# Analyzing Labor Productivity for Reinforcement Installation Using Artificial Neural Network in India

**Jignesh M. Mistry and Geetha K. Jayaraj**

**Abstract** The current investigation study aims to develop a productivity model analyzing the prediction performance for reinforcement installation activity for building projects using artificial neural networks. Fifty-six data were collected from Real Estate Regulatory Authority (RERA) registered residential projects across India. Soft computing tool of MATLAB was utilized for developing the productivity model. A multilayer feedforward network trained with backpropagation algorithm was used as basis, and further optimization of the network was done using Levenberg–Marquardt training function. Different network architectures and data points were tested for obtaining the superlative network for predicting labor productivity. The optimum network comprised of 16 input neurons, followed by 15 hidden neurons and single output fully connected. The developed model showed a respectable regression value between the predicted and the actual output with mean square error of less than seven. The findings of this research study provide awareness of the importance of documenting historical data for prediction of labor productivity.

**Keywords** Productivity · Artificial neural network (ANN) · Processing element (PE)

## 1 Introduction

The construction industry in developing nations faces various constraints in the different phases of the project. One of the major constraints is associated with construction labor, i.e., productivity. Construction labors are the most prominent choice for the various agencies involved in the industry for carrying out work, as

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they are effortlessly available and for affordable price [1]. Consequently, with the involvement of the labor for execution of the construction works, monitoring of the task work becomes indispensable to ensure that the work is completed effectively, within the specified limits of tolerance and of the required quality. The productivity of labor is often estimated by the senior execution engineer and/or project manager based on experience of the previous work of similar nature, but they are unable to structure a forecasting model for determination of productivity using statistical analysis, neither reflect upon the factors impacting the construction labor productivity [2]. Also, one of the major drawbacks in the developing nation is lack of proper documentation of the construction works which often leads to difficulty in the investigation of productivity of labor. The complex nature of productivity associated with the multiple factors and their interrelationship is determined based on previous works and knowledge by experienced personnel. Analogous to the functioning of the human brain to learn from previous experience [3], a similar soft computing technique could be utilized for prediction of labor productivity. Artificial Neural Network (ANN) has gained a lot of popularity among the researchers with its applications in various engineering problems over the past few decades, and the same can be utilized for the prediction performance of labor.

The working of the ANN is motivated from working of the human brain [3]. The human brain acquires knowledge and learns from huge set of memories in the past and generalizes the output to a new situation in comparison to the previous events from the past. Similarly, ANN has competence to learn from a given set of parameters for a defined problem and its associated output patterns (representing the decision). The network is trained with adequate amount of sample sets until the network is able to generalize the knowledge for the defined problem and becomes proficient in providing a solution for an entirely new problem of similar nature even if there are variations or noise in the dataset is available [4]. Variation in the productivity is caused because of the multiple factors, and resulting relationship between the influential parameters and productivity could be quantified using productivity model. ANN has also been successfully utilized by many researchers in the past for various prediction performances of labor for formwork installation, reinforcement installation, and concrete pouring and finishing works [4–8].

The current research study focuses on developing a simple yet effective prediction model of labor productivity for reinforcement installation activity across India for residential projects with the application of ANN.

