Civilla: Jurnal Teknik Sipil Universitas Islam Lamongan
Volume 11 Number 1 Year 2026
ISSN (*Online*) 2620-7222
ISSN (*Print*) 2503-2399

Available online at
https://jurnalteknik.unisla.ac.id/index.php/CVL

https://doi.org/10.30736/cvl.v2i2

Development of an ANFIS-Based Method to Improve the Accuracy of Owner's Estimated Cost in Construction Cost Management

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ARTICLE INFO

Article History :
Article entry : 19-02-2026
Article revised : 26-02-2026
Article received : 12-04-2026

Keywords :
ANFIS, capital expenditure procurement, Owner's Estimate Cost (OEC)

IEEE Style in citing this article :
Markhaban Siswanto and Machrus Ali, "Development of an ANFIS-Based Method to Improve the Accuracy of Owner's Estimated Cost in Construction Cost Management ", CVL, vol. 11, no. 1, pp. 113–122, Mar. 2026.

ABSTRACT

An inaccurate Owner's Estimate Cost (OEC) often triggers procurement failures in the purchasing process, thereby affecting cost performance and the success of government capital expenditure projects in Indonesia from a construction management perspective. The OEC serves as the primary benchmark for assessing the reasonableness of bids in construction procurement; calculation errors may lead to ineffective cost control, financial mismanagement, and regulatory non-compliance. Therefore, this study aims to improve OEC accuracy by developing an Adaptive Neuro-Fuzzy Inference System (ANFIS) model supported by a Linear Regression (LR) algorithm to predict price fluctuations that influence cost planning and procurement decisions for public building projects. Project data from state-owned building construction and unit price analysis data for the 2021–2024 period were analyzed to predict 2025 price changes (addenda) for various construction work items. The proposed model achieved strong accuracy, with Root Mean Squared Error (RMSE) values of 0.0108–0.0333 and Mean Absolute Error (MAE) values of 0.0099–0.0261 across multiple work descriptions, indicating a good model fit. These findings confirm that the model outperforms comparable studies in terms of precision and interpretability, and can serve as a data-driven approach to strengthen cost management, estimate planning, and procurement decision-making in construction management.

1. Introduction

Capital expenditure is a strategic function of public-sector organizations because it finances fixed assets—land, buildings, facilities, and equipment. In construction management, the effectiveness of capital expenditure procurement is an indicator of government spending performance and a lever for infrastructure delivery and economic activity. Therefore, governments aim to optimize revenue to fund these programs, as capital expenditure strongly influences the provision of basic infrastructure, service quality, and achievement of national development targets.

In Indonesia, capital expenditure implementation is frequently constrained by procurement failure, which disrupts project performance (time, cost, and compliance). Key contributors include regulatory non-compliance, limited estimator competence, errors in market surveys, inadequate banking support, and inaccurate calculation of the Owner's Estimate Cost (OEC)[1],[2]. The OEC is the owner's comprehensive estimate to complete a project/service from early planning to handover[3], and in government procurement it includes Value Added Tax (VAT) once technical specifications in the Terms of Reference (TOR) are defined. Inaccurate OEC values create managerial and contractual risks (including financial losses and legal exposure); hence, OEC preparation must be transparent and accountable, supported by reliable and up-to-date market data, and strengthened through market analysis before supplier selection[4].

At tendering, the OEC serves as a baseline to assess bid reasonableness against market conditions. An OEC that is too low reduces tender attractiveness, weakens competition, and can cause delays or tender failure; an OEC that is too high increases the risk of budget waste and governance issues[5]. Large gaps between OEC and winning bids also increase dispute potential and can pressure contractors' cash flow, leading to delays and possible quality degradation[6]. In practice, contract changes are common due to scope, schedule, and cost adjustments and may be documented as addenda, Contract Change Orders (CCO), or Variation Orders (VO)[7].

