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## Measurement of Relative Efficiency Using the Data Envelopment Analysis (DEA) Method to Improve Efficiency at Perum Pegadaian Syariah

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#### **ABSTRACT**

The development of the Islamic financial industry which includes banking, insurance and pawnshops is basically a very long historical process. Perum Pegadaian Syariah, as one of the state-owned enterprises, is faced with the challenge of competing and improving efficiency in the growing Islamic financial industry. This study aims to measure the operational efficiency of Islamic Pawnshops in East Java Province using the Data Envelopment Analysis (DEA) method. This study identifies the relative efficiency of each Pawnshop unit from several branches of Pegadaian Syariah, including Joko Tole, Babakan, Sidokare, Mayjend Sungkono, and Blauran. The results showed that four branches were efficient with a relative efficiency value of 1, while Sidokare branch showed inefficiency with a value of 0.908. Improvement recommendations for Sidokare branch include reducing service time, operating costs, and increasing the number of customers and collateral. This research is expected to guide Perum Pegadaian Syariah in contributing to improving efficiency and competitiveness in an increasingly competitive market.

**Keywords**: DEA, Efficiency, Islamic Pawnshops.

#### A. INTRODUCTION

The development of the Islamic financial industry in Indonesia has undergone a long and significant journey [1]. With the establishment of Bank Muamalat Indonesia, Islamic financial principles have expanded beyond the banking sector, including into pawnshop services. The introduction of Sharia-based pawn services (rahn) by Bank Syariah Mandiri marked the initial step toward expanding Islamic pawn services. This initiative demonstrated that pawn products are not solely within the domain of conventional pawnshops, but can also be accessed through Islamic banks. In this context, market competition has intensified, driving innovation and service improvement. As a state-owned enterprise, Perum Pegadaian launched Sharia Pawn services aimed at enhancing public welfare, particularly for the lower-middle-income groups, by providing funding that complies with Sharia law while avoiding usury and exploitative lending practices.

In response to the rapid development of the Islamic financial sector, Perum Pegadaian must evaluate its operational efficiency. Until now, efficiency measurement has not been conducted systematically, making it essential to apply analytical methods such as Data Envelopment Analysis (DEA). This method not only helps identify efficient and inefficient units but also establishes targets for improving underperforming branches. The present study aims to assess the efficiency levels of each branch of Perum Pegadaian Syariah in East Java and formulate improvement strategies for those branches deemed inefficient. To support this objective, the proposed hypothesis suggests a positive relationship between the systematic application of efficiency measurement methods and the improvement of operational

performance, as well as the identification of inefficiencies that may have previously gone undetected.

#### **B. LITERATURE**

#### 1. Productivity and Efficiency

Productivity and efficiency are two essential concepts in measuring performance. Efficiency is defined as the ratio between output (amount produced) and input (amount used) [7]. Enhancing operational efficiency in processes can significantly increase productivity and profitability, reduce production costs, and accelerate operations [16]. Relative efficiency refers to the efficiency of an object measured in comparison with similar objects, and it is often used when it is difficult to establish a precise relationship among variables, allowing the evaluation of an object's performance in comparison to its competitors.

According to Sumanth, efficiency focuses on how effectively resources are used to produce results, while effectiveness emphasizes achieving the desired outcomes. The combination of both defines productivity, which expresses the ratio between total output and total input. According to Gaspersz, improved efficiency leads to better resource utilization, reduced waste, and higher profitability. Sabarguna also noted that efficiency analysis in service organizations can be assessed through cost-benefit or cost-effectiveness evaluation. Meanwhile, relative efficiency is commonly used when comparing similar operational units, allowing for fair benchmarking between organizations. Furthermore, efficiency is not merely a technical concept but also a managerial and strategic measure that reflects an organization's ability to transform inputs such as labor, capital, and materials into valuable outputs with minimal losses. High efficiency indicates the optimal use of available resources, while low efficiency reflects potential weaknesses in process design, human resource allocation, or technology utilization. In a competitive industrial environment, maintaining a balance between efficiency and effectiveness is crucial to sustaining long-term productivity growth. The integration of both aspects enables organizations to achieve operational excellence, reduce production variability, and enhance customer satisfaction. Additionally, modern efficiency evaluation approaches, such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), provide quantitative frameworks that allow researchers to identify best practices and quantify performance gaps among comparable entities. Therefore, understanding efficiency not only supports performance measurement but also serves as the foundation for continuous improvement and strategic decision-making within both manufacturing and service sectors [17].

