IEREK PRESS Academic Research Community
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ISSN (Print: 2537-0154, online: 2537-0162)
ARChive

International Journal on: **The Academic Research Community Publication**

DOI: 10.21625/archive.v2i1.232

Utilization of Artificial Neural Networks in Managing and Planning of Urban Projects

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Keywords:

Artificial neural networks, Construction, Management, Urban projects.

Abstract:

Artificial neural networks (NN), have been applied to many construction management problems in urban projects. NN have showed some degree of success so the objective of this paper is to highlight some applications of this tool in the construction management field to help specialists find optimum solutions. A brief description of the input and output variables for each mentioned problem was illustrated in addition to the number and type of data set collected to train and test the neural network performance then the percentage error for each developed model was pointed out to demonstrate its accuracy.

1. Introduction:

Most construction management problems such as cost estimation, productivity modeling, budget control, mark-up estimation and others require expert knowledge, judgement and experience to consider all significant factors affecting these problems. Although research has been conducted using traditional decision analysis techniques such as regression analysis, multi attribute utility theory, fuzzy theory and others to solve these problems, the obtained results weren't satisfactory because these techniques depend on advanced mathematics which make them less acceptable to represent the construction personnel experience in addition to most of the research consider the effect of a single factor or just a few multiple factors.

After the researchers' efforts turned to using expert systems in the construction domain, knowledge acquisition has been considered as the major bottleneck in the development of these systems. They also lack the ability to learn by themselves, generalize solutions and respond to noisy, incomplete or unseen data and because of these limitations, artificial neural networks have been used as an alternative to represent implicit knowledge that can't be formalized.

2. Overview:

Artificial neural networks are computational models inspired by biological models of the brain. They have been used for a wide range of problems such as pattern classification, speech synthesis, recognition, clustering, forecasting and others. Neural computing approaches are different than programming approaches in the following aspects: the ability to learn and generalize using a set of given inputs and outputs, rules aren't visible, copes with noisy and incomplete data set and adapting solutions over time, the structure of neural network model is arranged in layers of units: (1) An input layer which receives input values from the outside; (2) An output layer that report the final answer; (3) A set of processing hidden units in the hidden layer which link the inputs to the outputs by weights as shown in figure (1).

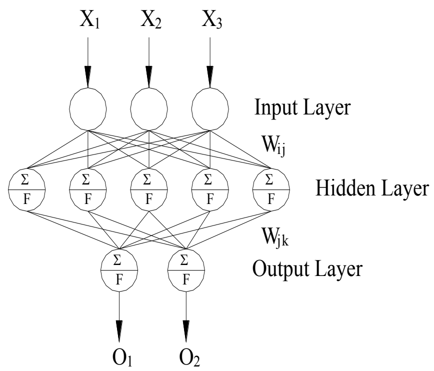

Fig. (1) Structure of Artificial Neural Network

Neural network models are built by modifying the weighted inputs for each unit using a transfer function to reach to the required output. The transfer function may be a linear or nonlinear function which includes sigmoid and tanh functions, these two functions are the most common in neural network applications. Two broad types of neural network architectures are feed forward and feed backward. The simplest and most common one is the multilayer feed forward network (back-propagation network) in which the information travels in one direction but feed backward network isn't common because it's difficult to train and analyze. There are no formal rules to determine the best number of hidden layers & the number of hidden nodes in each hidden layer to obtain the required accuracy for a certain problem so it's necessary to undergo a trial and error process to determine the best structure of neural network model. The learning rule for a neural network is the process of modifying the weights of a network to produce the desirable output, there are three types of learning rules: supervised, unsupervised and reinforcement. The most popular type of learning is supervised, which requires the existence of an external supervisor to control the performance of the network.

