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Artificial Neural Networks for Construction Management: A Review

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ABSTRACT

Construction Management (CM) has to deal with a variety of uncertainties related to Time, Cost, Quality, and Safety, to name a few. Such uncertainties make the entire construction process highly unpredictable. It, therefore, falls under the purview of artificial neural networks (ANNs) in which the given hazy information can be effectively interpreted in order to arrive at meaningful conclusions. This paper reviews the application of ANNs in construction activities related to the prediction of costs, risk, and safety, tender bids, as well as labor and equipment productivity. The review suggests that the ANN's had been highly beneficial in correctly interpreting inadequate input information. It was seen that most of the investigators used the feed forward back propagation type of the network; however, if a single ANN architecture was found to be insufficient, then hybrid modeling in association with other machine learning tools such as genetic programming and support vector machines were much useful. It was however clear that the authenticity of data and experience of the modeler are important in obtaining good results.

1. Introduction

The construction industry is highly competitive and faces challenges in the areas of costs of projects, delays in construction activities, labor productivity, disputes, tenders, bidding prices,

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safety aspects, the rate of materials, maintenance costs, risk analysis, etc. which are highly complicated in nature. To deal with these challenges, Artificial Intelligence (AI) techniques like fuzzy logic, case-based reasoning, probabilistic methods for uncertain reasoning, classifiers and learning methods, Artificial Neural Networks (ANN), Genetic Algorithms and hybrid techniques are widely used in the field of Construction Management (CM). In the last two decades of the twentieth century, there was a surge in publications dealing with Artificial Intelligent techniques and especially ANN in various aspects of CM. In 2001, Adeli and Yeh provided a comprehensive review of such applications made before the turn of the century [1]. The current work presents a review of about 70 papers published in the area of CM. The objective of the paper is to highlight the applications of ANN in the following fields of CM: Cost, Productivity, Risk Analysis, Safety, Duration, Dispute, Unit rate and Hybrid Models. Further critical review of the findings will help the readers to focus on important areas for potential use and development of ANN in the said areas of CM. The future scope will facilitate continued research efforts. The paper is further synthesized as follows: Initially, a brief introduction on ANN is presented and is followed by the assessment of their recent applications in the areas of Cost, Productivity, Risk Analysis, Safety, Duration, Dispute, Unit rate and Hybrid Models. Discussion and critical review are done in the preceding section followed by author’s comments on the findings and future scope.

2. Artificial neural network

ANN is a soft computing tool, mimicking the ability of human mind to employ modes of reasoning and pattern recognition effectively. ANN as a concept was existing for a long time; however, its application in civil engineering started in the late 1980’s primarily in construction activities [1]. ANN’s were found to learn from the relationships between input and output provided through training data and could generalize the output, making it suitable for non-linear problems where judgment, experience, and surrounding conditions are the key features. ANNs typically comprise of 3 layers viz. the input layer with input neurons, hidden layer(s) with hidden neurons and output layers with output neurons (figure 1).

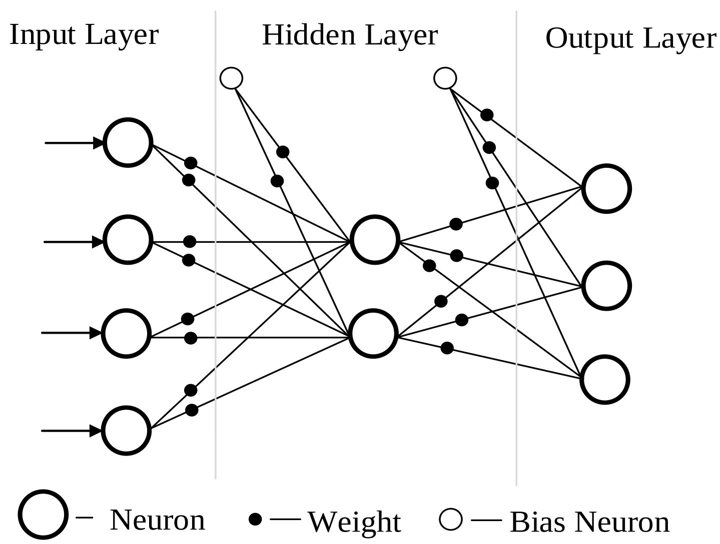

Fig. 1. Basic ANN architecture

Each neuron in the input layer is connected to each neuron in the hidden layer, and each neuron in a hidden layer is connected to each neuron in the output layer. The number of hidden layers and the number of neurons in each hidden layer can be one or more than one. The number of input neurons, hidden neurons, and output neurons constitutes the network architecture. Before its application the network is trained, i.e., the connection weights and bias values are fixed, with the help of a mathematical optimization algorithm and using part of the data set until a very low value of the error is attained. The network is then tested with an unseen data set to judge the accuracy of the developed model. The network is trained using various training algorithms which aim at minimizing the error between the observed and network predicted values. The networks are classified according to the passage of the flow of information either in the forward direction (feed forward) or reverse or lateral directions (recurrent network). Generally, three-layer feed-forward or recurrent networks are found to be sufficient in civil engineering practices. Other types of networks include the counter-propagation ANN, Hamming's network and the radial basis function network. For details, readers are referred to [2–6].

