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Labour Productivity Estimation Model for Reinforced Concrete Structural Works Using Artificial Neural Network

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Abstract

Labour productivity is a critical factor in determining the success of construction projects because it influences cost efficiency, schedule performance, and project quality. However, accurately estimating labour productivity remains challenging due to the complex interactions among workforce characteristics, management practices, resource availability, environmental conditions, and project-specific factors. Conventional estimation methods often fail to capture nonlinear relationships among these variables, resulting in limited prediction accuracy. This study aimed to develop an Artificial Neural Network (ANN)-based model for estimating labour productivity in reinforced concrete structural works and to identify the contribution of productivity factors influencing model predictions. A quantitative research approach was employed using data collected from 16 multistorey building construction projects in Bali, Indonesia. Productivity factors were identified through a literature review and selected using the Relative Importance Index (RII), while labour productivity was represented by the Productivity Index (PI). A Feedforward Neural Network trained using Bayesian Regularization (FNN-BR) was developed using 12 selected productivity factors and evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results showed that the optimal ANN architecture, consisting of 15 input neurons, 8 hidden neurons, and 1 output neuron, achieved strong prediction performance with an internal R^2 value of 0.8861, an RMSE of 0.0671, and a MAPE of 5.58%. External validation produced an R^2 value of 0.9178, an RMSE of 0.0524, and a MAPE of 4.06%, indicating good generalization capability. The contribution analysis identified site supervision quality as the most influential factor, followed by site accessibility, labour attendance, and workforce health conditions. This study concluded that the proposed ANN model provided an effective approach for estimating labour productivity and supporting data-driven decision-making in reinforced concrete construction projects.

INTRODUCTION

Labour productivity is one of the key determinants of construction project performance because it directly influences project costs, schedule performance, and quality. As a labour-intensive industry, construction projects rely heavily on workforce performance, with labour costs accounting for approximately 30–50% of total project costs (Alzubi et al., 2023). Consequently, fluctuations in labour productivity can adversely affect project efficiency and may result in schedule delays and cost overruns (Heravi & Eslamdoost, 2015a). Therefore, improving labour productivity and developing reliable estimation methods remain important objectives in construction management (El-Gohary et al., 2017a).

Accurate labour productivity estimation is essential for effective project planning and control. However, productivity estimation remains challenging, particularly in developing countries such as Indonesia (Kaming et al., 1997). Conventional estimation approaches commonly rely on historical averages, deterministic assumptions, or linear statistical models. Although these approaches are relatively simple to implement, they may not adequately represent the complex relationships among productivity factors, thereby reducing estimation reliability.

This challenge becomes more significant because labour productivity is influenced by numerous internal and external factors. Previous studies have identified factors related to workforce characteristics, management practices, construction methods, resource availability, environmental and site conditions, economic and market dynamics, as well as regulatory and stakeholder-related aspects (Kazaz et al., 2008; (Durdyev & Ismail, 2016; Heravi & Eslamdoost, 2015a); (El-Gohary et al., 2017a). Since these factors interact simultaneously throughout project implementation, labour productivity often exhibits complex and nonlinear behavior that is difficult to represent using conventional approaches.

To address these challenges, Artificial Neural Network (ANN) models have been widely applied in construction productivity estimation because of their ability to capture nonlinear relationships and learn complex patterns from historical data. Previous studies have successfully applied ANN models to estimate labour productivity in various construction activities, including concrete works, formwork operations, and masonry works (Ezeldin and Sharara 2006; Gerek et al., 2015). Subsequent studies further confirmed the effectiveness of ANN in estimating labour productivity under different project conditions and construction environments (Heravi & Eslamdoost, 2015a; (El-Gohary et al., 2017a), while more recent developments have combined ANN with optimization techniques to improve prediction performance and model generalization capability (Goodarzizad et al., 2023).

Although these studies demonstrate the potential of ANN for labour productivity estimation, differences remain regarding the construction activities, productivity measures, and influencing factors considered. Most existing studies focus on individual construction activities and employ different combinations of productivity factors depending on research objectives and project conditions. However, reinforced concrete structural works comprise reinforcement, formwork, and concrete casting activities with distinct productivity characteristics. Therefore, a labour productivity estimation model is needed that accommodates these activities within a single modeling framework while incorporating both internal and external productivity factors.