3. Labor Productivity:

Rifat Sonmez & James E. Rowings (Nov./Dec. 1998) presented an artificial neural network model to estimate labor productivity for concrete pouring, formwork and concrete finishing. The first step in developing this model was the identification of labor productivity factors for the three tasks which include: 1- Quantities completed; 2- Job size; 3-Crew size; 4-Percent overtime; 5-Percent labor; 6-Temperature; 7-Humidity; 8-precipitation; 9- Concrete pump. The same factors were identified for the formwork except the last factor but for concrete finishing, the concrete pump and job type weren't included. The second step was to develop a regression model based on the data obtained from eight building projects on a weekly basis. The number of weekly data points for concrete pouring, formwork and concrete finishing were 112, 76, and 46 respectively, the benefit of regression analysis is to determine the significance of the factors included in the model by calculating the mean square error (MSE) and the mean absolute percent error (MAPE) between the predicted and actual values. Two neural networks were trained for concrete pouring task to find the number of hidden nodes that result in the best prediction using the following inputs after dropping insignificant factors: quantities completed; crew size; temperature; job type and concrete pump. The first network contains 13 hidden nodes while the second network contains four hidden nodes. The performance of the second network was better than the regression model because the neural network includes the interaction between quantity and the concrete pump. As for formwork activity, the input variables used to train the two neural networks were the quantity completed and crew size, the first network contains five hidden nodes while the second network contains three hidden nodes. The prediction performance of the neural network wasn't better than the regression model, the same process was followed for the concrete finishing activity using the input variables quantity completed and temperature, the first network contains five hidden nodes while the second one has three hidden nodes, the first network shows a better performance than the regression model because neural network succeeded to represent the nonlinear relationship between temperature and production rate. Finally, a sensitivity analysis was done to illustrate the impact of significant factors identified during analysis on the productivity of the three tasks.

Lapidus, A. et al (2017) developed based on artificial neural networks (ANN) has been actively implemented in construction companies to support decision-making in the organization and management of construction processes. ANN learning is the main stage of its development. A key question for supervised learning is how many number of training examples we need to approximate the true relationship between network inputs and output with the desired accuracy. The design process of ANN architecture is related to a learning problem known as “curse of dimensionality”. This problem is important for the study of construction process management because of the difficulty to get training data from construction sites. In previous studies the authors have designed a 4-layer feedforward ANN with a unit model of 12-5-4-1 to approximate estimation and prediction of roofing process. This paper presented the statistical learning side of created ANN with simple-error-minimization algorithm. The sample size to efficient training and the confidence interval of network outputs defined. In conclusion, the authors predicted successful ANN learning in a large construction business company within a short space of time.

4. Budget Performance:

D.K.H. Chua, Y. C. Kog, P. K. Loh & E. J. Jaselskis (Sept. 1997) illustrated a back propagation neural network was presented to predict the budget performance of a construction project using key management factors. The data set was obtained from questionnaire surveys conducted by Jaselskis on 75 construction projects, 48 from contractor organizations and 27 from owner organizations. Half of the projects were cross plant while the other half were a combination of manufacturing office, power, pipeline and other types, the average size of the projects was $ 124,000,000 and the mean duration is 29 months and instead of using the data as measured it was classified according to a six point scale from (0 to 5), 27 management factors were identified to affect the construction budget performance, these factors were classified into four categories which include: (1) Project Manager(PM): some of these factors under this category is PM site visits, PM levels to craftsmen, PM education level, PM experience and others. (2) Project Team: which include team turnover and design incentives. (3) Planning: this category include design complete, start activities, budget contingency, constructability and modularization and others. (4) Control: under this category progress inspection, quality inspection, safety, control system budget……etc.

For detailed information about these factors, refer to appendix (1) at the end of the paper. During model development, the insignificant factors were dropped from the network to define the key factors for budget performance. This was done by dithering the input factors by +5% then if these factors showed a negative impact on the network output, they were discarded from the model. This resulted in identifying eight management factors used as inputs to train the neural network which include: project manager levels to craftsmen, project manager experience, team turnover, design level at construction start, constructability program, budget control system, construction control meetings and budget updates. Two hidden layers were used in the model, the first layer contains five hidden nodes and the second one contains three hidden nodes while the output is the budget performance which was classified to (good, slightly good, average, slightly bad and bad), the confidence level was determined using 20 test examples to be 95% with a standard deviation of (0.827), also the model had been evaluated for unseen and incomplete inputs. About 30% of the predictions were exactly as expected while nearly 70% of the predictions weren't more than one degree of deviation from the expected.

5. Construction Equipment Productivity:

Chao L. C. & Skibniewski M. J. (April 1994) developed two neural network models to estimate productivity of a hydraulic excavator. The data used to train the neural network was obtained using a desktop excavator robot with electric servomotors and to simulate the performance of the excavator, a computer program was used to send instructions from a basic program to control the robot’s motion. The first network estimates excavator's cycle time while the second one estimates the excavator efficiency. The excavator simulation process is based on two scenarios, the first one simulate mass excavation when the truck queue is empty so the excavator has to wait until a truck travels back, which leads to losses in productive time. However, the truck has to wait and if the excavator is busy working with other trucks, the second scenario simulates a substructure excavation job in which the excavator, after loading a truck, has to perform additional work such as repositioning, clearing and shaping which adds extra time before being ready to work with the next truck. The input data for the first scenario is the mean time to excavate and load a truck, mean cycle time for a truck, the standard deviation between excavating and loading time of the truck, number of trucks and the standard deviation of the mean cycle time of the truck. The same input data were used for the second scenario in addition to the mean time to perform an extra task, standard deviation of that extra time and probability of performing an extra task. After loading a truck, 86 training pairs were used to train the network for estimating the excavator cycle time with average error of 0.82% and the maximum error was 2.13% and 700 data points were used for testing the network with average error of 0.92% and the maximum error was 5.37%. This performance was obtained using one hidden layer and 16 hidden nodes. The second network was trained using 200 training pairs with an average error of 0.43% and maximum error of 2.57%, then the network was tested using 1000 data points which gives an average error of 0.53% and the maximum error of 3.15%, from these percentages it's obvious that the network achieves a sufficient accuracy level.