## 2 Literature Review

Starting in the late 1990s, several researchers have made a remarkable work for estimating the productivity of construction works using ANN model. Jason and Simaan [2] in Canada developed a model forecasting formwork for columns, slabs, and walls [2]. After conducting numerous tests on the different network architectures, a three-layered network with a fuzzy output was selected for the study. The selected model was then tested in a workshop, wherein only 2 out of 12 estimators were able to estimate the formwork productivity for foundation wall within 5% error range. In the following year, Rifat and James [4] in Iowa, United States of America made a comparison of regression model and ANN model for prediction of concrete pouring, concrete finishing, and formwork task [4]. The inputs were varied for different regressions and ANN model. Based on the tests performed on both models, ANN had a better prediction performance for formwork and concrete finishing activity, while regression model had better forecasting performance for concrete pouring activity. Later, Samer and Lokman [5] structured a productivity model for formwork erection, steel fixing, and concrete pouring task in Egypt [5]. Data for the study were collected from residential, commercial, and industrial projects of similar attributes of work. A feedforward network trained with backpropagation algorithm was utilized for developing ANN model for all three concreting activities. From sensitivity analysis factors like hot weather condition and skills of labor had a significant impact on productivity. Further, depending on accessibility to materials, the productivity is enhanced by 30% and with repetitive nature of work the productivity is excelled by 20% enhanced. Self-Organizing Map (SOM) model was developed for prediction of construction crew productivity for concrete pouring, formwork, and reinforcement activities by Emel and Mustafa in Turkey [9]. SOM-based model was able to effectively cluster the data into two-dimensional maps. Further, with the colorful maps guided, a visual environment for data analysis and the prediction performance of SOM-based model is analogous to similar preceding ANN model. In the succeeding year, Dikmen and Murat [6] developed ANN model in Turkey for forecasting man-hour required for formwork installation activity [6]. A multi-layered feedforward network trained with backpropagation was selected for the model. The selected model was then tested over two live projects of similar attributes. The errors in prediction of two projects were 5% and 15%, respectively, which were less in comparison to estimating using Turkish Ministry of Public Works and Settlement (MP + S). Sana et al. [7] developed a productivity model for forecasting production rates of formwork for high-rise structures in Malaysian construction industry [7]. The data were collected from seven different projects of similar nature. The forecasted model had a precise production rate estimation with minimum error in comparison to similar study conducted by Samer and Lokman [5]. Gholamreza and Ehsan constructed ANN model for predicting productivity of labor for concrete works in Iranian construction industry [8]. A total of 15 factors were identified, and the data for the same were collected from 39 different projects for concreting of foundation of gas, steam, and combined cycle power plant. A multi-layered feedforward network trained with backpropagation algorithm was used to develop the network. For optimization, Bayesian regularization had a better prediction performance than early stopping for the two projects which were utilized to test the network proficiency. As observed, several researchers have been able to successfully deploy ANN model to forecast production rates of labor for various concreting activities like steel fixing, formwork installation, concrete pouring, etc., in different countries; a similar research can be conducted for Indian construction industry. Thus, the study aims to utilize ANN for prediction of labor production rates for reinforcement installation activity in India.

## 3 Methodology

As shown in Fig. 1, the research conducted comprises four intervals: (1) identifying the significant factors; (2) formulating the data collected; (3) designing the neural network; and (4) post-training analysis.

