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RESEARCH PAPER

Performance Evaluation of Micro and Small Industries in East Java Province, Indonesia Using SMA and DEA: A Case Study

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ABSTRACT
Micro- and small-scale industries (MSIs) are the pillars of Indonesia's national economy. MSIs face several issues as their businesses grow. Performance evaluation is one way to identify MSI's effectiveness. The research objective is to evaluate the MSI's performance in East Java Province, Indonesia. It is an effort to improve the MSI's performance. The stepwise modeling approach (SMA) and data envelopment analysis (DEA) methods were applied to identify MSIs' effectiveness, determine the classification of inefficient MSIs, and formulate an inefficient MSI development strategy. In the existing SMA concept, the remaining variables in the END step are the selected variables (model X-Y). This study proposes that variables from the initial step to step n+1 are considered in creating efficiency score (ES) models. There are five proposed models, including model 4X-3Y, model 3X-3Y, model 3X-2Y, model 2X-2Y, and model 2X-Y. The research result indicated that the proposed ES model 3X-3Y is the best. 54% inefficient and 46% efficient DMUs make up the model 3X-3Y. Six cities and fourteen regencies make up the inefficient SMI classification. Cluster_A (50%) consists of four cities and six regencies. Cluster_B (25%) consists of two cities and three regencies. Cluster_C contains two regencies (10%). Cluster_D comprises three regencies (15%).

KEYWORDS: *Performance evaluation; Stepwise modeling approach; Data envelopment analysis; Micro- and small-scale industries.*

1. Introduction

The characteristics of the world of trade and business are complex and mysterious. Every competing company must understand important business strategies. Competitors will progressively eliminate businesses who are unable to meet customer satisfaction, adjust to changing market conditions, and keep up with changes in the market environment. Likewise, companies with a series of unstructured onboarding processes also have to leave the business.

Small and medium-sized industries, which account for over 50% of all employment and around 90% of businesses today, are crucial to the population and economy of every society and are the engine of economic growth. Today's global economy is centered around small and medium-sized industries. Due to a lack of understanding of business features, the majority of these industries are ultimately defeated. Hence, because of their great potential, these industries can contribute significantly to the local economy if they are exposed to new business practices. As a result, small and medium-sized industries should view the future of their industry from a long-term and global viewpoint [1].

Micro, small, and medium scale industries (MSMIs) have a significant role in the Indonesian economy, particularly in times of crisis. MSMIs managed to survive both the COVID-19 pandemic and the 1998 financial crisis. As demonstrated by the three roles that MSMIs play in the Indonesian economy (as a means of reducing poverty, leveling the economic playing field for the poor, and generating foreign exchange for the nation), MSMIs are an integral part of the nation's independent economy and have the potential to significantly improve the welfare of its citizens. According to figures from the Ministry of Cooperatives and Small and Medium Enterprises in 2021, there were 64.2 million MSMIs in Indonesia, contributing IDR 8,573.89 trillion, or 61.07%, to the country's GDP.

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MSMIs in Indonesia can employ 97% of the labor force and can garner as much as 64% of all investments. These figures indicated that Indonesia's high labor absorption capability and high MSMIs provide the country with the potential for a robust national economic base. There will be a decline in the unemployment rate in Indonesia as long as the percentage of MSMEs grow annually [2].

However, a number of issues, both technical and non-technical, arise when MSMIs try to develop their businesses. These issues include: (i) poor quality human resources; (ii) low capacity to use science and technology; (iii) working capital constraints; (iv) low managerial capabilities of MSMI actors; (v) unclear business prospects; (vi) poor business planning; (vii) disorganized vision and mission; (viii) using relatively simple technology; (ix) having inadequate access to capital (bankable); and (x) lacking a special system that separates business capital from personal capital (a consequence of being a family business). The inability to obtain information, particularly about markets, is another issue that exacerbates MSMIs' predicament and increases their vulnerabilities. The lack of strong global competitiveness and market orientation makes it difficult for MSMIs to promote their products and keeps them from making more focused and defined commercial progress, which leads to sluggish development [3]. MSMIs really need support to overcome obstacles in developing their businesses. For this reason, various efforts must be made to minimize MSMIs business obstacles. In this way, MSMIs in Indonesia will continue to survive, develop, and compete in global competition. Performance evaluation is one way to develop MSMIs [4].

The company needs performance evaluations to assess the economics and efficiency of sustainable operations and to gather data on business decisions. Performance evaluation can be used to improve the company's operating processes, and its role becomes very important if standards or benchmarks are not presented for evaluation. Performance can be measured using data envelopment analysis (DEA) [5]. The performance of a collection of identical entities is systematically compared in comparative performance evaluation, according to this definition. They are known as decision-making units (DMUs). Companies, societies, departments, and other entities make up DMUs. They are presumed homogeneous in the sense that they convert a similar group of sources into a similar group of services and/or products. DEA is mathematical programming based on technique. As a result, in real multiple inputs and outputs conditions, DEA is related to DMU comparison and piecewise frontier approximation. DEA and benchmarking have differences. Engineering fundamentals or statistical mean performances are both addressed by benchmarking. The excellent-practice DMUs under examination are appraised by the DEA for their effectiveness (especially their efficiency). As a result, DEA uses the least amount of a priori assumptions possible, allowing for the handling of a multidimensional picture of performance. DEA offers an extensive structure in a sequence of dissimilar optimization designs. It is used for interpreting work processes related to their performance [6].

DMUs with numerous inputs and multiple outputs are evaluated for relative efficiency using data envelopment analysis (DEA). The relative effectiveness of a group of DMUs that use many inputs to generate various outputs can be assessed using DEA technique. A 30-year survey of Cook and Seiford [7], a 40-year survey and bibliography of Emrouznejad and Yang [8], and a review of efficiency-ranking methods of Aldamak and Zolfaghari [9] have all reviewed studies that have been published since the groundbreaking work of Charnes et al. [10]. These studies express the methodology and application of DEA [11].