3. Applications

Since the late 1980's several investigators have applied ANN in civil engineering to carry out a variety of tasks such as prediction, optimization, system modeling and classification [7]. Applications can be seen in areas of i) construction costs ii) productivity iii) risk analysis and safety and iv) project duration, disputes and unit rates which are dealt with herein.

3.1. Cost

ANNs as a tool is used to estimate the costs of school buildings [8] residential projects, apartment projects [9,10], cost of structural systems of reinforced concrete skeleton buildings in early stage [11–13], costs of overall building projects [14,15], cost for highway [16,17], tunnels [18], general overheads [19], cost of deviation in reconstruction projects was predicted through a single quantifiable measure, the cost performance index [20]. Cost estimation of continuing care retirement community projects was done by developing regression and neural network models [21]. In 2013, Naik and Kumar utilized ANN for optimizing project cost with data of 512 houses in India [22]. Minli and Shanshan in 2012 used ANN to estimate the tender offer price based on environmental factors, business factors and project factors [23]. ANN was used for estimating the optimal contingency for an owner's funding of transportation construction projects that can achieve solutions that are closer to the optimum than existing tools [24], modeling of construction project management effectiveness in terms of construction cost variation [25], predicting maintenance cost of construction equipment [26], pre-estimating models to predict the final cost of highway projects constructed by the New Jersey Department of Transportation [27], contingency costs for road maintenance activities [28] and project cost along with schedule success prediction models [29]. ANN is also used as a tool to predict the cost premium of green buildings based on LEED categories [30]. In 2003, Apanaviciene and Juodis modeled cost variation and carried out a sensitivity analysis to reduce the input variables from 27 to 12 [25]. For maintenance cost forecasting of selected equipment groups, General Regression Neural Network (GRNN) models were developed and further compared in terms of complexity, interpretability, and forecasting accuracy with time series models in 2014 by Yip et al. [24]. In 2002, Williams developed pre estimating models using ANNs techniques to predict the final cost of highway projects and bid information was used as input for the models [27]. Development of a prototype model for estimating the cost of building construction projects at the conceptual stage depending on

the historical data of projects implemented in the Gaza strip between 2009-2012 was done [31].

3.2. Productivity

Applications of ANN exist in the area of productivity of labor and equipment. ANN was used to estimate daily productivity of dozer [32], estimate the productivity within a developing market for formwork assembly, steel fixing and concrete pouring activities [33], prediction of production rate values for installation of formwork of beams [34], estimation of the productivity of ceramic wall construction [35], estimation of labor productivity of marble finishing works [36], labor productivity for concreting [37,38], for estimating the bricklayer (Builder) productivity [39] and labor production rate i.e man-hours per unit for pipe installation activity [40,41]. In 2014, Maghrebi et al. modeled concrete volume productivity in m^3/hr with ten input parameters on 1673 projects. They found that the productivity for a range of concrete volume can be predicted precisely by ANN, however, for productivities, less than 5 (m^3/hr) and more than 15 (m^3/hr) the distribution of residuals expanded gradually and for that, the underlying process needs attention [42]. Self Organizing Maps was developed for prediction of construction crew productivity for ready mixed concrete, formwork and reinforcement crews with work definitions [43].

3.3. Risk analysis and safety

Risk Analysis and Safety are important aspects in CM in for identification of potential risk in the projects and safety indices are carried out. ANN-based procedures had been developed to predict the likelihood of contractor default in Saudia Arabia [44], and to estimate the risk index for an expressway construction stage using the principles of system theory, operability, independence and comparability [45]. ANNs were developed to estimate percentage variation between the forecasted and actual costs of floats at 30, 50, 70 and 100% completion stages based on 11 significant risk factors [46].). In 2014, Mehidi assessed the risk value for ten risk factors as mechanical failure, electrical failure, wrong vendor selection, etc. in cement industries in Bangladesh [47]. In 2007, Elhag and Wang compared the techniques of ANN and regression analysis to estimate the risk score and risk category for bridge maintenance projects [48]. Liu and Guo in 2014 proposed a risk assessment method using rough sets to reduce uncertainties and ANNs [49]. An ANN system was developed to identify the cost deviations that occur, due to the political risk involved in a construction project. The project manager can incorporate the risk consequences into a bidding decision, and generate revised and updated risk estimates systematically and easily during the progress of the project. A rating in the form of a percentage change in cost from the baseline cost forms the output vector for the neural network model [50]. An ANN model was developed to predict the safety climate of a construction project and evaluation of construction employees' safe work behavior [51,52]. ANN-based model was developed for predicting workers' fatigue in hot and humid environment [53]. In a study, ANN and Logistic Regression were utilized to model the occupational safety and health of construction workers and performance of the models were assessed by calculating the log-likelihood (LL) ratio [54]. In 2015, Chen and Liu developed a model based on the Bayesian network for performance assessment of the subway construction safety in China [55]. Mohammadfam et al. in 2015, used chain analytical approach which included rough set theory and ANN modeling and modeled the factors affecting the health of the workforce and predicting the severity of occupational injuries [56]. In 2013, Goh and Chua used a neural network to study the relationship between elements of safety management and accident severity and discussed on proactive management of accidents [57].