Hajjar D., AbouRizk S. & Mather K. (1998) had presented a method for integrating neural network developed to estimate productivity for earthmoving operations with a simulation model called AP-2 earth which helps earth contractors in preparing their estimates for large and complex projects. Microsoft visual C++ was used as an object oriented environment to provide both a common interface for all models and general linking structures between simulation models and other models which include cad models, estimate database, neural network model, optimization model and others. The proposed approach was implemented on a small scale where the neural network was trained to predict productivity for an EX-3500 Hitachi shovel, this equipment has a 24 cubic yard bucket and its production rate ranges from 800 to 1700 (BCM)/ hour. The input variables required to develop the neural network model includes the following: (1) Soil Classification: five types were identified to include overburden; silt; sand; clay and rock. (2) General Soil Conditions: the general soil condition was either soft; hard or frozen. (3) Excavator Footing Conditions: the condition of the excavator footing is either wet or dry. (4) Excavator and truck relative positioning: which refer to the average swing angle, and the percent of both side loading, generally the productivity is higher when both sides are being loaded and the swing angel is decreased. 132 training pairs were used to train the neural network using one hidden layer containing 4 intermediate nodes, 20% of the data were chosen randomly to test the performance of the network with average error for unseen data of 5.6% while the maximum absolute error was 43%.

6. Markup Estimation:

Moselhy O., Hegazy T. & Fazio P. (1991) had presented an artificial neural network model to estimate the optimum mark up under different bid situations, the input layer consisted of three attributes: The number of typical competitors (n), the mean distribution of the ratio of competitors bid prices to the contractors estimated cost in previous encounters (μ) and the standard deviation of the latter distribution (σ). The practical values of these attributes are from 0.7 to 1.4 for (μ), from 0.05 to 0.11 for (σ) and from 2 to 10 for (n). The output of the neural network is characterized by three values based on the three bidding strategy models, Friedman (1956), Gates(1967) and Carr (1987), these optimum markup were calculated using a computer program called (Bid). The values of output ranges from 0 to 1. The designed network was trained using 10 examples of practical bid situations, one hidden layer was selected for simplicity and the number of hidden nodes in that layer was varied to evaluate the performance of the network as shown in figure (2).

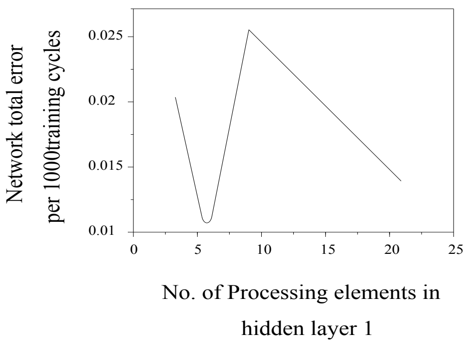

Fig. (2) Selection of Optimum Number of Hidden Nodes

It's obvious from this figure that the best performance of the network was at six hidden nodes in the hidden layer. Finally, the trained network was tested to evaluate the reliability of the network by comparing the predicted values with the actual ones, it is accurate in estimating the optimum markup for bidding, which encourages to put this network for actual use.

H. Li., L. Y. Shen & P. E. D. Love (May/June 1999) implemented a rule based expert system to extract explanation from a trained neural network, at first a neural network is trained using the inputs of the three following categories: firstly, Project Factors: (1) project size, (2) project type, (3) location, (4) Project complexity. Secondly, Company Factors: (1) Labor availability, (2) Current work load. Economic Factors: (1) Working cash requirement, (2) Number of competitors, (3) Market conditions, and (4) Overhead rate. The neural network consists of an input layer representing the input factors, an output layer representing the markup percentage and one hidden layer contains three hidden nodes representing the three categories. The network was trained using 25 bidding examples collected from a local contractor and tested using five examples with average error rate of 6.7% which means that ANN is a reliable tool in predicting markup percentage then an expert system was used to explain the choice of a certain markup percentage by the neural network which depends on using if - then rule.

