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RESEARCH PAPER

Construction Cost Estimation Model and Dynamic Management Control Analysis Based on Artificial Intelligence

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Abstract

Construction cost estimation is affected by a wide range of variables, including the area, type, duration, scheduling, and level of recycling of materials, in addition to the customary elements such as materials, labor, equipment, and method. Construction cost projections greatly support managers' decision-making processes, and risk assessment models reduce time delay. The cost of construction projects may be modeled and forecasted using artificial intelligence (AI) and machine learning (ML) approaches that require a huge amount of data. Hence, this paper proposes an AI-driven construction cost estimation and control analysis (AI-CCECA) model for analyzing the preliminary cost of building projects and dynamic management of the control system. The first step is to identify the most significant cost components and variables that affect overall building costs based on real-world data gathered from project bids and deep neural networks. As a result of this research, construction firms will benefit from improved operational efficiency and competitiveness from its ML and optimization framework. Machine learning could improve the cost estimation in the program phase of the construction process. Workflow optimization for cost savings and practical consequences for data-driven management may be achieved using machine learning models, as shown by the findings of this study.

Keywords Construction cost estimation model · Dynamic management control analysis · Machine learning · Artificial intelligence

1 Overview of Construction Cost Estimation Model and Dynamic Management Control Analysis

The increasing demand among urban residents for both consumer products and cultural institutions has contributed to the boom of the domestic building sector (Dadkhah et al. 2022). A cost estimate at the beginning of building projects has been a key concern for decades in the construction sector (Zhong et al. 2019). At an early point in the design development for a project, one of the most significant considerations is the budget (Wang and Hong 2020). Construction projects are judged on their success based on their ability to stay under budget, be completed on schedule, and meet or exceed customer expectations for quality of work (Akanbi and Zhang 2021). Managing the dynamic energy of a building requires a complex system. Both residential and commercial buildings may benefit from the system's ability to regulate energy management construction and various other factors. The term "digital technologies for energy management" refers to collecting, reporting, and analyzing data from building and process management systems and controlling costs and energy-consuming equipment utilizing computer programs. A budget cost estimate tool and a work schedule are essential for the construction manager or contractor (Ibrahim and Elshwadfy 2021). Any construction project's budget and projected costs must be carefully considered. An expected profit might swiftly become lost if the budget or cost forecasts are inaccurate (Hyung et al. 2019). The complex cost estimation problem in the building construction field is traditionally burdened by a lack of data, uncertainties, and risks, and at the same time, is critical for the success of construction projects (Wahab and Wang

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2021). In many cases, a lack of accuracy in the original cost estimate is the cause, due to the lack of data and the need to achieve results in a short amount of time (Arabzadeh et al. 2018). A superficial and inaccurate evaluation of the project results in several additional processes that might undermine the project's goals, with many negative consequences (Ekung et al. 2021). Regardless of the scope or scale of the project, the parties will need access to cost data as quickly as possible (Toutounchian et al. 2018). Smart buildings using sensors and artificial intelligence (AI) might revolutionize urban energy efficiency. AI technologies in smart buildings increase control, dependability, and automation, reducing energy use. This article reviews current research on the use of AI technology in buildings via building management systems and demand response programs. The most current research in this area along with the key AI areas, such as vitality, convenience, fashion, and servicing, are evaluated using a new assessment methodology that is presented in this work. This necessitates the development of an accurate and time-limited cost estimation system (Barros et al. 2018). Because of this, cost engineers, decision-makers and project managers find it difficult to estimate the conceptual cost accurately. Using qualitative methodologies or statistical studies such as stepwise regression or factor analysis, parametric cost modeling produces a model based on statistical or logical relationships of the critical cost drivers (Ahn et al. 2020). In addition, under the condition that the cost budget is not exceeded, the construction materials with better quality should be selected as much as possible to enhance the effect of dynamic management and control analysis of construction costs and effectively guarantee the structure quality (Meharie et al. 2019).

Drones, sensors, and cameras are just some of the autonomous equipment that project managers use to monitor the work site. AI can be used in dynamic control system management for the early cost analysis of construction projects. The takeoff process for building projects has been greatly accelerated with the use of AI estimate tools. Global construction leaders say that using technology has boosted productivity and enables more time to be devoted to value-added activities such as project scoping, pricing, and value engineering. Because of this, they can improve the efficiency of their estimators to achieve greater precision.

AI advances in the construction sector have enabled greater experimentation with construction and building design (Choi et al. 2022). There must be a strategy for introducing AI throughout the building phase. Because it is self-aware and can navigate without human assistance, AI is considered autonomous technology (Wang et al. 2021). In the early phases of a project, AI machines may collect enough data to build 3D maps, blueprints, and construction plans from a planned construction site. Building information modeling (BIM) may guarantee that historical information about a building's construction is preserved (Son and Khwaja 2022). AI methods such as neural networks are widely used in construction engineering. Another estimate that can be conducted using neural networks is estimating the material consumption for the construction of a facility (2021). Automating high-precision cost estimations based on acquired project data is a powerful feature of AI. For any construction project to succeed, it is essential to estimate costs accurately since cost overruns are a substantial unknown risk, particularly in light of the present focus on tight budgets (Pan and Zhang 2021). Furthermore, high costs may necessitate discontinuing a project. As a result, the primary need for designing a cost model is to improve forecast accuracy (Rafiei and Adeli 2018). The critical challenges during prediction modeling are the missing data values, small data size, computational complexity, maintaining ambiguity, and model elucidation (Tushar et al. 2018).

Construction organizations use AI to monitor construction sites and use predictive analytics to enhance project quality, safety, profitability, and schedules. AI helps builders monitor everything. The AI will analyze project bid data and deep neural networks (DNN) to discover which aspects most affect building costs. This study's ML and optimization framework will improve construction organizations' efficiency and competitiveness. In addition, machine learning may assist in predicting construction expenses during planning.

Electricity, computing power, and network constraints will limit commercial AI installations. Since some projects are remote, getting the software needed for AI operations may be complicated.