Because procurement absorbs a major share of national capital expenditure, inaccurate OEC values can hinder timely and cost-efficient infrastructure targets and weaken overall government performance. In the pre-tender phase, a wide OEC–bid gap may trigger cancellation, scope reduction, or schedule postponement, and can be exacerbated by economic instability, survey errors, and limited estimator experience[8]. Artificial Intelligence (AI), particularly the Adaptive Neuro-Fuzzy Inference System (ANFIS), can improve OEC accuracy by learning patterns from large datasets and modeling price dynamics to support procurement decisions and cost control[9][10]. Compared with traditional approaches, machine learning (ML) is more adaptive to market volatility and complex cost structures. Prior studies have applied neural-network-based models to improve OEC-related predictions; however, limited transparency can hinder adoption in public procurement[11]. To better align with accountability needs, this study employs an ANFIS model based on Linear Regression (LR) to provide clearer relationships between historical price adjustments (independent variables) and OEC (dependent variable).

Owner's Estimate Cost and Procurement Risk; In public-sector construction, capital expenditure planning and procurement performance depend strongly on the reliability of the Owner's Estimate Cost (OEC). Capital expenditure typically covers fixed-asset acquisition and is closely linked to service delivery and development outcomes. Inaccurate owner estimates may lead to tender failure, inefficient competition, and budget inefficiency, and can increase cancellation risk when the winning bid deviates substantially from the owner's estimate. Studies in public procurement emphasize the role of digital tools, governance, and process design in reducing inefficiency and supporting accountability. From a cost-engineering perspective, estimate classification guidance supports transparent communication of estimate maturity, data quality, and expected accuracy[12].

Change Orders, Variation Orders, and Price Addenda; Construction contracts commonly experience changes due to design development, site conditions, or policy and regulatory adjustments. Change orders and variation orders can increase cost and disrupt schedules, so quantifying their attributes and impacts is essential for contract administration[13]. During tendering, large gaps between bid prices and the owner's estimate can lead to disputes, cash-flow stress, or quality risks[6]. Therefore, addendum-based price adjustments and data-driven OEC updates are relevant tools for reducing contractual and financial risk.

Machine Learning for Cost Estimation and OEC Prediction; Systematic reviews show that machine learning (ML) can improve early-stage and pre-tender cost estimation by capturing nonlinear relationships and market volatility that are difficult to represent using simple statistical models[14]. Data-driven conceptual estimation frameworks and KNN-based preliminary models for tall buildings demonstrate the feasibility of predicting early cost indicators from limited project attributes. For procurement contexts, prediction of the lowest-bid ratio to the owner's estimate using FFNN-based models and forecasting of final contract cost from initial estimates support the relevance of ML to OEC management. Related studies also apply ML to cost estimation in design and production settings to support decision-making under uncertainty[15],[16].

ANFIS Framework and Model Evaluation; ANFIS combines fuzzy inference and adaptive learning to model complex, nonlinear relationships in construction-cost data. The fuzzy-set concept introduced by Zadeh and the Takagi–Sugeno fuzzy model structure provide the theoretical basis for ANFIS, while the learning architecture proposed by Jang enables data-driven tuning of membership functions and rule parameters[17],[18]. Neuro-fuzzy modeling has demonstrated robustness under uncertainty in other engineering applications. For public-sector adoption, model explainability is also important; local explanation methods such as LIME can help reveal how input factors influence predictions. Model accuracy should be assessed using complementary error statistics; RMSE is sensitive to large errors, while MAE is more interpretable in the original unit scale[19]. Additional goodness-of-fit measures and acceptance thresholds are commonly reported in engineering applications[20].

2. Research Method

This study aims to improve the accuracy of OEC prediction in capital expenditure procurement by developing an ANFIS model. To achieve this objective, a systematic method is used that combines theoretical understanding with practical implementation. The theoretical basis of the study draws on data-driven decision-making theory, which emphasizes the use of historical data and statistical modeling to improve predictive accuracy. To operationalize this approach, the Cross Industry Standard Process for Data Mining (CRISP-DM) framework is adopted. This framework consists of six iterative phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment[21].

In the business understanding phase, the study identifies the need to improve OEC accuracy for capital expenditure projects. In the data understanding phase, procurement contract data were obtained from a state-owned building construction project referred to as Project SM. The data were sourced from a Jakarta-based construction company and include historical records of items that underwent changes, price addenda, work quantities, and unit prices (work unit prices). The historical price data cover the 2022–2025 period and were selected due to completeness and relevance to the original contract and subsequent price adjustments in Project SM, helping to ensure consistent patterns for cost estimation. Post-2020 economic disruptions, such as the COVID-19 pandemic, were excluded to maintain dataset consistency. In addition, Exploratory Data Analysis (EDA) was conducted to verify the absence of missing values and to examine relationships among variables.