The selection of input and output variables is a significant factor in determining the DMU's effectiveness. This problem has not been significantly resolved. The focus of DEA research is mostly directed at model development. Regularly, input and output variables are chosen based on personal preferences. The stepwise modeling approach (SMA) method is used to select the optimal input and output variables for DEA. This approach is to develop a DEA model. The backward approach from the SMA procedure begins by examining all potential input and output variables. One input variable or one output variable is removed from the model alternately at each step of the stepwise approach (from the START step to the END step). Theoretically, the numerical procedure can be continued until there is only one input variable and one output variable remaining (END Step). The final result of this calculation can be considered a decision criterion for developing an optimal DEA model [12]. The selected variable in the END step is a model of the existing method. This research proposes that input-output variables from the initial step (START step) to step n+1 are also considered in an efficiency score (ES) model. Furthermore, the efficiency score results of all ES models were compared to determine the best ES model.

The objectives of this research are to evaluate the performance of micro and small industries (MSIs) in East Java Province, Indonesia. The research urgency is an effort to improve the MSI's performance. Hence, MSIs, as pillars of the national economy, can win competitive business competition. Performance evaluation is one way to identify effective and ineffective MSIs. The SMA and DEA input multipliers methods were applied (i) to identify efficient and inefficient MSIs; (ii) to determine the classification of inefficient MSIs; and (iii) to formulate an inefficient MSI development strategy. In the existing SMA concept, the remaining variables in the END step are the selected input-output variables. This study proposes that input-output variables from the initial step to step n+1 are also considered in creating efficiency score (ES) models. These variables are used to calculate the efficiency score using the DEA input multipliers method. Furthermore, the efficiency score results of all ES models were compared to determine the best ES model.

2. Literature Review

2.1. Performance measurement

A competitive atmosphere fosters more intense rivalry, which has a significant impact on a company's performance. Success level has a big impact on a company's ability to expand. It might be able to stay sustainable and expand its company in the right way. A company's performance can be used as a guide to manage successful operations that lead to sustainability and market dominance. The effective and efficient use of a company's business plan is correlated with its performance. Here are a few of the fundamental causes: (i) A firm's performance is based on the activity results that were present within the firm and influenced by both internal and external components in order to fulfill set goals within a given time frame; (ii) A company's capacity to produce outputs is what defines its performance; (iii) The company's performance refers to a multifaceted concept that goes beyond financial performance; (iv) The performance of the firm shows if the business objective or achievement level is adequate given the set output or attainment by the conclusion of the business term; and (v) The effectiveness of a company in achieving its goals is reflected in its performance [13].

According to traditional management, something that is not measured cannot be managed. Appropriate performance measures can be a bridge for well-defined and structured communication. Thus, the company's goals and targets can be achieved. To increase their global competitiveness, companies must be cost-efficient and able to develop their competitive advantages. Therefore, it is necessary to prepare, develop, and manage company activities that are in line with its objectives [14]. The framework concept in performance evaluation uses effectiveness based on customer needs and satisfaction. The following are some factors to consider when evaluating performance: (i) Fluctuating conditions of the company's operations; (ii) Intense business competition; (iii) A platform to improve company performance; (iv) Requirements to determine national and international quality; (v) The company's role in facing change; (vi) Continuously changing business conditions; (vii) External requirements; and (viii) The influence of information technology [15].

2.2. Data envelopment analysis method

Charnes and Cooper introduced the mathematical technique known as data envelopment analysis (DEA). DEA is based on linear programming. Health care services, manufacturing technique optimization, project selection, safety enhancement, and supply chain management are just a few of the situations in which this method has been applied. This technique can be used to determine the effectiveness of a collection of decision-making units (DMUs) with various inputs and outputs. This performance will serve as a benchmark for evaluating DMU's performance and drawing comparisons between them. DEA enables each DMU to declare a set of weights that represent a unit in the most advantageous scenario in order to calculate the weight of each input and output [16]. DMUs can be categorized as efficient or inefficient based on the efficiency score values. A DMU that is efficient has an efficiency score of one point, whereas one that is inefficient has a score that is less than one [17]. DMU results are compared using DEA, a categorization and ranking tool. The DEA is a useful technique for classification and ranking, as evidenced by the consistency of the results. DEA has therefore been validated as a method for classification and ranking [18]. The DMU efficiency ratings can be sorted from highest to lowest using a histogram graph. DMU clustering is identified using this strategy. Each group can then be given a threshold, which can serve as the basis for classification. As a result, the efficiency score distribution serves as the basis for the classification criteria for DMUs [19].

The DEA method can be implemented in decision-making by estimating the relative efficiency of the decision-making units (DMUs). DEA is a powerful method because it uses many inputs and outputs in its implementation. For this reason, DEA can be used in all areas of life, including solving problems that are correlated with multilateral production functions, such as the level of technological progress, productivity index, scale, issues of minimum price and maximum benefit, and so on. DEA is a purely technical method. Hence, DEA does not require initial parameter estimation of the production function. This is the main advantage of DEA over other methods. These characteristics make DEA useful for: (i) solving problems by correlating subjective factors; (ii) simplifying actions and reducing errors; and (iii) comparing the effectiveness of various distribution networks [20]. Other advantages of the DEA method include (i) simplicity in calculation, (ii) ease of access to computer software, and (iii) using multiple inputs and outputs. The application of DEA (to estimate relative effectiveness) has been implemented in many fields over the last five decades. These fields include financial and non-financial institutions, sports, hospitals, agriculture, and so on [21].

2.3. DEA input multipliers method

Weight multipliers are an important aspect of the DEA input multipliers method. The strength of the weight multiplier makes the DEA method different from other types of productivity and performance analysis. The scientific study by Charnes et al. determines the level of substitution threshold by applying a weight multiplier to the measure of overall productivity. The linear programming (LP) model is used to calculate the weight multiplier's value. The LP model is a basic aspect of the DEA method's implementation. Charnes et al. first introduced the concept of LP to effectively identify objects by implementing the DEA method. The DEA input multipliers method defines effectiveness as a weighted ratio of output to weighted input. This concept is shown in equations (1) to (4).

Subject to:

Maximum

$$\sum_{r=1}^{s} \mu r Yro \quad (1)$$

Constraints:

$$\sum_{r=1}^{s} \mu r Yrj \quad - \sum_{i=1}^{m} Vi\ Xij \leq 0 \qquad J = 1,\dots,n \quad (2)$$

$$\sum_{i=1}^{m} Vi\ Xio = 1 \quad (3)$$

$$\mu r,\ Vi \geq 0 \quad (4)$$

The μr and Vi notations are decision variables, namely: output and input multipliers, respectively. Other notations are as follows: Yro (rth output for DMUo), Xio (ith input for DMUo), DMUo (one of the n DMUs under evaluation), Yrj (jth DMU's ith outputs), r (number of outputs), Xij (jth DMU's ith inputs), i (number of inputs), j (number of DMUs), DMUs (decision-making units), s (last number of outputs), m (last number of inputs), and n (last number of DMUs). The level of effectiveness is in the range of 0 to 1. A value of 0 is the least efficient DMU, and a value of 1 is the most efficient DMU [22].

