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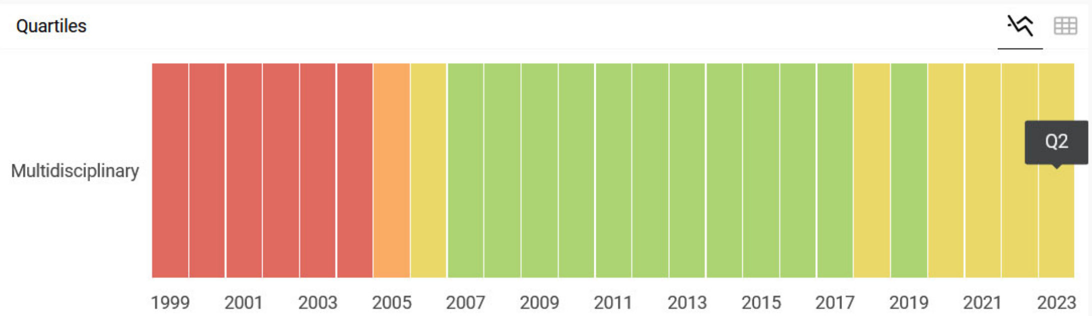

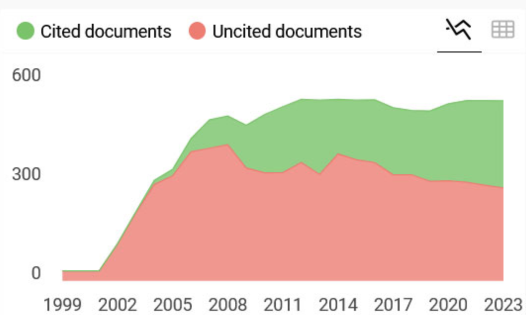

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Accept after minor changes to Journal of Southwest Jiaotong University, Volume 59 (3), 2024

7 pesan

editor@jsju.org <editor@jsju.org> 1 Juni 2024 pukul 00.19
Kepada: tommy.natasasmita@gmail.com

Dear Tommy Utama Natasasmita, Dyah Erny Herwindiati, Basuki Anondho,

We are pleased to inform you that our reviewers has been accepted and recommended your manuscript for publication in the forthcoming issue of Journal of Southwest Jiaotong University, Volume 59 (3), 2024

taking into account the correction of the following comments:

1-the scientific novelty is vague in the title. Besides, it is unclear what exactly you are proposing and what the article is about, what theoretical and practical contributions it makes.
Your title is the first thing anyone who reads your article is going to see, and for many it will be where they stop reading. Learn how to write a title that helps readers find your article, draws your audience in and sets the stage for your research. How your title impacts the success of your article. Researchers are busy and there will always be more articles to read than time to read them. Good titles help readers find your research, and decide whether to keep reading. Search engines use titles to retrieve relevant articles based on users' keyword searches. Once readers find your article, they'll use the title as the first filter to decide whether your research is what they're looking for. A strong and specific title is the first step toward citations, inclusion in meta-analyses, and influencing your field.
2- Abstract need to modify: the abstract should contain Objectives, Methods/Analysis, Findings, and Novelty /Improvement. It is suggested to present the abstract in one 200 words paragraph.
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Kind regards,
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JSJU 2024-05-28 07:45:

> Title of your paper: LASSO Regression Application on the EPC Design Model to the Contractor's Cost Overruns of the Industrial Construction Projects in Indonesia
> Corresponding Author's Email Address: tommy.natasasmita@gmail.com
> Author(s): Tommy Utama Natasasmita, Dyah Erny Herwindiati, Basuki Anondho
> Keywords: Machine learning, EPC design, cost overruns, multicollinearity, LASSO, double-jack-knife, industrial project.
> Abstract: A machine learning model was implemented to regress the EPC design model on the contractor cost overruns of industrial construction projects in Indonesia. This study aims to formulate a cost model to predict the final actual value of an EPC lump-sum contract with the lowest cost overrun target or a 10% maximum of the initial contract as a cost-performance benchmark. The research methodology was developed by compiling a predictor variable list and validation, a pilot survey, and questionnaire distribution for 40 project respondents. The Least Absolute Shrinkage and Selection Operator (LASSO) regression method was used to solve problems in the multicollinearity of predictor variables and limited sample number

availability. The LASSO analysis approach with the double-jackknife resampling algorithm showed promising accuracy model results with lambda = 0.8, MPE = 0,736%, and = 0.995. The conclusion is that the final EPC project price was significantly influenced by the initial contract price, which reflects the quality of the obtained tender result price, a 'legacy' of the previous process left behind in the burden of cost overrun due to the risk of design changes. These significant research findings are related to the obtained tender price results, EPC contractor experience, and quality of engineering design. This study encourages upgrading EPC contractors' performance qualifications and competence to fulfill the EPC bidder's requirement to improve the tender quality result.

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Kepada Yth Prof Dyah Erny Herwindiati
Cc. Bapak Dr. Ir. Basuki Anondho, MT.

Dengan hormat,
Alhamdullah makalah diterima dengan minor revision.

Salam hormat,
Tommy Natasasmita
[Kutipan teks disembunyikan]

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Dear Editorial Office of
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Following the confirmation of the acceptance manuscript with the title "The EPC Design Model on Cost Overruns Using the LASSO Regression Approach to Assess the Contractor's Cost Performance of Industrial Construction Projects in Indonesia," I am attaching the following:
1. Revision of Manuscript following the previous comment
2. COVER LETTER.
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Thanks and Best Regards,
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Dear Tommy Utama Natasasmita,

We acknowledge the revised article and the editing and publication fees.
Your article will be published on the journal's website in Volume 59 (3) 2024.
Volume 59 (3) will be published on the website in installments, starting in mid-end of July.
Thank you very much!

It is a pleasure to collaborate with you again.

Sincerely yours,
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Research article
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Engineering

THE EPC DESIGN MODEL ON COST OVERRUNS USING THE LASSO REGRESSION APPROACH TO ASSESS THE CONTRACTOR'S COST PERFORMANCE OF INDUSTRIAL CONSTRUCTION PROJECTS IN INDONESIA

Tommy Utama Natasasmita [a,*], Dyah Erny Herwindiati [b], Basuki Anondho [c]

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Abstract

The EPC planning process must be organized precisely to avoid contractor failure in managing the final project costs following the contract agreement. This study aims to formulate a new method assessment tool to predict the final cost of an EPC lump-sum contract with the lowest cost overrun target or a 10% maximum of the initial contract as a cost-performance benchmark. Advanced statistical techniques, such as the Least Absolute Shrinkage and Selection Operator (LASSO) regression with the double-jackknife resampling algorithm, are utilized to provide robust prediction results. The research methodology was developed by compiling data from 40 project respondents for the primary data analysis. The model results promise a more robust accuracy than the other methods, with an R-squared of 0.996. The significant research findings provided highly accurate results of the regression coefficient, showing the same project's final cost as the initial contract value when the project begins, reflecting the original previous tender results owing to the cost overrun risk for design changes, EPC contractor experience, and engineering design product quality. This assessment tool is valuable for scientific research novelty. It shows that cost overruns of design changes contribute up to 5.86% and recommends a roadmap for improving EPC contractor competence.

