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The Impact of The Wage System on Estimating Construction Worker Productivity

Mirnayani[1, a)] and Yunita Dian Suwandari[2, b)]

[1,2]*Mercu Buana University, Jakarta, Indonesia*

[a)] Corresponding author: mirnayani@mercubuana.ac.id

Abstract. A construction project's productivity significantly depends on its workforce's efficiency. This study examines the effect of different wage systems—daily wage and piece-rate (borongan) systems—on the productivity of construction workers, using a neural network model for analysis. Data were collected from workers at the ESP-Control Building Project of PLTU Units 9 & 10 through field observations and questionnaires. Productivity was assessed via the Work Sampling method, while SPSS software was employed to analyze key factors influencing worker performance. The results show that the piece-rate system is more effective in enhancing productivity than the daily wage system, as indicated by higher Labour Utilization Rates (LUR). A neural network model developed for productivity estimation achieved high accuracy, with R^2 values of 0.815 for the daily wage system and 0.817 for the piece-rate system. Practically, these findings can help project managers improve scheduling efficiency, minimize idle time, and reduce labor costs by adopting an appropriate wage system.

Keywords: Construction workers, Neural Network, Productivity, Wage system

INTRODUCTION

The success of construction projects is heavily influenced by the productivity of the workforce, which directly affects project timelines, costs, and overall efficiency. Productivity in construction is commonly defined as the ability of workers to deliver output efficiently within a specified period, making it a key performance indicator for project management [1]. Effective labor management is therefore essential to ensure that schedules are met, costs are controlled, and resources are optimized. High productivity levels are positively correlated with improved project outcomes in terms of both quality and cost performance.

Within the construction industry, two primary wage systems are commonly applied: the daily wage system and the piece-rate (borongan) system. The daily wage system compensates workers based on their working hours or days, while the piece-rate system rewards workers according to the volume or type of work completed. Previous studies have shown that wage systems significantly affect worker motivation, engagement, and performance [2]. The daily wage system, while providing stability, often results in lower motivation to maximize effort throughout the day, which may cause inefficiencies and project delays. Conversely, the piece-rate system incentivizes faster task completion, though it can also compromise quality and safety if not properly supervised [3]. Thus, inappropriate implementation of wage systems can reduce motivation, lower productivity, and contribute to project delays [4].

Recent scholarship has emphasized that appropriate labor management strategies are vital for optimizing on-site performance [5]. The piece-rate system often enhances productivity by directly linking compensation to performance, while the daily wage system, although stable, can reduce urgency and increase the risk of cost overruns [6], [7]. These contrasting outcomes highlight the need for a comprehensive analysis to identify each system's strengths, weaknesses, and suitability for construction projects.

In parallel, Artificial Neural Networks (ANN) have emerged as robust tools for analyzing complex productivity relationships in construction. ANN's ability to capture non-linear interactions allows it to model multiple interdependent variables influencing labor productivity with higher accuracy compared to traditional statistical approaches, such as linear regression [8], [9]. ANN has been successfully applied in various international contexts, including productivity estimation in high-rise building projects, road construction, and other specialized tasks, underscoring its versatility and predictive strength [10], [11]. Empirical evidence suggests that ANN significantly outperforms conventional methods in handling complex datasets and delivering reliable predictions in construction management [12], [13].

In the Indonesian construction sector, however, the application of ANN to evaluate the impact of wage systems on labor productivity remains scarce. While international studies have laid essential foundations, the Indonesian context—characterized by unique socio-economic conditions, labor characteristics, and management practices—requires targeted research. Applying ANN to this context enriches local and global literature by providing empirical insights into how wage systems affect productivity. Furthermore, integrating ANN with the Work Sampling method enables a more comprehensive analysis, combining predictive modeling with empirical observation of worker performance [14], [15].

This study focuses on the ESP-Control Building Project of PLTU Units 9 & 10, where productivity challenges associated with both wage systems have been observed. Under the daily wage system, workers were frequently involved in non-productive activities, causing project delays and increased costs. In response, managers shifted to a piece-rate wage system, which boosted productivity but raised concerns regarding work quality and the need for tighter supervision. These issues illustrate the necessity of identifying the optimal wage system that balances productivity, quality, and cost-effectiveness.

