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DEVELOPMENT OF THE CONSTRUCTION PRODUCTIVITY ESTIMATION MODEL USING ARTIFICIAL NEURAL NETWORK FOR FINISHING WORKS FOR FLOORS WITH MARBLE

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ABSTRACT

Estimation of the productivity is an important task in the management of construction projects. The quality of construction management depends on accurate estimation of the construction productivity. In this paper, Multi-layer perceptron trainings using the back-propagation algorithm neural network is formulated and presented for estimation of the productivity of construction projects. Data used in the study are for residential, commercial and educational projects from different part from Iraq. These are used in training the model and evaluating its performance. Ten influencing factors are utilized for productivity forecasting by ANN model, they include age, experience, number of the assist labor, height of the floor, size of the marbles tiles, security conditions, health status for the work team, weather conditions, site condition, and availability of construction materials. One model was built for the prediction the productivity of marble finishing works for floors. It was found that ANNs have the ability to predict the productivity for finishing works with a very good degree of accuracy of the coefficient of correlation (R) was 89.55%, and average accuracy percentage of 90.9%.

Keywords: forecast labor productivity, construction, finishing work, artificial neural network, coefficient of correlation.

INTRODUCTION

Estimation is a necessary assignment in construction management. It includes cost (bid preparation, budget), time (productivity, project schedule), or quality estimation. Despite from that, the estimation is complicated, intuitive and approximate. For the productivity estimation, there can be so many factors that influence the productivity of construction tasks because the tasks involve long sequential processes, craftsmanship, many materials and tools, and changeable site conditions. Some of the factors are easily recognized; some of them may not. Also, the extent of these factors affect the productivity is difficult to identify. To avoid these problems, Feed-forward neural network (NN) models have been successfully utilized in process productivity estimation.

Research objectives

The objective of this study is to develop a model using ANN for estimating the labor productivity of marble finishing works for floors. That provides reliable and accurate production rates that also take into account the influencing of the factors.

Research justifications

The reasons that stand behind the adoption of this study work are:

a) Contractors used previous projects production rates for estimation of future projects that required to be readjusted and recalculated for each project and takes into account the various site factors and conditions that influenced the labor productivity for construction operations.
b) Also absence of standard production rates measurement system is one of the reasons identified for the declination of construction productivity.
c) Reliable and accurate estimation of the projects are required to be done through use of modelling techniques to estimate the production rates.

The research hypothesis

The research hypothesis in this study is formulated as “Artificial Neural Network (ANN) has strong modeling technique with dynamic learning mechanism and effective recognition capabilities to estimate the production rates under any specific condition”.

Research methodology

The following methodology is depended to achieve the required objectives:

(i) Theoretical study is included reviewing of references, thesis’s, and papers published inside and outside the country of Iraq relating to the subject of research, in addition to national instructions.
(ii) Field work included four stages;

a) The preliminary stage, which involved data description and identification, which describes the factors affecting the productivity of marble finishing works for floors;
b) The secondary stage, included developing of the NN model to predicting productivity and discuses the results from training and testing the NN model ;
c) The thirdly stage, which presented the validation of the NN model;
d) The finally stage, conclusions and future work in this research area.

Available productivity estimation techniques

The productivity estimation is based upon the assumption that there are certain relationships between a set of influential factors and productivity in the past events. Therefore, the productivity of the future events can be estimated by determining these relationships and specifying values for the influential factors. This section investigates available techniques of determining the relationships.

The first technique is statistic-based called the multivariable linear regression. It attempts to map the relationships between the influential factors and the productivity with the explicit mathematical functions. The mapping functions are initially presumed and later evaluated. They could be linear functions (multivariable linear regression) or non-linear functions (multivariable non-linear regression). However, the statistical technique could oversimplify the relationships comparing with the neural network technique (Sonmez and Rowings, 1998).

The second technique that has been widely used in recent research for identifying the relationships is the neural network. The neural network technique imitates a pattern recognition process of a human brain (Wasserman, 1989). Rather than identifying explicit functions for the relationships, the neural network technique leaves the relationships in a 'black box'. The network 'learns' to map the input patterns with the output patterns during the training process and subsequently is applied to new and unseen data. The advantages of neural network over the statistical technique are the ability to capture complex multivariable non-linear relationships, and interrelationships among influential factors. Many applications of neural network in construction research have been found including the estimation of cost, quality, and productivity as shown in section below.

