural network cost model shall be used as a detailed estimation, giving separate estimates for each element. Ultimately, Neuroph Studio, which has neural network development ability, was used to create optimum neural network architectures for identified elements of the bridge construction. Though reducing the learning rate minimises MSE, iteration value tends to increase. Therefore, the learning rate should be a manageable size. According to the statistical data analysis, optimum neural network architectures have around 0.01 minimum MSE. Almost all the neural networks gained 90% accuracy during the cost model validation compared to the actual construction. The cost model was developed using Java programming language and NetBeans software, recognised as powerful software development tools. However, the study limitations are that the actual project'stotal construction cost was not covered in the full estimation of this cost model development stage. Some items were excluded from the model, e.g. the cost of cofferdam construction and dewatering. The ANN model was developed based on the material price indices of CIDA published in January 2021. This model is only capable of calculating the cost of river bridges since the cost model was developed based on the river concrete beam bridges which were already constructed. When applying the ANN model to practice, the estimated cost obtained using the model must be adjusted to the time factor using CIDA price indices %. Further studies, therefore, can be conducted on similar research within other developing countries and for different types of public sector infrastructure projects such as roads and tunnels.

References

Al-Zwainy, F.M. and Aidan, I.A.A. (2017), "Forecasting the cost of the structure of infrastructure projects utilising artificial neural network model (highway projects as a case study)", *Indian Journal of Science and Technology*, Vol. 10 No. 20, pp. 1-12.

Amin, M. (2017), "Development of cost estimation model for residential building", *International Journal of Structural and Civil Engineering Research*, Vol. 5 No. 1, pp. 1-4.

Amusan, M.T.O., Ayo, C.K. and Adeboye, A.B. (2013), "Expert system-based predictive cost model for building works: neural network approach", *International Journal of Basic and Applied Sciences IJBAS-IJENS*, Vol. 13 No. 1.

Billington, P.N., Billington, D.P. and Shirley-Smith, H. (2023), "Bridge", Encyclopedia Britannica, available at: www.britannica.com/technology/bridge-engineering (accessed 29 March 2023).

Bisbey, J., Nourzad, S.H.H., Chu, C.Y. and Ouhadi, M. (2020), "Enhancing the efficiency of infrastructure projects to improve access to finance", *Journal of Infrastructure, Policy and Development*, Vol. 4 No. 1, pp. 27-49.

Bouabaz, M. and Hamami, M. (2008), "A cost estimation model for repair bridges based on artificial neural network", *American Journal of Applied Sciences*, Vol. 5 No. 4, pp. 334-339.

Brandon, P.S. (1987), Building Cost Modelling and Computers, Spon Press, London.

Bruzelius, N., Flyvbjerg, B. and Rothengatter, W. (2002), "Big decisions, big risks. Improving accountability in mega projects", *Transport Policy*, Vol. 9 No. 2, pp. 143-154.

Central Bank of Sri Lanka (2021), “Annual report 2021”, available at: Annual Report 2021 | Central Bank of Sri Lanka (cbsl.gov.lk) (accessed 30 March 2023).

Chandanshive, V. and Kambekar, A.R. (2019), “Estimation of building construction cost using artificial neural networks”, *Journal of Soft Computing in Civil Engineering,* Vol. 3 No. 1, pp. 91-107.

Cheng, M.Y. and Wu, Y.W. (2005), “Construction conceptual cost estimates using support vector machine”, *22nd International Symposium on Automation and Robotics in Construction ISARC 2005, Ferrara, Italy*.

Chou, J.S., Lin, C.W., Pham, A.D. and Shao, J.Y. (2015), “Optimized artificial intelligence models for predicting project”, *Automation in Construction,* Vol. 54, pp. 106-115.

Cirilovic, J., Vajdic, N., Mladenovic, G. and Queiroz, C. (2013), “Developing cost estimation models for road rehabilitation and reconstruction: case study of projects in Europe and Central Asia”, *Journal of Construction Engineering and Management,* Vol. 140 No. 3.

Creswell, J.W. (2014), *A Concise Introduction to Mixed Methods Research,* SAGE publications.

Du, Z. and Li, B. (2017), “Construction project cost estimation based on improved BP neural network”, *2017 International Conference on Smart Grid and Electrical Automation (ICSGEA), IEEE,* pp. 223-226.

