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Building Engineering and Management using Artificial Neural Networks

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Research Article
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Abstract:

Recent years have seen a significant increase in the use of artificial neural networks in construction engineering and management. In order to investigate the trend and new directions of the applications of various ANN algorithms, more than 100 resources published in peer-reviewed journals and conference proceedings were screened and examined. According to the report, ANNs have been successfully used in cost prediction, scheduling and optimisation, risk assessment, claims and dispute settlement results, and decision making. It was noted that ANNs have been used to address issues that are challenging to resolve using conventional statistical and mathematical techniques. When compared to traditional ANNs, the integration of ANN with other soft computing techniques such as Genetic Algorithm, Fuzzy Logic, Ant Colony Optimisation, Artificial Bee Colony, and Particle Swarm Optimisation often showed better results. The paper offers a thorough evaluation of artificial neural networks (ANNs) in construction engineering and management for use in many fields for increased precision and trustworthy forecasts.

Keywords: Artificial Neural Network, construction management, construction engineering, construction cost estimation, con- struction scheduling

1 INTRODUCTION

Artificial Neural Networks (ANNs) are computational mechanisms that, given a collection of data indicating a function, can acquire, represent, and calculate the function from one multivariate space of information to another. For complex qualitative or quantitative problems where the parameters for traditional statistical and mathematical methods are highly interdependent and the data is inherently noisy, incomplete, or prone to error, artificial neural networks (ANNs), a functional abstraction of the biological neural structure of the central nervous system, are more effective than traditional methods (Rumelhart 1986; Adeli 2001; Aleksander and Morton 1993; Rudomin et al. 1993; Arbib 1995; Geon 2005; Sivanandam and Deepa 2006; Bala et al. 2014). It has been demonstrated that artificial neural networks (ANNs) are effective pattern recognisers and classifiers that function as a "black box" to identify important patterns in data (Adeli 2001; Jain and Pathak 2014). They are made up of several closely linked processing units called neurones that cooperate to address certain issues. The architecture (connection between neurones), activation function, and training or learning (determining the weights on the connections) are the essential characteristics of ANNS.
Previous use of ANN in engineering can date back to 1989. They have since been successfully used to address a wide range of technical and managerial issues. Construction cost estimation (Williams 1994; Emsley et al. 2002; Wilmot and Mei 2005; Sodikov 2005; Pewdum et al. 2009; Alex et al. 2009; Waziri 2010; Bala and Waziri 2012; Bala et al. 2014), project cash flow (Boussabaine and Kaka 1998), production forecast (Chao and Skibniewski 1994; Portas and AbouR-izk 1997; Boussabaine 1995; Savin et al. 1998; Al-Zwainy et al. 2012). Despite ANN's many advantages over traditional statistical tools, including adaptive learning, self-organization, real-time operation, and fault tolerance, it provides little explanation of the relationships between the modelling parameters, making it challenging to explain what the network learns (Paliwal and Kumar 2011). Therefore, it is anticipated that more investigation into the neural network's internal workings and structure will provide a clearer understanding of how independent factors affect the modelling process.
The basic back propagation method serves as the foundation for a wide range of ANN applications in the domains of construction engineering and management to solve important construction decisions. The most often used type and learning technique is the Back Propagation (BP) training algorithm. In order to address noise and over-fitting issues in data, a number of neural networks other than the BP were created, such as the regularisation neural network. An input layer, hidden layers, and an output layer make up the standard feed forward neural network design shown in Figure 1. The synaptic weights link the neurones in the input layer to those in the buried layers. The summation function and the sigmoid squashing function are often employed transfer functions.

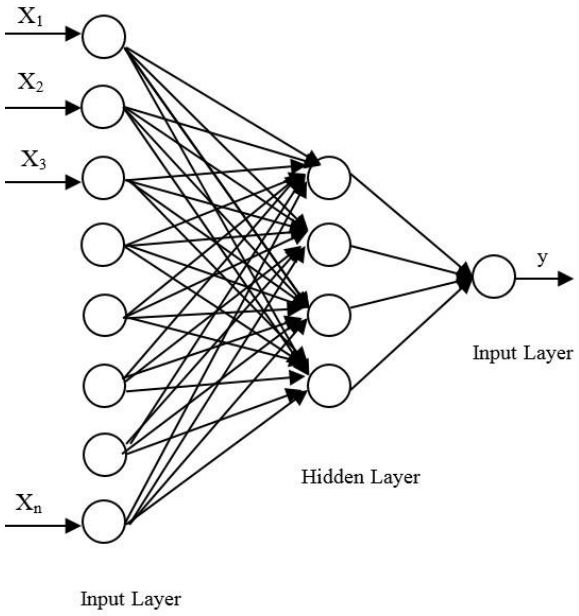


Figure 1. Feed forward neural network

The first mathematical representation of neuron (processing elements of the network) was attempted in 1943 by the Neu- ro physiologist Warren McCulloch and the Logician Walter Pits (Galkin 2002). The representation is shown in Figure. 2. The McCulloch and Pitts (MCP) neuron is binary activated.