Applications of ANNs in construction

A number of researchers have applied ANNs in construction management, principally for decision-making, forecasting, and optimization. Kamarthi *et al*. (1992) used a two-layered BP network for selecting vertical formwork systems. Murtaza and Deborah (1994) used an unsupervised neural network with the Khonen Algorithm for decision-making on construction modularization. Soemardi (1996) used two fuzzy neural networks for solving group decision-making in selecting a wall system under multiple criteria. William (1993) developed back-propagation networks for predicting changes in the construction cost index. Chao and Skibniewski (1994) used neural network and an observation- data-based approach to estimate construction operation productivity. Hegazy and Moselhi (1994) used back-propagation artificial neural networks to develop an optimum markup estimation model that derived solutions to new bid situations. Li (1996) used an ANN to model construction cost estimation. McKim *et al.* (1996) used a neural network to predict effectiveness of a construction firm. Elazouni *et al.* (1997) used ANNs to estimate the required resources of concrete silo walls at the conceptual design stage. ANNs can also be applied for design, planning, and management. Mawdesley and Carr (1993) investigated the possibility of using ANNs to produce project planning networks to substitute the shortage of skilled planners and the ever increasing complexity of projects. Chua *et al.* (1997) used ANNs to identify the key management factors affecting budget performance in a project. Al- Tabtabai *et al.* (1997) used a BP network to capture the decision-making procedure of project experts involved in schedule monitoring and prediction for multistory building projects under construction. Adeli and Wu (1998) developed a regularization neural network to estimate the cost of reinforced concrete pavement. Hegazy and Ayed (1998) used the neural network approach to develop a parametric cost-estimating model for highway projects. Thus, ANNs are being increasingly used for construction management research. A notable gap is that none of the aforementioned works is concerned with productivity forecasting for finishing works. Little number of researchers has applied ANNs in construction management in Iraq, Al-Zwainy. (2008) developed four models of the neural networks to estimate the total cost of highway projects. Al-Zwainy (2012) used Back-propagation Feed-forward neural networks for productivity estimation of the finishing works with stone tiles for building project.

Artificial neural networks: definitions and basic concept

Artificial neural networks (ANNs) may be called by different names: (1) connectionist models; (2) parallel distributed processing models; (3) neuromorphic systems; and (4) neural computing. ANN is a branch of artificial intelligence (AI) in which structures is based on the biological nervous system. It can exhibit a surprising number of the human brain's characteristics, e.g. learn from experience and generalize from previous examples to new problems. ANN can provide meaningful answers even when the data to be processed include errors or are incomplete, and can process information extremely rapidly when applied to solve real world problems (Lippmann 1988; Smith 1993). Neurocomputing architectures can be built into physical hardware (or neurocomputer, or machine) or neurosoftware languages (or programs) that can think and act intelligently like human beings. Among various architectures and paradigms, the back-propagation network is one of the simplest and most practicable networks being used in performing higher level human tasks such as diagnosis, classification, decision-making, planning, and scheduling. The neural network based modelling process involves five main aspects: (1) data acquisition, analysis and problem representation; (2) architecture determination; (3) learning process determination; (4) training of the network; and (5) testing of the trained network for generalization evaluation, (Wu and Lim 1993). Figure-1 shows how biological and artificial neural cells operate.

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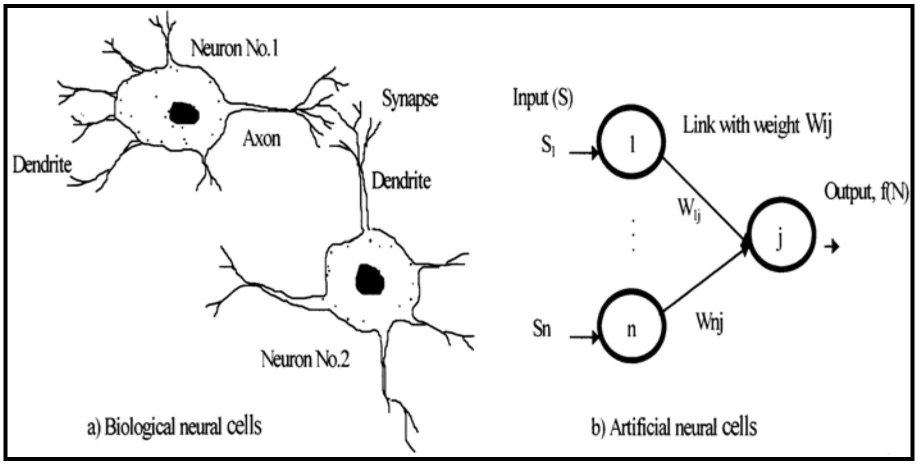

