Available online at: http://e-jurnal.lppmunsera.org/index.php/JSMI

Jurnal Sistem dan Manajemen Industri
(Journal System and Management of Industries)

ISSN (Print) 2580-2887 ISSN (Online) 2580-2895

Performance evaluation using data envelopment analysis - stepwise modeling approach: A case study of construction industries in Indonesia

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ARTICLE INFORMATION

Article history:

Received: June 23, 2024
Revised: October 8, 2024
Accepted: November 15, 2024

Keywords:

Performance evaluation
DEA
Stepwise approach
Variable selection

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ABSTRACT

The construction industries are inextricably linked to employment, investment, the quantity of infrastructure building projects, and other economic sectors in Indonesia. They serve as catalysts for the expansion of goods and service production. Apart from having a strategic role in the national economic, construction companies also experience various obstacles to developing their businesses. These obstacles include weakening the IDR exchange rate against the US dollar, regulatory and legal frameworks, labor and skills shortages, economic and financial instability, and environmental and sustainability concerns. In order for the construction industry to survive, develop, and remain competitive in the face of international competition, it is crucial to evaluate its performance constantly. This research aims to evaluate the construction industry's performance in Indonesia. There are 151,183 construction companies included in this study. Hence, these companies will continue to survive, grow, and compete in the face of global competition. The methods applied in this research are an input-oriented DEA envelopment model and a stepwise modeling approach. The research results indicated that 3% of the Indonesian construction industry is made up of efficient DMUs, and the remaining 97% are inefficient DMUs. DMUs are classified according to the distribution of efficiency scores. It is considered that for the classification of inefficient DMU, there exist four ranges, Rs: R1 (ES = 0.16-0.99), R2 (ES = 0.050-0.15), R3 (ES = 0.015-0.049), and R4 (ES = 0.000-0.014). The criteria for each classification, in terms of the level of effectiveness, are as follows: i) R0 Range (ES = 1]): Effective; ii) R1 Range (ES = 0.16-0.99): Relatively Low Ineffectiveness; iii) R2 Range (ES = 0.050-0.15): Moderate Ineffectiveness; iv) R3 Range (ES = 0.015-0.049): Significant Ineffectiveness; and v) R4 Range (ES = 0.000-0.014): Very High Ineffectiveness. The percentage of each classification is as follows: inefficient DMU-R1 0%, inefficient DMU-R2 30%, inefficient DMU-R3 37%, inefficient DMU-R4 30%.

1. INTRODUCTION

Infrastructure development is essential to any form of national development. Good infrastructure provides the necessary framework for facilitating the production and supply of numerous products and services, contributing to increased economic growth and regional economic equity. Infrastructure development is an important institutional and economic development aspect that enhances productivity. Infrastructure development, however, should not be delayed during the COVID-19 pandemic, which affected many industries, as this industry is considered one of the drivers of the national economy. The building construction industries cannot be separated from the level of employment, investment, and quantity of projects related to infrastructure building, among other economic sectors. They serve as catalysts for expanding goods and service production and mobility. Additionally, construction promotes equitable development across all sectors, including food security, electrification, supplying energy needs, upgrading educational and healthcare facilities, providing appropriate road access for transferring products and services, and enhancing the allure of tourism [1].

The construction sector is currently facing several challenges, one of which is the weakening of the IDR exchange rate against the US dollar. This condition directly impacts the increase in the cost of imported raw materials, such as iron, steel, cement, and heavy equipment, which ultimately impacts the overall production costs. This increase in costs is very burdensome for contractors and has the potential to hinder the smooth running of construction projects. The increase in import costs can disrupt the company's cash flow and potentially cause project delays because it is necessary to renegotiate the budget or find additional sources of funds. The weakening of the rupiah can also increase credit risk for companies and contribute to inflation, which will then burden operational costs [2].

Other challenges facing the construction industry are regulatory and legal frameworks, labor and skill shortages, economic and financial instability, and environmental and sustainability concerns. Various significant laws and provisions are present, to which the Indonesian construction industry adheres importantly, including but not limited to the Construction Law and Government Regulation No. 14 of 2021. In-depth understanding is greatly needed for smoothly and uninterruptedly following the regulations. Usually, skilled labor and qualified professions like engineers and architects are in short supply within the construction industry. It causes delays and increases project costs due to a shortage of skilled labor and professionals. The construction industry also depends on international economic conditions and localized financial instability. Other risks to current and future projects include inflation, material cost increases or other fluctuations, and changes in investment patterns. There is an increasing concern with sustainable construction practices. The companies would then need to integrate friendly methods and materials for the environment, in line with global sustainability standards, although this would be at a higher initial cost [3].

The survivability and development of the building industry to compete with international competitors is thus largely dependent upon continuous performance analysis. Qualification and performance-based measures of the activities are what are referred to as performance appraisals. Performance evaluation is a core function if the company is aggressive in a dynamic business environment. With this function, the business relies on it to work harmoniously. The effectiveness of the customer's requirements and satisfaction is the basis for the framework in performance evaluation. Some of the characteristics that are considered during the performance appraisal include the following: i) altered operating conditions, ii) competition with competitive drive, iii) a benchmark for improvement of the business, iv) need to check the national and international quality, v) organization's role in the change, vi) the conditions are never static, vii) external requirements, and viii) information technology effect [4]. Other factors considered to analyze the performance include input and output, technical efficiency, scale efficiency, multi-dimensional performance measurement, environmental factors, human resources, sustainability performance [5], operational efficiency, productivity, innovation, sustainability, quality of service, ability to adapt to changes, and human resource management. It will give a broader overview of the company's level of performance from an industrial point of view [6].

Performance evaluation aims to provide information for company decision-making while continually monitoring the economy and efficiency of the business's operations. Performance evaluation is a commonly employed technique to enhance organizational procedures. This approach becomes crucial if criteria or benchmarks are not provided for assessment. Benchmarking and performance assessment are usually applied approaches for the simultaneous enhancement of methods, and they will have particular significance in the absence of the already existing criteria (benchmarks) of estimation. Benchmarking is primarily applied as an instrument for the verification of the ratio among decision-making units (DMUs). Firms, associations, enterprise units, initiatives, etc., are some examples of DMUs [7]. Performance evaluation has enormous potentiality in human resource management and organizational development. From this perspective, performance evaluation is a systematic process for appraising and giving feedback about individuals or groups concerning their work results, skills, and contributions to the organizational objectives. The purposes of performance evaluation include feedback and development, human resource decisions, improvement of organizational performance, building communication, and establishment of goals [8]. Performance evaluation is one of the main parts of human resource management that tries to grade individual performance and improve general organizational performance. These objectives include performance measurement, employee development, goal setting, human resource decisions, improving organizational performance, and improving communication [9].

In modern enterprises, difficulties in practically applying efficiency analysis to improve decision-making processes are relatively common. It is important to be able to observe an industry's true extra output profit solely as a result of an increase in its efficiency [10]. For this purpose, several models have

http://dx.doi.org/10.30656/jsmi.v8i2.8936

been created and are still being developed to support the manager with the necessary help for the activities. Since operational research and many of its branches basically deal with wise business decisions, they flourish themselves, aside from these estimates. MCDM found their applications to real-life problems in works [11], [12], [13]. They were also concerned about the public's accessibility to such techniques. Among them, data envelopment analysis (DEA) has proved to be a multifunctional tool of great usability [14], [15].

The technique of DEA-mathematical programming is utilized to calculate the relative efficiency of a set of decision-making units (DMUs). It generates a huge number of outputs from a large number of inputs. Charnes, Cooper, and Rhodes initially proposed the DEA model in 1978 [16]; benchmarking and performance evaluation have demonstrated the value of the DEA methodology. They solved the DEA model under discussion to produce an efficiency score and benchmarking data for DMUs. The projection point offered by the best solution matches the benchmarking data, and the efficiency score equals the objective function's ideal value [17].

Initial parameter approximations are not necessary when using the DEA approach. As a result, this approach may be utilized to decrease mistakes, streamline processes, handle problems associated with subjective elements, and more. The primary benefit of the DEA method above other approaches is its purely technical nature. Thus, initial characteristics of the production function are not required to be supplied, and an optimal model is ensured to compare the efficiency of different distribution networks [18]. DEA continues to develop as a broad analytical tool and is applied in various fields, such as education, health, transportation, and business sectors, thus having a significant impact on improving the operational efficiency of various organizations and industries. DEA's main benefits include objective efficiency assessment, benchmarking, multiple inputs and outputs, endogenous weights, no prices or costs, and decision-making [19]. DEA is a flexible and versatile tool for measuring efficiency and productivity in various fields without requiring initial parameters. The benefits of DEA include broad evaluation tools, accommodating many inputs and outputs, identifying inefficiencies, not requiring prices, benchmarking, and flexibility [20].

The application of data envelopment analysis to the model requires the identification of input and output variables, which is an essential step. It's a systematic process for choosing variables stepwise by increasing or decreasing the average change in efficiency. Variables added to or deleted from the study resulted in this condition (DEA). A stepwise process was created to aid in selecting the input and output variables for DEA research. Information on changes in efficiency scores is used to support the approach. It requires little additional math or data storage, is straightforward to perform, and is objective [21].

Currently, the government focuses on expanding public and private investment to promote Indonesia's economic growth. The investment is mainly in the infrastructure sector, intending to improve connectivity throughout the archipelago. Infrastructure development is one of the reasons why the construction sector's involvement in the Indonesian economy has grown in recent years. It is reflected in the high contribution rate of 9.45% it provided to the GDP in the third quarter of 2022. Based on data from the Central Statistics Agency on Construction in 2022 figures, GDP distribution at current prices in the period under review is as follows: (i) construction contributes 9.45%, (ii) mining and quarrying 13.47%, (iii) manufacturing 17.88%, (iv) motor vehicle and motorcycle maintenance and also wholesale and retail trading 12.74%, (v) agriculture, forestry and fishing 12.91%, and other sectors take the greater share with 33.55% [1].

This research's primary contributions are as follows:

1. Evaluate the performance of construction industries in Indonesia using the DEA-Stepwise Modeling Approach method.
2. Propose a variable combination method for subtracting the number of variables that will be utilized in implementing the DEA method. This research applied eight alternatives for determining variable selection using the Stepwise Modeling Approach (SMA). Each of these alternatives consists of five stages (Step-Start, Step-1, Step-2, Step-3, and Step-END) and three components, such as remaining inputs (RI), remaining outputs (RO), and variable drops (VD).
3. Identify efficient and inefficient DMUs from the efficiency score of the best alternative of variable combination. The efficiency score of efficient DMU is 1, and that of inefficient DMU is between 0-0.99.
4. Classify DMUs by the dispersion of efficiency scores.

Wagner and Shimshak [22], enhance the work on variable reduction approaches in DEA by formalizing a stepwise approach to DEA modeling and emphasizing the management usage and insights derived from this methodology. This technique proposed some basic guidelines for eliminating variables backwards approach) or adding variables (forwards approach) in the DEA model, one by one. The backwards approach aims to eliminate variables that have the least effect on the set of efficient DMUs that constitute the reference set. This study proposes modifying the existing stepwise modeling approach (SMA) method to DEA modeling developed by Wagner and Shimshak [22]. This existing method only produces one alternative for determining variable selection. The proposed method can generate more than 1 alternative. In this research, eight alternatives are created for determining variable selection.