Accordingly, the objectives of this study are to: (1) measure and compare actual productivity under daily wage and piece-rate systems using Work Sampling, (2) identify the key factors influencing productivity within each system, (3) assess the impact of wage systems on overall worker performance, and (4) apply ANN modeling to estimate productivity levels for both systems. By achieving these objectives, this research aims to provide actionable insights for project managers in selecting the most effective wage system to enhance productivity, minimize delays, and improve cost efficiency.

In addition, this study aligns with Sustainable Development Goal (SDG) 9: Industry, Innovation, and Infrastructure. By leveraging machine learning for labor productivity management, it supports more efficient infrastructure development through reduced delays and optimized resource use, contributing to broader sustainability objectives [16].

In sum, examining labor productivity through the perspective of wage systems is crucial for project efficiency and cost management and has broader implications for labor policy in the construction sector. The integration of ANN provides a rigorous framework for deriving theoretical and practical insights, ultimately supporting more efficient, cost-effective, and sustainable construction practices.

METHODOLOGY

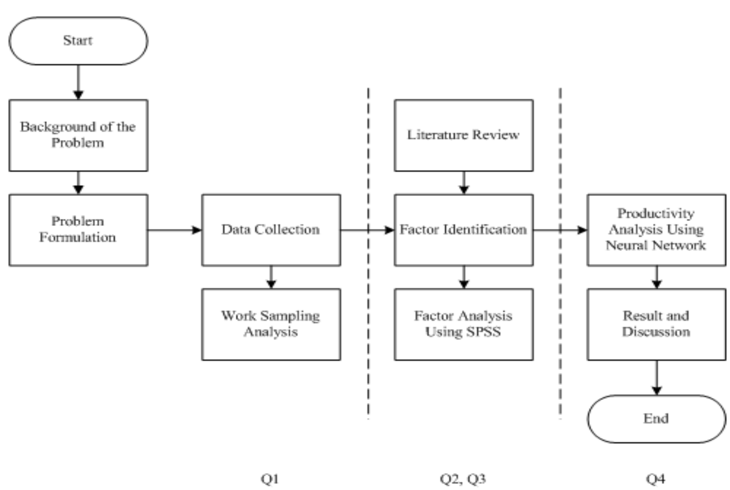

FIGURE 1. The Research Flow Diagram

This flow diagram illustrates the sequence of research stages (Figure 1). The process begins with identifying the problem and formulating research objectives. Data was collected using Work Sampling, supported by a literature review to identify relevant factors. Factor analysis using SPSS was conducted to determine the most influential variables. These inputs were then used in the Artificial Neural Network (ANN) model to analyze and estimate labor productivity under different wage systems. The research concludes with the results and discussion, which compare ANN predictions with actual field observations.

This study employed a quantitative approach combining empirical field observations with predictive modeling. The research was conducted at the ESP-Control Building Project of PLTU Units 9 & 10, focusing on masonry works performed under two wage systems: daily wage and piece-rate (borongan). Data collection comprised direct field observations using the Work Sampling method and structured questionnaires to capture key productivity-related variables.

1. **Work Sampling Method**

   The Work Sampling method measured worker productivity by recording activities at fixed intervals. Observations were conducted on 24 workers, divided into two groups based on the wage system. Stage 1 (March): daily wage system, observed for three consecutive days. Stage 2 (May): The piece-rate system was observed for three consecutive days.

   Each observation day lasted eight working hours (07.00–16.00, including a 1-hour break). Therefore, the total observation time per worker was:

   $$6 \text{ days} \times 8 \text{ hours/day} = 48 \text{ hours/worker}$$

   With 24 workers observed, the dataset represented :

   $$24 \times 48 = 1{,}152 \text{ labour-hours of observation}$$

   Worker activities were categorized into productive work (direct), supportive work (indirect), and non-productive activities, which were later used to calculate the Labour Utilization Rate (LUR).