Keywords: EPC design, cost overruns, cost performance, multicollinearity, LASSO, double-jack-knife, industrial project, assessment tool.

摘要 The authors may not translate the abstract and keywords into Chinese themselves.

关键词:

I. Introduction

The engineering-procurement-construction (EPC) system is growing and becoming a new challenge in the construction industry for contractors, where engineering, procurement, and construction are in one package contract system, offering integrated multidisciplinary service projects. According to the approved tender proposal, EPC contracts are handled using a lump-sum fixed-price system. This means that the contractor maintains the risk of changes in costs appearing from the contractor's design using front-end engineering design (FEED) as a document reference for further detailed designs [1], [2], [3] to prepare construction documents and to avoid contractor failure in managing the final project costs following the contract agreement.

A. The Past EPC Study Result

EPC systems are widely used to build industrial plants and their facilities, mainly chemical, petrochemical, hydrocarbon, oil, and gas processes, and other refinery plants because of the complexity and multidisciplinary scope of the projects required [4], [5]. Construction by the EPC system is completed faster than by the conventional "design-bid-build" system because it requires more time at the design stage. The contractor was responsible for every part of the initial design, giving the owner certainty regarding the final project cost. They are also responsible for determining the quantity and level of quality control in the initial project planning and implementing appropriate performance and reliability requirements to achieve the final quality guarantee at the operational stage that is met in an EPC project's success [6].

Many researchers have studied EPC and "design and build" construction contract systems for buildings, infrastructure, and industrial projects in Indonesia. However, their research focused mainly on project success in the procurement (P) and construction (C) stages, whereas this study focused on the engineering (E) stage. Previous studies [4], [7], [8], [9], and [10] stated that in the engineering stage, a high-risk rank to achieve project performance is influenced by changes in the quantity of work scope, posing a risk to cost and time performance, management of owner behavior, external risks related to project performance, the contractor's implementation capability posing risks to project performance, and the ability and leadership of the project manager posing a risk to project performance.

The results of [4] rank the EPC engineering variables at the top. The engineering phase played an essential role in project performance from the design concept stage to detailed engineering design. According to FIDIC Article 5.1, General Design Obligations [2], the initial activity of an EPC project is to create a basic engineering design carried out by the owner, using the deliverability of a basic design document called front-end engineering design (FEED). FEED is a tender document that forms the basis of a contractor's EPC offer. FEED documents can be done by an EPC contractor or an engineering consultant at the request of the Project Owner. However, if they do, the game's rules are that they cannot continue the construction phase.

Practical restrictions on implementing who will do the basic design and construction stages raise a gap between regulations and theories for achieving project success. On the one hand, the EPC contractor must understand the basic design criteria of the EPC project to avoid cost overruns owing to design risks. However, this execution restriction is still required so that all parties involved in the EPC contract can maintain their commitment to complete the work according to a basic design and cost agreed upon from the beginning and not easily change. For example, changes to downgraded material specifications due to increased prices and conflicts of interest occur because the basic designer and construction actors are the same executants.

The survey result found that cost overruns of 5%-10% occurred in domestic agro-industrial projects due to design changes [3]. Research by [11] reported a higher cost overrun percentage for overseas industrial projects than domestic projects, reaching 5–20%. According to [3], 82.50% of contractors increased their EPC tender price by 10–25% to anticipate cost overruns, incorporating a lack of design details as EPC project characteristics when submitting bid proposals. The bid price must be as watchful as possible owing to gaps in interpreting the technical requirements of tender documents, which involves a multidisciplinary scope in preparing the EPC tender proposal [11]. Therefore, EPC project characteristics must be considered when arranging the EPC cost model regarding cost overruns owing to design changes.

Project cost performance indicates the quality and quantity of progress required to assess the suitability of the project objectives [12]. On the contractor side, project costs emerge from the tendering process. Therefore, a previous study found that an EPC tender considers the sub-process of price analysis when preparing a tender offer. When submitting the bid price, the following design needs to be considered: (1) owing to the risks of the schematic design that need to be detailed and (2) owing to the accuracy of the tender cost estimation [5], [13], [14]. References [15], [16], and [11] recommend anticipating unexpected risk costs because the design requires further refinement.

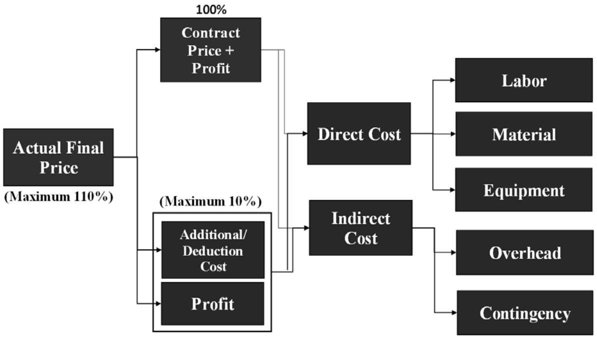

Figure 1. EPC project cost composition diagram [3], [14], [16]

This study discusses the EPC cost model of Crude Palm Oil (CPO) of the refinery project and supporting facilities in Indonesia with a multi-discipline scope of design work, referred to as agro-industrial projects. The cost model consists of the initial costs of the original contract price plus the increased/decreased costs due to design changes, including contractors' profits and taxes, as illustrated by the EPC cost diagram in Figure 1. [3], [14], [16]. The diagram guides the flow of cost overruns toward any direct or indirect cost budget item. To evaluate the project cost budget, the budget line predicts the flow of costs up to the lowest-cost item of the work breakdown schedule.

The study model uses project respondents' data resources by summarizing relevant variables from the latest research over the last ten years. These include variables from previous research gap findings and additional research variables as current demands for the contractor's ability to perform design optimization [3]. Through a questionnaire, the project respondents clarified the completeness and document accuracy factors of the basic design document provided by the owner during the tender process and the contractor's detailed engineering design (DED) during construction. Therefore, using the Least Absolute Shrinkage and Selection Operator (LASSO) method with a double-jack-knife resampling algorithm, the model combines these items as factors influencing the EPC design to assess contractor cost overruns.

B. Research Objectives

This study aims to generate a regression model of EPC design on the factors influencing cost overruns to assess the contractor cost performance of agro-industrial projects in Indonesia from 2013 to 2018, using the Least Absolute Shrinkage and Selection Operator (LASSO) method with a double-jack-knife resampling algorithm, which is a part of artificial intelligence (AI). As an assessment tool created in this study, this model seeks to predict the EPC project's final cost owing to design changes at the lowest target or a maximum of 10% of the initial contract value as a benchmark for Indonesia's contractor's cost performance [17]. The LASSO regression method was chosen to solve the problem of suspected multicollinearity of the predictor variables and the limited availability of the sample size of project respondents' data.

