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Analysis of Energy Efficiency of Indonesia's Sugar Industry

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ABSTRACT

Sugar industry in Indonesia has been experiencing rapid growth in local consumption, a decrease in domestic production, an increasingly growing import dependency, and a rise in the cost of energy use. This study explores the efficiency of energy use in the Indonesian sugar industry from 2010 to 2014 by applying the input distance function based on the trans-log model to all sugar mills across the country. The results revealed that substantial differences in energy efficiency exist across the provinces. The average energy efficiency is nearly 0.68, with the most efficient regions reaching nearly 0.77 and the lowest ones scoring about 0.62. The sugar mills in the provinces of Gorontalo, Banten, South Sulawesi, and East Java are more efficient than those of other provinces. The energy efficiency function suggested that increasing production volume can help to achieve more efficient energy use. Additionally, as labor and capital are substitute inputs, improvements in capital investment (technological upgrade) may yield larger outputs and contribute to more energy-efficient production. Meanwhile, raw materials and capital are complementary inputs, so improvements in energy efficiency via a larger mill size, bigger capital investment, and more efficient sourcing of raw materials can support the national government's production targets sustainably.

1. INTRODUCTION

As a key success factor of both business and environmental sustainability, energy efficiency has attracted researchers' attention in both the developed and developing world. Efficient energy use has important implications for industrial competitiveness, national security, economic prosperity, and a sustainable environment. Different methods for measuring energy efficiency have been proposed thus far, two of which are the energy intensity and total-factor energy efficiency (TFEE). The former aims at analyzing the use of energy at a societal level, mainly related to depletion and sustainable use of energy inputs. The latter compares the optimal to the actual use of energy inputs. In the TFEE context, developments in energy efficiency are associated with improvements in the total factor productivity and the efficient use of inputs relative to the optimal sectoral capability [1]. Stochastic Frontier Analysis (SFA) has been employed within the TFEE framework to study the efficient use of energy and the energy-saving potential within manufacturing activities [2].

In the TFEE approach, manufacturers use inputs (raw materials, energy, capital, and labor) to produce outputs. Under the assumption of a given technology, manufacturers produce their outputs at the lowest possible production cost with an appropriate inputs' combination. Nevertheless, in the real world, firms may not choose an input combination with the lowest costs and may only have access to outdated technology in the production. In these situations, they may use inputs inefficiently, including energy. As such, there needs to be an appropriate estimation of production's inefficiency by considering the microeconomic theory of production [3].

In Indonesia, manufacturing, and transportation activities are accountable for approximately 60% of the total energy consumption, with the average energy demand growing at 9.0%, 40% more than the average growth rate in non-manufacturing activities [4]. Within manufacturing, six sectors account for nearly 80% of the total energy demand—steel, pulp-paper, chemical, non-metallic minerals, food, and textiles [5]. The sugar industry has 46% higher specific energy consumption (SEC) than other industries within the food sector, with most energy being wasted by the heating system [4]. Such non-efficient energy use in the sugar industry is partly attributed to the mills' old age as more than 65% of them have been operating for 100 to 185 years. Sugar mills in Indonesia have indeed reported low efficiency as they work at low capacity, employ outdated, inefficient technology, and constantly face an increasing cost of inputs [6]. The manufacturing firms in Java have been experiencing decreasing productivity and a rise in

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the cost of energy and labor (almost duplicating in the last 15 years) [7]. As nearly 56% of sugar production is located within Java Island, it is likely that sugar production facilities will continue to face intense competitiveness pressures.

The literature on sugar production in Indonesia pointed out that the sector has met vital challenges. Despite the substantial government efforts, the plantation area decreased to less than 420,000 hectares (ha) in 2020. Similarly, production (total supply) has fallen from 29.5 million tons (MT) in 2018 to 27 MT in 2020 [8]. Aside from the aging mills, the challenges come from the decreased cultivated land, lack of suitable varieties, farm inefficiency, slow technological progress, and lack of product diversification [6]. Low productivity and technical inefficiency are often attributed to the lack of adequate research and development support [3]. For example, in Indonesia, producing one ton of sugar requires 5.98 barrel oil equivalent (BOE), substantially large compared to the general industry standard of 4.75 BOE[4].

Still, in Indonesia, sugar is a strategic industry, both to meet the annual consumption of nearly 7.2 million tons (estimated for 2021) and to support the related economic activities (*e.g.*, jobs along the value chain). In its golden times in the 1930s, Indonesia would be a net sugar producer, reaching exports of nearly 3 million tons [9]. Since then, sugar production has declined, stagnating at levels below 2.3 million tons a year [8], even below the self-sufficiency production target of 3.1 million tons [10]. While sugar demand for end-user consumption (retail) grew 30% from 2000 to 2014 (mainly locally produced), that of for industrial sector expanded 2.4 times (mainly import-dependent). Meanwhile, the productivity of sugarcane plantations in Indonesia declined at the level of 2.56 tons/ha, with the extraction rate also decreasing by 0.36 % compared to 2017, which is below the international levels. Because of this low productivity and high demand, the price of white crystal sugar in Indonesia remains substantially above the international market price. Although the government targeted to keep the retail price of white sugar at Rp 12.500/kg ($790/ton) the average plantation white sugar price in April 2020 reached more than Rp 18.500/kg ($1,174/ton) [8].