Therefore, the major contributions of the article are (i) the design of an AI-driven construction cost estimation and control analysis (AI-CCECA) model for dynamic management in the construction industry; (ii) introduction of a DNN to predict engineering service costs and enhance cost estimation efficiency; and (iii) implementation of the numerical results, showing that the recommended AI-CCECA model improves efficiency, prediction, and accuracy and decreases error compared to other existing models.

2 Related Studies

Yousif et al. (2020) discussed a web-based framework (WBF) for automating the cost estimation of concrete construction using the Active Server Pages network (ASP.NET), which provides a user-friendly interface to ensure that the task is performed sequentially. Other approaches (such as manual labor using paper or Excel) were evaluated using actual data and then confirmed by professionals and consulting firms, and the Quantity Surveying (QS) framework provided a reliable and time-efficient estimating method here.

The system made it easier to estimate expenses by automating the process of extracting project data from construction maps. Additionally, it might utilize Google Maps to automatically identify the project's location and promptly direct the user. To reduce human calculation errors, the proposed QS framework automates manual and Excel cost computation tasks with 99% accuracy. In addition, it reduced the calculation time from 3 weeks to only 3 days.

Fazeli et al. (2020) introduced the integrated BIM (IBIM) for cost estimation in construction projects. The system's performance was based on linking UniFormat and MasterFormat categorization standards with FehrestBaha cost estimation standards. IBIM-based extensions for Revit were used to automate calculating costs in the construction industry. The proposed method might be used by practitioners to quickly and accurately estimate the cost of various IBIM-based scenarios throughout the design process. Compared to more typical manual procedures, the semi-automated solution significantly decreases the time needed to estimate costs. A real construction project was utilized to test the efficacy of the recommended method to cost estimation, which estimates the architectural discipline's cost. An appropriate accuracy was achieved using a BIM-based technique to estimate the architectural discipline costs.

Tijanic et al. (2020) proposed an artificial neural network (ANN) for cost estimation in road construction. In this article, three different ANNs were used to predict the cost of building a road: the general regression neural network (GRNN), the multilayer perceptron (MLP) network, and the regional basic functional neural network (RBFNN). The model relies heavily on a database of highways constructed in Croatia. With a coefficient of determination of 0.9595 and mean absolute percentage error of 13%, the best neural network performance was achieved by the GRNN. Since there is generally only a small or partial set of data available for cost analysis in the early stages of design, neural networks have been shown to be a viable strategy. This method might provide considerably more accurate findings and minimize the estimated error.

Le et al. (2021) introduced a BIM-database integrated system (BIM-DIS) for accurate building cost prediction. The proposed system consists of four main parts: a database that is a relational administration module, a combined graphical BIM module, a cost estimation module, and a BIM-integrated report module. BIM models may be stored and updated using the relational database management module, which enables consumers to view complicated construction parts while cost estimation is provided via a BIM-integrated module. Components of the project's cost are computed using the cost estimation module. When estimating expenses, it may automatically adapt to changes in construction element specifications. Data entry and computation mistakes may be reduced using this module. The BIM-integrated system module makes it easy for users to obtain the data and understand it. The proposed technique provides a more effective means of calculating building costs using 3D models than typical 2D computer-aided design (CAD) drawings. It may save time, money, and mistakes in the construction procurement process.

Abioye et al. (2021) reviewed AI applications, methodologies, and construction industry opportunities and difficulties. Activity monitoring, risk management, resource and waste optimization, and AI applications in construction were critically examined. The authors also identified and highlighted the prospects and problems for AI in construction. The paper discusses significant AI applications for construction-specific difficulties and how to realize the advantages of AI in the construction sector.

Kyivska et al. (2021) proposed machine learning and fuzzy logic labeling of visual data, assessing it for dangers, and decreasing all risk. Machine learning technologies may eliminate project hazards before they harm earnings. Thus, AI and BIM technology may forecast building project work based on real-time data, prior actions, and other criteria to improve construction processes. The fuzzy logic technique has several aspects, including that machine learning algorithms become more complicated as they analyze more data. This reduces project risks and optimizes resource allocation. In addition, AI may incorporate statistical likelihood into designing a knowledge-driven safety management system to lessen the risks associated with construction projects.

In achieving high efficiency, prediction, accuracy, and error, existing models such as WBF, integrated BIM (IBIM), ANN, and BIM-database-integrated system (BIM-DIS) face numerous obstacles. Consequently, the AI-CCECA model has been proposed in this article. The following is a brief discussion of this model.

3 Artificial Intelligence-Driven Construction Cost Estimation and Control Analysis (AI-CCECA) Model

The cost estimation of a construction project is critical in the building industry since it affects whether the project can proceed. To arrive at a rational and realistic cost estimate, the potential variations in each construction procedure must be extensively considered throughout the project estimates. It is important to anticipate the project's current and future stages and any prospective issues that may arise during the course of the project (e.g., every year, month, and quarter). The rate of energy management can be increased, on-site generation can be facilitated, operating defects can be detected and minimized, and continuous energy savings can be controlled and ensured—all of which are challenges in establishing energy-efficient buildings—with the aid of AI. Complexity and high cost may result from having many control systems in a structure. Therefore, employing AI technologies with a digital transformation mentality will save operating costs and improve the building's energy efficiency. The DNN-based controller efficiently finds an almost globally optimal solution to a quadratic problem with mixed integers. Construction projects completed on schedule and under budget are considered a success. It is possible to assess and enhance a project's quality throughout the building period, although money and time must satisfy their contractual estimates. The research purpose of dynamic control engineering cost is to use technology and economics to predict engineering cost, control, analyze and optimize engineering cost to realize the best allocation of investment resources and the most significant economic benefits. During this project planning stage, there is a lot of uncertainty and risk since there is very limited knowledge about the project. Furthermore, the estimate must be produced within a certain time. Cost engineers, decision-makers and project managers thus find the process of developing an accurate conceptual cost estimate complex and critical. Developing cost-estimation models based on DNNs as AI and machine learning tools is a popular issue in construction management research and publishing. Hence, this paper proposes the AI-CCECA model for cost estimation and dynamic management control analysis in the construction industry. As data storage and processing capacity have increased and improved, statistical approaches, such as those based on AI and machine learning, have been developed, and building cost estimation based on DNN is now being investigated. This study investigated DNN, predicted building structural costs, and identified cost drivers. An ML-based cost prediction method for engineering service bids was tested. Creating and upgrading a neural network model approximated engineering service costs. The results showed that DNN could predict cost with less tendering data.