3.4. Duration, dispute and unit rate

In 2001, Leung et al. modeled the hoisting times of tower cranes using two types of architectures, namely, Multi-Layer Feed Forward (MLFF) with back-propagation based (BP) learning and General Regression Neural Network (GRNN) with a genetic algorithm based learning [58]. In 2003, Cheng and Ko developed an object-oriented Evolutionary Fuzzy Neural Inference System (OO-EFNIS) for predicting a subcontractor's performance and duration estimation of the slurry wall [59]. Sawalhi and Hajar in 2016 used ANN to study a more accurate selection of the best contractor in the Gaza strip. The network selected for the study were either MLP (multilayer perceptron) or GFF (General feed forward) [60]. ANN with back propagation was developed for estimation of cost and duration of 2 highway projects [61]. In 2000, Cheung et al. reported using ANN to classify projects in accordance with project "dispute resolution satisfaction (DRS)" which also identified the sensitive variables that distinguish projects with adverse DRS and favorable DRS [62]. In 2007, Chau used Particle Swarm Optimization based network for prediction of outcomes of construction litigation [63]. In a study identification of qualitative parameter was done and an Artificial Neural Network model was developed to minimize the construction dispute resolution and reduce the cost of the project by optimizing the parameters [64]. Yahia et al. in 2011 developed a project time prediction model using a number of change orders [65]. Scientific prediction of the economic strata (The difference between actual direct costs and prevailing market rates) was made in 2015 by Mwiya et al. using ANN by determining the proportionate breakdown of the cost factors in a given construction unit rate [66]. Recently Mensah et al. in 2016 predicted actual durations of bridge construction projects in which principal component analysis was employed to determine the significant items which can be used for model development and in detecting the multi-colinearity within the database [67].

3.5. Hybrid models

Owing to the complex nature of modeling CM parameters, hybrid models were created to combine the advantages of two different tools for the possible better performance of the model. It was shown that ANN was capable of learning from the data provided, but it cannot explain the reasoning behind the input-output mapping process while fuzzy reasoning provides a systematic reasoning method which leads to the development of neuro-fuzzy systems [68,69]. A neuro-fuzzy model based on the locally linear model tree algorithm was employed by Vahdani et al. in 2011 to precisely estimate the overall performance (qualitative and quantitative factors) of projects [70]. A real case study was selected in the construction industry in Iran to appraise and select the candidates for the investment (cladding in this case). Genetic Algorithm (GA) was utilized to optimize the parameters (processing elements or neurons) of the back-propagation network for predicting the construction costs of residential buildings [14]. ANN technique was used for development of parametric cost estimating a model which can be used in the early stage of the project life cycle for sterile buildings as pharmaceutical and food projects in Egypt and the further Genetic algorithm was used for optimizing the weights [71]. The neuro-fuzzy technique is also used for the creation of a classification system for Russian Federation according to the environmental safety level and forecasting of changes in their development due to the changes in the level of environmental safety [72]. Integrating a neuro-fuzzy system with conceptual cost estimation to discover cost-related knowledge from residential construction projects was proposed. The data used in this proposal was based on historical data from previous construction projects collected by the Ministry of Construction of PRC in the years between 1996 and 2002 [73]. In 2009, Cheng et al. proposed web-based conceptual cost estimates for construction projects, using an Evolutionary Fuzzy Neural Inference Model. Data were collected from 28 construction projects spanning the years from 1997 to 2001 in Taiwan [74]. In a study historical cost data of continuing care retirement community projects were compiled to develop regression and neural network models. The study showed that by using regression and neural network simultaneously a satisfactory conceptual cost model can be achieved [21].

4. Discussion and critical review

The foregoing sections presented an outline of applications of ANN in CM grouped in major areas. A detail discussion and critical review of these applications is presented in this section with respect to Method of data acquisition, Input parameters, data/sample size, network architecture, type of network, training, transfer function, overfitting, learning and momentum rate, performance function, number of epochs, performance measure, comparison with other methods and general comments.