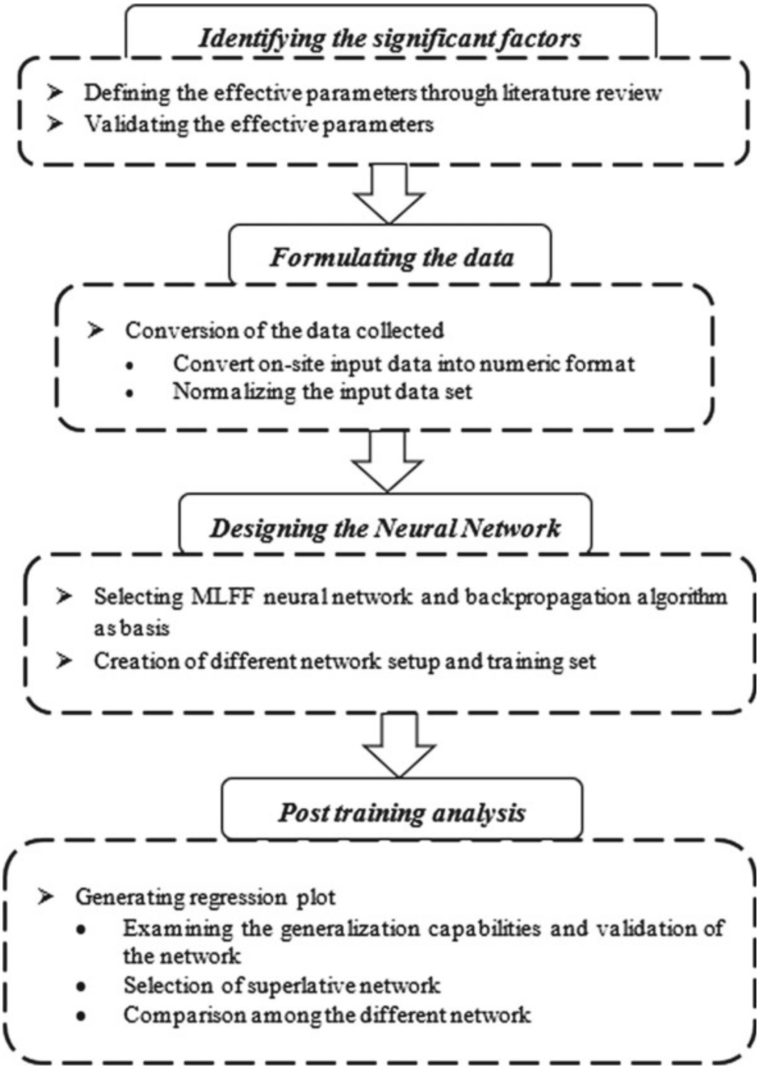


**Fig. 1** Research method's detailed structure

### 3.1 Identification of Significant Factors Affecting Productivity of Labor

The primary task to structure the proposed productivity model is to identify the parameters impacting the labor productivity for reinforcement installation task. The foremost 10 significant factors impacting the reinforcement installation activity in India were identified using relative importance index (RII) and ranked accordingly, and the details for the same ARE represented by Jignesh and Geetha [1].

### 3.2 Formulating the Data Collected

**Conversion of the data collected**. Productivity is simply defined as ratio of unit output per given unit input in theoretical terms [9]. But as mentioned by Abdulaziz and Camille [10], based on measurement objective and availability of the data, several definitions of productivity can be encountered [10]. Correspondingly, the measure of productivity for the same task work is conducted in different manners for varied region, thus making the resulted productivity not directly analogous [9]. For this study, the definition of productivity of labor is shown in Eq. 1 [5]:

$$\text{Labor Productivity} = \frac{\text{Crew Size} * \text{Duration}}{\text{Quantum of work}} (\text{man} * \text{days/unit}) \tag{1}$$

where units for measurement of productivity of labor for reinforcement installation are (man*days/tones). Initial questionnaire was prepared based on literature review. The survey form was rectified by three experts from construction industry registered with ISTE (Indian Society of Technical Education) membership to ensure that the factors are relatable for Indian construction industry for finalizing the questionnaire. The final survey form consisted of four sub-sections, viz., (i) general background of the respondent, (ii) general description of the project under execution, (iii) description of structural member under consideration for productivity measurement, and (iv) 23 factors listed affecting reinforcement installation activity. Under the third section, i.e., the description of the structural member considered for productivity measurement involved six questions: (1) structural member under consideration, (2) quantum of the work (ton), (3) duration of the task (days), (4) number of labors required to complete the task (nos.), (5) working condition, and (6) temperature consideration. Three factors, i.e., structural member under consideration, working condition, and temperature condition were in a linguist manner. The data points were converted into numeric format in order to develop ANN model. Table 1 depicts the scalar value for three factors.

**Normalizing the input data**. A total of 56 data were collected from residential projects registered under Real Estate (Regulation and Development) Act (RERA) in India [11]. The data collected were normalized which is a standard practice