Labour productivity has become a critical issue in the global construction industry because it directly determines project efficiency, cost control, schedule performance, and overall competitiveness. Construction projects remain highly dependent on human resources, making workforce productivity one of the most influential factors affecting project success. Globally, construction activities frequently experience delays, cost overruns, and productivity losses due to inefficient labour utilization, inadequate planning, and unpredictable project conditions. The increasing complexity of modern construction projects, including high-rise buildings and infrastructure developments, has intensified the need for accurate productivity estimation methods that support decision-making and improve project performance. Previous studies have emphasized that construction labour costs may account for approximately 30–

50% of total project costs, demonstrating the significant economic impact of labour productivity variations on construction outcomes.

The global construction sector continues to face productivity challenges despite technological advancements and improved project management practices. Previous construction management research indicates that labour productivity remains difficult to predict because it is influenced by multiple interacting variables, including workforce capability, management effectiveness, material availability, equipment conditions, environmental factors, and project-specific constraints. In developing countries, including Indonesia, these challenges are more pronounced due to variations in construction practices, resource limitations, and differences in workforce management systems. The inability to accurately estimate labour productivity may result in unrealistic project scheduling, inefficient resource allocation, and increased risks of project delays and financial losses. Therefore, developing reliable productivity estimation models has become an important research priority in construction engineering and management.

In Indonesia, reinforced concrete structural works represent one of the most important components of building construction because they involve complex activities, such as reinforcement installation, formwork preparation, and concrete casting. However, productivity estimation for these activities remains challenging because each construction activity has different characteristics and productivity determinants. Conventional estimation approaches commonly rely on historical productivity averages, standard coefficients, or linear statistical assumptions. Although practical, these approaches often fail to capture nonlinear relationships among productivity factors, resulting in limited accuracy when applied to dynamic construction environments. Existing estimation approaches may not adequately represent the complex interactions among productivity variables, reducing the reliability of productivity prediction.

Several previous studies have attempted to overcome productivity estimation limitations by applying Artificial Neural Network (ANN) techniques. ANN has gained attention in construction research because of its ability to identify complex nonlinear patterns from historical data and generate predictive models. Ezeldin and Sharara (2006) demonstrated that ANN could effectively estimate productivity in concrete construction activities, while Heravi and Eslamdoost (2015) confirmed its capability in measuring and predicting construction labour productivity under different project conditions. Furthermore, (El-Gohary et al., 2017a) applied ANN approaches to improve construction labour productivity prediction by incorporating multiple influencing factors. More recently, (Goodarzizad et al., 2023) combined ANN with optimization techniques to enhance prediction accuracy and model generalization capability. These studies indicate that ANN provides promising potential for addressing productivity estimation problems in construction projects.

Although previous studies have contributed significantly to the development of ANN-based productivity prediction models, several limitations remain. Most existing research has focused on specific construction activities, such as concrete works, masonry works, or individual productivity components, rather than developing an integrated model covering multiple reinforced concrete structural activities. In addition, previous studies have employed different productivity indicators and selected influencing factors based on specific project contexts, making direct application across different construction environments difficult. Reinforced concrete structural works involve interconnected activities with distinct productivity characteristics; therefore, a comprehensive model capable of estimating productivity across reinforcement, formwork, and concrete casting activities within a unified framework is still required.

The research gap identified from previous studies indicates the necessity of developing a more comprehensive and adaptive productivity estimation model. Existing models generally emphasize prediction accuracy but provide limited explanation regarding the contribution of individual productivity factors influencing model outcomes. Understanding these factors is essential because construction managers require not only accurate productivity predictions but also insights into variables that should receive priority improvement efforts. Therefore, integrating ANN modeling with productivity factor contribution analysis can provide a more informative decision-support mechanism for construction management practices.

This research is important because inaccurate labour productivity estimation can significantly affect construction project planning, resource allocation, and operational control. In large-scale building projects, minor productivity deviations can accumulate into substantial schedule delays and financial impacts. A reliable estimation model can assist project managers in anticipating productivity risks, adjusting workforce strategies, and improving construction efficiency. Furthermore, the increasing adoption of digital technologies and artificial intelligence in the construction industry creates opportunities to develop data-driven approaches that support smarter and more efficient project management systems.

The novelty of this research lies in developing an ANN-based labour productivity estimation model specifically designed for reinforced concrete structural works in multistorey building projects in Bali, Indonesia. Unlike previous studies that generally focus on individual construction activities, this research integrates reinforcement works, formwork works, and concrete casting works into a single modeling framework using the Productivity Index as a unified measurement approach. Additionally, this study incorporates internal and external productivity factors selected through the Relative Importance Index (RII) method and applies the connection-weight approach to identify the relative contribution of each influencing factor. This combination provides both predictive capability and interpretative insight into labour productivity determinants.