2.4. Variable selection in DEA method

The data envelopment analysis (DEA) method implements many input and output variables to evaluate effectiveness but does not provide directions for selecting these variables. In general, the selection of variables tends to apply various methods. If the number of variables implemented is too high or too low, it will affect the effectiveness of the DMU. This condition will determine whether all DMU is effective or ineffective. Limited DMU data will result in the number of variables being very large and unreasonable. The computing process will be directly affected by such conditions. In the desired condition, the number of DMUs must be three times greater than the quantity of variables in the input and output [12]. A successful implementation of DEA depends on the selection of input and output items. They need to present the decision-maker's purposes and perspectives on matters that could impact a decision-making unit's (DMU) effectiveness. The requisites for determining inputs and outputs have been expressed for a long time in the written works, and a quantity of pitfalls have also been recognized. There are four main presumptions regarding the selection of input and output sets. It includes (i) all resources used; (ii) records every level of activity and performance indicator; (iii) all DMUs share the same set of factors; and (iv) variations in the environment have been evaluated and recorded as needed [23]. Cost and benefit criteria are the two types of criteria used in the basic DEA model to determine input and output. It means that cost criteria are used as input criteria, whereas benefit criteria are used as output criteria. As a result, data transformation is necessary for the computations. This transformation divided the models under study into three groups. Initially, the cost criterion is recorded as an input and the benefit criterion as an output.

The outcome produced a nearly identical solution using two comparable but distinct economic messaging models. Another choice is to classify the criteria as either input or output, falling under the same category. An almost similar solution appears twice in the findings. In the third model, the criteria for both input and output can be determined exogenously. The results demonstrate that, when compared to the other two models, the efficiency is different. However, there is some similarity in the results of the two methods [24].

2.5. Stepwise modeling approach

The stepwise modeling approach (SMA) is a method for choosing the DEA's input and output variables. The basic procedure of the SMA uses a backward approach to model variables in the DEA input multipliers method. The procedure begins by implementing all input-output variables to calculate efficiency. At each subsequent stage, one of the input or output variables is removed intermittently from the numerical procedure. In the final stage, there is only one input variable and one output variable. Furthermore, the efficiency score can be calculated for each DMU. The final result of the calculation can be considered as a basis for determining the optimal decision (efficient or inefficient DMU). The stages of the backward approach are shown in Table 1 [25].

2.6. Literature review conclusion

Micro and small industries (MSIs) have a strategic role as the backbone of the Indonesian economy. Hence, performance evaluation is an important step to measure effectiveness and efficiency as well as formulate development strategies for business units that are less than optimal. Generally, the method used to assess efficiency is data envelopment analysis (DEA). This method is based on the analysis of relationships between different variables of inputs and outputs. It frequently has issues with variable selection, including the fact that it is frequently subjective and impacts the accuracy of the results. Another approach for identifying the best input and output variables in a systematic way is the stepwise modeling approach (SMA).

Tab.1. Steps of the stepwise modeling approach

Steps	Explanation
Initial Step/ START Step	Evaluation of input and output variables for which efficiency scores will be calculated using the DEA input multipliers method. Set all input variables (J) and output variables (K) on each DMU.
Step1	Create a series of procedures for calculating efficiency scores by implementing the DEA input multipliers method (where i= 1, ..., J+K). Alternately, eliminate one input variable or one output variable during each process. Correct the DMU effectiveness factor set (E1, i) for each i-process. Calculation of the difference in effectiveness factors for each suitable DMU (E*-E1, i). Calculate the average difference in the effectiveness value (according to row i of the difference). Determine one omitted input or output variable based on the minimum mean difference value. For the omitted variables, the results of the DEA efficiency score are marked with E1*.
Step n+1	Repeat each step by implementing a series of DEA input multipliers procedures (i= 1, ..., J+K–n). The variables are chosen and compared to the results (En+1, i). En* is the effectiveness factor from the previous stage. Next, select the removed variables based on the minimal mean difference in factor effectiveness.
Final Step/ END Step	The calculation is finished when there are just one input variable and one output variable left in the ES model.

This approach is carried out in steps, with each variable being eliminated one at a time until only one pair of variables is left in the last step (Step END). However, conventional SMA has limitations because the final results often do not reflect the complexity of MSI efficiency as a whole. Accuracy in selecting variables is a very crucial factor. Inappropriate selection of variables, either because the number is too many or too few, can reduce the accuracy of the DEA model, resulting in a biased DMU (decision-making units) classification. More complex variable associations that are required for a more thorough analysis are also at risk of being overlooked when concentrating on the variables in Step END of SMA. Despite this, DEA remains an effective tool for identifying efficient and inefficient DMUs, classifying them based on efficiency scores, and providing data-driven insights through visualizations such as histograms to support strategic decision-making.

2.7. Research gap

Based on the discussion of literature review conclusions, the following research gaps can be identified: Previous studies generally only use variables at Step END in the conventional stepwise modeling approach (SMA) to determine efficiency. This study fills a research gap by proposing an approach that considers variables in various stages (from the initial step to step n+1). Hence, this approach can provide more comprehensive evaluation results. Most previous data envelopment analysis (DEA) studies do not provide objective guidelines in selecting input-output variables. It may cause bias in the evaluation's findings. This study introduces a systematic approach using SMA to overcome the problem of subjectivity in variable selection. In addition, most DEA and SMA studies are conducted outside the Indonesian context. This study is different because it focuses on micro and small industries in East Java Province. It also provides more specific insights into the efficiency of micro and small industries (MSIs) in this province. Most DEA studies only stop at evaluating efficiency without formulating further development strategies. This study goes further by formulating strategies for the growth and stability of MSIs, such as product diversification, and improving the performance of inefficient MSIs.