**Table 1** Scalar value for factors to convert into numeric format

| Scaled value → Factors ↓ | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|
| Structural member | Overhead water tank | Prestressed slab | Slab | Column | Footing |
| Working condition | Mild | – | Moderate | – | Harsh |
| Temperature | Hot (26 to 42 °C) | – | Moderate (13 to 25 °C) | – | Cold (5 to 12 °C) |

for constructing ANN model. The numeric data were normalized in a range of (−1,1), because of such scaling an improvement is made over the data for the confined problem domain [12] allowing the neural network to pace up with the better generalized output results. The data is normalized using Eq. 2 given by [12, 13]

$$\text{Scale value} = \left(2 * \left[\frac{\text{Unscaled value} - \text{VariableMinimum}}{\text{VariableMaximum} - \text{VariableMinimum}}\right]\right) - 1 \quad (2)$$

where unscaled value is the value provided by the respondent on Likert scale, variable maximum is the maximum value of Likert scale, and variable minimum is the minimum value of Likert scale, respectively, for an individual factor. The total number of input parameters is 16, out of which 10 were identified determining the RII [1] as shown in Table 2 and 6 factors (structural member under consideration, quantum of the work, duration of the task, number of labors, working condition, and temperature) are also referred by [5] for developing ANN prediction model for concreting activities as shown in Table 3, respectively.

**Table 2** List of top 10 factors affecting labor productivity with RII [1]

| Factors | RII (%) | Rank | |
|---|---|---|---|
| Skills of labor [2, 5, 7, 8] | 87.50 | 1 | $\mathbf{X_1}$ |
| Supervision of foremen [8] | 85.00 | 2 | $\mathbf{X_2}$ |
| Stringent inspection by engineers and supervisor [8] | 84.29 | 3 | $\mathbf{X_3}$ |
| Material supplies on time [7, 8] | 83.57 | 4 | $\mathbf{X_4}$ |
| Overtime provision [4, 5, 8] | 82.86 | 5 | $\mathbf{X_5}$ |
| Safety measures [8] | 82.50 | 6 | $\mathbf{X_6}$ |
| Size of crew [2, 4, 5, 8] | 80.71 | 7 | $\mathbf{X_7}$ |
| Accuracy rates and details in design [2, 8] | 80.36 | 8 | $\mathbf{X_8}$ |
| Method of hauling [2, 7, 8] | 79.29 | 9 | $\mathbf{X_9}$ |
| Height of work [6] | 78.21 | 10 | $X_{\mathbf{10}}$ |

**Table 3** Other factors for ANN model development [5]

| Other 6 factors used for developing ANN model | |
|---|---|
| Structural member under consideration [4, 5] | $\mathbf{X_{11}}$ |
| Quantum of the work [2, 4, 5] | $\mathbf{X_{12}}$ |
| Duration for task completion [5] | $\mathbf{X_{13}}$ |
| Number of labors [2, 4, 5, 7] | $\mathbf{X_{14}}$ |
| Working condition [2, 5, 8] | $\mathbf{X_{15}}$ |
| Temperature [2, 4, 5, 7, 8] | $\mathbf{X_{16}}$ |

### *3.3 Designing the Neural Network*

For this investigation study, the network architecture of multilayer feedforward trained with backpropagation algorithm is utilized for developing the ANN model as shown in Fig. 2, as this has been successfully implied in various prediction models for concreting activities [2, 4, 6–8].

**Network architecture and learning algorithm for developing the network**. *Multilayer Feedforward network* (MLFF). A network comprising more than one computational node is referred to as multilayer feedforward network. These computational nodes are corresponding to the hidden neuron (processing elements) in the hidden layer. Hence, an MLFF network comprises input–hidden–output node, where each layer consists of processing elements (PEs) depending upon the model to be constructed. The PEs in each layer are characterized by a weight known as connection weight. The weighted sum of all the PEs is processed through each of the nodes with the help of activation (squashing/transfer) function, which is fundamental operation for mapping the inputs with the output. If the net input at each of the summing junctions is lesser/greater in order to acquire the desired output, an external bias is applied to increase/decrease the net input at the summing junction [3]. A precise detail for various network architectures and its fundamental is illustrated by Simon [3].

*Backpropagation (BP) Algorithm.* Also popularly known as the delta rule is one of the most popular training algorithms used for MLFF network. The network with multivariate random inputs with linear and non-linear computation and approximating any continuous function with the desired output can be efficiently performed using MLFF with BP algorithm [14]. One of the common problems for BP algorithm is that it may cause overfitting [8, 14], which simply implies that the error of the training set is driven to a very small value, but when a new set of data is presented to the same network, the error is large, indicating that NN has memorized the training dataset, but has not learned to generalize a new situation. In order to overcome this limitation, a faster BP algorithm, i.e., Levenberg–Marquardt (LM) is used [14]. This algorithm acquires a lower mean squared error (MSE) for function approximation problem in comparison with any other algorithm [15].