4.1. Method of data acquisition

In the works discussed, the data were obtained from past reports or by questionnaire survey, interviews, and case studies from construction projects. Unavailability of certain data can be a limitation for the model developed and thus a comprehensive dataset is required for achieving a meaningful output [20,29,30,52]. In a study data is collected through structured questionnaire and expert interviews which were used to identify the most influential factors on contract awarding system in the Gaza Strip [60]. Fifty four questionnaires, as a response rate of 77% of the total number of questionnaires, have been correctly answered and submitted. For the need of many data to develop the neural network model, many historical projects done between 2010 and 2012 in the Gaza Strip were collected from municipalities, government ministries, engineering institutions, contractors and consultants. [60]. In a study for developing Building Construction Projects Cost Estimating, Eighty questionnaires were distributed to various engineering institutions. Fifty-seven questionnaires with a response rate of 71% have been correctly received [31]. The questionnaires typically consisted of identified factors that affect parametric cost estimate of projects. Thirteen cost parameter in skeleton phase and eighteen finishing phase parameters which were identified from the literature were evaluated [31]. To determine the productivity of labor, a structured closed-ended questionnaire has been developed for gathering data on the basis of subjective judgment of productivity factors and the related productivity [38]. In a study direct observation method was used for collecting the data in this research. Pilot study was done by selecting ten construction projects in different parts of Iraq. Work sampling approach was used to measure the production rates at the site to calculate the duration of activity on daily basis at specific time interval using stopwatch [36]. For establishing reasonable safety evaluation index system is the key to the comprehensive evaluation of construction safety. A scientific, comprehensive evaluation index system of building construction safety has been established based on the analytic hierarchy process, which combined with the expert opinion and the suggestion [75]. The dataset used in research to predict the best contract in the Gaza strip, the data set used was part of a larger dataset collected from construction workers during 2005 and 2006 in the Cincinnati/Tri-State area using the Work Compatibility survey primarily. The Work Compatibility Model is a multidimensional diagnostic tool for human performance that measures the level of synchronization between the workforce and the work environment and contains 11 sections with 166 questions [60].

4.2. Input parameters

Selection of input parameters to develop a network relies on a priori knowledge of the subject, the characteristic of data source, experience and availability of data. The accuracy of ANN outcome depends on the quality of training data and the ability of the developer to choose truly representative input information. It was noticed that the correct selection of input parameters through a sensitivity analysis was very helpful in achieving better results [11,12,25]. Identification of input can also be done by methods such as the Delphi method, systems engineering, and factor analysis [49,51]. Statistical analysis of input parameters was made to understand the influence of various parameters on the labor productivity [34]. In 2003, Apanaviciene and Juodis modeled cost variation using 12 influential factors including seven for project manager category, one for the project team, two for planning and two for organization and control category [25]. Tools as factor analysis, principal component analysis and Box and Whiskas method for eliminating outliers were utilized [43,51,66]. While input selection can be done with the help of statistical parameters appropriate domain-specific knowledge significantly helps in this regard [76]. The input parameters selected for few of the works mentioned above are: In 2012, Minli and Shanshan used factors like environmental factors, business actors and project factors [23]. Input parameters as construction year, building type, city, and actual construction cost, scores achieved from LEED categories were used to predict the cost of premium Green buildings [30]. Kim et al. in 2013 used ten input parameters as a year, budget land and school building specifications to predict the cost of school building [8]. ANN model in predicting the productivity of concrete in m^3/hr for Sydney area utilized input parameters as weekday, starting time of first delivery, amount of ordered concrete, longitude and latitude of the project, number of orders received, number of assignments delivered [42]. To predict the likelihood of contract default, 23 factors related to contractor characteristics, 2 -particulars of the contract and 3 nature of the project were used as input variables [44]. In 2012, Chenyun et al. determined a risk index for an expressway construction stage using the principles of Scientific, system, theory for practice, operability, independence and comparability [45]. Prediction and evaluation of construction employees' safe work behavior were modeled using ANN with safety indices as inputs [52]. Input parameters as WBGT (Wet-bulb globe temperature), age, alcohol-drinking habit, smoking habit, work duration, job nature with output as a rating of Perceived exertion were utilized for determining the fatigue of construction workers [53]. Various cost estimations involved in construction works depend on either estimator-specific factors or design and project-specific factors [77]. 21 input parameters as bid prize, capital of the company, liquidity, debt volume, banking facilities, etc. were selected to predict the best contractor in the Gaza strip. Sensitivity analysis was carried out to evaluate the influence of each input parameter to the output variable for understanding the significant effect of input parameters on model output [60]. In the research four sections (due to obvious relation with occupational disorders and diseases among construction workers, but yet unknown in severity), were included i.e physical environment, economic factors, muscular activities, and experience at work which were subjectively answered by participating workers on a Likert scale of 5 (from 'not at all' to 'entirely') as input parameters [54]. Input parameters as political risk factors: Firm's relationship to the government, Firm's relationship to the power groups, Involvement of local business interests, Impact of regional and external factors, Nationalistic attitudes toward the firm and Project desirability to the host country were selected to predict the percentage change in cost from the baseline cost forms [50].

