NEURAL NETWORKS FOR ESTIMATING THE CERAMIC PRODUCTIVITY OF WALLS

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ABSTRACT

Productivity estimating of a construction operation is an essential tool for the successful completion of the construction process. Productivity of a construction operation is defined as output of the system per unit of time.

In this research Artificial Neural Networks approaches are presented. The main reason for using neural networks for construction productivity estimation is the requirement of performing complex mapping of environment and management factors to productivity.

A generic description of the artificial neural networks model is provided, followed by summarized factors that affect ceramic labor productivity, then neural-network model are developed for Estimating ceramic walls productivity, the input data for the model based on experienced superintendents employed by a leading construction general contractor, test results show that the ANN approach can produce a sufficiently accurate estimate with a limited data-collection effort, and thus has the potential to provide an efficient tool for construction productivity estimation.

الخلاصة

تخمين الإنتاجية لعملية البناء هي وسيلة أساسية من أجل النجاح في إتمام عملية البناء و تعرف إنتاجية البناء على انها ناتج النظام لكل وحدة من الوقت. في هذا البحث استخدمت الشبكات العصبية الاصطناعية. السبب الرئيسي لاستخدام الشبكات العصبية لتقدير انتاجية البناء هو متطلبات رسم الخرائط المعقدة للبيئة و عوامل ادارة الانتاجية.

وضع وصف عام لنموذج الشبكات العصبية الاصطناعية ، يليها تلخيص العوامل التي تؤثر على إنتاجية عمال السيراميك ، ثم طور نموذج من الشبكات العصبية المتقدمة لتخمين انتاجية السيراميك للجدران ، والبيانات المدخلة للنموذج اعتمدت على المراقبين ذوي الخبرة و الموظفين من قبل المقاول العام للانشاء ، تشير نتائج الاختبار الى أن الشبكات العصبية الاصطناعية يمكن ان تؤدي إلى تخمينات دقيقة بما فيه الكفاية مع جهود جمع بيانات محدودة ، وبالتالي فأن الاختبار لديه القدرة على توفير أداة فعالة لتخمين إنتاجية البناء.

KEYWORDS: NEURAL, NETWORKS, ESTIMATING, CERAMIC, PRODUCTIVITY, WALLS

INTRODUCTION

Estimating is an essential tool for successful completion of a construction process. The process for a construction activity can be broadly divided into the direct costs and the indirect costs plus contingency and profit. The direct costs include costs for materials, labors and equipment. The direct costs are reached when combining the quantitative finite factors to the qualitative subjective factors in the estimating process. The quantitative factors include unit prices of materials, labor wages and equipment depreciation. The qualitative subjective factors are more difficult to determine. They include, among others, productivity rates and associated construction risks. *(Gould 2002)*

Experienced estimators rely on their personal expertise to incorporate the effect of qualitative factors in their estimate. Less experienced estimators could benefit from tools that would incorporate such effects. Neural networks are tools that attempt to mimic the human brain functions. Like the brain, neural networks learn from past trails. They attempt to generalize on the data provided.

OBJECTIVES

The main objective of this research is to introduce alternative approach of using neural network for estimating productivity of ceramic. This objective is to be justified through the following procedures:

a- gathering background information by reviewing the previous studies related on the estimating the productivity of project activities techniques.

b- adjust the factors that affect the productivity rates of ceramic activities and there data gathering.

c- developing neural network model capable of predicting the productivity rates of ceramic for walls.

PRODUCTIVITY

One of the most contentious areas in construction claims is the calculation or estimation of lost productivity. Unlike direct costs, lost productivity is often not tracked or cannot be discerned separately and contemporaneously. As a result, both causation and entitlement concerning the recovery of lost productivity are difficult to establish. Compounding these situations, there is no uniform agreement within the construction industry as to a preferred methodology of calculating lost productivity. There are, in fact, numerous ways to calculate lost productivity. Many methods of calculation are open to challenge with respect to validity and applicability to particular cases -- thus making settlement of the issue on a particular project problematic. *(CII 1984)*

"Productivity is measured generally by the output per hour of input. *(Kavanaugh 1978)*

PRODUCTIVITY AND PRODUCTION

All too often in construction, the terms "productivity" and "production" are used interchangeably. This is, however, incorrect. Production is the measure of output (i.e., things produced) whereas productivity is the measurement of the production. The following two formulas can be used to calculate these two terms.

Productivity = Output (units completed) / Input (work or equipment hours)

Productivity Factor = Actual Productivity / Baseline or Planned Productivity

Given this set of operating terms, it is therefore possible for a contractor to achieve 100% of its planned production but not achieve its planned productivity. That is, a contractor could well be accomplishing the planned rate of production of 300 linear feet of pipe/day in the ground but be expending twice the amount of labor planned to accomplish this daily production rate, for example. In this case, the contractor would be accomplishing 100% of planned production but operating at 50% productivity. *(AACE 2004)*

THE FACTORS THAT AFFECT THE PRODUCTIVITY

Mukherjee and sing (1975) classified these factors into two groups which are:

- External factors that we cannot control them.
- Internal factors that we can control them.

Prokopenko (1987) classified these factors into three groups:

- Work related factors.
- Input or resource related factors.
- Boundary related factors.

Burnham (1982) made the best classification which classified into four levels:

a- State level that contains:
    1- Human recourses as general education level, work motivation systems, work circumstances cooperation in the decision making, age and experience of the laborers.
    2- Technology and the activities researchers and development.
    3- Instruction and the laws of work.

b- Sectors level that contains:
    - Product design and quantity engineering application.
    - Machine and equipment usage.
    - Training and development.
    - Production volume for each person.

c- Work quality level.

d- Man power level.