2.8. Research novelty

Based on the discussion of literature review conclusion and research gap, the novelty of this research can be identified through four main aspects. First, the modified stepwise modeling approach (SMA). This study introduces a variation on the SMA concept, namely by considering input-output variables from all stages of SMA (starting from the initial step to the step before the final, step n+1). This is different from the conventional or existing SMA method, which only maintains variables at the END step as selected variables. Hence, this study proposes several alternative efficiency models to identify the best efficiency model.

Second, evaluate the best efficiency score (ES) model based on several alternatives. In research with conventional or existing SMA methods, it tends to choose the final ES model without further evaluation. This study compares and evaluates between models to determine the best ES model. This determination is based on the optimal number of variables and efficiency results. The selection of an effective model shows a more comprehensive model evaluation approach.

Third, the classification of inefficient industries. In addition to identifying the efficient and inefficient of micro and small industries (MSIs), this study classifies inefficient MSIs into several cluster groups. This classification provides further information on the distribution and characteristics of regions (region-city) experiencing inefficiency, as well as providing more focused data to formulate development strategies.

Fourth, the direct implementation of MSIs in East Java Province. This study applies the SMA and DEA methods to evaluate the performance of MSIs. The combination of these methods provides new empirical insights into the effectiveness of MSIs. The results of this study are expected to provide specific strategic recommendations for improving the performance of MSIs in East Java Province that can be practically adapted. Hence, the novelty of this research can enrich the approach to the efficiency analysis of MSIs through variations in the SMA concept and DEA method. This also has the potential to produce more contextual and effective development strategies for inefficient MSIs.

3. Research Methodology

The following steps are included in problem-solving to evaluate the performance of micro and small industries (MSIs) in East Java Province, Indonesia: (i) research design and definition: (ii) preparation, data collecting, and evaluation; (iii) data processing; (iv) results analysis; and (v) conclusion. Table 2 provides a description of each of these phases.

3.1.1. Steps for validating and verifying the results in the combination of SMA and DEA methods

In efficiency analysis, it is important to validate and verify the results so that the method used produces accurate and reliable scores. The combination of the stepwise modeling approach (SMA) and data envelopment analysis (DEA) methods provides a structured approach to identifying optimal variables and calculating efficiency. The current approach not only improves the quality of the results but also ensures that the efficiency score would remain robust against changing conditions.

The following are steps toward validation and verification of the efficiency score results by using this approach. First, choose the relevant input and output variables for efficiency analysis. Then, by using SMA, there will be stepwise variable selection, which removes the insignificant variables and selects the best variable to use in the DEA model. After finding the optimal set of variables, the efficiency score of each DMU will be found by using the DEA method. Efficiency scores are checked for verification of the consistency of ranking between the models (using and without SMA). Furthermore, a sensitivity analysis is carried out by modifying the input or output, or adding back the deleted variables, to ensure that the efficiency score remains stable and reliable. The results of the analysis are also validated by comparing them with alternative methods or by cross-checking to ensure their accuracy. Finally, the performance of the DEA-SMA combination model is evaluated to ensure that this approach produces valid and reliable efficiency scores. All processes and results are analyzed and clearly documented to support the credibility of the analysis performed.

4. Results and Discussion

4.1. Input-output data components, variables, and DMUs

The data used in this study is from micro and small industries (MSIs) in East Java Province, Indonesia.

Tab.2. Phases for solving research problems

Phases	Explanation
Research design and definition	Determine the type of MSI data (regency-city name, number of companies, number of workers, investment value, and production value). Designing a research concept.
Preparation, data collecting, and evaluation	Classification of MSI input and output data. Determination of MSI input, output, and decision-making units (DMUs) data.
Data processing	Selection of DEA input multipliers input and output variables using the stepwise modeling approach.
	Setting input, output, and DMU data in Microsoft Excel spreadsheets consists of columns (a) DMU and DMU under evaluation data; (b) input and output data; (c) constraints and barriers; (d) efficiency; and (e) results from input multipliers and output multipliers.
	Calculation of DMU efficiency using Microsoft Excel (Solver).
Results analysis	Analysis of efficiency score results. Analysis of efficient DMUs. Analysis of inefficient DMUs. Analysis of comparisons between potential efficiency score models. Classification analysis of inefficient SMIs. Analysis of MSI's business development strategy.
Conclusion	The best efficiency score model. Percentage of efficient and inefficient MSIs. Inefficient MSI classification. MSI's business development strategy.

These data consist of regency-city name, number of companies, number of workers, investment value, and production value [26]. The two time periods for these data are 2017 (updated 2019) and 2019 (updated 2022). Based on these data, input-output variables and decision-making units (DMUs) can be determined, as shown in Tables 3 and 4. Table 5 gives a general overview of the input-output data used in this study.

Multiple efficiency factors in an integrated model are associated with the linear programming technique known as DEA. Multiple efficiency is measured in relation to input and output variables. The elements that are typically minimized are known as input variables; these include expenses, labor, materials consumed, etc. Typically, output variables such as profit, revenue, products, etc. are the ones that are maximized. Prior to applying the DEA approach, input and output variables are categorized and selected [12, 22].

In this study, the determination of input and output variables for DEA analysis is explained as follows: The input variables used in this study include the number of workers, the number of companies, and the investment value of MSIs. Workforce is a factor used to produce goods and services.

The number of workers reflects the human resources owned by MSIs, which function as input in the production process. Workforce is chosen as an input variable because of its very important role in producing products or services by MSIs.

The difference in the number of workers between 2019 and 2022 can provide an overview of the effect of changes in the number of workers on efficiency.The number of companies is used as an input variable to measure the operational efficiency of MSIs. As an input variable, the number of companies reflects the contribution of resources owned in the form of micro and small business units.