The main objective of this research was to develop and evaluate an Artificial Neural Network model capable of estimating labour productivity in reinforced concrete structural works based on selected productivity factors. Specifically, this study aimed to identify significant productivity factors affecting reinforced concrete construction activities, develop an ANN-based estimation model using actual project data, evaluate model performance through statistical indicators such as the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), and analyze the relative contribution of each productivity factor influencing productivity estimation results. Through these objectives, this research sought to provide a systematic approach for improving productivity prediction accuracy in construction projects.

The contribution of this research is both theoretical and practical. From an academic perspective, this study enriches construction productivity research by demonstrating the application of ANN for integrated productivity estimation across multiple reinforced concrete activities while incorporating factor contribution analysis. From a practical perspective, the developed model provides construction practitioners with a predictive tool to support project planning, monitoring, and productivity improvement strategies. The findings can assist project managers in identifying dominant productivity factors and implementing targeted interventions, such as improving site supervision quality, managing workforce conditions, and ensuring material availability. Ultimately, this research contributes to the advancement of intelligent construction management by supporting more accurate, data-driven, and efficient decision-making processes.

METHOD

Study design, case context, and data sources

This study employed a quantitative approach to develop an Artificial Neural Network (ANN)-based labour productivity estimation model for reinforced concrete structural works. The research was conducted on multistorey building construction projects in Bali, Indonesia, focusing on three major reinforced concrete activities: reinforcement works, formwork works, and concrete casting works. The selected projects had a minimum height of two storeys (Hasan & Lu, 2024; Güvel, 2025).

The study utilized primary and secondary data. Primary data were collected through questionnaire surveys administered to construction professionals directly involved in project execution, including project managers, site managers, site engineers, quantity surveyors, and supervisors. The questionnaire assessed project conditions related to productivity factors identified from the literature.

Secondary data were obtained from completed and ongoing building construction projects and included work quantities, actual labour composition, and project records required for productivity calculations. A total of 16 multistorey building construction projects were collected. Data from 15 projects were used for model development and internal evaluation, while data from the remaining project were used for external validation.

Research workflow

The research workflow adopted in this study is illustrated in Figure 1. The study began with a literature review to identify productivity factors relevant to reinforced concrete structural works. These factors were subsequently evaluated through a questionnaire survey and selected using the Relative Importance Index (RII). Primary and secondary project data were then collected to calculate actual labour productivity, which was subsequently converted into a Productivity Index using standard productivity values derived from the Indonesian Standard Analysis of Unit Prices (AHSP). The resulting dataset was prepared through one-hot encoding of construction activities and data normalisation before being used to develop a FNN trained using BR. Model performance was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), followed by an analysis of the relative contribution of each productivity factor using the connection-weight approach.

Figure 1. *Research Workflow of the Study*

Productivity Factor Selection

Productivity factors considered in this study were identified through a comprehensive literature review on labour productivity in construction projects. The identified factors were subsequently compiled into a questionnaire and evaluated by construction professionals with direct experience in reinforced concrete structural works. The questionnaire aimed to assess the relative importance of each factor in influencing labour productivity.

Factor selection was performed using the Relative Importance Index (RII) method, which is widely used in construction management research to prioritise productivity factors based on the judgement of construction professionals (Lim & Alum, 1995). The RII value for each factor was calculated using Equation (1).

$$RII = \frac{\sum W}{A \times N}$$

where W is the weight assigned by respondents, A is the highest possible weight, and N is the total number of respondents. A total of 65 productivity factors were initially identified from the literature review. Factors with an RII value of 0.80 or higher were retained for subsequent model development. Based on this criterion, 12 productivity factors were selected, comprising eight internal factors and four external factors, as presented in Table 2.

Table 2. Selected Productivity Factors based on RII Analysis

Category	Productivity Factor	RII
Internal	Technical skills	0.920
Internal	Material availability	0.896
Internal	Site supervision quality	0.888
Internal	Equipment condition and maintenance	0.872
Internal	Labour attendance	0.864
Internal	Scheduling accuracy	0.856
Internal	Site congestion	0.848
Internal	Health and fatigue condition	0.840
External	Rainfall	0.832
External	Site accessibility	0.824
External	National and religious holidays	0.816
External	Public/social disturbance	0.808

