Predicting Road Construction Project Costs In Municipalities Through Artificial Neural Network Modeling

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***Abstract*— The accuracy of cost estimates in the conceptualization stage of road construction projects can be affected by unforeseen factors and incomplete data, leading to delays in feasibility studies. To address this issue and optimize the utilization of government funds in Region II, this study proposes an efficient and effective early cost estimation method. An artificial neural network approach is employed to model the local cost of road projects. A dataset of 85 road projects is analyzed, collecting data on various factors including road type, location, road length, project duration, capacity, pavement thickness, pavement width, and shoulder width for each project. MATLAB software is utilized to conduct multiple simulations and determine the optimal model for total road project cost estimation. The model is trained using the Levenberg-Marquardt algorithm, enabling efficient parameter optimization to minimize road construction costs. This approach facilitates more accurate cost estimations, aiding decision-making throughout road construction projects. The most effective neural network architecture incorporates eight input variables, a hidden layer with 13 neurons, and one output variable. The proposed model demonstrates high accuracy in predicting the total cost of road projects, as evidenced by correlation coefficients of 0.99522, 0.9652, and 0.99635 during the training, validation, and testing phases, respectively. Implementing this neural network model enhances the accuracy of cost estimates, thereby facilitating informed decision-making and optimizing resource allocation in road construction projects.**

Keywords*— *road construction, prediction model, artificial neural network, project cost

I. Introduction

Accurate cost estimation plays a pivotal role in determining the success of a project. It not only ensures profitability for contractors but also enables clients to efficiently allocate their funds. Estimation involves forecasting future project costs and resource requirements [1]. However, inaccurate and unreasonable estimations can lead to project failure, as both underestimating and overestimating costs can have detrimental effects [2]. To minimize errors and provide reliable insights, it is imperative to devise an appropriate estimation strategy.

Construction projects, whether in the private or government sector, require feasibility studies to determine their viability. While the benefits of projects may vary based on individual perspectives, cost is a universal factor. Early-stage cost estimates enable businesses to compare projects, adjust their scope according to budget constraints, secure funding, and serve as a basis for cost control during construction [3]. Poor estimation strategies at the preliminary stage can easily turn expected profits into losses [3]. This is where conceptual or preliminary cost estimating comes into play.

The budget is the defining aspect of any project, encompassing major financial investments from owners and setting the scope of work for contractors, including planning, design, construction, assessment, and maintenance. Early cost estimates are prone to inaccuracies as they are primarily based on theoretical calculations with an engineering foundation. These estimates often fail to account for issues commonly encountered during construction, such as cost overruns, delays, and inflation, leading to reduced accuracy. Additionally, during the planning stage, engineering drawings and project-related documents are often incomplete [4]. Traditional manual calculations make construction cost estimation challenging [5]. Some approaches attempt to address uncertainties through methods like point estimates, range estimates, and "what if" scenarios [6]. However, these analyses are time-consuming and require extensive data.

With the advent of new technologies and advanced computer software, various estimation techniques have been developed to support the construction industry. One such method is the artificial neural network (ANN), which emulates human brain learning. Considering the anticipated growth of the transportation network in Region II, it becomes crucial to have a model that can provide reasonably accurate estimates even with limited information, thus minimizing losses in infrastructure projects. Consequently, this paper aims to develop an ANN model for estimating the costs of municipal road construction projects.

This study uses an Artificial Neural Network approach to estimate road construction project costs in municipalities. By improving the accuracy of construction cost estimation, this model can serve as a valuable tool for municipalities, enabling them to predict accurate estimates and make informed decisions during road construction projects.

II. Related Works

The advancement of computer software and technology has significantly enhanced cost estimation methods, leading to the emergence of artificial intelligence tools capable of replicating human decision-making processes. These tools excel in exploring complex relationships and generating realistic and accurate results. Artificial intelligence, a technology that originated in the 1950s, aimed to develop systems capable of rational thinking and decision-making similar to humans. Artificial Neural Network (ANN) is a specific type of artificial intelligence that leverages learning capabilities to mimic the data processing mechanisms of the human brain. Just as the human brain absorbs stimuli through the senses and analyzes the information through neurons to generate responses, ANN learns through pattern recognition and utilizes acquired knowledge to address complex problems with non-linear relationships between variables.

