

Cost Modeling of Road Maintenance Using the Cost Significant Method in Disaster Prone Areas of Solok Regency

Lucky Ramanur Sukandar¹, Purnawan^{1*}, and Elsa Eka Putri¹

¹*Departemen Teknik Sipil, Fakultas Teknik, Universitas Andalas, Padang, Indonesia*

**Corresponding author: purnawan@eng.unand.ac.id*

(Received: 17th February 2026 ; Revised: 12th May 2026 ; Accepted: 19th May 2026)

Abstract: This study aims to develop cost model for a periodic road maintenance project. The background is the lack of a simple and accurate calculation method to estimate the cost of the work. The model was developed using the Cost Significant Model (CSM) method and multiple linear regression, using historical data of periodic road maintenance work contracts at the Public Works and Spatial Planning Agency (DPUPR) of Solok Regency for the period 2018–2023. The analysis results show that the most significant work on the project cost is K-175 shoulder concrete, Class A Aggregate Foundation Layer (LPA), and Asphalt Concrete-Wearing Course (AC-WC). The resulting cost estimation model is $Y = 4,531.24 + 1.19 X_{14} + 1.35 X_{15} + 1.43 X_{19}$, with Y as the project cost per m², X₁₄ the price of K-175 shoulder concrete per m², X₁₅ the price of Class A LPA per m², and X₁₉ the price of AC-WC per m². This model has an average CMF value of 1.004 and a model deviation of 2.965%, much more accurate than the estimation method currently used by the Highways Division of the DPUPR of Solok Regency which has an average deviation of 29.951%. Thus, the developed CSM model is proven to be more accurate and suitable for estimating the costs of periodic road maintenance projects in Solok Regency.

Keywords : Cost significant model; Cost estimation; Cost estimation model; road maintenance in regency; Solok Regency

1. Introduction

Road infrastructure functions as the backbone of regional economic and social development. In Solok Regency, which is geographically situated within a disaster-prone zone, the road network is subjected not only to traffic loads but also to environmental pressures such as ground movement, high rainfall intensity, and seismic activity. These conditions accelerate the rate of pavement deterioration, thereby requiring higher frequency and intensity of maintenance interventions (Koks et al., 2019; Amin et al., 2020; Ferlisi et al., 2020).

Currently, road maintenance activities are frequently constrained by inaccuracies in preliminary cost estimation. To date, the Department of Public Works and Spatial Planning (DPUPR) of Solok Regency has not yet established a simple and reliable cost estimation method, particularly one capable of accommodating the additional complexities associated with disaster-prone characteristics (Batista et al., 2019; Postance et al., 2017; Rezvani, 2024). Consequently, substantial budget deviations often occur, potentially leading to project delays, financial inefficiencies, or even the failure to achieve targeted physical maintenance outcomes (Koks et al., 2019; Batista et al., 2019; Postance et al., 2017).

Disaster vulnerability introduces significant uncertainty variables into road maintenance cost components. Factors such as limited site accessibility, fluctuations in local material prices, and the need for specific technical specifications increase cost variability, which is difficult to predict using conventional estimation approaches (Flores & Ascaño, 2025; Petroutsatou et al., 2023). Detailed and comprehensive cost estimation methods are often impractical in planning contexts that demand rapid response and efficient resource allocation. Therefore, a modeling approach is required to simplify the estimation process without compromising accuracy, by prioritizing the most cost-significant elements (Rezvani, 2024).

In response to these challenges, this study proposes the application of the Cost Significant Model (CSM) as a solution for modeling road maintenance costs in disaster-prone areas. CSM is a parametric approach that filters work items contributing dominantly to total project costs based on historical data, and subsequently establishes simplified mathematical relationships among them (Muttaqin et al., 2024; Wang & Horner, 2007; Donal, 2014; Salindeho, 2022; Liu & Luo, 2023). This research aims to develop a cost estimation model based on road maintenance contract data in Solok Regency for the period 2018–2023. The resulting model is designed to be practical and easily applicable, thereby serving as a decision-support tool for planners in preparing budgets more efficiently.

2. Literature Review

2.1 Road Maintenance and Asset Preservation

Road infrastructure constitutes a strategic public asset that plays a critical role in supporting regional connectivity, economic productivity, and social mobility. In decentralized governance systems, district roads represent a substantial portion of the road network and are primarily managed by local governments. Effective maintenance strategies are therefore essential to ensure network reliability and long-term asset sustainability.

Road maintenance refers to preventive and corrective actions undertaken to preserve pavement condition and restore functional and structural performance within its design life. Periodic maintenance, in particular, is aimed at preventing progressive deterioration and restoring serviceability before severe structural failure occurs. Typical periodic maintenance interventions include asphalt overlays, base course rehabilitation, shoulder repairs, crack sealing, drainage improvements, and replacement of damaged complementary structures.

From an asset management perspective, timely maintenance significantly reduces life-cycle costs and prevents exponential increases in rehabilitation or reconstruction expenses. Empirical studies have consistently demonstrated that delayed intervention results in accelerated pavement deterioration and substantially higher vehicle operating costs. Therefore, maintenance planning must be supported by reliable cost forecasting mechanisms to ensure optimal allocation of limited public budgets.