Tab.3. Input and output variables

No.	Components	Input-Output	Variable
1	Number of MSI companies in 2019	Input_1	X1
2	Number of MSI workforce in 2019	Input_2	X2
3	Number of MSI companies in 2022	Input_3	X3
4	Number of MSI workforce in 2022	Input_4	X4
5	MSI investment value in 2019	Output_1	Y1
6	MSI production value in 2019	Output_2	Y2
7	MSI production value in 2022	Output_3	Y3

Tab.4. Decision making units (DMUs)

No.	Regency-City	DMUs	No.	Regency-City	DMUs
1	Malang	R_1	20	Pacitan	R_20
2	Mojokerto	R_2	21	Jember	R_21
3	Blitar	R_3	22	Situbondo	R_22
4	Jombang	R_4	23	Tulungagung	R_23
5	Trenggalek	R_5	24	Sampang	R_24
6	Bangkalan	R_6	25	Ponorogo	R_25
7	Madiun	R_7	26	Pamekasan	R_26
8	Nganjuk	R_8	27	Ngawi	R_27
9	Gresik	R_9	28	Kediri	R_28
10	Sumenep	R_10	29	Surabaya	C_1
11	Lamongan	R_11	30	Malang	C_2
12	Tuban	R_12	31	Pasuruan	C_3
13	Lumajang	R_13	32	Kediri	C_4
14	Pasuruan	R_14	33	Mojokerto	C_5
15	Probolinggo	R_15	34	Probolinggo	C_6
16	Magetan	R_16	35	Madiun	C_7
17	Banyuwangi	R_17	36	Blitar	C_8
18	Bondowoso	R_18	37	Batu	C_9
19	Bojonegoro	R_19			

Tab.5. Input-output data

No.	DMUs	X1	X2	X3	X4	Y1	Y2	Y3
1	R_1	48,918	190,031	39,722	83,605	4,105	14,188	3,318
2	R_2	34,740	134,671	20,817	46,057	2,915	9,122	3,566
3	R_3	33,527	131,020	35,498	74,533	2,819	9,153	2,977
4	R_4	33,208	127,979	32,798	89,900	2,781	8,709	6,666
5	R_5	30,673	119,002	28,043	58,482	2,591	8,060	1,539
6	R_6	30,360	117,877	19,188	28,755	2,561	7,986	649
7	R_7	27,661	107,403	10,299	19,296	2,319	7,800	1,248
8	R_8	26,966	106,532	13,277	26,787	2,265	7,087	2,663
9	R_9	27,051	104,982	14,146	31,291	2,272	7,112	1,596
10	R_10	26,907	104,342	42,967	121,883	2,264	7,070	1,844
11	R_11	26,127	101,437	30,772	93,791	2,193	6,868	4,692
12	R_12	25,451	98,941	14,275	30,885	2,140	6,714	4,179
13	R_13	25,479	98,569	11,223	24,441	2,132	6,678	2,707
14	R_14	24,691	96,592	23,730	44,242	2,086	6,515	3,453
15	R_15	24,581	95,596	39,597	152,627	2,086	6,496	2,044
16	R_16	24,508	95,233	21,235	34,248	2,036	6,415	946
17	R_17	23,476	93,597	34,811	50,398	1,955	6,156	1,775
18	R_18	23,317	90,682	43,001	109,411	1,967	6,140	1,884
19	R_19	22,310	87,561	35,771	91,438	1,891	5,858	2,019
20	R_20	22,442	87,060	40,441	70,729	1,878	5,897	1,667
21	R_21	20,146	80,763	37,254	82,924	1,694	5,287	3,463
22	R_22	19,410	76,784	35,924	106,438	1,617	5,111	1,034
23	R_23	19,775	76,000	40,588	77,928	1,642	4,993	4,444
24	R_24	15,904	62,725	18,288	95,781	1,315	4,180	1,791
25	R_25	15,844	61,565	23,536	42,144	1,324	4,167	1,362
26	R_26	14,399	55,134	46,714	453,547	1,183	3,742	1,140
27	R_27	9,373	36,825	13,586	26,635	774	2,446	923
28	R_28	8,348	33,168	23,613	43,858	686	2,169	4,051
29	C_1	31,644	123,055	15,650	38,176	2,676	8,305	2,929
30	C_2	22,857	88,688	13,111	27,356	1,915	6,008	1,621
31	C_3	11,041	42,637	5,591	16,805	914	2,952	1,670
32	C_4	8,777	33,466	4,007	7,398	715	2,266	620
33	C_5	8,295	32,134	2,250	4,632	689	2,243	272
34	C_6	7,662	30,546	3,941	6,762	633	2,015	744
35	C_7	7,883	30,509	3,848	7,189	655	2,068	294
36	C_8	7,747	30,039	3,714	8,145	642	2,035	550
37	C_9	7,166	27,687	3,494	8,314	592	1,877	434

This is important to analyze because the purpose of DEA is to assess the extent to which a business unit can convert inputs (such as the number of companies) into outputs (such as production value). Hence, the number of companies reflects how well these resources are put to work in producing the desired output. This is the value of investment, which refers to the sum of money that MSIs have invested in the support of their business activities by purchasing new machinery, constructing infrastructure, and developing production capacity. Investment is viewed as an input variable because investment is directly related to the production capacity of goods or services by MSIs and enhances production capacity. The output variables in this study consist of the production value of MSIs in two periods, namely 2019 and 2022. The production value includes the total goods and services produced by MSIs, which reflects the results of the use of input factors, such as labor and investment. This production value is used as the main measure to assess the results or output of MSIs.

By measuring the output in both periods, an evaluation of the efficiency of MSIs in producing value based on the available input can be carried out. The selection of output based on the year aims to analyze the performance of MSIs by looking at the production value in 2019 as an initial picture and the production value in 2022 to evaluate the development and performance achieved during that period.

4.2. Determination of input and output variable models

The DEA input multipliers method is used in this research to measure the DMU efficiency score. The type of input-output variable applied to measure the efficiency score is based on the concept of the stepwise modeling approach (SMA) method. As indicated in Table 6, there are six SMA stages for modeling input and output variables. There are four input variables (X1, X2, X3, and X4) and three output variables (Y1, Y2, and Y3) in the first step (START Step). In step 1, X1 is the eliminated variable (variable dropped, V-D). Thus, the remaining variables (R-I, R-O) are three input variables (X2, X3, X4) and three output variables (Y1, Y2, Y3). Furthermore, steps 2 through 4 will also eliminate one input variable and one output variable, respectively. The last step (END Step) leaves one input variable (X4) and one output variable (Y3).

In the existing SMA concept, the remaining variables from the END step are the selected input-output variables. Thus, the selected variable (S-V) from the existing method (EM) is model X-Y. This study proposes input-output variables in all SMA stages as the selected variables. Henceforth, these variables are used to calculate the efficiency score (ES). There are five types of proposed models (PM), including model 4X-3Y, model 3X-3Y, model 3X-2Y, model 2X-2Y, and model 2X-Y (Table 7).