According to InterCAFE [11], the increase in sugar prices is linked to the increased costs of inputs, the soaring fuel costs, and the per capita GDP growth that might drive food demand. The efficiency of sugar production, including the efficient use of energy, is also an essential determinant of sugar's selling price in the domestic market. As sugar production requires intense use of energy inputs [12], energy efficiency is at the core of sugar industry competitiveness. As such, it becomes crucial to analyze whether sugar mills in Indonesia use energy efficiently or not; and whether there is energy-saving potential that could be explored. Inefficiency and high operation cost are two of the causes of the low sugar mills' capacity in Indonesia, which is estimated to be below 75% [8].

This paper aims to analyze the efficiency of energy use in Indonesia's sugar industry using the Stochastic Frontier Approach (SFA). We cover a sample of 73 mills across provinces in Indonesia over the period 2010-2014 and analyze the efficiency levels. A trans-log production function allows for output estimation as a function of labor, capital, raw materials, and energy inputs. As sugar mills employ a mix of energy sources [4], we included all kinds of energy in the energy variable such as the consumption of petroleum fuels, biomass, coal, gas, and other fuels. Earlier studies on technical efficiency in Indonesia's manufacturing sector have included energy inputs within the production function [7],[13]-[15]. Nevertheless, the sugar industry is generally aggregated within the food sector or a wider group of sub-sectors. Other studies specifically looking at the sugar industry in Indonesia by employing non-total factor energy potential approaches highlight the importance of energy efficiency analysis for the sector, and that there was a large room for improvement in the energy use of the facilities [4]-[16]. However, studies measuring energy efficiency based on the production efficiency approach and using firm-level data in Indonesia's sugar industry are still limited. We aim to fill this research gap.

This paper proceeds as follows. In section 2, a brief literature review is presented. Data and methodology are discussed in section 3. Section 4 discusses our main findings. Finally, our conclusions are presented in section 5.

2. LITERATURE REVIEW

2.1 Production Function

The production function is a mathematical or quantitative expression of the various technical production possibilities encountered by a company" [17]. The production function gives the highest number of outputs in the physical sense of each level of inputs. This can be expressed as follow:

$$Q = f(X) \tag{1}$$

where Q is the outputs and X is the inputs. Production functions indicate what is technically possible when the firm operates efficiently—that is, when the firm uses each combination of inputs as effectively as possible [18].

In this study, the transcendental logarithmic (trans-log) production function is applied because of its flexibility in estimating the production frontier [19]. In contrast with the Cobb-Douglas production function, it does not take into account flexible properties, such as perfect substitution between factors of production or perfect competition on the production factors market [20]. The trans-log production function is mostly used to study the manufacturing sector because of its flexible functional form [21]. The general form of the trans-log function is as follows:

$$\ln(Y_{it}) = \beta_0 + \sum_{p=1}^{P} \beta_p \ln(X_{pit}) \tag{2}$$

$$+0.5\sum_{p=1}^{P}\sum_{z=1}^{Z}\beta_{pz}\ln(X_{pit})\ln(X_{zit})$$

2.2 Input Distance Function

An input distance function defines the production technology by looking at a minimal proportional contraction of the input vector, given an output vector [12]. This can be defined on the input set, P(y), as:

$$d_i(x,y) = \max\{\alpha: (x/\alpha) \in P(y)\} \tag{3}$$

where the output vector, y, can be produced by using the input set P(y) as an expression of the set of all input vector, x. That is,

$$P(y) = \{x: x \text{ can produce } y\} \tag{4}$$

In the production technology point of view, the input distance function has the following properties.

(i) it is non-decreasing in x and increasing in y;
(ii) it is linearly homogeneous in x;
(iii) if $x \in P(y)$, then $d_i(x,y) \geq 1$ and
(iv) distance is equal to one, $d_i(x,y) = 1$, if x is on the "frontier" of the input set (the isoquant y).

2.3 Energy Efficiency

Energy is an important element for social and economic development as it is needed to achieve social, economic, and environmental goals [23]. Appropriate energy policies are often portrayed as an indicator of sustainable development. As such, energy efficiency has attracted policymakers' attention across the globe. Specific to developing countries, the increase in energy consumption is closely linked to environmental degradation [24]. That is to say, a well-organized energy program is crucial not only to drive economic development and stabilize energy prices but also to secure supply and mitigate climate change.

A country's economy can be boosted by the rapid development of manufacturing activities, and this has long been associated with high demand for energy. China uses a substantial amount of power to support its manufacturing activities and this has contributed to the rapid economic growth [25]. Indonesia also shows rapid growth in manufacturing activities; hence the energy consumption [4]-[7]. Under the input-output optic, as energy is an essential input in production, there has to be an efficient model to minimize its use [26]. This is because sustainable and efficient economic development can only be achieved with the support of energy efficiency.