Elbeltagi, E., Dawood, M., Hosny, O. and Elhakeem, A. (2014), “BIM-based cost estimation/monitoring for building construction”, *International Journal of Engineering Research and Applications,* Vol. 4, available at: www.ijera.com

Elfaki, A.O., Alatawi, S. and Abushandi, E. (2014), “Using intelligent techniques in construction project cost estimation: 10-year survey”, Advances in Civil Engineering, Vol. 2014, p. 107926.

Elhag, T.M.S., Boussabaine, A.H. and Ballal, T.M.A. (2005), “Critical determinants of construction tendering costs: quantity surveyors’ standpoint”, *International Journal of Project Management,* Vol. 23 No. 7, pp. 538-545.

Elmousalami, H.H. (2020), “Artificial intelligence and parametric construction cost estimate modelling: a state-of-the-art review”, *Journal of Construction Engineering and Management,* Vol. 146 No. 1,p. 3119008.

El-Sawalhi, N.I. and Shehatto, O. (2014), “A neural network model for building construction projects cost estimating”, *Journal of Construction Engineering and Project Management,* Vol. 4 No. 4, pp. 9-16.

Ershova, I. and Posokhov, A. (2016), “Comparative analyze of infrastructure in developed countries”, *Procedia Economics and Finance,* Vol. 39, pp. 815-819.

Flyvbjerg, B., Holm, M.S. and Buhl, S. (2002), “Underestimating costs in public works projects: error or lie?”, *Journal of the American Planning Association,* Vol. 68 No. 3, pp. 279-295.

Flyvbjerg, B., Skamris Holm, M.K. and Buhl, S. (2004), “What causes cost overrun in transport infrastructure projects?”, *Transport Reviews*, Vol. 24 No. 1, pp. 3-18.

Fragkakis, N., Lambropoulos, S. and John-Paris, P. (2010), “A cost estimate method for bridge superstructures using regression analysis and bootstrap”, *Organisation, Technology and Management in Construction an International Journal*, Vol. 2 No. 2, pp. 182-192.

Fragkakis, N., Lambropoulos, S. and Tsiambaos, G. (2011), “Parametric model for conceptual cost estimation of concrete bridge foundations”, *Journal of Infrastructure Systems*, Vol. 17 No. 2, pp. 66-74.

Gohar, A.S., Khanzadi, M. and Farmani, M. (2012), “Identifying and evaluating risks of construction projects in fuzzy environment: a case study in Iranian construction industry”, *Indian Journal of Science and Technology*, Vol. 5 No. 11, pp. 3593-3602.

Greiman, V.A. (2013), *Megaproject Management: Lessons on Risk and Project Management from the Big Dig*, John Wiley & Sons.

Günaydin, H.M. and Dogan, S.Z. (2004), ˇ “A neural network approach for early cost estimation of structural systems of buildings”, International Journal of Project Management, Vol. 22 No. 7, pp. 595-602.

Gunduz, M. and Sahin, H.B. (2015), “An early cost estimation model for hydroelectric power plant projects using neural networks and multiple regression analysis”, *Journal of Civil Engineering and Management*, Vol. 21 No. 4, pp. 470-477.

Hegazy, T. and Ayed, A. (1998), “Neural network model for parametric cost estimation of highway projects”, *Journal of Construction Engineering and Management*, Vol. 124 No. 3, pp. 210-218.

Hollar, D.A., Rasdorf, W., Liu, M., Hummer, J.E. and Arocho, I.M. (2013), “Preliminary engineering cost estimation model for bridge projects*”, Journal of Construction Engineering and Management*, Vol. 139 No. 9, pp. 1259-1267.

Hurley, J., Morris, S. and Portelance, G. (2019), “Examining the debt implications of the belt and road initiative from a policy perspective”, *Journal of Infrastructure, Policy and Development*, Vol. 3 No. 1, pp. 139-175, doi: 10.24294/jipd.v3i1.1123.

Ji, S.H., Ahn, J., Lee, H.S. and Han, K. (2019), “Cost estimation model using modified parameters for construction projects”, *Advances in Civil Engineering*, Vol. 2019, doi: 10.1155/2019/8290935.

Jiang, Q. (2019), “Estimation of construction project building cost by back-propagation neural network”, *Journal of Engineering, Design and Technology*, Vol. 18 No. 3, pp. 601-609.

Juszczyk, M. (2019), “On the search of models for early cost estimates of bridges: an SVM-based approach”, *Buildings*, Vol. 10 No. 1, p. 2.

Kaliba, C., Muya, M. and Mumba, K. (2009), "Cost escalation and schedule delays in road construction projects in Zambia", *International Journal of Project Management*, Vol. 27 No. 5, pp. 522-531.