Figure-1. How biological and artificial neural cells operate.

Back-propagation networks have two main characteristics: (1) they are multilayered in structure; and (2) they incorporate transfer functions, e.g. sigmoid function for their processing elements. Learning or training takes place in an iterative fashion. The summation function, which finds the weighted average of all input elements to each processing element, then, multiplies the input values (*Si*) by the weight (*Wij*) and totals them together for a weighted sum (*aw*) plus a bias (*bj*), thus:

$$aw = \sum_{j=1}^{n} Si * Wij + bj \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

A continuous, nonlinear, and differentiable logistic function is used as a transformation function (or transfer function, or local memory). It yields output of real value between 0 and 1. When a node in the hidden or output layer receives its inputs from other nodes impinging on it, the activation levels will be computed. Based on this activation level, the node may or may not produce output by means of transformation. The learning rate, η, the constant of proportionality, provides dynamic access to the rate at which weights may be changed. A high learning rate corresponds to rapid learning which might push the training towards a local minimum or cause oscillation while small learning rates need a longer time to reach a global minimum (Khan *et al*., 1993; Smith, 1993). The remedy for the problem of balancing the learning rate is to apply a momentum factor, which is multiplied by the previous weight change so that while the learning rate is controlled the changes are still rapid.

Field work

The first stage, which involved data description and identification, describes the factors affecting the productivity of marble finishing works for floors.

Labor production rates are influenced by various factors present at the project site. These factors are very difficult to consider during the measurement and estimation of production rates due to its variable nature and also uniqueness of every project (Ayodele, 2002).

Through the literature review various factor that have been influencing the labor production rates at site are identified. Ten independent variables were carefully selected and were well defined for each construction project. These independent variables can be classified into two types: objective and subjective variables as shown in tables (1) and (2), respectively below.

Table-1. The objective variables.

Objective variables	Description	Units
X1	Age	Year
X2	Experience	Year
X3	Number of the labor	Number
X4	Height of the floor	Length (Meter)
X5	Size of the marbles tiles	Area

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Table-2. The subjective variables.

Subjective variables	Description	Units
X6	The security conditions	Category
X7	The health status for the work team	Category
X8	Weather conditions	Category
X9	Site condition	Category
X10	Availability of construction materials	Category

The security conditions can be classifies to security and non-security and assigns them the value 1 and 2, respectively. Also the health status for work team 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 classifies to complex and simple and assigns them the value 1 and 2, respectively. Where as the scale of 1 and 2 represent near and far, respectively about availability of construction materials.

Researcher has identified that suitable method of data collection influenced the accuracy of the production rates values. However questionnaire survey is the most commonly data collection method adopted by the researcher to collect information on factors and production rates in a cost effective way but the reliability and accuracy of the results cannot be proved.

Therefore, direct observation method has been selected for collecting the data in this research. Pilot study has been done by selecting ten construction projects in different parts of Iraq. Work sampling approach has been used to measure the production rates at site to calculate duration of activity on daily basis at specific time interval using stop watch. Researcher has been able to get fifteen (15) number of observation from each of ten (10) projects at different intervals. Among ten projects five residential, commercial and educational projects are from Baghdad, four residential projects is from Arbil and one commercial project is from Babylon as shown in Table-3. Therefore, total one hundred and fifty (150) number of data samples has been gathered.

The results of the pilot survey shows that the information gathered from the sites are applicable and it ensured the validity of the data instrument used, as shown in appendix (A).

Table-3. Construction project visited for measuring labor productivity rates.