**Creation of different network setups and training set**. A commercial tool of neural network toolbox MATLAB R2019 [16] software is utilized to train, validate,

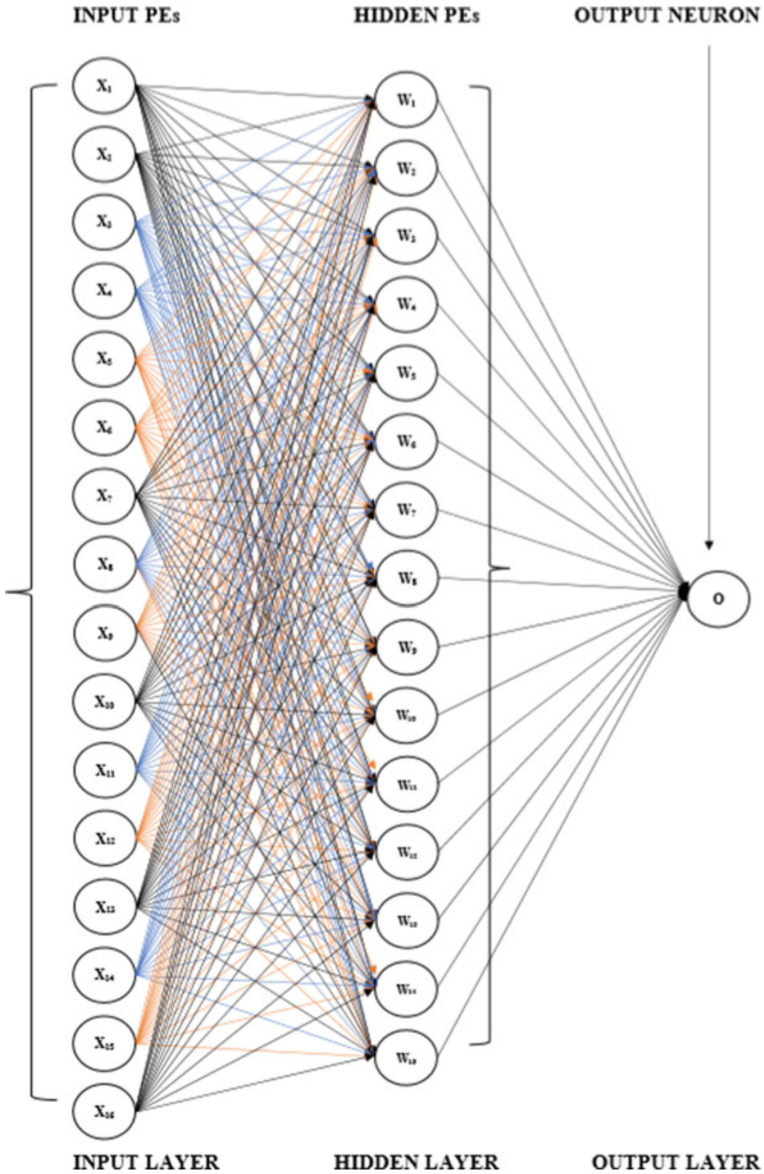


**Fig. 2** A multilayer feedforward NN

and test the networks for labor productivity. Network development is an experimental process, and a lot of trials and the various configurations were investigated in order to achieve the most appropriate network. Following are details of the configuration undertaken while developing the neural network model.

*Network Architecture and Learning Algorithm.* The neural network for this investigation study is an MLFF network with backpropagation algorithm in which the PEs for each of the nodes are fully connected.

*Training Function.* The network is trained with Levenberg–Marquardt (LM) backpropagation algorithm, i.e., "*trainlm*". For this type of network training function, the weights and biases are updated as stated to LM optimization. In comparison for the other training function for moderate-sized feedforward NN (i.e., up to several hundredweights), it is the fastest and requires more memory.