Productivity Measurement

abour productivity was represented using the Productivity Index (PI), defined as the ratio between actual productivity and standard productivity. This index was adopted to provide a common productivity measure across reinforcement, formwork, and concrete casting activities, which differ in physical output units and productivity characteristics. By expressing productivity as a dimensionless index, different reinforced concrete activities could be incorporated into a single ANN model. The Productivity Index was calculated according to shown in Equation (2).

$$PI = \frac{AP}{SP}$$

where PI is the Productivity Index, AP is the actual productivity, and SP is the standard productivity. Actual productivity was calculated from project records comprising completed work quantities, actual labour composition, and working durations. Because workforce composition varied among projects, the actual labour input was first converted into an equivalent workforce based on the labour coefficients specified in the Indonesian Standard Analysis of Unit Prices (AHSP). Labour productivity was then calculated as work output per equivalent labour-day for reinforcement, formwork, and concrete casting activities. Standard productivity values were obtained as the the inverse of the labour coefficients specified in the Indonesian Standard Analysis of Unit Prices (AHSP) issued by the Ministry of Public Works and Housing.

Table 3. Standard Productivity Values used for PI Calculation

Activity	Standard Labour Coefficient (OH/unit)	Standard Productivity
Reinforcement works	0.00352 OH/kg	284.09 kg/OH
Formwork works	1.034 OH/m²	0.967 m²/OH
Concrete casting works	0.550 OH/m³	1.818 m³/OH

A Productivity Index value greater than 1.0 indicates that actual productivity exceeds the corresponding standard productivity, whereas a value below 1.0 indicates lower productivity performance. The resulting PI values were subsequently used as the target output for ANN model development and performance evaluation.

FNN-BR Model Development

A Feedforward Neural Network trained using Bayesian Regularization (FNN-BR) was employed to develop the labour productivity estimation model. The model development process consisted of dataset preparation, network configuration, data normalisation, model training, and performance evaluation.

Dataset Preparation

The dataset used for ANN modelling was developed from the selected productivity factors identified through the RII analysis and productivity index values obtained from the investigated construction projects. The selected productivity factors were represented as input variables, while the Productivity Index (PI) served as the target output variable for model training.

To enable a single ANN model to estimate labour productivity across different reinforced concrete activities, activity types were encoded using the one-hot encoding technique. Three binary variables were introduced to represent reinforcement works, formwork works, and concrete casting works. Consequently, the final input layer consisted of 15 variables, comprising 12 productivity factors and three activity-type indicators. Table 4 presents the input and output variables used in the ANN model.

Table 4. ANN Input and Output Variables

Variable	Description
X1	Technical skills
X2	Labour attendance
X3	Health and fatigue condition
X4	Scheduling accuracy
X5	Site supervision quality
X6	Material availability
X7	Equipment condition and maintenance
X8	Site congestion
X9	Rainfall
X10	Site accessibility
X11	Public/social disturbance
X12	National and religious holidays
D1	Reinforcement works
D2	Formwork works
D3	Concrete casting works
Y	Productivity Index (PI)

The dataset was organised as an 80 × 16 matrix, where each row represented one observation and each column represented one variable, comprising 15 input variables and one output variable. Each observation represented the productivity assessment provided by one respondent for a specific construction project. With five respondents from each of the 16 investigated projects, the final dataset comprised 80 observations, which were subsequently used for model development and evaluation.

Data Normalisation

Prior to model training, all input and output variables were normalised using the min–max normalisation method to ensure a consistent numerical scale and improve training stability. In this study, normalisation was performed using the MATLAB mapminmax function, which transformed the data into the range of −1 to 1. The normalised value was calculated using Equation (3).

$$x' = 2\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) - 1$$

where x is the original value, x_{min} and x_{max} are the minimum and maximum values of the variable, respectively, and x' is the normalised value. The normalisation parameters were determined from the training dataset and subsequently applied to the external testing dataset to ensure consistency and prevent data leakage throughout the modelling process.

Network Architecture and Training

A Feedforward Neural Network (FNN) was employed to develop the labour productivity estimation model. The network consisted of an input layer, a hidden layer, and an output layer.

The input layer contained 15 neurons representing 12 productivity factors and three activity-type indicators obtained through one-hot encoding, while the output layer consisted of a single neuron representing the Productivity Index (PI). Each neuron processes weighted input signals and transforms them through an activation function according to Equation (4).

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where x_i denotes the input variables, w_i represents the connection weights, b is the bias term, and $f(\cdot)$ is the activation function.