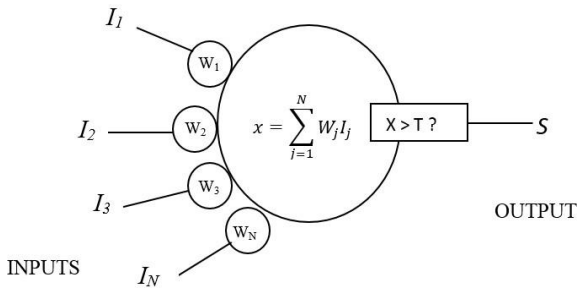


Figure 2. Artificial neuron

The paper reviewed literature form well over 100 resources published in refereed journals and conference proceedings with the view to exploring the trend and directions for the appli- cations of different ANN algorithms in construction engineer- ing and management. The resources were screened and selected based on relevance and significance toward understanding and documenting the trend and new direction of ANN application.

2 APPLICATIONS OF ANN IN CONSTRUCTION ENGINEERING AND MANAGEMENT

ANN have been successfully applied to predict tender price (McKim 1993; Li and Love 1999), construction cost prediction (Williams 1994; Emsley et al. 2002; Wilmot and Mei 2005; Sodikov 2005; Pewdum et al. 2009; Alex et al. 2009; Waziri 2010; Bala and Waziri 2012; Bala et al. 2014), project cash flow (Boussabaine and Kaka 1998), Labour productivity (Chao and Skibniewski 1994; Portas and AbouRizk 1997; Savin et al. 1998), earth moving operation (Shi 1999), contractors pre- qualification (Lam et al. 2001), contract performance (Zin et al. 2006; Waziri 2012), mark up estimation (Li and Love 1999) risk quantification (McKim 1993).

2.1 Cost Estimation

Every construction company relies on accurate cost estimates to run smoothly (ElSawy et al. 2011). Pearce (1997), Bhokha and Ogunlana (1999), Son-mez (2004), Sodikov (2005), Kim et al. (2005), Cheng et al. 2009a, 2009b, Arafa and Alqedra (2011), Waziri and Bala (2011), and Bala et al. (2014) are among the several research that have examined the use of ANN in cost estimate.

After using the BP algorithm to foretell one and six month changes in construction cost indices, Williams (1994) came to the conclusion that successfully forecasting the movement of the cost index is a complicated issue that defies prediction using the BP model. Optimal mark-up estimate was achieved by Hegazy et al. (1994) using ANN application, and the authors went on to describe the possible uses of ANN in construction engineering and management. An ANN-based parametric cost estimation model for highway projects was created by Hegazy and Ayed (1998). The research included two new methods for training network weights: simplex optimisation and genetic algorithm (GA). Reinforced concrete pavement project cost estimates were provided by Adeli using a regularisation neural network algorithm. Highway building prices are noisy, according to the research, because of the myriad of interrelated variables, including weather, human judgement, and fluctuations in the number of available construction bids. Reliability and consistency in highway project cost estimate were both shown by the RNN model. Using an artificial neural network (ANN), Geiger et al. (1998) created a model to predict the price of sheet metals based on the direct material cost and the cost of supplied parts. Within the investigated range, the findings demonstrated an accuracy of 5% to 15%. Elhag and Boussabaine (1998) used data from 30 finished projects to train two ANN models that could predict the lowest tender price for elementary and secondary school buildings. Both models learnt well throughout training and had strong generalisability skills, as seen by their respective prediction accuracy levels of 79.3% and 82.2%. In order to forecast the percentage rise in the cost of a typical highway project from a reference estimate, Al-Tabtabai et al. (1998) created an ANN model. The MAPE that the model attained was 8.1%. In their research, Bhokha and Ogunlana (1999) used historical data from 136 finished properties to generate an artificial neural network (ANN) model that could predict, during the pre-design stage, the construction costs of building projects in Thailand. As inputs, the research takes into account structural system, building purpose, exterior or finishing, building height, decorating class, and site accessibility as cost factors. Overall, the results of the validation showed a reasonable performance, with 42.7% of the sample being underestimated and 57.3% being overstated. Using a neural network technique, Fang and Froese (1999) determined a correlation between HPC quality, cost, and formwork for the

structural element of tall structures. The quantity and cost of HPC wall frame systems in tall commercial buildings were predicted using hybrid and hierarchical neural networks. The comparison between the two approaches showed that hierarchical models are more accurate but more difficult to deploy, while hybrid models are less accurate but easier to train. It became clear that both approaches would provide fruitful outcomes. The use of artificial neural networks (ANNs) and regression analysis was suggested by Shtub and Versano (1999) as a means to approximate the price of bending steel pipes. The assessment findings showed that the neural network model had better prediction ability than the linear regression model, while the regression model fitted the data the best. With the use of ANN, Assaf et al. (2001) looked at how Saudi Arabian construction companies handled their overhead costs. To win and successfully manage capital projects, construction companies should utilise the suggested approach to determine the optimal level of overhead expenses.

