PRODUCTIVITY ESTIMATION MODEL FOR BRACKLAYER IN CONSTRUCTION PROJECTS USING NEURAL NETWORK

Gafel Kareem Aswed
Email: gafelkareem@gmail.com
Assistant lecturer/ College of Engineering/ University of Kerbala/Iraq
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ABSTRACT

Construction labour productivity is a major determinant of success of a construction project. Time and cost overruns of construction projects are widely attributed to poor productivity of construction labour force. Though considerable research exists on productivity factors in other countries, very little studies have addressed productivity issues in Iraq. Brainstorming session and site interview survey was conducted in Karbala province in Iraq, to identify the productivity and the factors affecting bricklayer labor productivity. Thirteen influencing factors are utilized for productivity forecasting by artificial neural network (ANN) model, and they include Age, Experience, Gang health, Gang Number, Weather, wages, Site condition, Material availability, Wall length, Wall thickness, Wall height, Mortar type, and Security in site. One ANN prediction model was built for the productivity of bricklayer labors. It was found that the predict productivity approximately the same as the actual productivity with a good degree of accuracy of the coefficient of correlation (R=86.28%), and mean square error (MSE) of (1.32%) after testing the network. The developed ANN model can be used dependably for estimating production rates of bricklayer for any building construction project by incorporating the influence of selected factors.

KEWORDS: Production rates, Artificial neural network (ANN), Construction project, Labor productivity, Bricklayer labors, Modeling.

بناء نموذج لتخمين أنتاجية البنّاء بالطابوق في المشاريع الانشائية باستخدام الشبكات العصبية

غافل كريم أسود

Email: gafelkareem@gmail.com

مدرس مساعد/جامعة كربلاء –كلية الهندسة- قسم الهندسة المدنية

المستخلص:

إنتاجية عامل البناء من العوامل المهمة في تحديد نجاح المشروع الإنشائي وأن ضعف أو قلة انتاجية القوى العاملة أحد أهم أسباب التأخير في زمن التنفيذ وزيادة التكلفة في اغلب المشاريع الإنشائية .بالرغم من وجود عدد لا بأس به من الدراسات حول الانتاجية

والعوامل التي تؤثر عليها في بلدان عديدة، فأن عدد قليل جداً من هذه الدراسات حول موضوع الإنتاجية قد اجريت في العراق .ولتحديد الإنتاجية والعوامل المؤثرة على انتاجية عمال البناء بالطابوق أجريت جلسة للعصف الذهني تلتها مقابلات شخصية في مواقع العمل المختلفة في محافظة كربلاء وتم تحديد ثلاثة عشر عاملا من العوامل الهامة في التنبؤ بالإنتاجية وتضمنت :العمر، الخبرة، الحالة الصحية للعمال، عدد العمال، الحالة الجوية، طريقة دفع الأجور، ظروف موقع العمل، توفر المواد، طول الجدار، سمك الجدار، ارتفاع الجدار، نوع المادة الرابطة وأخيرا توفر الأمان في موقع العمل .تم بناء نموذج (موديل) واحد باستخدام الشبكات العصبية الاصطناعية للتنبؤ بإنتاجية عمال البناء بالطابوق وقد وجد ان الانتاجية التي تم الحصول عليها من (الموديل) مساوية تقريبا للأنتاجية الفعلية وبدرجة جيدة من الدقة بمعامل ارتباط مقداره (86.28%) ومعدل مربع الخطأ (1.32%) بعد تدريب وفحص الشبكة العصبية الاصطناعية .

1-INTRODUCTION

The output to the input ratio is the general definition of the productivity, which is widely studied. The success of construction project is completely related to the labour productivity [Anu & Sudhakumar 2013].

Too many factors that affect the productivity of construction tasks because it includes long sequential operations, workmanship, materials and tools, and variable conditions of project site. Some of the factors are readily identified and others may not. In addition, it is difficult to restrict the effect of these factors on the productivity. Determination of both qualitative and quantitative factors affecting the labor productivity on site such as weather condition, labor proficiency, equipment and material shortage, site conditions, project location, number of workers, etc. are widely researched [Makulsawatudom et al., 2004] and [Jiukun et al.2009)].

Many prediction-modeling techniques have been used in the last ten years such as "statistical model, action response model, factor model, linear regression model etc." [Oduba, 2002].

Even in developed countries, there are still many obscure productivity problems that in need to be further explored in spite of that the many researchers have been explored and tested the factors that affect the productivity [Makulsawatudom and Emsley, 2003].

It has been identified that the accurate prediction of production rates under any specific condition could be achieved using ANN modeling technique, which has the dynamic learning mechanism with effective recognition capabilities. This research, therefore, aims to predict the bricklayer productivity in Iraqi construction projects using ANN.

2-RESEARCH OBJECTIVE

Developing ANN model for estimating the bricklayer (Builder) productivity taking into account the influencing factors is the main objective of this study.

3-RESEARCH JUSTIFICATION

The causes that stand behind the dependence of this study are:

1. Production rates estimation of future projects depend on previous projects with re- adjustment for the various site factors and conditions influencing the builder productivity.
2. There is no standard production rates measurement system for bricklayer productivity.
3. Modeling techniques to estimate the production rates are most reliable and accurate estimation.

4-THE RESEARCH HYPOTHESIS

The research hypothesis is "Artificial Neural Network (ANN) model is a strong modeling technique to estimate the productivity of bricklayer (builder) when using some factors as predictors".

5- ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) achieved more reliable results than many developed modeling techniques for predicting labor production rates when incorporating the effect of different factors [Sana et al. 2011].