ANN has found application as a cost-estimating tool in various domains, including production, manufacturing, and automotive sectors. In the context of cost forecasting, ANN proves valuable as it learns from past projects and generalizes solutions for future endeavors [5]. For instance, a study proposed a feature-based cost estimation method utilizing the backpropagation neural network for packaging products based solely on design specifications [7]. This algorithm adeptly handles intricate products without necessitating detailed information on manufacturing processes. It can learn and approximate cost functions without relying on actual cost data and is adaptable to changes in manufacturing practices. The neural network approach facilitates the evaluation of different design alternatives. Another study utilized a neural network model to predict the cost of bending steel pipes using information from computer-aided design (CAD) systems [8]. The model outperformed traditional regression analysis, particularly benefiting situations involving new technologies or processes. In a comparison between neural network modeling and regression analysis for sheet metal parts, the former exhibited superior results, although the latter was preferred for its explanatory value and transparency [9]. Similarly, comparable outcomes were achieved using neural networks to estimate the cost of vertical high-speed machining centers [10]. Another study verified the reliability of neural network theory in approximating the manufacturing cost of a new type of brake disk [11]. The applications of neural networks extend to various other studies [12,13,14,15,16].

ANN has also been employed for cost estimation in the construction industry, encompassing residential and commercial buildings [17, 18, 19, 20, 21, 22], school buildings [4, 5, 23], structural systems [24], formwork labor [25], water infrastructure projects [26], retrofit costs [27], construction material prices [28], and more.

In a study focused on residential buildings in Korea, a genetic algorithm was utilized to determine neural network parameters for cost estimation [19]. The model proved more effective than the trial-and-error method, reducing the time and effort required for early-stage project cost estimation. While a neural network estimating model yields accurate results, case-based reasoning proves advantageous when considering long-term use, available information, and the trade-off between time and accuracy [18]. In the UK, ANN was employed to predict bid prices for primary and secondary school buildings, demonstrating good generalization capabilities and average accuracy percentages [5]. Additionally, neural networks were leveraged to develop a parametric cost-estimating model for site overhead costs as a percentage of the total project price in Egypt [29].

In the realm of transportation projects, ANN modeling has been previously implemented for cost estimation in road construction, pavement, and railway projects. Although it may require multiple attempts with various configurations, computer programs and software facilitate rapid and efficient simulation of ANN structures, enabling the identification of the most accurate approach. The authors of this study investigated the utilization of ANN for estimating the costs of road and bridge projects in the Philippines.

III. METHODS

A comprehensive dataset comprising information from a total of eighty-five (85) road construction projects across multiple municipalities was gathered for this study. The data collection process involved identifying and recording eight key factors associated with each project. These factors encompassed the following aspects: road classification, location (municipality), length of the road, duration of the project, capacity, pavement thickness, pavement width, and shoulder width. A detailed overview of the collected data is presented in Table I.

TABLE I. NET EFFICIENCY

No.	Road Factor	Description
1	Project Classification	1- Rehab of road 2- Road widening 3- Road Opening 4- Road Upgrading 5- Road Concreting
2	Location (Municipality)	1- Allacapan 2- Amulung 3- Baggao 4- Cabagan 5- Camalaniugan 6- Cauayan 7- Claveria 8- Cordon 9- Diadi 10- Echague 11- Enrile 12- Gonzaga 13- Ilagan 14- Lallo 15- Penablanca 16- Solana 17- Sta. Fe 18- Tuao 19- Tuguegarao 20- Tumauini
3	Length of Road	Between 0.24-8.25km Average ≈ 1.71km
4	Duration of Project	Between 5-405days Average ≈ 174days
5	Capacity	1-4 lanes
6	Pavement Thickness	Average ≈0.25m
7	Pavement Width	Average ≈4m
8	Shoulder Width	Average ≈1.1m
9	Detailed Cost Estimate	Average ≈ 39880413.4php

In the initial stage, the data was imported from the workspace and organized accordingly. The input variables were assigned to serve as predictors, while the output variable was designated as the response. To assess the model's performance, three distinct datasets were employed: training, validation, and testing datasets. The data was divided in a stratified manner, allocating 70% for training, 15% for validation, and the remaining 15% for testing purposes. This approach ensured a comprehensive evaluation of the model's predictive capabilities.

In this study, the Levenberg-Marquardt algorithm implemented in MATLAB was utilized as the optimization method for training the Artificial Neural Network (ANN) model. The algorithm's capability to handle nonlinear regression and curve-fitting problems made it well-suited for the specific objectives of the study. By leveraging the Levenberg-Marquardt algorithm, the researchers were able to effectively optimize the ANN's parameters, leading to improved accuracy in predicting road construction project costs. The algorithm's memory usage and execution time trade-off offered a practical solution for achieving efficient training and producing reliable results in the context of the study.

To gauge the model's effectiveness, correlation coefficients (R values) were computed for the training, validation, and testing phases. These coefficients served as a quantitative measure of the relationship between the predicted and actual values, indicating the model's ability to capture the underlying patterns in the data. Furthermore, a linear regression plot was generated using the datasets to visually depict the projected target variable. This plot provided a clear representation of the relationship between the input variables and the predicted outcome, allowing for a more intuitive understanding of the model's performance.