#### 2. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric approach based on linear programming used to measure the efficiency of Decision Making Units (DMUs) or working units [18]. Each DMU involves different inputs and outputs [2]. DEA, unlike traditional parametric methods, does not require the assumption of normality [12]. In the DEA analysis process, input and output variables are required. The efficiency score is calculated using the following formula:

$$efficiency\ score\ =\ \frac{{}^{Total\ output\ weight}}{{}^{Total\ input\ weight}} \tag{1}$$

It was first introduced by Charnes, Cooper, and Rhodes through the Constant Return to Scale (CRS) model and later extended by Banker et al. to the Variable Return to Scale (VRS) model. DEA simultaneously evaluates multiple inputs and outputs without requiring a predefined functional relationship. It determines which DMUs lie on the efficiency frontier and which are inefficient, while also identifying benchmark units for improvement. In essence, the CRS model assumes that output changes are directly proportional to input changes, implying constant efficiency regardless of scale, whereas the VRS model allows efficiency to vary with

the scale of operation, making it more suitable for analyzing organizations of different sizes. Through this flexibility, DEA can capture inefficiencies arising not only from managerial performance but also from scale effects. Moreover, DEA provides quantitative efficiency scores that enable decision-makers to identify best-practice units and measure the degree of inefficiency for each underperforming unit. This makes DEA a valuable analytical tool in performance evaluation, productivity measurement, and benchmarking across various sectors, including manufacturing, education, healthcare, and financial services [7].

#### 4. Correlation Analysis

Correlation analysis is the study of the degree of relationship between variables. The correlation coefficient is a statistical measure used to assess the strength and direction of this relationship, especially for quantitative data. Correlation analysis aims to determine whether a relationship exists between two variables in an observational dataset and how strong or weak that relationship is. In general, the correlation coefficient ranges from -1 to +1, where a value close to +1 indicates a strong positive relationship, a value close to -1 indicates a strong negative relationship, and a value near 0 suggests no significant correlation between variables.

In empirical research, correlation analysis is often used as a preliminary step before regression analysis to identify potential associations that may warrant deeper investigation. This method helps researchers and decision-makers understand whether changes in one variable are likely to be associated with changes in another variable, providing valuable insights for process improvement, policy evaluation, or operational efficiency studies. Furthermore, correlation analysis can be applied across various disciplines such as economics, engineering, and management to examine relationships between productivity indicators, cost components, or performance metrics.

It is important to note, however, that correlation does not imply causation; a strong correlation between two variables does not necessarily mean that one causes the other. Therefore, correlation analysis should be complemented by other statistical or experimental methods to establish causal relationships. In performance evaluation contexts, such as productivity or efficiency studies, correlation analysis is particularly useful in validating whether selected input and output variables move consistently and logically with operational changes, ensuring the robustness of subsequent analytical models [18].

#### 4. Cluster Analysis

The clustering process uses a hierarchical procedure based on the concept of a "treelike structure" as an agglomeration method. This method begins by grouping two or more variables with the highest similarity into a single cluster, and then continuously incorporates the next most similar variables into the group. In determining peer groups for inefficient units, a method that can classify units with similar characteristics is required. The method commonly used for this purpose is Hierarchical Cluster Analysis (HCA). The basic concept of HCA is a hierarchical clustering process based on a "tree-like structure." It begins by merging two objects with the highest similarity, which are then successively combined with other similar objects, forming a hierarchy that resembles a branching tree from roots to branches and leaves. This iterative process continues until a single large cluster encompassing all objects is formed. Such an approach is referred to as an agglomerative method and is visually represented by a diagram called a dendrogram. Through this structure, HCA enables the identification of groups with homogeneous performance characteristics, facilitating the establishment of meaningful peer groups in efficiency analysis [19].

#### C. RESEARCH METHOD

This study employs the mathematical DEA model to determine the efficiency level of each Decision Making Unit (DMU) [20]. The problem-solving procedure consists of the following steps:

- 1. Formulating the research problem, objectives, and benefits.
- 2. Grouping Input and Output variables related to the problem-solving.
- 3. Determining the DEA mathematical model using CRS and VRS Models as follows:

The DEA CRS Primal model is used to determine the maximum value of the output-to-input ratio from the DMU under the constraint that the relative efficiency ratio of all DMUs is less than or equal to 1 (one) [8]. Meanwhile, the DEA CRS Dual model is used to identify directions for productivity improvement that can be carried out by the DMU in terms of influencing factors. Objective function:

$$Maximize h_k = \sum_{r=1}^5 U_r Y_{rk} (2)$$

Minimize 
$$\theta_k - 10^{-6} \left( \sum_{r=1}^5 S_r^+ + \sum_{i=1}^5 S_i^- \right)$$
 (3)

The DEA BCC VRS model aims to separate the scale effect and to measure the pure technical efficiency of the evaluated unit [10]. Objective function:

Minimize 
$$\theta_k - 10^{-6} \left( \sum_{r=1}^{5} S_r^+ + \sum_{i=1}^{5} S_i^- \right)$$
 (4)

Data collection of Input-Output required in measuring efficiency from each Pegadaian branch office [13].