4.3. Organizing input and output data in Microsoft excel spreadsheets

The input and output data are compiled in Microsoft Excel spreadsheets to calculate the efficiency score. The spreadsheets are divided into 4 columns, namely, columns for (i) DMU data, (ii) input and output data, (iii) constraints, (iv) efficiency, (v) weights, (vi) input-output multipliers, (vii) DMUs under evaluation, and (viii) efficiency. Furthermore, the data is processed using the Solver function. In Microsoft Excel spreadsheets, the following models are used to organize input and output data: (i) Model 4X-3Y (4 input variables, 3 output variables); (ii) Model 3X-3Y (3 input variables, 3 output variables); (iii) Model 3X-2Y (3 input variables, 2 output variables); (iv) Model 2X-2Y (2 input variables, 1 output variable); and (v) Model 2X-Y (1 input variable, 1 output variable). Table 8 shows the organization of the data in the model 4X-3Y (4 input variables X and 3 output variables Y) in Microsoft Excel spreadsheets. In the same way, organizing data from other ES models can be done.

4.4. Efficiency score result

DEA implements multiple input and output variables to evaluate efficiency, but this method does not provide a technique for selecting the appropriate number of variables. In general, researchers have applied various types of methods. If the number of variables does not make sense, it will reduce the power of the efficiency score. This situation can result in all DMU values being efficient [6]. Table 9 presents the results of the efficiency score. A DMU's efficiency score of one indicates its efficiency.

DMUs with a low efficiency score, less than one, are considered inefficient.In this study, four ES models had an efficiency score (ES) of one in all their DMUs. These ES models consist of an existing ES model (model X-Y) and proposed ES models (model 3X-2Y, model 2X-2Y, and model 2X-Y). The inadequate number of input-output variables (less than 6 variables) causes these ES models to have weak efficiency scores.

Tab.6. SMA stages to model the selected input and output variables

Comp.	Start	Step1	Step2	Step3	Step4	END
R-I	X1 X2 X3 X4	X2 X3 X4	X2 X3 X4	X3 X4	X3 X4	X4
R-O	Y1 Y2 Y3	Y1 Y2 Y3	Y2 Y3	Y2 Y3	Y3	Y3
V-D	X1	Y1	X2	Y2	X3	
S-V						X4, Y3

Tab.7. Selected input and output variables

Model	Steps	Selected Variable (S-V)		S-V Model
		Input	Output	
Existing Model (EM)	End	X4	Y3	X-Y
Proposed Model (PM)	Start	X1, X2, X3, X4	Y1, Y2, Y3	4X-3Y
	Step1	X2, X3, X4	Y1, Y2, Y3	3X-3Y
	Step2	X2, X3, X4	Y2, Y3	3X-2Y
	Step3	X3, X4	Y2, Y3	2X-2Y
	Step4	X3, X4	Y3	2X-Y

Tab.8. Data organization in Microsoft Excel spreadsheets

No.	DMUs	X1	X2	X3	X4	Y1	Y2	Y3	Constraint	Efficiency
1	R_1	48,918	190,031	39,722	83,605	4,105	14,188	3,318	0.00	1.00
2	R_2	34,740	134,671	20,817	46,057	2,915	9,122	3,566	-0.02	1.00
3	R_3	33,527	131,020	35,498	74,533	2,819	9,153	2,977	-0.05	1.00
4	R_4	33,208	127,979	32,798	89,900	2,781	8,709	6,666	-0.01	1.00
5	R_5	30,673	119,002	28,043	58,482	2,591	8,060	1,539	-0.01	1.00
6	R_6	30,360	117,877	19,188	28,755	2,561	7,986	649	-0.01	1.00
7	R_7	27,661	107,403	10,299	19,296	2,319	7,800	1,248	0.00	1.00
8	R_8	26,966	106,532	13,277	26,787	2,265	7,087	2,663	-0.08	1.00
9	R_9	27,051	104,982	14,146	31,291	2,272	7,112	1,596	-0.02	1.00
10	R_10	26,907	104,342	42,967	121,883	2,264	7,070	1,844	-0.03	1.00
11	R_11	26,127	101,437	30,772	93,791	2,193	6,868	4,692	-0.03	1.00
12	R_12	25,451	98,941	14,275	30,885	2,140	6,714	4,179	-0.02	1.00
13	R_13	25,479	98,569	11,223	24,441	2,132	6,678	2,707	-0.02	1.00
14	R_14	24,691	96,592	23,730	44,242	2,086	6,515	3,453	-0.03	1.00
15	R_15	24,581	95,596	39,597	152,627	2,086	6,496	2,044	-0.01	1.00
16	R_16	24,508	95,233	21,235	34,248	2,036	6,415	946	-0.06	0.98
17	R_17	23,476	93,597	34,811	50,398	1,955	6,156	1,775	-0.15	0.99
18	R_18	23,317	90,682	43,001	109,411	1,967	6,140	1,884	-0.03	1.00
19	R_19	22,310	87,561	35,771	91,438	1,891	5,858	2,019	-0.04	1.00
20	R_20	22,442	87,060	40,441	70,729	1,878	5,897	1,667	-0.05	0.99
21	R_21	20,146	80,763	37,254	82,924	1,694	5,287	3,463	-0.13	1.00
22	R_22	19,410	76,784	35,924	106,438	1,617	5,111	1,034	-0.11	0.98
23	R_23	19,775	76,000	40,588	77,928	1,642	4,993	4,444	-0.05	1.00
24	R_24	15,904	62,725	18,288	95,781	1,315	4,180	1,791	-0.09	0.98
25	R_25	15,844	61,565	23,536	42,144	1,324	4,167	1,362	-0.04	0.99
26	R_26	14,399	55,134	46,714	453,547	1,183	3,742	1,140	-0.06	0.98
27	R_27	9,373	36,825	13,586	26,635	774	2,446	923	-0.05	0.98
28	R_28	8,348	33,168	23,613	43,858	686	2,169	4,051	-0.07	1.00
29	C_1	31,644	123,055	15,650	38,176	2,676	8,305	2,929	0.00	1.00
30	C_2	22,857	88,688	13,111	27,356	1,915	6,008	1,621	-0.02	0.99
31	C_3	11,041	42,637	5,591	16,805	914	2,952	1,670	-0.02	1.00
32	C_4	8,777	33,466	4,007	7,398	715	2,266	620	-0.02	0.99
33	C_5	8,295	32,134	2,250	4,632	689	2,243	272	-0.01	1.00
34	C_6	7,662	30,546	3,941	6,762	633	2,015	744	-0.05	0.99
35	C_7	7,883	30,509	3,848	7,189	655	2,068	294	-0.01	0.99
36	C_8	7,747	30,039	3,714	8,145	642	2,035	550	-0.02	0.98
37	C_9	7,166	27,687	3,494	8,314	592	1,877	434	-0.02	0.98
								Weights	1	
	Multipliers	0	4.E-05	9.E-07	0	2.E-03	4.E-05	0		
	DMU Under Evaluation	37								
	Efficiency	0.98								