Furthermore, the best alternative method is selected. It is the basis for classifying efficient and inefficient decision-making units (DMUs). Based on the existing and proposed methods, the research gap in the study can be identified as follows: (i) In the existing SMA, done by Wagner and Shimshak, only one alternative is returned on how to find out the variable selection in DEA. As such, this reduces the level of flexibility and depth that could be derived if there were more alternatives. The gap exists in coming up with more alternatives in the variable selection process as a way of availing comprehensive decision-making frameworks; (ii) Smoothing in DEA: The paper will seek to extend the stepwise approach by generating eight variable selection alternatives as opposed to the single alternative generated in the current approach. The prevailing gap, therefore, indicates the need for a more diversified approach to DEA modeling in offering multiple dimensions to decision-makers towards the efficient classification of inefficient DMUs; (iii) Deeper decisional insights: There is a need to enhance management usage and insight into the DEA methodology. Perhaps methods so far cannot give in-depth insight into management's decisions. Again, this forms a gap for further research in the formalization process and focuses on real-world applications; and (iv) Backward and Forward Approaches in Variable Reduction: Another lacuna that this paper points out is the clearer guidelines that concern how the backward approach—the elimination of variables in terms of impact—and the forward approach—the addition of impactful variables—should be handled. It, therefore, creates the need for more structured and formalized ways through which the DEA model approaches can be applied to optimise efficiency in decision-making.

The efficiency score values can be used to classify DMUs as efficient or inefficient. An efficient DMU has a one-point efficiency score, whereas an inefficient DMU has fewer than one. The following considerations explain why DMUs are efficient or inefficient: An efficient DMU generates more outputs with similar input consumption or the same number of outputs with less input consumption. In contrast, a DMU with low-efficiency ratings needs more input to produce the same output [23]. DEA is a classification and ranking tool that compares DMU results. The consistency of the results shows that the DEA is a viable categorization and ranking tool. Thus, DEA has been verified as a ranking and classification approach [24]. Putri *et al.* [25] research used a histogram graph to order the DMU efficiency ratings from highest to lowest. This method identifies DMU clustering. Then, as a foundation for categorizing, each category can be assigned a threshold. Category 1 threshold is one. Category 2 threshold is from 0.9986 to 0.9998. Category 3 criteria are 0.9971–0.9974. This work considered the four ranges, named Range 1 (R1), Range 2 (R2), Range 3 (R3), and Range 4 (R4), used to classify the inefficient DMU. The value of each classification range is R1 (0.16-0.99), R2 (0.050-0.15), R3 (0.015-0.049), and R4 (0.000-0.014).

This paper is organized as follows: Section 2 outlines the related work, Section 3 details the research methods, Section 4 contains the results and discussion, and Section 5 concludes.

2. RELATED WORK

Data Envelopment Analysis (DEA) is a tool for evaluating the performance of production units. In the previous 40 years, various methodological extensions have been created to increase its effectiveness in various ways. However, one critical problem that remains unanswered in the literature is the selection of inputs and outputs to include in the model. It is an issue that affects practically every DEA-based research item since the researcher must pick the variables before starting the analysis. This option is especially important when the sample size is small compared to the number of accessible variables since it is required to lower the dimensionality of the DEA model to maintain some discriminatory power. Many researchers regard this selection as a critical stage that precedes the implementation of the DEA model. It indicates that the ensuing analysis will be conditional on the variables selected in the first stage [26].

Selecting which variables to investigate in a DEA model is crucial. Generally, every resource a DMU utilises should be viewed as an input variable, with outputs determined by performance and activity metrics when the DMU converts its resources into commodities or services. However, the present literature does not guide the selection of appropriate input and output variables. Most existing research on DEA treats the input and output variables as given before proceeding to the analysis [27]. Table 1 compares the contribution of previous and current research in variable selection using DEA [28], [22].

3. RESEARCH METHODS

3.1. Performance evaluation

A corporation's ability to operate successfully in the face of constant changes in the workplace depends on its ability to monitor performance. It is the required goal for the company to remain viable. One An important method for quantifying activities is performance evaluation. Capacity and accomplishment serve as its foundation. Appraisal is employed well in the performance framework. The criteria and client satisfaction determine its assignment. The following are a few variables for performance measurement: (i) The business environment's stability; (ii) Entitlement to rivalry; (iii) increasing the company's size in comparison to both internal and external businesses; (iv) The need to receive rewards on a national and

http://dx.doi.org/10.30656/jsmi.v8i2.8936

Table 1. A comparison of the contribution of previous and current research in variable selection using DEA

No.	Authors	Result/contribution
1	Golany and Roll [29]	DMUs should be at least twice as many as inputs and outputs ($n \geq 2v$), where n denotes the number of DMUs and v indicates the number of variables.
2	Bowlin [30]	Each of the three DMUs requires one input and one output ($n \geq 3v$).
3	Dyson *et al*. [31]	To conduct a meaningful analysis, the minimum number of units should be twice the number of inputs and outputs, or $n \geq 3(m + s)$.
4	Cooper *et al*. [32]	Proposed $n \geq \max(m \times s, 3v)$ for three inputs and four outputs.
5	Payrache *et al*. [26]	Cardinality limitations can be implemented directly into the DEA model. The authors proposed a rule of thumb for determining the maximum number of inputs and outputs while considering the DEA estimator's convergence rate. The maximum number of variables the computer may choose should be calculated as a function of the sample size.
6	Banker [33]	Three statistical approaches are proposed to determine the significance of an input or output variable in the manufacturing process. The null hypothesis asserts that the variable under consideration has no influence on the production process.
7	Pastor *et al*. [34]	Evaluated two DEA formulations. The first formulation differs from the second by containing a testing variable known as a candidate. This variable's influence on efficiency is investigated using a binomial statistical test. The candidate variable is then added or removed per the ultimate choice.
8	Ruggiero [35]	A variable selection approach was proposed, in which an initial efficiency measure is computed from a set of known variables. The efficiency is then regressed against a set of specified variables. If the latter are proven to be relevant, they will be chosen. The analysis is performed until no more variables are significant.
9	Ueda and Hoshiai [36]; Adler and Golany [37]	Principle component analysis, or PCA, was used to minimize the number of inputs and outputs by substituting them with principle components.
10	Norman and [38]; Valdmanis [39]; Sigala *et al*. [40]; Wagner and Shimshak [22]	Measuring the average change in efficiency scores after experimenting with alternative model parameters.
11	Nataraja and Johnson [41]	Four approaches to defining variables in DEA were proposed: Monte Carlo simulations, a regression-based test, the efficiency contribution measure (ECM), and principal component analysis (PCA-DEA) for variable selection.
12	Li *et al*. [42]	Developed an approach for applying Akaike's information criteria (AIC) criteria to pick the appropriate collection of input and output variables for evaluation. This technique is primarily concerned with identifying the significance of a subset of the original variables rather than examining the marginal relevance of each variable separately.
13	Wagner and Shimshak [22]	Enhance the work on variable reduction approaches in DEA by formalizing a stepwise approach to DEA modeling and emphasizing the management usage and insights derived from this methodology. This technique proposed some basic guidelines for eliminating variables backwards approach) or adding variables (forwards approach) in the DEA model, one by one. The backwards approach aims to eliminate variables that have the least effect on the set of efficient DMUs that constitute the reference set.
14	This paper	This study proposes modifying the existing stepwise modeling approach (SMA) method to DEA modeling developed by Wagner and Shimshak [22]. This existing method only produces one alternative for determining variable selection. The proposed method can generate more than 1 alternative. In this research, create eight alternatives are created for determining variable selection. Furthermore, the best alternative method is selected. It is the basis for classifying efficient and inefficient decision-making units (DMUs).

international scale; (v) The organization has changed its working procedures to become productive and more effective; (vi) The insecurity of the corporate atmosphere; and (vii) Impact of information advancement [43].

Performance evaluations are essential for every business. The present and future success of the business is based on it. A company can gain three advantages by evaluating its performance: (i) understanding its strengths and weaknesses, (ii) better preparing its operations to fulfill customers, and (iii) identifying business opportunities for the company through the enhancement of current operational business processes and the creation of new goods, processes, and services [44].

Performance evaluation is recognized and defined as: (i) an essential measurement system; (ii) decision-making and communication procedures are created as initiatives for business improvement through performance measurement; and (iii) Performance measurement is an effort to grow the business by allocating decisions and procedures. It can be carried out in a number of ways, including combining, splitting, selecting, analysing, and publishing pertinent data [45].

3.2. Data envelopment analysis (DEA)

Referred to as benchmarking, relative performance measurement is the methodical assessment of a group of similar organizations called DMUs (decision-making units). DMUs might be businesses, divisions, projects, or other entities. In that they turn the same resources into the same products and/or services, they are meant to be homogeneous [31]. In this context, the Data Envelopment Analysis (DEA) model family and its stochastic extensions have been shown to be highly effective prescriptive analytics tools [46], [47]. They aid benchmarking systems in measuring, contrasting, and improving a variety of efficiency types, including technical, financial, and revenue efficiency [48], [49], [50].

The advantages of DEA in performance evaluation have led to its widespread use. Its merits include its emphasis on empirical research and the lack of presumptions inherent in other approaches, such as statistical regression analysis. Additionally, research on DEA benchmarking procedures has uncovered inefficiencies in some of the most profitable businesses. As a result, it has been found to be a better method for setting benchmarks than using profit as a criterion. Based on the actual observed inputs and outputs, DEA calculates every DMU's efficiency compared to all other DMUs. The DEA computations then yield the relative efficiency score for every DMU. Furthermore, for the observed population, DEA generates a piecewise efficient frontier that is representative of the best practice frontier. It, in turn, shows the maximum output that can be anticipated from each DMU in the population given the level of its inputs [51], [52].

The efficient frontier depicts the trade-off between the many input and output performance measures that are the most effective. The frontier makes it possible to recognize and enhance any currently ineffective performance. It was predicted that this would raise DMUs below the frontier to the efficient frontier. Additionally, DEA does not demand that the measured inputs and outputs match exactly. In other words, specific outcomes should be directly related to individual inputs. The DEA model successfully views the manufacturing process as a black box, concentrating on the resources that a business unit has access to (the "inputs") and examining how well they are transformed into the intended outputs [52], [53].

3.3. Input-oriented DEA envelopment model

An effective method for performance measurement is the DEA approach, which calculates the relative effectiveness of the organizational unit acting as the decision-making unit (DMU). It applies to every aspect of life. By examining the boundaries of commodities, which have several input and output factors, DEA also proves to be a potent means. Thus, the DEA approach may be applied to investigate issues related to multilateral production functions, such as the pace of technological advancement, the productivity index, size, and issues pertaining to minimal prices and maximum benefits. Since the DEA approach is not necessary for preliminary parameter estimation, its superiority in overcoming subjective influences, streamlining processes, lowering mistakes, etc., has been understated. The primary benefit of the DEA method over alternative approaches is its purely technical nature. It guarantees an excellent model for comparing the efficiency of different distribution networks and does not need to provide preliminary known values of the production function [54].

$$\theta^* = \min \theta$$

$$\text{Subject to} \tag{1}$$

$$\sum_{j=1}^{n} Xij\,\lambda j \leq \theta\, Xio, \quad i = 1, \dots, m \tag{2}$$

$$\sum_{j=1}^{n} Yrj\,\lambda j \geq Yro, \quad r = 1, \dots, s \tag{3}$$

$$\sum_{j=1}^{n} \lambda j = 1 \tag{4}$$

$$\lambda j \geq 0 \quad j = 1, \dots, n$$

The input-oriented DEA envelopment model is a technique where the output is a reminder of the most recent grade, and the input is decreased or reduced. Equations 1 through 4 present the formulation of this model. The formulation in question assesses n DMUs, one of which is called DMUo. Xio is the DMUo's ith

 http://dx.doi.org/10.30656/jsmi.v8i2.8936

input. Yro is the rth output of DMUo. Unknown weights, which can be between one and n, are represented by the symbol j. n is the representation of the DMU number. The DEA efficiency values are represented by the decision variable θ. θ* provides the best or optimal choice for DMUs. A DMU is also the effective DMU category if the θ* result is one. If the θ* result is less than one, the DMU is classified as inefficient [55].