Project No.	Location	Sample data	Type of project
Prj.1	Baghdad City	15	residential project
Prj.2	Baghdad City	15	residential projects
Prj.3	Baghdad City	15	educational projects
Prj.4	Baghdad City	15	educational projects
Prj.5	Baghdad City	15	commercial project
Prj.6	Erbil City	15	residential projects
Prj.7	Erbil City	15	residential projects
Prj.8	Erbil City	15	residential projects
Prj.9	Erbil City	15	residential projects
Prj.10	Babylon City	15	commercial project

Development of artificial neural network model

Several functions can be used for studying the relationships among the variables of a given data which were stated previously at previous section. Back propagation Network function is adopted in the research since the BPNN is the most widely used type and consists of many simple processing elements called neuron grouped in layers and connected by interconnections called synapses. Also, this type of network function implements a gradient descent in parameters space to minimize the output error.

Back propagation was created by generalizing the Widrow-Hoff learning rule (Widrow-Hoff, 1960) known as the delta rule or the Least Mean Square (LMS) method, where it involves gradient descent techniques in which the performance index is mean square error (MSE). Gradient descent is the technique where parameters such as weight and biases are moved in the opposite direction to the error gradient. Each step down the gradient results in smaller

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errors until an error minimum is reached. During training, the network parameters (weights and biases) are adjusted in an effort to optimize the "performance" of the network. A performance surface is created through optimization containing the minima and maxima points generated by the function parameters. The rule is an illustration of supervised training, where the net learns in the presence of a "teacher". The teacher is based on the level of hidden layer that is responsible for learning an associative map between the input level and the output level. The input is taught to accommodate changes and appropriately alter the output layer. As each input is applied to the net, the network output is compared to the target. The algorithm will adjust the weights and biases of the net in order to minimize the MSE, where the error is the difference between the target output and the network output. Hence, the rule is applied to a set of pairs of input and target output patterns being associated. The term of multilayer refers to the structure of the network because there are at least three levels of nodes resulting in two or more layers. The three node levels are input, hidden and output levels.

Figure-2 shows the schematic of the (NEUFRAME 4) program which is built to determine the relationship between the independent variables (inputs) and the dependent variable (output).

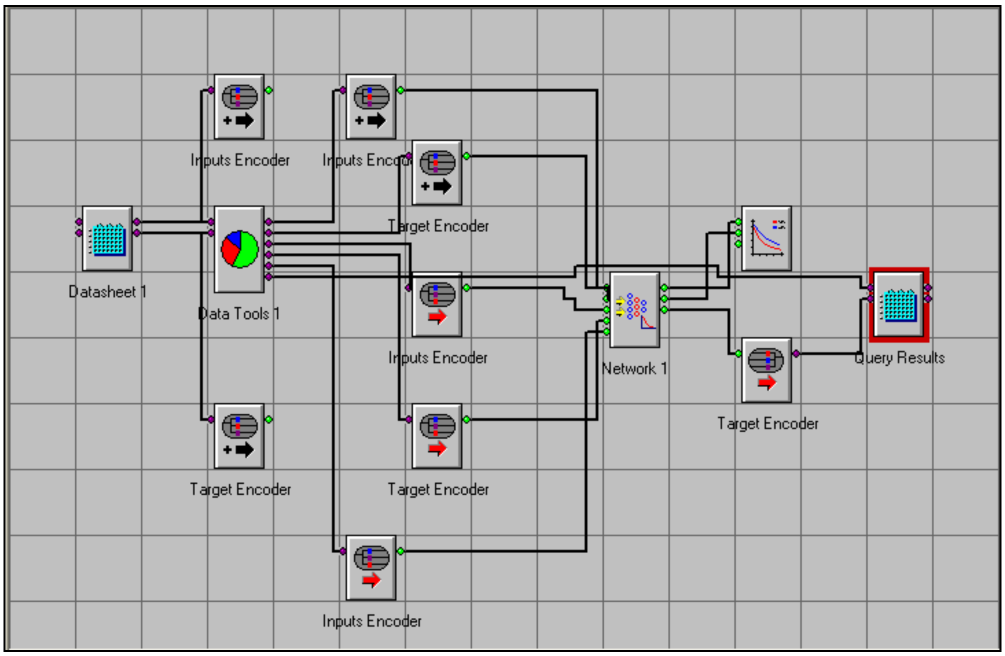

Figure-2. Graphing components of Neuframe program.