Efficiency is generally defined as the ratio of useful output to input. According to World Energy Council [27], energy efficiency can be interpreted as a ratio of the energy service output to energy input. Based on the classical definition, energy efficiency means using the minimum amount of energy without changing the amount of total output [28]. It could also be calculated as a ratio of the target consumption and the actual consumption. The closer the rate is to one, the more efficient it is. But a consensus to define energy efficiency today is yet to be sought.

There are four indicators to measure energy efficiency—the thermodynamic indicators, the physical-thermodynamic indicators, the economic-thermodynamic indicators, and the economic indicators [28]. Economic-thermodynamic indicators and economic indicators such as the energy to GDP ratio are more beneficial for macro-level policy study. However, they miss separating the effects of technical energy efficiency trends. These indicators can spur misunderstanding in the interpretation as efficiency can only be presented in a numerical value [29]. The energy to GDP ratio does not consider the substitution or complement of other inputs [30]. In recent years, alternative methods to measure energy efficiency based on the economic foundation have been proposed [1].

In this study, energy efficiency is calculated from an economic point of view and is measured based on the total-factor productivity theory [25]. In measuring energy efficiency, the Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are popular methods. These two methods estimate the efficient benchmark on the effective frontier and then define the efficient indicators as the relative distance between the real output or input and the efficient benchmark. Even though DEA imposes fewer restrictions to calculate the firm efficiency, this method cannot directly explain the statistical noise [31]-[32]. This could be solved by using technical efficiency measures based on the SFA framework's production function as it can capture the statistical noise and consider exogenous factors in the production function [33].

Previous studies employing the TFEE approach have been conducted in countries like China [1]-[2], Japan, and other developed economies [31], finding important differences in the energy use across sectors and regions. Previous studies in Indonesia's energy efficiency have examined whether ownership, firm size, and sectoral activities are sources of energy intensity differences [14]. However, to our knowledge, no previous study has employed the TFEE approach has been applied to the sugar industry in Indonesia, comparing the spatial differences across provinces.

3. DATA AND METHODOLOGY

3.1 Data and Variables

This study uses secondary data from the large and medium manufacturing industry survey of Indonesia Statistics (Badan Pusat Statistik) over 2010-2014. The data employed cover mills under the sugar sub-sector, ISIC code number 10721. The panel data of observations in 73 mills (cross-sectional data) and five years (a timer series from 2010-2014) are used to evaluate the energy efficiency using Frontier Version 4.1 software. All variables are expressed in monetary terms and adjusted based on the wholesale price index (WPI) published by Indonesia Statistics (BPS) at a constant price of 2010. The variables used in this empirical study are output, labor, capital, raw materials, and energy. Each output variable is defined as the sum of each mill's production value in a specific year. The capital stock is calculated by fixed assets' replacement value, which contains three types of investment: land and buildings, machinery, and other capital goods and vehicles. Labor is calculated by the number of workers instead of person-hours due to data availability. The raw material is the sum of the cost of raw inputs, including the domestic and imported. Energy includes the sum of all expenditure on all kinds of energy sources used in the production process. The physical energy units include gasoline, diesel fuel, kerosene, coal, coal briquettes, gas, liquefied petroleum gas, lubricants, and other fuels (coke, fuel oil, and bunker C).

Table 1 depicts the summary statistics of the Indonesian sugar industry. The average value of output was merely IDR 591.84 billion (USD 65.11 million). The minimum and maximum output values are IDR 3.19 billion (USD 0.35 million) and IDR 20.345 billion (USD 2.24 million), respectively, suggesting that each mill's production level is very different. As noted by Toharisman and Triantarti [6], nearly 50% of mills have production capacity on tons-of-cane/day (TCD) of 2,000-4,000 TCD, and less than 5% of mills produce more than 8,000 TCD, which are optimal size. The average value of capital is equal to IDR 31.87 billion (USD 3.51 million). The minimum values of capital suggest that several mills employ low physical investment compared to the total average value of capital in the sector. In the Indonesian sugar industry, an average firm employs IDR 316.51 billion (USD 34.82 million) as a cost of raw materials. The average energy expenditure is IDR 26.08 billion (USD 2.87 million) with a standard deviation of IDR 99.35 billion (USD 10.93 million), a relatively large variation. Across the mills, the maximum and minimum value of energy cost is IDR 1,457.20 billion (USD 160.30 million) and IDR 0.0043 billion (USD 0.0005 million), respectively. For the labor variable, the Indonesia Statistics Survey includes only medium (20 up to 99 workers) and large enterprises (more than 99 workers). The maximum number of workers is 7,862, while the average number of employees is 926.

Table 1. Summary statistics of variables.