In the data preparation phase, data were processed and transformed into a structured format for ANFIS modeling. Unit prices were classified into the independent variable (Year) and the dependent variable (Work Item Price). For the OEC calculation, the study used information on items that changed in Project SM, including quantities and unit prices. The data were analyzed using coefficients from unit price analysis and basic unit prices for labor, materials, and equipment, sourced from historical data published in the Journal of Unit Prices for Building Materials. This analysis is important for understanding standards, specifications, and material costs associated with works subject to price adjustment, thereby providing a detailed basis for model development.

A unit price analysis model developed based on the Regulation of the Minister of Public Works and Housing (PUPR) No. 28 of 2016 was integrated into a unit-price database derived from the calculated unit prices for construction works that experienced price-addendum adjustments. This database served as the basis for identifying attributes used in developing the ANFIS model. Several assumptions were applied to ensure model reliability: (1) the price-trend representation reflects cost adjustment factors in construction projects; (2) the dataset contains no missing values, as verified through EDA; and (3) the price trend is linear and follows a consistent pattern across the analyzed years.

3. Application of ANFIS in Construction Management

Construction management focuses on planning, organizing, executing, and controlling project resources to achieve cost, time, quality, safety, and compliance objectives. The dynamic nature of construction projects—characterized by uncertainty and multiple stakeholders—means that managerial decisions are often influenced by market variability, site conditions, and scope changes. In this context, ANFIS is relevant as a data-driven analytical tool capable of capturing nonlinear relationships and accommodating uncertainty through fuzzy representation[10].

In cost management, ANFIS can be applied to improve the accuracy of cost estimates during the pre-tender stage and budget planning. Model inputs may include material price indices, project location, work quantities, labor productivity, and other market variables affecting cost. Outputs may include item-level cost estimates (e.g., by bill of quantities component), price escalation forecasts, or deviations from baseline. This supports cost planning and cost control by providing estimates that are more adaptive to price fluctuations and complex cost structures.

In procurement management, ANFIS can support a more reliable OEC setting as a benchmark for bid reasonableness. By learning patterns of historical price adjustments and market dynamics, ANFIS helps reduce the risk of setting the OEC too low (which may reduce tender participation and trigger procurement failure) or too high (which may result in budget waste). Accordingly, ANFIS contributes to more objective, consistent, and accountable procurement decision-making.

In time management, ANFIS can help predict activity durations or delay probabilities by considering factors such as productivity, weather, logistics access, work complexity, and potential rework. More accurate predictions are useful for developing realistic schedules, determining buffers, and planning mitigation when disruptions occur. This supports schedule control and increases certainty in project completion. ANFIS can also be utilized in risk management and contract management. Models can be developed to assess the risk level of cost overrun, delay risk, or the potential for claims/variations due to scope changes, design changes, and price instability. By mapping inputs into fuzzy categories (e.g., low–medium–high risk), ANFIS helps project managers prioritize mitigation, control strategies, and more measurable contingency plans.

In quality and safety management, ANFIS can be used to predict the likelihood of quality defects/rework and safety incident risk based on parameters such as work processes, material characteristics, work-area density, working hours, and workforce competence. These predictions strengthen Quality Assurance/Quality Control (QA/QC) and Health, Safety, and Environment (HSE) programs through targeted interventions before issues occur.

Methodologically, applying ANFIS in construction management studies requires systematic stages: (1) defining the model objective and input–output variables; (2) collecting representative data and preprocessing (cleaning, normalization, outlier handling); (3) designing membership functions and rules; (4) training with an appropriate scheme; and (5) evaluation using relevant metrics such as RMSE and MAE for numerical prediction. Robustness testing across different market periods is also important to ensure the model remains reliable for project management decision-making.

The modeling phase involved developing an LR-based ANFIS model implemented in Python 3 within a Jupyter Notebook environment. The LR algorithm was selected because it can predict continuous variables using historical data and is readily interpretable in explaining relationships between independent and dependent variables. The model was trained using an 80:20 train–test split, allowing it to learn patterns from the training data while evaluating accuracy on unseen data [38]. Predictions for the year 2021 were generated using the trained model by analyzing price trends for different work items.