By analyzing building system data, AI may enhance energy efficiency, indoor air quality, and other performance indicators. AI simulations can identify energy-wasting regions for improved building design and construction. AI, like machine learning, knowledge-based systems, and optimization, has improved profitability, efficiency, safety, and security in various sectors.

Figure 1 shows the bid structure and analysis in construction projects. The total project cost comprises both direct and indirect project costs. Direct project expenditures are included in the project's direct cost; those that the project's

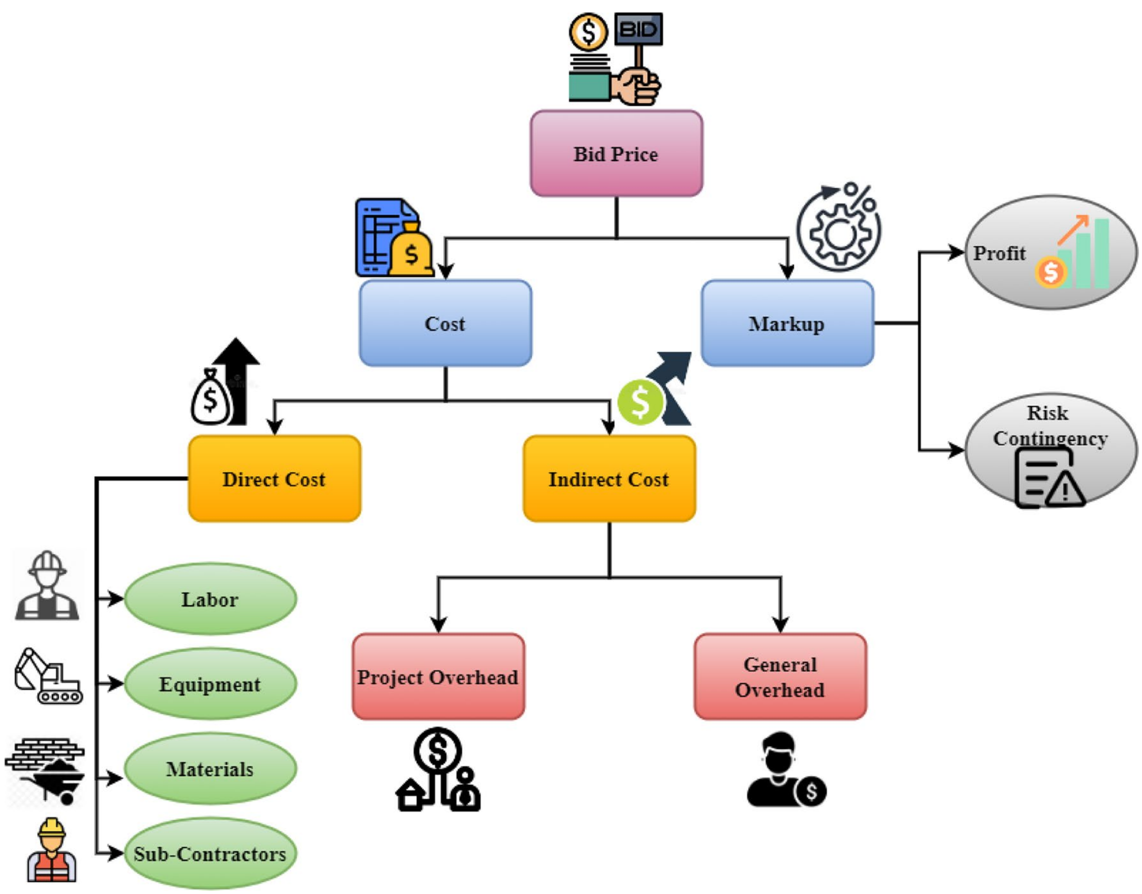


Fig. 1 Bid structure and analysis in construction projects

employees incur are included in the project's indirect costs. As a general rule for determining overhead costs, general overheard does not apply to each project; rather, it is the overall cost of a contractor's organization, which may be ascribed to each project proportionately based on its total cost. The total of the project's costs, the company's bid price, and an amount referred to as markup consists of the following sums of money. The amount of money ascribed to a company's profit varies depending on its goals, industry competitiveness, and how much the contractor is willing to spend to win the project over its competitors. Contingency for risk or recognized risks or unknowns is put aside in the case of unexpected occurrences or labor concerns that might impact the project's outcome.

Labor, materials, and tools are all direct expenditures connected to a particular project. Expenses such as rent, utilities, and management fees are indirect expenditures that cannot be ascribed to a single project. Some expenses, both direct and indirect, may be written off. Direct expenses include fixing the manufacturing line used in the firm and are thus deductible from profits. Rent, utilities, and certain insurance premiums may all qualify as indirect charges that may be deducted from taxable income.

Figure 2 shows the DNN model, which helps to improve a model's performance accuracy. They will enable a model to take a set of inputs and give outputs. Using a DNN is as simple as copying and pasting a line of code for each layer. Input nodes, hidden nodes, and output nodes are the three standard components of a basic ANN model. It is possible that DNNs, which may have many hidden layers, are more versatile. The number of hidden layers identifies the architecture's profundity. Every hidden layer has activation functions and multiple nodes (neurons). Typically, one activation function is utilized for every neuron within a layer.

Each hidden layer consists of neurons linked to all neurons in the layer above it. The output of a layer is produced by passing the result of the layer below it through a nonlinear map, f(.). The last neural network layer is likewise ultimately linked, which is called the "output layer," and it displays the network's final output classifications. Separate counts are kept on input and output layers. The output of each layer is created by using a nonlinear map. Vector vl represents the lth layer's output in an L-layer network, where layers 0 and L+1 represent the input and output, respectively. A unique activation function for the output layer must be selected to complete a classification job. During training, the weight matrices, W, and bias vectors, b, for each layer are determined so the system can perform the classification task. Training may be accomplished by finding the optimal value of the following cost function.