The hidden layer employed the hyperbolic tangent sigmoid (tansig) activation function, whereas the output layer used a linear (purelin) activation function because the target variable was continuous. A single hidden layer was adopted because it is generally sufficient to approximate complex nonlinear relationships while maintaining a relatively simple network architecture. Model training was performed using the Bayesian Regularization backpropagation algorithm (trainbr) implemented in MATLAB.

To identify the most suitable network architecture, eight alternative hidden-layer configurations consisting of 3, 5, 8, 10, 12, 15, 18, and 20 hidden neurons were evaluated. The optimal architecture was selected based on the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) obtained during internal model evaluation.

Internal and External Validation

To evaluate model performance and generalisation capability, the dataset was divided into internal and external datasets. The internal dataset consisted of observations obtained from Projects P1–P15 and was used for model development and internal evaluation. The external dataset consisted of observations from Project P16, which was excluded from the model development stage and reserved exclusively for external testing.

For internal model evaluation, the internal dataset was randomly divided into training, validation, and testing subsets with proportions of 70%, 15%, and 15%, respectively, using the dividerand function in MATLAB. The training subset was used to adjust the network weights and biases, whereas the validation and testing subsets were retained for performance evaluation. Although Bayesian Regularization does not rely on the validation subset for early stopping, this data partitioning was maintained to provide a consistent evaluation framework throughout the model development process. To ensure reproducibility, a fixed random seed was specified using rng(1).

The optimal network architecture was selected based on its estimation performance during the internal evaluation stage using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Subsequently, the selected model was evaluated using the external dataset to assess its ability to estimate labour productivity under project conditions that were not included during model development

Model Performance Evaluation

The estimation performance of the developed ANN models was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These performance metrics were selected because they are widely used to evaluate the accuracy of regression models and the agreement between actual and estimated values.

The coefficient of determination (R^2) measures the proportion of variance in the observed data that can be explained by the estimation model. It is calculated using Equation (5).

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

where SS_{res} is the residual sum of squares and SS_{tot} is the total sum of squares (Chicco et al., 2021).

RMSE measures the average magnitude of estimation errors by calculating the square root of the mean squared difference between actual and estimated values. It is expressed as Equation (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where y_i is the actual value, $\hat{y}_i$ is the estimated value, and n is the number of observations (Hyndman & Koehler, 2006).

MAPE measures the average percentage difference between actual and estimated values and is calculated using Equation (7).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

In addition to model performance evaluation, the relative contribution of each input variable was analysed using the optimal ANN model. The analysis was performed using the connection-weight approach proposed by Olden and Jackson (2002), in which the connection weights between the input, hidden, and output layers were combined to quantify the relative contribution of each input variable to the estimated Productivity Index. The resulting contribution values were subsequently normalised into percentages to facilitate comparison among variables.

RESULTS AND DISCUSSION

This section presents the results obtained from the development and evaluation of the FNN-BR model for labour productivity estimation. The discussion covers the selection of the optimal network architecture through internal evaluation, evaluation of model performance using external testing data, and analysis of the relative contribution of productivity factors to the model output using the connection-weight approach.

Internal Evaluation Results

The performance of the FNN-BR model was evaluated using eight alternative hidden-layer configurations consisting of 3, 5, 8, 10, 12, 15, 18, and 20 hidden neurons. Model performance was assessed using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results are presented in Table 5.

Table 5. Performance Comparison of Alternative Hidden Neuron Configurations

Hidden Neuron	R^2	RMSE	MAPE (%)
3	0,7857	0,0922	8,38
5	0,7860	0,0918	8,13
8	0,8861	0,0671	5,58
10	0,7859	0,0919	8.32
12	0,8126	0,0859	7,69
15	0,8100	0,0867	7,66
18	0,7843	0,0924	8,43
20	0,8038	0,0880	7,96

As shown in Table 5, the network architecture with 8 hidden neurons achieved the best overall performance among the evaluated configurations, yielding the highest coefficient of determination ($R^2 = 0.8861$), the lowest RMSE (0.0671), and the lowest MAPE (5.58%). These results indicate that the selected architecture provided the most accurate estimation of the Productivity Index while maintaining the lowest prediction error.

The results also demonstrate that increasing the number of hidden neurons did not consistently improve model performance. Although architectures with more hidden neurons increased network complexity, their R^2 values generally decreased while RMSE and MAPE increased. This finding indicates that a more complex network does not necessarily produce better estimation performance and may reduce the model's ability to generalise the relationships learned from the training data. Figure 2 illustrates the variation in model performance across the evaluated hidden-layer configuration. Figure 2 illustrates the variation in model performance across the evaluated hidden-neuron configurations.