2.2 Construction Cost Estimation in Infrastructure Projects

Cost estimation is a fundamental component of project planning and financial decision-making in construction management. At the early stage of a project, cost estimates serve as the primary basis for feasibility assessment, budgeting, and funding allocation. However, early-stage estimation is characterized by limited information, high uncertainty, and restricted design detail.

Construction cost estimation methods can generally be categorized into several approaches, including:

- a) Parametric estimation methods, which relate cost to physical parameters such as area, length, or volume;
- b) Unit price methods, which calculate total cost based on measurable quantities and standardized unit rates;

- c) Elemental cost analysis, which decomposes projects into functional components;
- d) Historical data-based methods, which utilize previous project records to develop predictive models;
- e) Regression-based statistical modeling.

Traditional detailed cost estimation (e.g., quantity take-off and bill of quantities preparation) provides high accuracy but requires extensive documentation and time. Conversely, simplified approaches, such as average unit cost per square meter, are faster but often lack analytical robustness and may produce significant deviations when project characteristics vary.

In public infrastructure projects, especially at the district level, practical cost estimation methods must balance speed, simplicity, and acceptable accuracy. This necessity has encouraged the development of statistical models derived from historical project data.

2.3 Cost Significant Model (CSM)

The Cost Significant Model (CSM), originally developed by Poh and Horner (1995), is a regression-based cost forecasting approach that emphasizes the identification of dominant cost components within a project. The model is grounded in the Pareto principle, which suggests that approximately 80% of the total project cost is typically represented by about 20% of cost items.

Rather than analyzing all bill of quantity components, CSM focuses only on “*cost-significant items*” those that collectively contribute the largest proportion of total cost. These dominant components are then used as independent variables in a multiple regression model to predict total project cost. The methodological stages of CSM typically include:

- a) Collection of historical project data from similar types of work;
- b) Adjustment of cost data to a common base year using inflation or future value calculations;
- c) Identification and ranking of cost components based on their proportional contribution;
- d) Selection of items contributing cumulatively to approximately 80% of total cost;
- e) Development of a regression model using the selected cost-significant variables;
- f) Model calibration and validation using cost model factors (CMF) and accuracy testing.

The advantages of CSM include:

- a) Reduced data complexity compared to full bill-of-quantity estimation;
- b) Faster estimation at conceptual stages;
- c) Statistical transparency through regression analysis;
- d) Practical applicability in repetitive or homogeneous project types.

However, CSM requires high-quality historical data and assumes relative homogeneity among projects. Model accuracy strongly depends on data consistency and proper variable selection.

In road maintenance projects, dominant cost components often include asphalt concrete layers, base course aggregates, and structural concrete elements, which tend to account for the majority of budget allocation. Therefore, CSM is particularly suitable for periodic road maintenance projects with repetitive technical characteristics.

2.4 Inflation Adjustment and Time Value of Money in Cost Modeling

When historical project data span multiple fiscal years, direct comparison of nominal costs may introduce distortion due to inflation. Adjusting past costs into a common reference year is therefore essential to maintain model validity. The time value of money concept is applied using the Future Value (FV) from eq. 1.

$$FV = PV (1 + i)^n \dots\dots\dots (1)$$

Where:

- FV* : *future value* (monetary value at period n)
PV : *present value* (current monetary value)
 i : Interest rate
 n : *compounding* (number of compounding intervals)

Failure to account for inflation may bias regression coefficients and reduce predictive reliability. Incorporating inflation-adjusted values ensures that cost-significant items reflect real price structures rather than nominal fluctuations.

2.5 Model Validation and Accuracy Assessment

Model validation is a critical step in cost forecasting research. Regression-based models are commonly evaluated using:

- a) Coefficient of determination (R^2) to assess explanatory power;
- b) F-test and t-test to examine statistical significance;
- c) Normality testing to verify parametric assumptions;
- d) Cost Model Factor (CMF) for calibration;
- e) Percentage deviation or error rate for accuracy measurement.

In infrastructure cost modeling, an average deviation below 10% is generally considered highly satisfactory for early-stage estimation, while deviations above 20–30% may indicate insufficient predictive capability. Comparative evaluation between statistical models and conventional estimation approaches provides practical insight into the relative efficiency and reliability of alternative methods

3. Research Method

3.1 Research Data

The data utilized in this study consist of secondary data. These data comprise contract documents of periodic maintenance projects for regency roads obtained from the Highway Division (Bina Marga) of the Department of Public Works and Spatial Planning of Solok Regency for the period 2018–2023. In addition, provincial inflation data for West Sumatra Province covering the period 2018–2022 were incorporated, sourced from the Central Bureau of Statistics (BPS) of West Sumatra Province.

3.2 Variable Identification

Variable identification was conducted to obtain an optimal modeling outcome. At this stage, work package data from each project were classified according to the type of work items. In general, each project package was divided into two categories of variables: dependent and independent variables. The total project cost was designated as the dependent variable, while the individual work item types were defined as independent variables. The number of independent variables depended on the variety of work items within each project, whereas the dependent variable consisted of a single variable for each project package.

