

Prediction of Construction Labor Production Rates for Malaysian Construction Industry Using ANN

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Abstract

Construction labor productivity in Malaysian industry has been declining over a decade due to lack of standard productivity measurement system. Beside this the influences of various qualitative factors on labor productivity have not been incorporated accurately during the scheduling and estimation of the project durations. Therefore, the aim of this research is to predict the production rates by using Artificial Neural Network (ANN) which incorporates the factors. Qualitative factors influencing the rates such as weather, project location, site conditions, etc. have been identified on project sites during the measurement of production rates values for concreting of a slab. Data obtained from seven building project sites have been used in the ANN for predicting labor production rates. The results obtained with the least error can be used as reliable and valid production rates for building projects estimation in the Malaysian construction industry.

Keywords

Labor production rates, influencing factors, ANN, work sampling.

1. Introduction

The construction industry is the main indicator of the economic growth of any country. Construction industry incorporates the GDP growth of 7-10% in the developed countries whereas in under developed countries the percentage is only 3-6% (Wibibo 2003). The construction industry is also an important element in the economic growth of Malaysia and it constitutes almost 5% of the GDP of the country (Madya *et al.* 2004). 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. It also constitutes large portion of the project cost. It has been constantly declining over the decades. Decline in labor productivity has a greater influence and impact on overall productivity of the construction industry (Juikun *et al.* 2009). According to the statistics mentioned in the Malaysian Productivity Corporation in 2009 productivity growth rate of the construction industry is only 5% compared to the rate of increase in other sectors (Productivity Performance of Malaysia, 2009).

Labor productivity is mostly affected by factors such as material availability, incompetent supervision, lack of tools and equipments, poor communication, absenteeism, rework, inspection delays etc (Arun *et al.* 2004). Also, research done in Malaysia in 2005 has found that the lack of local workers, late issuance of payment, late material supply etc are the factors that highly influence labor productivity in the Malaysian construction industry (Roshana and John 2003, Oduba 2002).

Several models and techniques have been developed that consider these factors for estimation of labor productivity. Unfortunately, there is inadequate information available for labor production rates for the project estimator. Inconsistent and inadequate availability of productivity data are the major constraints towards successful execution of construction productivity prediction models (Song *et al.* 2008).

Productivity Models that have been developed includes the Factor Model for predicting productivity using factors (Thomas and Yiakoumis 1987), the Expectancy model for predicting performance of workers to estimate productivity (Maloney and Fillen 1985), the Action Response model to evaluate losses in construction productivity (Halligan 1994), the Statistical model developed to identify the effects of factors on productivity (Herbsman and Ellis 1990), and the Expert Simulation model developed to identify the combined effects of all the factors on productivity (Boussabiane and Duff 1996). However, Artificial Neural Network (ANN) model is found to be one of the artificial intelligence modeling techniques that has stronger prediction and learning capabilities as compare to the models mentioned above (Chan *et al.* 2006).

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. It can be arranged in different layers: input, hidden, and output as shown in figure 1.

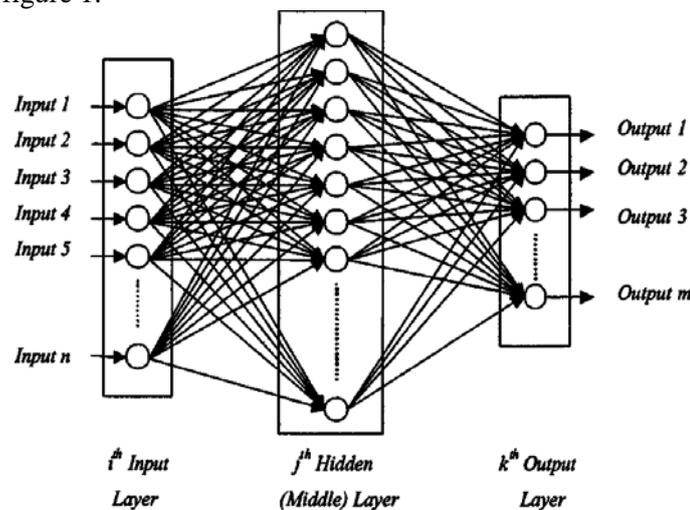


Figure 1: Typical structure of Feed forward ANN

Therefore, the objectives of this study are to measure the labor production rates for the concreting of slabs and to identify the factors influencing labor productivity during slab concreting at the site. This establishes a model using ANN for predicting the production rates of labor.

