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Cost Analysis of Construction Using the Cost Significant Model and Artificial Neural Network or Feasibility Study Cost Estimation in Process Industry (Case Study: Feasibility Study Projects in the Process Industry Sector in Indonesia)

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ABSTRACT

The process industry plays a vital role in the global economy, with increasing complexities necessitating significant capital investment for projects. Accurate cost estimation during the early project phases is essential to prevent cost overruns, schedule delays, and compromised quality. In the feasibility study phase, precise cost estimation is particularly critical for ensuring project viability and success. This research aims to develop a cost estimation model utilizing the Cost Significant Model (CSM) and to validate its predictive accuracy using Artificial Neural Networks (ANN) for feasibility studies within Indonesia's process industry. The study applies the CSM methodology to identify the principal cost drivers influencing total capital expenditure and benchmarks the model's accuracy against actual costs from 50 process industry projects in Indonesia, spanning 2010 to 2024. Artificial Neural Networks (ANN), specifically employing the backpropagation algorithm, are used to validate the model and to compute the Mean Absolute Percentage Error (MAPE) as an accuracy metric. The analysis reveals that major cost components—Mechanical ISBL (55.89%), Mechanical OSBL (7.65%), Electrical (6.06%), and Superstructure (15.07%)—collectively account for 84.66% of total project costs. The ANN-ALL model demonstrates the highest accuracy (L: -4.76%, H: 0.55%), followed by CSM Model 3, ANN-CSM, and others, in accordance with AACE International guidelines. Models that exceed Class 4 benchmark thresholds are deemed unsuitable for feasibility study applications. Data analysis integrates regression techniques using SPSS and ANN-based modeling with MATLAB, underscoring the superior performance of the ANN-ALL model in cost estimation accuracy for process industry projects.

KEYWORDS *Cost Significant Model (CSM), Artificial Neural Network (ANN), Feasibility Study, Cost Estimation Accuracy, Process Industry Projects.*

INTRODUCTION

The process industry is a crucial sector of the economy, focused on the mass production of goods through *physical*, *chemical*, or *biological* processes, where raw materials are transformed into finished products with added value (Blichfeldt &

Faullant, 2021; Enyoghasi & Badurdeen, 2021; Kamalaldin et al., 2021; Santos et al., 2017; Yang et al., 2021). Characterized by the use of specialized machinery, large-scale material processing, strict quality control, and adherence to environmental and safety regulations, *process control* is critical to ensuring stable and safe production (Nian et al., 2020; Sałaciński et al., 2023; Simkoff et al., 2020; Viharos & Jakab, 2021; Weng et al., 2023). Products from this industry include food and beverages, chemicals, pharmaceuticals, petrochemicals, oil and gas, pulp and paper, textiles, and repetitive manufacturing industries such as automotive and electronics. According to Indonesia's Central Statistics Agency (*Badan Pusat Statistik*, BPS) in 2020, there are 13,762 industrial centers in the country, with the manufacturing sector contributing 19.88% to GDP. However, significant capital investment remains a challenge, requiring efficiency and resource optimization to maintain competitiveness. Accurate cost estimation at the early stages of process industry projects is vital to avoid cost overruns, delays, and quality issues. This research employs the *Cost Significant Model* (CSM) to analyze influential cost elements in construction projects, producing an estimation model and accuracy assessment (Astana, 2017; Falahis et al., 2015; Paikun et al., 2020; Yuliana et al., 2020). *Artificial Neural Network* (ANN) methods are used to validate these models, with *Mean Absolute Percentage Error* (MAPE) applied to evaluate prediction accuracy, enabling effective cost analysis for feasibility studies in Indonesia's process industry projects.

The process industry plays a pivotal role in global economic development, encompassing sectors such as petrochemicals, pharmaceuticals, and food production, which rely heavily on large-scale capital investments. However, these projects often face challenges such as cost overruns, delays, and quality issues, particularly during the feasibility study phase. Previous studies have explored cost estimation methods, including the *Cost Significant Model* (CSM) and *Artificial Neural Networks* (ANN), to improve accuracy in construction and infrastructure projects. For instance, research by Aprianti et al. (2021) demonstrated the effectiveness of CSM in bridge construction, while Elmousalami (2019) highlighted ANN's predictive capabilities for early-stage cost estimation. Despite these advancements, gaps remain in applying these models specifically to the process industry, where project complexity and scale demand tailored solutions.

A critical research gap lies in the limited integration of CSM and ANN for cost estimation in process industry projects, particularly in emerging economies like Indonesia. Existing studies often focus on standalone models or less complex industries, leaving room for innovation in combining these methods for higher accuracy. Additionally, while CSM identifies significant cost drivers, its reliance on historical data may overlook dynamic factors such as inflation and market fluctuations. ANN, though robust in pattern recognition, requires extensive validation to ensure reliability in diverse project contexts. Bridging these gaps is essential to develop a comprehensive framework that enhances cost estimation precision during feasibility studies, where early decisions significantly impact project outcomes.