*Number of Layers.* The common practice to structure a neural network model for most of the problems is to initially start with two layers (one hidden) and then increase to 3 layers (two hidden layers) provided the network performance with two layers is not satisfactory. The performance of the network was adequate at two layers (one hidden), and the same was selected for this study.

*Number of Neurons.* The PEs for the input nodes are 16 and for the output node was 1. The PEs in the hidden node were varied, in order to compare the computational performance potential of the network under diverse condition. But too many PEs in the hidden node lead to complexity and requires more time for computation. To overcome this problem, [17] recommended as a thumb rule, the number of hidden neurons should be less than 2x the number PEs in the input node. The hidden neurons were varied starting from 5, and the performance of the network for its mean squared error was checked at each of the intervals for training, validating, and testing.

*Training, Validation, and Test Data.* The raw data for the test were distributed using different sampling points for input parameters, and the outcome of this sampling on the output parameters was consequently noted. The raw data were distributed into three parts: training, validation, and testing. The varied combinations for training data set were 90%, 85%, and 80%; for validation 5%, 10%, and 10%; and for testing the network 5%, 5%, and 10%, respectively.

*Activation Function.* The commonly implied activation functions for MLFF networks are the log-sigmoid (*logsig*), tan-sigmoid (*tansig*), and linear (*purelin*) in MATLAB. A combination of this activation function is used in various research studies for solving a variety of problems [8]. Since the inputs varied in the range of −1 to 1, *tansig* function was utilized between the input and hidden nodes to limit the inputs to the hidden layer. While *purelin* function was used between hidden and output nodes, as the output layer of the MLFF is function approximator. The details of the activation function and its use for solving various approximation problems are given in [3].

### *3.4 Post-training Analysis*

**Generation of Regression Plot**. After several trials and variations made in the network architecture and data points for training, the most significant network was opted which had a better generalization capability and validation of the network grounded on regression plot. Following are few observations made with respect to the network training and validation: (1) the PEs in the hidden node were varied in the interval of five, as the performance of the network at other intervals had a catastrophic failure; (2) out of three data points, the most significant results were generated at 85 − 10 − 5% for variation made in consideration to all the PEs in the hidden node; (3) the network performance is based on regression and mean square error (MSE), the data point 80 − 10 − 10% had significant results at $(2n - 1)$; 85 − 10 − 5% at $(n - 1)$; and for 90 − 5 − 5% at $(2n - 2)$ where $n$ is the number of inputs. The details of varied network characteristics and its performance are represented in Table 4.

## 4 Results and Discussion

The network with the most significant results was selected based on the generalizing competency and test performance of the network using the regression plot. The significant results were obtained at 85% training (47 samples), 10% validation (6 samples), and 5% testing (3 samples) dataset. The performance measure for the network was mean square error (MSE)—which is the ratio of total sum squared of difference between the actual output and the predicted output to the total number of samples. With variation in the PEs, i.e., from 20 to 31 had a decent network performance, but the testing of the network had a very low rate of performance measure (MSE), followed to which the performance measure further degraded with PEs of 10 and 5. At 15 hidden PEs, the MSE of 0.07 for training, testing, and overall performance of the network indicating a stronger correlation between the predicted output and the actual output. The regression plot is shown in Fig. 3 which is the correlation between the targeted output and the predicted output.

For perfect fit, the data points should lie at 45° line (dotted line), where the regression value is 1 and MSE is minimum, i.e., 0 [15], and for this case is 0.07. The network is first trained with a set of parameters (training set), after which the performance of the trained network is validated (validation set), and finally a new set of data is represented (testing set) to incorporate how the network response to entirely new data points not utilized for its training and validation (generalization capability).

Table 5 represents the performance of the network over testing data points. The prediction error for the second and third project is lesser than 0.07, while that for the first project is of 0.12. The predicted output for all the three projects is marginally greater than the actual output, indicating that the performance of the network for an entirely new data points had a respectable prediction performance.