4.3. Normalization of data

Neural network training could be made more efficient by using neural network processing functions which transforms inputs into a better form for the network use. Such scaling should improve the density of the data over the problem domain and allow the neural networks to converge faster and later to generalize better outputs [33].It is especially useful for modeling application where the inputs are generally on widely different scales. Different techniques can use different rules such as max rule, min rule, sum rule, product rule, etc. [78]. In most of the papers reviewed, preprocessing of the data in the form of normalization between -1 to 1 was done to increase the performance of the network [11,30]. Normalization of the data using Z-scores was used which leads to an increase in performance of the trained ANN [61]. Normalization of data between 0 and one was also seen prominently [64].

4.4. Data/sample size

In case of the adequate sample size to be used while training and testing of the network as well as the split of data into training and testing, a large variation was observed in the past works. In general, 60%-80% of the data was used for training and remaining for validation (as one of the steps to take care of overfitting) and or testing in the papers reviewed. Data of direct cost of school buildings were presented to ANN with 20 for testing, 67 cross-validations and 130 for training [8]. A network was developed which consists of 27 project data which was trained with 85% of the data set (33 records) that were randomly picked, while 15% (6 records) were used for testing [41]. Out of the total sample consisting of 506 input-output pairs in their work Elhag and Wang in 2007 used around 77 % for training and remaining for testing while Minli and Shanshan (2012) employed 30 pairs for training and one only for testing [23,48]. It remains to be seen how far such validation is sustained. An appropriate splitting of data is required in such a way that the model should be trained with all data patterns to predict meaningful results. In 2016, Sawalhi and Hajar utilized 91 tenders for selection of a best contractor in the Gaza strip. Of the 91 tender's data, 66% were utilized for training, 18% for Cross validation set and 16% for testing phase [61]. Selection of subject for data collection also plays a vital role. Out of 191 subjects to assess the performance of ANN and Logistic Regression by calculating the log-likelihood (LL) ratio, 188 were male, and one was female, and the gender of the two subjects was missing. The average height and weight of the sample were 179.8 cm and 87.42 kg, with a standard deviation of 6.49 cm and 15.97 kg, respectively. The height of two subjects and the weight of the five subjects were missing. Seventy-two subjects (38.29%) were smokers, and 116 subjects (61.70%) and health 137 were non-smokers, and the smoking status of three subjects was missing. Because of the large size of the initial dataset and the limited resources available for high-volume computation and data analysis, the dataset was divided into 160 subsets based on outcome variables and for each subset, separate LR and ANN models were developed, 70% of each dataset was used to train the network and the remaining 30% was used to validate the results [54]. The sample size for Development of Awarding System for Construction Contractors in the Gaza Strip was 54 respondents which consist of 33% as public owners, 6% as donors, 19% as NGOs, 15% as implementing agencies, 11% as consultants and 17% as other organizations [60]. 169 was the data set that was divided logically randomly, according to literature, into three sets 66% for training, cross-validation 16% and 15% of test data for the estimated construction cost of building projects [31]. Examining the sufficiency of the data for modeling purposes, scatter plots were produced to draw a trend line between each independent variable and the calculated CPI (cost performance index) in various case studies, which showed that all trend lines exhibit logical relationships, thus confirming the sufficiency of the data [20].

4.5. Presentation of data

Artificial networks only deal with numeric input data. Therefore, the raw data must often be converted from the external environment to numeric form. In the study to predict the best contractor in the Gaza Strip, the data were converted to numeric form by dividing the inputs for each factor to ranges which were represented as numeric [60]. Data was also presented in a combination of binary and raw form for Analysis of construction Dispute Resolution with input parameters as project month, year location in binary form and parameters as labor estimate, equipment and material estimate in the raw form [64]. In research to develop a Neural Network Model for Building Construction Projects Cost Estimating, the data was textual and numeric, and it was encoded in the numeric form [31]. Data in the form of a numerical scale from 1-5 as positive factors and -1 to -5 for negative factors was given to network to predict the productivity of labor [38]. In 2016, Aswed in their study for productivity estimation model for a bricklayer, two classes of independent variables are found: objective and subjective variables [39]. The measurable (objective) variables according to their units of measure, such as age and experience are measured in years, gang number is measured in number, the wall thickness is measured in centimeters, and wall length is measured in meters. The coding system is used to measure the qualitative (subjective) variables; for example, the gang health can be classified to bad moderate and good and assigns them the value 1, 2 and three respectively. Quantification of each input variable (into one of seven values) was done in a study to model the political risks in the construction industry. For example, Attribute 1 (Firm's Relationship to Government) had a range value between 1 (Very Good) to 7 (Very Poor). When an attribute is labeled as “very good,” it refers to the best favorable condition that an expert can think of regarding that attribute, while an attribute labeled as “very poor” refers to the maximum worst condition that an expert can think of regarding that attribute [50]. In a study to predict the productivity of labors, the inputs were divided into objective and subjective parameters. The objective variables like age(in years), experience(in years), Number of labor(number) etc. and subjective variables as the security conditions (category assign value between 1 and 2), health (category- which specifies as good, moderate and bad, it assigns them the values of 1, 2 and 3, respectively. While the weather condition; sunny (1), rainy (2). The site conditions can be classified into complex and simple and assign them the value 1 and 2, respectively. Whereas the scale of 1 and 2 represent near and far, respectively about the availability of construction materials [36].