Input, hidden and output which is arranged in sequence layers along with the connectivity between them are the main components of the ANN. Input layer in the ANN receives data from the outside world with their initial weights passed into hidden layers, which has no connectivity with outside world, to the output layers [Zayed and Halpin , 2005].

Typical feedforward ANN consist of several neuron in their layers linked together with connection weights as shown in **Fig. (1).**The number of required values to predict is the issue that decide the number of neuron in the output layer of the ANN. The input and hidden layer contains bias value that is due to absence of some input factors. ANN has the capability to infer meaning from intricate or inaccurate data. Complex patterns and trends detection which is not verified by other humans or computer techniques are analyzed with ANN. It is important to have enough, reliable and accurate data for the successful implementation of ANN. Depending on the situation, the ANN has the ability to change their status by what it learns from provided experience and examples. ANN's resembles computer programs, which stimulate the biological structure of the human brain in obtaining and storing knowledge by the learning process**.**

The ANN procedure is receiving the inputs through neurons and combine their weights together [Tayfur, 2012].Thousands of cycles from inputs and outputs data are presented to the ANN at the training stage of the network. Inputs are the issue factors and outputs are its solution. At the end of each training cycle, the error between the real and coveted output will be evaluated by the network. According to the selected training algorithm, this error is used to update the values of the connection weights.

learning and generalization of the problems in the ANN models could be achieved in spite of incomplete or erroneous data. The data used to test the prediction capability of the network is selected from the total data set. After a predetermined number of iterations, the network training and testing is stopped whereas no amelioration is done in the output. The output of one neuron is the input to the next layer neurons, which is mathematically represented as in equations (1) and (2) [Ming et al., 2000].

$$\mathbf{I_j=\Sigma w_{ji}x_i+\theta_j} \qquad \mathbf{(1)}$$

$$\mathbf{y_j=\mathit{f}(I_j)} \qquad \mathbf{(2)}$$

A different type of neural network model and learning procedure were founded multilayer perceptron (MLP) neural network with back propagation algorithm is adopted in this research which is most important ANN. It consist from input layer with multiple input factors of linear function, hidden layer, and output layer with nonlinear activation function to calculate single output (productivity). Random values are set to the weights at the start of training of ANN and the interconnecting weights are updated until the overall error is reduced. MLP could be used when we have no definite information about the relationship between the input and the output. The activation function used in this study is Tanh function: f(x) = Tanh(x) (Karlık and Olgac, 2011).

5-1 Applications of ANNs in Productivity Estimate

ANN has many applications in construction management especially in labor productivity forecasting. Ming et al., 2000 improved Jason 1996 model, which is a probability inference neural network (PINN) to predict the productivity of formwork activity. The PINN was tested on real historical productivity data at a local construction company and compared with the classical feed forward back-propagation neural network model.

AbouRizk et al**.** (2001) developed a predicted model for Labor productivities of welding and pipe installation in industrial construction activities.

Moseley et al. (2005) studied the impact of change order on labor productivity using neural network model.

Samer and Lokman (2006) identifying the factors affecting concreting activities using questionnaire survey and to develop the labor productivity neural networks.

Moselhi and Khan (2010) studied the effect of a number of factors on labour productivity such as temperature, relative-humidity, wind speed, precipitation, gang size, crew composition, height of work, type of work and construction method employed using the neural network modeling. Temperature, height, and the work type were found the most factors of considerable effect on productivity.

Sana et al. (2011) studied the factors that might be affected the productivity rates of column concreting through direct measurement from site work in Malaysia using the neural network model with minimal errors.

Sawsen and Ali (2011) developed ANN model to estimate the ceramic productivity of walls in Iraq. Five input factors were used as independent variables, which is ganger experience, ganger age, number of assistant labors, area of ceramic tile, site complication, height level of the work, and weather condition. It was found that height level of the work is the most significant effect on the predicted total productivity.

Al-zwainy et al. (2012) developed ANN model to estimate the productivity of marble floor finish in Iraq. Ten factors were used as influence factors which is: Age, Year, Experience, Number of the labor, Floor height, Tiles Size, The security conditions, The work team health, Weather conditions, Site condition, and the Availability of construction materials. The most important factors in estimating the productivity of marble floor finishing works is; the age, experience and number of assist labor.

Mady (2013) trained many neural network models and he found that the generalized feed forward (GFF) model was the best one in predicting the labor productivity for casting concrete slabs for formwork in Gazza- Palestine.

Heravi and Eslamdoost (2014) developed an artificial neural network models to measure and predict labor productivity in developing country of Iran. They investigated the influential factors on labor productivity using the Bayesian regularization and early stopping methods. Their work involved in installing the concrete foundations of gas, steam, and combined cycle power plant construction projects. The developed models are implemented at two real power plant construction projects.

In this research the effect of different factors on production rates of bricklayer, as a single activity, has been taken into account to produce more accurate ANN model.

6- RESEARCH METHODOLOGY

To achieve the objective of the study, the below mentioned methodology is adopted

6-1 Data Collection

The previous studies have been identified many factors that have been influencing the labor productivity at site. Brainstorming session has been made to select the most important factors. Out of Forty-five invitations issued, thirty-two participants from different agencies in Karbala province related to construction projects are accepted to implement the brainstorming session. They told what the aims of the session are before they come to it, so that they can start to think about possible contributions to the problem under discussion. These participants are divided into two groups of diverse and relevant backgrounds, asked (based on their local experience) to write down the parameters that they expect to be used as predictors of the bricklayer production rate of construction projects.