Emsley et al. (2002) used a dataset consisting of 288 properties to evaluate the prediction capabilities of ANN and regression analysis. Site- and design-related factors were among the 41 independent variables examined in the research. According to the findings, the model predicted a Mean Abs-solute Percent Error (MAPE) of 17% under ideal conditions. The size of this error term prevents the model from being used in a practical setting. Also, it was hard to implement during the early stages of design since the required input variables were lengthy. The cost estimation model for institutional buildings developed by Setyawati et al. (2002) using neural networks achieved an accuracy of 16%. In the Bhopal area of India, Pathak and Agarwal (2003) suggested an ANN-based software for the design, estimate, and pricing of intz and circular overhead water tanks. A ratio of height to diameter, an angle of the conical wall, and the number of columns are the input parameters for the program. The trained network achieved satisfactory results in predicting the cost of new tanks, with an error margin of just 3.16%. When choosing tanks for design and construction, having a fast and accurate cost estimate is beneficial. In order to estimate the cost of structural systems for reinforced concrete skeleton buildings in Turkey, Günaydın and Doğan (2004) created an ANN model. The ANN approach was trained and tested using cost and design data from thirty (30) projects with eight (8) parameters. The average accuracy of the cost estimate was 93%. In the early stages of a project, the model helps design experts make good selections.

The independent variables in Sonmez's (2004) conceptual cost estimating comparison between regression and neural network models were the year of construction, location index, fraction of parking space, and area for communications. The research used three models: two NN and one regression. For conceptual cost estimates, one NN model reached an acceptable 12% accuracy level. The effectiveness of neural networks, case-based reasoning, and multiple regression analysis in predicting the cost of construction projects was investigated by Kim et al. (2004). While case-based reasoning showed superior performance over the long term, the findings showed that the neural network model made the most accurate predictions. The neural network model for cost estimate of building structural systems was suggested by Günaydın and Doğan (2004), and it reached an accuracy level of 93%. They came to the conclusion that neural networks may lessen the uncertainty of estimates for designing structural systems. Using cost data from 530 residential building projects in Korea, Kim et al. (2004) examined the predictive capabilities of ANN, CBR, and regression analysis. In comparison to CBR and regression analysis, the findings show that ANN models have the ability to provide more accurate outcomes. Using artificial neural network (ANN) models, Wilmot and Mei (2005) connected the dots between the material, labour, and equipment costs and the total highway building costs, as expressed by the highway construction cost index. According to the research, the model somewhat accurately reproduced the patterns in highway building costs in Louisiana in the past. Using ANN, Sodikov (2005) investigated highway project cost estimates and found that neural networks are good at handling complicated situations and imperfect data. The results show that the back propagation neural network is capable of making more accurate predictions and has strong nonlinear approach abilities. In order to lessen the likelihood of project cost overruns, Sayed, Iranmanesh, and Zarezadeh (2008) demonstrated how to use ANN to predict the real cost of building projects using the Earned Value Management system (EVMS). The MAPE criteria demonstrated that the model performed well in its evaluation. In 2008, Bouabaz and Hamami put out an ANN-based model for developing-world bridge repair and maintenance cost estimates. In order to train their network model, Sonmez and Ontepeli (2009) utilised regression analysis and artificial neural networks (ANN) to create parametric models for predicting the construction cost of urban railway systems. The models were able to attain an accuracy level of 96%. As an alternative to the regression model, two neural networks that include distinct independent variables were investigated for the purpose of identifying non-linear relationships. One of the NN models produced the most accurate findings, according to the models' performance rating. In order to estimate the expenses of highway construction, Wang et al. (2010) used BP neural networks. To facilitate rapid cost estimation, the model was trained using data collected from a number of completed roadway engineering projects. The findings showed that the model was feasible and reliable, which bodes well for the future of BP-NN in highway engineering construction cost estimation.

An effective model for early-stage building construction cost estimation was developed by Arafa and Alqedra (2011) using ANN. An analysis of 71 construction projects in the Gaza Strip was conducted. The model development process made use of significant parameters that were available during the pre-design phase as input variables. According to the study's findings, the most important factors that impact preliminary cost estimates for a building are its ground floor space, number of stories, foundation type, and elevator count. In order to forecast the Egyptian site overhead cost, ElSawy et al.