The activation function is denoted by l in Eq. (1), al denotes the bias vector, and the weight matrices are denoted by Sl. Predictions for the objective parameter, or input layer x, are made using the hidden layer g^l. Nonlinear connections between input and output may be mapped using an activation function.

The input $x$and the output vector y of layer l are calculated utilizing the output g^{l-1} of the previous layer $l-1$, shown as Eq. (1).

$$g^l = \rho^l\left(a^l + S^l g^{l-1}\right) \tag{1}$$

In Eq. (1), ρ^l denotes the activation function, a^l indicates the vector of the bias value, S^l signifies the weights matrices.

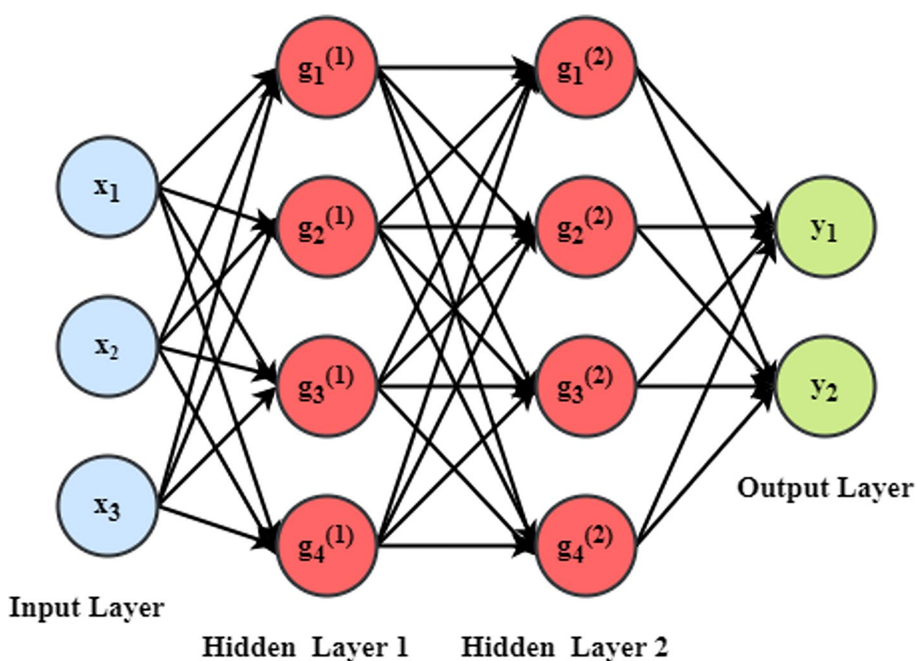


Fig. 2 DNN model

Predictions for the target parameter, or input layer x, are made using the hidden layer g^l.

The activation function enables mapping of the non-linearity relationships between output and input. There are numerous activation functions, such as *tanh*, sigmoids, linear and rectified linear unit (ReLu). This research uses *tanh* activation functions for input layers. ReLu activation functions are chosen for the hidden layers because not every neuron will be activated every period, facilitating model training. Since the ultimate goal of this work is to anticipate building costs as a regression problem, linear activation functions are used for the output layers. The formulation of these three activation function

$$\begin{aligned} \tanh h : \tanh h(y) &= \frac{e^y - e^{-y}}{e^y + e^{-y}} \\ \text{relu} : x(y) &= \max(0, y) \\ \text{linear} : x(y) &= y \end{aligned} \tag{2}$$

As inferred from Eq. (2), the value of bias vectors is set to be persistent, and the weight in every layer is adjusted arbitrarily at the beginning of training. Optimization models would update the weights to reduce the difference among the forecasted and the real output parameters.

An explanation method is the interpretable estimate of the actual model in the additive feature attribution techniques. Shapley Additive Explanations (SHAP) use game theory principles to understand the output of machine learning. The explanation method h is a linear function of the binary variable:

$$h\left(z'\right) = \theta_0 + \sum_{j=1}^{N} \theta_j z'_j \tag{3}$$

In Eq. (3), $z' \in \{0,1\}^N$, N denotes the simplified input feature and $\theta_0 \in \mathbb{R}$. z'_j indicates the feature is unknown $\left(z'_j = 0\right)$ or perceived $z'_j = 1$ and θ_j signifies the feature attribution values.

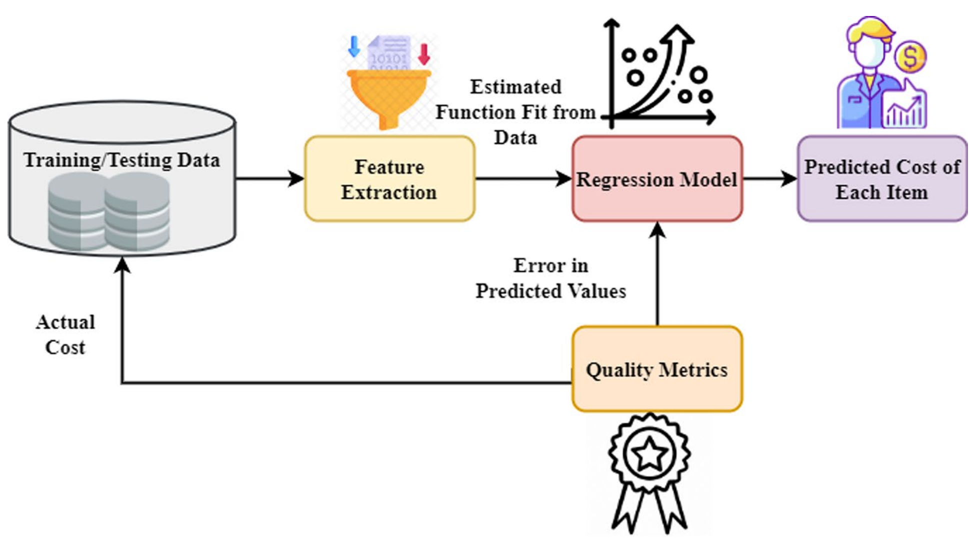
In general, activation functions transform the linear neuronal outputs into nonlinear ones, allowing a neural network to acquire nonlinear behaviors. The ReLU returns x whenever x is greater than zero and 0 otherwise. When the output range of the tanh function is −1 to 1, it is identical to the sigmoid/logistic activation function. Since the sigmoid is not linear, the output of this device is also not linear in terms of the sum of its weighted inputs.