II. LITERATURE REVIEW

A. Why Use the LASSO Method

When constructing a model, researchers often need assistance solving statistical problems related to the limited number of samples and the predictor's suspected multicollinearity relationship, which causes the parameters to be aberrated, underestimated, or overestimated. Regression analysis is a statistical technique commonly used to model event relationships and is required to solve problems using many explanatory variables. This study used the LASSO method with a double-jack-knife resampling algorithm to regress the observed 40 data samples of EPC project respondents.

Among the statistical techniques, Least Absolute Shrinkage and Selection Operator (LASSO) regression with a double-jack-knife resampling algorithm was chosen because it allowed us to upgrade the number of data samples required for the research object population and ignored the suspected multicollinearity relationship of the predictor. LASSO is a technique for selecting variables in data with large dimensions and can reduce the regression coefficient to zero [18].

The difference between LASSO and ridge regression lies in estimating the regression coefficient, where the ridge regression coefficient can only be reduced to close to zero. By contrast, the LASSO regression coefficient allows it to shrink to zero precisely. The advantage of the LASSO regression is that it can select independent variables in the model such that only influential variables are included, making it easier to interpret the regression model. The most famous nickname for the LASSO method is its fast calculation for solving convexity optimization problems [19]. Therefore, the correct match in the LASSO method used a double-jack-knife resampling algorithm to obtain better results.

B. Jack-knife Resampling Method

The jack-knife method is a nonparametric method introduced by [20] and [21]. Resampling is a technique used to create new samples from data or observations. One frequently used resampling method is the jack-knife resampling method [22]. The basic concept of the jack-knife method is to remove one observation from a set of data and use the remaining data to obtain a new data sample. For example, if it is known that the original observation data is $X = \{X_1, X_2, \dots, X_n\}$, with n showing several data, then jack-knife the-i *or* $X_{[i]}$ is the same as equation (1). The number of samples obtained by the jack-knife resampling is also n.

$$X_{[i]} = \{X_1, X_2, \dots, X_{i-1}, X_{i+1}, \dots, X_{n-1}, X_n\} \quad (1)$$

It should be noted that the i-th jack-knife sample or $X_{[i]}$ and the i-th observation data were not included in the jack-knife sample. A jack-knife data sample is obtained by repeating this process for $i = 1, \dots, n$. The jack-knife process is carried out twice, in the sense that after obtaining the resampling results, the Jack-knife is 2n and then resampled again to obtain 4n-sized data, which is called a double jack-knife.

The next step is to calculate $f(X_{[i]})$ to obtain new data by resampling, which is then added to the original observation data. For example, function $f(X_{[i]})$ can be a mean or median function. This study used the average or mean function shown in equation (2). LASSO is the development of the OLS method above, which adds a limit or penalty when searching for the best coefficient value.

$$f(X_{[i]}) = \frac{1}{n}\sum_{j=1}^{m} X_{[i],j} \quad (2)$$

The jack-knife method estimates standard errors and confidence intervals for population parameters, such as mean, median, proportion, correlation, and regression coefficients, without always paying attention to distribution assumptions. This method also estimates a statistical estimator's bias and variance and measures the estimate's uncertainty. Sub-samples in the available sample are recalculated by the jack-knife method to provide estimates of bias and standard error. Subsequently, jack-knife resampling is performed by sequentially deleting one case from the original sample (delete-one Jack-knife). The more common jack-knife technique uses resampling based on deleting many cases (deleted Jack-knife).

The benefits of jack-knife methods are that they can be used with small or insufficient sample sizes, the data distribution is unknown, and the measurement accuracy of parameter estimates is accurate. However, in Jack-knife, parameter estimates are typically calculated from the complete sample and subsequent estimates by removing one observation. The jack-knife estimation method is typically used when other estimator methods are difficult or impossible to perform for the following reasons:

- No theoretical basis is available for the estimates
- Statistical functions are complex to work with because functions without closed form integrals, so the delta method, is not possible to do
- For large samples, the jack-knife method is almost equivalent to the delta method

The jack-knife method can be used for the following purposes.

- Measuring Robustness Estimator
  Observing variations in the estimator as the data change gradually, the jack-knife method can help identify potential anomalies or extreme influences in the data.
- Bias and Variance Estimation
  This method helps measure how close the estimator is to the actual value (bias) and how sensitive the estimator is to changes in the data (variance).
- Measuring uncertainty
  The jack-knife method can help calculate confidence intervals and quantify the uncertainty in estimates by generating several estimators based on an observation-less dataset.
- Testing the Reliability of the Estimator
  The jack-knife method can help identify whether an estimator is sensitive to specific observations or if there are outliers that significantly impact the results.

C. Multicollinearity Test

The multicollinearity test detects whether there is a high or perfect correlation between predictor variables before deciding on the regression model to be used. The term multicollinearity was first proposed by Frisch, where there is initially a linear relationship between some or all of the predictor variables in the regression model [23]. According to [24], the variance inflation factor (VIF) indicates multicollinearity problems in the predictor variables, which are determined using the following formula:

$$VIF_{(j)} = \frac{1}{(1-R_j^2)} \tag{3}$$

Where $j = 1,2, \ldots, k$

R_j^2 is the coefficient of determination obtained from predictor variable X_j, which is regressed against the other predictor variables. Multicollinearity occurs if the $\mathrm{VIF}_{(j)}$ value exceeds 10. According to [25], the LASSO shrinkage estimator was used to overcome multicollinearity problems. The alternative steps toward overcoming the multicollinearity problems are as follows:

1. Replacing or removing variables with a high correlation value
2. Increase the number of observations
3. The data were transformed into other analyses using the nonparametric LASSO Method.

D. The Theoretical Basis of the LASSO Method

The Least Absolute Shrinkage and Selection Operator (LASSO) method was introduced by [18]. Suppose a set of observations is known $(x_{i,1}, \ldots, x_{i,m}, y_i)$, $i = 1, \ldots, n$ where $x_{i,j}$ is the independent or predictor variable, y_i is the dependent or target variable. In that case, n is the number of observations, and m is the number of predictor variables, then a linear regression model can be formed with the equation:

$$\hat{y}_i = \beta_{i,0} + \beta_{i,1} x_{i,1} + \cdots + \beta_{i,}\, m x_{,m} \tag{4}$$

Where $\hat{y}_i$ is the output you want to predict and $\beta_{i,j}$ is the regression coefficients. Figure 2 illustrates a linear function that was searched for using linear regression.

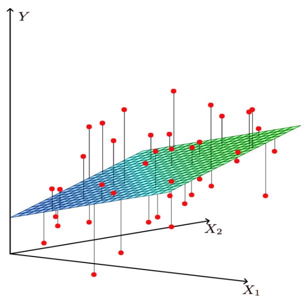

Figure 2. Illustration of searching for a linear function that models the most minor error value.