(2011) introduced a BP neural network model. Data from 52 actual projects executed between 2002 and 2009 were used for training purposes in the research, whereas data from five (5) fresh initiatives were utilised for validation. An accuracy level of 80% and a Root Mean Square Error (RMS) value of 0.2764 were shown in the findings. For only one project out of twenty in the test set, the model was shown to incorrectly estimate the proportion of site overhead expenses. Using information from 98 water-related projects completed in Scotland between 2007 and 2011, Ahiaga-Dagbui and Smith (2012) built an ANN model to predict the ultimate goal cost of these projects. In order to enhance the performance of the final models, several models were created to normalise the target cost and log of the target cost variables. Weight decay regularisation was also investigated. The study found that ANN picked up on the interplay between the predictor factors and the end price.

During the early stages of a project's lifespan, Vahdani et al. (2012) introduced a computationally efficient model called the support vector machine (SVM) to improve the accuracy of conceptual cost estimates. After a cross-validation training process, the model's performance was evaluated against that of BP-NN and non-linear regression; the findings showed that SVM performed the best. Another study that used ANN to provide a new framework for LCCA of building projects was Alqahtani and Whyte (2013). The model determines the total life cycle costs of construction projects by identifying the key cost components using the cost of significant items (CSI). The models were developed using MATLAB and Excel solver using a dataset consisting of twenty construction projects. The findings showed that the Excel solution had a 2% accuracy rate, whereas the MATLAB solver had a 1% rate.

In order to forecast the overall structural cost of Philippine construction projects, Lyne and Maximinio (2014) used data from 30 completed projects to train an ANN model. We used 60% of the data for training, 20% to validate performance, and 20% as a completely independent test for network generalisation. The data was split randomly. There were a total of six input parameters utilised: basement count, floor space, number of stories, concrete volume, formwork area, and reinforcing steel weight. With successful training and testing, the findings demonstrated that the ANN model adequately estimated the overall structural cost of construction projects. Neural networks outperformed CBR and multiple regression analysis in a study by Kim et al. (2004) that compared several parametric cost estimating methods for building projects. El-Sawah and Moselhi (2014) used regression analysis models and Back Propagation Neural Networks (BP-NN), Probabilistic Neural Networks (PNN), and Generalised Regression Neural Networks (GRNN) to estimate the costs and orders of magnitude of low-rise structural steel structures. The investigation's findings showed that the MAPE for the regression model was 23.72%, whereas it varies from 16.83% to 19.3% for the neural network models. The PNN network showed the highest degree of stability (maximum difference in MAPE: 2.46%), in contrast to the linear regression model, which was more affected by changes in the quantity of training data. Maximum MAPE differences for BPNN GRNN, regression model, and other models were 19.47%, 17.91%, and 61.45%, respectively. For the purpose of predicting the structural cost of residential structures, Yadav et al. (2016) developed a method for cost estimation that is grounded on ANN principles. In order to train and test networks, data was retrieved from schedule of rates records spanning twenty-three years. Cost of cement, sand, steel, aggregates, mason, and trained and non-skilled workers were among the criteria gathered. The NEURO XL version 2.1 was used for parameter simulation. With a correlation coefficient (R) of 0.9960 and an R2 value of 0.995, the neural model accurately predicted the overall structural cost of construction projects.

2.2 Construction Scheduling

When solving the issue of when to build highways, Adeli and Karim (1997) used a generic mathematical method. In order to reduce the direct building duration, a neural dynamic model was used to tackle the non-linear problem. With this model, you may get the best possible schedule at the lowest possible cost by combining the features of the Critical Path Method (CPM) with those of a linear scheduling strategy. The technique is deemed adequate for resolving the highway construction cost-duration trade-off issue. A new generalisation of more adaptable and accurate construction scheduling systems may be built upon the study's base. Assumed to have strong ties to construction operations, Graham et al. (2006) used ANN to forecast how long Ready Mixed Concrete (RMC) would take. Months of operation, types of operations, total operation volume, average inter-arrival time, number of loads, truck volume, and number of rejected loads were some of the variables considered in the research, which drew from four separate studies. To improve the reliability of their model, Yahia et al. (2011) used ANN to determine how much time should be added to the project completion timetable as a contingency. The support vector machine (SVM) was introduced by Petruseva et al. (2013) as a supervised learning approach for estimating how long a building project would take. A total of 75 building construction projects in the Federation of Bosnia and Herzegovina were surveyed in order to collect actual and contracted pricing data. These projects were started and finished between the years 1999 and 2011. Improving the accuracy of project time prediction was the goal of the research, which included regression analysis and SVM networks. The findings show that SVM has far better predictive power.

In order to forecast how long a concrete operation would take, Maghrebi et al. (2014) used ANN with an emphasis on RMC supply chain factors. A real-life dataset of a Sydney metropolitan region RMC with 17 depots and around 200 vehicles was used to test the model. Findings from this study were in good agreement with those of previous research that had focused only on building factors as a means of forecasting concrete production. In order to estimate how long it will take to complete significant tasks involving the structural components of concrete frame structures, Golizadeh et al. (2016) suggested a tool. For the purpose of calculating how long it takes to install column reinforcement, beam reinforcement, column concreting, and beam concreting, four AN models were developed. Afterwards, an automated tool for estimating duration based on ANN was built as a web-based programme for more accurate activity duration prediction.