4.6. Network architecture

The first step in designing a network is to determine the number of input nodes, hidden nodes, and output nodes. The selection of these parameters is problem dependent, and there is no simple and clear-cut method for these. In most of the papers studied, Neural network development was done with three layers, i.e., input layer, single hidden layer and an output layer with few exceptions, e.g., for cost estimation of a highway project in Thailand dataset the architecture used was 4-10-6-1 [16]. The no. of neurons in hidden layers was computed using the trial and error method [34,46]. The optimum numbers of hidden neurons were also computed by calculating correlation (r) between the actual and predicted outputs against an increasing number of hidden neurons as they are added to the network and graphed [44]. MAPE and MSE of the training were computed and plotted on a graph corresponding to the number of hidden neurons, and the no. of neurons with the lowest MAPE and MSE were selected [51]. An attempt was made to increase the number of hidden layers from 2 to 10, and a slight improvement in results was observed; however, the differences were not significant [42]. The Multilayer Perceptron (MLP) developed to select the best contractor in the Gaza strip includes one input layer with 21 input neurons and one hidden layer with (30 hidden neurons – selection through trial and error method) and finally one output layer with one output neuron (the best contractor) [60]. Different network architectures were seen for different factors as analyzing the economic condition factors had the 7–5–6 network structure., for work experience factors was 15–6–6, for physical, environment 10–5–6, and the network structure for muscular activities for the upper body joints was 15–6–6 and for lower body joints 22–6–6, in which the numbers represent the number of neurons (nodes) in input, hidden, and output layers, respectively [54].

4.7. Type of network

In majority of works discussed in the preceding sections the FFBP type of architectures was used [11,19,38,39,51,67]. For estimating labor production rates in 2000, Lu et al. used Probability inference neural network (PINN) which contains the Kohonen classifier and a Bayesian layer. The developed PINN model outperforms the back-propagation neural network model regarding point prediction accuracy, by coming closer to the actual output values [40]. Modeling construction Unit Rate Factor was done using Kohonen Self Organizing Map network was used in 2015 by Mwiya et al. [66]. ANN ensemble models (bootstrap aggregating and adaptive boosting ANNs classifiers) were also found to produce better results than FFBP when used for project cost along with schedule success prediction models [29]. A construction cost forecasting model based on RBF neural network was developed which showed better performance over ANN (back propagation BP) [79]. In 2015, Bayram et al. carried out a study to estimate construction costs in Turkey using multilayer perceptron (MLP), Radial Basis Function (RBF) and unit area cost method and it was found that the performance of RBF was superior to MLP [15]. A SOM (Self-organizing Map) based model was developed to both analyze the effect of various variables on crew productivity and to predict the crew productivity values [43]. Leung et al. (2001) utilized General Regression Neural Network (GRNN) with a genetic algorithm based learning for modeling hoisting times of tower cranes [58]. Object-oriented Evolutionary Fuzzy Neural Inference System (OO-EFNIS) was used for predicting a subcontractor's performance and duration estimation of the slurry wall [59]. Particle Swarm Optimization (PSO) based network for prediction of outcomes of construction litigation was developed to give a successful prediction rate of up to 80%. The PSO-based perceptron was found to work better and faster than BP-based perceptron [63]. Thus, though in most of the reviewed papers use of FFBP network was widely seen, other types of networks were seldom used. Thus a need arises to explore the use of other network types for various applications and standardized the need of a particular network to a particular application. In 2016, Sawalhi and Hajar utilized MLP (multilayer perceptron) or GFF (General feed forward) for predicting the best contractor [60]. In a study, the safety evaluation model was established for building construction with taking expert scoring as network input, security class as the output based on Hopfield neural network. Research shows that Hopfield neural network has very strong memory and association function, and reflects the digital characteristics of sample data [75].