Variables	Sample	Unit	Mean	Std.Dev	Min	Max
Energy (E)	340	Billion Rupiahs	26.08	99.35	0.0043	1,457.20
Output (Y)	340	Billion Rupiahs	591.84	1,581.82	3.19	20,345.13
Capital (K)	340	Billion Rupiahs	31.87	118.01	0.0051	1,811.75
Labor (L)	340	Number of person	926	866.83	20.00	7,862
Raw Materials (R)	340	Billion Rupiahs	316.51	1,047.28	171.02	14,805.19

Source: BPS, Annual Manufacturing Survey, by own calculation (Note: 1 USD = 9090.43 IDR).

3.2 Methodology

Following Zhou *et al.* [34] and Honma and Hu [35], this study examines a production process in sugar mills where four inputs (X_i), capital stock (K), labor force (L), energy (E) and raw materials (R) are used to produce sugar crystal (Y). Conceptually, the production technology (T) can be described as:

$$T=\{(X_i, Y):(X_i) \text{ can produce } Y\} \tag{5}$$

All the feasible input-output vectors are contained in T, frequently indicated as the production technology graph, which can also be denoted by its equivalent input set or output set [36]. In the theory of production, T is frequently supposed to be a closed and bounded set. Additionally, the inputs and output are frequently supposed to be strongly disposable. It says that $(X_i^{'}, Y)\in T$ if $(X_i^{'})\geq(X_i)$ and $Y^{'}\leq Y$.

To measure energy efficiency from the perspective of the production function, the Shephard sub-vector input distance function for energy use (the Shephard energy distance function) can be utilized as follows:

$$\begin{aligned} D_E &= (X_i, Y) = (K, L, R, E, Y) \\ &= \sup\{\alpha: (K, L, R, E/\alpha,\ Y)T\} \end{aligned} \tag{6}$$

Equation 6 attempts to diminish energy to the maximum viability with given combination of input-output with the production technology set as characterized by Equation 5. Subsequently, E/ D_E = (K, L, R, E, Y) shows the hypothetical energy use if the firm is efficient in energy. At that point, the proportion of hypothetical energy use to real energy use is equivalent to the reciprocal of the sub-vector distance function. This can be specified as the firm's energy efficiency, *ie*.

$$\begin{aligned} EE &= \frac{E/D_E(K,L,R,E,Y)}{E} \\ EE &= \frac{1}{D_E(K,L,R,E,Y)} \end{aligned} \tag{7}$$

Energy efficiency measures the energy intensity level in an industry, whose scores are between zero and one. Following Honma and Hu [35], the stochastic frontier input distance function based on trans-log production model is as follows:

$$\begin{aligned} LnD_E(K_{it}, L_{it}, R_{it}, E_{it}, Y_{it}) = {} & \beta_0 + \beta_K LnK_{it} + \beta_L lnL_{it} + \beta_R lnR_{it} + \beta_E lnE_{it} + \beta_Y lnY_{it} + \\ & 0.5\beta_{KK}(lnK_{it})^2 + 0.5\beta_{LL}(lnL_{it})^2 + 0.5\beta_{RR}(ln R_{it})^2 + 0.5\beta_{EE}(lnE_{it})^2 + \\ & 0.5\beta_{YY}(lnY_{it})^2 + \beta_{KL}(lnK_{it})(lnL_{it}) + \beta_{KR}(lnK_{it})(lnR_{it}) + \beta_{KE}(lnK_{it})(lnE_{it}) + \\ & \beta_{KY}(lnK_{it})(lnY_{it}) + \beta_{LR}(lnL_{it})(lnR_{it}) + \beta_{LE}(lnL_{it})(lnE_{it}) + \beta_{LY}(lnL_{it})(lnY_{it}) + \\ & \beta_{RE}(ln R_{it})(ln E_{it}) + \beta_{RY}(lnR_{it})(lnY_{it}) + v_{it} \end{aligned} \tag{8}$$

Here $D_E(.)$ is a distance function, K_{it} is capital, L_{it} is labor, $\ln R_{it}$ is raw material, E_{it} is energy input, *i* refers to regions, t refers to the time, and v_{it} is a random noise, which is assumed to be normally distributed and errors of estimation. Because the Shephard energy distance function is linearly homogeneous in energy and setting $u_{it} = \ln D_E(K_{it}, L_{it}, R_{it}, E_{it}, Y_{it})$ by following Lin and Long [2], Equation 8 becomes:

$$\ln D_E(K_{it}, L_{it}, R_{it}, E_{it}, Y_{it}) = \ln E_{it} + \ln D_E(K_{it}, L_{it}, R_{it}, 1, Y_{it}) \tag{9}$$

The conditions for linear homogeneity in K, L, R are shown as follows [2].

$$\beta_K + \beta_L + \beta_R = 0$$

$$\beta_{iK} + \beta_{iL} + \beta_{iR} = 0\,; \quad i = K, L, R$$

$$\beta_{KY} + \beta_{LY} + \beta_{RY} = 0$$

By substituting Equation 8 to Equation 9 and rearranging. It implies that

$$\beta_{KE}(\ln K_{it}) + \beta_{LE}(\ln L_{it}) + \beta_{RE}(\ln R_{it}) + \beta_{YE}(\ln Y_{it}) = 1 - \beta_E \tag{10}$$