PERFORMANCE

The word performance contains two related concepts they are:

- Performance is the results that individual can achieve in work.
- Performance is all that individual do to affect the work results. ***(Lefton 1982)***

Which means that the performance is continues operation the action refers to the inputs and the results are the outputs. ***(Feldman 1983)***

On the other hand Bain (1982) found another definition for (performance) as mathematic equality as the following:

- Performance = skill + motivation
- Skill = training + experience
- Motivation = attitude + environment

The last mentioned definition is so important, that we have the two performance's elements (skill + motivation) to get a particular performance level, so at any level there is no copasity to compensate the lake of skill by increasing motivation or the reverse.

Scientifically, it can't put a maximum level for the motivation but it is possible to find maximum man capability according to the indicators of mantel and physical nature of human body.

ARTIFICIAL NEURAL NETWORKS

Over the past two decades there has been an increased interest in a new class of computational intelligence systems known as Artificial Neural Networks (ANNs). This type of networks (i.e. ANNs) has been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved to be useful for solving certain types of problems which are too complex to understand, too poorly to analyze, or too resource-intensive to tackle using more traditional computational methods.

ANNs have been successfully used for many tasks including pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control. As ANNs can be useful complement to more traditional numerical and statistical methods, their use merits continued investigation. *(TRB, 1999)*

ARTIFICIAL NEURAL NETWORK STRUCTURE AND OPERATION:

A typical structure of ANNs consists of a number of artificial neurons variously known as processing elements (PEs), or nodes, or units that are usually arranged in layers: an input layer, an output layer and one or more intermediate layers called hidden layers.

The input from each (PE) in the previous layer (x_i) is multiplied by an adjustable connection weight (w_{ij}) at each PE, the weighted input signals are summed, and a threshold value (θ_j) may be added. This combined input (I_j) is then passed through a transfer (activation) function ($f(.)$) to produce the output of the PE (y_j). The output of one PE provides the input to the PEs in the next layer. This process is summarized in equations:

$$I_J = \sum w_{ij} x_i + \theta_j \quad (.1)$$

Summation

$$y_j = f(I_j) \quad (2)$$

transfer

Where

I_j = the activation level of node j;

W_{ij} = the connection weight between nodes i and j;
x_i = the input from node i , i = 0,1,……,n;
θ_j = the bias or threshold for node j;
y_j = the output of node j; and
f(.) = the transfer (activation) function

The propagation of information in ANNs starts at the input layer where the input data are presented. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error. This process is called 'learning' or 'training'. Once the training phase of the model has been successfully accomplished, the performance of the trained model has to be validated using an independent testing set.

As described above, ANNs learn from data examples presented to them and use these data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs. Consequently, ANNs do not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANNs as compared with most empirical statistical methods. ***(Shahin 2003)***

TRANSFER (ACTIVATION) FUNCTIONS

Transfer functions can take a variety of forms. The logistic sigmoid and hyperbolic tangent transfer functions are the most common functions in neural networks. The logistic sigmoid function is usually used when the desired range of output values is between 0 and 1, whereas the hyperbolic tangent function is often used when the desired range of output values is between –1 and 1. The logistic sigmoid and hyperbolic tangent transfer functions are shown in figure and equations, respectively. Usually, the same transfer function is used for all processing elements in a particular layer. ***(Shahin 2003)***

$$f(I_j)=\frac{1}{1+e^{-(I_j)}} \tag{3}$$

$$f(I_j)=\frac{e^{(I_j)}-e^{-(I_j)}}{e^{(I_j)}+e^{-(I_j)}} \tag{4}$$

TYPES OF NEURAL NETWORKS:

FEED-FORWARD NEURAL NETWORK:

The feedforward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. *(Roman 2009)*

RADIAL BASIS FUNCTION (RBF) NETWORK:

Radial Basis Functions are powerful techniques for interpolation in multidimensional space. A RBF is a function which has built into a distance criterion with respect to a centre. Radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoid hidden layer transfer characteristic in Multi-Layer Perceptions. RBF networks have two layers of processing: In the first, input is mapped onto each RBF in the 'hidden' layer. The RBF chosen is usually a Gaussian. In regression problems the output layer is then a linear combination of hidden layer values representing mean predicted output. The interpretation of this output layer value is the same as a regression model in statistics. In classification problems the output layer is typically a sigmoid function of a linear combination of hidden layer values, representing a posterior probability. Performance in both cases is often improved by shrinkage techniques, known as ridge regression in classical statistics and known to correspond to a prior belief in small parameter values (and therefore smooth output functions) in a Bayesian framework. *(Roman 2009)*

KOHONEN SELEF – ORGANIZING N ETWORK:

The self-organizing map (SOM) invented by Teuvo Kohonen performs a form of unsupervised learning. A set of artificial neurons learn to map points in an input space to coordinates in an output space. The input space can have different dimensions and topology from the output space, and the SOM will attempt to preserve these. *(Roman 2009)*

RECURRENT NETWORK:

Contrary to feed forward networks, recurrent neural networks (RNs) are models with bi-directional data flow. While a feed forward network propagates data linearly from input to output, RNs also propagate data from later processing stages to earlier stages, there are many types of recurrent network, and these types are: *(Roman 2009)*