The regression method uses ordinary least squares (OLS) for parameter estimation, which estimates the regression coefficient (β) by minimizing errors. The OLS or ordinary least squares method can be used to determine the best regression coefficient $\beta_{i,j}$ for the linear regression model above. This method estimates the coefficient value by determining the value that produces the squared error or least-squares residual, as defined in equation (5).

$$\mathrm{E} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{5}$$

Equation (6) shows the exact calculation method of the OLS method to get the best β^{OLS} regression coefficient with X indicating the predictor variables $x_{i,j}$, which form a matrix, X^T indicating the transpose of the matrix X, and y from the set y_i [26]. LASSO is the development of the OLS method, which adds a limit or penalty when searching for the best coefficient value.

$$\beta^{\mathrm{OLS}} = (X^T X)^{-1} X^T y \tag{6}$$

This study references the LASSO method, which has been widely implemented for various research problems, including cancer detection [27], Chron's disease detection [28], water quality prediction [29], and ranks land-use changes from green or partially green areas to impervious areas in Jakarta's buffer city [30]. This study used the LASSO method to create an EPC design model for cost overruns influenced by design changes in agro-industrial construction projects. The equation for finding the regression coefficient is as in equation (7), with the value of in this equation being a specified constant and $\sum_{j=1}^{m} |\beta_j|$ called a penalty in the form of ℓ_1 -norm of the regression coefficient [18].

$$\beta^{\mathrm{LASSO}} = \underset{\beta}{\mathrm{argmin}} \left\{ \frac{1}{2} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{m} x_{i,j} \beta_{i,j} \right)^2 + \lambda \sum_{j=1}^{m} |\beta_j| \right\} \tag{7}$$

The solution to equation (7) cannot be solved precisely like the OLS method in equation (6) [25]. Therefore, an approximation method called cyclic coordinate descent [32] was used to calculate the LASSO regression coefficients. The algorithm for the cyclic-coordinate descent method is as follows:

1) Initialize the initial value of β=0.
2) Repeat for t=0,1,2,…, until it converges or a certain T-value limit:

a) Calculat3e $\beta^t = \sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{m} x_{ij}\beta_{ij}\right)$
b) Repeat $j = 1, 2, \dots, m$
   i. Calculate $\beta^{t-1} = \beta^t + x_j w_j$
   ii. Update regression coefficients $\beta = \sum_{i=1}^{n} x_{ij}\beta^{t-1}$
   iii. Calculate $\beta^t = \beta^t - x_j w_j$

E. Evaluation Metrics

The performance or accuracy of the regression model must be quantitatively evaluated [33] after modeling and prediction processes using LASSO regression. The evaluation metrics used in this study are the mean squared error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2).

The first evaluation metric is the MSE, which measures the error or prediction error that is squared and averaged. Equation (8) shows how to calculate MSE if it is known that y_i is the original output and $\hat{y}_i$ is the predicted output [34]. The difference in the original output value compared to the prediction is called an error or residual. The Mean Squared Error (MSE) expresses the expected distance between the estimator and the proper function; the bias is minimized if the estimator can and does, in expectation, get close to the actual value, and the variance expresses how far the estimator can get from its expected value depending on the observations.

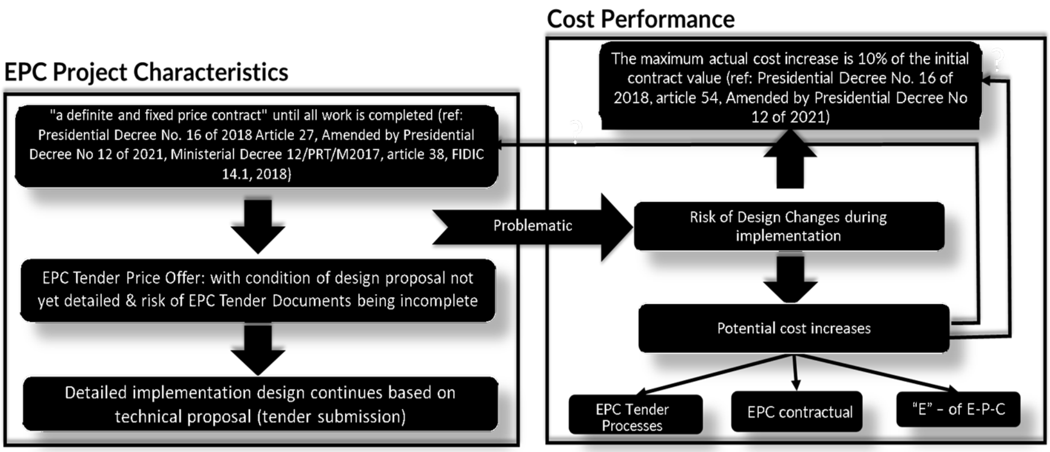

Figure 3. Research Frame Work

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

MAPE is another evaluation metric used to evaluate the performance of regression, which has an error interpretation that is easier to understand in the form of percentages. However, based on the calculation formula, MAPE has the limitation that it can only be used for positive number type data [34]. Equation (9) shows how to calculate MAPE with ϵ being a small positive number to avoid division by 0. The M*ean Absolute Percentage Error* (MAPE) is easy to interpret since it shows the percentage error values. For example, ten percent of MAPE means that the actual and predicted values are off by ten percent.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{\max(\epsilon, |y_i|)} \tag{9}$$

The final evaluation metric is the coefficient of determination, usually written as R^2. This metric shows the proportion of the target output that can be explained by independent variables in the regression model [35]. This R^2 value shows how well this regression model makes predictions and can be calculated as in equation (10).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

The value R^2=1.0 is the best score, which shows that the resulting regression model can predict very well [34]. R^2 is the coefficient determination that presents how well the model fits the dependent variables.

III. Research Methodology

A. Research Frame Work

Figure 3, the research framework, shows that the EPC project begins by considering the EPC project characteristics, where the EPC project is carried out at a lump sum price, the price offer submitted during the tender process uses basic design drawings of FEED document, and the detailed design during construction uses tender-proposal document. This creates risks with potential design changes during construction, with additional cost implications.

Therefore, the rising question is whether the percentage of cost overruns owing to design changes is still within a reasonable cost performance limitation. Then, potential cost increases are investigated from the upstream to downstream phase approaches of the EPC tender process, EPC contractual, and detailed engineering design during construction.

B. Research Strategy

The research methodology was developed using a step-by-step strategy as follows:

1) A list of variables was compiled from the literature and validated as a draft measuring tool for the questionnaire.

2) Conduct a pilot survey of three potential project respondents to ensure that their grammar and writing align with the same perceptions as the research objective.

3) Questionnaires were randomly distributed to potential respondents of EPC-based agro-industrial projects in various regions of Indonesia. One respondent's questionnaire reflected the data for each project.

4) The contractor respondents filled out project data on the original contract value, final account project cost, and cost increase owing to design changes indicated in the cost overruns of the direct and indirect construction costs, engineers' availability in the engineering section, and company experience in the EPC project.