By substituting Equation 10 to Equation 8 and rearranging, it becomes

$$\begin{aligned}-\ln E_{it} &= \beta_0 + \beta_K \mathrm{Ln} K_{it} + \beta_L \ln L_{it} + \beta_R \ln R_{it} + \beta_Y \ln Y_{it} + \beta_E \ln 1 + 0.5\beta_{KK}(\ln K_{it})^2 \\ &+ 0.5\beta_{LL}(\ln L_{it})^2 + 0.5\beta_{RR}(\ln R_{it})^2 \\ &+ \beta_{KL}(\ln K_{it})(\ln L_{it}) + \beta_{KR}(\ln K_{it})(\ln R_{it}) \\ &+ \beta_{KY}(\ln K_{it})(\ln Y_{it}) + \beta_{LR}(\ln L_{it})(\ln R_{it}) \\ &+ \beta_{LY}(\ln L_{it})(\ln Y_{it}) + \beta_{RY}(\ln R_{it})(\ln Y_{it}) + v_{it} \\ &- \ln D_E(K_{it}, L_{it}, E_{it}, R_{it}, Y_{it})\end{aligned} \tag{11}$$

So,

$$\begin{aligned}\ln\left(\frac{1}{E_{it}}\right) &= \beta_0 + \beta_K \mathrm{Ln} K_{it} + \beta_L \ln L_{it} + \beta_R \ln R_{it} + \beta_Y \ln Y_{it} \\ &+ 0.5\beta_{KK}(\ln K_{it})^2 + 0.5\beta_{LL}(\ln L_{it})^2 \\ &+ 0.5\beta_{KK}(\ln R_{it})^2 + 0.5\beta_{YY}(\ln Y_{it})^2 \\ &+ \beta_{KL}(\ln K_{it})(\ln L_{it}) + \beta_{KR}(\ln K_{it})(\ln R_{it}) \\ &+ \beta_{KY}(\ln K_{it})(\ln Y_{it}) + \beta_{LR}(\ln L_{it})(\ln R_{it}) \\ &+ \beta_{KY}(\ln K_{it})(\ln Y_{it}) + V_{it} - u_{it}\end{aligned} \tag{12}$$

where, $u_{it} = \ln D_E(K_{it}, L_{it}, E_{it}, R_{it}, Y_{it})$ is a positive variable accounting for energy efficiency.

As a result, the SFA model shown in Equation 12 can be estimated by the maximum likelihood technique. From Equation 12, the energy inefficiency component $\widehat{u_{it}}$ can be calculated, and the energy efficiency can be further estimated with EE = exp $(-\widehat{u_{it}})$. u_{it} is assumed to be a truncated normal distribution. All the unknown parameters in Equation 12 can be estimated with the Frontier 4.1 Program (free software version), supported by Coelli [37].

4. RESULTS AND DISCUSSION

This section presents the energy efficiency estimates of the Indonesian sugar industry. Mill efficiency was estimated by using the software Frontier 4.1. Before analyzing the results, it is necessary to choose the best production function for this industry. Two production functions are compared, the Cobb-Douglas and the trans-log model. The likelihood ratio (LR) test is applied to select the best model by comparing the value of λ with the chi-square table's value. The null hypothesis is that the Cobb-Douglas form is a suitable frontier production function against the trans-log function. The LR test is $\lambda = -2\ \{\ln\ [L(H_0)] - \ln\ [L(H_1)]\}$ in which $\ln[L(H_0)]$ is the log-likelihood value of Cobb-Douglas model, and $\ln\ [L(H_1)]$ is the log-likelihood value of the trans-log model. The degree of freedom is the number of parameters used as restrictions in the model. The test statistic value, $\lambda = 6.034$, is greater than the value of χ^2 (13.28 at 1% significance), suggesting the rejection of the Cobb-Douglas model. Therefore, the trans-log model is a more appropriate model for the sugar industry in Indonesia.

Table 2 displays the estimation of the parameter of the energy input distance function. All the data employed are normalized around their means. Thus, the estimated first-order parameters in the trans-log function can be directly interpreted as production elasticities [38]. Because the energy variable is a reciprocal and an exogeneous one, a negative (positive) coefficient explains that this variable is a factor increasing (decreasing) energy efficiency [39]. The elasticity of output has a negative sign and is significant at 1%. A coefficient for output suggests that increasing production will positively impact the efficient use of energy. The coefficient of capital and labor interaction is positive and statistically significant, which indicates that inputs are substitutes. For instance, improvements in investment (*e.g.,* technological upgrading and new equipment) may be necessary to increase production and improve energy efficiency. Factories may be employing an insufficient ratio of capital to workers. The coefficient of capital and raw material interaction is statistically significant, with a negative sign at a 10% significance level, showing that this combination increases energy consumption. Capital and raw materials have complementary effects suggesting that higher production requires increases in both inputs, supporting the point that sugar is energy-intensive. The value of γ in Table 2 indicates that the variance of inefficiency is 21.84% of the total variance of error components.