- 1. Correlation analysis is conducted by performing a Correlate Bivariate Pearson Correlation test using SPSS software, with Pearson Correlation value as the parameter [15].
- 2. Calculation of relative efficiency for each DMU using DEA factor analysis with the DEA CCR CRS and BCC VRS models assisted by LINDO 6.1 Software [3].
- 3. Determining efficient and inefficient DMUs. If a DMU is efficient, it will be ranked. If it is inefficient, it will proceed to the next stage. A DMU is declared efficient if DMU = 1 and inefficient if DMU < 1.
- 4. The Cook and Kress (CK) mathematical model is used to rank the Decision Making Units (DMUs). This model aims to determine the relative efficiency of each DMU and provide ranking based on the analysis results.
- 5. Determining Peer Groups using the HCA (Hierarchical Cluster Analysis) model with SPSS 11.00 software [9].
- 6. Calculating efficiency targets for Input and Output for efficient and inefficient DMUs.
- 7. Improvement strategy and sensitivity analysis, which are used to improve less efficient DMUs with the Most Productive Scale Size (MPSS) model.

Input: 
$$x_{j} = \left[\frac{h^{*}_{0}}{\sum_{j=1}^{n} \lambda^{*}_{j}}\right] x_{ij0}$$

Output:  $y_{r} = \left[\frac{h^{*}_{0}}{\sum_{j=1}^{n} \lambda^{*}_{j}}\right] y_{ij0}$ 

(5)

#### D. RESULT AND DISCUSSION (Font size: 12, Times New Roman, bold)

### 1. Selection of Decision Making Unit (DMU)

The DMUs studied consist of 5 Pegadaian branches:

TABLE 1
Symbol of Decision Making Unit (DMU)

Symbol of Decision Making Unit (DMU)					
Symbol	DMU				
j	<b>PEGADAIAN</b>	CITY			
J = 1	Joko Tole Branch	MADURA			
J = 2	Babakan Branch	SURABAYA			
J = 3	Sidokare Branch	SIDOARJO			
	Mayjend Sungkono				
J = 4	Branch	SURABAYA			
J = 5	Cabang Blauran	SURABAYA			

#### 2. Grouping of Input and Output Based on Correlation Results

The grouping of input and output variables that influence the selection of efficient Pegadaian branches is shown in Table 2.

The analysis was conducted using SPSS to determine the relationships between factors. A correlation close to 1 indicates a strong relationship, meaning the input variables influence the output [14]. After analysis, variables with high correlation were reduced.

**TABLE 2 Input and Output Factors for Further Analysis** 

input und Susput i dettis for i di thei finalysis					
No	Input	No	Output		
1	Number of Employees	1	Number of Customers		
2	Service Time	2	Total Revenue		
3 Operational Costs 3		2	Number of		
		3	Collaterals		
		4	Loan Amount		

Table 2 shows 3 input variables and 4 output variables.

#### 3. Calculation of Relative Efficiency and Inefficient DMU

The calculation of relative efficiency uses the DEA CRS Primal Mathematical Model to determine the productivity index of DMUs based on production scale. Afterwards, the determination of Efficient and Inefficient DMUs is conducted based on the relative efficiency value (Technical Efficiency = TE).

TABLE 3
Input and Output Factors for Further Analysis

input and Output Factors for Further Analysis					
Relative Efficiency Value	Desc.				
1,0000000	Efficient				
1,0000000	Efficient				
0,9083784	Inffficient				
1,0000000	Efficient				
1,0000000	Efficient				
	Relative Efficiency Value 1,0000000 1,0000000 0,9083784 1,0000000				

#### 4. DEA Factor Analysis

The DEA factor analysis aims to determine the weights assigned by the DEA CRS Primal model to each factor. Smaller weights indicate a lower impact on productivity.