3.4. Variable selection in DEA

The performance of production units can be assessed using data envelopment analysis (DEA). Many methodological adjustments have been made in the last forty years to enhance the approach's efficacy across various areas. However, selecting which inputs and outputs to add to the model is a crucial issue for which the literature has yet to provide a solution. The selection of inputs and outputs is an important stage frequently accomplished before using the DEA model [26]. Identifying the various variables that could be used in a DEA model is essential. Theoretically, every resource that a DMU uses must be viewed as an input variable. The outputs that are produced when the DMU modifies its resources to create services or products are performance and activity measurements.

However, the optimum input and output variable selection has not gotten much attention in the literature to date. The input and output variables are taken for granted in the vast bulk of previously conducted DEA research. The next step is the analysis. Variable selection is really important. The weights allocated to the variables will be restricted when there are more input and output variables. It led to a less thorough study of the findings. There is no consensus on the best technique to choose the variables. The literature has offered a variety of regulations to control the ratio of DMUs to variables. In general, max (m x s, 3(m + s)) should be equal to or larger than n (the number of DMUs) in the DEA envelopment model. The input and output variables are denoted by m and s, respectively. DEA seeks to identify a parsimonious model that uses all input and output variables while utilizing the fewest possible. The complexity of the solution space for a linear programming problem increases as the number of input and output variables in a DEA increases, and the analysis becomes less discriminating [27].

The DEA approach does not specify any guidelines for selecting variables. Estimate, policy, user experience, and qualifications all play a role. As a result, every researcher will hold different views. Some issues that surfaced during the variable selection process were (i) inappropriate data; (ii) high dimensions of sampling during the manufacturing process; and (iii) incorrect input and output data. One of the fascinating research tasks of the DEA approach is selecting the proper input and output variables. The following issues come up during processing: (i) the selection process; (ii) the correlation analysis; and (iii) the input and output variable categorization. The weighted variable ratio of input to output is the definition of effectiveness. In their seminal study, Charnes *et al*. [54] provided evidence of it. Other researchers improved upon this approach. A key component of every formulation is selecting the variables. Selecting the input and output variables is a critical stage that researchers should consider in addition to choosing the DEA model.

3.5. Stepwise modeling approach

The input and output variables must be carefully selected for effective data envelopment analysis (DEA) modeling. A formal process for variable selection is the stepwise modeling technique. The basic step-by-step process operates in reverse. This technique corrects the average change in efficiency for variables added or removed from the DEA analysis. Evaluate each and every potential input and output variable for the DEA model as the first step in the backward procedure. A single variable is eliminated from the model at each stage by looking at the DMUs' efficiency ratings. The process can be carried out again until the model has just one input and one output variable. Actually, by using stopping rules based on the decision criteria, lean DEA models may be developed. Presume there are two sets of variables: j = 1,...,J is the set of input variables, and k = 1,...,K is the set of output variables.

The steps in the stepwise modeling approach are: (a) In a single DEA analysis, utilize all J input and K output variables. (b) Take note of each DMU's efficiency rating in this run (set E*). Step 1: (a) One input variable at a time should be removed first, then one output variable at a time, in a series of i = 1,..., J + K DEA analyses. Regarding each analysis: For each i run, record the efficiency ratings for each DMU (set E1, i). Next, determine the differences between the associated DMU efficiency ratings (E*-E1, i). For each DMU, determine the average efficiency difference (over the collection of i differences). (a) Select the variable with the lowest average difference in efficiency scores to remove one input or output. At least one input and one output variable must be retained in the analysis. A separate variable must be examined using the selection procedures if just one input or output variable remains in the model. (c) Assign the removed variable to the E1* label in the DEA results. E1* is computed using the efficiency ratings of the DMUs for the remaining input and output variables. Step n + 1: (a) Examine the following items in the following order: i = 1,..., J + K - n. (b) Utilizing the remaining J + K + n input and output variables, compare the results of the efficiency scores, En+1, i, and En, from the previous step. The minimal average difference in efficiency ratings determines which variable should be eliminated. (c) Compare the findings En+1, i, and En (the efficiency scores from the previous phase) with the remaining J + K - n input and output variables to decide which variable should be deleted based on the least average difference in efficiency ratings. Stop: The procedure is finished when the model contains only one input variable and one output variable. On the other hand, conditions might be created to allow the process to end sooner, as when the efficiency score change hits a certain threshold [21], [22].

3.6. Research methodology

The four phases of performance evaluation in this research consist of (i) definition and design; (ii) preparation, data collection, and data evaluation; (iii) data processing; (iv) analysis of research results; and (v) conclusion. The performance evaluation procedure for this research is presented in Fig. 1.

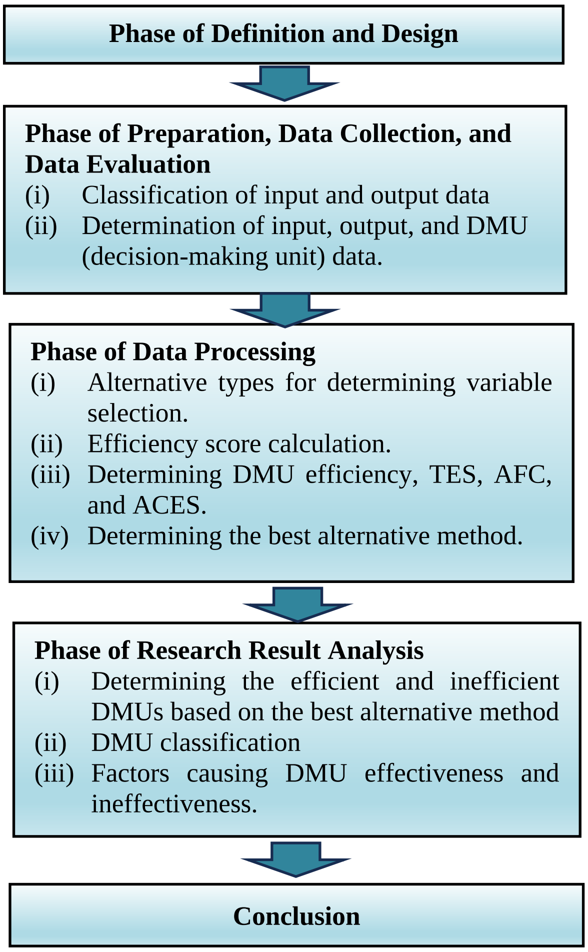

Fig. 1. Flowchart of research method

3.6.1. The method of data collection

This study uses secondary data from the Central Bureau of Statistics, Indonesia. Data used are construction industries in 30 provinces of Indonesia, namely: Province, abbreviation: Aceh (A), North Sumatra (SU), West Sumatra (SB), Riau (R), Jambi (J), South Sumatra (SS), Bengkulu (B), Lampung (L), Bangka Belitung Islands (KBB), Riau Islands (KR), DKI Jakarta (DKI), West Java (JB), Central Java (JT), DI Yogyakarta (DIY), East Java (JTi), Banten (B), West Nusa Tenggara (NTB), East Nusa Tenggara (NTT), West Kalimantan (KB), Central Kalimantan (KT), South Kalimantan (KS), East Kalimantan (KTi), North Kalimantan (KUt), North Sulawesi (SUt), Central Sulawesi (STe), South Sulawesi (SSe), Southeast Sulawesi (STe), West Sulawesi (SBa), Maluku (M), dan Papua (P).

The secondary data in this research was sourced from the official reports of BPS, containing statistics on the performance and activities pertinent to the building sector of each province. Setting forth the reasoning behind using secondary data in this analysis, one should point out that the latter describes comprehensive and reliable data collected systematically by official governmental institutions.

This study allows having wide and reliable data coverage from BPS. Additionally, it ensures that the data consistently follows the quality and methodology during collection. Input variables here are labor, capital, and operational costs, while the output variables are construction volume and income; all of these can be relevant to be analyzed using the DEA method.

Data were collected by gaining access to the BPS statistical reports, published periodically. The researchers downloaded and extracted the data from the official publication of BPS through its website. All the variables in the present study were selected based on the availability of data within the BPS reports directly relevant to the performance of each province's construction industry.

Secondary data is used because it has a few advantages, is much easier to obtain concerning time and cost, and data collected by official institutions such as BPS is reliable. Moreover, it covers more representatives so that wider coverage can be achieved in order to analyze the efficiency of the construction industry in Indonesia more representatively.

3.6.2. Justification for the choices of variables for DEA analysis

In this research, the choice of the variables for DEA analysis is informed by the need to evaluate efficiency performance in Indonesia's construction industry based on labor aspects, the number of companies, and the value of output produced. Such variables are supported in earlier literature to be important variables that determine the efficiency of labor, number of firms, compensation, and value of construction output.

The input variables represent the resources used by the construction companies in their operations, which include: (i) Number of skilled construction workers (Data-1): The skilled workers are human resources

http://dx.doi.org/10.30656/jsmi.v8i2.8936

possessing special skills that are crucial in determining the construction industry's productivity. In a DEA context, the number of skilled workers is considered one of the main inputs because of their contribution to working on construction projects; (ii) Number of expert construction workers (Data-2): Expert workers have higher competence in planning and executing construction projects; therefore, they are considered important inputs in efficiency analysis. Expert workers improve construction projects' quality and final result in a major way; (iii) Number of permanent workers of construction companies (Data-3): Permanent workers reflect stability in the workforce and the company's in-house capacity for developing projects. Therefore, this variable has been selected as input because it gives a view of the company's internal strengths; and (iv) Number of construction companies (Data-4): This variable represents the industry's overall capacity in delivering construction services. The more companies, the greater would be the inputs available for producing output in this sector.

The output variable is the outcome or value created from the consumption of inputs, including (i) Median of construction value (Data-5): This represents the total value of construction projects carried out by firms in a province. Construction value is the major indicator of the sector's production output; hence, it is selected as an output in the efficiency analysis; and (ii) Median of compensation and wages of workers monthly (Data-6): The value of compensation reflects the welfare of workers and can be regarded as an output that describes the economic effect on workers when operating a construction company. Worker welfare is also a success indicator for the industry.

DMUs in this study consist of 30 provinces in Indonesia, which were selected based on the availability of performance data from the construction sector in each province. DMUs are units of analysis whose efficiency level is to be evaluated and compared, where each province will be compared with each other based on the use of inputs against the outputs produced. Overall justification: the choice of those variables is relevant because input variables like the number of skilled workers and construction firms describe the great use of resources in the construction sector. In contrast, output variables like construction value and workers' compensation show the real results produced by the sector. Therefore, such a combination of variables allows DEA to clearly outline the efficiency with which resources are used in various provinces to produce the desired output.