After screening the brainstorming session results, it is found that the variables, which might affect the bricklayer productivity of construction projects, are Age, Experience, Gang health, Gang Number, Weather, wages, Site condition, Material availability, Wall length, Wall thickness, Wall height, Mortar type, and Security in site. Two classes of independent variables are found: objective and subjective variables. The measurable (objective) variables according to their unit of measure, such as age and experience are measured in years, gang number is measured in number, wall thickness is measured in centimeters, and wall length is measured in meters. Coding system is used to measure the qualitative (subjective) variables, for example, the gang health can be classifies to bad moderate and good and assigns them the value 1, 2 and 3 respectively. On site interviews have been carried out among (32) builders to gather (118) cases of production rate of bricklayer. Respondents are required to write down the factor under which he can achieve the specific production rate as shown in **Fig. (2)**.

6-2 Modeling Software

NeuroSolutions version 6.0.0 is used in this study, which works in Microsoft Excel as shown in **Fig.(3)**. NeuroSolutions is easy to use, powerful and flexible software [NeuroDimension, Inc., 2014].

At the beginning, data should be arranged in Microsoft Excel. Excel toolbar "NeuroSolutions" is added to build and design the model. NeuroSolutions software is based on columns called input and output column. Comparison is made between the obtained results from these columns. Input and output column should be assigned before the training process of the ANN. Then, data sets of training, cross validation, and testing should be prepared. These data sets are separated in default percentages or as the user wish option. The results is presented for each function and the graphics automatically reflecting the values of the functions. Different type of neural network are founded but multilayer perceptron (MLP) neural network is used. The system was designed as to have three hidden layers having same features.

Tangent axon is chosen as the activation function for both hidden and output layer. Constant learning rate parameter of (0.1) and momentum term factor of (0.7) are used during the training of network. The mean square error (MSE) at 1000 epochs is calculated during training.

7- MODEL DEVELOPMENT

Thirteen valuable factors, as described in earlier section, in need for thirteen (13) input neurons in the first layer of the ANN.Trial and error has been done to detect the number of neurons in a single hidden layer. It has been found that the (3) neurons showed least error. Maximum convergence is achieved in (1000) epochs. Gradient decent with momentum backpropagation with hyperbolic tangent sigmoid transfer function is used as a learning algorithm. Learning rate of (0.1) and (0.7) momentum term factor values is used in model development. Mean Square Error (MSE) has been calculated to check the model accuracy as in the equation (3) below (Battaglia, 1996):

$$\mathbf{MSE} = \frac{1}{n}\sum(\boldsymbol{Actual} - \boldsymbol{Predicted\ Rates})^2 \qquad (3)$$

It is the difference between the observed data and calculated by the ANN model responses for all data in the training set to check how well the network outputs fit the data. Batch method is used for weights updating in the (1000) epochs. Both of the output and hidden layer is of Tanh-sigmoid activation function. The test results are shown in **Table (1), and Fig. (4) and (5).**The MSE and R training and cross validation phases are calculated. The best value of R is (0.8628) accompanied with small values of MSE equal to (0.0074) and (0.0269) for the training and cross validation phases respectively. Tanh-hyperbolic function is found the best activation functions for both hidden and output layer. The actual productivity compared with estimated productivity for cross validation data set is shown in **Fig. (6)**. It is noted that there is a slight difference between two productivity lines except for exemplar seven and ten.

7-1 Sensitivity Analysis of the ANN Model Inputs

Sensitivity analysis was carried out by NeuroSolution tool to evaluate the influence of each input parameter to output variable for understanding the significance effect of input parameters on model output. The sensitivity analysis for the best ANN model was performed and the result is summarized and presented in **Fig. (7).**

It can be seen from **Fig. (7)** that the wall thickness (X_{10}) parameter has the greatest effect on the productivity output where its influence exceeds the impact of other factors combined. The value (180) for the wall thickness input parameter is the value of the standard deviation for output values. These output values are recorded after training the model with fixing the best weights on a matrix data. All inputs are fixed on the mean value for each raw except the wall thickness value which varied between (the mean – standard deviation) to (the mean + standard deviation). It is clear that the productivity increased along with the wall thickness increase.

The gypsum mortar type (X_{12}) and the lump sum wage payment method (X_6) ranked second and third respectively. Gang number (X_4) and sunny weather (X_5) has the fourth and fifth sensitive factor. It is clearly from **Fig. (7)** that the remaining parameters have low impact on the output (productivity).

7-2 Model Formulation

The resulted equation is too long as shown in **Fig. (8)**, so program named FORMULA WAND is used to get the connection weights of the neural network from NeuroSolutions software in Excel or VBA as shown in **Fig.(9)**. The researcher built the required equation model using Excel programmed sheet. Only input data is required in the programmed Excel to predict production rate automatically and the results appeared in column named predicted production as shown in **Fig. (10)**.

7-3 Model Validation

One of the most important steps in developing any model is to test its accuracy and validity. This process is also refers to as the model validation. It involves testing and evaluating the developed model with some test or validation data. The validation data should be some representative data from the targeted population but have not been used in the development of the model. In this study, the validation data are extracted from the same historical data file. They are not a part of the data used in the development of the model. The predicted productivity of these twelve cases computed using the model equation are compared with real data records (observed) and the results of this comparison are shown in **Table (2).**

Plotting the observed Vs. the predicted values of productivity which is showing R=83.27% and R^2=69.35% for cross validation test set. It gives a good agreement between the actual and predicted values draws a 45-degree line, which means that the actual productivity values are approximately similar to the predicted ones and indicates a reasonable concentration of the predicted values around the 45-degree line as shown in **Fig. (11)**.