TABLE 4
DEA CRS Primal Calculation Results

		2212 01	12 1 1 1 1 1 1 1 1	3	110011100		Ayaraga
Dat	a Factors	ors Decision Making Unit (DMU)				Average Weight	
Dut	a i actors	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	_ ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
	Number of						0,1300226
	Employees	0,000001	0.000001	0.217830	0,270158	0,000001	
	Service Time	0,000000	0,000000	0.000000	0,000000	0,000000	0,0000004
INPUT	Operational						
	Costs	0,000000	0,000000	0.000000	0,000000	0,000000	0,0000000
	Number of						0,0000006
	Customers	0,000001	0,000001	0,000001	0,000001	0,000001	
	Total						0,0000000
OUT	Revenue	0,000000	0,000000	0,000000	0,000000	0,000000	
PUT	Number of						
PUI	Collaterals	0,000001	0,000001	0.000001	0,000001	0,000001	0,0000006
	Loan						0,0000000
	Amount	0,000000	0,000000	0,000000	0,000000	0,000000	
$\mathbf{E}$	fisiensi	1,000000	1,000000	0,908378	1,000000	1,000000	

From the table above, it can be concluded that:

- 1. The factor with the highest weight is Number of Employees (0.1300226), indicating a strong influence on DMU efficiency.
- 2. Other factors such as Number of Customers and Number of Collaterals (0.000006), Service Time (0.000004), and others have very small weights.

DMU 3, with a relative efficiency of 0.9083784, is below the efficient threshold of 1, indicating a need for improvement by reducing input and increasing output.

#### 5. Determination of Peer Group

The purpose of forming a peer group is to enhance the productivity of inefficient DMUs. The method used is Hierarchical Cluster Analysis.

Cluster Membership						
Case	4 Clusters	3 Clusters	2 Clusters			
1:DMU 1	1	1	1			
2:DMU 2	1	1	1			
3:DMU 3	2	2	2			
4:DMU 4	3	3	2			
5:DMU 5	4	3	2			

Figure 1. Cluster Result

#### **Proximity Matrix** Squared Euclidean Distance 1:DMU 1 2:DMU 2 3:DMU 3 4:DMU 4 5:DMU 5 Case 1:DMU 1 .000 1.2E+18 2.2E+19 7,4E+19 4,7E+19 2:DMU 2 3.3E+19 1.2F+18 000 1.3F+19 5 6F+19 3:DMU 3 2,2E+19 1,3E+19 ,000 1,6E+19 4,9E+18 4:DMU 4 7,4E+19 5,6E+19 1,6E+19 ,000 3.1E+18 5:DMU 5 4.7E+19 3.1E+18 .000

This is a dissimilarity matrix

Figure 2. Euclidean Distance of DMUs (Proximity Matrix)

TABLE 5
Peer Group of Inefficient DMU

Teel Group of Internctent Divid					
Inefficient DMU Peer DMU Euclidean Distant					
DMU 3	DMU 5	4,9E+18			

The cluster results show that DMU 3 and DMU 5 are in the same group, with the smallest Euclidean distance (4.9E+18). DMU 3 will refer to DMU 5 as a benchmark for productivity improvement.

#### 6. Calculation of Target Input and Output for Productivity Improvement

The target calculation aims to improve DMU performance, focusing on adjustments to input and output levels. Inefficient DMUs must set targets to become efficient, while already efficient DMUs strive to maintain their efficiency levels.

#### 7. DEA CCR CRS Dual Model

The DEA CRS Dual Model is used to calculate relative efficiency. A DMU is considered efficient if its efficiency score is 1.0. The analysis was carried out using LINDO software, and the results are shown in Table 6 [6].

Optimal Variable Values – DEA CRS Dual Model

	Optimal Variable Values – DEA CRS Dual Model					
DMU	<b>EFFICIENT</b>	θ	SLACK	DMU WEIGHT		
1	1,0000000	1,0000000		$\lambda_1 = 1,00000000$		
2	1,0000000	1,0000000		$\lambda_2 = 1,00000000$		
			$S_1^+ = 608,042358$			
			$S_3^+ = 42906,3125$	$\lambda_1 = 0.0111230$		
3	0.9083784	0.9083784	$S_4^+ = 3391,32373$	$\lambda_2 = 0,6654310$		
			$S_1^- = 1,91907700$			
4	1,0000000	1,0000000		$\lambda_4 = 1,0000000$		
5	1,0000000	1,0000000		$\lambda_5 = 1,00000000$		

#### 8. DEA BCC VRS Dual Model and Scale Efficiency (SE)

The DEA VRS Dual Model is used to calculate relative efficiency, distinguishing between technical and scale efficiency [11]. The Scale Efficiency (SE) is calculated as the ratio of CRS technical efficiency to VRS technical efficiency.

