Prediction Modeling of Construction Labor Production Rates using Artificial Neural Network

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Abstract—Construction productivity is the main indicator of the performance of construction industry. It is constantly declining over a decade due to the lack of standard productivity measurement system. The impact of the various factors influencing labor productivity is also neglected. Various labor productivity models developed have not been implemented successfully due to the availability of unreliable data. Also influencing factors which are subjective such as weather, site conditions etc are usually ignored by the estimators. Although there are various modeling techniques developed for predicting production rates for labor that incorporate the influence of various factors but neural networks are found to have strong pattern recognition and learning capabilities to get reliable estimates. Therefore the objective of this research study is to develop a neural network prediction model for estimating labor production rates. The developed model has also taken into account the subjective factors. Production rates data for concreting of columns of different high rise concrete building structures has been obtained through direct observation method.

Keywords—Construction productivity, Labor production rate, neural networks, influencing factors.

I. INTRODUCTION

Construction industry is the main indicator of the economic growth of the country throughout the world. Construction industry is the significant contributor in the economic growth of any country. In developed countries, the construction industry incorporates the GDP growth of 7-10% whereas in under developed countries the percentage is only 3-6% [1]. Construction industry is also an important element in the economic growth of Malaysia and it constitutes almost 5% of the GDP of the country [2]. Construction labor productivity is the key indicator of the performance of construction industry as labor is the most crucial resource used to measure construction productivity and it also constitutes large portion of the project cost and requires to be fully utilized. Many researchers are analyzing labor productivity as it has been declining constantly over a decade. According to the statistics mentioned in Malaysian Productivity Corporation report that productivity growth rate of construction industry is only 5% as compared to the rate of increase in other sectors [3].

It has been found that contractors used previous projects production rates for estimation of future projects that required to be readjusted and recalculated for each project and takes into account the various site factors and conditions that influenced the labor productivity for construction operations [4].

Also absence of standard production rates measurement system is one of the reasons identified for the declination of construction productivity.

II. INFLUENCING FACTORS

Labor production rates are influenced by various factors present at the project site. These factors are very difficult to consider during the measurement and estimation of production rates due to its variable nature and also uniqueness of every project [5]. Extensive work has been done by the researchers in terms of identifying the factors influencing the productivity of labor on site such as weather, lack of equipment and material, labor skills, incompetent supervision, incompetent drawing, poor communication, change orders, late payments etc [6], [7], [8]. Also many researchers such as Researchers have also studied the relationship of these factors with productivity to evaluate the impact of those factors [9], [10], [11], [12]. Other research has also found 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 [12].

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III. VARIOUS PREDICTION MODELS

In addition, various techniques and models have been developed for predicting labor productivity that considered specific construction operation by identifying the factors influencing that construction activity through work sampling. Productivity Models that have been developed includes Factor Model for predicting productivity using factors [9], Expectancy model for predicting performance of workers to estimate productivity [13], Action Response model to evaluate losses in construction productivity [14], Statistical model developed to identify the effects of factors on productivity [15], An expert simulation model developed to identify the combined effects of all the factors on productivity [16], Feed forward back propagation neural network model developed to estimate the production rates of formwork [17] and Fuzzy expert system to predict the production rates of labor [5].

Various shortfalls of all the models mentioned above have been found by researchers [5]. Among those models neural network is more effectively and commonly used by the estimators.

IV. ARTIFICIAL NEURAL NETWORK (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 [18]. 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 [19]. 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. Due to strong adaptive learning and fault tolerance capabilities many researchers have used neural network as prediction model in the field of construction management. Various neural network models have been developed for estimating labor production rates for different construction activities [20], [21], [22], [23], [24], [25].

Thus the objectives of this research study are to measure the labor production rates for concreting of column and identify the factors at the site influencing those rates. Then to establish a model using neural network to predict the production rates of labor in relation with the factors that influenced them.