   The Work Sampling method measured worker productivity by observing and recording the time spent on productive and non-productive activities. [17]. Productivity is calculated using the Labour Utilization Rate (LUR) [18]:

   $$LUR = \frac{Effective\ Work\ Time + 0{,}25\ Contributory\ Time}{Total\ Observation\ Time} \quad \text{a)}$$

   Where: Effective Work Time refers to time spent directly on construction tasks, and Contributory Time covers activities indirectly contributing to the task (e.g., preparation, supervision). Non-productive Time includes idle time, such as unnecessary breaks. A team is considered productive if the average LUR exceeds 50%.

2. **Factor Identification**

   To determine the variables influencing productivity, two sets of questionnaires were distributed:

   - **Expert questionnaire:** Sent to experts, including project managers and HR personnel, to validate the relevance of productivity factors.
   - **Worker questionnaire:** Distributed to 60 respondents—30 workers paid under the daily wage system and 30 under the piece-rate system. The questionnaire covered factors. These factors were identified based on previous research and adapted to the context of the construction project.

3. **Statistical Analysis with SPSS**

   The data collected through the questionnaires were analyzed using SPSS to identify the relationship between wage systems and productivity. The following steps were followed:

   - **Validity and Reliability Tests:** Cronbach's Alpha was used to ensure the reliability of the questionnaire, with values above 0.8 considered highly reliable.
   - **Multiple Linear Regression:** This analysis was performed to determine the effect of wage systems on productivity. The regression model was formulated as:

     $$Y = a + b1X1 + b2X2 \quad \text{b)}$$

     Where:

     Y = Productivity, **X_1** = Daily Wage, **X_2** = Piece-rate Wage, **a** = Intercept,

     b_1, b_2 = Coefficients for independent variables
   - **ANOVA Test: This test is used to test the significance of the overall regression model.**

4. **Neural Network Modeling for Productivity Estimation**

Using MATLAB to predict productivity under both wage systems, a neural network model was developed. This method was chosen for its ability to model non-linear relationships between multiple variables [13]. The ANN was designed as a Multilayer Perceptron (MLP) with the following configuration:

- Input Layer: worker age, experience, skill level, wage system, and motivation scores.
- Hidden Layer(s): one hidden layer with 10 neurons, optimized after preliminary tests.
- Activation Function:
- Hidden layer: ReLU (Rectified Linear Unit)
- Output layer: Linear activation, since productivity is a continuous variable.
- Training Algorithm: Backpropagation with gradient descent optimization.
- Learning Rate: 0.01.
- Epochs: maximum 1,000 epochs.
- Stopping Criteria: training terminated with early stopping if validation error did not improve after 20 consecutive epochs.
- Training/Validation Split: dataset randomly divided into 70% training and 30% validation subsets.

5. **Model Evaluation**

Model performance was evaluated using the Coefficient of Determination (R^2) and Mean Squared Error (MSE). Predicted productivity from the ANN model was then compared with actual field productivity values derived from Work Sampling for both wage systems.

RESULT AND DISCUSSION

1. **Productivity Measurement with Work Sampling**

The Labour Utilization Rate (LUR) was calculated for both wage systems to measure the efficiency of workers. The LUR indicates the percentage of time spent productively by workers during their shifts.

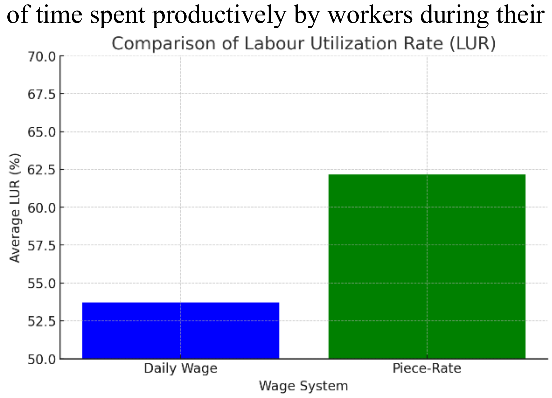

FIGURE 2. Comparison of Labour Utilization Rate (LUR) between two wage systems

Based on Figure 2, Daily Wage System: The labor utilization rate (LUR) under the daily wage system is approximately 53.73%. This indicates that, on average, a little over half of the available working time is spent productively, while the remaining time may include breaks, delays, or other non-productive activities. The relatively low LUR suggests that workers under this system might lack sufficient motivation to maximize efficiency since their compensation is not directly tied to the amount of work completed.