3.3 Future Value Calculation

The calculation of future value is necessary because annual inflation causes changes in the real value of money over time. To ensure comparability between past contract values and present monetary conditions (Oktavia et al., 2023), contract amounts were adjusted using the future value approach. The future value formula is presented in Eq. 1.

3.4 Identification of Cost Significant Items (CSI)

Cost Significant Items (CSI) are defined as the major cost components that cumulatively account for $\geq 80\%$ of the total project cost. Independent variables classified as CSI were identified by ranking the proportion of each cost component from the largest to the smallest contribution. The cost proportions were then accumulated sequentially. Cost components whose cumulative contribution first reached or exceeded 80% of the total cost were designated as Cost Significant Items (CSI) (Sugiyarto et al., 2015; Sugiyarto et al., 2016). The independent variables included in the model were those representing dominant cost components with a cumulative total contribution of at least 80% of the overall project cost.

3.5 Data Normality Test

The normality test was conducted to determine whether the collected data were normally distributed or originated from a normally distributed population. Data normality constitutes one of the fundamental assumptions in parametric statistical analysis; therefore, the dataset must be tested prior to performing such analyses. Examples of parametric tests include Pearson's correlation (product-moment correlation), the t-test, and linear regression. The normality test was performed by comparing the probability value (p-value) with the significance level ($\alpha = 0.05$). The data were considered normally distributed if the probability value (p) > 0.05 , thereby satisfying the assumption required for parametric analysis.

3.6 Data Analysis

Data analysis was conducted using the correlation coefficient (r) to determine the strength of the relationship between the independent variables and the dependent variable. The value of the correlation coefficient ranges from -1 to 1. If $r = 0$ or approaches zero, the relationship between variables is very weak. If r approaches 1 or -1, the relationship between the independent variable (X) and the dependent variable (Y) is very strong and either positive or negative.

To determine how well the regression line represents the observed data, the coefficient of determination (R^2) was used, with values ranging from 0 to 1. If $R^2 = 0$, there is no relationship between X and Y , meaning that the regression model is unable to explain the variation in Y . If $R^2 = 1$, the regression model perfectly explains the variable Y . Therefore, the value of R^2 indicates the magnitude of the influence of the independent variable on the dependent variable.

In addition, the regression results provide the value of Significance F , which indicates whether all independent variables simultaneously have a significant effect on the dependent variable. If Significance $F < 0.05$, the regression model is considered significant, indicating that the independent variables jointly influence the dependent variable. Conversely, if Significance $F > 0.05$, the regression model is considered not significant. To assess the suitability of each independent variable in the model, a t-test was conducted. The t-test was performed to evaluate the partial effect of each independent variable on the dependent variable by comparing the significance value (sig.) of t-hitung with the significance level $\alpha = 0.05$. A variable is considered to have a significant effect if sig. < 0.05 .

3.7 Model Testing Using the Cost Model Factor (CMF)

The CMF value is obtained by dividing the project cost estimated by the model by the actual project cost (Sayed et al., 2020). Mathematically, the CMF formula is presented in Equation 2.

$$CMF = \frac{Ev}{Av} \dots\dots\dots (2)$$

Where:

Ev : predicted cost
 Av : actual cost

The deviation between the actual project cost and the predicted cost was calculated using Equation 3 (Poh & Horner, 1995).

$$\text{Deviasi} = \frac{Ev - Av}{Av} \times 100\% \quad \dots\dots\dots (3)$$

Where:

Ev : predicted cost
 Av : actual cost

4. Result and Discussion

4.1 Research Data

The data used in this study consist of contract documents for periodic maintenance work packages of regency roads under the Department of Public Works and Spatial Planning of Solok Regency, covering 17 road sections during the period 2018–2022. The cost values used in the analysis represent contract values excluding Value Added Tax (VAT). The dataset includes the year of implementation, road section name, road area, contract value, and detailed work item breakdown.

In the process of variable classification and identification, the total project cost (Y) was defined as the dependent variable, while the independent variables consisted of various work items, namely: project signboard (X1), mobilization (X2), excavation for drainage ditches and waterways (X3), ditch cleaning (X4), stone masonry with mortar (X5), reinforced concrete pipe culvert with a diameter of 55–65 cm (X6), common excavation (X7), asphalt pavement excavation without cold milling machine (X8), common embankment (X9), selected embankment (X10), subgrade preparation (X11), land clearing and grubbing (X12), aggregate base course Class C (X13), concrete shoulder K-175 (X14), aggregate base course Class A (X15), aggregate base course Class S (X16), asphalt prime coat (X17), asphalt tack coat (X18), asphalt concrete wearing course / AC-WC (X19), anti-stripping agent (X20), medium-strength concrete $F_c' = 20$ MPa (X21), cyclopean concrete $F_c' = 15$ MPa (X22), plain reinforcing steel BJ 24 (X23), deformed reinforcing steel BJ 32 (X24), stone masonry (X25), plastering (X26), demolition of stone masonry (X27), thermoplastic road marking (X28), aggregate base Class A for minor works (X29), aggregate for unsealed pavement for minor works (X30), and hot mix asphalt for minor works (X31).