Karasu, S., Altan, A., Saraç, Z. and Hacioğlu, R. (2017), "Estimation of fast varied wind speed based on NARX neural network by using curve fitting", *International Journal of Energy Applications and Technologies*, Vol. 4 No. 3, pp. 137-146.

Ketterer, J. and Powell, A. (2018),"Financing infrastructure", IADB.

Khalaf, T.Z., Çağlar, H., Çağlar, A. and Hanoon, A.N. (2020), "Particle swarm optimization based approach for estimation of costs and duration of construction projects", *Civil Engineering Journal*, Vol. 6 No. 2, pp. 384-401.

Kim, B.S. (2011), "The approximate cost estimating model for railway bridge project in the planning phase using the CBR method", *KSCE Journal of Civil Engineering*, Vol. 15 No. 7, pp. 1149-1159.

Kim, G.H., An, S.H. and Kang, K.I. (2004), "Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning", *Building and Environment*, Vol. 39 No. 10, pp. 1235-1242.

Kim, K.Y. and Kim, K. (2010), "Preliminary cost estimation model using case-based reasoning and genetic algorithms", *Journal of Computing in Civil Engineering*, Vol. 24 No. 6, pp. 499-505.

Kovacevic, M., Ivanisevic, N., Petronijevic, P. and Despotovic, V. (2021), "Construction cost estimation of reinforced and prestressed concrete bridges using machine learning", *Građevinar*, Vol. 73 No. 1, pp. 1-13, doi: 10.14256/JCE.2738.2019.

Lanka, S. (2023),"Ministry of finance 2020".

Lauren, T. (2021), "Building resilience new strategies for strengthening infrastructure resilience and maintenance".

Lee, K.M., Cho, H.N. and Choi, Y.M. (2004), "Life-cycle cost-effective optimum design of steel bridges", *Journal of Constructional Steel Research*, Vol. 60 No. 11, pp. 1585-1613.

Locatelli, G., Mikic, M., Kovacevic, M., Brookes, N. and Ivanisevic, N. (2017), "The successful delivery of megaprojects: a novel research method", *Project Management Journal*, Vol. 48 No. 5, pp. 78-94.

Mahalakshmi, G. and Rajasekaran, C. (2019), "Early cost estimation of highway projects in India using artificial neural network", in Das, B. and Neithalath, N. (Eds), *Sustainable Construction and Building Materials*, Springer, Singapore, pp. 659-672.

Mahamid, I. (2013), "Effects of project's physical characteristics on cost deviation in road construction", *Journal of King Saud University – Engineering Sciences*, Vol. 25 No. 1, pp. 81-88.

Mahamid, I. and Bruland, A. (2010), "FS 4E-Critical infrastructure development Ibrahim Mahamid and Amund Bruland preliminary cost estimating models for road construction activities preliminary cost estimating models for road construction activities".

Marcous, G., Bakhoum, M.M., Taha, M.A. and El-Said, M. (2001), “Preliminary quantity estimate of highway bridges using neural networks”, *Proceedings of the Sixth International Conference on the Application of Artificial Intelligence to Civil and Structural engineering, Stirling, Scotland.*

Marinelli, M., Dimitriou, L., Fragkakis, N. and Lambropoulos, S. (2015), “Non-parametric bill of quantities estimation of concrete road bridges’ superstructure: an artificial neural networks approach”, *Proceedings 31st Annual ARCOM Conference, Lincoln, United Kingdom.*

Markiz, N. and Jrade, A. (2022), “Integrating an expert system with BrIMS, cost estimation, and linear scheduling at conceptual design stage of bridge projects”, *International Journal of Construction Management*, Vol. 22 No. 5, pp. 913-928.

Ministry of Finance (2020), “Annual report 2020” available at: Sri-Lanka-financial-statements.pdf (ifac. org) (accessed 30 March 2023).

Ministry of Finance (2021), “Annual report 2021”, available at: a7a35d1a-556f-49b2-81e0-20294eb5a519 (treasury.gov.lk) (accessed 30 March 2023).

Mitchell, T.M. (1997), Machine Learning, McGraw-Hill, New York, NY, Vol. 1, No. 9.

Mohamed, A. and Celik, T. (2002), “Knowledge based-system for an alternative design, cost estimating and scheduling”, *Knowledge-Based Systems*, Vol. 15 No. 3, pp. 177-188.

Mostafa, E.M. (2003), “Cost analysis for bridge and culvert”, *Seventh International Water Technology Conference IWTC7, Cairo*.