V. METHODOLOGY

The methodology adopted to achieve the objective is described below:

A. Data collection

Various ongoing concrete building structures have been identified in different parts of Malaysia like Ipoh, Kuala Lumpur, Grik, Subang, Selangor, Perak and Melaka. Work sampling approach has been used to measure the production rates at site to calculate duration of activity on weekly basis at specific time interval using stop watch. Author has been able to get twelve (12) number of observation from each of seven (7) projects at different intervals. Among seven projects five residential, institutional and educational projects are from Perak, one residential project is from Selangor and one commercial project is from Melaka as shown in Table: 1. Therefore total eighty four (84) number of data samples has been gathered.

<table>
<thead>
<tr>
<th>Project Code</th>
<th>Location</th>
<th>Sample Data</th>
<th>Type of Project</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1001</td>
<td>Selangor</td>
<td>12</td>
<td>Residential</td>
</tr>
<tr>
<td>P1002</td>
<td>Perak</td>
<td>12</td>
<td>Educational</td>
</tr>
<tr>
<td>P1003</td>
<td>Melaka</td>
<td>12</td>
<td>Commercial</td>
</tr>
<tr>
<td>P1004</td>
<td>Perak</td>
<td>12</td>
<td>Residential</td>
</tr>
<tr>
<td>P1005</td>
<td>Perak</td>
<td>12</td>
<td>Educational</td>
</tr>
<tr>
<td>P1006</td>
<td>Perak</td>
<td>12</td>
<td>Educational</td>
</tr>
<tr>
<td>P1007</td>
<td>Perak</td>
<td>12</td>
<td>Institutional</td>
</tr>
</tbody>
</table>

B. Data Analysis

Factors that influence the productivity of labor on site identified through literature review includes lack of material and equipments, inadequate drawing, weather, location of project, incompetent site supervision, change orders, absenteeism etc. Among these, the most common factors present have been identified during data collection. They are weather, lack of availability and equipment, location of project, site conditions and number of workers. These factors are recorded simultaneously during measurement of production rates at the sites on the severity scale of 1 to 3 where 1 indicates highly severe and 3 shows low severe. The severity indexes of these factors have been calculated to rank them.
Availability of material and equipment has been ranked first among all the five factors whereas numbers of workers, weather, site conditions and location of project have been ranked as second, third, fourth and fifth as shown in Table 2.

**TABLE 2. RANKING OF FACTORS USING SEVERITY INDEX**

<table>
<thead>
<tr>
<th>Description</th>
<th>Low</th>
<th>Average</th>
<th>High</th>
<th>Total</th>
<th>Mean</th>
<th>Severity Index</th>
<th>Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability of material &amp; equipment</td>
<td>45</td>
<td>27</td>
<td>12</td>
<td>84</td>
<td>2.393</td>
<td>192.57</td>
<td>1</td>
</tr>
<tr>
<td>Location of the project</td>
<td>13</td>
<td>31</td>
<td>40</td>
<td>84</td>
<td>1.679</td>
<td>112.90</td>
<td>5</td>
</tr>
<tr>
<td>Weather</td>
<td>39</td>
<td>30</td>
<td>15</td>
<td>84</td>
<td>2.286</td>
<td>181.46</td>
<td>3</td>
</tr>
<tr>
<td>Site Conditions</td>
<td>23</td>
<td>46</td>
<td>15</td>
<td>84</td>
<td>2.095</td>
<td>165.46</td>
<td>4</td>
</tr>
<tr>
<td>No. of workers</td>
<td>40</td>
<td>31</td>
<td>14</td>
<td>85</td>
<td>2.306</td>
<td>186.12</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 2 shows that the projects observed have issues of shortage of material and maintenance of equipment on site. This indicates that labor productivity has been greatly influenced by the improper management and handling of material on site. Also regular maintenance and inspection of the equipment is an important factor that affects the productivity of labor.

**C. Model Development**

Matlab 7.0.4 MathWork has been used to developed neural network model. 72% of the total number of data has been used for training neural network whereas 28% has been used for testing. Five input neuron has been used as total five influencing factors are calculated to have high correlation with rates as described in earlier section. One hidden layer used with three hidden neurons. Number of epochs used are 1300 at which network shows maximum convergence as shown in figure 2. Learning algorithm used is gradient decent with momentum back propagation with log sigmoid transfer function. Learning rate and momentum factor used in the model is 0.5 and 0.9. The architecture and parameters of the neural network model followed is similar to the model developed by Rifat (1996) with different number of observation and input neurons. Percentage error and Mean Square Error (MSE) have been found out by using the formulas as given below:

\[
\text{MSE} = \frac{1}{N} \sum (\text{Actual rate} - \text{Predicted rate})^2
\]

\[
\text{Percentage Error} = \left( \frac{\text{Actual rate} - \text{Predicted rate}}{\text{Actual rate}} \right) \times 100
\]

