PREDICTING CONSTRUCTION CREW PRODUCTIVITY FOR CONCRETE POURING OPERATIONS OF RC COLUMNS USING ANN

PARTH PATEL, DHARMIK V. PATEL, VISHAL H. LAD, ANKITKUMAR PATEL, KASHYAPKUMAR A. PATEL, and DILIPKUMAR A. PATEL

Dept of Civil Engineering, Sardar Vallabhbhai National Institute of Technology (SV-NIT), Surat, India

In current practice, construction crew productivity (CCP) assessment solely relies on traditional methods like personal judgements or past published data. However, a systematic approach is required to measure and predict the CCP. Modelling with artificial neural networks (ANNs) can be useful for examining interrelationships between factors affecting CCP. The present study aims to predict CCP for concrete pouring operation of reinforced concrete (RC) columns using ANN. To achieve this, 14 factors like crew size, average age of crew, average experience of crew, extent of supervision, working hours, lead distance, working height, location of columns, number of concrete bucket carriers, method of concrete supply, temperature, wind speed, column length, and column width were identified from literature study and industry experts. These identified factors were considered as inputs, while CCP was the output variable for ANN model. The study collected 187 samples from 11 residential and commercial construction sites located in four cities of India. A single-layer feed-forward back propagation neural network was used for prediction. The developed model can estimate productivity rates reasonably with least range of errors. Outcomes of study can be useful to improve the crew’s productivity at construction sites for concrete pouring works of RC columns.

Keywords: CCP, Concrete pouring work, Reinforced concrete column, Artificial neural networks.

1 INTRODUCTION

Technological developments are rising and replacing traditional work methods, but the construction industry is still labor intensive. Lee et al. (2002) and Ghodrati et al. (2018) stated that labor contributes approximately 30-50% of overall construction project costs around the globe. Labors working in a crew are predominant determinants, denoting the success or failure of concrete pouring activity. Thus, variations in CCP may affect building project financing. El-Gohary et al. (2017) advocated that CCP estimate depends mainly on conventional approaches like human assessment, public productivity figures, and prior project data. However, relying on the accuracy of these traditional and subjective methods may affect CCP. For this, modelling CCP is essential for improving productivity estimates and eliminating subjectivity and inapplicability of traditional methods. Therefore, this study aims to develop a model for predicting CCP of RC columns for concrete pouring activity using ANN.
2 LITERATURE REVIEW

Construction labors are a critical resource in every construction project; hence labor productivity has attracted researchers and practitioners for two decades. Several researchers such as Enshassi et al. (2007), Jarkas et al. (2015), El-Gohary et al. (2017), Alaghbari et al. (2019), Karthik and Kameswara Rao (2022), and Golnaraghi et al. (2019) have identified and worked with several influencing factors in order to compute or improve labor productivity. These studies also indicate the interdependency between influential factors and CCP. To investigate this interdependency, many modelling strategies have been proposed using applications like expectancy models, action-response models, statistical and regression models, expert systems, and ANNs. Heravi and Eslamdoost (2015) stated that expectancy and action-response models help understand productivity changes but can't quantify effect of elements affecting construction productivity. They also advocated that expert systems have limited mapping function and solution-finding skills. Thus, developing a model for evaluating and forecasting crew productivity needs a comprehensive mapping of impacting factors because various factors impact crew productivity at same time. Further, this mapping incorporates quantification of effects of factors on crew productivity and evaluates interactions between factors. ANN can learn from experience in order to improve its performance and adapt to changes in environment. Further, Heravi and Eslamdoost (2015) stated that ANN model can discover the same output pattern when provided with new input pattern. They can manage missing or noisy data and can be quite efficient, especially in cases where relationships between inputs and outcomes are poorly understood. As a result, ANNs may be a good choice for predicting labor productivity.