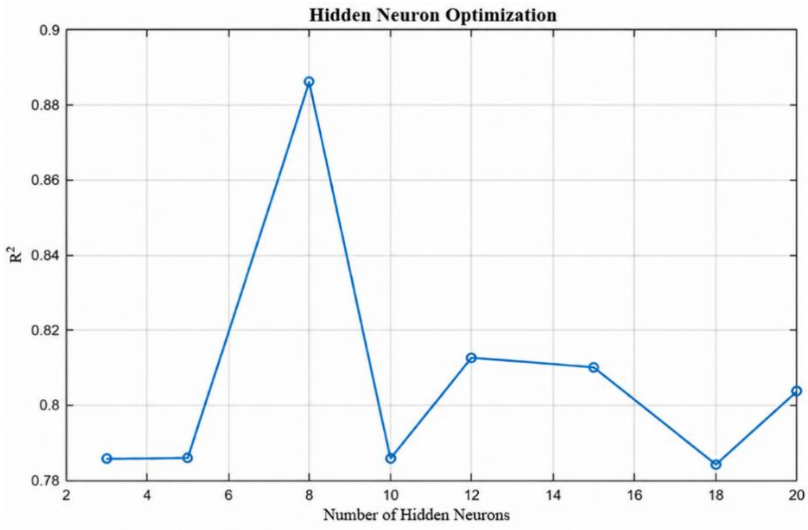

Figure 2. The Variation in Model Performance Across the Evaluated Hidden-Neuron Configurations

Figure 2 illustrates the regression relationship between the actual and predicted Productivity Index values. The developed FNN-BR model achieved correlation coefficients (R) of 0.9566 for the training dataset, 0.8671 for the testing dataset, and 0.9413 for the combined dataset. These results indicate a strong agreement between the predicted and actual values, confirming that the proposed FNN-BR model successfully learned the underlying nonlinear relationship between the selected productivity factors and the Productivity Index.

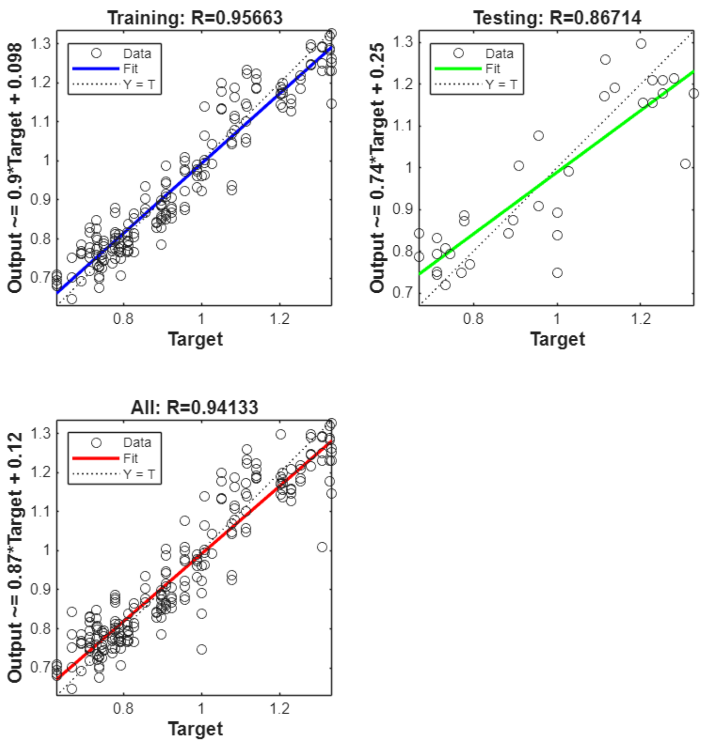

Figure 3. Relationship Between Actual and Predicted Productivity Index Values

External Validation Results

Following the internal evaluation stage, the optimal FNN-BR model was evaluated using an external dataset obtained from Project P16, which was excluded from the model development process. This evaluation aimed to assess the model's ability to estimate labour productivity under previously unseen project conditions. Table 6 summarises the performance of the selected FNN-BR model on the external testing dataset.

Table 6. External Testing Results of the Selected FNN-BR Model

Performance Metric	Value
R^2	0,9178
RMSE	0,0524
MAPE (%)	4,06%

The external testing results indicate that the developed model maintained satisfactory estimation performance when applied to previously unseen project data. The model achieved an R^2 value of 0.9178, indicating a strong agreement between the actual and estimated Productivity Index values. Furthermore, the RMSE of 0.0524 and MAPE of 4.06% indicate that the estimation errors remained relatively small, demonstrating the capability of the proposed FNN-BR model to provide accurate labour productivity estimates under different project conditions.