Piece-Rate System: The labor utilization rate under the piece-rate system is significantly higher, reaching 62.17%. This increase reflects a more productive workforce, likely driven by the financial incentives inherent in the piece-rate system. Workers are motivated to complete tasks quickly to maximize their earnings, resulting in less idle time and better use of working hours.

The comparison demonstrates that the piece-rate system outperforms the daily wage system in terms of labor utilization. With a higher LUR, the piece-rate system effectively promotes productivity by aligning worker incentives with performance. However, while the piece-rate system encourages faster task completion, additional measures such as quality control and supervision may still be necessary to ensure that the speed does not come at the cost of quality.

2. Operationalization of Research Variables

The operationalization of variables explains the factors used in this study clearly and measurably. In this research, the independent variables influence worker productivity, based on the daily wage system and the piece-rate system. The dependent variable is worker productivity.

TABLE 1. Factors Influencing Worker Productivity

	Factor	Description	Source
X1	Motivation	The encouragement provided to workers to ensure their work aligns with the given guidelines, aiming for optimal performance.	[2],[18]
X2	Work Speed	How quickly a worker completes assigned tasks within a specific period.	[19]
X3	Work Quality	The extent to which the output meets the expected or established standards.	[20]
X4	Work Flexibility	The ability of workers to adapt to changing conditions or job requirements.	[21]
X5	Supervision and Control	The process of monitoring workers' activities to ensure they meet the required standards of quality, time, and cost.	[22]
X6	Worker Well-being	Workers' physical, mental, and social well-being encompasses fair wages, safe working conditions, work-life balance, and job satisfaction.	[23]
X7	Efficiency and Completion Time	Efficiency refers to the optimal use of resources to achieve desired results, while completion time refers to the duration needed to complete a task or project.	[24]
X8	Worker Capability and Skill	Capability refers to the individual's capacity to perform specific tasks, while skill reflects the level of competence and expertise the worker possesses.	[25]
X9	Adaptability to Change	The ability of workers to adjust to changing conditions, situations, or job requirements.	[26]
X10	Job Complexity	The level of difficulty and challenges workers face in completing specific tasks.	[27]

The above factors will be assessed through questionnaires distributed to respondents, who will evaluate these factors for the daily wage and piece-rate systems. This structured evaluation allows the study to measure how each factor contributes to worker productivity under the two wage systems, offering data-driven insights to optimize workforce performance.

3. Statistical Analysis with SPSS

The results of the multiple linear regression and ANOVA tests indicate the significance of wage systems in influencing productivity. The regression analysis tested the relationship between the wage systems (independent variables) and worker productivity (dependent variable).

Regression Equation: $Y = 1{,}429 + 0{,}046\, X1 + 0{,}680\, X2$

Interpretation based Regression Equation: The coefficient for the piece-rate system is 0.680 ($p < 0.001$), indicating a substantial and statistically significant positive impact on productivity. This suggests that workers under the piece-rate system are more likely to perform better. The coefficient for the daily wage system is 0.046 ($p = 0.623$), showing a small and insignificant effect on productivity, meaning that the time-based system is less effective in driving worker performance.

The ANOVA (Analysis of Variance) at Table 2 provides insights into how well the independent variables—Daily Wage System (Upah Harian) and Piece-rate System (Upah Borongan)—explain the variance in worker productivity (Y). Below is a breakdown of the results:

TABLE 2. ANOVA Results Interpretation

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.067	2	1.534	17.255	.000[b]
	Residual	2.400	27	.089		
	Total	5.467	29			

a. Dependent Variable: Y

b. Predictors: (Constant), Daily Wage System, and Piece-rate System

The ANOVA (Analysis of Variance) test produced an F-value of 17.255 ($p < 0.05$), confirming that the regression model is statistically significant. This indicates that the wage systems have a meaningful impact on worker productivity, and the model explains a significant portion of the variance in productivity levels.