8-CONCLUSIONS

The measurement of bricklayer production rates in construction projects, which is the main goal of this research, is achieved successfully. The developed ANN model has predicted the production rates of bricklayer accurately with least error. It is found that the wall thickness parameter has the greatest effect on the productivity output. It has been also found out that the lump sum wage payment method and the gypsum mortar type are extremely correlated with the production rates of bricklayer at sites. The developed ANN model predicted reliable values of production rates of bricklayer by incorporating the influencing factors. The MSE of the developed ANN model, which is the measure of model performance, to predict production rates of bricklayer has been determined. From the above-mentioned findings, it can be concluded that the developed ANN model can be used dependably for estimating production rates of bricklayer for any building construction project by incorporating the influence of selected factors.

The performed sensitivity analysis was in general logically where the wall thickness, mortar type, and wage payment had the highest influence, while Gang number, weather, Gang health, Wall length, Wall height, and age respectively has moderate effect on productivity. Therefore, it can be said that the variability of builders production rates are due to the considerable effect of the influencing factors at the sites. Surveyors can be easily used the proposed Excel sheet to predict the bricklayer production rates in order to estimate the required time for brick work activity in bidding new jobs.

9- RECOMMENDATIONS

1. Other neural network models for plastering, tiling, painting and other construction works should be performed.

2. Government agencies and engineering associations are recommended to establish a database for executed projects for researchers to develop productivity estimation process.

3. Contractors should be encouraged to keep historical data of productivity study in finished projects to improve the effectiveness and accuracy of estimation for future projects.

10-LIMITATION

The research limitations are:

1. The data is collected from builders in Karbala construction projects during summer 2015 other provinces, adjustment may be needed.
2. Actual production rates, by observing new project site, should be collected to evaluate the model results.

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Table (1): Training Report of ANN model

Best Networks	Cross Validation	Training
Run #	2	1
Epoch #	3	1000
Minimum MSE	0.013235436	0.007426251
Final MSE	**0.026911242**	**0.007426251**
R	**0.862862782**	**--------**

Table (2): Comparison of predicted and observed Productivity

Case No.	1	2	3	4	5	6	7	8	9	10	11	12
Observed	3000	2000	1000	2500	2000	900	2000	1700	1000	2200	1900	1100
Predicted	2710.045	1833.888	759.664	2869.506	2184.749	1111.471	3183.341	1906.771	1633.732	2998.397	2393.752	833.079

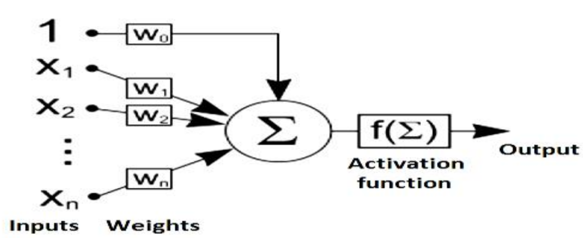

Figure (1): Artificial neural network structure (Haykin, 1999).

Appendix A

No.	Productivity – Brick/ day	Age (year)(X_1)	Experience (year)(X_2)	Gang health(X_3)			Gang Number	Weather (X_5)		Wages (X_6)		Site condition (X_7)		Material availability (X_8)		Wall dimension				Mortar type (X_{12})		Security in site (X_{13})	
																		Height (X_{11})					
				bad	Moderate	Good		Rainy	Sunny	Daily	Lump sum	Complex	Simple	Far	Near (2)	Length(X_9)	Thickness(X_{10})	Scaffold	No scaffold	Gypsum	Cement	Non-Secure	Secure
1	4000	30	8			3	5		2		2		2		2	10	36		2		2		2
	3100	30	8			3	5		2	1			2	1		10	36		2	1			2

Figure (2): Productivity Questionnaire Form

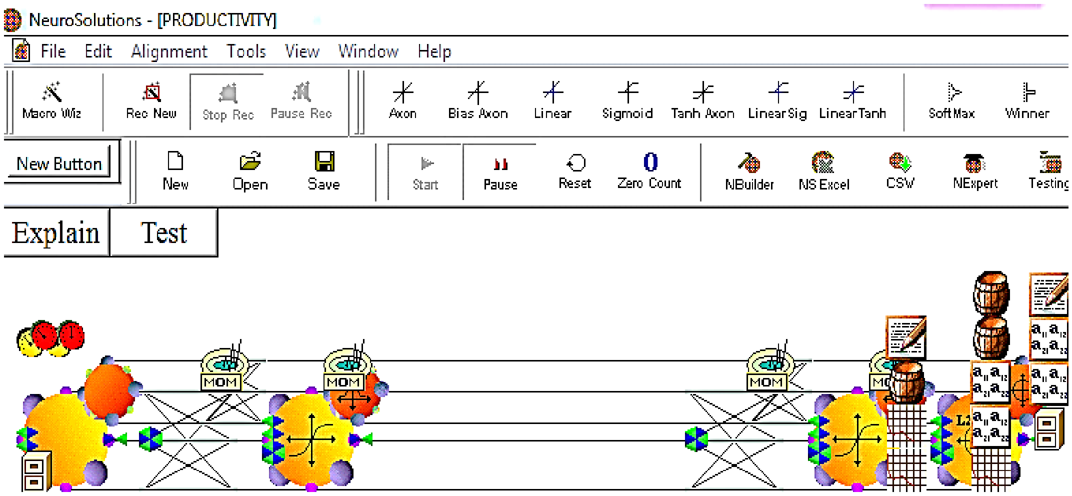

Figure (3): NeuroSolutions Software version 6.0 (NeuroDimension, Inc., (2014).