2.3 Making Choices

The selection of formwork systems was done using a two-layer BP neural network by Kamarthi et al. (1992). A acceptable performance was suggested by the research. Based on five groups of decision attributes—plant location, environmental and organisational factors, labour related factors, plant characteristics, and project risks—Murtaza and Fisher's (1994) artificial neural network (ANN) model allows for the choice between modularisation and the conventional method for constructing an industrial processing plant. Cases gathered from several engineering consultancy and client organisations were used to train the NN model. A neural network approach for predicting building cost and productivity was created by Boussabaine (1995). The model establishes the practicability of a knowledge-based system that integrates all relevant aspects for building planning and efficiency.

To identify changes in the structure-related properties of unidentified systems, Masri et al. (1996) introduced an ANN method. Using vibration readings from a healthy system, the neural network was trained for identification. In order to monitor the structure's health, the trained network was supplied with similar vibration data taken from the same structure under varied reaction settings. Even with noisy vibration measurements, the suggested approach was able to identify tiny changes in the structural characteristics, according to the research. In order to identify the determinants of project costs and to provide cost-based risk predictions, Pearce (1997) used ANN. This research looked at how well ANN could identify possible major cost drivers in construction projects and how well it could forecast risk related to the ultimate cost of the project. The maximum cost versus probability curves were generated using neural network models that were trained across a set of input variable permutations. These curves may be used to assess the risks of cost increase from the conceptual design phase all the way to project completion. The research revealed many cost factors, such as floor-to-floor height, number of levels, outside wall size, exterior window area, and more. Research also showed that ANN is a powerful tool for approximated multivariate analysis. To find the most important metrics that impact a project's budget performance, Chua et al. (1997) suggested an ANN model. Although the functional interrelationships between input elements and output performance may not be precisely defined, the approach nevertheless has the capability to model. Scope, design completion, number of organisational lev-els between project manager and craftsmen, experience on simi- lar projects, constructability program, project team turnover rate, frequency of budget updates, frequency of control meetings during construction, and control system update were the eight (8) critical variables identified in the study that cover aspects related to project managers, project teams, and planning control efforts. In order to improve project management, the model may foretell several management approaches that would make the most efficient use of available resources. Yeh (1998) showed that it is possible to modify ANN in order to forecast HPC concrete's compressive strength. The models were trained and tested using a set of experimental batches that were created in the lab. The findings showed that compared to a regression-based model, the ANN model performed better. According to the research, ANN models are straightforward to use and provide convenient numerical trials for reviewing the impacts of variable parameters on the concrete mix.

In their 2012 article, Elhassan et al. explored the idea of using optimisation approaches to tackle the challenges of construction management decision making. When it comes to building project management, the research found that optimising tools provide the foundation for making the best decisions. They noted the possibilities of artificial intelligence (AI) systems like ANN for future studies and came to the conclusion that there are many study gaps in the use of techniques for optimal decision making. In order to estimate worker productivity rates for industrial building operations, AbouRizk et al. (2001) used a two-stage neural networks methodology. A 15% accuracy rate was achieved by the method's predictions. In their 2001 study, Sawhney and Mund used artificial neural networks (ANN) based on Bayesian classifiers to choose a crane model and type. When it came to choosing cranes according to their kind and model, the model performed well. Using data of previous circumstances, Lou et al. (2001) used ANN to forecast the near-term future state of pavement cracks. By producing promising results, the model proved the feasibility of using ANN for such forecasts. Morcous (2002) compared CBR and NN in a bridge degradation model using deck data from the Quebec Ministry of Transportation. The goal was to help transportation agencies choose the best technique by exposing the benefits of both systems.

An ANN-based maintainability grading system was introduced by Chew and Tan (2003) to help with better design decisions for wet regions. Interviews with pertinent building experts and thorough condition inspections of 450 tall structures were used to develop the model. The research found 16 risk variables that were relevant and examined them based on how sensitive they were to changes in the maintainability score of damp regions. In order to find the optimal solutions for technical features that result in the lowest feasible lifetime maintenance cost, the system allows for the comprehensive examination of many alternative designs, construction, materials, and maintenance procedures. In order to foretell the likelihood of contractor failure in Saudi Arabian Armed Forces building projects, Al-Sobiei et al. (2005) used ANN and GA. You may use the research to help you decide whether to hire a contractor. Because it suggests a method that may enable the application of a reasonable and successful policy, the research's finding is significant for clients and other sponsors of building projects. In order to forecast the efficacy of construction project management from the viewpoints of construction management organisations, Apanaviciene and Juodis (2005) used NN to create a model. The model was developed using performance data from construction management organisations in the USA and Lithuania, which consisted of twelve important elements. In order to aid in competitive bidding and assess management risk in construction projects, the research suggests using the Construction Management Performance Evaluation Model (CMPEM).