4.8. Training

As regards training methods Jacobian matrix [56], gradient descent [34], Levenberg-Marquardt [10,13,51], and resilient backpropagation [25,28], methods had yielded remarkable results. Bayesian regularization backpropagation was used [61]. The scaled conjugate gradient backpropagation called trainscg is used for the early stopping method and Regularization is done in an automated fashion by using the Bayesian framework which is implemented in the training function trainbr [38].

4.9. Transfer function

In general hyperbolic tangent and, log-sigmoidal type functions were common. Use of non-sigmoidal type (polynomial, rational function, and Fourier series) transfer functions was seldom seen and needed to be explored in areas of CM. In a study, various transfer functions and the results regarding root mean square was compared displaying the sigmoidal as the best transfer function [71]. The sigmoid function is a good candidate to be used as activating functions because they are continuous and derivative at all points and very similar to LR model, which can help analyze similar non-linearity among variables [54]. In a study to predict the productivity of labor, the following points were encountered during training of the networks: (1) using logsig function in the networks trained with trainscg brought less accurate results; however, the trainbr exhibited a good response when using logsig; (2) utilizing the tansig function in the output layer of the networks trained with trainbr caused failing of the networks [38].

4.10. Overfitting

Sometimes, ANNs have overfitting problems and addressing this problem, simple architecture of the network, sufficient numbers of data samples, provision of the dataset for validation, use of faster convergence, and early stopping criteria are recommended during the development of the network. In order to prevent networks from overfitting and improve their generalization, early stopping and Bayesian regularization were implemented [38]. In order to avoid the problem of fitting this problem, the researcher utilized a trial-and-error approach by running each ANN model with different values for some parameters such as learning rate and acceptable error. This method helped to identify the best performing ANN model [54].

4.11. Learning and momentum rate

Mention of learning rate and momentum rate can be seen in a few papers which is either considered or adopted by software [11,19,20,34,36,46]. It was found that a specific rule could not be found for changing the learning rate as well as the momentum rate. Few of the papers mentioned that the learning rate adopted were 0.0001 [23] and 0.5 [19,34] and maximum momentum rate of 0.9 [35] for developing a network. A learning rate of 0.15 was arbitrarily chosen to ANN model for political risk in construction Industry since larger learning rates often have been found to lead to oscillations in weight changes resulting in a never-ending learning process. One way to allow faster learning without oscillations is to make the weight change, in part, a function of the previous weight changes. A momentum coefficient represents this portion of the weight change. In this study, a coefficient of 0.7 was found to perform well [50].

4.12. Performance function

Generally network were trained to achieve low Mean squared error [19,23,38,44,63], absolute error [45,46,49] between the network predicted and observed values. In 2003, Apanaviciene and Juodis utilized modified regularization error function to study the network performance [25]. For Bayesian Regularization- the sum of squares of the network errors were used to predict the construction labor productivity [38].

4.13. Number of epochs

A performance percentage graph with no. of iterations/epoch was generally seen in papers reviewed [11,19,38,62]. To mention a few studies, In 2014, Mehidi showed that the highest performance percentage obtained after 9000 iterations and the performance percentage was 95.45% with lowest possible error of 0.00045 in an application to assess risk in cement industries [47]. For predict the duration of concrete operations, in 2014, Maghrebi et al. utilized Mean square error as performance function and the best result was obtained at 14 epoch with MSE=10.94 [42]. In a study epoch number 10,000 was found adequate for the final training process in a series of test runs. The performance of the network deteriorated for fewer iterations than 10,000 and the network began to memorize the output values for iterations more than 10,000 [11]. 20, 000 iterations were planned for the final training process, as this was found adequate in a series of test runs during modeling of political risk in construction Industry [50].

4.14. Performance measure

In most of the works listed above, the model performance was validated by using statistical measures of correlation coefficient, coefficient of determination, mean squared error, mean absolute percentage error and percentage error [11,36,70]. Average accuracy percentage (AA%) was utilized with other performance parameters [11]. Most of the researchers adopted only one or two measures to judge the model performance and very few utilized more than two performance indicators [20,34,37,48,51]. Adopting a set of linear and non-linear error measures as performance indicators for a developed ANN model was beneficial as observed in 2014 by Deshpande et al. [76]. In 2014, Lhee et al. judged the model performance through one-step and two-step kurtosis in an application related to transportation construction projects. Visual interpretation of results in terms of Network interpretation diagram can be utilized [24]. Lu et.al. in 2000 estimated labor production rates using the probability inference neural network (PINN) model and presented them in the form of probability density function graphs [10]. In 2001, AbouRizk et.al. presented histograms reflecting the likelihood of labor production rate with Kohonen Learning Vector Quantization type of classification networks [41]. To select the best contract in the Gaza strip, the performance measure of accuracy performance (AP) was utilized along with correlation coefficient and mean absolute error. The accuracy performances defined as (100−MAPE) %. [60]. The LL value is an estimate that is parallel to F and R^2 and was used to evaluate the goodness of fit for ANN and Logistic Regression (LR) models. LL is the criterion for selecting parameters in an LR model. When two models were compared, the larger the LL value, the better was the model performance [54].