4.2 Variable Identification

Subsequently, data screening was performed using the Cost Significant Model (CSM) method by eliminating cost components that had minimal influence and did not consistently appear in each work package. In addition, row-level data screening was conducted, whereby six data rows that did not appear consistently across all work packages were excluded from the analysis. Consequently, the number of observations used in the subsequent stage was reduced to 11 work packages.

The screening results indicated that several cost components consistently appeared in every project and could therefore be considered constant variables. These components included project signboard (X1), mobilization (X2), aggregate base course Class C (X13), concrete shoulder K-175 (X14), aggregate base course Class A (X15), asphalt prime coat (X17), asphalt concrete wearing course / AC-WC (X19), anti-stripping agent (X20), and stone masonry (X25). Meanwhile, other work items that were inconsistent or appeared only in certain work packages were eliminated from further analysis. This process aimed to enhance the model's validity and reduce potential bias arising from differences in work composition across packages.

4.3 Future Value (FV)

Differences in budget years across work packages resulted in cost values that were not directly comparable. Therefore, price adjustments were necessary to ensure that all data were standardized to a single base year. To address this issue, this study applied the future value approach to obtain more realistic and comparable cost values. The adjustment was conducted using inflation data for West Sumatra Province obtained from the Central Bureau of Statistics (BPS) for the period 2018–2022, as presented in Table 1.

Table 1. Inflation Data of West Sumatra Province

No.	Year	Inflation(%)
1	2018	2,60
2	2019	1,66
3	2020	2,11
4	2021	1,40
5	2022	7,43

Source: BPS Provinsi Sumatera Barat

The inflation rates were subsequently incorporated into the future value equation to project all cost data to a uniform base year. As a result, observed cost differences were no longer influenced by changes in purchasing power, but rather reflected technical differences in field implementation. This procedure was intended to enhance the model's accuracy and ensure that each variable was evaluated on a comparable monetary basis.

In addition to inflation adjustment, the data were standardized into cost per square meter (Rp/m²). This standardization was necessary because each road section varied in length and width, resulting in non-uniform surface areas across work packages. By converting the data into a per-square-meter unit, all observations became directly comparable.

4.4 Identification of Cost Significant Items (CSI)

Subsequently, the proportion of periodic road maintenance works in Solok Regency was determined to identify the average contribution of each cost component per square meter of road area. The proportion was calculated by comparing the cost of each work item to the total contract value excluding VAT, expressed as a percentage.

Cost components with the largest percentage contributions were then identified as Cost Significant Items (CSI), defined as work items that cumulatively contribute $\geq 80\%$ of the total cost. These cost proportions served as the basis for selecting the research variables. The ranking of cost proportions for periodic regency road maintenance works in Solok Regency for the period 2018–2022 is presented in Table 2.

Table 2. Ranking of Cost Proportions for Periodic Regency Road Maintenance Works in Solok Regency (2018–2022)

Work Division Item	Variable	Percentage (%)
Asphalt Concrete - Wearing Course (Fine/Coarse Gradation)	X19	47.13
Base Course, Class A Aggregate	X15	15.88
Concrete Shoulder	X14	8.55
Sub-Base Course	X13	5.80
Stone masonry	X25	3.19
Liquid Asphalt Prime Coat	X17	2.69
Mobilization	X2	1.32
Anti-Stripping Agent	X20	0.23
Project Signboard	X1	0.03
Total		84.80

Cost Modeling of Road Maintenance Using the Cost Significant Method in Disaster Prone Areas of Solok Regency

Based on Table 2, the Cost Significant Items (CSI) consist of asphalt concrete wearing course (AC-WC) (X19) at 47,13%, aggregate base course Class A (X15) at 15,88%, concrete shoulder K-175 (X14) at 8,55%, aggregate base course Class C (natural material) (X13) at 5,80%, and stone masonry (X25) at 3,19%. When accumulated, these components account for 80,54% of the total project cost. Accordingly, the dependent and independent variables used in this study are presented in Table 3 and Table 4.

Table 3. Dependent and Independent Variables

Year	No	Project Cost (Rp/m ²)	Aggregate Base Course Class C (Natural Material) (Rp/m ²)	Concrete Shoulder K-175 (Rp/m ²)
		Y	X13	X14
2018	1	252,754.71	21,665.73	11,039.72
	2	287,999.86	21,998.53	3,351.88
2019	3	334,944.99	46,600.38	967.67
2020	4	337,582.80	31,552.37	39,273.86
	5	377,531.50	9,403.31	48,635.85
2021	6	513,284.48	4,783.46	32,622.67
2022	7	333,330.53	44,431.28	42,843.25
	8	305,317.94	1,614.49	30,630.85
	9	94,312.62	2,695.81	56,261.53
	10	284,925.79	1,610.43	32,956.88
	11	342,068.83	18,864.36	12,779.14

Table 4. Dependent and Independent Variables (Continued)

