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# CONSTRUCTION LABOR PRODUCTION RATES MODELING USING ARTIFICIAL NEURAL NETWORK

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***SUMMARY:*** *Construction productivity is constantly declining over a decade due to the lack of standard productivity database system and the ignorance of impact of various factors influencing labor productivity. Prediction models developed earlier usually neglect the influencing factors which are subjective in nature such as weather, site conditions etc. Many modeling techniques have been developed for predicting production rates for labor that incorporate the influence of various factors but artificial neural network (ANN) has been found to have strong pattern recognition and learning capabilities to get reliable results. Therefore the objective of this research is to develop a neural network prediction model for predicting labor production rates that takes into account the factors which are in qualitative form. The objectives of the research have been achieved by collecting production rates data for formwork of beams from different high rise concrete building structures by direct observation. Reliable values of production rates have been successfully predicted by ANN. The average value of 1.45xE-04 has been obtained for Mean Square Error (MSE) after testing the network. These results indicate that the ANN has predicted production rates values for beam formwork successfully with least range of errors.*

**KEYWORDS**: *Production rates, influencing factors, work sampling, artificial neural network (ANN).*

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# 1. INTRODUCTION

It has been identified from the literature that construction productivity is the main indicator of the performance of construction industry. Construction productivity is directly related with labor as it is the most crucial and flexible resource used in the construction projects. Labor productivity is influenced by various factors present on the project site. These factors are very difficult to consider during the measurement and estimation of production rates due to varied and unique nature of every project (Oduba 2002). Extensive work has been done by the researchers in terms of identifying the both the qualitative and quantitative factors influencing the productivity of labor on site such as weather, lack of equipment and material, labor skills, incompetent supervision, incompetent drawing, site conditions, project location, poor communication, number of workers, change orders, late payments etc Arun *et al* (2004), Ehshani *et al* (2007), (Jiukun Dai *et al*. 2009). Also many researchers such as Thomas and Yiakoumis (1987), Olomolaiye (1988), Horner and Talhouni (1990), Christain and Hachey (1995) have studied the relationship of these factors with productivity to evaluate the impact of those factors.

Abdul Kadir *et al*.( 2005) has also identified in his studies that lack of local workers, late issuance of payment, late material supply etc are the factors that highly affects labor productivity of Malaysian construction industry. There is lack of standard productivity measurement system and also ignorance of the factors influencing labour productivity at site. Researchers have found that it is constantly declining over a decade in the construction industry.

During the project planning and scheduling estimators mostly rely on the past project information and their personal judgement and experience due to the absence of adequate information on the production rates value and also on the factors that influence the production rates of labor at site is the reason identified behind the declination of labor productivity.

Thus, the construction projects are estimated using the inadequate information of the estimators which results in the cost overrun and time overrun of the projects (Song *et al.* 2008). Therefore, reliable and accurate estimation of the projects are required to be done through use of modeling techniques to predict the production rates of the building project.

Many prediction modeling techniques have been used through a decade such as statistical model, action response model, factor model, linear regression model etc. (Oduba, 2002). Examples of these techniques includes Factor Model by Thomas and Yiakoumis (1987) for predicting productivity using factors, Expectancy model by Maloney and Fillen (1985) for predicting performance of workers to estimate productivity, Action Response model by Halligan (1994) to evaluate losses in construction productivity, Herbsman and Ellis (1990) have developed statistical model to identify the effects of factors on productivity, An expert simulation model is developed by Boussaabaine and Duff (1996) to identify the combine effects of all the factors on productivity. These modelling techniques were usually developed for specific conditions and their implementation was mostly restricted with the information available (Oduba 2002).

It has been identified that artificial neural networks is the strong prediction modeling technique which has dynamic learning mechanism with effective recognition capabilities to predict the production rates under any specific condition.