Figure 3 shows the cost prediction model. Extraction of the independent variable, or feature, from the training dataset, is known as feature extraction. The year is an independent variable in the training dataset since it comprises each item's cost over 12 years. The ML model uses a year of feature extraction as input. The training dataset's dependent variable (the actual cost of the items) is included in the quality measure. Errors in our anticipated values provided by quality metrics may be utilized to minimize the prediction error further. A linear regression machine learning model is employed to estimate the function. The additive feature attribution class models have a unique element: there is an exclusive resolution in this class with three necessary elements, i.e., consistency, missingness, and local accuracy. Where these three elements are encountered and Eq. (3) is followed, there is only one probable clarification model h:

$$\theta_j(f, y) = \sum_{z' \subseteq y'} \frac{|z'|\left(N - |z'| - 1\right)}{N} \left[f_y\left(z'\right) - f_y\left(\frac{z'}{j}\right) \right] \tag{4}$$

In Eq. (4), f indicates the actual prediction model, $\left|z'\right|$ denotes the number of the $\neq 0$ entry in z', $z' \subseteq y'$ symbolizes

Fig. 3 Cost prediction model



all z' vector where the $\neq 0$ entry is a subset of the $\neq 0$ entry in y', $\frac{z'}{j}$ denotes the setting $z' = 0$. The SHAP (Shapley Additive Explanations) value is the solution to Eq. (4) and specifies a suitable measure of parameter significance in the DNN regression model.

Before training the DNN model and the other ML techniques, this research utilized feature scalings. The input parameters have been converted into the interval of [1, 0], correspondingly:

$$x(y_j) = \frac{y_j - y_{\min}}{y_{\max} - y_{\min}} \quad (5)$$

The model used to estimate costs is shown in Fig. 3. Feature extraction is the process of removing the independent variable from the dataset used for training.

The training dataset includes the annual cost of each item over 12 years, making the year an independent variable.

A year's worth of feature extraction data is fed into the ML model. The quality metric incorporates the training dataset's dependent variable (the products' real prices). Quality measures may be used to correct errors in our predicted values to reduce the prediction error further. Finally, the function is estimated using a machine-learning linear regression model.

One distinctive facet of models for attributing additive features is that a resolution is available only for this class, provided that three conditions are met: consistency, absence, and local precision.

There is only one possible clarifying model h when these three components are present, and Eq. (3) is followed.

This study used feature scaling before the DNN model and other ML approaches were trained.

Figure 4 shows the machine learning regression framework. It involves data processing, machine learning regression models, and DNN model assessment. The actual data, described as those gathered from the enterprise without any modification, have been initially examined utilizing numerous processing approaches, like data checking and data normalization. The training dataset is utilized as the input for the machine learning models that have been validated using the test dataset. During this process, parameter tuning has been achieved to maximize/improve the model accuracy.

Model construction is the procedure in regression analysis when a probabilistic model is created to characterize the connection between the dependent and independent variables. In civil engineering, complex prediction and classification issues are often tackled using regression methods due to their relative ease of use. The term "linear regression" (LR) refers to a statistical method for progressively valuing a linear connection between dependent and independent variables. Determining which independent variables affect the dependent variable is the goal of a regression analysis.

Then, all observations are randomly divided into two parts to predict the probable overfitting problem and achieve optimal DNN models that require comparison and testing of several models. Linear regression (LR) represents the progression of valuing the linear relationship between dependent parameters and independent parameters. An overall model of linear regression:

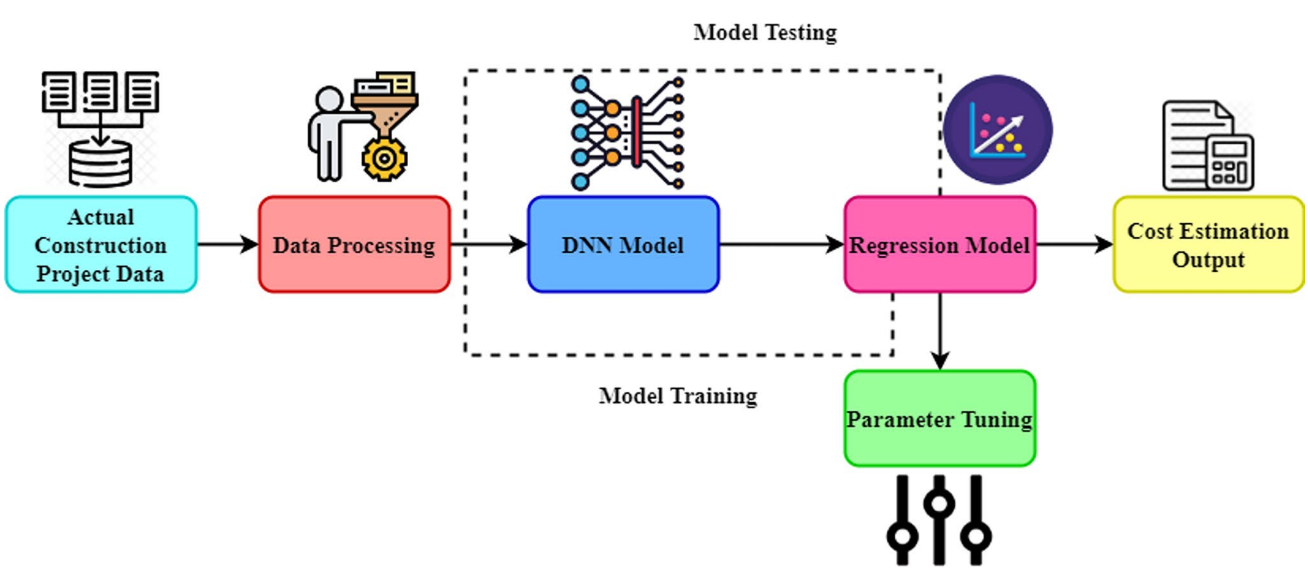


Fig. 4 Machine learning regression framework

$$X = \alpha_0 + \alpha_1 Y_1 + \alpha_2 Y_2 + \cdots + \alpha_q Y_q + \varepsilon \tag{6}$$

In Eq. (6), X represents the estimated final cost, and $Y_1, Y_2, \ldots Y_q$ are the features of the project and the exterior economic factor, $\alpha_0, \alpha_1, \alpha_2, \ldots \alpha_q$ are the variables to be assessed utilizing the least-squares criterion, and ε denotes error terms with arbitrary normal distributions.