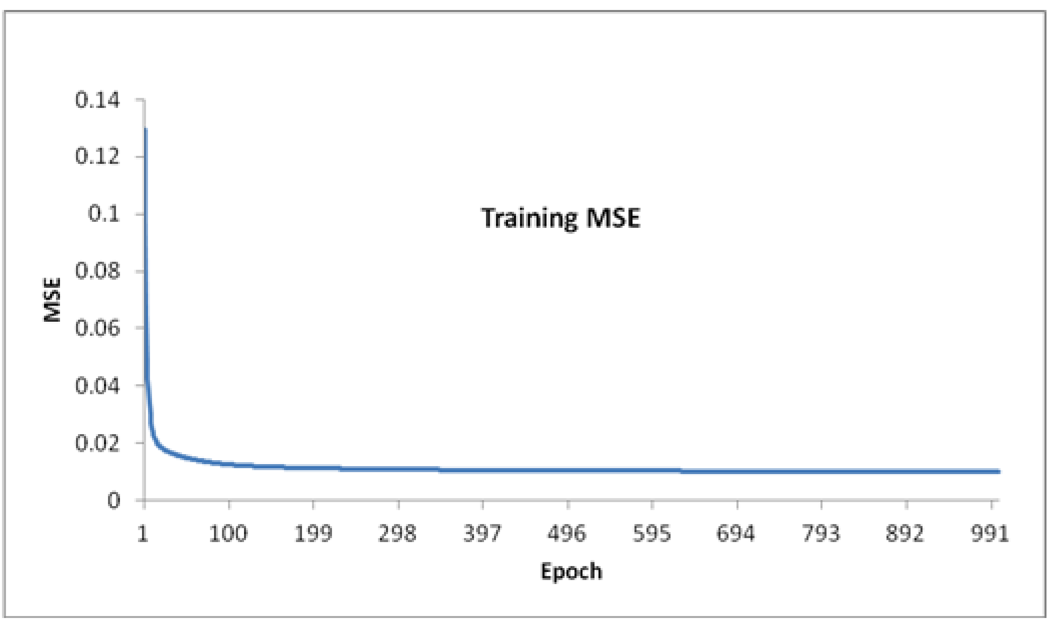

Figure 4: Training Mean Square Error

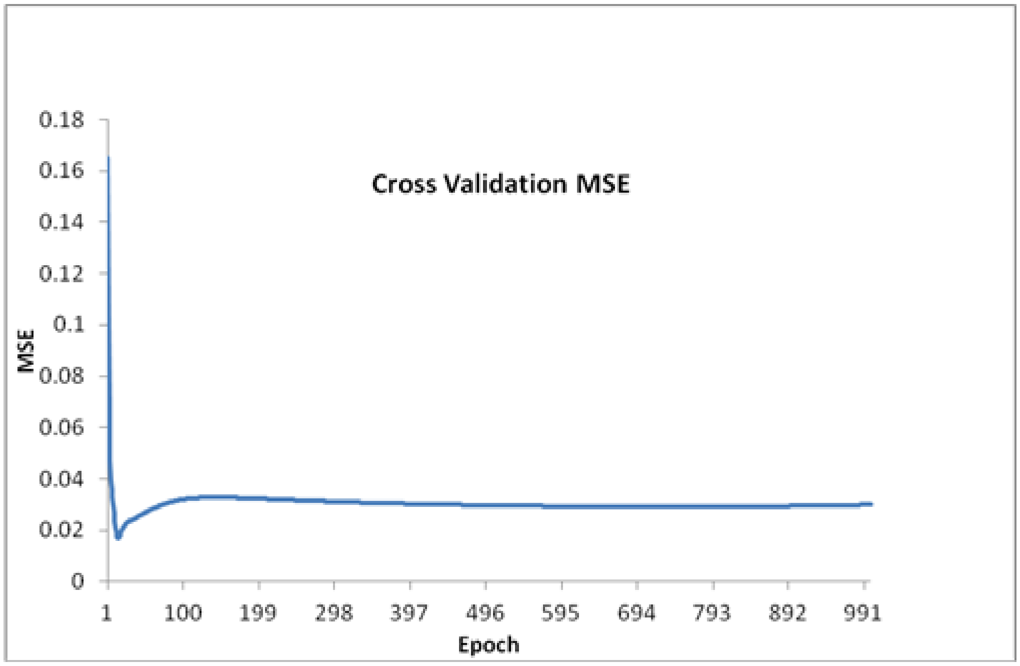

Figure 5: Cross Validation Mean Square Error

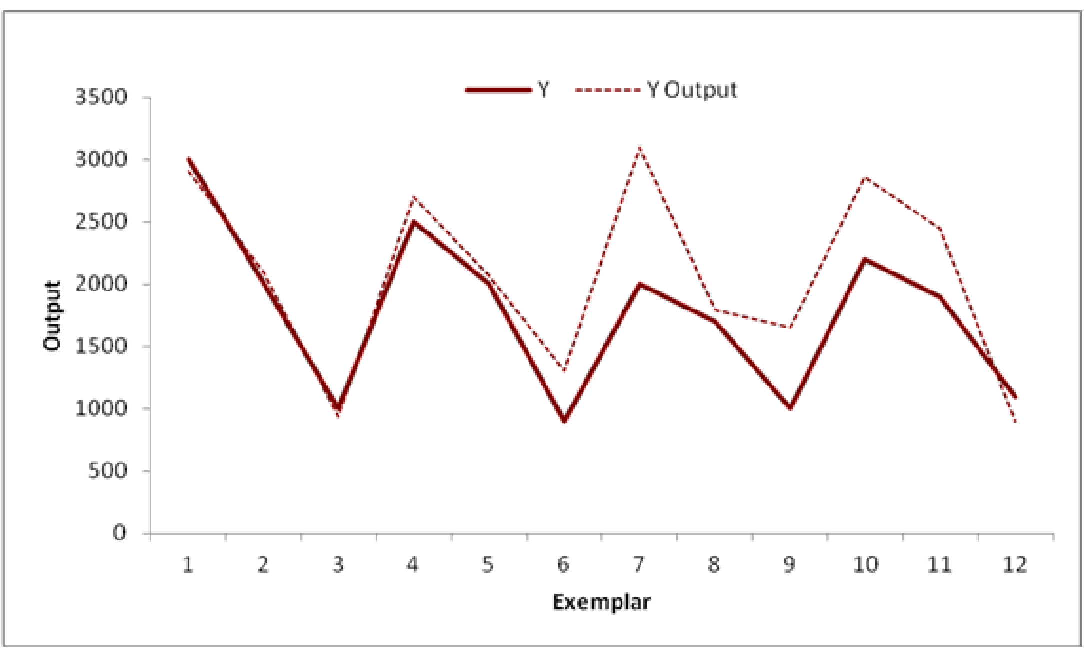

Figure 6: Desired Output and Actual Network Output

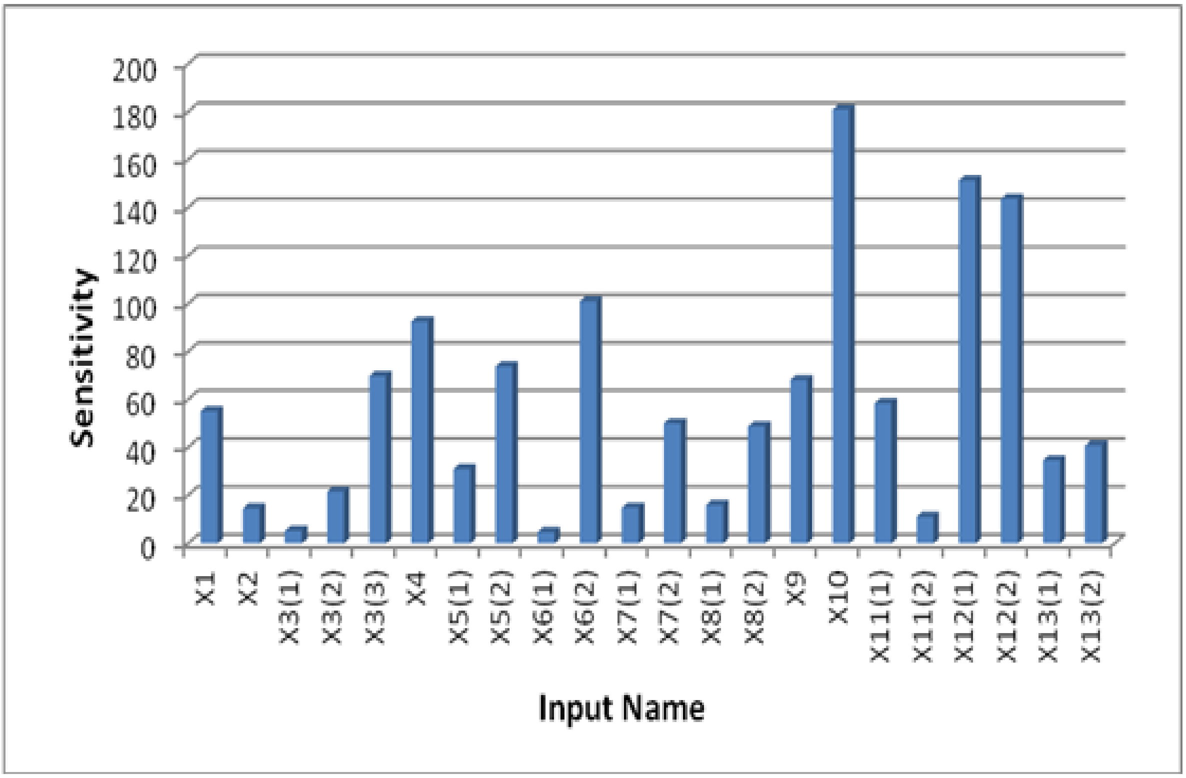

Figure 7: Sensitivity of Input Factors about the Mean

Appendix B

Output Formula

Productivity (Y) =

(((((tanh(((B2* (3.83e-002) + (-1.86))*(1.172e-001))+ ((C2* (6.43e-002) + (-1.35))*(-1.63e-001))+ ((D2* (1.8) + (-9e-001))*(2.196e-
001))+ ((E2* (1.8) + (-9e-001))*(2.6e-002))+ ((F2*(1.80) + (-9e-001))*(1.77e-001))+ ((G2* (9e-001) + (-4.5e+000))*(2.14e-001))+
((H2*(1.8) + (-9e-001))*(8.07e-002))+ ((I2* (1.8) + (-9e-001))*(1.19e-001))+ ((J2* (1.80) + (-9e-001))*(-1.305e-001))+ ((K2* (1.8) + (-
9e-001))*(-1.259e-001))+ ((L2* (1.8) + (-9e-001))*(-8.75e-002))+ ((M2* (1.8) + (-9e-001))*(-1.71e-001))+ ((N2* (1.8) + (-9e-001)
)*(5.15e-002))+ ((O2* (1.8) + (-9e-001))*(-8.24e-002))+ ((P2* (1.8) + (-9e-001))*(-1.87e-002))+ ((Q2* (9.47e-002) + (-1.468))*(9.94)
)+ ((R2* (7.499e-002) + (-1.799))*(-3.109e-002))+ ((S2* (1.8) + (-9e-001))*(-1.437e-001))+ ((T2* (1.8) + (-9e-001))*(-1.63e-002))+