# ARTIFICIAL NEURAL NETWORKS; (ANN)

Artificial neural networks consist of a large number of artificial neurons that are arranged into a sequence of layers with random connections between the layers (Tsoukalas and Uhrig 1997). It can be arranged in different layers: input, hidden, and output. The hidden layer has no connections to the outside world because they are connected only to the input and output layers (Zayed and Halpin 2005). Fig. 1 shows a typical feed forward artificial neural network structure that consist of several neuron in input layer, hidden layer and output layer where weights can be assigned to each connection between two consecutive neurons.

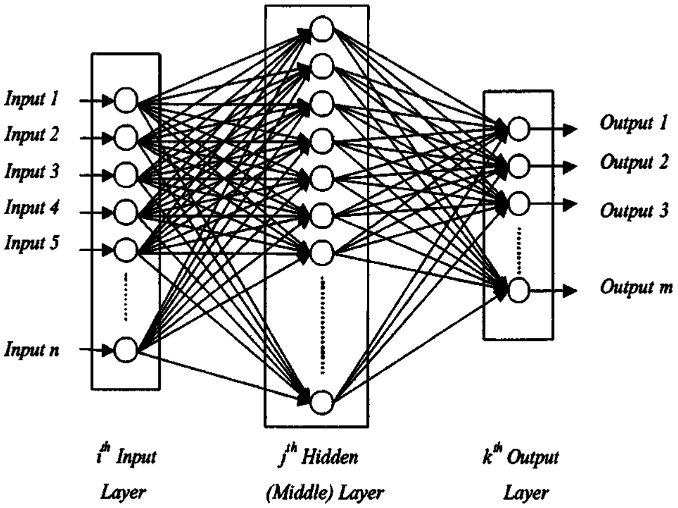


FIG. 1: *Typical structure of ANN (Zayed and Halpin 2005)*

Artificial neural network has the ability to drive meaning from complicated or imprecise data and it can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. For the successful implementation of artificial neural network, availability of reliable and accurate data is important.

There are many applications of ANN in the field of construction management for predicting labor productivity. Such as productivity of excavation and hauling time have been estimated using neural networks by Chao (1994). Two networks have been developed for estimating excavator capacity and excavator efficiency and results indicates accurate estimates with limited data. This approach is selected over a pure empirical approach because it generalizes the cause-effect relationships between input and outputs and provides a binding mechanism to maintain the consistency of an estimate.

Rifat (1996) has done construction labor productivity modeling using neural networks and regression analysis. Factors influencing construction operations have been identified and construction productivity of concrete pouring, formwork, concrete finishing and granular fill have been calculated to developed feed forward back propagation neural networks. These models have been proved to provide more accurate results with less error as after comparing with regression models.

Ming (2000) has estimated labor productivity using probability inference neural network which is the extension of neural network model developed by Jason in 1996 for estimating productivity of formwork activity. In this research classification and prediction models have been developed using kohenon learning vector quantization network and feed forward back propagation neural network. After classifying typical and non typical activities through kohenon classification network probabilistic inference neural network used to predict productivity of formwork activity with point estimates as an output along with the zones of production rates describing range of productivities.

Labor productivities for industrial construction activities have been predicted by AbouRizk *et al.* (2001). Using historical information factors affecting construction productivity of welding and pipe installation. An artificial neural network is used to predict production rates for welding and pipe installation activities and results are then compared with existing estimating practices.

Moselhi *et al.* (2005) has developed a model using neural network for estimating change order impact on labor productivity. By doing field investigation change order factors that affect labour productivity has been identified. Artificial neural network has been developed to predict the productivity loss occurred due to the impact of the change orders on construction operations. Neural network provides better results as compare to the other models that have been developed using different software.

Samer (2006) has estimated construction labor productivity for concreting activities using neural networks. Factors affecting concreting activities have been identified using questionnaire survey. Three networks using feed forward back propagation neural networks using hyperbolic tan transfer function have been developed for formwork activity, steel fixing and concrete pouring activities. These networks show adequate convergence with reasonable generalization capabilities.

Production rates for concreting of columns and influencing factors have been measured through Direct Observation from Malaysian construction Industry. Feed forward back propagation neural network has estimated the rates with least range of errors (Sana *et al.* 2011).