The article discusses widely used measures, including the root mean square error (RMSE), the regression coefficient of correlation (R2), the mean average percentage error (MAPE), and the mean of absolute error (MAE) to evaluate the DNN's effectiveness in construction cost predictions:

$$\begin{aligned}
R^2 &= 1 - \frac{\sum_{j=1}^{n} \left(x_j - \hat{x}_j\right)^2}{\sum_{j=1}^{n} \left(x_j - \bar{x}\right)^2} \\
\mathrm{RMSE} &= \sqrt{\frac{1}{n} \times \sum_{j=1}^{n} \left(\hat{x}_j - x_j\right)^2} \\
\mathrm{MAE} &= \frac{1}{n} \times \sum_{j=1}^{n} \left|\hat{x}_j - x_j\right| \\
\mathrm{MAPE} &= \frac{1}{n} \times \sum_{j=1}^{n} \left|\frac{\hat{x}_j - x_j}{x_j}\right|
\end{aligned} \tag{7}$$

In Eq. (7), x_j denotes the observed target variable, $\hat{x}_j$ indicates the forecasted target variables, and $\bar{x}$ represents the mean of x_j.

Figure 5 shows the construction cost estimation flow chart and dynamic management control analysis. It is possible

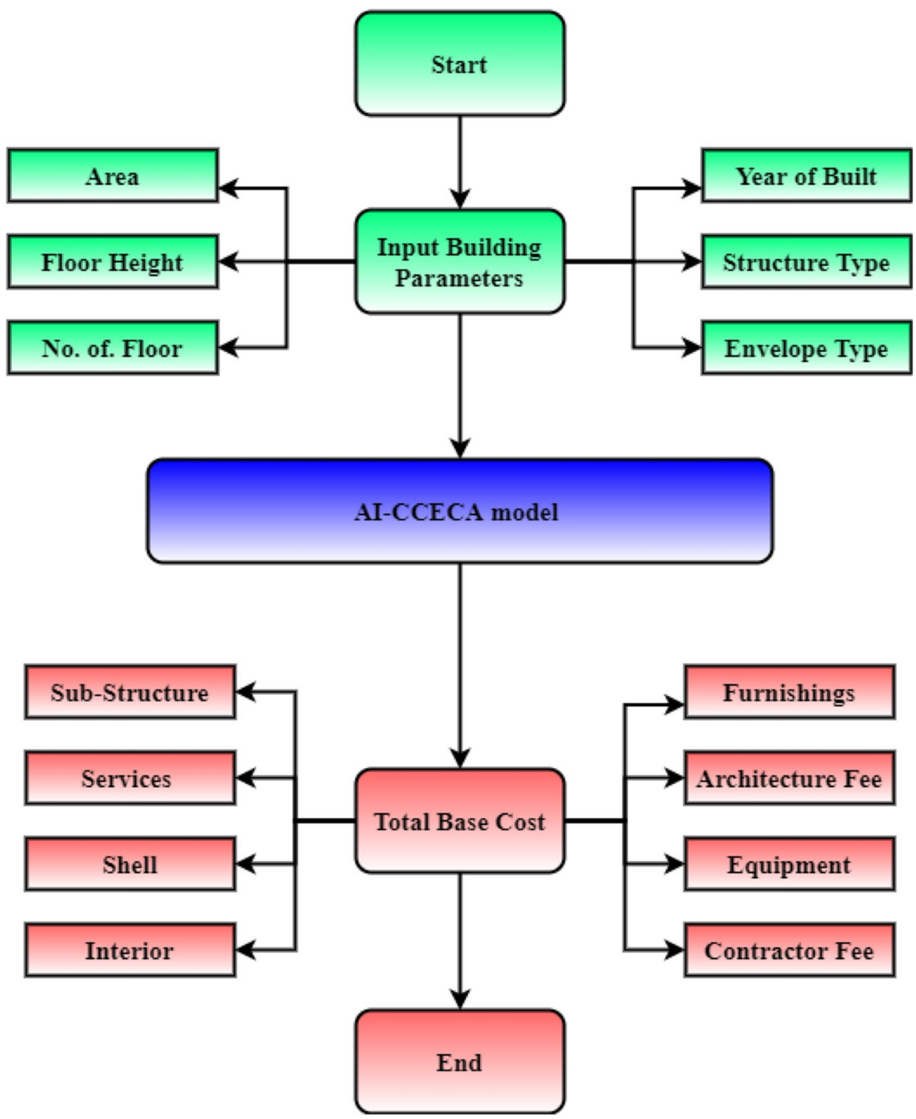


Fig. 5 Flow chart of construction cost estimation and dynamic management control analysis

to calculate the start-up costs utilizing steel and concrete construction types in the model. There was a correlation between the size of the building, the number of stories, and the height of the floors. Model creation, validation, and early diagnostics on data quality were the three primary steps in developing the model. The breakdown cost components include substructure, superstructure, interiors, equipment and furnishings, and architectural fees. The subtotal cost is then added to the contractor's and architect's fees to arrive at the final construction cost after the breakdown component prices have been estimated. Location and age of the building are two examples of factors that have become more consistent. An important factor in early costs is the structure-envelope and its height and number of stories. These variables are considered to determine whether they are linked to the resultant front expenses (dependent factor). Even though building processes, materials, and technology constantly evolve, the approach used to control project costs remains static. Because of this, conventional management practices no longer work in today's dynamic market economy. The proposed AI-CCECA model increases the accuracy, efficiency, prediction, and decision-making ratio and decreases the error ratio compared to other popular models.