4. RESULTS AND DISCUSSION

4.1. Input and output data

The data used in this study are the construction industries in Indonesia (by province), as shown in Table 2 [1]. There are 30 provinces, including: Aceh (A), Sumatera Utara (SU), Sumatera Barat (SB), Riau (R), Jambi (J), Sumatera Selatan (SS), Bengkulu (B), Lampung (L), Kep. Bangka Belitung (KBB), Kep. Riau (KR), DKI Jakarta (DKI), Jawa Barat (JB), Jawa Tengah (JT), DI Yogyakarta (DIY), Jawa Timur (JTi), Banten (B), Nusa Tenggara Barat (NTB), Nusa Tenggara Timur (NTT), Kalimantan Barat (KB), Kalimantan Tengah (KT), Kalimantan Selatan (KS), Kalimantan Timur (KTi), Kalimantan Utara (KUt), Sulawesi Utara (SUt), Sulawesi Tengah (STe), Sulawesi Selatan (SSe), Sulawesi Tenggara (STe), Sulawesi Barat (SBa), Maluku (M), and Papua (P)

The data consists of five types, as follows: (i) number of skilled construction workers (Data-1); (ii) number of expert construction workers (Data-2); (iii) number of permanent workers of construction companies (Data-3); (iv) number of construction companies (Data-4); (v) median of the value of construction (Data-5); and (vi) median of compensation and wages of workers monthly (Data-6). Based on this type of data, the input-output variables (Table 3) and decision-making units (DMUs) (Table 4) can be determined.

4.2. Alternative types for determining variable selection

There are eight alternatives for determining variable selection using the Stepwise Modeling Approach (SMA). Each of these alternatives consists of seven stages and three components. The stages in SMA consist of Step-Start, Step-1, Step-2, Step-3, and Step-END. The components in SMA consist of remaining inputs (RI), remaining outputs (RO), and variable drops (VD). Table 5 describes the variable selection process using SMA. The SMA process for Alternative 1 is explained as follows: Step-Start consists of four input variables (X1, X2, X3, X4) and two output variables (Y1, Y2). In Step 1, X1 is an input variable dropped. Therefore, the remaining variables are three inputs (X2, X3, X4) and two outputs (Y1, Y2). In Step 2, Y1 is an output variable dropped. Therefore, the remaining variables are three inputs (X2, X3, X4) and one output (Y2). In Step 3, X2 is an input variable dropped. Therefore, the remaining variables are two inputs (X3, X4) and one output (Y2). In Step-End, X3 is an input variable dropped. Therefore, the remaining variables are one input (X4) and one output (Y2). Therefore, X4 is the input variable, and Y2 is the output variable. The efficiency scores for every step were variants. It had an impact on the number of efficient and inefficient DMUs. The SMA process for Alternatives 2–8 is the same as Alternative 1. The variable selection at the Step-End for each SMA alternative is as follows: Alternative 1 (X4, Y2), Alternative 2 (X4, Y1), Alternative 3 (X3, Y2). Alternative 4 (X1, Y1), Alternative 5 (X1, Y2), Alternative 6 (X2, Y1), Alternative 7 (X3, Y1), and Alternative 8 (X2, Y2).

Table 2. Construction industries in Indonesia

No.	Prov.	Data-1	Data-2	Data-3	Data-4	Data-5	Data-6
1	A	22,423	9,711	9,721	5,448	65,000	35,000
2	SU	14,795	3,733	39,952	6,956	80,000	38,880
3	SB	27,353	8,470	9,492	5,258	60,000	40,500
4	R	112,417	42,644	25,270	7,798	60,000	36,000
5	J	9,994	2,893	7,917	2,958	70,000	52,560
6	SS	19,446	5,194	18,378	3,554	67,200	47,040
7	B	3,887	894	6,316	1,346	75,000	42,900
8	L	10,818	1,774	12,749	4,073	60,000	35,200
9	KBB	19,442	6,432	6,055	928	70,000	42,000
10	KR	131,767	49,523	18,329	2,014	79,000	53,760
11	DKI	34,522	32,931	424,892	9,714	45,000	72,800
12	JB	38,291	14,717	101,057	11,098	64,000	53,914
13	JT	26,774	7,013	42,400	11,453	60,000	51,215
14	DIY	6,589	2,381	6,978	1,791	50,000	58,250
15	JTi	31,986	12,404	140,956	19,430	60,000	38,400
16	B	17,940	6,840	57,583	3,144	60,000	50,400
17	NTB	11,034	1,690	6,653	3,698	56,912	45,000
18	NTT	6,767	2,529	12,353	5,871	60,000	20,400
19	KB	14,650	4,144	14,873	5,458	63,500	35,880
20	KT	4,766	1,827	10,940	1,912	70,000	33,800
21	KS	8,133	1,158	7,534	3,710	72,050	36,000
22	KTi	9,481	4,527	31,036	4,468	80,000	38,370
23	KUt	2,257	113	5,207	1,313	70,000	42,000
24	SUt	27,310	12,311	6,183	1,995	60,000	21,600
25	STe	14,882	4,321	9,642	3,088	58,383	25,550
26	SSe	19,253	9,140	23,198	11,017	77,000	43,710
27	STe	6,923	1,669	7,271	3,287	50,000	31,601
28	SBa	7,044	3,221	2,338	1,198	89,000	32,320
29	M	4,991	1,902	4,439	1,823	80,000	28,000
30	P	7,725	1,586	34,932	5,382	90,000	37,890

Table 3. Input and output variables

I - O	Var.	Data	Explanation
Input1	X1	Data-1	Number of Skilled Construction Workers (People)
Input2	X2	Data-2	Number of Expert Construction Workers (People)
Input3	X3	Data-3	Number of Permanent Workers (People)
Input4	X4	Data-4	Number of Construction Companies
Output1	Y1	Data-5	Median of Value of Construction (Thousand Rupiahs)
Output2	Y2	Data-6	Median of Compensation and Wages of Workers Monthly

Table 4. Decision-making units (DMUs)

No.	DMUs	No.	DMUs	No.	DMUs	No.	DMUs	No.	DMUs
1	DMU_A	7	DMU_B	13	DMU_JT	19	DMU_KB	25	DMU_STe
2	DMU_SU	8	DMU_L	14	DMU_DIY	20	DMU_KT	26	DMU_SSe
3	DMU_SB	9	DMU_KBB	15	DMU_JTi	21	DMU_KS	27	DMU_STe
4	DMU_R	10	DMU_KR	16	DMU_B	22	DMU_KTi	28	DMU_SBa
5	DMU_J	11	DMU_DKI	17	DMU_NTB	23	DMU_KUt	29	DMU_M
6	DMU_SS	12	DMU_JB	18	DMU_NTT	24	DMU_SUt	30	DMU_P

4.3. Efficiency score calculation

This study implements the input-oriented DEA envelopment model with variable returns to scale to determine each DMU's efficiency score. A few reasons lying behind the choice of VRS over CRS are discussed as follows: First, in the world of construction, companies differ in their sizes and capacities; hence, an increase in certain inputs, like labor or building material, does not yield a proportional output. Hence, VRS is quite flexible in reflecting any kind of imbalance between input and output due to the fact that the CRS model always assumes proportional relations.

 http://dx.doi.org/10.30656/jsmi.v8i2.8936

Table 5. Variable selection process using SMA

Alt.	Comp.	Step					Alt.	Comp.	Step				
		Start	**1**	**2**	**3**	**END**			**Start**	**1**	**2**	**3**	**END**
1	RI	X1	X2	X2	X3	X4	5	RI	X1	X1	X1	X1	X1
		X2	X3	X3	X4				X2	X3	X3	X4	
		X3	X4	X4					X3	X4	X4		
		X4							X4				
	RO	Y1	Y1	Y2	Y2	Y2		RO	Y1	Y1	Y2		
		Y2	Y2						Y2	Y2		Y2	Y2
	VD	X1	Y1	X2	X3			VD	X2	Y1	X3	X4	
2	RI	X1	X1	X1	X2	X4	6	RI	X1	X2	X2	X2	X2
		X2	X2	X2	X4				X2	X3	X3	X4	
		X3	X4	X4					X3	X4	X4		
		X4							X4				
	RO	Y1	Y1	Y1	Y1	Y1		RO	Y1	Y1	Y1	Y1	Y1
		Y2	Y2						Y2	Y2			
	VD	X3	Y2	X1	X2			VD	X1	Y2	X3	X4	
3	RI	X1	X1	X1	X2	X3	7	RI	X1	X1	X1	X3	X3
		X2	X2	X2	X3				X2	X3	X3	X4	
		X3	X3	X3					X3	X4	X4		
		X4							X4				
	RO	Y1	Y1	Y2	Y2	Y2		RO	Y1	Y1	Y1	Y1	Y1
		Y2	Y2						Y2	Y2			
	VD	X4	Y1	X1	X2			VD	X2	Y2	X1	X4	
4	RI	X1	X1	X1	X1	X1	8	RI	X1	X1	X1	X1	X2
		X2	X2	X2	X3				X2	X2	X2	X2	
		X3	X3	X3					X3	X4	X4		
		X4							X4				
	RO	Y1	Y1	Y1	Y1	Y1		RO	Y1	Y1	Y2	Y2	Y2
		Y2	Y2						Y2	Y2			
	VD	X4	Y2	X2	X3			VD	X3	Y1	X4	X1	

The construction industry is a very heterogeneous market structure, where each project has its scale and different characteristics. VRS allows for a closer analysis of this diversity, while CRS tends to be inflexible. Many construction firms face conditions of technological and capacity limitations that impede proportional increases in output despite increased input. The VRS model better accommodates the conditions. Third, VRS allows researchers to analyze whether the firms are operating at an optimal scale, which is problematic to deal with under CRS. Hence, VRS is more realistic and appropriate in handling operational complexity in the construction industry [56], [57], [58]. The efficiency score in Alternative 1 is shown in Table 6.

The efficient DMU has an efficiency score of 1, and the inefficient DMU has a score of 0. Based on the efficiency score, it can be calculated the number of efficient DMUs, the total efficiency score (TES), the average efficiency score (AFC), and the average change in efficiency score (ACES) at each SMA step of Alternative 1. Furthermore, the efficiency score on alternatives 2–8 can be calculated similarly to Alternative 1.

4.4. DMU Efficient, TES, AFC, and ACES

In Alternative 1, the number of DMUs efficient for each step is as follows: Step Start (11 DMUs), Step 1 (11 DMUs), Step 2 (11 DMUs), Step 3 (8 DMUs), and Step End (6 DMUs). Step End has the smallest number of DMUs. The total efficiency score (TES) and average efficiency score (AFC) for every alternative is explained as follows: Step Start has the biggest values, 14.62 and 0.49, respectively. The smallest numbers are on Step End: 9 and 0.30, respectively. Based on the average change in efficiency score (ACES), Step 1 provides the smallest ACE (0.01), and Step-END provides the biggest value (0.09). Step-END has the smallest number of DMUs efficient, TES, and AFC, as well as the biggest value of ACES. Therefore, Step-END is the best result in Alternative 1. The results of Alternatives 2–8 are the same as those of Alternative 1. The Step-END result of those alternatives is also the best result.