- **Simple recurrent network:**
- **Hopfield network:**
- **Echo state network:**
- **Long short term memory network:**

STOCHASTIC NEURAL NETWORKS:

A stochastic neural network differs from a typical neural network because it introduces random variations into the network. In a probabilistic view of neural networks, such random variations can be viewed as a form of statistical sampling, such as Monte Carlo simulation, Boltzman machine. *(Roman 2009)*

MODULAR NEURAL NETWORK:

Biological studies have shown that the human brain functions not as a single massive network, but as a collection of small networks. This realization gave birth to the concept of modular neural networks

NEURO – FUZZY NETWORKS:

A neuro-fuzzy network is a fuzzy inference system in the body of an artificial neural network. Depending on the *FIS* type, there are several layers that simulate the processes involved in a *fuzzy inference* like fuzzification, inference, aggregation and defuzzification. Embedding an *FIS* in a general structure of an *ANN* has the benefit of using available *ANN* training methods to find the parameters of a fuzzy system. *(Roman 2009)*

IDENTIFICATION OF ANN MODEL VARIABLES

The neural network application for ceramic productivity estimation is *an* example of causal forecasting. This type of forecasting considers a number *of* variables that affect the variable to be predicted. This type of forecasting is more powerful than the traditional methods. The purpose of productivity estimation is to predict or estimate the productivity from known or assumed values of other variables related to it. One of the most important tasks of this objective is to determine which variables are important indicators. Once the appropriate variables have been determined, the productivity estimation can be performed either using a neural network or any other tool, such as regression analysis.

This research describes the development of neural network models of ceramic activity productivity based on current projects data. The initial impetus for the research was the paucity of data available that can provide reliable information about the ***productivity***. The data collection method used in this study is the direct data gathering from projects and the direct interview with the concerned engineers and foremen. This method faces a great difficulty nowadays because of the unsecured status of the country, and the shortage in projects.

Independent variables were carefully selected and well defined as follows:

V1 Ganger experience.
V2 Ganger age.
V3 Number of assistant laborers.
V4 Area of ceramic tile.
V5 Site complication.
V6 Height level of the work.
V7 Climate status (Weather).

MODEL IINPUTS AND OUTPUTS

It is generally accepted that seven parameters have the most significant impact on the productivity estimation of ceramic activity, and are thus used as the ANN model inputs.

The output of the model is the total productivity of ceramic activity. A code is used in this chapter to identify the names of the different models developed. The code consists of two parts separated by a hyphen. The first part represents an abbreviation of the current output (i.e. Total productivity, ID). The second part denotes the model number. Hence, for example "TP—1" represents Total productivity model. The available data extracted from the database in appendix A.

PRE-PROCESSING AND DATA DIVISION

Data processing is very important in using neural networks successfully. It determines what information is presented to create the model during the training phase. It can be in the form of data scaling, normalization and transformation. Transforming the output data into some known forms (e.g. log., exponential, etc) may be helpful to improve ANN performance.

The next step in the development of ANN models is the division of the available data into their subsets, training, testing and validation sets. Trail-and-error process was used to select the best division, by using *Neuframe* software. The network that performs best with respect to testing error was used in this work (compared with other criteria to evaluate the prediction performance, training error and correlation of validation set). Using the default parameters of the software, a number of networks with different divisions were developed and the results are summarized in Table below.

It can be seen that the best division is 60% for training set, 30% for testing set, and 10% for validation set, according to the highest coefficient of correlation (r) and the low difference between the values of testing error. Thus, this division was adopted in the model.

The effect of using different choices for divisions (i.e. striped, blocked, and random) was investigated and shown in Table below. It can be seen that the performance of ANN model was relatively insensitive to the method of division. The better performance was obtained when the striped division was used.

SCALING OF DATA

Once the available data have been divided into their subsets, the input and output variables are pre-processed by scaling them to eliminate their dimension and to ensure that all variables receive equal attention during training. Scaling has to be commensurate with the limits of the transfer functions used in the hidden and output layers (i.e. —1.0 to 1.0 for tanh transfer function and 0.0 to 1.0 for sigmoid transfer function). The simple linear mapping of the variables' extremes to the neural networks practical extremes is adopted for scaling, as it is the most commonly used method, *(Shahin, 2003)*. As part of this method, for each variable x with minimum and maximum values of x_{min} and x_{max}, respectively, the scaled value xn, is calculated as follows:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (5)$$

MODEL ARCHITECTURE, OPTIMIZATION AND STOPPING CRITERIA

One of the most important and difficult tasks in the development of ANN models is the determination of the model architecture (i.e. the number and connectivity of the hidden layer nodes). A network with one hidden layer can approximate any continuous function, provided that sufficient connection weights are used, ***(Shahin et al 2002)***.

Consequently, one hidden layer is used in this research. The general strategy adopted for finding the optimal network architecture and internal parameters that control the training process is as follows: a number of trials were carried out using the default parameters of the software used with one hidden layer and starting with one hidden node and then slightly increasing the number of the nodes until no significant improvement in the model performance, was gained.

The network that performs best with respect to the lowest testing error followed by training error and high correlation coefficient of validation set was retrained with different combinations of momentum terms, learning rates and transfer functions in an attempt to improve model performance.

Consequently, the model that has the optimum momentum term, learning rate and transfer function was retrained a number of times with different initial weights until no further improvement occurred.