To further evaluate model performance across different reinforced concrete activities, the estimated Productivity Index values were compared with the corresponding actual values for reinforcement, formwork, and concrete casting works. The comparison is presented in Table 7.

Table 7. Comparison of Actual and Estimated Productivity Index Values by Activity Type

Activity	Mean PI (Actual)	Mean PI (Predicted)	Mean Error (%)
Reinforcement	0,94135	0,89839	4,66
Formwork	1,1127	1,1293	2,59
Concrete Casting	0,79289	0,76345	4,92

As shown in Table 7, the developed model successfully reproduced the overall Productivity Index across all activity types. Formwork achieved the lowest mean estimation error (2.59%), followed by reinforcement (4.66%) and concrete casting (4.92%). Although slight differences were observed among the three activities, the estimation errors remained relatively low, indicating that the model consistently estimated labour productivity across different reinforced concrete structural works.

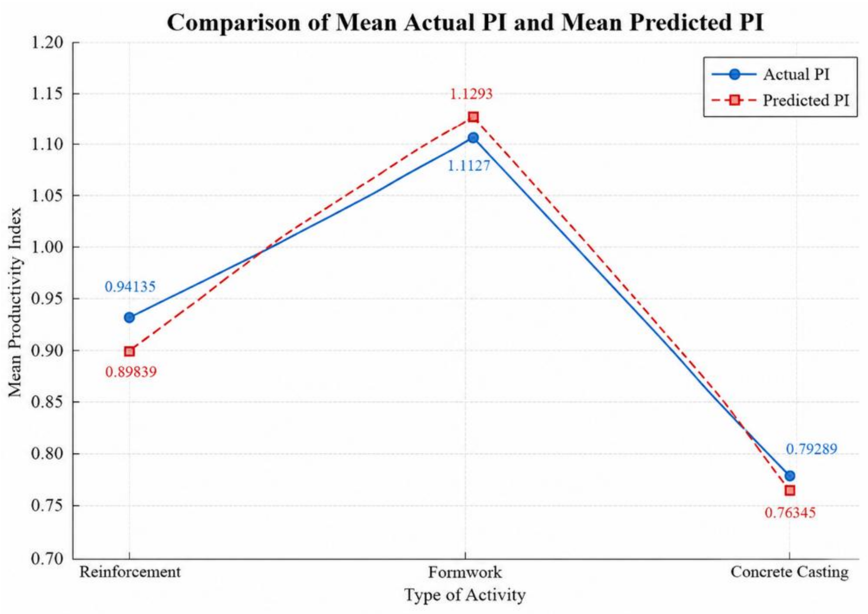

Figure 4. Comparison of Actual and Estimated Mean Productivity Index Values by Activity Type

The close agreement between the actual and estimated Productivity Index values shown in Figure 4 further demonstrates the model's good generalisation capability. The consistent estimation performance obtained from the external testing dataset indicates that the proposed FNN-BR model is capable of providing reliable labour productivity estimates for reinforced concrete structural works under project conditions that were not included during model development.

Relative Contribution Analysis

The relative contribution of each input variable was analysed using the optimal FNN-BR model to quantify the contribution of each input variable to the estimated Productivity Index. The results of the global relative contribution analysis are presented in Table 8.

Table 8. Global Relative Contribution Analysis Results

Rank	Variable	Contribution (%)
1	X5 – Site supervision quality	15.39
2	X9 – Site accessibility	10.17
3	X2 – Labour attendance	9.39
4	X3 – Health and fatigue condition	9.36
5	X10 – Rainfall	8.97
6	X11 – Public/social disturbance	8.60
7	X1 – Technical skills	7.65
8	X8 – Site congestion	6.86

Rank	Variable	Contribution (%)
9	X6 – Material availability	6.31
10	X7 – Equipment condition and maintenance	6.28
11	X4 – Scheduling accuracy	5.61
12	X12 – National and religious holidays	5.53

As shown in Table 8, site supervision quality (X5) was identified as the variable with the highest relative contribution, accounting for 15.39% of the estimated Productivity Index, whereas national and religious holidays (X12) exhibited the lowest contribution at 5.53%. These findings indicate that site supervision quality contributes more strongly to the model output than the other input variables. The results also show that both internal and external factors contribute to labour productivity variation, although their relative contributions differ among the productivity factors.