TABLE 7
Optimal Variable Values – DEA VRS Dual and Scale Efficiency

	Optimai va	illabic valu		VIXO Duai anu	Scare Efficiency
DMU	TE CRS	TE VRS	SLACK	DMU WEIGT	Scale Efficiency (SE)
1	1,0000000	1,0000000		$\lambda_1 = 1,00000000$	1,0000000
2	1,0000000	1,0000000		$\lambda_2 = 1,00000000$	1,0000000
3	0.9083784	1,0000000		$\lambda_3 = 1,00000000$	0.9083784
4	1,0000000	1,0000000		$\lambda_4 = 1,00000000$	1,0000000
5	1,0000000	1,0000000		$\lambda_5 = 1,00000000$	1,0000000

The above table shows that DMU 3 has better relative efficiency under the VRS model.

#### 9. Target Calculation

Target calculation involves using slack variables to set productivity improvement targets. Targets are set by minimizing inputs and optimizing outputs. Table 8 shows the target reference values for DMU 3 to achieve efficiency.

Target Reference for DMU 3

Factor		DEA CDC Dwal	Immorrant (0/ of Astro-1
Factor	Actual	DEA CRS Dual	Improvement (% of Actual
		Target	Value)
Number of Customers	4,171	4,779	15
(persons)			
Number of Collaterals	4,275	4,705	10
(units)			
Total Revenue (Rp)	420,127,250	420,127,250	0
Loan Amount (Rp)	6,387,476,0	6,387,479,400	5.3
	00		
Number of Employees	3	3	0
(persons)			
Service Time (minutes)	14	11	-21
Operational Costs (Rp)	6,437,000	5,847,232	-9

These targets provide direction for DMU 3 to achieve efficiency by maximizing output and minimizing input.

#### 10. Improvement Strategy and Sensitivity Analysis

Sensitivity analysis aims to determine the impact of changes in factor values on DMU relative efficiency, especially for the inefficient DMU (DMU 3). The dual price value is used to identify the contribution of each factor to relative efficiency. The sensitivity analysis results for DMU 3 are shown below.

TABLE 9
Sensitivity Analysis Results

Factor	<b>Dual Price</b>	Increase or	Contribution	Improvement
	Value	Decrease	to Relative	in Relative
			<b>Efficiency</b>	<b>Efficiency</b>
Number of Employees	0.213638	0	0.0000000	0.9083784
Service Time	0.000001	3	0.0000003	0.9083787
Operational Costs	0.005578	5.79330	0.0323150	0.9104874
Number of Customers	0.000001	584	0.0000584	0.9089626
Total Revenue	0.000200	0	0.0000000	0.9083784
Number of Collaterals	0.000001	428	0.0000428	0.9088062
Loan Amount	0.000001	338,536.228	0.3385362	1.2469149
TOTAL			0.3709527	

After improvements in input and output levels based on the target recommendations from the DEA CRS Dual Model, the relative efficiency score of DMU 3 can be increased from 0.9083784 (inefficient) to 1.0000000 (efficient).

#### 11. DMU Ranking

Ranking was performed using the Cook and Kress approach. The final ranking of DMUs based on cross-efficiency is shown in Table 10.

TABLE 10 Sensitivity Analysis Results

NI.	Before Ranki		ing After Ranking		
No	DMU	<b>Cross Effciency</b>	DMU	<b>Cross Effciency</b>	
1	1	0,955995	1	0,955995	
2	2	0,847316	2	0,847316	
4	4	0,194907	5	0,329265	
5	5	0,329265	4	0,194907	

The ranking order of the efficient DMUs is DMU 1 (Pegadaian Branch Joko Tole Madura), DMU 2 (Pegadaian Branch Babakan (Surabaya), DMU 5 (Pegadaian Branch Baluran Surabaya) and DMU 4 (Pegadaian Branch Mayjend Sungkono Surabaya).

#### E. CONCLUSION

h There are four (4) efficient and effective Sharia Pawnshop branches in the Surabaya Regional Office, namely Joko Tole, Babakan, Mayjend Sungkono, and Blauran, with a relative efficiency value of 1.0000000. Conversely, the Sidokare Sharia Pawnshop branch is classified as inefficient, with a relative efficiency value of 0.9083784. To increase the relative efficiency of the Sidokare branch to 1 (100%), improvements must be made to the input and output factors that influence efficiency. Improvement steps include increasing efficiency by reducing service time by 21% and reducing operational costs by 9%. Meanwhile, to improve effectiveness, steps include increasing the number of customers by 15%, the number of collaterals by 10%, and the loan amount by 5.3%. Total revenue and the number of employees do not require improvements because they do not have a significant impact on increasing efficiency and effectiveness.

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