Hence, those ES models are removed from the list of the best ES model candidates. The remaining proposed SE models, model 4X-3Y and model 3X-3Y, have the best potential for the ES model. In the 4X-3Y model, there are 23 DMUs that are efficient and 14 that are not. The 3X-3Y model has 17 efficient and 20 inefficient DMUs.

4.5. Comparisons between potential ES models

Table 10 presents the potential ES models. That is model 4X-3Y and model 3X-3Y. There are 24 efficient and 14 inefficient DMUs in the Model 4X-3Y. 20 inefficient and 17 efficient DMUs make up the Model 3X-3Y. The DMU efficiency percentages for models 4X-3Y (62%) and 3X-3Y (46%), respectively. Compared to model 4X-3Y, model 3X-3Y has a smaller percentage.

Tab.9. Efficiency score results

No.	DMU	4X-3Y	3X-3Y	43X-2Y, 2X-2Y, 2X-Y, X-Y
1	R_1	1	1	1
2	R_2	1	1	1
3	R_3	1	0.99	1
4	R_4	1	1	1
5	R_5	1	1	1
6	R_6	1	1	1
7	R_7	1	1	1
8	R_8	1	0.98	1
9	R_9	1	1	1
10	R_10	1	1	1
11	R_11	1	0.99	1
12	R_12	1	1	1
13	R_13	1	1	1
14	R_14	1	0.99	1
15	R_15	1	1	1
16	R_16	0.98	0.98	1
17	R_17	0.99	0.96	1
18	R_18	1	1	1
19	R_19	1	0.99	1
20	R_20	0.99	0.99	1
21	R_21	1	0.96	1
22	R_22	0.98	0.97	1
23	R_23	1	1	1
24	R_24	0.98	0.96	1
25	R_25	0.99	0.99	1
26	R_26	0.98	0.98	1
27	R_27	0.98	0.97	1
28	R_28	1	1	1
29	C_1	1	1	1
30	C_2	0.99	0.99	1
31	C_3	1	1	1
32	C_4	0.99	0.99	1
33	C_5	1	1	1
34	C_6	0.99	0.99	1
35	C_7	0.99	0.99	1
36	C_8	0.98	0.98	1
37	C_9	0.98	0.98	1
	Efficient DMUs	23	17	1
	Inefficient DMUs	14	20	1

Tab.10. Potential ES models

No.	DMU Type	Model Type			
		4X-3Y		3X-3Y	
		Q	%	Q	%
1	Efficient DMU	23	62	17	46
2	Inefficient DMU	14	38	20	54

These results indicated that model 3X-3Y performs better than model 4X-3Y. The reason for this is that model 3X–3Y has fewer variables (6 variables) than model 4X–3Y (7 variables). Therefore, model 3X-3Y is the best ES model. Furthermore, this model was applied to determine the classification of inefficient SMIs.

4.6. Classification of inefficient SMIs

Figure 1 presents the distribution of efficiency scores for inefficient DMUs. Based on this distribution, the classification of inefficient SMIs can be determined. There are four categories of inefficient SMI classification, namely: Cluster_A (ES= 0.99), Cluster_B (ES= 0.98), Cluster_C (ES= 0.97), and Cluster_D (ES= 0.96).

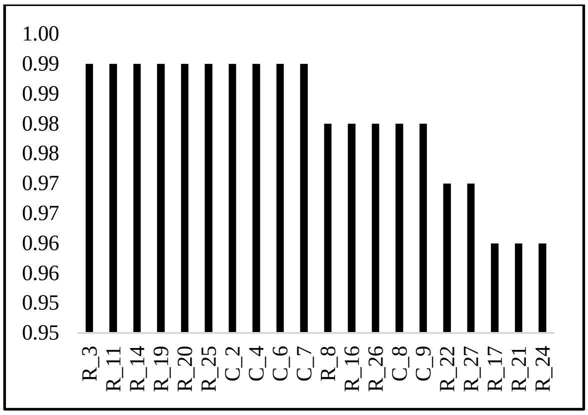

Fig.1. Distribution of efficiency scores for inefficient DMUs

There are 14 regencies and 6 cities in the inefficient SMI classification, as presented in Table 11. Six regencies (Blitar-R-3, Lamongan-R-11, Pasuruan-R-14, Bojonegoro-R-19, Pacitan-R-20, Ponorogo-R-25) and four cities (Malang-C-2, Kediri-C-4, Probolinggo-C-6, Madiun-C-7) are included in the category Cluster-A (ES= 0.99), with a percentage of 50% (10/20x100%). Three regencies (Nganjuk-R-8, Magetan-R-16, Pamekasan-R-26) and two cities (Blitar-C-8, Batu-C-9) are included in the Cluster-B category (ES= 0.98), with a percentage of 25% (5/20x100%). Two regencies (Situbondo-R-22, Ngawi-R-27) are included in the Cluster-C category (ES= 0.97), with a percentage of 10% (2/20x100%). Three regencies (Banyuwangi-R-17, Jember-R-21, Sampang-R-24) are included in the Cluster-D category (ES= 0.96), with a percentage of 15% (3/20x100%). Figure 2 presents the percentage (%) of inefficient MSI classification. The research result indicated that the percentage of inefficient MSIs decreased from Cluster-A to Cluster-C. However, there was an increase of 5% in Cluster-D. The proportion of Cluster-A is the highest (50%). Cluster-B and Cluster-D have a percentage of 25% and 15%, respectively. The lowest percentage is 10% in Cluster-C.