7. Project Cost Estimation:

Tarek Hegazy & Amr Ayed (May/June 1998) developed a neural network simulation model in a spreadsheet format to estimate the construction cost of highway projects. The inputs used for the model are the factors affecting the cost of highway projects which include: project type, project scope, construction year, season, location, duration, project size, capacity, water bodies, and soil conditions.

After setting up the excel template with initial weights of ones the next step was to determine the NN weights that optimize the NN performance, this has been done using three approaches:

1- Back propagation neural network using a commercial NN software, the NN consists of three layers an input layer containing ten hidden nodes representing input factors, an output layer representing the total construction cost and one hidden layer contains five hidden nodes. The neural network was trained using 14 projects and tested using 4 examples with minimum weighted error of 10.34%, 1.43% on the training cases and 19.33% on the test cases.

2- The second approach to obtain the optimum weights for NN was the simplex optimization which was applied using the excel add–in program called solver. The optimization objective is to minimize the NN weighted error, the optimization variables are the weights from inputs to hidden layer and from hidden layer to output layer, the optimization constraints were to limit the percentage error to 2% for training examples and 5% for test examples. Using the trial and error method the optimum weights were reached with a weighted error of 0.71% for training sets and 1.25% for test sets.

3- Genetic algorithm is the third approach used to obtain the optimum weights for NN model, a population of possible solutions is created, then a cross over process is used to obtain the most fit offspring that solves the problem. After many generations, the optimum solution is obtained and this approach has been applied using a commercial software called (Gene Hunter).

The optimization objective and constraints were like the objective and constraints performed using Excel's solver, the weighted error was noticed to be 22.48% for training set and 21.11% on the test set.

The comparison between the results of the three methods is shown in fig. (3).

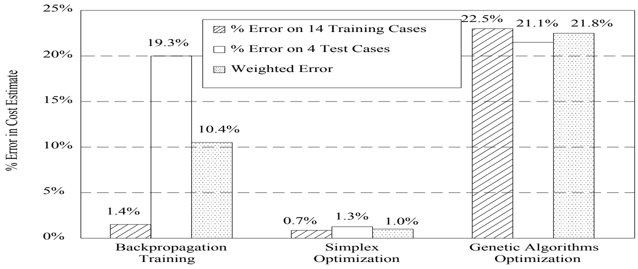

Fig. (3) Comparison between Weight Determining Methods

It is evident that the excel solver provides the minimum error percentage in determining the optimum weights of NN. A sensitivity analysis module also was incorporated in the developed NN model to consider the uncertainty in project factors, this feature put the developed model for actual use in predicting the budget cost for new highway projects.

Pearce A. R., Gregory R. A. & Williams R. developed an artificial neural network model for estimating the risk of cost escalation for construction projects which help planners and designers in identifying the potential of cost variation. The data required to train and validate the neural network had been obtained using the parametric automated cost engineering system (PACES) for vertical construction ranging from communication centers to medical facilities and living quarters. Twelve factors had been identified based on informal interviews with cost engineering experts to be the input variables of the neural network. These factors are building perimeter, floors above grade, roof area, foot print, floor to floor height, exterior doors, exterior wall area, exterior window area, number of stairwells, number of elevators, heating and cooling load, while the output was the cost of seven categories which include substructure, super structure, exterior closure, roofing, interior construction, conveying systems and heating, ventilation and air conditioning. A total of 46 training pairs were used to train the network in addition to five cases were used to test the performance of the model. The acceptable limit of error for the cost estimation problem ranges from +25% to -10% based on standard practice for vertical construction projects. Various architectures of ANN were tested ranging from one hidden layer of 0 processing elements to three hidden layers consisting of 21 hidden nodes. The best performance of the neural network was by using one hidden layer with five hidden nodes with average error of -3.79% and maximum error of -7.22% as shown in figure (4).