Odeck, J. (2014), “Do reforms reduce the magnitudes of cost overruns in road projects? Statistical evidence from Norway”, *Transportation Research Part A: Policy and Practice,* Vol. 65 No. 2, pp. 68-79.

Oladokun, M.G., Adeyinka, A., Oladokun, I. and Odesola, A. (2013), “Accuracy of pre-tender cost estimates of consultant quantity surveyors in Nigeria”, *A Compendium of International Real Estate and Construction Issues 1*, (May), pp. 39-52.

Ongkowijoyo, C.S., Gurmu, A. and Andi, A. (2021), “Investigating risk of bridge construction project: exploring Suramadu strait-crossing cable-stayed bridge in Indonesia”, *International Journal of Disaster Resilience in the Built Environment*, Vol. 12 No. 1, pp. 127-142.

Organisation for Economic Co-operation and Development (OECD) (2023), “DAC list of ODA recipients”, available at: www.oecd.org/dac/financing-sustainable-development/development finance-standards/daclist.htm (accessed 31 March 2023).

Pesko, I., Trivunic, M., Cirovic, G. and Mucenski, V. (2013), “A preliminary estimate of time and cost in urban road construction using neural networks”, *Technical Gazette*, Vol. 20 No. 3, pp. 563-570.

Public finance (2021), available at: https://publicfinance.lk/en/topics/2021-budget-allocation-for-road development-1622193157 (accessed 25 March 2023).

Qian, L. and Ben-Arieh, D. (2008), “Parametric cost estimation based on activity-based costing: a case study for design and development of rotational parts”, *International Journal of Production Economics,* Vol. 113 No. 2, pp. 805-818.

Rafiq, M.Y., Bugmann, G. and Easterbrook, D. (2001), “Neural network design for engineering applications”, *Computers and Structures,* Vol. 79 No. 17, pp. 1541-1552.

Ranasinghe, W.M.D.N. (2019), “Guidelines for preparing total cost estimates”, Provincial Engineering Organisation Western Provincial Council, Sri Lanka.

Raymond, J. (2008), “Benchmarking in public procurement”, *Benchmarking: An International Journal,* Vol. 15 No. 6, pp. 782-793.

Saunders, M., Lewis, P. and Thornhill, A. (2011), Research Methods for Business Students, 5th ed., Pearson, Bengaluru.

Sodikov, J. (2005), “Cost estimation of highway projects in developing countries: artificial neural network approach”, *J East Asia Soc Transp Stud,* Vol. 6, pp. 1036-1047.

Srī Lankā Maha Bankuva. Mudal Maṇḍalaya (2023), “Annual report of the monetary board to the Hon’ble Minister of Finance for the Year 2014”.

Tijanic, K., Car-Pušic, D. and Šperac, M. (2020), “Cost estimation in road construction using artificial neural network”, *Neural Computing and Applications,* Vol. 32 No. 13, pp. 9343-9355.

Wang, X. (2017), “Application of fuzzy math in cost estimation of construction project”, *Journal of Discrete Mathematical Sciences and Cryptography,* Vol. 20 No. 4, pp. 805-816.

Wegener, C., von Spreckelsen, C., Basse, T. and von Mettenheim, H.J. (2016), “Forecasting government bond yields with neural networks considering cointegration”, *Journal of Forecasting,* Vol. 35 No. 1, pp. 86-92.

Weiwei, L. and Yoda, T. (2017), “Bridge engineering: classifications, design loading, and analysis methods”, Butterworth-Heinemann.

Wilmot, C.G. and Mei, B. (2005), “Neural network modelling of highway construction costs”, *Journal of Construction Engineering and Management,* Vol. 131 No. 7, pp. 765-771.

Xu, X. and Zhang, Y. (2022a),“Canola and soybean oil price forecasts via neural networks”, *Advances in Computational Intelligence,* Vol. 2 No. 5, p. 32.

Xu, X. and Zhang, Y. (2022b), “Neural network predictions of the high-frequency CSI300 first distant futures trading volume”, *Financial Markets and Portfolio Management,* pp. 1-17.

Xu, X. and Zhang, Y. (2022c), “Steel price index forecasting through neural networks: the composite index, long products, flat products, and rolled products”, *Mineral Economics,* pp. 1-20.

Xue, X., Jia, Y. and Tang, Y. (2020), “Expressway project cost estimation with a convolutional neural network model”, *IEEE Access*, Vol. 8, pp. 217848-217866