5) Analysis and discussion.

a) The first step was factored analysis to determine the most dominant variables.

b) The multicollinearity of each independent variable (X) was detected by examining each variable's Variance Inflation Factor (VIF) to check whether multicollinearity occurred in the relationship between the predictor variables.

c) The next step is a regression analysis to create an EPC design model that correlates with cost performance using the LASSO method with a double-jack-knife resampling algorithm to predict the final project cost based on primary survey data. This analysis generated a model of the final project cost, initial contract value, and

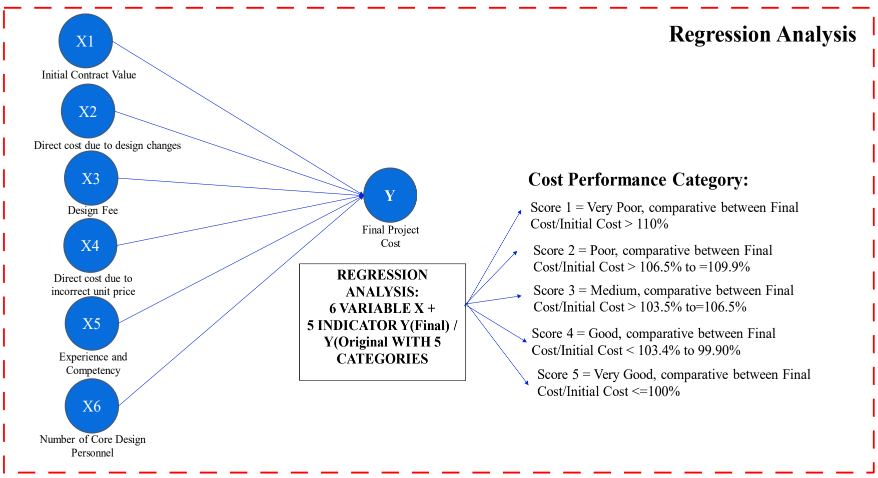

Figure 5. Initial Cost Model for Regression Analysis

potential cost overruns caused by design changes.

C. Input Data for Regression Analysis

The LASSO method regresses the data of dependent variable Y as the project's final cost. The predictor variables are the initial contract value = X1 (unit in Billion IDR), direct and indirect costs due to design changes = X2 (unit in Billion IDR), indirect cost for engineering service fee = X3 (unit in Billion IDR), direct costs due to unit price analysis errors = X4 (unit in Billion IDR), company experience in EPC projects = X5 (unit in years), and the availability of core personnel in the engineering section = X6 (unit in number of personnel). The scores of the cost performance categories were as follows:

- Score 1 = Very Poor, comparative between Final Cost/Initial Cost > 110%
- Score 2 = Poor, comparative between Final Cost/Initial Cost > 106.5% to =109.9%
- Score 3 = Medium, comparative between Final Cost/Initial Cost > 103.5% to=106.5%
- Score 4 = Good, comparative between Final Cost/Initial Cost < 103.4% to 99.90%
- Score 5 = Very Good, comparative between Final Cost/Initial Cost <=100%

D. Step-by-Step Analysis

The steps for creating and testing a regression model to predict project costs are shown in Figure

Figure 4. Steps for creating and testing a regression model [36]

4. Initial data with 40 observations were

resampled using the double-jack-knife method to obtain 160 rows of data.

The next step is to perform feature scaling or normalization, which transforms the values in the data into a range of 0 to 1. Figure 4 shows the creation and testing of the regression model [36]. This is important because the range of values in the initial dataset varies; for example, some are worth up to billions, and some are only tens or units. This normalization can improve the prediction results [36].

A regression model is better if the data used to form the model differ from those used for testing when measuring the performance of the data. The data used to form this model are called the training data, whereas the testing data are called the testing data. This study used six observations from the original data that still need to be resampled as test data. Figure 5 shows the initial model with six predictor variables (X) and one dependent variable (Y).

IV. Analysis Results

A. Detecting Multicollinearity of Data Samples

The initial analysis stage determines whether the sample predictor variables in this study experience multicollinearity problems before alternative analysis methods can be determined. The results of the correlation analysis between the predictor variables of the original 40 samples are presented in Table 1.

Table 1.
Data Correlation (r) of Prediction Variables

	X1	X2	X3	X4	X5	X6
X1	1					
X2	-0.3226	1				
X3	0.1153	-0.2482	1			
X4	-0.4545	0.9657	-0.1958	1		
X5	0.9749	-0.5349	0.1277	-0.9614	1	
X6	0.0199	-0.0128	0.2526	0.0054	-0.0684	1

Table 2 shows the output of statistical data analysis, in which three of the 15 predictor variables interconnected with each other used in the research have a high correlation. In other words, the sample data for the predictor variables showed a multicollinearity problem, in which the model results became biased and inconsistent. Therefore, the LASSO method with the double-jack-knife resampling algorithm is suitable for regression analysis to overcome multicollinearity.

Table 2.
Data Analysis of VIF Value

No.	Correlation	R-Value	R^2	$1 - R^2$	$VIF = 1/(1-R^2)$	Remark
1	rX1_X2	- 0.3226	0.1041	0.8959	1.116	VIF < 10
2	rX1_X3	0.1153	0.0133	0.9867	1.013	VIF < 10
3	rX1_X4	- 0.4545	0.2065	0.7935	1.260	VIF < 10
4	rX1_X5*)	0.9749	0.9505	0.0495	20.186	VIF > 10
5	rX1_X6	0.0199	0.0004	0.9996	1.000	VIF < 10
6	rX2_X3	- 0.2482	0.0616	0.9384	1.066	VIF < 10
7	rX2_X4*)	0.9657	0.9326	0.0674	14.830	VIF > 10
8	rX2_X5	- 0.5349	0.2862	0.7138	1.401	VIF < 10
9	rX2_X6	- 0.0128	0.0002	0.9998	1.000	VIF < 10
10	rX3_X4	- 0.1958	0.0384	0.9616	1.040	VIF < 10
11	rX3_X5	0.1277	0.0163	0.9837	1.017	VIF < 10
12	rX3_X6	0.2526	0.0638	0.9362	1.068	VIF < 10
13	rX4_X5*)	- 0.9614	0.9244	0.0756	13.223	VIF >10
14	rX4_X6	0.0054	0.0000	1.0000	1.000	VIF < 10
15	rX5_X6	- 0.0684	0.0047	0.9953	1.005	VIF < 10

B. The LASSO Summary Result

The regression model was constructed using Python and the Scikit-Learn library. The lambda (λ) values during model formation and training were 0.8, 0.9, and 1.0, respectively. After obtaining the regression model, it was tested using five test data observations and MSE, MAPE, and R^2. The resampling technique carried out the observations twice, expanded them to 80 data points, and finally to 160 data points until the analysis resulted in the best regression model. In the final step, a regression validity test was conducted by substituting the variable data samples from the survey/actual results of the predictor variables into the obtained regression equation as the Y predicted result and comparing it with the Y of the actual data. The difference between Y-Predicted and Y-Actual compared to Y-Actual did not exceed 5% as the regression validity limitation.