The selection of inputs and outputs is an important stage frequently accomplished before using the DEA model [26]. DEA analyzes efficiency using various input and output factors but does not give assistance in selecting those variables. Researchers typically employ

Table 6. Efficiency score

Comp.	Step				
	Start	1	2	3	END
Remaining inputs (RI)	X1	X2	X2	X3	X4
	X2	X3	X3	X4	
	X3	X4	X4		
	X4				
Remaining outputs (RO)	Y1	Y1	Y2	Y2	Y2
	Y2	Y2			
Variable Dropped (VD)	X1	Y1	X2	X3	
DMUs	**Efficiency scores**				
DMU_A	0	0	0	0	0
DMU_SU	0	0	0	0	0
DMU_SB	0	0	0	0	0
DMU_R	0	0	0	0	0
DMU_J	1	1	1	1	0
DMU_SS	0	0	0	0	0
DMU_B	1	1	1	1	1
DMU_L	0	0	0	0	0
DMU_KBB	1	1	1	1	1
DMU_KR	1	1	1	1	1
DMU_DKI	0	0	0	0	0
DMU_JB	0	0	0	0	0
DMU_JT	0	0	0	0	0
DMU_DIY	1	1	1	1	1
DMU_JTi	0	0	0	0	0
DMU_B	0	0	0	0	0
DMU_NTB	1	1	1	0	0
DMU_NTT	0	0	0	0	0
DMU_KB	0	0	0	0	0
DMU_KT	1	1	1	0	0
DMU_KS	1	1	1	0	0
DMU_KTi	0	0	0	0	0
DMU_KUt	1	1	1	1	1
DMU_SUt	0	0	0	0	0
DMU_STe	0	0	0	0	0
DMU_SSe	0	0	0	0	0
DMU_STe	0	0	0	0	0
DMU_SBa	1	1	1	1	1
DMU_M	1	1	1	1	0
DMU_P	0	0	0	0	0
Efficient DMU	11	11	11	8	6
TES	14.62	14.32	13.6	11.7	9.00
AFC	0.49	0.48	0.45	0.39	0.30
ACES	-	0.01	0.02	0.06	0.09

many methodologies. The number of variables employed will have an impact on the efficiency value if it is not reasonable. It reduces the strength of the efficiency value, allowing all DMU values to be efficient [59]. It indicates that the smallest values of DMU efficiency will be the best methods. In addition, this condition also creates the smallest values of TES, AFC, and ACES. Based on this finding, Step END always gives the best result for all the alternatives. This is because Step END has the smallest values of DMU efficiency, TES, AFC, and ACES.

4.5. Determining the best alternative method

The results of DMU efficiency, Total Efficiency Score (TES), Average Efficiency Score (AFC), and Average and Change in Efficiency Score (ACES) in Step-END are presented in Table 8. Alternatives 1 and 2 have the largest number of DMUs (6). Alternative 2 also has the biggest values of TES (15.37) and AFC (0.51). The biggest value of ACES is Alternative 6. Alternative 8 has the smallest values of DMU efficiency (1), TES (2.95), AFC (0.1), and ACES (0.18).

The selection of inputs and outputs is an important

 http://dx.doi.org/10.30656/jsmi.v8i2.8936

Table 7. DMU efficient, TES, AFC, and ACES

Alternative	No.	Comp.	Start	Step 1	Step 2	Step 3	END
Alt 1-(X4, Y2)	1.	DMU Eff.	11	11	11	8	6
	2.	TES	14.62	14.32	13.60	11.70	9
	3.	AFC	0.49	0.48	0.45	0.39	0.30
	4.	ACES		0.01	0.02	0.06	0.09
Alt 2-(X4, Y1)	1.	DMU Eff.	11	9	7	7	6
	2.	TES	25.62	21.96	18.43	18.11	15.37
	3.	AFC	0.85	0.73	0.61	0.60	0.51
	4.	ACES		0.12	0.12	0.01	0.09
Alt 3-(X3, Y2)	1.	DMU Eff.	11	9	9	9	4
	2.	TES	25.62	21.46	20.72	20.21	12.09
	3.	AFC	0.85	0.72	0.69	0.67	0.40
	4.	ACES		0.14	0.02	0.02	0.27
Alt 4-(X1, Y1)	1.	DMU Eff.	11	9	5	4	3
	2.	TES	25.62	21.46	15.43	13.93	9.69
	3.	AFC	0.85	0.72	0.51	0.46	0.32
	4.	ACES		0.14	0.20	0.05	0.14
Alt 5-(X1, Y2)	1.	DMU Eff.	11	9	11	8	2
	2.	TES	25.62	23.27	24.50	19.74	8.29
	3.	AFC	0.85	0.78	0.82	0.66	0.28
	4.	ACES		0.08	-0.04	0.16	0.38
Alt 6-(X2, Y1)	1.	DMU Eff.	11	11	8	7	1
	2.	TES	25.62	25.32	20.22	18.11	3.01
	3.	AFC	0.85	0.84	0.67	0.60	0.10
	4.	ACES		0.01	0.17	0.07	0.50
Alt 7-(X3, Y1)	1.	DMU Eff.	11	11	7	6	1
	2.	TES	25.62	25.27	19.00	15.49	6.45
	3.	AFC	0.85	0.84	0.63	0.52	0.21
	4.	ACES		0.01	0.21	0.12	0.30
Alt 8-(X2, Y2)	1.	DMU Eff.	11	9	8	2	1
	2.	TES	25.62	21.96	19.74	8.29	2.95
	3.	AFC	0.85	0.73	0.66	0.28	0.10
	4.	ACES		0.12	0.07	0.38	0.18

Table 8. DMU Efficient, TES, AFC, and ACES in Step-END

No.	Step-END	DMU efficient	TES	AFC	ACES
1	Alternative 1	6	9	0.3	0.09
2	Alternative 2	6	15.37	0.51	0.09
3	Alternative 3	4	12.09	0.4	0.27
4	Alternative 4	3	9.69	0.32	0.14
5	Alternative 5	2	8.29	0.28	0.38
6	Alternative 6	1	3.01	0.1	0.5
7	Alternative 7	1	6.45	0.21	0.3
8	Alternative 8	1	2.95	0.1	0.18
	Smallest Value	1	2.95	0.1	0.18

stage frequently accomplished before using the DEA model [26]. DEA analyzes efficiency using various input and output factors but does not give assistance in selecting those variables. Researchers typically employ many methodologies. The number of variables employed will impact the efficiency value if it is not reasonable. It reduces the strength of the efficiency value, allowing all DMU values to be efficient [59]. It indicates that the smallest values of DMU efficiency will be the best methods. In addition, this condition also creates the smallest values of TES, AFC, and ACES. Therefore, based on this finding, Alternative 8 is the best method for SMA.

4.6. Integration with previous research

This study proposes modifying the existing stepwise modeling approach (SMA) method to DEA modeling developed by Wagner and Shimshak [22]. This study applied four input variables (X1, X2, X3, X4) and two output variables (Y1, Y2). Modifying the existing stepwise modeling approach (SMA) method to DEA modeling creates eight alternatives for determining variable selection. Alternative 1 is the existing method of SMA. Alternatives 2 to 8 are the proposed methods of SMA. The results of variable selection from each alternative are as follows:

Alternative 1 (X4, Y2), Alternative 2 (X4, Y1), Alternative 3 (X3, Y2). Alternative 4 (X1, Y1), Alternative 5 (X1, Y2), Alternative 6 (X2, Y1), Alternative 7 (X3, Y1), and Alternative 8 (X2, Y2). Furthermore, the best alternative method is selected. The criteria for the best alternative method are as follows: the smallest values (DMUs efficient, TES, and AFC) and the biggest value (ACES). Based on the best alternative method, we can determine the classification of efficient and inefficient decision-making units (DMUs).

In the comparison of all alternatives based on DMUs efficient, Total Efficiency Score (TES), Average Efficiency Score (AFC), Average and Change in Efficiency Score (ACES) in Step-END, Alternatives 1 (existing method) and 2 have the largest number of DMUs (6). Alternative 2 also has the biggest values of TES (15.37) and AFC (0.51). Alternative 6 has the biggest value of ACES (0.5). Alternative 8 has the smallest values of DMU efficiency (1), TES (2.95), AFC (0.1), and ACES (0.18). Therefore, Alternative 8 (proposed method) is the best method for SMA.

It indicated that the proposed method (Alternative 8) performs better than the existing method (Alternative 1) of the stepwise modeling approach (SMA). A comparison of the existing and proposed method of SMA based on DMU Efficient, TES, AFC, and ACES in Step-END is presented in Table 9. Compared to the existing method, the proposed method has the smallest values (DMUs efficient, TES, and AFC) and the biggest value (ACES).

This existing method only produces one alternative for determining variable selection. The proposed method can generate more than one alternative. By generating many alternatives on variable selection, optimal results will be obtained. It is an advantage of the research results. The weakness of the proposed method is that it requires more detailed calculations. It is the impact of the many alternatives created for determining variable selection.

Table 9. Efficient and inefficient DMUs

Component	Existing method alternative 1	Proposed method alternative 8
DMU efficient	6	1
TES	9	2.95
AFC	0.3	0.1
ACES	0.09	0.18

Further research is needed to implement more variables than this research to determine variable selection in DEA modeling. It aims to strengthen the analysis that the proposed method performs well than the existing method. Thus, the proposed method in this study contributes to solving the problem of input and output variable requirements in DEA. It is because the DEA itself does not provide guidance for the requirements of the input and output variables.

Based on the best method for SMA (Alternative 8), the efficient and inefficient DMUs can be determined. The efficient DMU has an efficiency score of 1, and the inefficient DMU has a score between 0-0.99. Table 10 presents the efficient and inefficient DMUs.

Table 10. Efficient and inefficient DMUs

DMU Status	No	DMU	ES
Efficient	1	DMU_KUt	1
Inefficient	1	DMU_A	0.010
	2	DMU_SU	0.028
	3	DMU_SB	0.013
	4	DMU_R	0.002
	5	DMU_J	0.049
	6	DMU_SS	0.024
	7	DMU_B	0.129
	8	DMU_L	0.053
	9	DMU_KBB	0.018
	10	DMU_KR	0.003
	11	DMU_DKI	0.006
	12	DMU_JB	0.010
	13	DMU_JT	0.020
	14	DMU_DIY	0.066
	15	DMU_JTi	0.008
	16	DMU_B	0.020
	17	DMU_NTB	0.072
	18	DMU_NTT	0.022
	19	DMU_KB	0.023
	20	DMU_KT	0.050
	21	DMU_KS	0.084
	22	DMU_KTi	0.023
	23	DMU_SUt	0.005
	24	DMU_STE	0.016
	25	DMU_SSe	0.013
	26	DMU_STe	0.051
	27	DMU_SBa	0.027
	28	DMU_M	0.040
	29	DMU_P	0.064

4.7. DMUs classification

DEA is a classification and ranking tool that compares DMU results. The consistency of the results shows that the DEA is a viable categorization and ranking tool. Thus, DEA has been verified as a ranking and classification approach [24]. Putri *et al.* [25] research used a histogram graph to order the DMU efficiency ratings from highest to lowest. This method identifies DMU clustering. Then, as a foundation for categorizing, each category can be assigned a threshold. Hence, the criteria for classifying DMUs are based on the distribution of efficiency scores. Fig. 2 presents the distribution of efficiency scores in a histogram graph for efficient and inefficient DMUs. An efficient DMU has a one-point efficiency score (ES), whereas an inefficient DMU has fewer than one. The results of this study indicated that there are one efficient DMU and 29

http://dx.doi.org/10.30656/jsmi.v8i2.8936

inefficient DMUs. There are huge differences in efficiency score values between DMU-KUt and the other 29 DMUs. The underlying reasons are explained as follows: An efficient DMU generates more outputs with similar input consumption or the same number of outputs with less input consumption. In contrast, a DMU with low-efficiency ratings needs more input to produce the same amount of output [23]. Fig. 3 presents the distribution of efficiency scores in a histogram graph for inefficient DMUs. There are four ranges (Rs) to classify the inefficient DMU, namely: is R1 (ES=0.16-0.99), R2 (ES=0.050-0.15), R3 (ES=0.015-0.049), and R4 (ES=0.000-0.014). Table 11 presents the DMU classifications into five: efficient DMU, inefficient DMU-R1, inefficient DMU-R2, inefficient DMU-R3, and inefficient DMU-R4. The level of effectiveness of each classification is as follows: (i) R0 Range (ES = 1) – Effective; (ii) R1 Range (ES = 0.16 - 0.99) - Relatively Low Ineffectiveness; (iii) R2 Range (ES = 0.050 - 0.15) - Moderate Ineffectiveness; (iv) R3 Range (ES = 0.015 - 0.049) - Significant Ineffectiveness; and (v) R4 Range (ES = 0.000 - 0.014) - Very High Ineffectiveness.