Using the default parameters of the software (learning rate =0.2 and momentum term = 0.8 and the transfer functions in hidden and output layer nodes are sigmoid), a number of networks with different numbers of hidden layer nodes were developed and results are summarized in Table below for ANN model, since maximum no. of nodes equal to (2I+1) where (I) the number of input nodes. (i.e. max. nodes=15).

It can be seen from that there are slightly 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.

The effect of the internal parameters controlling the back-propagation algorithm (i.e. momentum term and learning rate) on the model performance was investigated for the model with one hidden layer node. The effect of the momentum term on model performance is summarized in Table below:

It can be seen from that the performance of the ANNs model is relatively insensitive to the variation of the momentum term, particularly in the range 0.01 to 0.5. Then the test errors slightly decrease at the range 0.55 to 0.95. Thus, the obtained optimum value for the momentum term is 0.9 which have the lowest values of testing error (8.88%) and training error (9.34%) and maximum correlation coefficient (r) (87.68%), hence it was used in this model. In addition, the effect of the learning rate on the model performance was investigated (momentum term = 0.9). The results are summarized in Table below. The optimum value for learning rate is 0.6 which has the lowest prediction error, hence it used in this model.

It can be seen from that the performance of the ANN model is relatively insensitive to the variation of the learning rate. Thus, the obtained optimum value for the learning rate is 0.6, which has the low value of testing error, low value training error and high coefficient of correlation (86.33%); hence it was used in this model.

The effect of using different transfer functions (i.e. sigmoid and tanh) was investigated and it was shown in Table below. It can be seen that the performance of ANN model was relatively insensitive to the type of the transfer function. The better performance was obtained when the sigmoid transfer function was used for both hidden and output layers.

To ensure the data that were carried out by *Neuframe* software for training, testing, and validation sets to represent the same statistical population, a statistical parameters estimation was carried out, including the mean, standard deviation, minimum, maximum, and range, as shown in Table:

The results indicated that the training, testing, and validation sets are generally statistically consistent.

SENSITIVITY ANALYSIS OF THE ANN MODEL INPUTS

In an attempt to identify which of the input variables have the most significant impact on the ***output*** predictions, a sensitivity analysis was carried out on the ANN model. A simple and innovative technique proposed by ***Garson (1991) {AS Mentioned in Shahin et.al, 2002}*** was used ***to interpret the*** relative importance of the input variables by examining the connection weights of the trained network. For a network with one hidden layer, the technique involves a process of partitioning the hidden output connection weights into components associated with each input node. For this model, the method is illustrated as follows. The model has seven input nodes, one hidden node, and one output node with connection weights as shown in Table:

The computational process proposed by Garson (1991) is as follows:

- For each hidden node i, obtain the products P_{ij} (where j represents the column number of the weights mentioned above) by multiplying the absolute value of the hidden-output layer connection weight by the absolute value of the hidden-input layer connection weight of each input variable j.
- For each hidden node, divide P_{ij} by the sum of all input variables to obtain Q_{ij}. For each input nodes, sum Q_{ij} to obtain S_j. in this case the Q_{ij} will be equal to S_j.
- Divide S_j by the sum for all input variables to get the relative importance of all output weights attributed to the given input variable. The results of the above technique were presented in Table:

These results indicate that the variable (V6) have the most significant effect on the predicted total productivity with a relative importance (27.93%). The results also indicate that (V1, V2 and V5) have a moderate impact on prediction with a relative importance equals to 11.77%, 18.97% and 15.31% respectively, while the variables (V3, V4 and V7) have the smallest impact on prediction with the relative importance of 8.51%, 9.97% and 7.53% respectively. The results are also presented in the figure:

ANN MODEL EQUATION:

The small number of connection weights obtained by ***Neuframe*** for the optimal ANNs model enables the network to be translated into relatively simple formula. While as connection weights and threshold levels (bias) are summarized in Table below:

Using the connection weights and the threshold levels shown in Table above, the prediction of the equation total productivity for wall ceramic can be expressed as follows:

$$TP = \frac{1}{1+e^{(-3.3789+4.4862\tanh x)}} \qquad (6)$$

Where:

$$X = \{\theta_8 + (W_{8,1}*V1) + (W_{8,2}*V2) + (W_{8,3}*V3) + (W_{8,4}*V4) + (W_{8,5}*V5) + (W_{8,6}*V6) + (W_{8,7}*V7)\} \qquad (7)$$

And it can be written as:

$$TP = \frac{}{1+e^{(-3.3789+4.4862\tanh x)}} + 0.94 \qquad (8)$$

It can be noted that, before using Equation (2), all input variables (i.e. V1, V2 ..... ,V7) need to be scaled between 0.0 and 1.0 and the data ranges in the ANN model training. It should also be noted that the predicted value of the total productivity obtained from Equation (1) is scaled between 0.0 and 1.0.

CONCLUSIONS

Through the research work, there are groups of conclusions that can be summarized by the following points:

- The study shows that neural networks are able to model the complex relationships between the job conditions and the productivity of an operation and achieve an acceptable accuracy in estimation.
- The presented approach agrees well with the way in which a contractor makes an intuitive estimate, based on developed experience that comes from observation. However, the superiority of the approach over a pure empirical method is that it generalizes the cause-effect relationships and provides a binding mechanism to maintain the consistency of an estimate.
- The model was never designed to replace the estimator, only to be another tool to formulate final labor productivity for an estimate. An estimator's judgment would always be the final approval before a labor productivity estimate is completed.
- The productivity rate models derived in this research enable planners and construction operation researchers studying the ceramic productivity more accurately than previous approaches.
- The sensitivity analysis indicated the following:
- *The* results obtained using this model indicate that the variable (V6) have the most significant effect on the predicted total productivity with a relative importance (27.93%).
- The results also indicate that (V1, V2 and V5) have a moderate impact on prediction with a relative importance equals to **11.77%**, **18.97%** and **15.31%** respectively,
- while the variables (V3, V4 and V7) have the smallest impact on prediction with the relative importance of **8.51%**, **9.97%** and **7.53%** respectively.