Several research studies have developed an ANN model to compute or predict labor productivity for several different construction activities. Moselhi and Khan (2010) used ANN modelling to explore the influence of various factors on labor productivity for formwork operations in building construction. Heravi and Eslamdoost (2015) developed an ANN model to forecast construction productivity rates for foundation work. Aswed (2016) developed an ANN model and predicted realistic estimates of bricklayer labor productivity rates. El-Gohary et al. (2017) used ANN to simulate construction labor productivity for RC rafts and RC isolated footings of commercial and residential structures. Golnaraghi et al. (2019) used the ANN model to assess the labor productivity for formwork assembly activity. Bokor et al. (2021) showed network configurations of the ANN model to forecast the productivity of bricklaying activity. Thus, the literature review explores the previously developed ANN models used to predict labor productivity in construction projects for various trades. Moreover, most of the aforementioned studies have used qualitative data to develop an ANN model. Furthermore, only a few studies address concrete pouring activity by developing an ANN model, such as Ezeldin and Sharara (2006) employed ANN to predict CCP for concrete pouring activities using factors such as structural element, concrete quantity, crew size, pouring method, supervision, labor skills, overtime, task complexity, material accessibility, degree of repetition, and temperature conditions. However, present study aims to develop a novel prediction model that can predict CCP for concrete pouring activity by considering some significant factors from the study of Ezeldin and Sharara (2006) such as temperature, supervision, crew size, pouring method, and task complexity, along with six novel factors (identified by authors) such as working hours, lead distance, location of column, number of concrete bucket carriers, column length, and column width. It is essential to note that some of factors were either eliminated based on their insignificance or modified based on the requirements. Present study makes more emphasis on unskilled labors working in crew and only considers RC columns as a structural element for developing an ANN model in building construction projects.
3 RESEARCH METHODOLOGY

A four-step methodology was developed, and it is described as follows:

3.1 Determination of Input and Output Factors

In the first step, a total of eight factors that influenced CCP of concrete pouring operation for RC columns were identified from the literature review. Then, a face-to-face interview with an open-ended questionnaire was conducted with 30 industry professionals having average experience of 12 years. All the experts were satisfied with these factors, but they also suggested to add six more factors that influenced CCP of concrete pouring activity for RC columns. Thus, these 14 factors showed in table 1 were considered as input, while CCP was the output in the development of the model. Further, the identified factors were categorized into two types: objective and subjective variables. The objective variables were measured in their respective measuring units (Table 1). The subjective variables such as the extent of supervision, location of column, and method of concrete supply were computed using a three-point Likert scale. The Likert scale conversion is as follows: supervision (1-Little, 2-Moderate, 3-Strict); location of column (1- Four side access, 2-Three side access, 3- Two side access); and method of concrete supply (1- Concrete pump, 2-Concrete lift, 3- Other). Figure 1 shows the pictorial representation of column location, which is converted into the Likert scale. The CCP rates of concrete pouring operation for RC columns (output factor) have been recorded by field observations. Additionally, the rate of influencing factors was measured for individual pouring operations.

![Figure 1. Description of column location in the Likert scale.](image)

3.2 Selection of Training and Architecture Criteria

In the second step, the supervised backpropagation feed-forward neural network was adopted. Logistic sigmoid function (logsig) was used as an activation function at hidden neurons, whereas linear transfer (purelin) function was used as an activation function at output neurons. For training, the Levenberg-Marquardt learning algorithm (trainlm), an enhanced version of the classic backpropagation technique, was employed. Then, the learning rate, which is one of the most influential criteria, was applied, as it reduces the training error in each iteration during the training. The learning rate normally ranges from 0.0 to 1.0, where high value gives divergent oscillations and low-value results to slow training. In this regard, the learning rate for the current study was considered to be 0.5. Lastly, the momentum coefficient, which aids in quickly arriving at the best value for reducing noise in gradient updating, was assumed as 0.2.