To further investigate the contribution of productivity factors across different reinforced concrete activities, activity-specific relative contribution analyses were also conducted. The results showed that health and fatigue condition (X3) was the dominant factor for reinforcement works, site supervision quality (X5) for formwork works, and material availability (X6) for concrete casting works. These findings suggest that the relative contribution of productivity factors varies according to the characteristics of each construction activity.

Discussion in Relation to Previous Studies

The results demonstrate that the developed FNN-BR model is capable of estimating labour productivity in reinforced concrete structural works with satisfactory accuracy. These findings are consistent with previous studies that successfully applied Artificial Neural Networks (ANN) to labour productivity estimation in construction projects. Ezeldin and Sharara (2006) reported that ANN could effectively model labour productivity in concrete works, while Heravi and Eslamdoost (2015) demonstrated the capability of ANN to estimate productivity under varying project conditions. Similarly, the findings of the present study indicate that the developed FNN-BR model is able to learn the nonlinear relationships between the selected productivity factors and the Productivity Index.

The external testing results further indicate that the developed model maintained satisfactory estimation performance when applied to previously unseen project data. This finding is consistent with previous studies that reported satisfactory model performance and good generalisation capability of ANN-based models for construction labour productivity estimation (Goodarzizad et al., 2021).

The relative contribution analysis identified site supervision quality as the most influential factor in the global model. In addition, the activity-specific relative contribution analysis revealed different dominant productivity factors across reinforced concrete activities. Health and fatigue condition was identified as the most influential factor for reinforcement works, site supervision quality dominated formwork works, and material availability had the highest contribution in concrete casting works. These findings are consistent with El-Gohary et al. (2017), Goodarzizad et al. (2021), and Nguyen et al. (2023), who reported that labour productivity is influenced by a combination of workforce, managerial, technical, and environmental factors. The results also suggest that the relative importance of productivity factors varies according to the characteristics of each reinforced concrete activity.

Compared with previous studies, the present research contributes by developing an ANN-based labour productivity estimation model that incorporates reinforcement, formwork, and concrete casting activities within a single modelling framework while integrating selected internal and external productivity factors.

In addition, the use of the Productivity Index as the model output and the application of the connection-weight approach provide further insight into the relative contribution of productivity factors to labour productivity in reinforced concrete structural works.

Practical implication and limitation

The developed FNN-BR model provides a practical tool for estimating labour productivity in reinforced concrete structural works based on project-specific conditions. The connection-weight analysis further indicates that different reinforced concrete activities are influenced by different dominant productivity factors. Therefore, project managers may improve labour productivity by focusing on activity-specific priorities, such as workforce health and fatigue management for reinforcement works, site supervision quality for formwork works, and material availability for concrete casting works.

Despite the satisfactory estimation performance obtained in this study, several limitations should be acknowledged. First, the dataset was derived from reinforced concrete structural works in multistorey building construction projects with characteristics similar to those considered in this study. Consequently, the applicability of the developed model to substantially different project types, construction methods, or project environments may require further validation. Second, the developed model was evaluated using a Feedforward Neural Network trained with Bayesian Regularization and was not compared with other machine learning techniques. Future studies may consider incorporating larger and more diverse datasets, evaluating alternative machine learning approaches, or developing hybrid models to further improve estimation accuracy and model generalisation (Xu et al., 2021;Sadatnya et al., 2023).

CONCLUSION

This study developed an Artificial Neural Network (ANN)-based labour productivity estimation model for reinforced concrete structural works in multistorey building construction projects. A total of 12 productivity factors, comprising internal and external factors, were selected using the Relative Importance Index (RII) and used as input variables for model development. Labour productivity was represented by the Productivity Index (PI), enabling reinforcement, formwork, and concrete casting activities to be incorporated into a single estimation model.

The optimal model employed a Feedforward Neural Network trained using Bayesian Regularization (FNN-BR) with a 15–8–1 network architecture. The developed model demonstrated satisfactory estimation performance during internal evaluation and external testing, indicating its capability to estimate labour productivity and maintain good generalization performance when applied to previously unseen project data.

The analysis of the relative contribution of input variables identified site supervision quality as the most influential factor in the overall model. Activity-specific analyses further revealed different dominant factors across reinforced concrete activities, with health and fatigue conditions being the dominant factor for reinforcement works, site supervision quality for formwork works, and material availability for concrete casting works. These findings indicate that the relative contribution of productivity factors varies according to the characteristics of each reinforced concrete activity and highlight the importance of considering activity-specific conditions when estimating and managing labour productivity.

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