The data in this figure are divided into three categories, the training data, testing data and querying data. In the BPNN the difference in values for the output units is computed using the observed error (training error) then propagate the differences values back to the previous layer starting with output layer with updating the weights between two layers. This process is repeated for each layer in the network until earliest hidden layer is reached.

Input/target data format

The format of the input data will consist of the field data for productivity rates studied and equals to the number of the independent variables. These variables were fed in the program as follows:

a) Age
b) Experience
c) Number of the assist labor
d) Height of the floor
e) Size of the marbles tiles
f) The security condition
g) The health status for the work team
h) Weather conditions
i) Site condition
j) Availability of construction materials

The hidden layer is nonlinear combinations of the network inputs that are computed. Sigmoid function is used in the program which represents the nonlinear function. The output level computes nonlinear combinations of the hidden nodes outputs equal to the dependent variables. The format of the output data will consist of the field data for productivity rates studied and equals to one variable as the dependent variable this variable is actual productivity of marble finishing works for floors.

Output transforms

There are a number of output transforms known as transfer functions. The net input is introduced to this function. It is also important to note the architecture of the

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net, where each layer can have multiple neurons each neuron has different transfer functions. The transfer function used is a hyperbolic tangent sigmoid function.

Data division in the neural network analysis

ANNs are similar to conventional statistical models in the sense that models parameters (e.g. connections weights) are adjusted in a model calibration phase called (training) so as to minimize the error between model outputs and the corresponding measured values for a particular data set (the training set), The number of training must be greater than the number of the network inputs (independent variables) if the network needs to learn complex relationships within the training data. Generally, training is stopped once the error in the testing set increases.

In this research, the inputs data are divided into training, testing and validation (or query) subset by using data tools shown in Figure-1. The data tools in the Neuframe program gives three choices for divisions (strips, blocks and randomly) divisions in additions to give a freely allocations manually. Strip division was followed in this work because the inputs data contain the data for six sites, so the data was divided as (60% Training, 25% testing and 15% validation).

Effects of hidden nodes and hidden layers on performance of neural network

An artificial neural network (ANN) is a signal processing unit, mapping a set of input data to a set output data. The basis of the ANN is the node. Therefore, the estimation of hidden nodes is essential in the neural network.

In this research, an examination of the number of hidden nodes is performed through increase in hidden nodes by one and the network weights are reinitialized and the training starts again until reaching to the optimum numbers of hidden nodes and hidden layers corresponding to the observation of training error, testing error and regression square. Then for optimum nodes, the number of hidden layers is achieved. Figure-3 shows the effect of numbers of hidden nodes on the performance of neural network.

It can be seen from Figure-3 that there are slight differences in testing error; therefore, one hidden node was chosen in this model. It is believed that the network with one hidden node is considered optimal, since the network have minimum the training error equal to 4.6% and minimum testing error equal to 3.24% and maximum coefficient correlation 90%.

After defining the numbers of hidden nodes in the hidden layers, the learning rate and damping parameter or momentum must be selected.

Learning rate is the factor that determines the size of the steps that the network takes in navigating through the weight space in order to minimize the magnitude of the validation error. Generally, the error back propagation algorithm guarantees convergence to a training error minimum in the limit of an arbitrary small learning rate.

To evaluate the neural network model, the learning rate of (0.2) and momentum rate of (0.8) are suitable for estimation of the productivity of marble finishing works for floors by the neural network which represents the default value of Neuframe 4 program. These parameters are in agreement with recommendations suggested by Shahin *et al.* (2002) and followed by Al-Zwainy (2008).