5. Comparison with other methods

In some of the works discussed above the results of ANN models were compared with models made using other tools, e. g., statistical regression analysis, case-based reasoning, genetic algorithm and support vector machine. It was seen that generally, the ANN models performed better than these [8,9], although data adaptability was noted to be better in some alternatives [9]. To predict the owner’s contingency on transportation construction projects, one step ANN model predicts the contingency amount directly as its output and two-step predicts the contingency rate which is then multiplied by the adjusted original contract amount to get the contingency amount. Both the one-step and two-step ANN-based models demonstrated good learning for the training dataset based on the high correlation values of 0.827 and 0.863, respectively [24]. In a study, Support Vector Machines were found to work better than an ANN-based model for prediction of the cost of buildings in Taiwan [29]. However in a study to estimate costs of the school building in Korea it was seen that the ANN model gave more accurate estimation results than the Regression Analysis and Support vector regression models [9]. In a study it was seen that Neural networks and multiple regression technique can be used to model hoisting times of tower cranes however the predictive performance of GRNN with genetic algorithm models was found to be better than that of the multiple regression model and the MLFF network with BP algorithm in modeling the hoisting times [58]. In a study carried out 160 LR and ANN models were made, and their performances were assessed by estimating the LL ratio. The result of a t-test showed that the ANN models performed significantly better than LR models (P-value,0.001). This means that regardless of the type of variables, ANN models can predict the outcome more accurately than LR models. A need for Hybrid models arises which can display higher accuracy and can utilize the advantage of other tools. The lack of homogeneousness in the data set used in research, choice of training algorithm, and ANN model structure is considered to be the potential reasons that 33 of LR models outperformed the ANN models [54]. Comparison of expert and the predicted values by the neural network for the complete data set of the political source decision variables was done which shows the neural network solutions to be accurate [50].

6. General comments

Some of the constraints while using ANNs in CM can be summarized as the absence of structured methodology to decide on various control features and parameters and its black box nature which could not explain the underlying input-output process [8]. Use of input parameters with ordinal variables only can seldom be seen in literature, and it needs to study further for better understanding. So far, all the studies have compared the ANN and LR models only with binary or continuous variables [54]. The knowledge of the relationship between input and output parameters modeled using ANN is locked up in trained weights and biases. A need thus arises to unlock it and thereby interpret the results. Though in most of the studies reviewed it was shown that ANN model performs better than the other models for the accuracy of estimation, it will be difficult for the user to understand and explain the estimation results from this ANN model [9]. Dedicated work towards this area will popularize the technique with regular users. Acceptability of ANNs for routine practical works can increase if its portability (in terms of an easy GUI or interface with commonly used software) and standardization issues e.g standardization of minimum accuracy level required for acceptance of a model, minimum and important input parameters required for a particular project with specified output, minimum learning rate and momentum rate, minimum number of neurons in hidden layers etc. are addressed. The developed neural network-based political risk model can be integrated into spreadsheets used for cost estimation. Such integration facilitates the practical use of the proposed approach by consulting engineers performing supervision and by construction managers responsible for project risk management and control functions [50].

Case studies were considered for the collection of data and further development of the model. However only a few present the use of them for practical applications [22,25,57,72]. Limited studies were observed in using ANN in the area of safety evaluation in hot and humid environments [53] and construction unit rates [66].

7. Concluding remarks

In the current paper, an extensive review of past works dealing with recent applications of ANN in areas of Cost, Productivity, Risk Analysis, Safety, Duration, Dispute, Unit rate and Hybrid

Models is done. The review confirms the usefulness of ANNs in carrying out a variety of prediction, classification; optimization and modeling related tasks in areas of CM. ANNs are based on the input-output data in which the model can be trained and can always be updated to obtain better results by presenting new training examples. ANN thus has significant benefits that make it a powerful tool for solving many problems in the field of CM. However large scope is still found to exist in experimenting with a variety of network architectures, training algorithms and hybrid type of methods, which could lead to a higher level of model performance. Acceptability of ANN for routine use in CM can be increased if clear guidelines to select input, network architecture, learning algorithms and other network control parameters are evolved from an exhaustive assessment of all past works. Providing a standard benchmark for determining the accuracy level of the construction proposals will help to increase the use of ANN in CM. Large-scale attempts in future to unlock potential knowledge in the network system can also go a long way in increasing user confidence in the ANN use. Only a few instances are seen about the use of developed ANN models for practical applications. Implementation of ANN for live projects and a step towards understanding the user related problems towards implementation of the same should be done.

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