IV. Results and Discussion

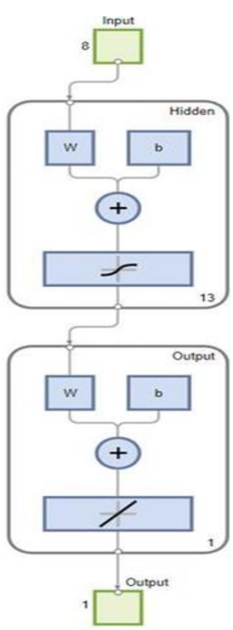

Fig. 1. The ANN Model with an 8-13-1 structure

The evaluation of multiple models for the Artificial Neural Network (ANN) led to the identification of the most accurate architecture, depicted in Fig. 1. This selected model consisted of 8 input variables, 13 nodes in the hidden layer, and the total road project cost as the output variable.

The results obtained from the ANN model, as presented in Fig. 2, showcased its outstanding performance. The correlation coefficients (R) achieved remarkable values of 0.99522, 0.9652, and 0.99365 for the training, validation, and testing phases, respectively. These high correlation coefficients indicate a strong linear relationship between the observed and predicted values, demonstrating the model's ability to accurately estimate the total road project cost.

When all the data points were considered together, the model achieved an impressive correlation coefficient of 0.99071. This comprehensive assessment of the model's performance further solidifies its effectiveness in capturing the underlying patterns and relationships within the dataset.

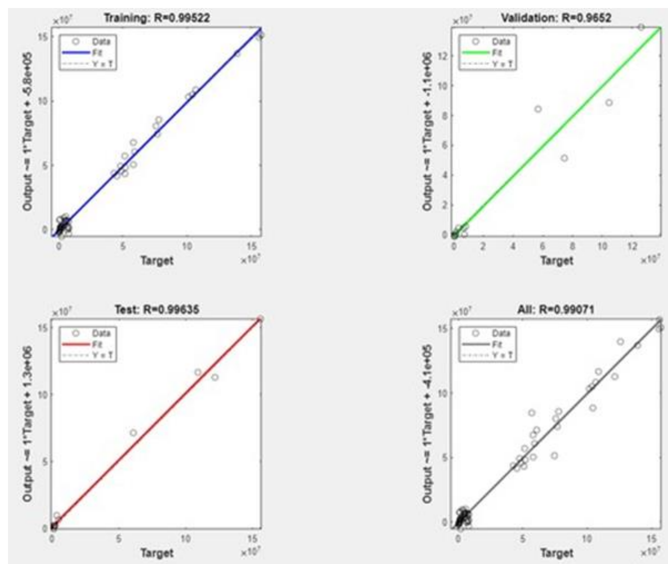

Fig. 2. Regression lines for ANN structure 8-13-1

Furthermore, the R^2 values for the datasets were approximately 0.9, indicating a robust fit of the model with the data. This high R^2 value signifies that a significant proportion of the variability in the target variable can be explained by the model's inputs. Such a strong fit highlights the model's capability to accurately predict the total road project cost based on the selected input variables.

To ensure the reliability and stability of the chosen ANN architecture, the researchers conducted additional simulations. These subsequent simulations consistently produced results that aligned with the initial model predictions. This verification process reinforces confidence in the model's predictions and affirms its reliability in estimating the total road project cost.

In summary, the evaluated ANN architecture demonstrated exceptional performance in accurately predicting the target variable and capturing the complex relationships between the input and output variables. The high correlation coefficients, R^2 values, and consistent simulation results validate the effectiveness, robustness, and reliability of the chosen model. These findings provide valuable insights for improving cost estimation accuracy and supporting decision-making in road construction projects.

V. CONCLUSION

This study successfully developed and evaluated an Artificial Neural Network (ANN) model for estimating the cost of road construction projects in municipalities. Through careful evaluation of different model architectures, the most accurate configuration with 8 input variables, 13 nodes in the hidden layer, and total road project cost as the output variable was identified. The results obtained from the ANN model were highly promising, demonstrating its high performance and accuracy. The correlation coefficients (R) achieved remarkable values for the training, validation, and testing phases, indicating a strong linear relationship between the observed and predicted values.

Based on these findings, several recommendations can be made. Firstly, municipalities and organizations involved in road construction projects should consider adopting ANN models for cost estimation due to their accuracy and reliability. Integrating ANN models into the decision-making process can significantly enhance project planning and resource allocation. Continuous improvement of the ANN model is also crucial. Further research can explore additional input variables, refine the model's architecture, and incorporate more extensive datasets to enhance accuracy and applicability. Collaboration and data sharing among municipalities and stakeholders are recommended to build robust datasets and improve the performance of cost estimation models.

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