2. Research Methodology

The Activity sampling approach has been used to measure production rates by observing various ongoing concrete building structures in Malaysia. Seven building projects under JKR (Jabatan Kerja Raya) have been observed that includes building complexes in Ipoh, Kuala Lumpur, Grik, Subang and Pengkalan Hulu whose cost range from RM21 million to RM35 million.

Data Collection: Standard production rates of data collection are commonly used by various contractors for the estimation of rates. It contain quantities of work done, unit of measurement, gang size used and

severity of common influencing factors as shown in Table 2. Five commonly influential factors that are identified from the literature reviewed have been recorded at the sites including weather (F1), availability of material; equipment (F2), location of project (F3), site conditions (F4) and number of workers (F5). The form has been revised and rechecked by the author after getting comments from the contractors at the sites during the pilot survey. A stop watch has been used to calculate duration of activities at specific time interval.

The duration of slab concreting activity has been measured at each site in the morning and in the afternoon. The observer has managed to get twelve (12) samples of data for slab concreting from each project site. The data includes 84 samples from seven projects.

Data Analysis: After getting the production rates from the field the data have been moderated using descriptive analysis. In order to rank the influencing factors recorded at sites, a severity index has been calculated. Availability of material and equipment has been ranked first among all 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 1.

Table: 1 Descriptive Analysis

Description	Low	Average	High	Total	Mean	Severity index	Ranking
	3	2	1				
Availability of material & Equipment	45	27	12	84	2.393	192.57	1
Location of the project	13	31	40	84	1.679	112.90	5
Weather	39	30	15	84	2.286	181.46	3
Site Conditions	23	46	15	84	2.095	165.46	4
No. of workers	40	31	14	85	2.306	186.12	2

Model Development: Matlab 7.0.4 has been used to develop the ANN model. Seventy two percent (72%) of the total number of data have been used for training the ANN model whereas twenty eight percent (28%) have been used for testing. The number of input neurons is equivalent to the number of influencing factors recorded at sites which are equal to five (5). There is one hidden layer used with three hidden neurons. The number of epochs used is 1300 at which the network shows maximum convergence as shown in figure 2. A learning algorithm is used as gradient descent with momentum back propagation using log sigmoid transfer function. The 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 modification in number of data and number of input neurons. Mean Square Error (MSE) has been found by using the formulas as given below:

$$MSE = \frac{1}{N} \sum (ActualRate - PredictedRate)^2$$

3. Result and Discussion

The ANN model has been trained by using 72% of the data samples. Five neurons have been used in the input layer including F1, F2, F3, F4 and F5 with one output neuron as production rate in the output layer. There is one hidden layers comprising three hidden neurons. Out of seven projects, five project data have been used for training the network (72% of total data) and the remaining two projects data (28%) have been used for testing. The trial and error method has been used to reduce the MSE by varying the number

of neurons in the hidden layer and number of epochs. Minimum MSE has been achieved with three numbers of hidden neurons and 1300 number of epochs as shown in figure2.

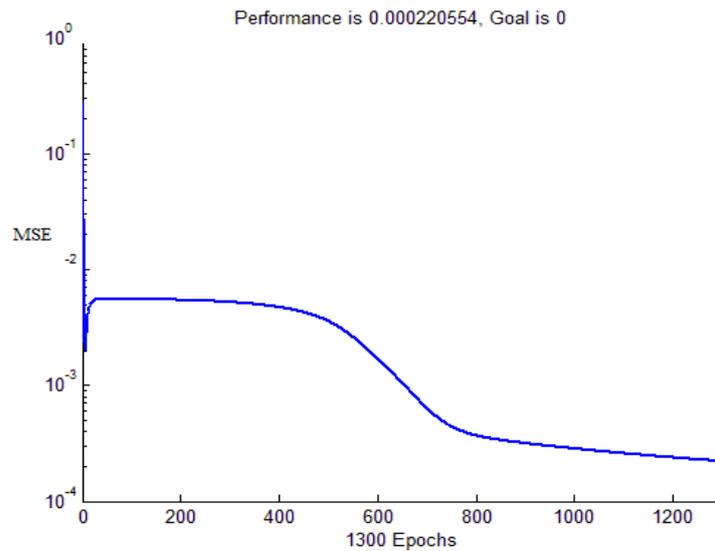


Figure 2: Network Training

During training, the network has predicted the production rates with lower values of MSE and follows similar trends and patterns of target values as shown in figure 3.