RECOMMENDATIONS:

The construction management should also be familiar with powerful estimate tools such as ANN. This invitation is not optional, but rather inevitable, if the challenges of the forthcoming period, which Iraq is marching towards, are to be faced and overcome.

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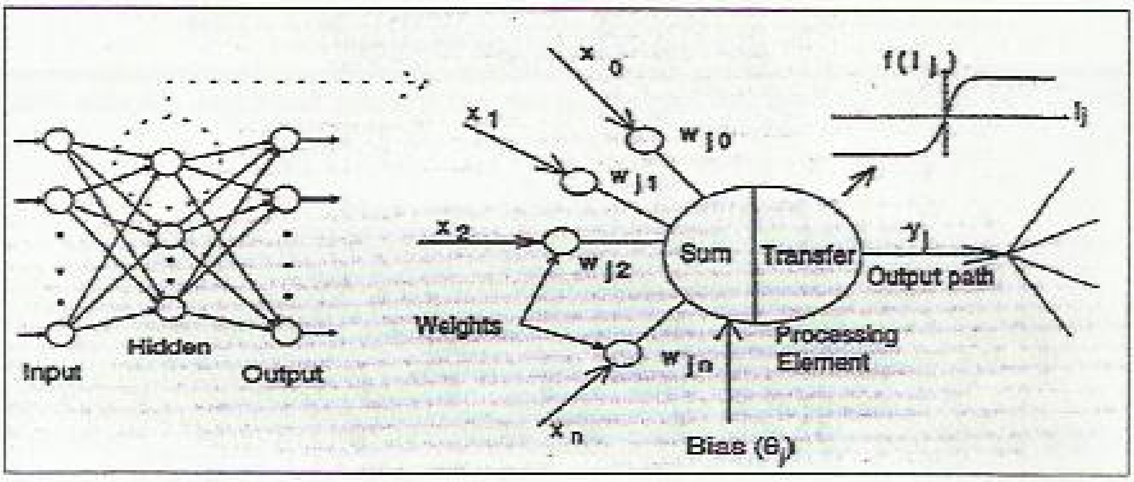
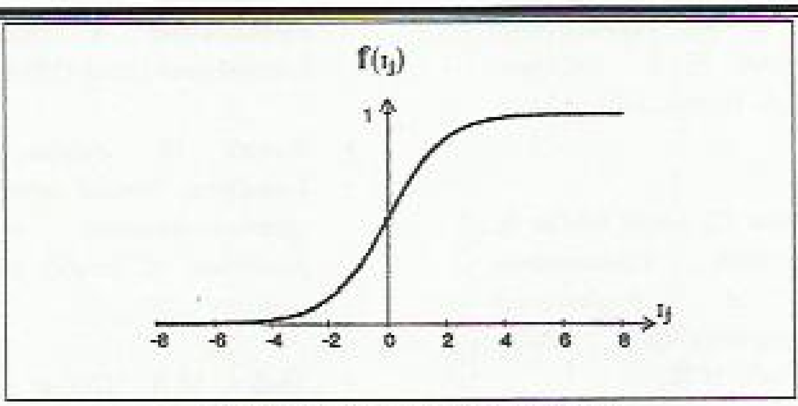
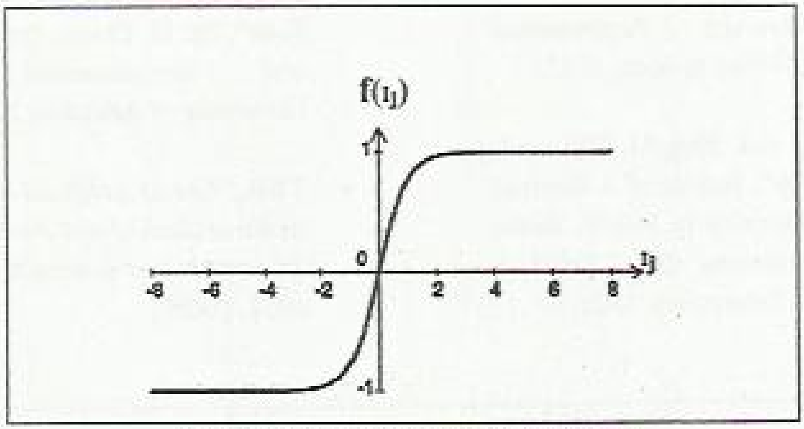


Figure (1) Typical structure and operation of ANNs (Shahin 2003).



(a) The logistic sigmoid function



(b) The hyperbolic tangent function

Figure (2) The logistic sigmoid and hyperbolic tangent transfer functions. ***(Shahin 2003)***

Table (1) Divisions developed and results.