Table 3 presents the energy efficiency scores based on the SFA model by province. The average energy efficiency score in 2014 is 0.6775, slightly lower than in

2010. The mean energy efficiency scores of the sugar industry by province are shown in Figure 1. Four provinces score the highest efficiency intensities: East Java, Banten, South Sulawesi, and Gorontalo, with energy efficiency estimates scoring above 0.70. Among all regions, Gorontalo has sugar mills (foreign-owned) with the highest energy performance of nearly 0.78. The province of East Java has the highest efficiency production level in Java. It also has the largest number of sugar mills in the country (45%), as well as the longest-held tradition of sugar plantations and sugarcane processing. The high performance of mills in East Java could be associated with its higher scale capacity and extensive experience in the production process. The variation in energy efficiency scores between East Java and other provinces ranges from 6% to 8%. Considering the high energy intensity used in sugar mills, 8% is a substantial difference. On average, mills in North Sumatra report the lowest efficiency scores, while those in Gorontalo showed the highest scores. Still, many mills are located on the island of Java (78%), remaining as the country's main sugarcane engine. As noted in previous studies, the scale of sugar mills in Indonesia requires an increase to meet the minimum capacity, from a current average of 3,900 TCD to at least 6,000 TCD per mill [6]. Additionally, to meet national targets for efficient sugar production, sugar mills may need to produce at a level of 6,000 to 15,000 TCD. Compared to other studies, the average sugarcane production in countries like China is 6,003 TCD, where a large mill produces at a mean energy efficiency level of 0.85 [1]. By contrast, the mean efficiency of a comparable sugar mill in Indonesia is 0.6775.

Table 2. Maximum likelihood estimation on the parameters.

Variables	Coefficient	St.Dev	t ratios	Sig
Constant	0.4126	0.2309	1.7870	***
Capital (lnK)	0.0584	0.0388	1.4102	
Labor (lnL)	0.0363	0.0655	0.5538	
Raw Material (lnR)	0.0704	0.0856	0.8220	
Output (ln Y)	-1.1388	0.0990	-11.4984	*
lnK × lnK	0.0549	0.0368	1.4939	
ln L × ln L	-0.0772	0.0735	-1.0500	
ln R × ln R	-0.0098	0.1806	-0.0541	
ln Y × ln Y	-0.2735	0.2337	-1.1704	
ln K × ln L	0.1251	0.0425	2.9425	*
ln K × ln R	-0.0855	0.0490	-1.7470	***
ln K × ln Y	0.0652	0.0611	1.0676	
ln L × ln R	-0.0764	0.0958	-0.7976	
ln L × ln Y	0.0272	0.0993	0.2736	
ln R × ln Y	0.1067	0.1896	0.5625	
sigma-squared	0.4666	0.1117	4.1766	*
gamma	0.2184	0.1808	1.2078	
mu	0.3086	0.5339	0.5780	
eta	-0.0022	0.0735	-0.0295	
Number of observations	340			

* sig at 1%, ** sig at 5%, *** sig at 10% (Source: Compilation by the author).

Table 3. Average energy efficiency scores of mills in sugar industry by province.

Province	2010	2011	2012	2013	2014	Average
North Sumatera	0.6241	0.6235	0.6229	0.6223	0.6217	0.6229
Jambi	-	0.6418	0.6412	0.6406	0.6400	0.6409
South Sumatera	0.7414	0.2087	0.7405	0.7400	0.7395	0.6340
Lampung	0.6547	0.6541	0.6536	0.5732	0.6525	0.6376
West Java	0.6892	0.6804	0.6779	0.6774	0.6768	0.6803
Central Java	0.6400	0.6394	0.6388	0.6382	0.6396	0.6392
Daista Yogyakarta	0.6547	0.6541	0.6535	0.6529	0.6524	0.6535
East Java	0.7055	0.7050	0.7045	0.7040	0.7035	0.7045
Banten	0.7306	0.7302	0.7297	0.7395	0.7288	0.7318
South Sulawesi	0.7224	0.7220	0.7215	0.7210	0.7206	0.7215
Gorontalo	0.7762	0.7758	0.7754	0.7750	0.7746	0.7754
Average	0.6939	0.6395	0.6872	0.6804	0.6864	0.6775

Source: Compilation by the author.