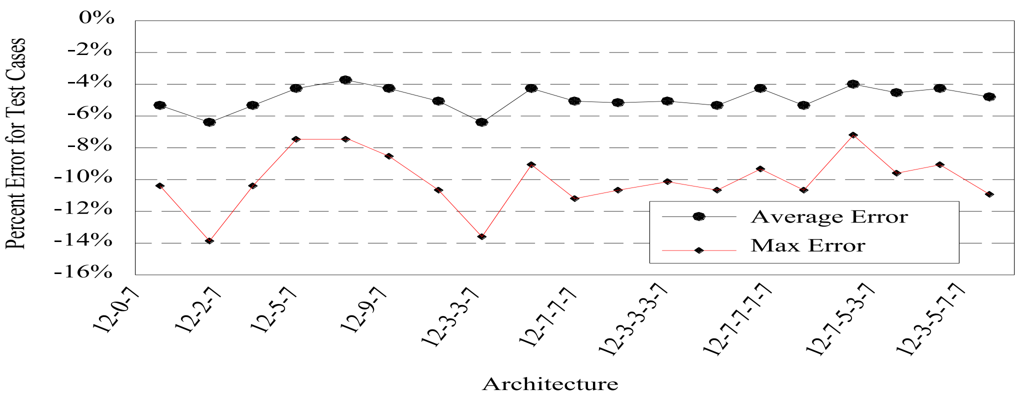

Fig. (4) Neural Network Architectures vs. Error

The trained network was used to generate cost/probability function by increasing three independent variables: number of stories, building perimeter and floor to floor height thus a larger number of cases was generated while the other input variables were calculated using (PACES) equation which depends on the three independent variables. This data set will be squashed and used to generate output values using the trained network then these outputs were not squashed and plotted as a histogram to obtain the cost/probability curve which illustrates the variations in the final cost based on the required level of confidence.

Anthony Harding, et al. (2000) stated that a neural network approach to estimate the total cost to the client for a building project according to different procurement routes has been developed. Two networks were trained to predict two measures of cost, the natural log of the cost and the cost/m2, thus four networks were obtained, two with the inclusion of procurement route and two without inclusion of the procurement route to assess the effect of the procurement route on the total project cost. The input variables for the ln(cost) model were location, natural log of the gross internal floor area, stores above, height, internal doors, while the inputs for the (cost/square meter) model were function, piling, internal doors, ceiling, the same inputs for the other two models but with inclusion of procurement route. The data set used to train the neural network was 58 projects of different functions (administrative, residential, industrial) with gross internal floor areas between 154 m2 and 11605 m2. Of the data set, 34 are design and build and the remaining 24 were procured by the traditional route. The data set was split to 32 projects for training, 13 projects for verification and 13 projects for test.

Table (1) illustrates the R^2 values for the four networks, it's clear that the neural networks are not generalizing well and the values of mean absolute percentage error (MAPE) for neural networks is lower than those for regression models which are developed to predict the (cost/m^2) and natural log of cost using the same inputs to the neural networks. Table (2) demonstrates this comparison.

A, B models without procurement

C, D models with procurement

Table (1) Performance of Neural Network

Model	R^2, training	R^2, verification	R^2, testing
Lncost A	0.971	0.992	0.837
Cost/m2 B	0.718	0.865	0.348
Ln (cost) C	0.969	0.990	0.843
Cost/m2 D	0.702	0.859	0.252

Table (2) Comparison Between NN model & Regression model

	NN Errors			Regres. Errors		
Model	R^2	MAPE%	APE%	R^2	MAPE%	APE%
Lncost A	0.933	25	18	0.985	13.8	12.1
Cost/m2 B	0.538	31	22	0.979	15.6	11.0
Ln (cost) C	0.945	23	13	0.985	13.9	12.2
Cost/m2 D	0.696	27	25	0.979	15.4	10.1

This means that the accuracy of neural networks is less than the accuracy of regression models. The reason for this bad performance is due to using a small data set which isn't enough to represent the real relationships between the variables and cost. Another important thing to be mentioned is that the models contain procurement route yield some improvement, this means that the procurement route have some effect on the cost, but it can't be identified without increasing the data set. The future development of this model is to increase the data set between 400 and 500 projects in addition to increasing the number of input variables to cover a wide range of project types and options. It's also important to include the client costs in the model.

Michał JUSZCZYK (2017) established that cost analyses are of the key importance for the success of the construction project. BIM as developing and disseminating technology brings several advantages to the construction industry especially for the several analyses carried out during the construction project and cost analyses among them. This paper presents a discussion of the concept of combining the idea of BIM and the use of artificial neural networks for the purposes of macro level cost analysis. The author's intention is to present considerations about potential benefits as well as the nuisances of the proposed approach.

8. Conclusions:

Based on the results of the studies reviewed in this paper, it's evident that artificial neural network performs better than conventional methods in many situations such as productivity modeling for concrete pouring, formwork and concrete finishing activities in addition to predicting excavator productivity, markup estimation, budget performance, cost estimation for highway projects and the risk of cost escalation. However, the last application for estimating the total construction cost based on procurement route still needs much research to put this model for practical use.

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