Data Division %			Training Error %	Testing Error %	Coefficient of Correlation (r) %
Training	Testing	Querying			
70	10	20	8.09	9.38	72.53
68	12	20	7.78	14.28	76.34
66	14	20	8.35	8.70	73.50
65	15	20	8.36	9.04	78.52
65	20	15	8.28	11.94	76.57
60	20	20	7.98	11.06	77.52
60	25	15	8.93	9.23	66.57
60	30	10	9.51	8.99	88.23
56	24	20	8.11	10.31	75.80
55	30	15	9.81	7.99	71.94
55	25	20	9.81	7.99	-63.64
55	20	25	9.81	7.99	-79.43
50	30	20	8.56	9.31	77.77
50	35	15	8.79	9.24	77.07

45	35	20	8.11	10.31	-61.30

Table (2) Effect of using different choices of divisions.

Data Division %			choices of division	training error%	testing error%	coefficient correlation(r)%
Training	Testing	Querying				
60	30	10	Striped	9.51	8.99	88.23
60	30	10	Blocked	9.51	8.99	-66.24
60	30	10	Random	8.04	9.73	34.34

Table (3)), Effect on networks with different numbers of hidden layer nodes .

No. of Nodes	Training Error %	Testing Error %	Coefficient of Correlation (r) %
1	9.51	8.99	88.23
2	9.54	9.17	88.25
3	9.58	9.11	88.37
4	9.65	9.15	89.07
5	9.74	9.26	89.41
6	9.67	8.98	88.63
7	9.75	9.15	89.04
8	9.82	9.05	89.13
9	9.92	8.96	88.65
10	9.73	8.98	88.99
11	9.30	9.01	89.04
12	9.79	9.56	90.70
13	9.81	9.10	89.42
14	9.68	9.62	90.31
15	9.77	9.19	89.71

Table (4) effect of the momentum term on model performance.

Parameters Effect	Momentum Term	Training Error %	Testing Error %	Coefficient Correlation(r)%

Model No. 1 Choices of division (striped) Learning Rate (0.2) No. of Nodes (1) Transfer function in hidden layer (sigmoid) Transfer function in output layer (sigmoid)	0.01	9.80	9.02	88.49
	0.05	9.81	9.02	88.48
	0.1	9.80	9.02	88.49
	0.2	9.78	9.02	88.49
	0.3	9.76	9.02	88.49
	0.4	9.72	9.02	88.48
	0.5	9.71	9.02	88.47
	0.55	9.67	9.01	88.45
	0.6	9.66	9.01	88.44
	0.7	9.59	9.01	88.36
	0.8	9.51	8.99	88.23
	0.9	9.34	8.88	87.68
	0.95	9.19	9.08	87.25

Table (5) Effect of the learning rate on the model performance .

Parameters Effect	Learning Rate	Training Error %	Testing Error %	Coefficient Correlation(r)%
Model No. 1 Choices of division (striped) Momentum Term (0.9) No. of Nodes (1) Transfer function in hidden layer (sigmoid) Transfer function in output layer (sigmoid)	0.02	12.47	11.34	82.01
	0.05	9.65	8.99	88.40
	0.1	9.50	8.95	88.19
	0.15	9.41	8.86	87.94
	0.2	9.34	8.88	87.68
	0.3	9.28	8.70	87.34
	0.4	9.24	8.82	86.94
	0.5	9.21	9.17	86.60
	0.55	9.21	8.98	86.53
	0.6	9.20	8.65	86.33
	0.7	9.22	8.41	85.80
	0.8	9.78	8.28	85.90

Table (6) Effect of using different transfer functions.

Parameters Effect	Transfer Function		Training Error %	Testing Error %	Coefficient Correlation(r)%
	Hidden Layer	Output Layer			
Model No. 1 **Choices of division** (striped) **No. of Nodes** (1) **Momentum Term** (0.9) **Learning Rate** (0.6)	Sigmoid	Sigmoid	9.20	8.65	86.33
	Sigmoid	Tanh	62.14	66.76	---
	Tanh	Sigmoid	9.26	9.89	79.47
	Tanh	Tanh	62.14	66.76	---

Table (7) Data statistical parameters.

Statistical parameter	Output	Input Variables						
	productivity	V1	V2	V3	V4	V5	V6	V7
	Training set							
MAX	3.83	15	46	2	0.1	1	2	2
MIN	0.94	3	26	1	0.06	0	0	0
RANGE	2.89	12	20	1	0.04	1	2	2
MEAN	2.0335	9.45	36.13333	1.416667	0.086	0.466667	0.45	0.283333
S.D	0.636571	4.114567	7.247365	0.497167	0.01924	0.503098	0.648989	0.490301
	Testing set							

MAX	3.07	15	46	2	0.1	1	2	1
MIN	0.9	3	26	1	0.06	0	0	0
RANGE	2.17	12	20	1	0.04	1	2	1
MEAN	1.866667	10	37	1.566667	0.084	0.533333	0.6	0.333333
S.D	0.449623	3.99137	7.22066	0.504007	0.019931	0.507416	0.723974	0.479463
	Validation set							
MAX	3.12	15	46	2	0.1	1	1	1
MIN	1.33	3	26	1	0.06	0	0	0
RANGE	1.79	12	20	1	0.04	1	1	1
MEAN	2.021	10.1	37.1	1.6	0.084	0.5	0.4	0.1
S.D	0.519154	3.984693	7.340148	0.516398	0.020656	0.527046	0.516398	0.316228

Table (8) Output nodes with connection weights.

Hidden Nodes	Weights							
	V1	V2	V3	V4	V5	V6	V7	output
Hidden 1	0.929928	1.498832	-0.67265	-0.787878	1.209671	2.206048	0.594394	-4.486283

Table (9) Technique results.