((U2* (1.8) + (-9e-001))*(1.319e-001))+ ((V2* (1.8) + (-9e-001))*(-9.07e-003))+ ((W2* (1.8) + (-9e-001))*(-9.084e-002))+ ((X2* (1.8)
+ (-9e-001))*(-1.267e-001))+ (1.173e-001)))*(9.7147e-001)))+ (((tanh(((B2* (3.8297e-002) + (-1.857e+000))*(-1.155e-001))+ ((C2*
(6.4285e-002) + (-1.35))*(-8.647e-002))+ ((D2* (1.8) + (-9e-001))*(-1.3937e-002))+ ((E2* (1.8) + (-9e-001))*(-1.871e-001))+ ((F2*
(1.8) + (-9e-001))*(-3.401e-002))+ ((G2* (9e-001) + (-4.5))*(-4.6384e-002))+ ((H2* (1.8) + (-9e-001))*(-1.442e-002))+ ((I2* (1.8) + (-
9e-001))*(-1.5e-001))+ ((J2* (1.8) + (-9e-001))*(1.921e-001))+ ((K2* (1.8) + (-9e-001))*(8.505e-002))+ ((L2* (1.8) + (-9e-001))*(-
5.01e-002))+ ((M2* (1.8) + (-9e-001))*(1.554e-001))+ ((N2* (1.8) + (-9e-001))*(5.508e-002))+ ((O2* (1.8) + (-9e-001))*(8.559e-003)
)+ ((P2* (1.8) + (-9e-001))*(-4.307e-002))+ ((Q2* (9.47e-002) + (-1.468e+000))*(2.4032e-002))+ ((R2* (7.499e-002) + (-1.799)
)*(3.081e-003))+ ((S2* (1.8) + (-9e-001))*(-1.387e-001))+ ((T2* (1.8) + (-9e-001))*(-1.44e-001))+ ((U2* (1.8) + (-9e-001))*(-1.169e-
001))+ ((V2* (1.8) + (-9e-001))*(-4.696e-002))+ ((W2* (1.8) + (-9e-001))*(5.615e-002))+ ((X2* (1.8) + (-9e-001))*(-1.144e-001))+