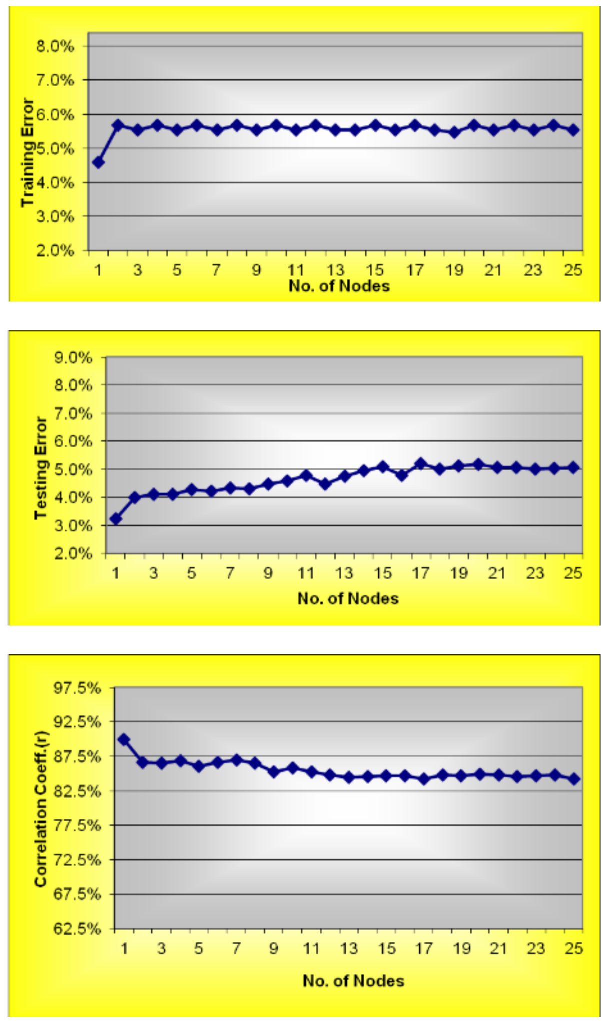

Figure-3. Performance of ANNs model with different hidden nodes.

Equations of ANN models

(ANN) equation gives the value at any one output node as a function of the values at the input nodes and the connection weights.

In this research, the connection weights are obtained for the optimal ANN models which are listed in the Figure-4 below. So, the weights may be translated into formula.

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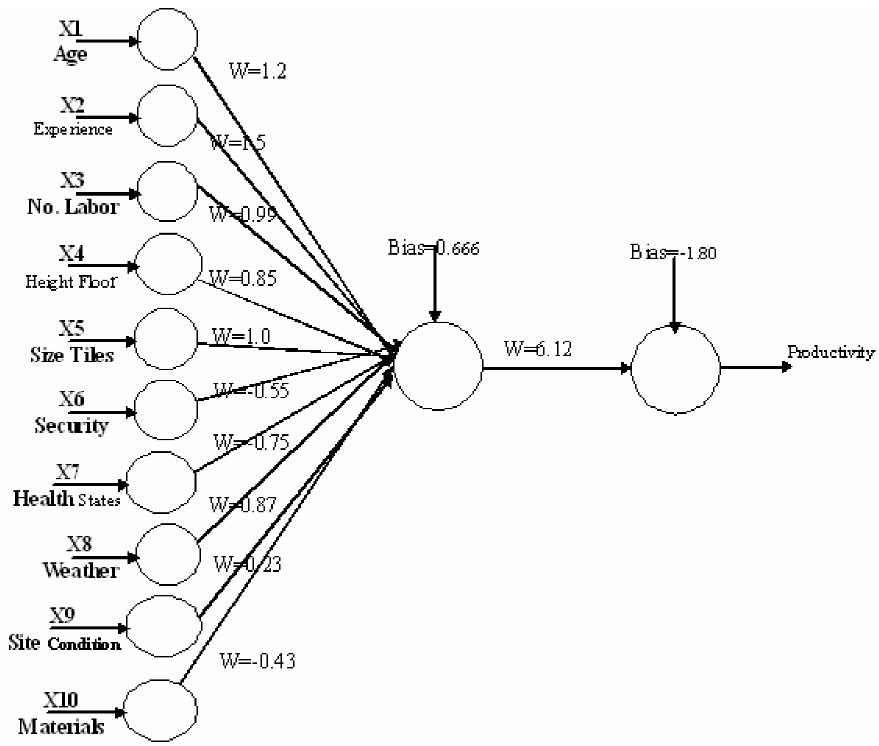

Figure-4. Structure of the ANNs optimal model.