Year	No	Aggregate Base Course Class A (Rp/m ²)	Asphalt Concrete Wearing Course (AC-WC) (Fine/Coarse Gradation) (Rp/m ²)	Stone Masonry (Rp/m ²)
		X15	X19	X25
2018	1	48,822.88	134,830.00	8,252.47
	2	54,446.90	134,830.00	35,914.18
2019	3	74,928.45	153,466.26	15,691.13
2020	4	63,119.36	153,721.24	568.41
	5	71,731.42	143,577.55	7,771.26
2021	6	88,950.04	245,359.75	16,553.93
2022	7	57,241.56	138,578.68	4,190.19
	8	21,986.58	156,910.29	9,378.56
	9	21,527.98	138,091.93	6,454.35
	10	18,060.67	151,688.97	4,985.63
	11	72,110.61	163,977.53	3,186.44

4.5 Data Normality Test

The data normality test was conducted using the Kolmogorov–Smirnov method by comparing the probability value with the significance level ($\alpha = 0,05$). The data were considered normally distributed if the probability value (p) $> 0,05$. This normality test aimed to determine whether the residual values were normally distributed, as a good regression model requires normally distributed residuals.

Based on the test results obtained using SPSS, the Exact Sig (Exact Binomial) value was 0,907. Since this value is greater than 0,05, it can be concluded that the residual data are normally distributed. The normality test graph is presented in Fig. 1.

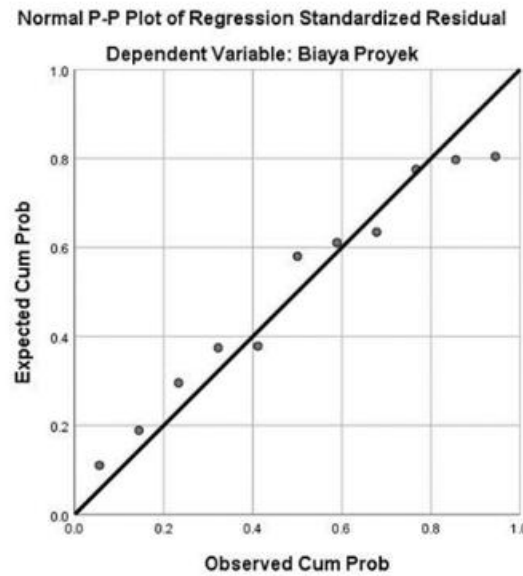


Fig. 1. Data Normality Test Graph

From Fig. 1, it can be observed that the data are normally distributed, as indicated by the residual points clustering around the normal line. Therefore, it can be stated that the regression model satisfies the normality assumption.

4.6 Data Analysis

Regression analysis was conducted to determine the relationship between variables through an equation. The regression calculations were performed using the Data Analysis feature in Microsoft Excel by inputting the data of cost components per m² of road. The model calibration produced values for R², calculated F, and calculated t. In this study, regression analysis was carried out on 31 alternative models. The best model was determined based on the criteria of calculated $t > t\text{-table}$, calculated $F > F\text{-table}$, and the coefficient of determination closest to 1. Based on the calibration results, three models met the criteria and were acceptable, as presented in Table 5.

Table 5. Models Meeting the Selection Criteria

Model	Equation	R Square
4	$Y = 27259.15 + 1.96 X19$	0.788
13	$Y = 32791.36 + 0.98 X15 + 1.59 X19$	0.877
22	$Y = 4531.24 + 1.19 X14 + 1.35 X15 + 1.43 X19$	0.968

Among the three alternative models that met the criteria, the best model was selected by considering the highest coefficient of determination (R²). Based on these results, Model 22 was identified as the best model, with the corresponding equation presented in Equation 4.

$$Y = 4531.24 + 1.19X14 + 1.35X15 + 1.43X19 \quad \dots\dots\dots (4)$$

Where:

- Y: periodic road maintenance contract price per m² of road area, excluding VAT (Rp/m²)
- X14: unit price per m² of K-175 shoulder concrete (Rp/m²)
- X15: unit price per m² of Class A aggregate foundation layer (Rp/m²)
- X19: unit price per m² of AC-WC surface course (Rp/m²)

4.7 Model Testing

The best-fit model equation obtained was used to predict the periodic road maintenance costs by inputting the unit prices of K-175 shoulder concrete, Class A aggregate foundation layer, and AC-WC surface course into the equation. The predicted road maintenance costs were then evaluated using the Cost Model Factor (CMF) method, which involves comparing the predicted costs with the actual project costs. The results of the model verification are presented in Table 6.

Table 6. Model Verofocation Testing

Tahun	No.	Actual Cost (Rp/m ²)	Prediction Cost (Rp/m ²)	CMF
2018	1	48,822.88	134,830.00	8.252,47
	2	54,446.90	134,830.00	35.914,18
2019	3	74,928.45	153,466.26	15.691,13
2020	4	63,119.36	153,721.24	568,41
	5	71,731.42	143,577.55	7.771,26
2021	6	88,950.04	245,359.75	16.553,93
2022	7	57,241.56	138,578.68	4.190,19
	8	21,986.58	156,910.29	9.378,56
	9	21,527.98	138,091.93	6.454,35
	10	18,060.67	151,688.97	4.985,63
	11	72,110.61	163,977.53	3.186,44
Jumlah		3,664,054.07	3,673,312.76	11.05
Rata-rata		333,095.82	333,937.52	1.004
Standar Deviasi		69,015.25	68,077.62	

Based on Table 6, the average project cost per m² of road section was calculated by summing all project costs and dividing by the number of samples, which consisted of 11 road sections. This calculation was performed for both the actual costs and the predicted costs. Subsequently, the standard deviation was calculated using the STDEV function in Microsoft Excel for the project costs. The conclusions drawn from these calculations are presented in Table 7.