4. Neural Network Analysis for Productivity Prediction

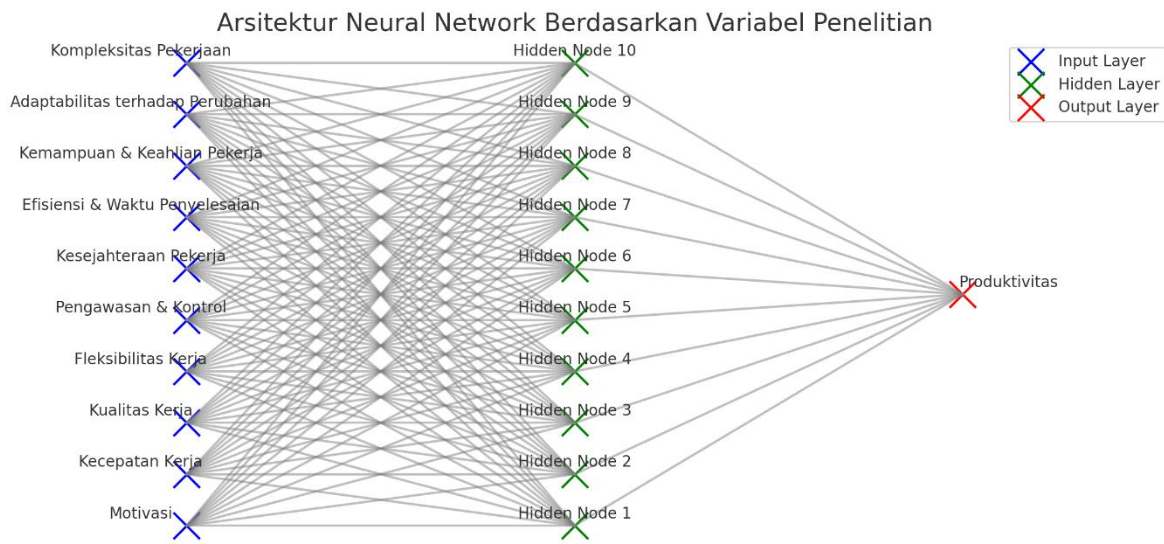

FIGURE 3. Neural Network Architecture Based on the Research Factors

Figure 3 illustrates the architecture of the Artificial Neural Network (ANN) model developed for productivity prediction. The input layer consists of ten research variables: Job Complexity, Adaptability to Change, Worker Capability and Skill, Efficiency and Completion Time, Worker Well-being, Supervision and Control, Work Flexibility, Work Quality, Work Speed, and Motivation. These factors were identified through literature review and factor analysis as the most influential variables affecting construction labor productivity.

The model includes one hidden layer of ten neurons (Hidden Node 1–10), enabling the ANN to capture complex, non-linear relationships among the input variables. Each input node is fully connected to all hidden nodes, and the hidden layer is connected to a single output node representing productivity. The output layer generates continuous values that reflect the predicted productivity of workers under different wage systems.

This architecture was designed to balance model complexity and computational efficiency, ensuring accurate predictions without overfitting. The chosen structure demonstrated strong performance, with R^2 values above 0.81 for daily wage and piece-rate systems, confirming its suitability for productivity estimation in construction projects.