As mentioned above, many researchers have used ANN for modelling production rates of different construction activities which includes concrete pouring, installing formwork, welding and installation of pipes etc. These researchers have taken more than one activities at a time, thus an influence on the production rate of individual activity has not being clearly identified and usually neglected. If influence of various factors on production rates of a single activity can be identified then prediction modelling can be done more accurately. Therefore, the objective of this study is to establish a prediction model through analyzing data using ANN. To achieve this objective, this research has taken into consideration the modelling of production rates for only installation of formwork of beams. In this research the production rates of beams formworks has been measured and influencing factors on scale at project sites have been recorded and then analysis of the production rates with influencing rates has been done statistically.

## 3. METHODOLOGY

To achieve the objectives mentioned above the methodology adopted is described below:

### 3.1. Data collection

Through the literature review various factor that have been influencing the labor production rates at site are identified. Questionnaire survey has been carried out to identify the importance of all those factors identified through literature, those factors have been divided into two categories; management related factors and site related factors. Respondents are required to mark the each factor on the likert scale of 1 to 5 where 1 means not important and 5 means extremely important as mentioned in the questionnaire below, according to their importance in influencing labor productivity at sites.

**<u>Questionnaire:</u>**

Please rate the following factors according to its contribution in labor productivity by circling the appropriate number based on the guide below:

| **Unimportant** | **Not Much Important** | **Moderately Important** | **Very Important** | **Extremely Important** |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

**a) Management Factors**

| | | | | | | |
|---|---|---|---|---|---|---|
| 1. | Motivation & Incentive | 1 | 2 | 3 | 4 | 5 |
| 2. | Labor work load | 1 | 2 | 3 | 4 | 5 |
| 3. | Inspection Delays | 1 | 2 | 3 | 4 | 5 |
| 4. | Lack of Equipment | 1 | 2 | 3 | 4 | 5 |
| 5. | Disruption of Power/Water Supplies | 1 | 2 | 3 | 4 | 5 |
| 6. | Poor Scheduling and Coordination | 1 | 2 | 3 | 4 | 5 |

**b) Site Level Factors**

| | | | | | | |
|---|---|---|---|---|---|---|
| 1. | Weather (comfort level) | 1 | 2 | 3 | 4 | 5 |
| 2. | Materials Shortages | 1 | 2 | 3 | 4 | 5 |
| 3. | Delays in materials deliveries to site | 1 | 2 | 3 | 4 | 5 |
| 4. | Rework (corrective after wrongdoing or changes) | 1 | 2 | 3 | 4 | 5 |
| 5. | Congested work area (within site project) | 1 | 2 | 3 | 4 | 5 |
| 6. | Site Access (access to the project) | 1 | 2 | 3 | 4 | 5 |
| 7. | Absenteeism At Worksite | 1 | 2 | 3 | 4 | 5 |
| 8. | Communication Problems With Local & Foreign Workers | 1 | 2 | 3 | 4 | 5 |
| 9. | Labor Disruption (e.g. manpower shortages , strikes) | 1 | 2 | 3 | 4 | 5 |
| 10. | Skill level of labour | 1 | 2 | 3 | 4 | 5 |
| 11. | Crew Size | 1 | 2 | 3 | 4 | 5 |

A total of 300 questionnaires have been distributed and almost 10% (30) questionnaires have been returned. Based on the questionnaires returned, the factors which are highly significant that have been identified are weather (F1), availability of material and equipment (F2), project location (F3), site conditions (F4) and number of workers (F5). These five (5) selected factors have been considered to be used in the study for recording at the project sites on the same likert scale of 1 to 5 where 1 means low severe and 5 means highly severe the brief description of these influencing factors has been mentioned in Table 1.