## 5 Conclusion

The purpose of this investigation study was to develop a model for quantifying and predicting the construction labor productivity for reinforcement installation activity

**Table 4** Statistical analysis of the ANN productivity model using different network architectures and data points

| Hidden PEs | Datasets | 90 − 5 − 5% | | 85 − 10 − 5% | | 80 − 10 − 10% | |
|---|---|---|---|---|---|---|---|
| | | Statistical parameters | | | | | |
| | | $R^2$ | MSE | $R^2$ | MSE | $R^2$ | MSE |
| 5 | Training | 0.597 | 0.2723 | 0.941 | 0.0970 | 0.952 | 0.0349 |
| | Validation | 0.605 | 0.1232 | 0.981 | 0.0919 | 0.184 | 0.3749 |
| | Testing | 0.779 | 0.4382 | 0.855 | 0.2396 | 0.928 | 0.1917 |
| | Overall | 0.577 | 0.2732 | 0.935 | 0.1041 | 0.834 | 0.0881 |
| 10 | Training | 0.924 | 0.0404 | 0.983 | 0.0232 | 0.880 | 0.0920 |
| | Validation | 0.466 | 0.1050 | 0.770 | 0.3237 | 0.836 | 0.1482 |
| | Testing | 0.924 | 0.0404 | 0.778 | 0.5348 | 0.836 | 0.1170 |
| | Overall | 0.912 | 0.0465 | 0.938 | 0.0828 | 0.800 | 0.1007 |
| 15 | Training | 0.861 | 0.0954 | 0.948 | 0.0726 | 0.915 | 0.0482 |
| | Validation | 0.299 | 0.2062 | 0.967 | 0.1002 | 0.638 | 0.1564 |
| | Testing | 0.498 | 0.5025 | 0.999 | 0.0075 | 0.478 | 0.1336 |
| | Overall | 0.824 | 0.1231 | 0.945 | 0.0721 | 0.830 | 0.0882 |
| 20 | Training | 0.935 | 0.0427 | 0.996 | 0.0055 | 0.725 | 0.1360 |
| | Validation | 0.955 | 0.1932 | 0.815 | 0.3030 | 0.647 | 0.2241 |
| | Testing | 0.972 | 0.0884 | 0.936 | 0.1771 | 0.628 | 0.2427 |
| | Overall | 0.912 | 0.0532 | 0.968 | 0.0465 | 0.681 | 0.1569 |
| 25 | Training | 0.861 | 0.1247 | 0.996 | 0.0053 | 0.745 | 0.1360 |
| | Validation | 0.470 | 0.2446 | 0.829 | 0.2826 | 0.421 | 0.2307 |
| | Testing | 0.994 | 0.1664 | 0.980 | 0.1390 | 0.673 | 0.1225 |
| | Overall | 0.833 | 0.1334 | 0.969 | 0.0422 | 0.693 | .01447 |
| 30 | Training | 0.997 | 0.0022 | 0.880 | 0.1902 | 0.999 | 0.0009 |
| | Validation | 0.931 | 0.0307 | 0.884 | 0.1760 | 0.353 | 0.7500 |
| | Testing | 0.997 | 0.1225 | 0.966 | 0.0887 | 0.579 | 0.2287 |
| | Overall | 0.956 | 0.0250 | 0.864 | 0.1833 | 0.834 | 0.1056 |
| 31 | Training | 0.620 | 0.2223 | 0.999 | 0.0017 | 0.996 | 0.0026 |
| | Validation | 0.713 | 0.5860 | 0.948 | 0.1337 | 0.698 | 0.2148 |
| | Testing | 0.146 | 0.3023 | 0.879 | 0.2321 | 0.725 | 0.4385 |
| | Overall | 0.517 | 0.2461 | 0.981 | 0.0277 | 0.902 | 0.0720 |

for residential projects in India, using ANN. The factors impacting the labor productivity were identified through literature review and consulting the experts from the industry. These factors were scaled and normalized in order to be utilized for the developed model. Furthermore, to quantify the non-linear and complex relationship between the productivity of the labor and the factors identified, a multilayer feedforward network trained with backpropagation algorithm was used as a basis