The capacity to facilitate process modification by any role, at any time, with extremely minimal latency is what is meant by "dynamic management" in the proposed approach. Dynamic management is effective since it centralizes information and many systems. It's useful since it enhances comprehension, visibility, and speed, all of which contribute to more expedient problem solving.

DNN models provide a potential solution for overcoming these limitations of the matrix factorization technique. The flexible input layer of the DNN allows for the simple incorporation of query characteristics and item attributes, which together may better capture a user's unique interests and lead to more accurate proposals.

4 Numerical Results and Discussion

This study offers the AI-CCECA model for cost estimation and dynamic management control analysis in the construction industry. This study analyzes the proposed model's performance parameters, namely accuracy, efficiency, prediction, and error rate. The dataset used to evaluate the AI-CCECA model's efficiency (https://www.accasoftware.com/en/construction-cost-estimating-database). ACCA Software is a pioneer in the software industry, delivering innovative tools for building planning, construction management, and upkeep to clients all around the globe. Customers may learn about novel approaches to architecture layout, architectural planning, evaluation and computations, resource management, volume assessment, health and safety on building sites, servicing, and BIM process management.

4.1 Accuracy Ratio of the AI-CCECA Model

Construction projects need strict budgeting, planning, and monitoring to ensure that the customer's available budget, timeline, and outstanding work are being met. Cost estimates range in precision from one set of experts to the next. Estimation methods, however, need to be quick, realistic, and somewhat accurate throughout the tender stage of a project. Using AI applications, it has been shown that even with insufficient information, it is feasible to obtain accurate cost estimates. The owners' decision-making is influenced by the accuracy of the construction cost estimate, which is critical to the project's success. The reliability of the DNN model in estimating building costs has been determined using Eq. 2. The proposed AI-CCECA model improves the accuracy ratio by 98.7% in comparison to other approaches. The accuracy ratio is shown in Fig. 6.

4.2 Prediction Ratio of the AI-CCECA Model

The goal of automated cost estimation is to identify the links between the significant elements and the project cost using prediction models or algorithms. Eliminating the regression equation based on the input method of the independent variables was one of the steps taken in the process of using regression analysis to create a construction cost prediction model for facility construction. One model was constructed using regression analysis, while the other model used DNNs to estimate main construction costs. Both models were designed to help estimate primary building expenses. Equation 3 was used for the calculation, which yielded the

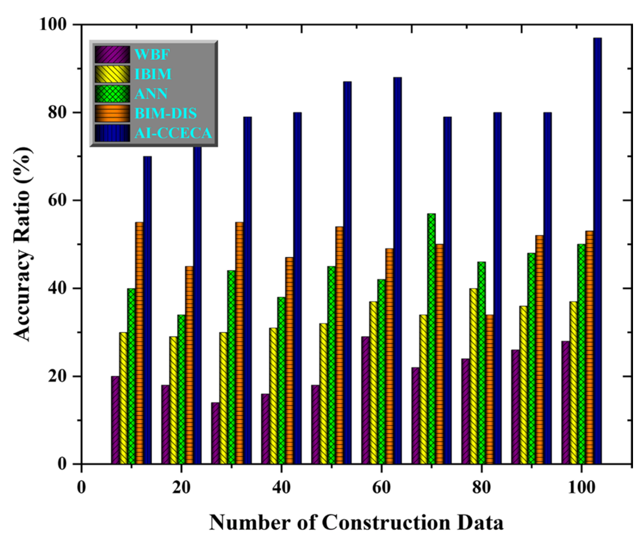


Fig. 6 Accuracy ratio of the AI-CCECA model

prediction ratio. When compared to other models that are already available, the recommended AI-CCECA has a prediction ratio that is 97.9% more accurate. The prediction ratio is shown here in Fig. 7.

Figure 7 shows that the profitability of a business is quantified by calculating its efficiency ratio, which is obtained by dividing the total assets by the sum of the current liabilities and current assets. A firm's capacity to convert its resources into earnings may be measured using efficiency ratios.

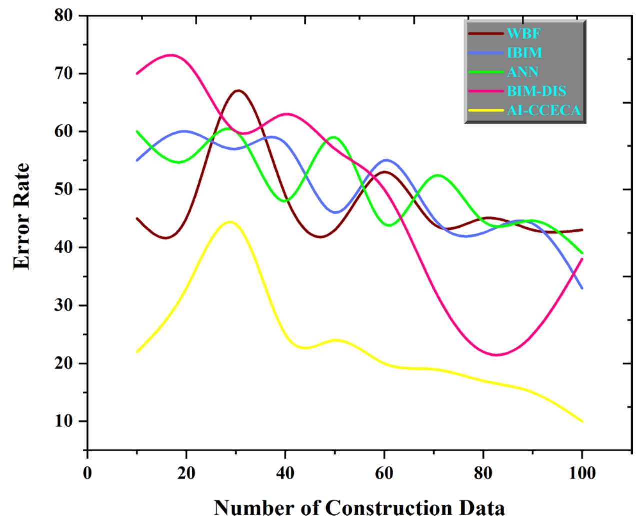


Fig. 8 Error rate of the AI-CCECA model

4.3 Error Rate of the AI-CCECA Model

The accuracy of the DNN model is within the range of models produced in comparative studies in the literature, which is impressive. The DNN generates outputs in random order using the inputs and weights. The loss function employed in this research is the mean square error. Equation 7 demonstrates and calculates the error rate. The proposed AI-CCECA model reduces the error rate by 9.8% compared to other existing models. Figure 8 shows the error rate.

According to the findings of this research, the mean square error is the loss function of choice. The method's inaccuracy is measured by how much the actual results differ from predictions. The error is expressed as a percentage if the targeted values are categories. The accuracy of a machine learning model is quantified by how many classes it correctly predicted out of the total number of predictions the model made.