This study introduces novelty by integrating CSM and ANN to create a hybrid cost estimation model specifically designed for the process industry. Unlike previous research, which often treats these methods independently, the proposed approach leverages CSM to identify key cost components and ANN to refine predictions, ensuring adaptability to project-specific variables. The model is validated using real-world data from 50 Indonesian process industry projects (2010–2024), incorporating inflation adjustments to enhance realism. Furthermore, the study benchmarks results against *AACE International* standards, providing a measurable assessment of model accuracy. By addressing the unique challenges of the process industry, this research offers a scalable solution for improving cost estimation in capital-intensive projects.

The primary objective of this research is to develop and validate a cost estimation model that combines CSM and ANN for feasibility studies in the process industry. Specifically, the study aims to identify the most significant cost components, assess the predictive accuracy of hybrid models, and compare their performance against conventional methods. The research also seeks to evaluate the impact of inflation-adjusted data on estimation reliability, ensuring the model's applicability in dynamic economic environments. These objectives align with the broader goal of enhancing decision-making in early project stages, where accurate cost forecasts are critical for securing funding and minimizing risks.

The implications of this research extend beyond academic contributions, offering tangible benefits for industry practitioners and policymakers. For project managers, the hybrid model provides a reliable tool to reduce cost overruns and optimize resource allocation, thereby improving project feasibility and profitability. Policymakers can leverage the findings to develop standardized cost estimation guidelines for the process industry, fostering more efficient capital investment strategies. Additionally, the study's focus on Indonesia addresses a regional need for localized solutions, which can be adapted to similar emerging economies. By advancing cost estimation methodologies, this research supports sustainable growth in the process industry, aligning with global demands for efficiency and competitiveness.

This study bridges theoretical and practical gaps in cost estimation for the process industry by integrating CSM and ANN into a cohesive framework. The research not only enhances the accuracy of feasibility studies but also provides a foundation for future innovations in predictive modeling. As the process industry continues to expand, the demand for precise and adaptable cost estimation tools will grow, making this study a timely contribution to both academia and industry. The findings underscore the importance of interdisciplinary approaches in addressing complex project challenges, paving the way for further exploration of hybrid models in construction and engineering management.

RESEARCH METHOD

This study aims to develop a cost estimation model using the Cost Significant Model (CSM) and validate it with the Artificial Neural Network (ANN) method. The Cost Significant Model employs a cost estimation approach focused on identifying and analyzing documented past projects to determine the most influential elements affecting total construction project costs. The research adopts a quantitative methodology that emphasizes measurable variables, with multiple linear regression analysis conducted using SPSS software. For the implementation of ANN, the developed models are validated through testing using MATLAB software to evaluate cost forecasting accuracy. The next stage involves assessing the accuracy of each model by calculating the Mean Absolute Percentage Error (MAPE), a statistical measure of prediction accuracy in cost estimation. Secondary data for this research includes literature reviews, budget plans from 2010–2024 for 50 process industry projects, and other supporting data sourced from consulting service providers specializing in the process industry.

RESULT AND DISCUSSION

Development of Research Variables

The research data consists of project costs from the process industry from 2010 to 2024, comprising 50 data points organized based on the dependent variable (Y) and several independent variables (X). The dependent variable (Y) represents the total cost of construction projects in the process industry, specifically the total value of the work. The independent variables (X) are factors influencing the dependent variable (Y), which include cost elements impacting the total project cost (Y) as outlined below. Detailed data on project costs analyzed from 2010 to 2024. Table 1. summarizes the research variables that serve as the basis for the study.

Table 1. Dependent and Independent Variables in the Study

No	Field of Work Types in the Process Industry		Pipeline		Industrial		Power Plant	
	Cost Variables							
1	Process Safety	X1	Rp	12,349,939,341	Rp	72,563,952,595	Rp	37,601,336,319
2	Mechanical ISBL	X2	Rp	2,496,824,282,422	Rp	3,751,932,580,294	Rp	2,365,197,414,350

3	Mechanical OSBL	X3	Rp	221,564,929,592	Rp	611,130,761,033	Rp	315,003,870,798
4	Piping	X4	Rp	207,916,392,680	Rp	356,583,722,913	Rp	181,664,620,569
5	Electrical	X5	Rp	154,565,523,126	Rp	394,147,010,009	Rp	351,984,643,974
6	Instrumentation	X6	Rp	89,401,246,984	Rp	214,743,938,548	Rp	138,666,286,044
7	Foundation Structure	X7	Rp	454,415,604,520	Rp	299,271,874,003	Rp	177,255,788,050
8	Superstructure	X8	Rp	253,695,491,960	Rp	1,227,238,035,606	Rp	885,703,693,650
9	Architecture	X9	Rp	2,122,546,516	Rp	45,218,917,107	Rp	34,133,105,103
	Total Cost	Y	Rp	3,892,855,957,141	Rp	6,972,830,792,108	Rp	4,487,210,758,857

(Source: Calculation Results, 2025)

The calculation is obtained by summing X1 through X9 to determine the value of Y, as follows:

$$Y = X1 + X2 + \cdots + X9$$
$$Y = 12{,}349{,}939{,}341 + 2{,}496{,}824{,}282{,}422 + \cdots + 2{,}122{,}546{,}516$$
$$Y = 3{,}892{,}855{,}957{,}141$$

Calculating Monetary Value Against Inflation

The research data used varies, covering the years 2010 to 2024. To obtain values equivalent to the present, an analysis of the data based on the previous year's budget plan must be performed using Equation 1. This ensures the analyzed data is more optimal in terms of cost equivalence.