The purpose of DMU classification using the DEA method is to provide clearer insight into the relative efficiency and performance of each decision-making unit analyzed. These activities include: (i) assessing the relative efficiency of DMUs; (ii) identifying inefficient DMUs and sources of inefficiency; (iii) benchmarking; (iii) performance improvement; (iv) better decision-making; and (v) testing the consistency and stability of efficiency.

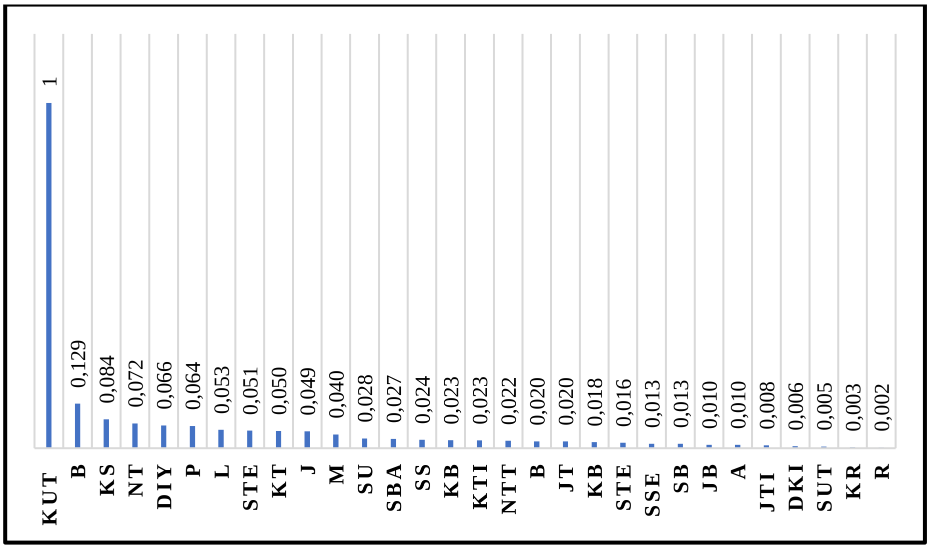

Fig. 2. The distribution of efficiency scores in a histogram graph for efficient and inefficient DMUs

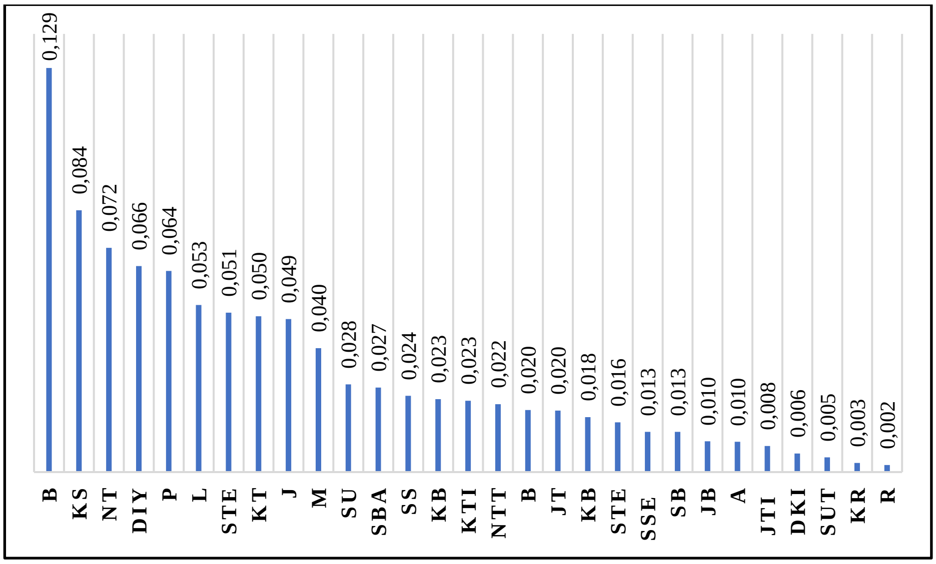

Fig. 3. The distribution of efficiency scores in a histogram graph for inefficient DMUs

Table 11. DMUs classification

No.	DMU class.	ES range (R)	Level of effectiveness	Number of DMU	DMU	ES
1.	DMU-R0	R0 = 1	Effective	1	DMU_KUt	1
2.	DMU-R1	R1 (0.16-0.99)	Relatively Low Ineffectiveness	0	-	
3.	DMU-R2	R2 (0.050-0.150)	Moderate Ineffectiveness	9	DMU_B	0.13
					DMU_KS	0.08
					DMU_NTB	0.07
					DMU_DIY	0.07
					DMU_P	0.06
					DMU_L	0.05
					DMU_STe	0.05
					DMU_KT	0.05
					DMU_J	0.05
4.	DMU-R3	R3 (0.015-0.049)	Significant Ineffectiveness	11	DMU_M	0.040
					DMU_SU	0.028
					DMU_SBa	0.027
					DMU_SS	0.024
					DMU_KB	0.023
					DMU_KTi	0.023
					DMU_NTT	0.022
					DMU_B	0.020
					DMU_JT	0.020
					DMU_KBB	0.018
					DMU_STE	0.016
5.	DMU-R4	R4 (0.000-0.014)	Very High Ineffectiveness	9	DMU_SSe	0.013
					DMU_SB	0.013
					DMU_JB	0.010
					DMU_A	0.010
					DMU_JTi	0.008
					DMU_DKI	0.006
					DMU_SUt	0.005
					DMU_KR	0.003
					DMU_R	0.002

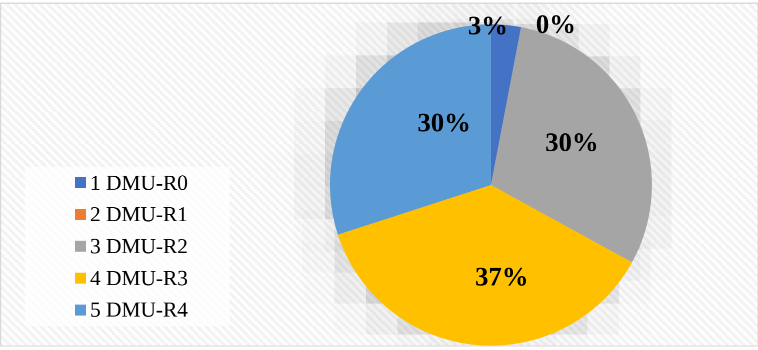

Fig. 4. Percentage composition (%) of the DMU classification

DEA is used to measure the relative efficiency of each DMU in using inputs to produce outputs. By classifying, companies can distinguish which DMUs are efficient (on the efficiency frontier) and which are inefficient (below the efficiency frontier). Inefficient DMUs can be identified, and with further analysis, companies can find out which factors or inputs cause inefficiency. By classifying efficient DMUs, companies can determine which DMUs serve as benchmarks or references for less efficient DMUs. Inefficient DMUs can refer to efficient DMUs for improvement.

DMU classification allows organizations or management to design performance improvement strategies by focusing on inefficient DMUs as well as emulating practices from efficient DMUs. By grouping DMUs based on their efficiency levels, decision-makers can more easily prioritize resource allocation or determine interventions needed in different DMUs.

 http://dx.doi.org/10.30656/jsmi.v8i2.8936

DMU classification also helps in checking the consistency and stability of efficiency analysis results over time or under various environmental and policy conditions [32], [60], [61].

Fig. 4 presents the percentage composition (%) of the DMU classification. Efficient DMU has the percentage (3%). Inefficient DMU-R1 has the percentage (0%). The biggest percentage (37%) is in the inefficient DMU-R3. Inefficient DMU-R2 and inefficient DMU-R4 have the same percentage (30%).

4.8. Originality of this study

The novelty of this paper lies in the fact that it proposes a classification of inefficient DMUs at several levels based on ES values, which may provide more in-depth insight into efficiency performance measurement. It constitutes the more structured new tool in a different evaluation provided by either researchers or practitioners in understanding and improving efficiency in various contexts. Novel aspects that can be identified as follows:

1. New Classification of Inefficient DMUs: This paper introduces four ranges of values of ES, R1, R2, R3, and R4, classifying inefficient DMUs. Each of these ranges corresponds to a grade of ineffectiveness that goes from relatively low up to very high. New features include Utilizing more detailed criteria to group inefficient DMUs instead of simply efficient versus inefficient. The introduction of a finer range to assess the degree of inefficiency of a DMU may not have been explicitly done in the past.
2. Classification of Five-Category DMUs by Effectiveness: This study categorizes DMUs into five categories, ranging from efficient DMUs (R0) to highly inefficient DMUs (R4). Novelty of the finding: This, in fact, provides a more measurable assessment instrument to help the practitioner or researcher understand where their DMUs are positioned on the efficiency spectrum to formulate more appropriate improvement strategies then.
3. Use of ES for establishing ineffectiveness: A new approach in the art consists of applying ES while developing and normalizing limits as an index of the effectiveness level. The novelty in the invention is a method that fully quantifies the aspect of ineffectiveness; it sets limits defined strictly numerically, such as R1 = 0.16-0.99 and R4 = 0.000-0.014. It may be a new evaluation model that can be adopted in different industries or sectors using efficiency measurement for managing DMU performance.
4. Contribution to Efficiency Measurement Methods Development: Conscientiously, this paper theoretically contributed to the development of methods that estimate efficiency since it divided DMUs into more specific ranges and labelled them clearly in relation to the level of ineffectiveness. It can be considered an innovation regarding model development from DEA or any other method used in efficiency measurement while introducing the concept of a more specified categorization. Providing a framework that can be used in further studies wanting to evaluate or improve the efficiency of DMUs in various fields.

4.9. Contributions, policy, practical, and theoretical implications of the study

This research's primary contributions are as follows: (i) Evaluate the performance of construction industries in Indonesia using the DEA-Stepwise Modeling Approach method; (ii) Propose a variable combination method for subtracting the number of variables that will be utilized in implementing the DEA method. This research applied eight alternatives for determining variable selection using the Stepwise Modeling Approach (SMA). Each of these alternatives consists of five stages (Step-Start, Step-1, Step-2, Step-3, and Step-END) and three components, such as remaining inputs (RI), remaining outputs (RO), and variable drops (VD); (iii) Identify efficient and inefficient DMUs from the efficiency score of the best alternative of variable; and combination. The efficiency score of efficient DMU is 1, and that of inefficient DMU is in a range between 0-0.99; and (iv) Classify DMUs by the dispersion of efficiency scores.

A number of practical implications of this study can be carried out in the construction industry in Indonesia and by policymakers in terms of industry efficiency. It will also be important to consider how construction companies could use these results as a yardstick to recognise their relative efficiency position vis-à-vis other competitors. The companies which were declared inefficient could then use the results of this study as a basis for managerial or operational improvements, optimization of resource usage, and increasing productivity and company performance. The implications of this study for policymakers will be the basis for regulators or government agencies in formulating a policy or incentive that will encourage efficiency within the construction industry. Knowing the pattern of efficiency distribution among DMUs, there is the ability to design policies targeting companies that are not yet efficient to improve their performance.