TABLE 1: *Influencing Factors*

| **Factors/ Likert Scale** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| | **Low Severe** | **Slightly low Severe** | **Moderate** | **Slightly high severe** | **Highly severe** |
| **Weather (F1)** | Very Pleasant | Pleasant | Moderate/sunny | Hot weather | Very hot weather/heavy rain |
| **Availability of material and Equipment (F2)** | Completely available | Adequately available | Inadequately available | Shortage of material | Completely unavailable |
| **Location of project (F3)** | Accessible/Urban area | Sub-urban area | Rural-urban | Sub-rural area | Inaccessible/ Rural area |
| **Site conditions (F4)** | Very clear | clear | Slightly congested | congested | Very congested |
| **Number of workers (F5)** | Completely available | Adequately available | Inadequate Availability | Shortage of workers | Completely unavailable |

Field observations have been done to measure and record the production rates of formwork installation of beams and influencing factors at project sites. Construction work of formwork installation of beam has been selected for this research as formwork installation is the most significant construction activity in the overall project. Various ongoing concrete building projects have been identified in different parts of Malaysia that includes Perak, Selangor and Melaka. Total seven (7) numbers of projects have been observed as shown in Table 2. Data collection form has been developed for measuring duration of construction work require for formwork of beams by using stop watch. Unit of measurement has been set to hours required divided by the quantity of work done. Weekly site visits had been done and the rates are recorded at three intervals of every 3 hours. Eighty four (84) numbers of observations have been collected.

TABLE 2: *Project Sites Observed*

| **Projects** | **Location** | **No. of Observation** |
| --- | --- | --- |
| Project 1 | Selangor | 12 |
| Project 2 | Perak | 12 |
| Project 3 | Melaka | 12 |
| Project 4 | Perak | 12 |
| Project 5 | Perak | 12 |
| Project 6 | Perak | 12 |
| Project 7 | Perak | 12 |

## 3.2. Data Analysis

Five significant Influencing factors identified through questionnaire survey are then recorded at project sites on the likert scale of 1 to 5 during data collection. Factors recorded are then statistically analyzed by calculating Severity Index (S.I) as shown in Table 3. S.I of the factors has been calculated by using the formula, based on the study of Hammad and Assaf (1996) as mentioned below. These factors are ranked based on the values of S.I calculated as shown in Table 3. Availability of material and equipments is ranked first with high value of S.I which is equal to 324 where as number of workers; site conditions, location of the project and weather are ranked as second, third, fourth and fifth with S.I values 315.6, 275.6, 256.6 and 212.16.

$$\textbf{Severity Index (S.I)} = \left(\frac{\sum_{i=1}^{5} a_i \times x_i}{5\sum_{i=1}^{5} x_i}\right) \times 100$$

Where **"$a_i$"** indicates the likert scale marked from 1 to 5 and **"$x_i$"** shows the frequency of each likert scale marked.

TABLE 3: *Severity Index*

| Description | | highly low | slightly low | moderate | slightly severe | high severe | Total | Mean | S.I | Ranking |
|---|---|---|---|---|---|---|---|---|---|---|
| | $a_i$ | **1** | **2** | **3** | **4** | **5** | | | | |
| Weather (F1) | | 2 | 36 | 10 | 26 | 10 | 84 | 3.071 | 256.6 | **4** |
| Availability of material and equipment (F2) | | 0 | 12 | 20 | 20 | 32 | 84 | 3.85 | 324 | **1** |
| Location of the project (F3) | $x_i$ | 14 | 36 | 12 | 10 | 12 | 84 | 2.64 | 212.1 | **5** |
| Site Conditions (F4) | | 2 | 13 | 37 | 22 | 10 | 84 | 3.29 | 275.6 | **3** |
| No. of workers (F5) | | 2 | 9 | 25 | 18 | 30 | 84 | 3.77 | 315.6 | **2** |

These factors are then correlated with the production rates by calculating the correlation coefficient as shown in table 4. A correlation coefficient is a single number that describes the degree of relationship between two variables such as “x” and “y”.Correlation coefficient ‘R’ has been calculated by using the formula mentioned below:

$$\textbf{Correlation Coefficient (R)} = \frac{N\sum XY-(\sum X)(\sum Y)}{\sqrt{[N\sum X^2-\sum X^2][N\sum Y^2-\sum Y^2]}}$$

Where N: number of observations, $\sum XY$: sum of products of variable “X” and “Y”, $\sum X$: sum of “X” score, $\sum Y$: sum of Y score, $\sum X^2$: sum of squared x score, $\sum Y^2$: sum of squared y score. The value of ‘ R’ can be in the range of 0 to 1 where ‘1’ indicates the two variables are perfectly correlated and ‘0’ means there is no correlation between the two variables.