Model accuracy was evaluated in the evaluation phase using two metrics: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These metrics are useful because they express error in the same unit as the predicted variable, facilitating interpretation [31]. RMSE is widely used for evaluating regression models and is the square root of the mean squared differences between predicted and observed values across all data points [32], [30], expressed as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(yi-\tilde{y}i)^2}{n}} \tag{1}$$

where yi is the observed value, ŷi is the predicted value, i is the index of the data point in the dataset, and n is the total number of data points.

MAE is determined by calculating the absolute error between each predicted value and the corresponding actual value and then averaging across the dataset, expressed as:

$$\mathrm{MAE} = \frac{1}{n}\sum xi - x \tag{2}$$

where xi is the actual value, x̂i is the predicted value, and n is the total number of values.

In this analysis, RMSE and MAE values of 0 indicate a perfect fit [33]. Values less than half of the standard deviation of measured data are considered reasonable; both metrics are appropriate for

ISSN (*Online*) 2620-7222
ISSN (*Print*) 2503-2399

model evaluation. RMSE tends to emphasize larger errors because residuals are squared, while MAE provides a direct measure of average error.

Although this study did not include full implementation of the deployment phase, adopting the CRISP-DM framework yielded a structured and transparent methodology for developing and validating the ANFIS model. Figure 1 illustrates the ANFIS structure in construction management.

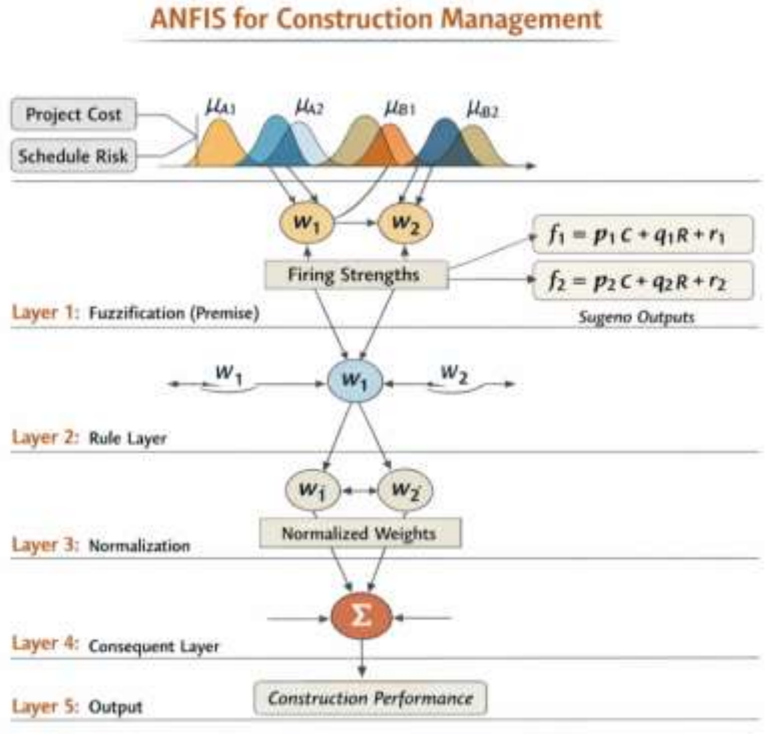

Figure 1. ANFIS structure in construction management.

4. Results and Discussions

4.1. Variable Identification for ANFIS Model Development

The contract data include both the initial OEC value and the revised prices subsequently applied. Table 1 presents the adjustments in detail, particularly for architectural works. Six work items that experienced price changes from the 2025 original contract were selected for further analysis. This analysis was required to develop an ANFIS model capable of predicting near-term price trends. The adjustments were required because the initial OEC did not account for post-award price increases.

The items categorized as sub-items of the six work items in Table 1 comprise data requiring detailed review. Each sub-item relates to a specific contract with a third-party contractor for construction procurement and contains confidential information on prices and contract terms. The availability of quantity and unit price data is critical for accurately computing the OEC for each sub-item. After identifying work items subject to price adjustment through addenda, 16 unit-price work items were extracted for further analysis using the 2022–2025 unit price analyses. The dataset was run 10 times for each unit-price item, resulting in 64 data points. The data were processed 640 times within the ANFIS model to ensure robustness and to provide sufficient data volume and variation for effective model training.