4.4 Efficiency Ratio of the AI-CCECA Model

This study used a systematic methodology to create and optimize DNN cost estimations. Ensembles of DNNs may be used to model air pollution, estimate concrete compressive strength for high-performance concretes, forecast building electrical demand levels, and analyze labor efficiency in construction projects. Equation 5 was used to determine the AI-CCECA model's efficiency ratio. When compared to other widely used models, the efficiency ratio is improved by 96.4% when using the proposed AI-CCECA model. Figure 9 shows the productivity index.

Predictive modeling, in Fig. 9, shows the results for data mining methods used to provide a prediction ratio that can be used to predict potential future developments. This is possible in fields as varied as meteorology, finance, medicine, and business analytics.

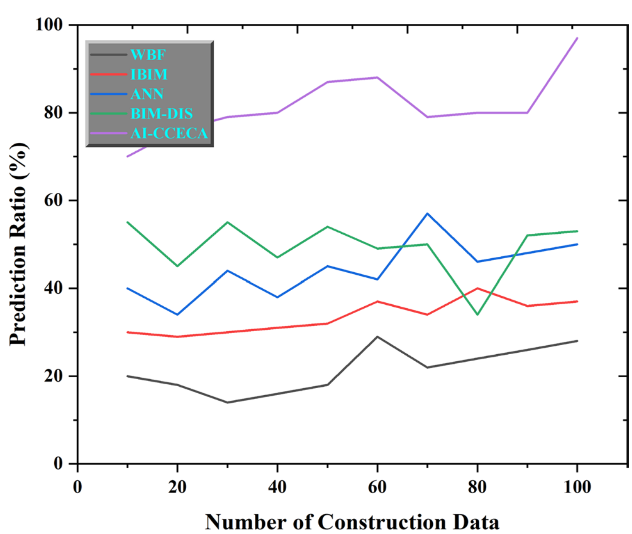


Fig. 7 Prediction ratio of the AI-CCECA model

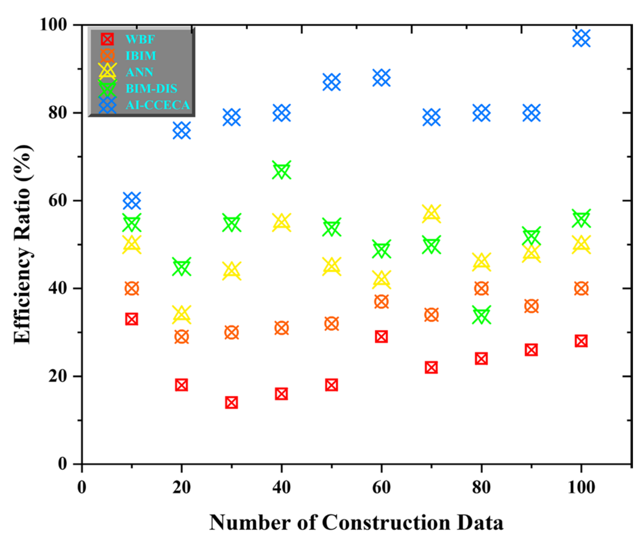


Fig. 9 Efficiency ratio of the AI-CCECA model

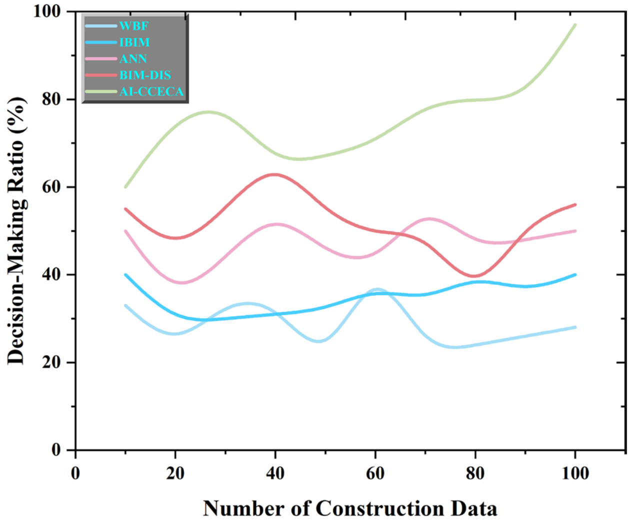


Fig. 10 Decision-making ratio of the AI-CCECA model

4.5 Decision-Making Ratio of the AI-CCECA Model

An accurate prediction is possible only if input data are represented appropriately using machine learning. A model built to anticipate whether a construction contractor will bid on a project does not need to examine the contractor physically. Instead, the model uses data from the contractor's previous bids to determine the answer. A feature is a graphical depiction of a project's attributes that aids the computer in making a decision. Finally, this study indicated that modern technologies might predict the cost of construction projects with promising results. Equation 6 shows the proposed AI-CCECA model's decision-making ratio. When compared to other available approaches, the proposed AI-CCECA model obtains a high decision-making ratio of 95.6%. The proportion of decisions made is shown in Fig. 10.

The proposed AI-CCECA model improves the prediction, efficiency, accuracy, and decision-making ratios and decreases the error ratio compared to other popular models, including WBF, IBIM, ANN, and BIM-DIS.

Business owners may use decision-making ratios to gauge how well their operations are performing in comparison with those of competitors. The connection between two or more elements in a set of financial statements may be evaluated using ratios. When comparing outcomes across periods, they provide valuable insight. Ratio analysis makes it possible to quantitatively assess a company's liquidity, operational efficiency, and revenue based on information found in financial statements like the balance sheet and the income statement.

5 Conclusion and Future Scope

This paper presented a new construction cost estimation model utilizing improved machine-learning techniques. The study aimed to explore the DNN technique, forecast the total structural cost of buildings, and identify the factors affecting the cost, in order to determine whether an accurate ML-based cost prediction approach for bidding engineering services could be developed. Initial expenses for engineering services were estimated by methodically creating and improving a neural network model. The findings revealed that a reasonable cost estimate could be obtained using DNN, even with fewer data points provided during the tendering process. AI-CCECA is projected to generate impressive project management and civil engineering outcomes because of its high accuracy.

In the subsequent work, we plan to develop and test the DNN-based model against benchmark models in a real-world building testbed. We are conducting residential and business energy studies to obtain sufficient data. Then, models will be tested and retrained using accurate data. We intend to test the concept at different timescales.

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