In this research, production rate value of beam formwork is taken as ‘Y’ and influencing factor has been considered as ‘X’. Correlation coefficient has been calculated by for determining relationship of production rate ‘Y’ with each influencing factors ‘X’ separately as shown below in Table 4.

TABLE 4: *Correlation Analyses*

| Influencing Factors | Weather (F1) | Availability of Material & Equipment (F2) | Location (F3) | Site condition (F4) | No. of Workers (F5) |
|---|---|---|---|---|---|
| **Correlation coefficient (R)** | 0.26 | 0.131 | 0.134 | 0.141 | 0.258 |

The values of (R) calculated as shown in table 4 represent that weather and number of workers are highly correlated with production rate as compare to other influencing factors with a value 2.68 and 2.58. This indicates that if the weather is hot or rainy the productivity is severely influenced and also if the number of workers is not adequately enough for installation of formwork in beams then the productivity of formwork installation is highly affected. Site conditions, location of project and availability of material and equipment are not much correlated with production rate as indicated by the correlation coefficient values 0.141, 0.134 and 0.131. This shows that the variation in the site conditions, project location and material and equipment availability is not significantly influencing the productivity of formwork installation of beams at the project sites.

## 4. MODEL DEVELOPMENT

For development of ANN model, cross validation technique which is commonly used to estimate the prediction performance of the model has been used. By applying *k-fold* cross validation technique, total eighty four numbers of observations has been divided into 10 equivalent parts using *k=10* folds. MATLAB version 7.8.0 has been used to developed ANN model. Five *(5)* input neurons have been used for five influencing factors which are significant as identified from study as described in earlier section. One hidden layer has been used with *(20)* twenty neurons .Trial and error has been done at each fold by varying different number of neurons in the hidden layer such as *5, 10, 15, 20, 25, 30* and *35* but hidden layer with *20* neurons has shown least error. Number of epochs used is equal to *1000* at which network shows maximum convergence. Learning algorithm used is gradient decent with momentum back propagation with hyperbolic tangent sigmoid transfer function. Learning rate and momentum factor used in the model is *0.5* and *0.9*.

Keeping the parameters constant, the developed model has been executed *k (10) times* (Ron, 1995). In each k-fold data have been randomly divided into 10 folds. For every K-fold analysis, as the data have been divided into n (10) folds and each time different fold is used for testing while n-1 folds are used for training. After executing every K-fold, simulated outputs have been compiled and accuracy of the model has been determined by calculating Mean Square Error (MSE) by using the formula given below:

$$\mathbf{MSE}=\frac{\mathbf{1}}{\boldsymbol{N}}\times\sum(\boldsymbol{Actual}-\boldsymbol{Predicted\ Rates})^{\mathbf{2}}$$

For every 10 K-folds analyses Average of MSE has been calculated. Total average of MSE has been finally measured by taking the average of MSE of 10l K-folds analyses by using the formula:

$$\mathbf{Average\ MSE}=\frac{\mathbf{1}}{\boldsymbol{N}}\times\sum_{\mathbf{1}}^{\mathbf{10}}(\boldsymbol{Average\ MSE})$$

## 5. RESULTS & DISCUSSION

After training the network k times the testing outputs have been obtained after executing each fold of ANN models is shown in Table 5.