An ANN model for conventional contract project time performance prediction was introduced by Zin et al. (2006). Using data from nine different projects, we created and evaluated several neural network models. A multi-layer perforated (MLP) BP network with eight input nodes, five hidden nodes, and three output nodes is the optimal model for the prediction task. It has a very low prediction error rate. A framework for planning the work breakdown structure of building projects based on artificial neural networks was provided by Golpayegani and Emamizadeh (2007). The method forms the model's output and its modules using the project control (PWBS), functional (FWBS), and relative (RWBS) work breakdown structures. The intended WBS and activities met the expectations with varying degrees of validity, according to the findings of the framework's testing on a sample domain. Real estate investors and builders may rely on the ANN-based model presented by Khalafallah (2008) to forecast the performance of the housing market. In order to foretell unexpected future performances, the research trained the NN using a dataset of past market performance. The results of the validation showed that the forecast fell somewhere between -2% and 2% increase. High performance concrete (HPC) compressive strength and workability predictions may be made with the use of simulators and intelligent systems, as Jamil et al. (2009) showed. This model's good performance in learning the input/output patterns suggests that artificial neural networks (ANNs) are a good fit for HPC mix design.

In order to quantitatively and objectively estimate the flaws in projected cost estimates of new projects, Aibinu (2011) suggested a learning algorithm that is based on the characteristics of completed projects. We built a three-layer feedforward artificial neural network (ANN) model to generalise nine features from one hundred finished projects. A total of nine input variables were utilised: project size, procurement route, project kind, project location, principal structural material, sector, estimating technique, and projected amounts. The model's performance metrics were as follows: 73% R-squared, 3% MAE, and 0.2 MSE. The BP NN model was created by Al-Zwainy et al. (2012) to estimate the construction productivity of finishing operations for marble flooring. Data from residential, commercial, and educational projects throughout Iraq were analysed in this research. Age, experience, number of assist workers, floor height, marble tile size, security, team health, weather, site circumstances, and availability of building materials were the ten (10) main input variables. With a correlation value of 87.55% and a prediction accuracy of 90.9%, the findings demonstrated that ANN can forecast productivity for completing tasks. In order to forecast Iraqi worker productivity using thirty different variables, Aswed (2016) used ANN. Considerations like as age, experience, gang health, gang number, wages, weather, material availability, site circumstances, wall length, wall height, mortar type, wall thickness, and site security are included as input variables. An R-squared value of 86.28% indicates that the model was quite accurate in predicting real labour productivity. Research shows that the model may be used to forecast worker productivity in any construction project by identifying the elements that have an impact. For the purpose of estimating soil properties, Sharmik et al. (2016) introduced a feed forward BP-NN with a supervised learning method that is both time and cost efficient. Comparing the model's predictions with the measured values of soil properties showed promising outcomes.

2.4 Resolving Disputes and Litigation

In an effort to decrease the likelihood of litigation by estimating the impact of modification orders on project performance, Yitmen and Soujeri (2010) used an ANN model. Conducting a field survey to contractors in North Cyprus served as the foundation for developing a model that identifies significant elements describing the negative impact of modification orders on project performance. To ensure that construction operations are not disrupted to an excessive degree due to disagreements amongst project stakeholders, the model handles change orders throughout the whole project lifecycle. The study's data came from 35 cases, which were gathered from 22 different construction contractors. The data included 11 input factors and how those variables affected performance. An effective method for determining the likelihood of a disagreement with regard to the specified parameters has been found in the suggested model. Public-Private Partnership (PPP) projects' dispute management techniques may be predicted using a model proposed by Chou (2012). The study employed a variety of methods to improve performance for a set of PPP data. These methods included machine learning (ANN, SVM, and Tree Augment-ed Name; TAN), Bayesian, classification and regression based techniques (CART), Quick Unbiased and Efficient Tree (QUEST), Exhaustive Chi-square Au-tomatic Interactive Detection (Exhaustive CHAID), and C5.0. When it came to predicting the outcomes of conflict resolution (mediation, negotiation, arbitration, litigation, adjudication, appeals, or no disagreement at all), the findings revealed that the combination of the approaches of QUEST + CHAID + C 5.0 produced the greatest classification accuracy, at 84.65%. The most accurate categorisation, at 69.05%, was shown by the CART model. Public infrastructure projects may benefit from early dispute settlement via the study's demonstration of successful categorisation application. In order to minimise construction conflicts and save costs, Fatima et al. (2014) developed an ANN model by optimising the identified critical qualitative characteristics. By combining the idea of ANN with the existing estimating system, the methodology optimises the occurrence frequency of conflict parameters, resulting in a decrease in project cost.