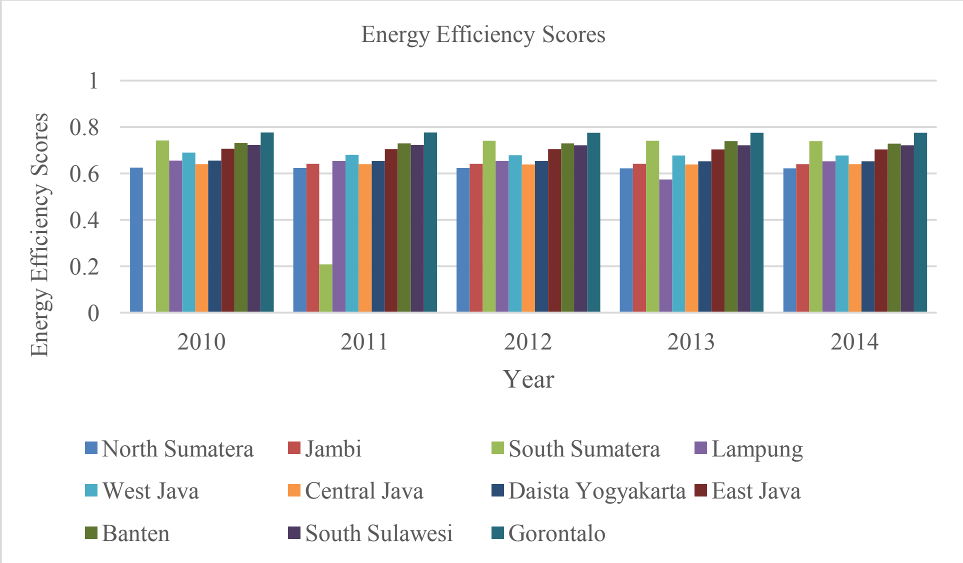

Fig. 1. Average energy efficiency scores of mills in sugar industry by province

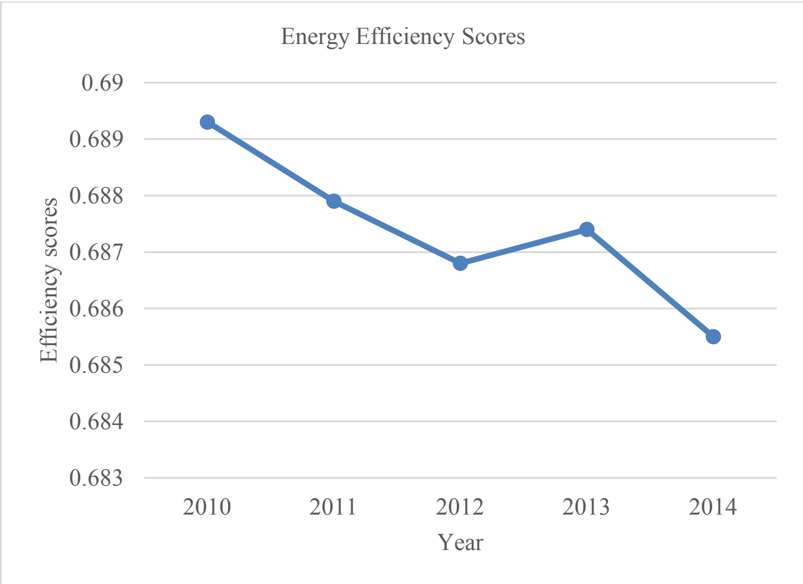

Fig. 2. Average energy efficiency scores for sugar industry (2010-2014).

Figure 2 presents the average energy efficiency scores between 2010 and 2014. Although there were slight downward trends in the efficiency scores, the overall efficiency did not change substantially during the period. The little progress in the efficient use of energy in Indonesia is problematic considering the substantial increases in the local demand, which should be an incentive to greater efficiency. Additionally, growing global competition suggests that more efficient international producers may outstrip their Indonesian counterparts. As noted in Vivadinar *et al.* [4], the specific energy consumption (SEC) of sugar facilities in Indonesia is nearly 25% larger than their global peers. Chang and Hu [25] noted that Chinese manufacturing mills experience efficiency gains of 0.6% a year in energy use. Furthermore, government efforts to control sugar prices may entail higher fiscal costs as the domestic and global price of sugar may widen over time. Currently, sugar for end-user consumption (retail) is restricted to local producers with the government intervening in the pricing.

Table 4 presents the average energy efficiency scores of mills in the sugar industry by regency from 2010 to 2014. In this result, only 35.6% of mills have relatively high energy efficiency scores with values above 0.70. In East Java, the energy efficiency of Probolinggo regency is the highest (0.8390). Regionally, East Java has the highest energy efficiency scores. The differences in energy efficiency at the mill level may suggest technological gaps among mills. Similarly, managerial know-how may differ across companies, causing gaps in energy efficiency across provinces. While more foreign-owned mills are allowed to operate in the country, they still account for less than a third of total sugarcane mills.

Table 4. Average energy efficiency scores of mills in sugar industry by regency during period 2010 to 2014.