This study also contributes significantly on theoretical grounds in some ways. The development of the DEA method using the SMA approach proposes finding a combination of variables to reduce the number of variables in applying DEA. This study gives an excellent overview of how the improvement of accuracy and practicality can be achieved by using DEA. It opens perspectives towards considering more efficient variable selection when performing performance analysis in the construction industry and other sectors. DMUs' efficiency classification: This paper contributes to the literature on industry efficiency by classifying DMUs concerning the distribution of efficiency scores and thus opens opportunities for further studies to explore the relationship between the characteristics of DMUs and their operational efficiency in various contexts of industries. The findings of the present study contribute not only to useful, practical insights for the construction industry in Indonesia but also provide theoretical contributions that might be adopted by other researchers in efficiency and performance management studies in other industry sectors.

4.10. Strategies to maintain and improve efficiency based on DMU classification

The results of this study indicated that there is one efficient DMU and 29 inefficient DMUs. We classify DMU_KUt as an efficient DMU with the R0 (ES=1) symbol. There are four ranges (Rs) to classify the inefficient DMU, namely: R1 (ES=0.16-0.99), R2 (ES=0.050-0.15), R3 (ES=0.015-0.049), and R4 (ES=0.000-0.014). The level of effectiveness of each classification is as follows: (i) R0 Range (ES = 1) – Effective; (ii) R1 Range (ES = 0.16 - 0.99) - Relatively Low Ineffectiveness; (iii) R2 Range (ES = 0.050 - 0.15) - Moderate Ineffectiveness; (iv) R3 Range (ES = 0.015 - 0.049) - Significant Ineffectiveness; and (v) R4 Range (ES = 0.000 - 0.014) - Very High Ineffectiveness.

a. R0 range (ES = 1) - Effective

Efficiency scores of exactly 1 define the R0 range, including DMUs operating at maximum efficiency. In other words, the DMU most desirably utilizes all available resources. Hence, DMUs that belong to this range are efficient, and they are in an optimal position regarding resource utilisation, such that no further waste can be minimized. Some features of DMUs belonging to the R0 range are as follows: (i) Perfect Resource Utilization: DMUs of this range can perfectly optimize all the inputted resources to achieve maximum output, thereby confirming a good management scenario; (ii) High and Stable Performance: It is usual for DMUs within this range to usually operate at a stable performance level during operations, thus gaining a benchmarking status among other DMUs; and (iii) Innovation and Adaptation: In fact, DMUs belonging to the R0 Range normally engage in incessant innovation techniques to maintain this productivity status, always willing to face new challenges. The two effects of full efficiency are: i) Competitive Advantage: DMUs falling within this range enjoy a relatively strong competitive advantage in contrast with the other inefficient DMUs because they can produce maximum output at minimum cost, and ii) Resistance to Change: Efficient DMUs usually resist market changes and can adapt quickly to new conditions.

Strategies for efficiency-sustaining in R0 are as follows: i) Periodic monitoring and evaluation through performance audits; activities are done to ensure operations are at maximum efficiency and thus know possible problems. ii) Continuous research and development—invest in R&D to continuously find new ways to improve processes and products. iii) Human resource development through continuous training. Regular training of staff for the enhancement of skills and knowledge; iv) Benchmarking through best practice comparison: Comparing practices with other efficient DMUs continuously to locate new avenues for innovation; and v) Monitoring and Evaluation, including: a) KPI and periodical review: Laying down key performance indicators and conducting periodic reviews to ensure DMU stays on track in respect of maximum efficiency; and b) Feedback and adjustment: Stakeholder feedback regarding new areas of potential improvement, despite being an efficient DMU. These strategies would allow DMUs falling in the range of R0 to continue being highly efficient and remain competitive in a dynamically growing market. This was suggested by Charnes *et al.* [16], Cooper *et al.* [49], Zhu [62], Emrouznejad and Yang [63], and Thanassoulis *et al.* [64].

b. R1 range (ES = 0.16 - 0.99) - Relatively low ineffectiveness

The R1 range includes DMUs with fairly good efficiency, indicated by an efficiency score (ES) between 0.16 and 0.99. it indicates that the DMU operates at a fairly high-efficiency level, using between 16% and 99% of the maximum potential of available resources. Therefore, although not as good as a DMU that scores 1, which means full efficiency, DMUs in this range also exhibit quite good performance but with further scope for improvement. Major characteristics of DMUs in the R1 Range: i) Good Resource Utilization: DMUs falling under this range utilize resources fairly efficiently, though further scope still lies in minimizing waste. ii) Stable Performance: DMUs falling in the R1 range normally show stability in operations along with better results than DMUs of the R2 and R3 ranges. iii) Potential for Innovation: These DMUs are very open to innovation and process improvement, though they may not be in need of radical changes. The impacts of ineffectiveness in the R1 range include: (i) Operational Costs: Despite good performance, DMUs in this range may still experience higher costs than they would have if no improvements were made; and (ii) Competitive: With lower efficiency than a fully efficient DMU (score 1), there is a risk of losing competitiveness if improvements are not made.

R1 range efficiency improvement strategies include: (i) Process Analysis and Continuous Improvement; (a) Routine Evaluation: lays down operational procedures that are continuously analyzed and evaluated, and potential areas where improvement is needed are determined; (b) Six Sigma Implementation: application of six sigma techniques to remove variations, ensuring output quality improves; (ii)

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Human Resource Development: (a) Training and Development, and (b) Motivation Enhancement: rewards and incentives are applied to enable employees to take creative approaches to improve efficiency. (iii) Adoption of Better Technology: (a) Management Information Systems: information-gathering data and analysis management systems that are more efficient, and (b) Innovation in Process: new technology that increases productivity with minimal input, (iv) Improving Cooperation and Communication: (a) interdisciplinary teams, and (b) stakeholder feedback: customers and partners' feedback collected on which approach will help to improve the performance, and (v) Monitoring and Review, (a) KPI and periodic review: ensuring that the key performance indicators have been set and reviewed periodically to ensure that the DMU is on track to attaining maximum efficiency, and (b) feedback and adjustment, with feedback from stakeholders on areas that, despite being efficient, may still require attention. These strategies would allow the DMUs in Range R1 to progressively enhance their operational efficiency and become more competitive in the marketplace [16], [56], [65], [66].

c. R2 range (ES = 0.050 - 0.15) - Moderate ineffectiveness

The R2 range exhibits low-efficiency DMUs, with efficiency scores ranging from 0.050 to 0.15. That means the DMU is operating with efficiency between 5% and 15% of the maximum potential of its available resources. Thus, DMUs in this range indicate inefficiencies worth attention but are not as grave as those in the R3 range. The characteristics of DMUs in the R2 Range include: i) Resource Utilization: DMUs in this range use resources in a suboptimal manner, though less severely than DMUs falling within the R3 Range; ii) Operational Issues: Problems of operational management are there, but not all need major restructuring; and iii) Potential Improvement: DMUs in R2 often have the possibility of easier and quicker improvement compared to those in R3. The impacts of inefficiencies in the R2 range include: i) Costs and profitability: DMUs in this range may also experience higher costs than they should, impinges on profitability. ii) Opportunities to Improve Performance: There are opportunities to improve the performance without requiring extreme changes.

Improvement strategies in the R2 range: (i) Process Review and Improvement: (a) Process Review: reviewing the operational processes to identify steps that may be inappropriate; and (b) Waste Minimization: focusing on the minimization of wastes found rather than full restructuring; (ii) Training and Development Improvement: (a) Employee Training: Providing trainings to improve the ability and efficiency of employees; and (b) Efficiency Awareness Development: Building a culture of efficiency in the organization; (iii) Acquisition of the Right Technology: (a) Alternative Technology Solutions not too costly but may lead to an improvement in efficiency, such as simple management software; and (b) Small process automation to reduce man-power involvement in some of the steps of the process; (iv) Performance Evaluation and KPIs: (a) Development of Feasible KPIs: Developing the performance indicators so that efficiency improvements are measurable; and (b) Periodic Review: periodical reviews to ascertain how much progress is being made and areas for improvement; and (v) Monitoring and Evaluation: (a) Feedback Loop: fashioning a feedback mechanism from employees and other stakeholders on the effectiveness of changes; and (b) Continuous Improvement: committing to continuous improvement, ensuring that the DMU is always striving for more efficiency. With the use of these strategies, DMUs in R2 Range will be able to achieve optimal operations and realize a significant gain in terms of efficiency [49], [67], [68], [69].

d. R3 range (ES = 0.015 - 0.049) - Significant ineffectiveness

TR3 refers to a very low-efficiency range of DMUs whose Efficiency Score ranges from 0.015 to 0.049. This implies that the DMU effectively utilizes a paltry of 1.5–4.9 percent of the available resources. Hence, the DMUs within this range display remarkable resource wasting and cannot operate optimally. The following are the characteristics of DMUs in the R3 Range: i) Suboptimal Resources: Often, these DMUs consume a large amount of resources without producing comparable outputs—be it capital, labor, or material; ii) Managerial Problems: Generally, there is some problem in management and organization due to which operations cannot be conducted efficiently. Impacts of ineffectiveness within the range of R3 include: i) high cost—in this range, DMUs tend to have high operating costs that may pose a burden on profitability; and ii) sustainability—on the grounds of no significant improvement, DMU may present risks in its long-term sustainability.

The strategies that optimize efficiency in the R3 lineup are as follows: (i) Operational Restructuring: (a) Process Analysis: actual scrutiny of operational procedures to identify areas with less productive work; and (b) Structural Adjustment: there might be a need to change the organization structure or the procedure followed at work for optimized efficiency; (ii) New Technology Application: (a) Automation: application of technology in automating manual procedures thus saving time as well as diminishing costs; (b) AI-Based Solution: adoption of systems powered by AI to scan data at a faster rate, thus speeding up decision-making; and (c) Digitalization: installing digital management systems that enhance transparency as well as efficiency in supply chain flow; (iii) Alliances or Partnerships: (a)

Search for Strategic Partners: search for strategic partners who are likely to have more approaches to effective as well as efficient resources or technologies to undertake the burden jointly; and (b) Joint Procurement: coming together to jointly purchase materials or services at minimal costs; and (iv) Monitoring and Evaluation: (a) KPIs (Key Performance Indicators): clearly specify indicators of performance that monitor how things are going in case changes are undertaken; and (b) Periodical Review: Review of strategies taken, whether they have generated the desired outcomes or not. The DMUs of the R3 Range are, therefore, in view of their irrationality, suitably improved with a planned and wholesale approach that enhances their operational efficiencies [16], [56], [66], [70].

e. R4 range (ES = 0.000 - 0.014) - Very high ineffectiveness

In this range (R4), very inefficient DMUs are observed for which the ES would vary between 0.000 and 0.014, implying that these DMUs effectively used 0% to 1.4% of the maximum potential of the available resources. Because of this fact, DMUs in this range show acute ineffectiveness, needing immediate intervention with considerable intervention to bring effectiveness to their performance. The typical characteristics of DMUs in the R4 Range include, but are not limited to: Resource Waste: DMUs in this range manifest considerable resource wastages in terms of time, labor, and materials; Serious managerial problems: There are likely to be deep-seated managerial problems, including inefficient organization structures, a lack of skills, and a lack of standardized processes. Sustainability Risks: With a high risk to sustainability, DMUs in the R4 Range may also face serious problems with regard to profitability and competitiveness. The consequences of inefficiency in the R4 range include: i) financial loss: DMUs operating at a very low level of efficiency may incur substantial financial losses and hence pose a threat to operational continuity; and ii) bad reputation: patent inefficiency may ruin the reputation of a DMU within a market and hence lead to loss of customers as well as business associates.