Table 3.
The Summary Test Results

Test	Prediction Value
MSE	1.92296E+17
MAPE	0.00736
R-squared	0.9959

Table 4.
The LASSO Regression Coefficients Results

Variable	Atribute	Coefficients	Value	Regression Equation
X1	Original contract value	β_1	1.0245	$\hat{Y}_{Final\ Cost} = 1.0245 * X1 + 0.0586 * X2 - 0.0329 * X3 + 0.0226 * X4 - 108{,}460{,}783 * X5 + 201{,}033{,}869 * X6$
X2	Direct and indirect costs due to design changes	β_2	0.0586	
X3	Indirect cost for engineering service fee	β_3	- 0.0329	
X4	Direct costs due to unit price analysis errors	β_4	0.0226	
X5	Company experience in EPC project	β_5	- 108,460,783	
X6	The availability of core personnel in the engineering section	β_6	201,033,869	

The following conclusions were obtained from the testing analysis results: The best lambda value was 0.8. Based on the modeling results in Table 3, the LASSO model can model datasets that contain multi-collinearity optimally for datasets with a total of 160 samples. The resulting LASSO regression model can be predicted very well from the evaluation metrics below. A plot of the predicted results compared to the actual output is shown in Figure 6. The regression coefficient from the analysis using LASSO can be seen in Table 4.

C. Regression Validity Test

In the first step, using the resampling technique, 40 data samples were expanded to 80 and 160 data points. Consequently, after substituting the value of variable X into the obtained equation, the (Y-actual minus Y-predicted) values compared to the Y-actual data were close, with a deviation of < 5%. Figure 6 shows a similar graph of the sword with bold marks: Level 3 higher is the Y-predicted value, Level 2 middle is the Y-actual value, and Level 1 lower is the value of the predictor variable (X). Fluctuating values were observed in the original data samples, from 1 to 40 sample points. Figure 7 shows the clustered column lines explaining the regression validation results of Y-Actual vs. Y-Predicted. This graph shows that substituting all variables X into the obtained regression of 160 sample points produced the predicted Y values and actual Y values with a less than 5% differentiation for each variable X.

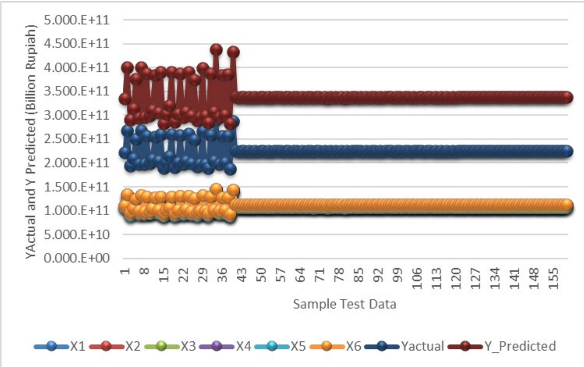

Figure 6. LASSO double-jack-knife Result

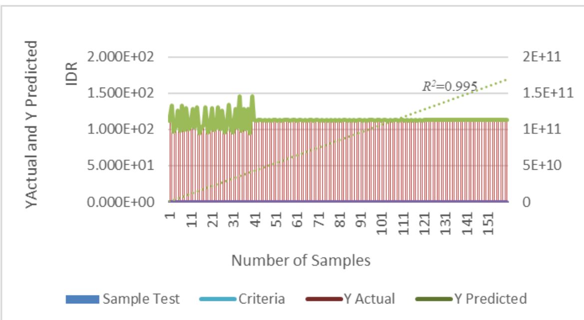

Figure 7. LASSO Regression Validation Result of Y-Actual Vs Y-Predicted

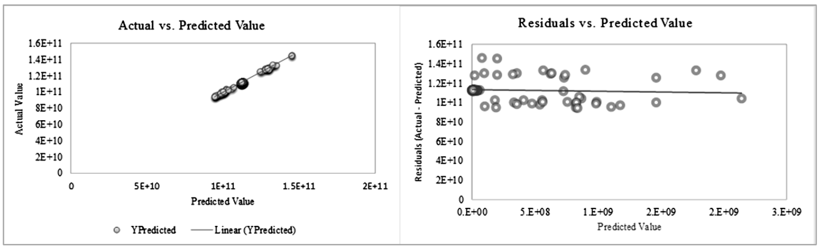

Figure 8. Plot of LASSO regression prediction results

Thus, it was clearly described that by increasing the sample data to 160 samples, smoother results and promising accuracy results were obtained, with lambda parameters of $\lambda = 0.8$, MAPE = 0,736%, and R^2 = 0.995, and the deviation of the Y-predicted results from the Y-actual results being less than 5%.

Figure 8 shows the optimal regression results, because the regression line in the model produces the smallest error. The best is the regression line produced to estimate or forecast the data distribution, which produces a minor error after applying the error correction model. The dataset used different units for billion Rupiahs (X1, X2, X3, X4), unit year (X5), and number of people (X6).

D. Statistical Learning Evaluation

Machine learning was evaluated for statistical learning in the next step to obtain a 95% confidence interval for the coefficient of the explanatory variable. This confidence interval was used to test the hypothesis that the value of the coefficient of an explanatory variable being examined is significant in this study. The hypotheses tested are $H_0 : \beta_x = 0$ $H_1 : \beta_1 \neq 0$.

Table 5.
Statistical Analysis Output

Variable	t-Stat		P-value		Remark
	Output value	limit value	Output value	limit value (α = 5%)	
X1	194.6637	|t-stat| > 2	0.00	< 0.05	$\beta_1 \neq 0$, H_0 is rejected, so, X1 significant variables influence Y
X2	6.4912	|t-stat| > 2	0.00	< 0.05	$\beta_2 \neq 0$, H_0 is rejected, so, X2 significant variables influence Y
X3	- 5.8214	|t-stat| > 2	0.00	< 0.05	$\beta_3 \neq 0$, H_0 is rejected, so, X3 significant variables influence Y
X4	3.9496	|t-stat| > 2	0.00	< 0.05	$\beta_4 \neq 0$, H_0 is rejected, so, X4 significant variables influence Y
X5	- 2.4904	|t-stat| > 2	0.01	< 0.05	$\beta_5 \neq 0$, H_0 is rejected, so, X5 significant variables influence Y
X6	5.9518	|t-stat| > 2	0.00	< 0.05	$\beta_6 \neq 0$, H_0 is rejected, so, X6 significant variables influence Y

H_0 is rejected if the 95% confidence interval (α=5%) of the parameter β_x does not include a zero value, P-value < α = 0.05, and |t-stat| > 2. The α value is the probability of error in rejecting H_0. If the result of hypothesis testing rejects H_0, then the coefficient of the β_x-th explanatory variable is significant at α=5%. However, if the result of hypothesis testing is that H_0 is not rejected, then no conclusion can be drawn because the probability of an error in not rejecting H_0 is unknown. Table 5 shows the statistical output results from the data analysis to confirm the probability of these variables being included in the model and the strength of their relationship to Y by considering the required t-stat and P-value.

E. Discussion and Findings

Forty questionnaires were distributed across 14 provinces in Indonesia: Sumatra, Java, Kalimantan, Sulawesi, Maluku, and West Papua. The respondent's companies as the research object were Limited Liability Companies (PT) at 70 %, public companies (Tbk.) at 22.5%, and state-owned enterprises (BUMN) at 7.5% of the total project respondents. The contract value of the respondents' projects ranged from IDR 50 billion to IDR 150 billion, with a project duration of eight–15 months for each project from 2013 to 2018.