Tabel 7. Conclusion of the Model Verification

	Sampel Size	Mean	Standard Deviation
Actual Cost	n ₁ = 11	$\bar{x}_1 = 333,095.82$	S ₁ = 69,015.25
Project Cost	n ₂ = 11	$\bar{x}_2 = 333,937.52$	S ₂ = 68,077.62

Statistical testing was conducted to determine whether there is a significant difference between the mean actual project costs and the mean predicted costs from the model. The sample size for each dataset was 11 road sections (n₁ = n₂ = 11), with a mean actual project cost of 333,095.82 and a mean predicted cost of 333,937.52. Based on a 95% confidence level ($\alpha = 0.05$) and the degrees of freedom (n₁ + n₂ - 2), the t-table value was obtained as 1.725. Subsequently, the calculation was performed using the independent two-sample t-test formula, as presented in Equation 5.

$$t_{hitung} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\left\{ \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} \right\} \left\{ \frac{1}{n_1} + \frac{1}{n_2} \right\}}} \dots\dots\dots (5)$$

$$t_{hitung} = \frac{333,095.82 - 333,937.52}{\sqrt{\left\{ \frac{(11 - 1)69,015.25^2 + (11 - 1)68,077.62^2}{11 + 11 - 2} \right\} \left\{ \frac{1}{11} + \frac{1}{11} \right\}}} = -0.041$$

Since the calculated t-value falls between $-t\text{-table}$ and $t\text{-table}$ ($-1.725 < -0.041 < 1.725$), H_0 is accepted. This indicates that there is no significant difference between the actual project costs and the costs predicted by the model. The normal distribution curve for the two-tailed hypothesis test is presented in Fig. 2.

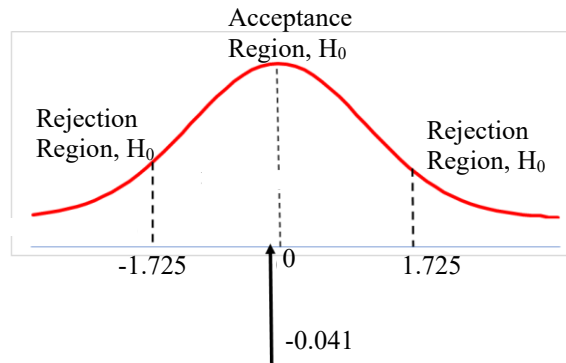


Fig. 2. Normal Distribution Curve

Next, the model was validated using project data from other road sections that were not included in the model. The results of the model validation test are presented in Table 8.

Table 8. Validation Testing Using Out of Sample Data

Year	No.	Actual Cost (Rp/m ²)	Prediction Cost (Rp/m ²)	CMF
2023	1	401,895.25	134,830.00	8.252,47
	2	411,621.03	134,830.00	35.914,18
	3	399,309.74	153,466.26	15.691,13
	4	502,853.73	153,721.24	568,41
	5	416,127.10	143,577.55	7.771,26
Total		2,131,806.84	2,076,832.39	4.85
Mean		426,361.37	415,366.48	0.97
Standar Deviasi		43,311.32	66,045.22	

Based on a 95% confidence level ($\alpha = 0.05$) and the degrees of freedom ($n_1 + n_2 - 2$), the $t\text{-table}$ value was obtained as 1.860. The calculation was then performed using the independent two-sample $t\text{-test}$ formula, as presented in Equation 5, resulting in a calculated $t\text{-value}$ of 0.311.

Since the calculated $t\text{-value}$ falls between $-t\text{-table}$ and $t\text{-table}$ ($-1.860 < 0.311 < 1.860$), H_0 is accepted. This indicates that there is no significant difference between the actual project costs and the costs predicted by the model. The normal distribution curve for the two-tailed hypothesis test is presented in Fig. 3.

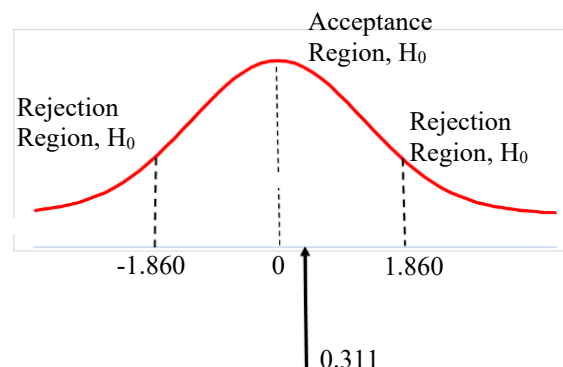


Fig. 3. Normal Distribution Curve

Cost Modeling of Road Maintenance Using the Cost Significant Method in Disaster Prone Areas of Solok Regency

Next, a comparison was conducted between the CSM model and the PU method in estimating road maintenance project contract costs to determine which method provides more accurate predictions. The predicted project costs using the CSM model and the PU method are presented in Table 9 and Table 10, respectively.