(1.89e-001)))*(3.998e-001)))+ (((tanh(((B2* (3.8297e-002) + (-1.857))*(4.2867e-002))+ ((C2* (6.428e-002) + (-1.35))*(-3.367e-002)
)+ ((D2* (1.8) + (-9e-001))*(-1.2135e-001))+ ((E2* (1.8) + (-9e-001))*(6.763e-002))+ ((F2* (1.8) + (-9e-001))*(7.726e-004))+ ((G2*
(9e-001) + (-4.5))*(7.124e-002))+ ((H2* (1.8) + (-9e-001))*(-1.8189e-001))+ ((I2* (1.8) + (-9e-001))*(-9.667e-002))+ ((J2* (1.8e+000)
+ (-9e-001))*(-2.471e-002))+ ((K2* (1.8) + (-9e-001))*(8.0226e-002))+ ((L2* (1.8) + (-9e-001))*(1.078e-001))+ ((M2* (1.8) + (-9e-
001))*(3.873e-002))+ ((N2* (1.8) + (-9e-001))*(-1.1257e-002))+ ((O2* (1.8) + (-9e-001))*(5.556e-002))+ ((P2* (1.8) + (-9e-001)
)*(6.26e-002))+ ((Q2* (9.4737e-002) + (-1.4684e+000))*(-8.981e-002))+ ((R2* (7.499e-002) + (-1.7999e+000))*(2.0308e-001))+ ((S2*
(1.8) + (-9e-001))*(-1.2366e-001))+ ((T2* (1.8) + (-9e-001))*(-1.553e-001))+ ((U2* (1.8) + (-9e-001))*(-6.4148e-002))+ ((V2* (1.8) +
(-9e-001))*(1.142e-002))+ ((W2* (1.8) + (-9e-001))*(-6.836e-002))+ ((X2* (1.8) + (-9e-001))*(-4.4149e-002))+ (-7.824e-002)
))*(2.058)))+ (-4.2284e-001))-(-1.3154)) / (5.5384e-004)