The base budget year is set to 2024, so budget values from previous years need to be adjusted to future value for the 2024 budget using Indonesia's inflation data. Inflation data is sourced from the Central Statistics Agency (BPS) for the years 2010 to 2024, as shown in Table 2 below.

Table 2. Inflation Data in Indonesia from 2010 to 2024

Year	Inflation (%)
2010	6.96%
2011	3.79%
2012	4.30%
2013	8.38%
2014	8.36%
2015	3.35%
2016	3.02%
2017	3.61%
2018	3.13%
2019	2.72%

Year	Inflation (%)
2020	1.68%
2021	1.87%
2022	5.51%
2023	2.61%
2024	0.82%

(Source: Central Statistics Agency)

The future value calculation uses Equation 1. Detailed data on project costs analyzed from 2010 to 2024, which have undergone future value calculations. Table 3 summarizes the research variables after future value calculations, as follows:

Table 3: Dependent and Independent Variables After Future Value Calculation

No	Field of Work Types in the Process Industry Cost Variables		Pipeline	Industrial	Power Plant
1	Process Safety	X1	Rp 15,365,092,054	Rp 105,782,598,025	Rp 53,377,838,114
2	Mechanical ISBL	X2	Rp3,314,559,810,118	Rp 5,082,832,315,799	Rp3,481,336,508,567
3	Mechanical OSBL	X3	Rp 304,616,093,962	Rp 851,475,139,750	Rp 469,418,277,161
4	Piping	X4	Rp 277,573,001,972	Rp 522,623,140,087	Rp 277,530,701,096
5	Electrical	X5	Rp 204,645,068,997	Rp 559,163,861,933	Rp 522,539,013,344
6	Instrumentation	X6	Rp 118,895,164,756	Rp 310,345,730,150	Rp 206,228,252,349
7	Foundation Structure	X7	Rp 602,007,484,438	Rp 388,314,911,305	Rp 267,063,639,287
8	Superstructure	X8	Rp 336,093,099,935	Rp 1,545,752,010,313	Rp1,322,021,768,506
9	Architecture	X9	Rp 2,824,489,301	Rp 61,322,762,344	Rp 51,417,347,766
Total Cost		Y	Rp 5,176,579,305,538	Rp 9,427,612,469,704	Rp6,650,933,346,195

(Source: Calculation Results, 2025)

An example calculation uses data from Appendix 1, specifically entry number 23 (Ammonium Nitrate Granulation Plant – Year 2020), where the following is obtained:

PV = X1 = 1,309,798,981
Inflation rate for the year 2020 = 1,68%
Average Inflation Rate from the year 2020 – 2024 (r) = 2,50%
Jumlah periode (n) dari 2020 ke 2024 = 4

$$Fv = Pv\ x\ (1 + r)^n$$
$$Fv = 1{,}309{,}798{,}981\ x\ (1 + 2{,}5\%)^4$$
$$Fv = 1{,}445{,}660{,}162$$

Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) analysis method is used to validate the model previously developed based on the cost significant model method. In the ANN analysis, two models will be used, namely ANN-ALL and ANN-CSM. In

ANN-ALL, the modeling uses input data from Appendix 2, which includes all dependent variables (Y) and independent variables (X1 – X9). In ANN-CSM, the modeling uses input data from Table 4.6, which is based on the cost significant items that were analyzed. The purpose of using these two models is to improve the validation results related to the accuracy of the planned model.

CONCLUSION

The research identifies that the most significant cost components in process industry projects are Mechanical ISBL (55.89%), Mechanical OSBL (7.65%), Electrical (6.06%), and Superstructure (15.07%), together accounting for 84.66% of total costs. Among the models evaluated, Model 3—using multiple linear regression within the Cost Significant Model (CSM)—demonstrates the best performance among CSM-based approaches. However, validation using Artificial Neural Network (ANN) methods reveals that the ANN-ALL and ANN-CSM models achieve the highest prediction accuracy, both with Mean Absolute Percentage Error (MAPE) values below 10%, and the ANN-ALL model stands out with a superior MAPE of just 0.28%. These findings indicate that ANN-based models provide more accurate cost estimates than traditional CSM approaches. For future research, it is suggested to focus on specific process industry sectors to enhance modeling precision, expand the dataset to improve model robustness, and compare the performance of ANN with alternative approaches such as fuzzy models to further advance the accuracy and applicability of cost estimation in feasibility studies.

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