Tabel 9. Comparison of Project Cost Estimation Result Using he CSM Model

No.	Contract Non PPN (Rp)	CSM Method	Deviation (%)
1	1,595,866,546.97	1,479,999,997.62	7.26
2	392,978,101.09	359,582,070.74	8.50
3	1,028,088,277.17	998,265,928.44	2.90
4	468,707,355.81	494,752,453.23	5.56
5	476,960,026.74	468,736,837.21	1.72
Total			14.83
Average			2.97

Tabel 10. Comparison of Project Cost Estimation Result Using the CSM Model with the PU Method

No.	Contract Non PPN (Rp)	PU Method	Deviation (%)
1	1,595,866,546.97	2,183,968,609.87	36.85
2	392,978,101.09	525,089,686.10	33.62
3	1,028,088,277.17	1,416,065,022.42	37.74
4	468,707,355.81	512,652,146.06	9.38
5	476,960,026.74	630,403,587.44	32.17
Total			149.75
Average			29.95

Based on the model testing using data from other project packages outside the modeling dataset (Table 8), differences were observed in the closeness of the predicted costs to the actual contract costs. This indicates that the developed model needs to be compared with commonly used methods to assess the accuracy of each approach in estimating road maintenance costs.

The results show that using the Cost Significant Model (CSM) method produces deviations from the actual costs that are relatively small, ranging from 1.72% to 8.50%, with an average deviation of 2.965%. The relatively small deviations indicate that the predicted costs using the CSM method closely reflect the actual costs in the field. In contrast, cost predictions calculated using the PU method show much larger deviations, ranging from 9.38% to 37.74%, with an average deviation of 29.951%. The large deviations indicate that the PU method tends to produce less accurate cost estimates compared to the actual contract data.

Considering the average deviations of the two methods, it can be concluded that the CSM method provides a significantly higher level of accuracy than the PU method. This demonstrates that the CSM model developed in this study is capable of representing the actual cost conditions of periodic road maintenance projects, as it is based on significant cost components that directly influence the total project cost.

5. Conclusion

Based on the results of this study, it can be concluded that the cost estimation model for periodic road maintenance at the regency level using the Cost Significant Model (CSM) method in Solok Regency is suitable for use. The best model obtained is expressed as follows:

$$Y = 4,531.24 + 1.19X_{14} + 1.35X_{15} + 1.43X_{19}$$

where:

Y : periodic road maintenance contract price per m² of road area, excluding VAT (Rp/m²)

X₁₄ : unit price per m² of K-175 shoulder concrete (Rp/m²)

X₁₅ : unit price per m² of Class A aggregate foundation layer (Rp/m²)

X19 : unit price per m² of AC-WC surface course (Rp/m²)

Verification testing of the model indicated that the Cost Model Factor (CMF) ranged from 0.95 to 1.09, with an average value of 1.004. A CMF value close to 1 indicates that the predicted costs are very close to the actual project costs, demonstrating a high level of accuracy.

Furthermore, the hypothesis testing results reinforced the model's reliability, with H₀ accepted, indicating that there is no significant difference between the predicted costs and the actual project costs for road maintenance.

In terms of deviation percentage, the CSM method produced relatively small deviations, ranging from 1.72% to 8.50%, with an average of 2.965%. In contrast, the conventional method commonly used by the Public Works and Spatial Planning Office (DPUPR) of Solok Regency, namely the PU method, showed larger deviations, ranging from 9.38% to 37.74%, with an average of 29.95%.

Based on these results, it can be concluded that the CSM method provides more accurate, stable, and realistic cost estimates. Therefore, the CSM method is recommended as a more reliable alternative for estimating periodic road maintenance costs at the regency level in Solok Regency, particularly during the early planning stage.

6. Recommendations

Based on the findings of this study, it is recommended that the Public Works and Spatial Planning Office (DPUPR) of Solok Regency adopt the CSM method for the initial stage of preparing budget estimates for periodic road maintenance projects. For future studies, it is suggested to develop models using the same method for other regency road construction projects.

7. Acknowledgments

This research was funded by the Directorate of Research and Community Service, Directorate General of Research and Development, Ministry of Higher Education, Science, and Technology, under the Master's Thesis Research Scheme, in accordance with Research Contract Number: 060/C3/DT.05.00/PL/2025 for the Fiscal Year 2025.