TABLE 3. Neural Network Model Performance Metric

Wage System	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R^2 (Coefficient of Determination)
Daily Wage	0,0107 (1,07%)	0,0108 (1,08%)	0,815 (81,5%)
Piece-rate Wage	0,0124 (1,24%)	0,0124(1,24%)	0,817 (81.7%)

Table 3 shows the performance of the Artificial Neural Network (ANN) model in predicting construction labor productivity under both wage systems. The results indicate that the ANN achieved high predictive accuracy, with R^2 values of 0.815 for the daily wage system and 0.817 for the piece-rate wage system. These values demonstrate that more than 81% of the variability in productivity can be explained by the input factors included in the model. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values are both relatively low (ranging from 0.0107 to 0.0124), corresponding to error margins of approximately 1–1.2%. This confirms that the ANN model provides reliable estimations with minimal deviation from observed values.

Interestingly, although the piece-rate system yielded a slightly higher R^2, it also exhibited a marginally higher error rate than the daily wage system. This suggests that while the piece-rate wage system enhances productivity in practice, the daily wage system provides slightly more consistent patterns that are easier for the ANN model to capture. Overall, these findings validate the robustness of ANN as a predictive tool for productivity estimation and highlight the nuanced differences between wage systems in terms of actual performance and predictability.

5. Discussion

The results of this study demonstrate that the piece-rate wage system leads to higher productivity compared to the daily wage system, as indicated by higher Labour Utilization Rates (LUR) and supported by the Artificial Neural Network (ANN) analysis. These findings are consistent with international studies, particularly those by [6] and [7], who reported linking pay directly to output, motivates workers to deliver higher performance levels. Similarly,[5] Confirmed that well-structured incentive systems effectively minimize idle time and enhance worker motivation. This alignment reinforces the robustness of the present findings within the broader body of construction management literature.

However, the literature also highlights potential risks associated with piece-rate compensation systems. [28] and [29] noted that prioritizing speed can compromise work quality, particularly when supervision is insufficient. [30] safety risks may increase under piece-rate arrangements, as workers may overlook safety procedures for higher earnings. Additionally, [31] observed that such systems can lead to workforce instability, as skilled workers are often drawn to projects offering more lucrative contracts. These risks imply that project managers must implement strict quality assurance and safety monitoring practices while productivity gains are evident to prevent unintended consequences.

The contextual factors of the ESP-Control Building Project provide further explanation for the observed outcomes. The repetitive and standardized nature of masonry and piping tasks made them well-suited to output-based compensation, reflecting [32] argument that task type significantly influences the effectiveness of wage systems. Moreover, intense supervision in this project helped mitigate risks of quality reduction, echoing the importance of managerial oversight highlighted by [33]. The socio-economic conditions of Indonesia, where baseline wages are relatively low, also amplified worker responsiveness to financial incentives, supporting findings by [34] that wage sensitivity is heightened in such environments.

From a practical perspective, the results suggest that piece-rate systems can effectively boost productivity in construction projects, provided that risks are carefully managed. Integrating ANN into the analysis further strengthens decision-making by offering accurate productivity predictions under different wage schemes. This allows project managers to enhance efficiency and anticipate potential challenges related to quality, safety, and labor retention.

In sum, the findings of this study contribute to both theory and practice by confirming that wage systems significantly influence productivity outcomes. The piece-rate system emerges as a promising strategy for increasing productivity in Indonesia's construction sector. Still, its success depends on adequate supervision, balanced incentive structures, and integration of predictive tools such as ANN to support sustainable labor management.

CONCLUSION

This study concludes that wage systems significantly influence labor productivity in construction projects. The Work Sampling analysis revealed that the piece-rate system generated higher productivity than the daily wage system, as workers were more motivated to maximize performance. In contrast, the daily wage system often required stronger supervision and control. Key factors affecting productivity included motivation, task efficiency, supervision, and worker capability, with varying levels of influence between the two systems. The Artificial Neural Network (ANN) model effectively captured these relationships, achieving high predictive accuracy with R^2 values of 0.815 for the daily wage system and 0.817 for the piece-rate system, supported by low MAE and RMSE values that confirm its reliability. Overall, the findings demonstrate that the piece-rate system is more effective in enhancing productivity. In contrast, the daily wage system demands tighter supervision to sustain performance, providing project managers with practical insights for selecting appropriate wage systems to optimize labor productivity, ensure project efficiency, and balance cost, quality, and safety.

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