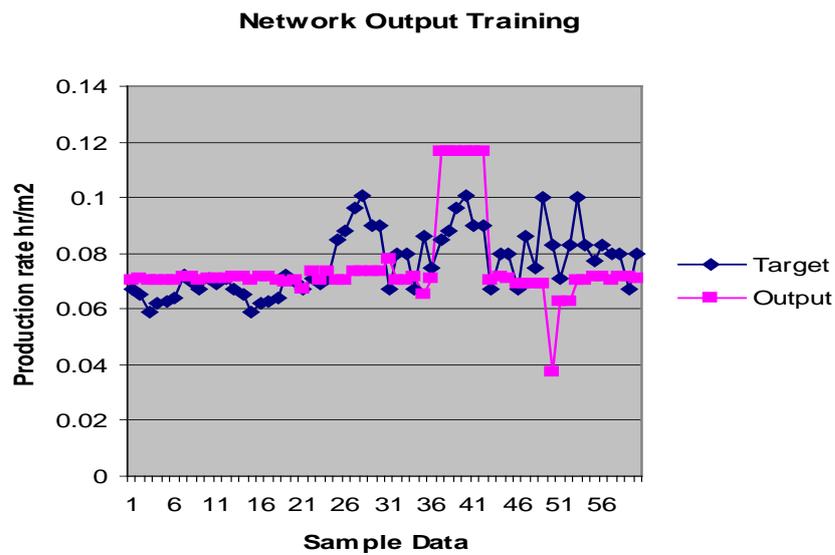


Figure 3: Network Output Training Error

Production rate values predicted during the testing of the network are within the range of target values although the trend between target and output values has variation as shown in figure 4.

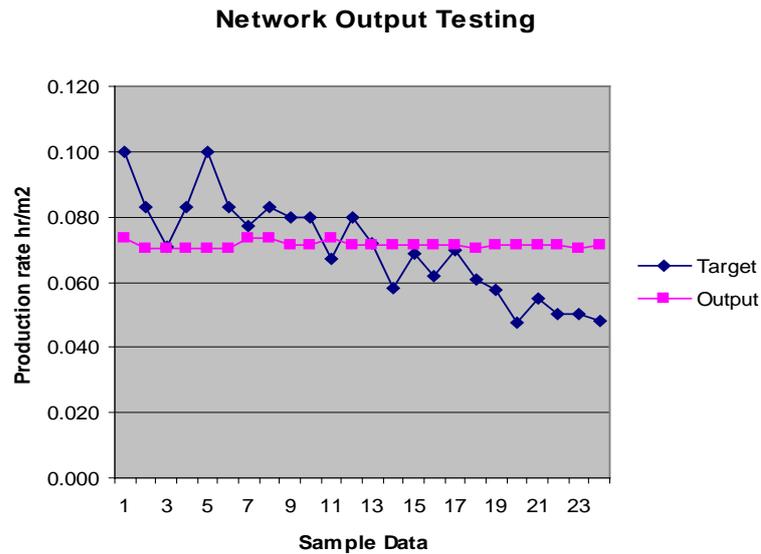


Figure 4: Network Output Testing Error

Mean Square Error (MSE) has been calculated from the outputs of training and testing of the network as shown in Table 2. The results show that MSE of training and testing is not greater than 10^{-3} , hence the network has achieved better convergence.

Table: 2 Artificial Neural Network Results

	Project Code	Avg. Actual Rate (hr/m)	Predicted Rate (hr/m)	MSE
Training	P1001	0.0666	0.0707	0.00003
	P1002	0.0666	0.0708	0.00006
	P1003	0.0720	0.0711	0.00033
	P1004	0.0748	0.0762	0.00071
	P1005	0.0762	0.0744	0.00119
	Average MSE (Training)			0.00046
Testing	P1006	0.0822	0.0716	0.00020
	P1007	0.0707	0.0713	0.00045
	Average MSE (Testing)			0.00032

4. Conclusion

The Artificial Neural Network model developed has been able to achieve the objectives of this paper. With strong learning capability and pattern recognition the ability of the neural network to estimate the production rate for slab concreting have been predicted accurately with acceptable error. Production rates values of concreting slabs have been calculated on site by observing seven different types of building projects.

Factors influencing these rates include weather, availability of material and equipment, location of project, site conditions, and the 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. This has a greater influence on the accurate estimation of production rates.

Reliable values of production rates with incorporation of these factors have been successfully predicted by the ANN model. Performance of the model has been determined by calculating the MSE (Mean Square Error) of the predicted production rates. The values calculated for MSE of training and testing outputs are 45×10^{-4} and 32×10^{-4} . These results indicate that the ANN model has predicted production rates values for slab concreting reasonably within acceptable range of errors.

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