Reference

- [1] Amin, M., Tamima, U., & Amador, L. (2020). Towards resilient roads to storm-surge flooding: case study of Bangladesh. *International Journal of Pavement Engineering*, 21, 63 - 73. <https://doi.org/10.1080/10298436.2018.1436706>
- [2] Batista, E., De Brum Passini, L., & Kormann, A. (2019). Methodologies of Economic Measurement and Vulnerability Assessment for Application in Landslide Risk Analysis in a Highway Domain Strip: A Case Study in the Serra Pelada Region (Brazil). *Sustainability*. <https://doi.org/10.3390/sul1216130>.
- [3] Donal, R. (2014). *Pemodelan Estimasi Biaya Awal Proyek Rekonstruksi Jalan Dengan Metode Cost Significant Model "Studi Kasus Paket Rekonstruksi Jalan Nasional Wilayah II Sumatera Barat* [Early Cost Estimation Modeling for Road Reconstruction Projects Using the Cost Significant Model Method: A Case Study of the National Road Reconstruction Package Region II, West Sumatra]. Tesis Program Magister Teknik Sipil-Fakultas Teknik-Unand" <http://scholar.unand.ac.id/13007/>
- [4] Flores, V., & Ascaño, G. (2025). Quantitative Risk Analysis Framework for Cost and Time Estimation in Road Infrastructure Projects. *Infrastructures*. <https://doi.org/10.3390/infrastructures10060139>.
- [5] Ferlisi, S., Marchese, A., & Peduto, D. (2020). Quantitative analysis of the risk to road networks exposed to slow-moving landslides: a case study in the Campania region (southern

- Italy). *Landslides*, 18, 303-319. <https://doi.org/10.1007/s10346-020-01482-8>.
- [6] Koks, E., Koks, E., Rozenberg, J., Zorn, C., Tariverdi, M., Voudoukas, M., Fraser, S., Hall, J., & Hallegatte, S. (2019). A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, 10. <https://doi.org/10.1038/s41467-019-10442-3>.
- [7] Liu, M., & Luo, M. (2023). Cost estimation model of prefabricated construction for general contractors based on system dynamics. *Engineering, Construction and Architectural Management*. <https://doi.org/10.1108/ecam-03-2023-0304>.
- [8] Muttaqin, Z., Sugiarto, S., & Saleh, S. (2024). Developing a cost estimation model for efficient road improvement planning: A case study in Aceh Jaya regency. *IOP Conference Series: Earth and Environmental Science*, 1356. <https://doi.org/10.1088/1755-1315/1356/1/012079>.
- [9] Oktavia, L. S., Aldina, L., Nurdianto, & Yulaeli, T. (2023). *Faktor-faktor yang mempengaruhi Nilai Waktu Uang: Future Value, Present Value, dan Annuity* [Factors Affecting the Time Value of Money: Future Value, Present Value, and Annuity]. *Jurnal Publikasi Ilmu Manajemen (JUPIMAN)*, 2(3), 153–168. <https://doi.org/10.55606/jupiman.v2i2.206>.
- [10] Postance, B., Hillier, J., Dijkstra, T., & Dixon, N. (2017). Extending natural hazard impacts: an assessment of landslide disruptions on a national road transportation network. *Environmental Research Letters*, 12. <https://doi.org/10.1088/1748-9326/aa5555>.
- [11] Petrousatou, K., Vagdatli, T., & Maravas, A. (2023). Probabilistic approach of pre-estimating life-cycle costs of road tunnels. *Structure and Infrastructure Engineering*, 20, 1896 - 1911. <https://doi.org/10.1080/15732479.2023.2165120>.
- [12] Rezvani, S., Silva, M., & De Almeida, N. (2024). Urban Resilience Index for Critical Infrastructure: A Scenario-Based Approach to Disaster Risk Reduction in Road Networks. *Sustainability*. <https://doi.org/10.3390/su16104143>.
- [13] Sayed, M., Abdel-Hamid, M., & El-Dash, K. (2020). Improving cost estimation in construction projects. *International Journal of Construction Management*, 23, 135 - 143. <https://doi.org/10.1080/15623599.2020.1853657>.
- [14] Salindeho, B., Dundu, A. K. T., & Supit, C. J. (2022). *Model Estimasi Kontruksi Jalan Dengan Metode Cost Significant Model (Studi Kasus Pada Konstruksi Jalan di Manado)* [Road Construction Estimation Model Using the Cost Significant Model Method: A Case Study on Road Construction in Manado]. 12(3), 191–204. <https://ejournal.unsrat.ac.id/v3/index.php/jime/article/view/46687>
- [15] Falahis, V. D., Sugiarto., Laksito, B. (2015). *Cost Significant Model Sebagai Dasar Pemodelan Estimasi Biaya Konstruksi Jembatan Beton Bertulang* [Cost Significant Model as a Basis for Cost Estimation Modeling of Reinforced Concrete Bridge Construction]. *e-Jurnal Matriks Teknik Sipil*, 957–964. <https://doi.org/10.20961/mateksi.v3i4.37224>
- [16] Sugiarto, Muali, A., Hartono, W. (2016). *Estimasi Biaya Konstruksi Bangunan Gedung Dengan Metode Cost Significant Model* [Building Construction Cost Estimation Using the Cost Significant Model Method]. *e- Jurnal Matriks Teknik Sipil*, 498. <https://doi.org/10.20961/mateksi.v4i2.37005>
- [17] Wang, N., & Horner, M. (2007). CSI model for estimating road maintenance projects. *Construction Management and Economics*, 25, 1269 - 1281. <https://doi.org/10.1080/01446190701670373>.