To fulfill the currently required contractor competency requirement, by observing the tender process, this study found that contractors must comply with Certified Construction Competency, which is proof of job classification competency in the construction services sector in Indonesia, as required by the Republic of Indonesia's law regarding Construction Services in 2017 [39].

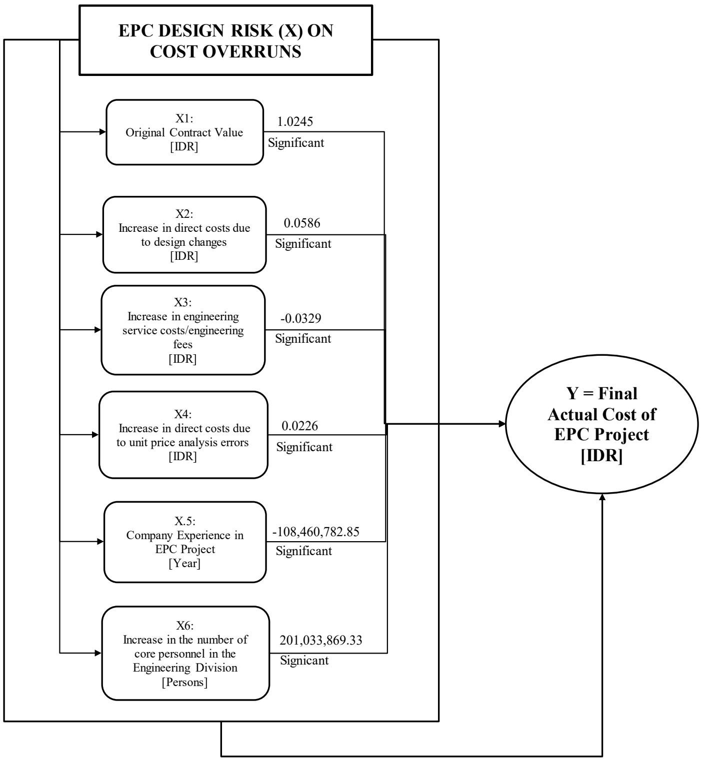

Figure 9. The LASSO Diagram Model of EPC Design Risk on Cost Overruns

The primary data of the project respondents were analyzed to construct the best model with the number of variables exceeding the number of observations using the nonparametric LASSO method with the double-jackknife resampling algorithm. Figure 9 shows the best regression model formed from the analysis results of the LASSO diagram model for the EPC design risk on cost overruns.

According to the LASSO analysis results, at α=5%, Figure 9 shows the diagram model with the highest sorted coefficient values.

i. The most significant influence is found in the variable coefficient of the availability number of people in engineering sections; the obtained β_6 is 201,033,869 (X6), which significantly positively influences the final price (Y). This means that for every increase in core engineering staff per unit personnel, the final contract will increase by 201,033,869.32 units of Rupiah. Increasing the number of core personnel in an engineering team must effectively prevent an increase in a company's overhead costs of indirect costs.

As per the findings, the proposal to increase engineering personnel is directly linked to preventing cost increases. They aimed to enhance the personnel competency of the engineering team in handling EPC project design. This optimization is necessary to offset the potential increase in the final project costs. The proposed personnel increase can effectively prevent cost escalation by anticipating the risk of cost increases owing to design changes and expediting the design process as the project progresses. The risk of design changes that could inflate costs during implementation can be mitigated by ensuring qualified human resource support and competence for project success [7], [9], [10].

ii. The negative influence of variable X5 (contractor experience in an EPC project; obtained β_5 is -108,460,783) on the final price (Y) is significant. This means that for every one-year increase in the company's experience level in the EPC project, the final cost will decrease by 108,460,782.85 units of Rupiah. This study found that a company's experience (in years) in handling an EPC project can significantly reduce its final costs. Contractor experience in EPC can ensure satisfactory project results compared to ordinary contractors in terms of cost, time, quality, and construction safety following initial planning. Therefore, cost overruns owing to design changes can be significantly reduced by an experienced contractor.

This finding is relevant to the condition that experienced contractors demonstrate their proactive approach by maintaining a record of the top 10 rankings of previous project risk events [7], [9], [10] to anticipate potential issues.

a) the condition of the field site does not comply with the contract,
b) more or less work (change orders),
c) incomplete work scope, not by drawings and specifications, for example, unclear material, the nature of the project within the scope of work is new or has never been carried out before, with a certain level of construction difficulty,
d) change/postponement of work schedule at the owner's request,
e) Weaknesses in controlling payment receipts include payment for work that must be done on time.

iii. The obtained coefficient β_1 for the initial contract value X1 is 1.0245, where X1 positively influences the final actual value Y, meaning that with an input value X1 of one unit Billion Rupiah will equal 1.0245 unit of Billion Rupiah for Y value, the project's final actual value (Y) will equal the original contract (Y = X1). This appears to be the result of the original tender when the project begins with X2 = 0, X3 = 0, X4 = 0, X5 = 0, and X6 = 0. This result aligns with a previous study showing that EPC characteristics influence the initial contract value with a lump-sum contract and no escalation costs, and the bid proposal uses references with no detailed basic design (FEED document) [37], [1], [5]. The contract price is influenced to the size of the project in terms of the scope of work, organization, costs and time for completing the work will be determined by the level of importance according to the priority scale [9], [10]. This tender result reflects inherent obstacles because they depend on the qualifications and experience of the bidder of the EPC contractor.

The EPC system was meticulously accommodated to align with the laws of the Republic of Indonesia [38] and Article 15 (2. b) engineering, procurement, and construction. Findings related to the tender process results cannot be separated from the qualifications and experiences of the contractors participating in the tender. To identify tender obstacles related to the contractor's qualifications and bidder requirements, an action plan was outlined to obtain the contractor's qualifications based on the EPC's future global challenges. Further implementation followed government regulations [39], and under the government's Republic of Indonesia regulation through Law Number 6 of 2023 [40] concerning job creation stipulation, Law Number 2 of 2022 [40], because this system can reduce the time and bureaucratic chain that must be passed to obtain the business requirements.

iv. Variable X2, a critical factor in our analysis, represents the direct and indirect costs incurred owing to design changes (with a value of β_2 is 0.0586). Its role in determining the project's final price (Y) is significant. This means that a slight increase in direct costs due to design changes can lead to a substantial 5.86% increase in the final contract for every one billion Rupiah of increased cost or contributing up to 5.86%.