Figure (8) : Output Formula

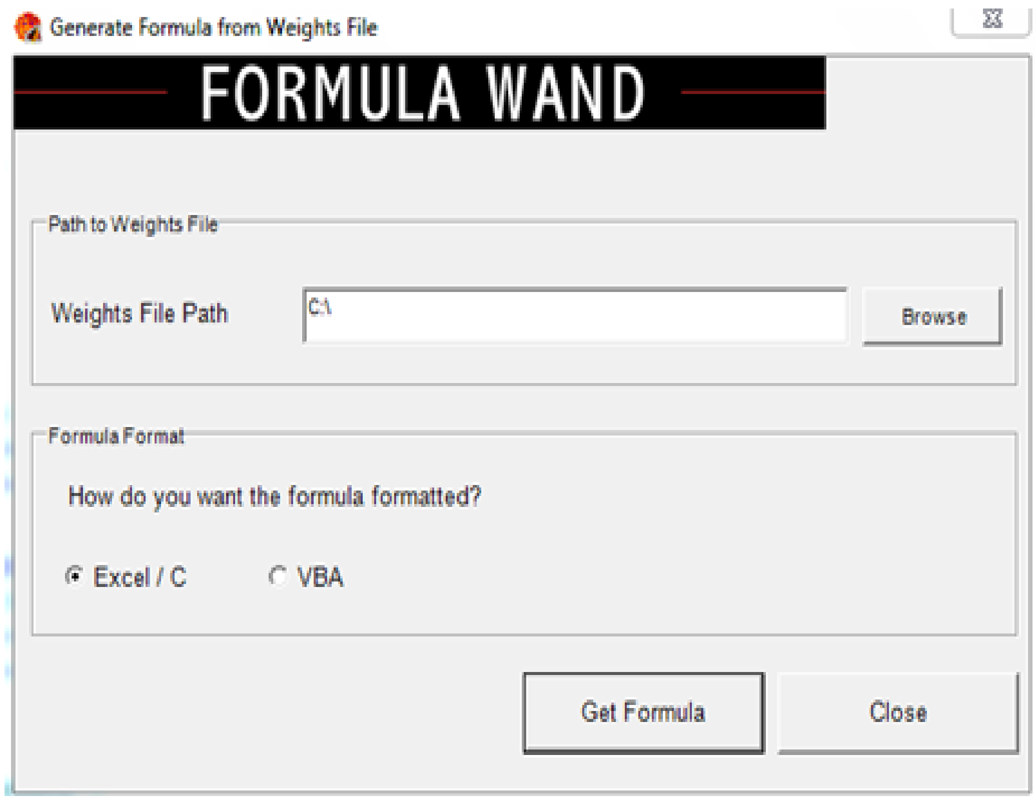

Figure 9 :FORMULA WAND Program

Predicted Production	X13(2)	X13(1)	X12(2)	X12(1)	X11(2)	X11(1)	X10	X9	X8(2)	X8(1)	X7(2)	X7(1)	X6(2)	X6(1)	X5(2)	X5(1)	X5(0)	X4	X3(3)	X3(2)	X3(1)	X2	X1
2710.0451	1	0	0	1	0	1	36	16	0	1	1	0	1	0	1	0	0	5	1	0	0	25	49
1833.88841	1	0	1	0	1	0	24	14	1	0	1	0	0	1	1	0	0	4	0	1	0	25	49
759.663965	1	0	1	0	0	1	12	9	0	1	1	0	0	1	0	1	0	4	0	1	0	25	49
2869.50579	1	0	0	1	1	0	36	18	1	0	0	1	1	0	0	1	0	5	1	0	0	15	38
2184.74921	1	0	1	0	0	1	24	15	0	1	1	0	0	1	1	0	0	5	0	1	0	15	38
1111.47055	1	0	1	0	0	1	12	7	1	0	1	0	0	1	0	1	0	4	0	1	0	15	38
3183.34064	1	0	0	1	1	0	36	17	0	1	1	0	1	0	1	0	0	5	1	0	0	12	40
1906.77091	1	0	1	0	1	0	24	15	1	0	1	0	0	1	0	1	0	4	0	1	0	12	40
1633.73183	0	1	1	0	0	1	12	7	0	1	1	0	1	0	1	0	0	4	1	0	0	12	40
2998.39732	1	0	0	1	1	0	36	15	0	1	1	0	0	1	1	0	0	5	1	0	0	8	25
2393.75195	1	0	1	0	0	1	24	15	1	0	0	1	1	0	1	0	0	5	0	1	0	8	25
833.07902	1	0	0	1	0	1	12	7	0	1	1	0	0	1	0	1	0	4	0	1	0	8	25

X1=Age (year)/ X2=Experience(year)/X3= Gang health (1) bad,(2)middle,(3)good/X4=Gang number/X5=Weather (1)rainy, (2)sunny/ X6=Wages (1) daily,(2)lumpsum/
X7=Site condition (1)complex,(2)simple/X8=Material avaliability (1)far,(2)near/X9=Wall length/X10=Wall thickness/X11=Wall height (1)scaffold, (2)no-scaffold/
X12=Morter type (1) cement, (2) gypsum/X13=Sicurity in site (1)non-secure, (2) secure.

Figure 10: Programmed Excel Sheet for ANN Equation

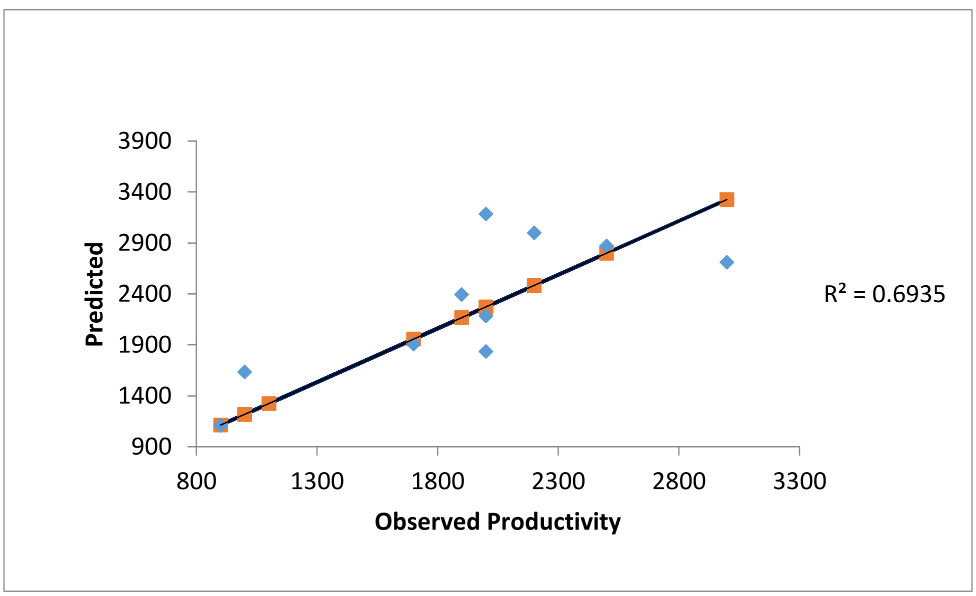

Figure (11): Observed Vs. the Predicted Values of Bricklayer Productivity