Input Variables	Weights (from input to hidden) absolute	Hidden node	Weights (from hidden to output) absolute	Output node	P_j	$Q_{ij}=P_j/\sum P_j$	$S_{ij}=\sum Q_{ij}$	R.I%
V1	0.929928377880479	1	4.4862833213507	1	4.171922172	0.117721328	0.117721328	11.77%
V2	1.4988328523284				6.724188827	0.189739983	0.189739983	18.97%
V3	0.672650849930333				3.017702289	0.085152097	0.085152097	8.51%
V4	0.787878018353824				3.534644013	0.099738914	0.099738914	9.97%
V5	1.20967140631394				5.426928654	0.153134508	0.153134508	15.31%
V6	2.20604809276063				9.896956765	0.279267649	0.279267649	27.93%
V7	0.594394785685078				2.666623413	0.075245519	0.075245519	7.53%
				$\sum P_j=$	35.43896613	$\sum S_{ij}=$	1	100.00%

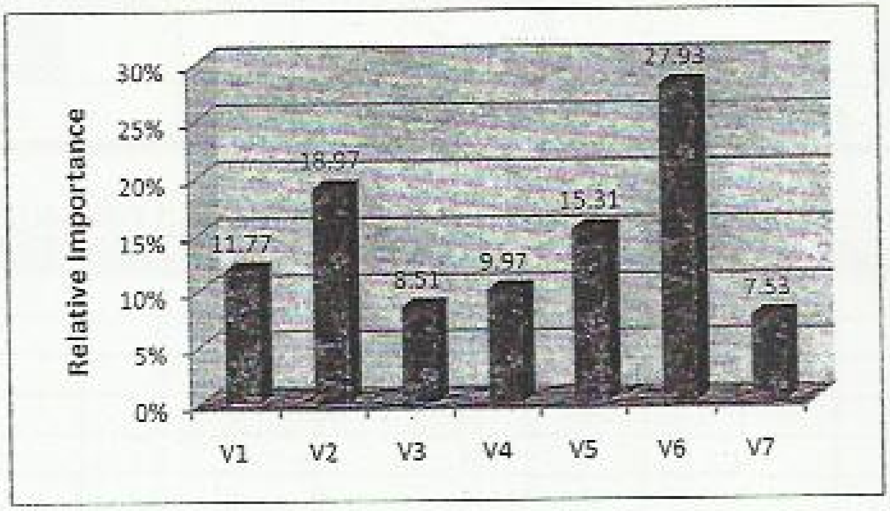


Figure (3) Relative importance of the input variables for the Model

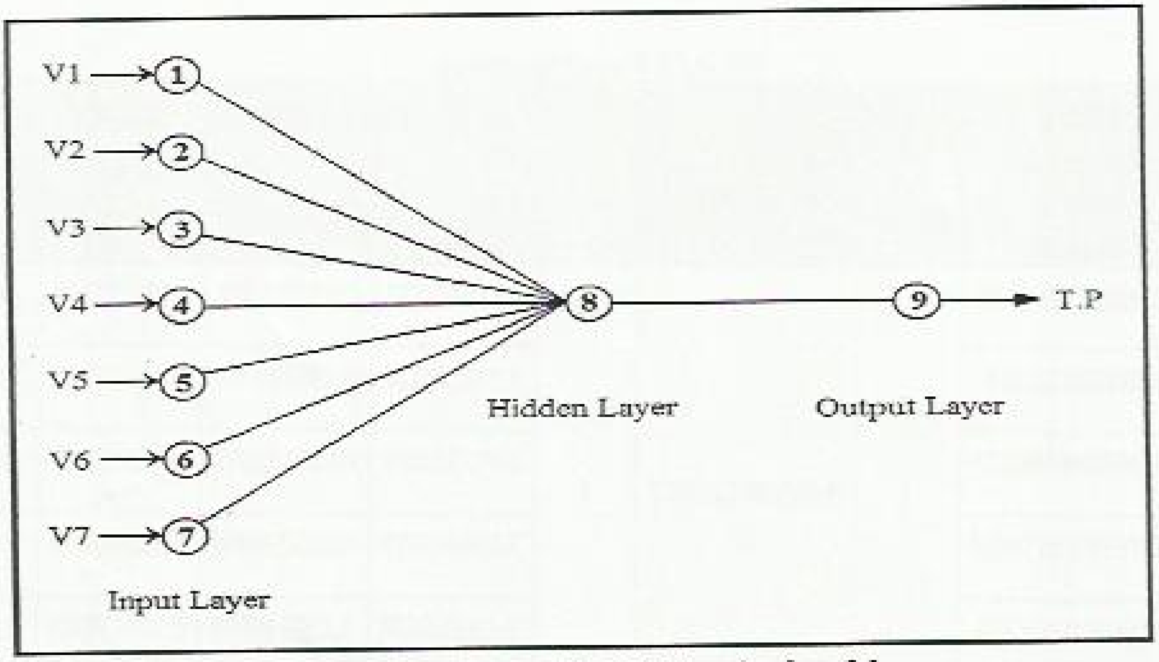


Figure (4) Structure of the ANNs optimal model

Table (10) Connection weights and threshold levels 0f modele.