When the connection weights and bias are used, the productivity of marble finishing works for floors can be expressed as follows:

$$Productivity = \frac{1}{1 + e^{-(-1.80 + 6.12 \tanh[x])}} \quad (2)$$

where:

$$x = 0.666 + 1.2x1 + 1.5x2 + 0.99x3 + 0.85x4 + 1.0x5 - .55x6 - 0.75x7 + 0.87x8 + 0.23x9 - 0.43x10 \quad (3)$$

It should be noted that, before using Equation (x), all input variables must be scaled between (0.0) and (1.0) using the data ranges in the ANN model training and with application the following Equation:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

where

x = input variable.
x_{max} = maximum value of input variable (x)
x_{min} = minimum value of input variable (x)
x_n = scaled value of input variable (x).

Also, the predicated value of the productivity of marble finishing works for floors should be scaled between 0.0 and 1.0 and in order to obtain the actual value of this coefficient has to be re - scaled using Equation (4) and inputs data ranges. The final equation can be rewritten as follows:

$$Productivity = \frac{11}{1 + e^{-(-1.80 + 6.12 \tanh[x])}} + 15 \quad (5)$$

And

$$x = 8.89 + 3.2x1 + 2.5x2 + 3.3x3 + 0.57x4 + 1.4x5 - 0.89x6 - 0.54x7 + 1.43x8 + 1.2x9 - 1.1x10 \quad (6)$$

Validity of ANN model

The comparison between the predicated and measured the productivity of marble finishing works for floors is plotted in Figure-5. It is clear from this Figure, the ability of artificial neural network to predict the productivity of marble finishing works for floors for any of data set within the range data used in training the neural network approach.

The coefficient of determination (R^2) is (80.15 %), therefore it can be concluded that ANN models show very good agreement with actual measurements.

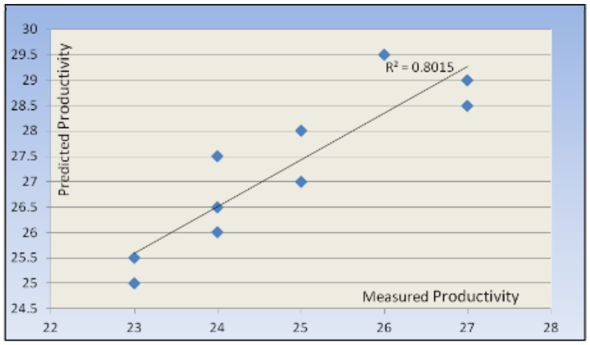

Figure-5. Comparison of predicted and observed productivity for validation data.

The statistical measures used to measure the performance of the models include:

a) Mean Absolute Percentage Error (MAPE),

$$MAPE = \left(\frac{\sum |A - E|}{A} * 100\% \right) /n \qquad (7)$$

where

A = actual value
E = estimated value or predicted value
n = total number of cases (23 for validation)

b) Average accuracy percentage (AA %) AA% = 100% - MAPE (8)

c) The Coefficient of determination (R^2)

d) The Coefficient of correlation (R)

The results of the comparative study are given in Table-3. The MAPE and Average Accuracy Percentage generated by ANN model (TP1) were found to be (9.1%) and (90.9%) respectively. Therefore, it can be concluded that the ANN model (Model 1) show very good agreement with the actual measurements.

Table-3. Results of the ANN model.

Description	ANN for model 1
MAPE	9.1%
AA%	90.9%
R	89.55%
R^2	80.19%

CONCLUSIONS

From the results presented in this research, the following conclusions can be made:

a) Artificial neural network can be used to examine several variables at once and the interrelationships between them;

b) Artificial neural networks (ANNs) have the ability to predict the productivity of marble finishing works for floors with high degree of accuracy with 90.9%;

c) The backpropagation neural network (PBNN) model used in this work has proven to be very successful in modelling nonlinear relationships. Therefore, ANNs can be used instead of statistical programs to show the nonlinear function for any problem;

d) In this research, ten variables in input layer and one hidden layer with one hidden nodes and one node (productivity) in output layer, are practically enough for the neural network analysis to define the network parameters. Also, the percentage of training data used for modeling productivity is always greater than the data used for testing to ensure that the network has been trained adequately. Therefore in this research, data have been divided into 60% for training and 25% for testing and 15% for validation has been chosen; and

e) The age, experience and no. of assist labor have most significant effect on the productivity of marble finishing works for floors. While the other input variable have moderate impact on the productivity.

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