Table 1. Initial OEC and price addendum in Project SM

No.	Work Description	OEC 2024 (IDR)	Additional Works (IDR)	2025 Revised Contract (IDR)
A	Architectural Works			
I	Preparatory Works	115.455.000	-	115.455.000
II	Demolition Works	-	-	-
	A. Main Building	325.560.000	-	325.560.000
	B. Auxiliary Building	30.105.000	-	30.105.000
	C. Exterior Area	63.570.000	-	63.570.000

No.	Work Description	OEC 2024 (IDR)	Additional Works (IDR)	2025 Revised Contract (IDR)
III	Brick Masonry Works	-	-	-
	A. Main Building Lantai Dasar	22.530.000	22.110.000	243.270.000
	B. Main Building Lantai Atas	61.725.000	-	61.725.000
	C. Front Supporting Facility Building	20.865.000	-	20.865.000
	D. Rear Supporting Facility Building	23.220.000	1.260.000	2.460.000
	E. Exterior Area	65.025.000	-	65.025.000
IV	Installation of Gypsum Partition Walls + Hollow Steel Framing	-	-	-
	A. Main Building Lantai Dasar	74.970.000	3.960.000	78.915.000
	B. Main Building Lantai Atas	3.585.000	-	3.585.000
V	Floor and Wall Finishing Works	-	-	-
	A. Main Building Lantai Dasar	431.580.000	32.280.000	43.965.000
	B. Main Building Lantai Atas	76.560.000	-	76.560.000
	C. Front Supporting Facility Building	75.000	-	72.945.000
	D. Exterior Area Depan	16.710.000	4.905.000	170.145.000
	E. Rear and Side Areas	22.095.000	7.665.000	227.580.000

These trends provide a baseline understanding of price changes over time and help predict short-term cost trends more effectively, as shown in Table 2. Table 2 presents the unit price analyses for the 2021–2024 period used to classify work items. This classification sets YEAR as the input variable (x). At the same time, the price of each work item is defined as the dependent response variable (y) and labeled WORK1 through WORK16. The LR-based ANFIS model was used to predict forward price trends for these items.

Table 2. Sixteen work items subject to price adjustment and unit price analysis (2021–2024)

No	Work Type	Model	2021 (IDR)	2022 (IDR)	2023 (IDR)	2024 (IDR)
1	Standard brick wall masonry (1/2-brick thickness)	Work Item 1	92.250	99.150	106.200	118.200
2	Standard plastering + finishing	Work Item 2	92.250	96.000	98.700	105.600
3	Doors and window sills	Work Item 3	152.400	179.700	181.200	276.300
4	Brickwork for foundation walls	Work Item 4	94.650	102.450	110.550	123.150
5	Waterproof plastering + finishing	Work Item 5	69.600	76.350	78.300	84.300
6	Gypsum partition wall installation	Work Item 6	286.500	299.700	356.400	327.150
7	Hollow steel partition framing	Work Item 7	287.400	294.750	296.100	323.250
8	Floor paving	Work Item 8	184.050	180.900	185.550	199.500
9	Wall installation and supply	Work Item 9	84.000	87.450	89.100	100.800
10	Fill / red soil (planting medium)	Work Item 10	547.050	561.150	599.400	624.900
11	Granite flooring	Work Item 11	189.000	185.550	191.100	204.750
12	Kerbstone installation and supply	Work Item 12	656.700	631.200	663.300	738.450
13	Polished granite tile flooring	Work Item 13	334.800	366.150	385.500	559.950
14	Rough-pattern ceramic tile flooring	Work Item 14	299.850	315.600	319.500	400.200
15	Granite wall tiling	Work Item 15	90.450	84.450	82.200	85.800
16	Floor skirting	Work Item 16	90.450	8.445.000	8.220.000	85.800

4.2. ANFIS Model Development

The ANFIS model was developed using Python 3 in a web-based Jupyter Notebook application. The first step is to import the required libraries. Pandas is used for data manipulation and organization, Matplotlib for visualization, and mathematical functions for this research.