2.5% Risk Evaluation

As a result of the unpredictability of building projects, Odeyinka et al. (2002) sought to quantify the discrepancy between expected and actual cash flows. To create a model for evaluating risk in cost flows, they used BP neural networks. At the30%,70%, and 100% mark, the model satisfactorily predicted the variance between the actual and forecasted cost flows for 20 new projects. Analysing the effects of environmental risk on Puebla, Mexico, building projects, Maria-Sanchez (2004) used a neural network technique. Data from private contractors, who are continually involved in projects with environmental concerns, was used to train and test the network. This methodology shows how artificial neural networks (ANNs) may be used to assess environmental hazards and provide useful results for government agency project managers. An further promising feature of the system is its ability to estimate the potential monetary worth of all environmental hazards. By using a dataset consisting of bridge risk data, Wang and Elhag (2007) assessed the efficacy of Evidential Reasoning (ER), Neural Network (NN), and Multiple Regression Analysis (MRA). The results showed that in the case study under consideration, ANN outperformed ER and MRA.

A BPÍCNN-based approach for evaluating the behavioural risk of main project partners was suggested by Xiang and Luo (2012). The risk appraisal procedure was made more objective by using the BP. The risk variables that were found during the field survey were evaluated using a Likert scale that ranged from 1 to 5. The model is suitable and feasible, according to the findings of the network simulation. Additionally, Polat (2012) suggested an ANN-based contingency estimating methodology to help managers objectively and systematically evaluate project risk, which in turn would allow them to estimate the cost contingency amount with better reliability and accuracy. The records of 195 completed international projects by 85 large-scale contractors in Turkey were used to acquire training and testing data. Results from the statistical analysis show that the model is correct and accounts for a large part of the complicated nonlinear connection between the bid price's contingency amount and the risk variables.

For transportation building projects, Lhee et al. (2014) laid forth a two-stage neural network-based approach to optimum contingency estimation. In order to help the owner make better budgeting choices and lessen the likelihood of under- or overcommitting cash, the model offers an optimal solution. Using neural networks and rough sets, Liu and Guo (2014) built a model for evaluating the risk of project construction quality. Utilising research tools of Rosetta based on rough sets and MATLAB 7.0, the accuracy of the model was tested using a dataset of residential construction projects in the Guangzhou development zone. The model has significant practical implications, as shown by empirical evidence.

Construction Engineering and Management using an Evolutionary Neural Network 2.6

Yeh (1998) optimised the layout of a building site using a Simulated Annealing Neural Network (SA-NN). SA is a probabilistic hill-climbing search technique that uses a combination of gradient descent and a random process to obtain a global minimum of the performance function. The algorithm's performance is good when paired with ANN. A method known as BP-GA was developed by Kim et al. (2004) to estimate costs. It combined the BP neural network model with the Genetic Algorithm (GA). The purpose of including the GA into the research was to enhance the precision of the BPN. For the purpose of training and performance assessment, we used cost

data from 530 Korean residential structures that were built between 1997 and 2000. In comparison to the trial-and-error BP model, the hybrid BP-GA model yielded more effective and dependable outcomes (Kim et al. 2004).
To estimate the preliminary expenses of residential constructions, Kim et al. (2005) released a hybrid model that combined artificial neural networks (ANN) with genetic algorithms (GA). The training was based on South Korean residential building data that was started and finished between 1992 and 2000. When looking at the ratio of actual to expected expenses, the mean is 0.960, the standard deviation is 0.420, and the coefficient of determination (R2) is 97%. The findings shown that GA is capable of resolving the issue of insufficient guidelines for ANN parameter determination. When analysing the results of building claims in Hong Kong, Chau (2007) used ANN based on Particle Swarm Optimisation (PSO) to take into account cultural, social, psychological, environmental, and political aspects. The findings showed that PSO-ANN could achieve an 80% success rate in making predictions. Additionally, the method outperforms basic BP neural networks in terms of speed and accuracy. You may choose in the model whether to go to court or not. In their study, Cheng et al. (2009a) introduced the Evolu-tionary Fuzzy Hybrid Neural Network Model (EFHNN), an approach that integrates genetic algorithms, fuzzy logic theory, and neural networks. The suggested method was created for the purpose of estimating project costs in the design phase in Taiwan. Incorporating neural networks and high-order neural networks (HNN) that function with nonlinear and linear neurone layer connectors as alternatives is the strategy. To deal with unknowns, the method also makes use of fuzzy logic. Fuzzy hybrid neural networks (FHNNs) are hence the method of choice. In order to optimise the FHNN, GA was used, leading to the creation of EFHNN. One drawback of using GA is the long processing time it requires, which led to an overall estimate inaccuracy of 10.36% in the model. A web-based hybrid model known as the Evolutionary Fuzzy Neural Inference Model (EFNIM) was introduced by Cheng et al. (2009b). This model combines genetic algorithms, fuzzy logic theory, and neural networks. On the other hand, since GA is used, EFNIM also runs for a long period.
In their research, Shi and Li (2010) used fuzzy logic, PSO, and ANN to evaluate building projects' quality. A construction quality evaluation model was established and its components were defined using fuzzy logic in the research. The perception in evaluating and forecasting the quality of Chinese building projects was trained using an adjusted PSO. The results of the simulations of the quality assessment of construction projects show that when comparing BP-NN and GA-NN, the network trained with PSO produced more accurate results in terms of Sums of Squares Error (SSE) and required fewer iterations and less simulation time. An optimisation approach to cost estimate was introduced by Feng and Li (2013), who combined the GA and BP techniques. To evaluate the model's generalisability, eighteen project examples and two testing samples were used. Though it takes more time to execute, the GA-BP model outperforms traditional BP models in terms of prediction inaccuracy and iterations. They came to the conclusion that the model works well for estimating building costs.
Hong et al. (2014) put forward a construction engineering cost evaluation model and application based on RS-IPSO BP neural network called “the model of construction engineering cost evaluation of optimized particle swarm and BP neural network”. PSO was adopted to optimize the initial weights and threshold of ANN. The main aim of the hybrid method is to improve the rate of convergence of ANN and the ability to search for global optimum. This method is considered to have a high practical value and it can be applied to make scientific evaluation of construction costs. Kayarvizhy et al. (2014) compared the improvement in the prediction accuracy of ANN when it is trained using swarm intelligence algorithms. Several models were formulated for evaluating the various ANN-swarm intelligence combinations. The swarm intelligence algorithms considered in the study are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) and Firefly. The hybrid models were compared for their convergence speed and prediction accuracy over traditional ANN models. The resul- ts showed that swarm intelligence has higher convergence speed and accuracy over ANN trained with gradient descent. Lee et al. (2016) presented a hybrid model for estimating the quantity and cost of waste in the early stage of construction. The approach used ACO algorithm to optimise the selection of ANN parameters. The proposed model can be used to address the cost overruns and improve construction waste management. The hybrid model predicted more effectively the amount of waste concrete in early project stage. The comparison of prediction results of ANN and ANN-ACO showed that the hybrid model had minimum er- ror demonstrating a higher accuracy than ANN.