This finding aligns according to [7], [8], [9], [10] that design changes can occur owing to:

a) One of the main reasons for design changes is errors in the detailed design process. To mitigate this, it is crucial that the contractor's engineering team strictly adheres to the quality control system outlined in the standard operating procedures (SOP). This control process, implemented by the owner, is specifically designed to prevent the risk of design changes due to deviations between the initial design and the actual conditions of the work at the time of implementation.
b) Lack of EPC Contractor capability in FEED verification and initial design in the tender process in justifying complex and multi-disciplinary owner requirements due to limited EPC contractor resources
c) Correction of the bid costs is unexpected because the design needs to be more detailed when submitting the bid. This increases the project's final cost if the final bid costs still need to be corrected post-negotiation.
d) Uncertain land causes uncertainty and changes in site plans. If the site plan contract process is not fixed, it will contribute to additional costs owing to design changes, direct costs, and land preparation costs.

v. Varible X3 (indirect cost for engineering service fee, obtained β_3 is - 0.0329) indicates a negative influence on the project's final price (Y), which means that for every increase in the design service costs due to design changes of one unit, the final contract will decrease by 3.29% increase in the final contract for every one billion rupiah of increased cost. This indicates that the contractor must maintain sufficient design fees to satisfy design requirements during construction and reduce the final price (Y). A sufficient design fee must be sustainably maintained during implementation to anticipate construction errors and repetitive work, thereby reducing overruns and final costs. Lowering the additional design costs proportional to the design scope indicates that the optimal design products are met at the project site.

It is imperative that the contract include a provision for the design engineering service fee to anticipate design changes if requested by the owner. This provision provides certainty to the contracting parties and helps manage costs, as design changes can contribute to added costs to the final value owing to increased indirect costs and preparatory work [3].

a) *Engineering* is an iterative activity that involves the production of designs guided by applicable standards and codes. Professional organizations and certified experts perform this crucial task, ensuring quality and adherence to standards.

b) *Design* is an engineering deliverable that transforms ideas into reality during the engineering phase to fulfill the designer's final goals according to specifications or objectives.

vi. The lowest influence is found in the variable coefficient of the error when analyzing the unit price (X4, obtained β_4 is 0.0226), which has a weak positive influence on the final price (Y). This means that for each increase in direct costs due to unit price errors of one unit billion Rupiah, the final contract will increase by 2.26 % in billion Rupiah for every one billion Rupiah increase in cost. The survey results indicated that the contractor was able to make a more accurate offer. In other words, errors in the unit price analysis of the tender process do not significantly influence the final price of the project (Y).

This finding aligns with the adequacy value of the cost-bid proposal during the tender process. The unit price of work must be analyzed according to technical specifications, basic design drawings, field observations of the project location, transportation facilities, local cost factors, and the chosen construction method. Unit price analysis errors contribute to the final cost of the project [7] [8] [9] [10].

V. CONCLUSION

A. The conclusion

This study, conducted using rigorous methodology and comprehensive data analysis of the LASSO method with the double-jack-knife resampling algorithm, unequivocally found that the final EPC project value aligns with the original contract value when the project begins. This robust finding, backed by empirical evidence, underscores the reliability of the hypothesis and dispels any doubts about the accuracy of the original contract value reflecting the quality of the obtained tender result price, which is a 'legacy' of the previous process, bear the cost overruns due to the risk of design changes.

This research considers that the framework describes the EPC design model review of cost overruns from the upstream process of the tender phase and the downstream process of detailed engineering during construction. Significant research findings, expressed in the model diagram, related to the quality of the obtained tender result price for the tender process must be addressed from the qualifications and competence of the EPC bidder. Concerning the laws of the Republic of Indonesia [38], contractors' qualifications and competencies have been outlined and considered in the EPC's future global challenges. Further implementation of this law follows government regulations [39].

This study highlights efforts to strengthen the government's regulation of human resources for construction services [39] to face global competition that requires regulatory implementation. This law regulates classification and qualifications, construction workforce training, work competency certification, registration of professional experience, construction labor wages, and the regulation of foreign construction workers and professional responsibilities

This study encourages active participation in EPC businesses to upgrade their performance qualifications and professionalism as EPC contractors. The contractor must possess an electronically integrated standard certificate issued through an online single-submission (OSS) system under the government's Republic of Indonesia regulation through Law Number 6 of 2023 [40], concerning job creation stipulation Law Number 2 of 2022 [40]. This certificate validates the contractor's competence as a business entity carrying out integrated construction service activities. The implementation of this standard certificate was further validated by attaching a construction service business entity certificate, construction work certificate, and association membership. The OSS system plays a crucial role in this process, considering the integrated qualification and risk-basis rapprochement from low-, medium-, and high-risk to the bidder's pre-qualification stage as applicable provisions.

Therefore, this study presents tender findings regarding the risk of cost overruns owing to design changes and provides a roadmap for improving an experienced contractor's professional competence in an EPC project. This knowledge empowers parties to run an EPC project with the following impacts:

- Having a clear and detailed work contract of scope definition,
- Commitment to the end product quality
- Having a clear construction schedule and methods,
- Having Experience in EPC engineering projects with certified professional engineers by mastering field requirements to avoid design errors that result in cost overruns and aggressively implementing design optimization for balancing the cost,
- Regular upgrading programs are essential to improve the quality of human resources in engineering services, a constant need in a dynamic industry field.
- Health safety and environmental control should be considered throughout the construction life cycle.
- Finally, work is conducted using mutually agreed bills of quantities and price schedules by contract agreement with minimum additional costs.

This study created an EPC design model for the contractor's cost overruns of an industrial construction project in Indonesia as a prototype measuring tool that can be developed into an end-user application after the upstream process tender solution is settled. This model seeks to predict the EPC project's final cost due to design changes by cost balancing at the lowest target or a maximum of 10% of the initial contract value as a benchmark contractor's cost performance in Indonesia. This model is expected to become a valuable scientific research novelty by creating an assessment tool to reduce the risk of cost overruns in EPC lumpsum projects when the project begins post-tender, during construction, and in the final account phase.

The results of this study have limited implications for research on agro-industrial construction projects based on EPC contract systems. However, they cannot be applied to evaluate the costs influenced by the risk of design changes in other construction projects, because they have different project characteristics and require adjustment of the conditions if they are to be implemented.

B. Recommendation

Clarify the contractor's role in implementing the obtained assessment tool in the EPC post-contract phase. The contractor can use this tool to devise effective strategies. These strategies aim to manage and anticipate the rising costs that may arise during construction. These costs could result from design changes inherent in the quality of the tender results, which might be due to design inaccuracies during the tender proposal preparation.

Finally, the discussion results recommend proposals to promote the implementation of future research to expand the benefits of research results on other project aspects, both in procurement and construction aspects, as well as with another construction system, excluding the EPC system.

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DECLARATIONS

Author Contributions

Conceptualization, T.U.N.; methodology, T.U.N.; software, T.U.N. and D.E.H.; validation, T.U.N., D.E.H. and B.A.; formal analysis, T.U.N. and D.E.H.; investigation, D.E.H. and B.A.; resources, T.U.N.; data curation, T.U.N. and D.E.H.; writing—original draft preparation, T.U.N.; writing—review and editing, TUN., D.E.H. and B.A.; visualization, T.U.N.; supervision, D.E.H. and B.A.; project administration, T.U.N.; funding acquisition, T.U.N. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

Data sharing was not applicable. Restrictions apply to the availability of such data. Data were obtained from a third party and are available to the authors with permission from the third party.

Conflicts of Interest

The authors declare no conflicts of interest related to this manuscript.

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