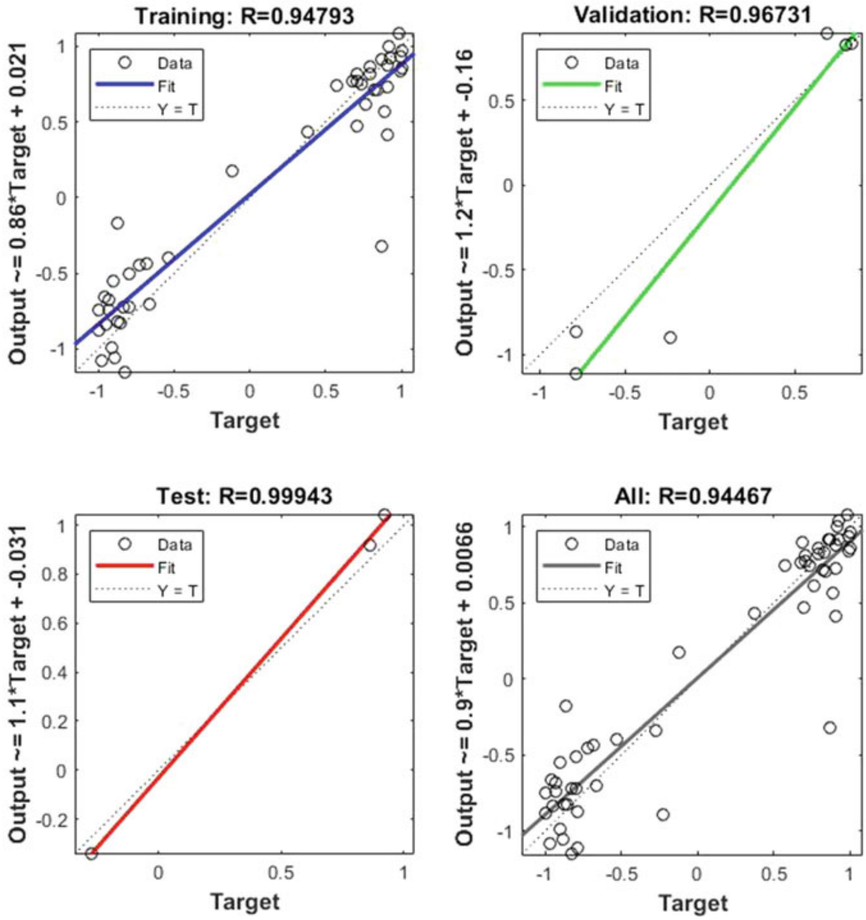


**Fig. 3** Regression plot of the optimum developed productivity model

**Table 5** Actual output and predicted output of the developed model over test data

| Projects → | I | II | III |
|---|---|---|---|
| Actual output (normalized output in man*days/tons) | 0.9222 | 0.8599 | −0.2737 |
| Predicted output (normalized output in man*days/tons) | 1.0421 | 0.9196 | −0.3409 |
| Error (normalized output in man*days/tons) | 0.1199 | 0.0597 | 0.0672 |

and trained with Levenberg–Marquardt training function. The network architecture and the data point for training the network were varied and compared for obtaining the superlative outcomes. The most significant network for the prediction of the labor productivity was verified by performing network estimate on a test data, which had a virtuous prediction performance of the construction labor productivity for reinforcement installation activity.

The forecasting of work performed by labor is conducted by the senior engineers and project managers based on their experience of their previous works. The data of these previous works need to be carefully documented, such that future investigation related to labor performance could be made possible. Also, ANN as soft computational technique can be utilized for estimating the labor productivity of the labor during the different phases of the construction and the same could also be verified for the ongoing projects. The limitation of this investigation study was for prediction of productivity of labor for reinforcement installation task; it could be also utilized for forecasting formwork installation task, concrete pouring and finishing, masonry work, floor finishing, and overall factors impacting labor productivity.

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