3.3 Training, Validation, and Testing of Data

In the third step, first data were collected from 11 ongoing residential and commercial projects located in four cities (Surat, Ahmedabad, Gandhinagar, and Bhavnagar) of India. Project scale and project duration of these projects range from USD 55 to 263 million (INR 43 to 205 crore) and 15 to 36 months, respectively. Moreover, the number of construction workers working on individual sites ranges from 27 to 145 persons.
When choosing the projects for the research, three primary characteristics were considered. First, the project must contain a lot of recorded concrete work. Second, the construction methods employed in executing the concrete operations were identical and need to be completed within 1–2 years after acquiring the data. Third, the concrete element in the data should be reflective of a comparable element in the market. As mentioned above, just RC columns were chosen as the concrete element for this study. From these 11 projects, a total of 187 field observations were collected for the 14 factors and CCP rates. The data for the 14 factors were as per their measurement units of measurement (Table 1). In contrast, the CCP rate was quantified as the ratio of the quantity of work done (in m³) to hours required. Then, the collected 187 data were divided into 80%, 10%, and 10% for training, validation, and testing, respectively.

### 3.4 Finalization of Network Configuration

In the fourth step, one hidden layer was used to decrease the computational effort and complexity of explicit expressions. However, the number of neurons in the hidden layer was finalized through a trial-and-error process. A vast number of trials with varied numbers of hidden neurons in the layer were undertaken for training. Overtraining can occur if a large number of hidden neurons are chosen. As a result, training begins with a modest number of hidden neurons and gradually increases while concurrently checking all three sets for errors. Based on the errors for all sets, the number of hidden neurons was determined. The architecture of the ANN was finalized at 14-16-1,
where 14, 16, and 1 are the numbers of input, hidden, and output neurons.

4 RESULT AND DISCUSSION

The research methodology described in the previous section was performed using MATLAB (R2015a version). The MSE value was achieved as 0.00280, 0.00565, 0.01042 for training, validating, and testing, respectively. This shows that ANN was well-trained without being overtrained. The bar chart presented in Figure 2 shows the 18 data sets which were used for testing purposes while developing the ANN model. It can be said that difference between actual and predicted rates is comparatively lower and acceptable.

Average absolute difference calculated for testing and validating is 14.23% and 13.44%, respectively. It shows that percentage error of training and validating is within 15% of actual productivity rates and the values calculated for MSE of testing and validating are 0.01042 and 0.00565, respectively. However, in the study of Ezeldin and Sharara (2006), target range of MSE for testing was 0.1. In addition, at 70%, 80% and 90% accuracy level for concrete pouring activity, percentages of acceptable exemplars were 65%, 55%, and 42%, respectively. Thus, it has generated least number of acceptable exemplars. But, in present study the obtained accuracy for training and validation set was greater than 85%, which shows an improvement is obtained.

![Figure 2. Comparison of the testing data set.](image)

Further, the results also illustrate the influence of some significant input factors on CCP. Such as, CCP may increase up to 160%, if average experience of crew increases to 16 years from 4 years. CCP may change by ±130%, depending on the extent of supervision. An average of 84% decrease in CCP may result if lead distance increases to 85 steps from 3 steps. CCP may reduce by one third if average age of crew increases from 23 to 36 years. Up to a 72% increase in CCP may result if column width increases to 0.45 m from 0.15 m. Similarly, CCP may increase by 46% by increasing column length.

Thus, the findings of present study is in line with acknowledgement of the Ezeldin and Sharara (2006) that a large set of quantitative data for training and testing would improve the percentages of acceptance errors at all the levels and, as such, the confidence in the output. Simultaneously, it can be stated that the findings from the present study have shown good learning and generalized
capabilities of proposed model. Further, based on the obtained results, an explicit expression is still required to be developed with the final weights and biases for the prediction of the CCP on actual building projects.

5 CONCLUSIONS

In present study, the ANN framework for forecasting the CCP of concrete pouring operations was trained and tested for RC columns by incorporating the measurable influencing factors. The mean square error (MSE) was used to determine the model's performance and the observed value was 0.010. Results indicate adequate network convergence and generalization. CCP studies for concrete pouring operation of RC columns with this large data sets and number of affecting factors have not been explored before in literature. The current research is effective for predicting productivity rates considering stated influencing factors. But, the performance of the model can be improved by collecting more data sets. The scope of the present pilot study is limited to the manual concrete pouring operations with RC columns. It can be extended for RC slabs, beams, foundations, and other structural members.

References