TABLE 5: *ANN Model Testing Outputs*

| ITERATIONS | Avg. Actual Rate (hr/m$^2$) | Predicted Rate (hr/m$^2$) | AVERAGE MSE |
|---|---|---|---|
| K-FOLD 1 | 0.0471 | 0.0487 | 1.45E-04 |
| K-FOLD 2 | 0.0467 | 0.0396 | 1.67E-04 |
| K-FOLD 3 | 0.0466 | 0.0399 | 1.74E-04 |
| K-FOLD 4 | 0.0455 | 0.0395 | 1.73E-04 |
| K-FOLD 5 | 0.0447 | 0.0392 | 1.93E-04 |
| K-FOLD 6 | 0.0457 | 0.0395 | 1.77E-04 |
| K-FOLD 7 | 0.04617 | 0.0393 | 2.15E-04 |
| K-FOLD 8 | 0.0471 | 0.0398 | 2.02E-04 |
| K-FOLD 9 | 0.0436 | 0.0392 | 2.01E-04 |
| K-FOLD 10 | 0.00446 | 0.0396 | 1.79E-04 |
| **Total Average (MSE)** | | | 1.82E-04 |

K-fold cross validation technique has been applied and the model has been trained and simulated 10 times. Each time K-fold analysis is done by randomly dividing the data into 10 folds and average MSE has been calculated for every K-fold as shown in Table 5. Average values of each K-fold actual rates and predicted rates have been calculated then the MSE have been determined for all the K-folds. Table 3 above shows that minimum average MSE that has been achieved is equal to 1.45 E-04,at K-fold 1 whereas the average is calculated by considering average of all the averages MSE which is equal to 1.82E-04 which indicates that the network has achieved better convergence. Thus, the production rates values are predicted with lower values of MSE and with less variation among actual and predicted values as shown in Fig 2.