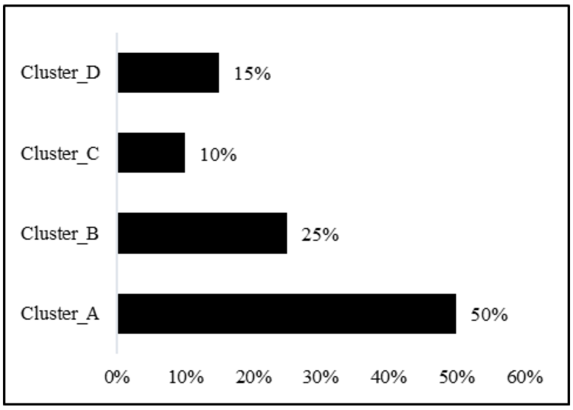

Fig.2. Percentage (%) of inefficient MSI classification

4.7. MSI's Business development strategy

The micro- and small-industry (MSI) business is hindered by a number of factors, such as inadequate product marketing, ineffective promotion, competitor product innovation, fierce competition, high inflation, and the need to satisfy consumer demand for high-quality products at competitive prices.

Other factors include process production that still uses outdated technology, the emergence of numerous new competitors, a lackluster supply of trained and educated human resources, a plethora of options for consumers purchasing the same product, complaints from customers, rising raw material prices, the country's economic downturn, and the rupiah's exchange rate against the US dollar. To overcome various obstacles in MSI's business, the company's business development strategy needs to be optimized.

The relevant strategy to improve MSI's business performance is a diversified competitive strategy, which consists of a growth and stability strategy. The growth strategy directs MSI's growth to diversify its products. The stability strategy will maintain the implementation of the strategy in accordance with the basic direction of business objectives. With this strategy, MSI is required to continuously improve its business weaknesses.

Tab.11. Classification of inefficient SMIs

SMI Class	ES	Regency-City
Cluster-A	0.99	R-3(0.99), R-11(0.99), R-14(0.99), R-19(0.99), R-20(0.99), R-25(0.99), C-2(0.99), C-4(0.99), C-6(0.99), and C-7(0.99)
		Blitar(R-3), Lamongan(R-11), Pasuruan(R-14), Bojonegoro(R-19), Pacitan(R-20), Ponorogo(R-25), Malang(C-2), Kediri(C-4), Probolinggo(C-6), and Madiun(C-7)
Cluster-B	0.98	R-8(0.98), R-16(0.98), R-26(0.98), C-8(0.98), and C-9(0.98)
		Nganjuk(R-8), Magetan(R-16), Pamekasan(R-26), Blitar(C-8), and Batu(C-9)
Cluster-C	0.97	R-22(0.97) and R-27(0.97)
		Situbondo(R-22) and Ngawi(R-27)
Cluster-D	0.96	R-17(0.96), R-21(0.96), and R-24(0.96)
		Banyuwangi(R-17), Jember(R-21), and Sampang(R-24)

MSI is required to improve (i) resources (human, machine, raw materials, methods, and capital), (ii) product quality to meet customer satisfaction, (iii) establish good relationships with suppliers and buyers, and (iv) create new market opportunities [27].

The engagement of micro and small industries (MSIs) is one of the elements influencing economic growth in Indonesia. According to Article 33, Paragraph 4 of the 1945 Constitution, MSI is a sector of the national economy that is independent and has a significant opportunity to raise society's welfare. MSIs are essential to the nation's economic development for several reasons, including: (i) there are a lot of MSIs in isolated, rural, and urban locations; (ii) MSIs require a lot of labor because they can make more money and have access to great job opportunities; (iii) MSIs employ a sizable number of people with less education.; (iv) MSIs are capable of enduring the financial crisis; (v) MSIs serve as a platform for entrepreneurship growth and the beginning of investment mobility in rural areas; and (vi) The local government of East Java Province strives to develop micro and small industries continuously. These efforts include: (i) encouraging and facilitating synergies in the preparation of business development programs; (ii) capacity building for human resources; (iii) product quality improvement; (iv) ease of access for business strengthening; (v) market and capital expansion for business development; (vi) development of product quality through activities on both a national and international scale; (vii) ease and acceleration of obtaining business legality permits; (viii) providing people's businesses with credit assistance and revolving funds; and (ix) facilitating integrated business legality [28].

5. Conclusion

The stepwise modeling approach (SMA) and data envelopment analysis (DEA) methods were applied to identify efficient and inefficient MSIs, to determine the classification of inefficient MSIs, and to formulate an inefficient MSI development strategy.

In the existing SMA concept, the remaining variables from the END step are the selected input-output variables. In this research, the selected variable from the existing method is model X-Y. This study proposes that input-output variables from the initial step to step n+1 are also considered in creating efficiency score (ES) models. Henceforth, these variables are used to calculate the efficiency score using the DEA input multipliers method. There are five types of proposed models (PM), including model 4X-3Y, model 3X-3Y, model 3X-2Y, model 2X-2Y, and model 2X-Y.

Four ES models had an efficiency score of one in all their DMUs. These ES models consist of an existing ES model (model X-Y) and proposed ES models (model 3X-2Y, model 2X-2Y, and model 2X-Y). The inadequate number of input-output variables causes these ES models to have weak efficiency scores. Hence, those ES models are removed from the list of the best ES model candidates. The remaining proposed SE models, model 4X-3Y and model 3X-3Y, have the best potential for the ES model.

Compared to model 4X-3Y, model 3X-3Y has a smaller percentage. These results indicated that model 3X-3Y performs better than model 4X-3Y. The reason is that model 3X–3Y has fewer variables than model 4X–3Y. Therefore, model 3X-3Y is the best ES model. Inefficient and efficient DMUs make up the Model 3X-3Y.

Furthermore, this model was applied to determine the classification of inefficient SMIs. The classification of inefficient MSIs consists of Cluster-A, Cluster-B, Cluster-C, and Cluster-D. The growth of the micro and small industry (MSI) is hindered by multiple factors. To overcome various obstacles in MSI's business, the company's business development strategy needs to be optimized. The relevant strategy to improve MSI's business performance is a diversified competitive strategy, which consists of a growth and stability strategy. The growth strategy directs MSI's growth to diversify its products. The stability strategy will maintain the implementation of the strategy in accordance with the basic direction of business objectives.

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