The data were loaded into two primary columns serving as the modeling variables. The first column, labeled “Year”, was defined as the independent variable (x), while the second column, “Work Item”, was defined as the dependent variable (y). After loading, the system displayed the number of records, data types, and memory allocation to ensure accuracy and consistency before proceeding.

Next, missing values were checked. A value of zero indicated that no missing data were present, allowing the analysis to proceed without imputation. The subsequent step was EDA, beginning with bivariate analysis of the relationship between “Year” and “Work Item” using a scatter plot. This plot helped visualize the relationship between the two factors prior to modeling. The correlation coefficient was also computed and yielded a value of 0.7, indicating a strong positive relationship between “Year” and “Work Item”. This result suggests that changes in “Year” are closely associated with changes in “Work Item” prices.

The core ANFIS modeling process started after completing the preceding steps. This process included defining X and Y variables, splitting data into training and testing sets using an 80:20 ratio, and applying the LR algorithm to train the model. During this phase, the model learned from the input data and identified the slope and coefficients required to produce accurate predictions. Finally, the model was run through multiple iterations to adjust and optimize predictions, ensuring that the model outputs are reliable for improving OEC estimation accuracy in building construction projects.

4.3. Evaluation of ANFIS Prediction Accuracy

The developed ANFIS model produced optimal predictions through repeated runs that account for variance, where each run used slightly different training and testing datasets. Variance refers to the sensitivity of an algorithm to the specific data used during training; this characteristic can produce different outcomes when small changes occur in the data or the training procedure [39].

Some ANFIS algorithms that are non-deterministic can be classified as stochastic, meaning their behavior is influenced by randomness during training [40]. However, stochastic behavior does not necessarily imply that the model is fully random. Stochastic ANFIS algorithms still learn from the available historical data, but small decisions during learning may vary randomly from one iteration to another. Consequently, when a stochastic ANFIS algorithm is executed on the same data, the resulting model can differ slightly, and the predictions on the test data may also vary. The performance of such stochastic models can be viewed as a distribution with an expected mean error (or accuracy) and a standard deviation that reflects the degree of randomness in prediction outcomes.

The final prediction results provide estimated prices for each work item, enabling a more accurate analysis of future trends. After training, testing, and smoothing the prediction distribution, the ANFIS prediction results are presented in Table 3.

Table 3. ANFIS prediction results with estimated prices (2021–2025)

No.	Work Type	2021 (IDR)	2022 (IDR)	2023 (IDR)	2024 (IDR)	2025 (IDR)
1	Standard brick wall masonry (1/2-brick thickness)	148.200	173.850	173.250	267.600	289.350
2	Standard plastering + finishing	92.250	99.150	106.200	118.200	125.850
3	Doors and window sills	92.250	96.000	98.700	105.600	109.200
4	Brickwork for foundation walls	152.400	179.700	181.200	276.300	299.850
5	Waterproof plastering + finishing	94.650	102.450	110.550	123.150	131.700
6	Gypsum partition wall installation	69.600	76.350	78.300	84.300	88.200
7	Hollow steel partition framing	286.500	299.700	356.400	327.150	358.650
8	Floor paving	287.400	294.750	296.100	323.250	330.300
9	Wall installation and supply	184.050	180.900	185.550	199.500	201.900
10	Fill / red soil (planting medium)	84.000	87.450	89.100	100.800	104.550
11	Granite flooring	547.050	561.150	599.400	624.900	651.000
12	Kerbstone installation and supply	189.000	185.550	191.100	204.750	207.300
13	Polished granite tile flooring	656.700	631.200	663.300	738.450	750.000
14	Rough-pattern ceramic tile flooring	334.800	366.150	385.500	559.950	585.300
15	Granite wall tiling	299.850	315.600	319.500	400.200	409.950
16	Floor skirting	90.450	84.450	82.200	85.800	82.800

The OEC price increase percentage was analyzed by multiplying the unit-price database and predicted prices by the building quantities in Project SM. The percentage increase between 2023 and 2025 was then computed. In addition, the percentage increase was determined for both predicted and actual Project SM data for each work sub-item to evaluate and compare the ANFIS prediction accuracy, as shown in Table 4.