Provinces	Regency	Energy Efficiency
North Sumatera	Toba samosir	0.5023
	Mandailing Natal	0.7460
South Sumatera	Ogan Ilir	0.7419
	Palembang	0.7207
Lampung	Tulang Bawang	0.6066
	Tanggamus	0.8128
	Waykanan	0.5730
	Lampung Utara	0.6693
	Lampung Timur	0.7569
West Java	Cirebon	0.6674
	Majalengka	0.7677
	Subang	0.6268
	Ciamis	0.6909
	Bogor	0.7406
Central Java	Tegal	0.6120
	Kudus	0.6975
	Brebes	0.7222
	Pekalongan	0.6886
	Pemalang	0.7501
	Klaten	0.5180
	Sragen	0.6794
	Karanganyar	0.7566
	Pati	0.5736
	Kendal	0.4678
	Blora	0.6630
East Java	Tunungagung	0.6352
	Lumajang	0.6002
	Malang	0.7634
	Magetan	0.7682
	Pasuruan	0.7790
	Probolinggo	0.8390
	Jombang	0.7082
	Ngawi	0.5120
	Sidoarjo	0.6621
	Mojokerto	0.7928
	Madiun	0.7540
	Situbondo	0.6481
	Nganjuk	0.5983
	Jember	0.6916
	Magetan	0.7577
	Bondowoso	0.6909
	Kediri	0.6834
	Ngawi	0.7386
Daista Yogyakarta	Bantul	0.6552
South Sulawesi	Barru	0.7326
	Takalar	0.7019
Gorontalo	Boalemo	0.7764
Banten	Cilegon	0.7852
	Serang	0.6734
Jambi	Kerinci	0.6426

Source: Compilation by the author.

As noted in earlier studies in Indonesia, the exorbitant amount of energy used in sugar facilities indicates that there is room for improvement. For example, sugar facilities can employ self-sufficient energy systems to operate [12]. In longer periods, sugar factories should be able to become energy producers. While our study does not aim at analyzing the potential of implementing self-sufficient energy plants, we claim that the low improvement in energy efficiency indicates that little has been done in the last years. Sulaiman *et al.* [40] noted that current sugar mills need to implement superior technologies to increase energy and water efficiency if they aim to increase production capacity sustainably. Technical efficiency improvements in sugarcane plantations are making more substantial progress, either due to the government's promotion to adopt new seeds [41] or via expansion of production/field areas.

The fast-growing rate of sugar consumption in Indonesia and its growing dependency on imports suggest that the government needs to take more relevant roles in supporting the efficient plantation of sugarcane and the production of sugar. To no surprise, Indonesia is the largest sugar importer in the world. The stagnation in energy efficiency in this industry—which requires high energy and constantly faces a rapid growth of energy cost—suggests that the country may experience further decreases in domestic production of sugar, losing to its Asian competitors [13]. The Ministry of Industry in Indonesia has launched the Indonesian Sugar Industry Road Map 2010-2014 [40], aiming at the development of the sugar industry through support programs to gear towards more efficient plantations, processing, marketing, and distribution. However, it seems that more efforts in the implementation are needed. Annual production targets of 3.1 million tons were not met, while consumption went beyond the expected figures.

5. CONCLUSION

In this paper, we employed a Stochastic Frontier Analysis (SFA) input distance function to measure the energy efficiency of all sugar mills across provinces in Indonesia from 2010 to 2014. The average energy efficiency is estimated at 0.6775, suggesting a large room for improvement. The energy efficiency in mills facilities is high in the provinces of Gorontalo (0.7754), South Sulawesi (0.7215), Banten (0.7318), and East Java (0.7045) (home to 45% of mills). By contrast, the energy performance in other regions is still below the industry's average level, often by a substantial difference (even at a 15% disparity). The differences across provinces suggest that technological gaps and managerial expertise may differ substantially across mills, suggesting that convergence in energy use across sugar facilities may take a long time.

The distance function suggests that higher energy efficiency could be achieved by increasing the output production of mills. The current average production of 3,900 TCD per mill may need to expand to the targeted 6,000 to 15,000 TCD per mill. Additionally, the significant effect of the interaction between capital and labor (substitute inputs) signals that further increases in the capital may be needed to increase the energy efficiency, suggesting that technological improvements in equipment may be required. Capital and raw materials appear as complementary inputs, signaling that increasing energy-efficient production requires more capital investments. As such, government policies should build more extensive facilities with superior technology.

Policies supporting research and development, development of human resources, finance/banking facilitation, and more integrated transportation under the Indonesian Sugar Industry Road Map should continue albeit with the much-needed improvements in the implementation. To accomplish this road map, the government should also consider sugar mills' energy efficiency in processing facilities, considering the substantial energy required in sugar production. Energy remains an important input in sugar production, essential to achieve competitive and sustainable production. The government should encourage efficiency improvement by taking measures such as by upskilling workers along with the provision of higher technology in mill facilities. Allowing foreign technology to be adopted in the sugar industry may support further improvements in energy efficiency in the sugar production process, as provinces with foreign-owned facilities recorded higher efficient use of energy than those with mainly domestic-owned mills. Finally, because of the limitation of data, other factors that impact the energy efficiency of sugar mills and environmental factors should be considered in further studies.

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