**VI. RESULTS & DISCUSSION**

Neural network model has been trained by using 72% of data samples. Five neurons have been used in the input layer including F1, F2, F3, F4 and F5 whereas of production rate has been given as targets in the output layer with one hidden layers comprising three hidden neurons. Trial and error has been done to reduce the error by varying the number of neurons in the hidden layer and number of epochs. Minimum error achieved with three numbers of hidden neurons and 1300 number of epochs as shown in figure 2.

Out of seven projects, five projects data has been used for training the network (72% of total data) and remaining two projects data (28%) has been used for testing. During training the network has predicted the production rates with lower values of MSE and follows similar trend and pattern of target values as shown in figure 3.
Production rates values predicted during testing of the network also have lower error values and follows almost similar trend and pattern with slight variation at the end as shown in figure 4.

Average values of each project predicted rates have been calculated then the percentage error and MSE of training and testing predicted rates have been determined for training and testing as shown in Table 4. Average errors calculated for training is 7.76% and 0.00112 whereas testing error are slightly higher than training error with values 12.29% and 0.0015. Then average of percentage error and MSE has been calculated of all the projects. The results shows that the percentage error of training and testing is within 15% of the actual production rates and also the values calculated for MSE of training and testing is $10^{-3}$ shows that the network has achieved better convergence.

<table>
<thead>
<tr>
<th>Project Code</th>
<th>Avg. Actual Rate (hr/m)</th>
<th>Predicted Rate (hr/m)</th>
<th>%age Error</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1001</td>
<td>0.258</td>
<td>0.279</td>
<td>9.04</td>
<td>0.0007</td>
</tr>
<tr>
<td>P1002</td>
<td>0.288</td>
<td>0.290</td>
<td>8.03</td>
<td>0.0005</td>
</tr>
<tr>
<td>P1003</td>
<td>0.299</td>
<td>0.321</td>
<td>7.48</td>
<td>0.0006</td>
</tr>
<tr>
<td>P1004</td>
<td>0.317</td>
<td>0.319</td>
<td>7.08</td>
<td>0.0018</td>
</tr>
<tr>
<td>P1005</td>
<td>0.309</td>
<td>0.316</td>
<td>7.20</td>
<td>0.0002</td>
</tr>
<tr>
<td>P1006</td>
<td>0.336</td>
<td>0.317</td>
<td>6.47</td>
<td>0.0012</td>
</tr>
<tr>
<td>P1007</td>
<td>0.234</td>
<td>0.274</td>
<td>18.11</td>
<td>0.0002</td>
</tr>
<tr>
<td>Average Error (Training)</td>
<td>7.76</td>
<td>0.00112</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Error (Testing)</td>
<td>12.29</td>
<td>0.0015</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

VII. CONCLUSION

Neural network model developed has been able to achieve the objectives of this paper. With strong learning capability and pattern recognition ability of neural network the production rate for concreting have been predicted accurately with acceptable error. Production rates values of concreting in columns have been calculated on site by observing seven different types of building projects. Factors influencing these rates such as weather, availability of material and equipment, location of project, site conditions and number of workers which are subjective in nature, have been recorded on scale at sites. To determine the individual effect and severity level of each factor severity indices have been calculated. Availability of the materials and equipment is the most severe factor identified that indicates that improper management of materials and handling of equipments has greater influence on the accurate estimation of production rates.

Reliable values of production rates with incorporation of these factors have been successfully predicted by neural network model. Performance of the model has been determined by calculating the percentage error and MSE (Mean Square Error) of the predicted production rates. The percentage error values of 7.76% and 12.29% have been obtained for training and testing output results whereas 0.00112 and 0.0015 are the values calculated for MSE of training and testing outputs. These results indicate that the network model has predicted production rates values for concreting in columns reasonably within acceptable range of errors.
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REFERENCES