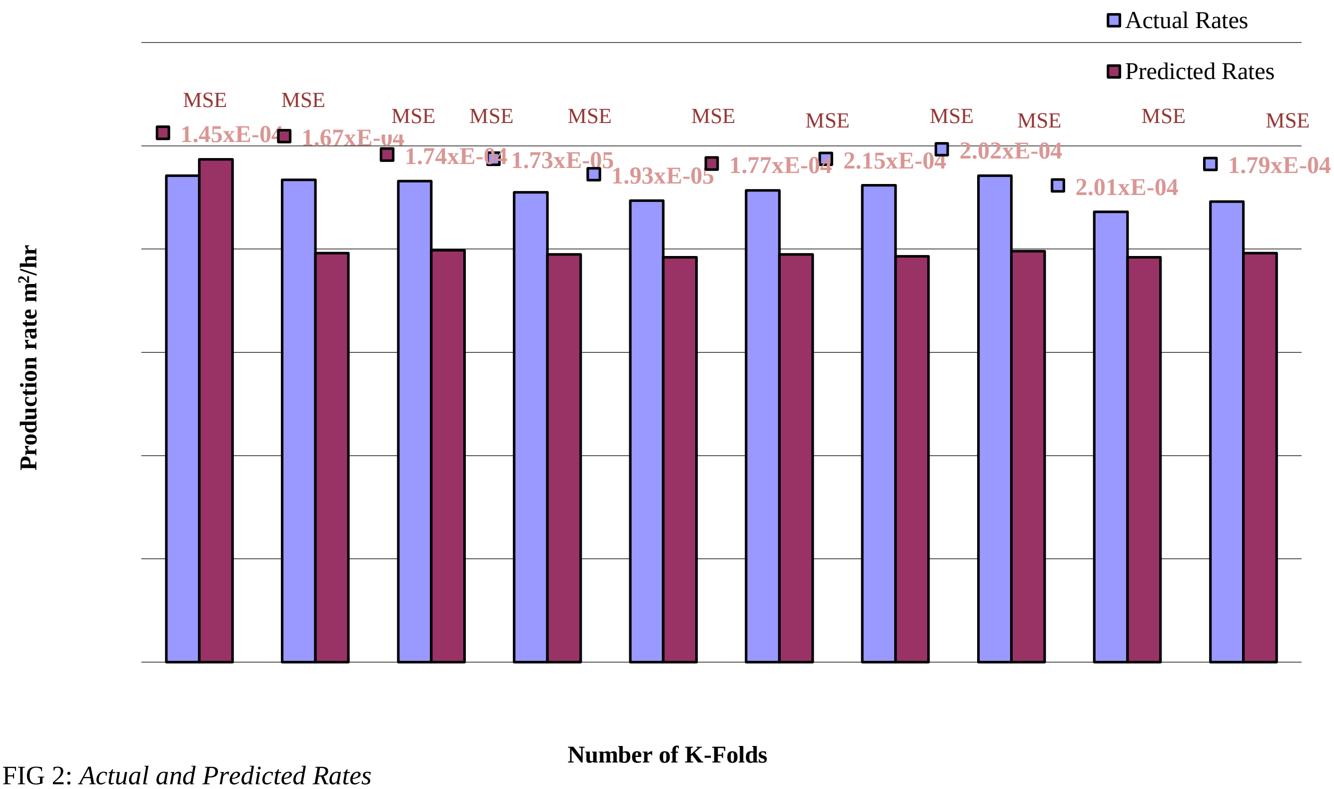


FIG 2: *Actual and Predicted Rates*

Fig. 2 shows that production rates have been accurately predicted as indicated by the smallest values of MSE. However, only slightly increase in the average MSE of K-folds 7, 8 and 9 have been found which are equal to 2.15E-04, 2.02E-04 AND 2.01E-04. Hence, the minimum and maximum values of average of MSEs that have been obtained by ANN model are in acceptable range as compared to the MSE of 1.00 x E-06 obtained by Samer (2006) in his study conducted for estimating production rates of formwork using ANN model.

At sites production rate values measured for installation of formwork of beams has range of 0.04366 hr/m$^2$ to 0.0471hr/ m$^2$ whereas the range of predicted production rates is 0.0392 m$^2$ /hr to 0.0487 hr/ m$^2$ /hr indicating lower variation between actual and predicted rates as shown in Table 3. As the statistical analysis has been done in the previous section by calculating the S.I and Correlation Coefficient of the data collected. In the analysis, availability of material and equipment is ranked as the most severe influencing factor and also highly correlated with production rates, also number of workers has been calculated as second most highly correlated factor with production rates. This shows that, improper management on the availability of materials and inadequate supervision of the maintenance of equipment and number of workers at the sites affects the better performance of the construction operations which ultimately influenced the labor productivity. Therefore, it can be interpreted that the minimum values of production rates of formwork installation of beams that have been measured on sites are due to the significant presence of the above influencing factors at the sites.

## 6. CONCLUSION

The objectives of the research have been successfully achieved through the measurement of production rates of formwork of beams by observing seven different types of building projects sites. Also, the factors influencing these rates such as weather, availability of material and equipment, location of project, site conditions and number of workers have been recorded on scale at sites. Finally, ANN model developed has predicted the production rates for beams formwork accurately with least error.

By statistical analysis, availability of the materials and equipment is the most severe factor identified It has been also found out that availability of material and; equipment and number of workers are highly correlated with the production rates at sites. Thus, indicating that the labor productivity is significantly affected by the improper management of availability of material and equipment and inadequate supervision of maintenance of equipment and number of workers at the sites.

Reliable values of production rates with incorporation of the influencing factors have been successfully predicted by ANN model. Performance of the model has been determined by calculating the MSE (Mean Square Error) of the predicted production rates. The average values of 1.82 E-04 have been obtained for MSE. These results indicate that the ANN model has predicted production rates values for bean formwork successfully and reasonably with least range of errors as compared to the MSE obtained in the study conducted by Samer in 2006.

It can be concluded from the above findings that, by incorporating the influence of selected factors on the production rates, the ANN model developed can be used reliably for estimating production rates of installation formwork of beams for any building construction project.

## 7. LIMITATIONS

The limitations of the research have been mentioned below:

- As the budget available for the research is limited therefore only seven project sites have been visited which resulted in getting only eight four number of observations.
- Also, only 10% of questionnaires have been returned during the survey done for identifying the significant influencing factors. The low percentage may be due to the lack of understanding of the respondents on the influencing factors of production rates at the sites.
- Smaller number of observations used in ANN for predicting production rates has been resulted in lack of generalization and recognition capabilities in the model.
- The results of the model are needed to be validated by comparing with the actual production rates that should be collected by observing new project site.

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