Hidden layer nodes	W_{ji} (weight from node i in the input layer to node j in the hidden layer)							Hidden layer threshold θ_j
	i=1	i=2	i=3	i=4	i=5	i=6	i=7	
j=8	0.9299	1.4988	-0.6726	-0.7878	1.2096	2.2060	0.5943	0,4247
Output layer nodes	W_{ji} (weight from node i in the hidden layer to node j in the output layer)							Output layer threshold θ_j
	i=8	-	-	-	-	-	-	
j=9	-4.4862	-	-	-	-	-	-	3.3789

APPINDIX A: INPUTS AND OUTPUT VARIABLES USED FOR MODEL

Productivity	Height	complication	Labors	Age	Experience	Weather	Area of ceramic
1.64	0	1	2	35	10	0	0.06
0.9	1	1	2	35	10	0	0.06
1.94	0	1	2	35	10	0	0.06
1.82	0	1	2	35	10	0	0.06
2.1	0	0	2	35	10	0	0.06
1.22	1	1	2	35	10	0	0.06
1.2	2	1	2	35	10	0	0.06
1.36	1	1	2	35	10	0	0.06
1.32	0	1	2	35	10	0	0.06
1.44	0	1	2	35	10	0	0.06
1.7	1	1	2	35	10	0	0.06
1.1	2	1	2	35	10	0	0.06

1.9	0	0	2	35	10	0	0.06
1.6	0	1	2	35	10	0	0.06
1.49	0	1	1	35	10	0	0.06
3.15	0	0	2	35	10	0	0.06
0.94	2	1	1	35	10	0	0.06
1.68	0	1	1	35	10	0	0.06
1.59	0	1	1	35	10	0	0.06
1.63	1	1	1	35	10	0	0.06
1.86	0	0	1	46	15	0	0.06
1.84	0	0	1	46	15	0	0.06
1.8	1	0	1	46	15	0	0.06
1.76	0	0	2	46	15	0	0.06
2.08	0	0	2	46	15	0	0.06
2.12	0	0	2	46	15	0	0.06
1.7	0	0	2	46	15	0	0.06
1.4	0	1	2	46	15	0	0.06
1.37	0	1	2	46	15	0	0.06
1.42	0	1	1	46	15	0	0.06
1.33	1	1	1	46	15	0	0.06
1.6	2	0	2	46	15	0	0.06
1.88	1	0	2	46	15	1	0.06
1.49	1	0	2	46	15	1	0.06
2.32	0	0	1	46	15	1	0.06
1.92	0	0	2	46	15	1	0.06
1.87	0	0	2	46	15	1	0.06
1.82	0	0	2	42	12	1	0.1
2.15	0	0	1	42	12	1	0.1
1.67	1	0	1	42	12	1	0.1
2.37	0	0	2	42	12	0	0.1
2.08	0	0	2	42	12	0	0.1
1.57	0	0	1	42	12	0	0.1
1.9	0	0	1	42	12	0	0.1
1.76	1	0	1	42	12	0	0.1
1.89	0	0	1	42	12	0	0.1
1.88	0	0	1	42	12	0	0.1
1.76	0	0	1	42	12	0	0.1
2.02	0	0	1	42	12	0	0.1
1.87	0	0	1	42	12	0	0.1
1.56	1	0	1	42	12	1	0.1
2.76	0	0	2	42	12	1	0.1
3.07	0	0	2	42	12	0	0.1
1.76	0	0	1	42	12	1	0.1
1.49	2	0	1	42	12	1	0.1
2.05	0	0	2	42	12	0	0.1
1.69	0	0	1	41	12	1	0.1
2.17	0	0	2	41	12	2	0.1
1.78	0	0	1	41	12	1	0.1

1.43	1	0	1	41	12	0	0.1
2.31	0	0	1	41	12	0	0.1
2.33	0	1	2	41	12	0	0.1
2.13	1	1	2	41	12	0	0.1
1.79	0	1	1	41	12	0	0.1
1.92	1	1	1	41	12	0	0.1
2.07	0	1	1	41	12	0	0.1
3.03	0	1	2	41	12	0	0.1
2.33	1	1	1	41	12	0	0.1
1.76	1	1	1	29	6	0	0.1
2.33	0	1	1	29	6	0	0.1
2.23	1	1	2	29	6	0	0.1
1.95	1	1	1	29	6	1	0.1
2.39	1	1	1	29	6	0	0.1
2.13	1	1	1	29	6	1	0.1
1.54	1	1	1	29	6	1	0.1
2.86	1	1	1	29	6	0	0.1
2.51	1	1	1	29	6	1	0.1
1.88	2	1	1	29	6	0	0.1
2.46	1	0	1	29	6	0	0.1
2.46	1	1	2	29	6	1	0.1
3.12	0	0	2	29	6	0	0.1
2.17	0	1	1	29	6	1	0.1
1.94	2	1	1	29	6	0	0.1
2.17	1	0	2	26	3	1	0.1
2.79	0	0	2	26	3	0	0.1
3.67	0	0	2	26	3	1	0.1
2.73	0	1	2	26	3	1	0.1
2.08	1	1	2	26	3	0	0.1
3.7	0	0	2	26	3	0	0.1
1.07	2	1	2	26	3	0	0.1
2.09	0	1	2	26	3	0	0.1
1.24	1	1	2	26	3	0	0.1
1.23	2	1	1	26	3	1	0.1
1.76	0	1	1	26	3	1	0.1
3.08	0	0	1	26	3	0	0.1
3.83	0	0	1	26	3	0	0.1
2.45	1	0	1	26	3	0	0.1
2.68	0	0	1	26	3	0	0.1
1.77	1	0	1	26	3	1	0.1
2.26	0	1	1	26	3	0	0.1