3 DISCUSSION OF FINDINGS

ANN has been widely used in the last several decades to address difficult, non-linear issues in the fields of construction engineering and management. They used ANN to predict construction costs, schedules, productivity, the occurrence and resolution of disputes, and contract performance, all of which defied traditional mathematical and statistical methods. This shows that ANN has robust potential for solving these problems. Data quality and quantity are crucial for training artificial neural networks (ANNs), which in turn affects the accuracy of predictions, recognition, and classification (Hegazy and Ayed, 1998; Waziri and Bala, 2011).
A major advantage of ANN over traditional approaches is the accuracy of its predictions, which contributes to its widespread use and popularity. As shown in studies by Geiger et al. (1998), Alqahtani and Whyte (2013), and Bala et al. (2014), the accuracy levels of most ANN-based prediction and forecasting applications may reach as high as 98% across test samples. The minimal errors over test samples, as assessed by MSE, MAE, MAPE, and SSE, are used to record these achievements. Additionally, the results reveal that ANN often exhibits a high degree of data fitting, with a correlation coefficient typically above 90%, in the majority of prediction problems (Kim et al. 2005).
Optimal decision making is a crucial activity in construction engineering and management, and neural network models are a good fit for parametric modelling. They are often used as an alternative to classical modelling techniques, particularly for datasets with nonlinear relationships, and they form the basis of decision support tools that use supervised learning algorithms. According to Sonmez (2004) and Sonmez and Ontepeli (2009), it outperforms other parametric models, such regression analysis, in these types of applications. It has the ability to map learning uncertainty and is ideal for making short-term forecasts.

There is a lack of a universal technique for selecting ANN's starting weights and other parameters for effective application, despite the fact that ANN is resilient and has exceptionally high benefits for parametric modelling and other decision making applications. Also, it's not good for trend forecasting or other long-term predictions (Kim et al. 2004). To compensate for this shortcoming, hybrid models that include various optimisation tools and learning algorithms have been created. The results showed that GA, ACO, PSO, and fuzzy logic were all successfully integrated with ANN, with the exception of ANN-GA, which ran slowly and took a long time to run, giving ANN better performance than simple neural network algorithms.

4 CONCLUSION

When faced with situations requiring complicated quantitative and qualitative thinking, ANNs have shown to be more effective than conventional mathematical and statistical approaches. In construction engineering and management, they have been successfully used to solve a plethora of complicated nonlinear issues including prediction, estimation, decision making, optimisation, classification, and selection. Their ability to handle noisy data and provide accurate and dependable predictions and forecasts has been recognised. To further enhance accuracy, reduce data over- or under-fitting, and accelerate convergence, Neural Networks have been integrated with various soft computing paradigms like Case Based Reasoning, Ant Colony Optimisation, Fuzzy Logic, Particle Swarm Optimisation, Artificial Bee Colony, and Firefly.

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