Efficiencies in the R4 Range can be achieved through (i) Total Restructuring, which includes (a) Comprehensive Audit. Conduct a thorough audit of all operations, finding the cause or root of inefficiency; and (b) Managerial Change: Consider leadership or management changes to correct this; (ii) Introduction of Technology and Innovation: This includes (a) Investment in Technology: Introduce new technologies that can improve efficiency and eradicate unnecessary use or wastage, such as automation processes; and (b) Digitalization: Introduce digital systems tracking and monitoring the work done, bringing about better management of the work; (iii) Human Resources Training and Development: These include (a) intensive training programs: Train the employees so that they understand the significance or meaning of the efficiency and perform within it; and (b) Development of Improvement Culture: A culture where every employee feels responsible for improvements in efficiency; (iv) Strategic Partnerships: These include (a) Collaboration with Third Parties: Collaboration with third parties to make more optimal use of their skill, resources, and hence expertise; and (b) External Consulting: Hiring experts who have a history of restructuring and generating improvements in operation; and (v) Review and Monitoring: This includes (a) clear performance metrics: There needs to be real markers of changes and progress effected after the implementation of improvement; and (b) Periodic Review: These are regular review processes that determine the effectiveness of efforts made towards improving efficiency. The DMUs in Range R4 must undertake urgent and all-round actions to resolve the very high issues of ineffectiveness [16], [56], [69], [71].

4.11. Policy implications in the application of the research

Some of the policy implications in implementing the results of this study are presented below: i. Targeted Interventions for Inefficient DMUs: Classification of DMUs in the differing efficiency range (from R1 to R4) yielded valuable information for policymakers. Pinpointing the respective inefficiencies within the groups will help formulate targeted interventions. The DMUs that fall into the category of R4, Very High Ineffectiveness, might need immediate and intensive support regarding training programs and resource allocation to improve their performances. (ii) Performance Benchmarking Initiatives: The selection of DMU_KUt as an efficient unit in R0 can be used as a benchmark by the remaining construction firms. Policymakers should, henceforth, facilitate the sharing of knowledge and best practices from this efficient DMU by providing a forum for collaboration between firms to learn from each other and enhance their operational processes; iii) Investment in Training and Development: With the level of inefficiency observed from the results, policies should ensure training and development of employees is emphasized in the construction sector. Programs should focus on enhancement of skills and operational efficiencies that could help raise performance levels of inefficient DMUs, especially those belonging to the categories of moderate and significant ineffectiveness; iv) Encouragement to Innovation and Technology Adoption: There is a need for encouragement by policymakers in the use of innovative practices and technologies within the construction industry. It can be done by providing incentives or subsidiaries to those firms that introduce new construction methods, project management software, or any other efficiency-enhancing technology.

In this way, the inefficiencies will be reduced, and performance will improve overall; (v) Regular

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Performance Assessments: Setting up a regular performance assessment framework using DEA will monitor the efficiency of construction firms over time. Policymakers can make it binding to conduct annual appraisals so that firms are in constant pursuit of improvement and refine policies with changes in the industry; (vi) Encouragement to Collaborate: Those policies which encourage collaboration among the firms of the construction industry, like joint ventures or partnerships, may result in shared resources and knowledge, hence an improvement in overall efficiency. It may be especially helpful for those firms that are ranked inefficient, as collaboration would enhance their knowledge of the best practices as well as technological capabilities; and (vii) Sustainability and Efficiency Standards: Finally, it is advocated that the policymakers establish standards that allow sustainability to be embedded in the construction industry efficiency criteria. Because the industry would be working towards long-run sustainability, keeping environmental factors coupled with efficiency measurements in view, performance would be enhanced. Therefore, this will provide actionable recommendations that could be instituted by stakeholders in the construction industry and policymakers to bring efficiency and performance improvement by incorporating these policy implications into application.

4.12. Recommendation and suggest improvements

This research aims to evaluate the construction industry's performance in Indonesia. Hence, these companies will continue to survive, grow, and compete in the face of global competition. The methods applied in this research are an input-oriented DEA envelopment model and a stepwise modeling approach. Improvement suggestions are therefore discussed based on the managerial and policy aspects of findings from this study on DMU efficiency in the Indonesian construction industry. From this classification of the DMU, the results of the study that the company manager can undertake to evaluate the performance based on the classification are: (i) Performance Evaluation Based on DMU Classification: Since the classification provides the basis for attention by a manager, knowing the efficiency position (R0 to R4), the managers can design appropriate interventions to improve performance by the implementation of appropriate strategies for each category; (ii) Best Practice Adoption from R0: The DMUs comprised in R0 must act as benchmarks for the best practices adoption. In this respect, managers of other units may use these DMUs to benchmark with them to comprehend the best practices and how to optimize resources. It involves innovations and methodology adoption, which have already proved their efficiency; (iii) Human Resource Development: Since the DMUs in categories R1 to R4 have scope for improvement, managers should consider elevating HR through training and skills development to achieve better operational efficiency; (iv) Process Analysis and Technology Use: Through the use of process analysis to find out the inefficient steps in a given process and applying newer technologies to bring in more efficiency. Management will check whether the existing technologies can be improved to achieve more efficiency; and (v) Continuous Monitoring and Evaluation: Regular performance audits should be conducted to ensure the instituted strategy's relevance and effectiveness. Also, the managers need to set clear KPIs for every category of DMU and carry out periodic reviews of the achievements.

The government will use the findings of this research to establish policies aimed at improving industrial efficiency and competitiveness through the following: (i) Efficient DMUs Encouragement: Tax breaks or special funding by the government given to those DMUs that obtained a high R0 efficiency score will create efficiencies in the best practices to accelerate innovation within the sector; (ii) Standardization of Industry Practices: Establish norms for industry practices that the DMUs should follow to achieve better efficiency. In fact, it could involve best practice guidelines on resource management that might help the less efficient DMUs, R1-R4, in improving their operations; (iii) Training and Development Programs: The government can initiate training programs with the intent of improving managerial and technical skills in the construction sector. It can liaise with educational institutions by providing relevant training to the available labor force; (iv) The collaboration with the private sector will ensure knowledge and resources are shared between the government and the private sector. The result is an improvement in innovationists to mention that all policies should be supportive of the quest to improve efficiency and competitiveness within the sector, which allows less efficient DMUs to learn from better ones; and (v) Monitoring and Evaluation: A monitoring system should be implemented to observe the various effects such policies would have when put into action. Not to mention that all policies should support the quest to improve efficiency and competitiveness within the sector. These recommendations can be taken as a form of cooperation between the company's management and the government to increase efficiency and competitiveness in Indonesia's construction industry.

4.13. Limitations of the used methodology and directions for further research

Limitations of the methodology refer to all kinds of constraints or limitations that could affect the validity, reliability, and generalization of the research results and provide an important perspective in understanding the nuances and scope of the findings produced. Some of the methodological limitations in this study are as follows: (i) Homogeneity assumption: The efficiency scores using DEA are based on the assumption that the DMUs under evaluation are relatively homogeneous. However, characteristic features of construction industries may vary a lot in terms of their size, operational complexity, and prevailing market conditions, which again influences the efficiency results; (ii) Sensitivity to Input and Output Selection: Efficiency scores obtained through DEA can be extremely sensitive to input and output selections. One reason is that the selected variables are inadequate representatives of the true processes of the construction industry, and the efficiency measures then cannot be a good representation of true performance; (iii) Static Nature of DEA: The DEA represents a snapshot of efficiency at a particular point in time. This static nature thus may miss dynamic changes and improvements over time for construction projects, which can further lead to misleading conclusions from the overall performance of DMUs; (iv) inability of benchmarking: While DEA identifies efficient DMUs, it does not provide insights into the best practices leading to efficiency. It will limit the extent to which actionable strategies can be articulated from such findings, and (v) Data Quality and Availability: the quality of analysis is directly related to the quality and completeness of the data used. Partial or biased data might, to a large extent, affect the outcome and result in incorrect classification of DMUs as being efficient or inefficient.

Directions for further research have played a vital role in enriching knowledge and the movement of better practices that characteristically opened the way for major innovation and progress. Some of the interesting directions for further research that could be explored from the results of the present study are enumerated below: (i) Qualitative Factors to be Included: Qualitative assessment through DEA, including expert interviews or case studies, would shed more light into which operational practices bring efficiency in future studies within the construction sector; (ii) Dynamic DEA Models: Investigation of the dynamic DEA models that take into consideration efficiencies changing over time may completely capture the trend in performance; (iii) Cross-Industry Comparison Studies: The research, if extended to a cross-industry comparison, may underline some unique challenges and strategies at work that could further improve the efficiency of the construction sector; (iv) Alternative Efficiency Measurement Methods: Analysis of the other methodologies of performance evaluation will provide additional perspectives and confirm the results of the DEA method; and (v) In-depth Analysis by Project Types: Efficiency analysis by type of project, such as residential versus commercial projects, may suggest that specific project-type factors impact performance.

5. CONCLUSION

This study proposes modifying the existing stepwise modeling approach (SMA) method to DEA modeling, developed by Wagner and Shimshak. The proposed method in this study contributes to solving the problem of input and output variable requirements in DEA. It is because the DEA itself does not provide guidance for the requirements of the input and output variables. This existing method only produces one alternative for determining variable selection. The proposed method can generate more than one alternative. By generating many alternatives on variable selection, optimal results will be obtained. It is an advantage of the research results.

This study applied four input variables (X1, X2, X3, X4) and two output variables (Y1, Y2). Modifying the existing stepwise modeling approach (SMA) method to DEA modeling creates eight alternatives for determining variable selection. This study applied four input variables (X1, X2, X3, X4) and two output variables (Y1, Y2). Modifying the existing stepwise modeling approach (SMA) method to DEA modeling creates eight alternatives for determining variable selection. Alternative 1 is the existing method of SMA. Alternatives 2 to 8 are the proposed methods of SMA. The results of variable selection from each alternative are as follows: Alternative 1 (X4, Y2), Alternative 2 (X4, Y1), Alternative 3 (X3, Y2). Alternative 4 (X1, Y1), Alternative 5 (X1, Y2), Alternative 6 (X2, Y1), Alternative 7 (X3, Y1), and Alternative 8 (X2, Y2). Furthermore, the best alternative method is selected. The criteria for the best alternative method are as follows: the smallest values (DMUs efficient, TES, and AFC) and the biggest value (ACES). Based on the best alternative method, we can determine the classification of efficient and inefficient decision-making units (DMUs).

The research results indicated that there are four ranges in the classification of inefficient DMU, namely: R1 (ES = 0.16-0.99), R2 (ES = 0.050-0.15), R3 (ES = 0.015-0.049), and R4 (ES = 0.000-0.014). The criteria for each classification, in terms of the level of effectiveness, are as follows: i) R0 Range (ES = 1]): Effective; ii) R1 Range (ES = 0.16-0.99): Relatively Low Ineffectiveness; iii) R2 Range (ES = 0.050-0.15): Moderate Ineffectiveness; iv) R3 Range (ES = 0.015-0.049): Significant Ineffectiveness; and v) R4 Range (ES = 0.000-0.014): Very High Ineffectiveness. The percentage of each classification is as follows: inefficient DMU-R1 0%, inefficient DMU-R2 30%, inefficient DMU-R3 37%, inefficient DMU-R4 30%.

The weakness of the proposed method is that it requires more detailed calculations. It is the impact of the many alternatives created for determining variable selection. Therefore, more variables than this research are needed to determine variable selection in DEA modeling. It aims to strengthen the analysis that the proposed method performs well than the existing method.

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