Table 4. Comparison of OEC price increases between actual data and ANFIS predictions

No.	Work Description	Initial Contract (IDR)	Price Addendum (IDR)	Price Increase (%)
1	III.A Brick masonry work (Main Building)	225.300	243.270	8,0%
2	III.D Brick masonry work (Rear Auxiliary Building)	23.220	24.600	5,9%
3	IV.A Gypsum partition wall installation (Main Building)	74.970	78.915	5,3%
4	V.A Floor and wall finishing (Main Building)	431.580	439.650	1,9%
5	V.D Floor and wall finishing (Front Exterior Area)	167.100	170.145	1,8%
6	V.E Floor and wall finishing (Rear and Side Areas)	220.950	227.580	3,0%

In construction cost analysis, accurate cost estimation is crucial to project success [41]. The predicted price increase from 2024 to 2025 was compared with the actual price increase data from Project SM to evaluate improvements in OEC calculation accuracy for capital expenditure procurement using the ANFIS model. The RMSE and MAE evaluation results indicate that the ANFIS predictions achieved high accuracy and good agreement with actual data, as shown in Table 5.

Table 5. Normalized RMSE and MAE results: comparison of ANFIS prediction accuracy with actual project data

No.	Work Description	RMSE	MAE
1	III.A Brick masonry work (Main Building)	0,0180	0,0135
2	III.D Brick masonry work (Rear Auxiliary Building)	0,0162	0,0144
3	IV.A Gypsum partition wall installation (Main Building)	0,0279	0,0225
4	V.A Floor and wall finishing (Main Building)	0,0333	0,0261
5	V.D Floor and wall finishing (Front Exterior Area)	0,0126	0,0108
6	V.E Floor and wall finishing (Rear and Side Areas)	0,0108	0,0099

The findings show that the developed ANFIS model performs well, with RMSE values ranging from 0.0108 to 0.0333 and MAE values ranging from 0.0099 to 0.0261. However, it should be noted that these values are still presented on the normalized scale because the model was trained using normalized data. Therefore, from a practical perspective, these values should be denormalized before being interpreted in the discussion. After denormalization, the RMSE values indicate the average magnitude of prediction error in Rupiah, allowing readers to understand how far the model predictions deviate from the actual work-item prices in real monetary terms. Likewise, the denormalized MAE values show the average absolute difference between predicted and actual prices in Rupiah. This interpretation is more relevant for construction cost management because it directly reflects the practical accuracy of the model in estimating the Owner's Estimate Cost (OEC).

By comparison, Zhang et al. [26] used a combination of extreme gradient boosting (XGBoost) and Bayesian optimization (BO) and reported RMSE of 0.7821 and MAE of 0.4387. Their higher errors are likely due to their focus on conceptual cost estimation across diverse infrastructure projects with heterogeneous datasets and greater variability. The LR-based model in this study achieved higher precision because it focuses on a more specific procurement dataset with consistent characteristics. In addition, Sanni-Anibire et al. [27] used k-Nearest Neighbors (KNN) to model cost estimation for high-rise buildings and reported an RMSE of 6.09. The large error in that study was associated with a broader project scope and more varied cost structures. In contrast, the LR approach in this analysis benefited from a more specific dataset.

Methodological choices also influence outcome variation because this study uses LR for simplicity and interpretability, whereas other studies rely on more complex algorithms. While such algorithms can capture nonlinear relationships more effectively, they are often accompanied by reduced interpretability and increased computational requirements.

5. Conclusion and Suggestion

5.1 Conclusion

In conclusion, the ANFIS-based model developed in this study was able to improve the accuracy of Owner's Estimate Cost (OEC) prediction for capital expenditure procurement. The model showed low RMSE and MAE values, indicating good agreement between predicted and actual prices.

However, because the model was trained on normalized data, the reported RMSE and MAE values are still on a normalized scale. Therefore, in practical interpretation, these error values should be denormalized so that readers can understand the average prediction error in Rupiah rather than only in the 0–1 interval. This denormalized interpretation is important because it provides a clearer picture of the model's usefulness in real construction cost estimation and procurement decision-making. Presenting denormalized RMSE and MAE is highly recommended because it allows the model error to be interpreted directly in Rupiah, making the results easier to understand and more useful for practitioners and decision makers.

5.2 Suggestion

Future research can incorporate more recent data and explore advanced ANFIS approaches, such as deep learning-based models to further improve OEC prediction precision for capital expenditure procurement.

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