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MEASURING THE EFFECTIVENESS OF ELECTRICITY DISTRIBUTION IN INDONESIAN PROVINCES USING DEA BOOTSTRAP

[1]Amalia Rahmawati, [2]Setyo Tri Wahyudi, [3]Rachmad Kresna Sakti
[1,2,3]Faculty of Economics and Business, Universitas Brawijaya, Indonesia

Corresponding author:
amaliarahmawati1997@gmail.com

Abstract

Purpose
The aims of this research are to measure the efficiency of electricity distribution in 33 Indonesian provinces from 2010 to 2019.
Design/methodology/approach
The efficiency was measured using a two-step bootstrap analysis, i.e. DEA BCC and DEA Bootstrap.
Findings
This study finds that the efficiency estimation uses DEA BCC overestimate and that the proximity between electrical sources and customers becomes one of the supporting factors for the electricity distribution process and reduces losses. Furthermore, workforce input, nameplate capacity, and network length will be adjusted to customers; electricity demand needs as a component of the electricity distribution process from plants to consumers.
Research limitations/implications
This study uses the output of the number of customers and the amount of electricity distributed while the input variables use the amount of labor, installed capacity, and length of the distribution network.
Originality/value
This study uses DEA Bootstrap and the variables used in the study is a combination of variables that have been proven to affect electricity distribution and have never been applied in Indonesia.

Keywords: Efficiency, Electricity Distribution, DEA Bootstrap, Indonesia

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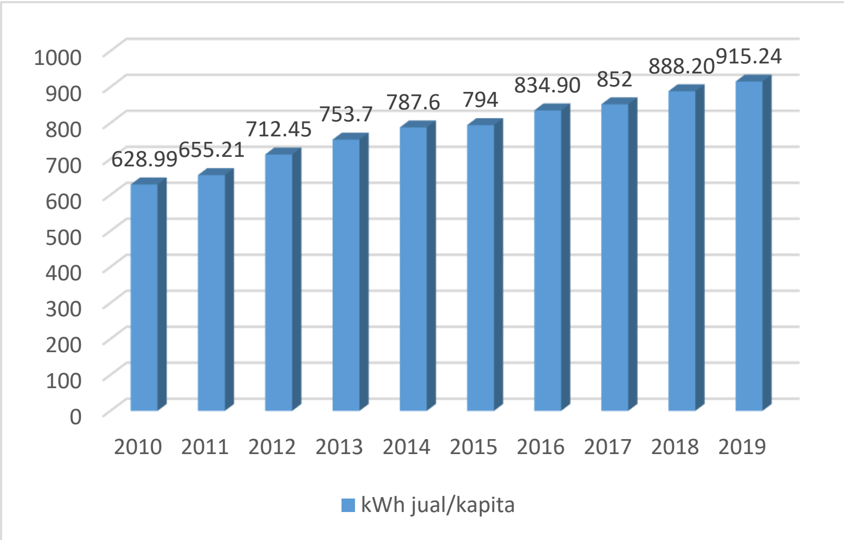
1. INTRODUCTION

The efficiency of electric power distribution has received important attention in the last two decades, mainly due to restructuring in the power sector, such as privatization (Bobde & Tanaka, 2018). Most utilities in the world have been liberalized by governments to increase efficiency in the electricity sector. Its main objective is to increase efficiency and sector performance and reduce the government's fiscal burden. Including Indonesia, since 1990, the electricity sector has been deregulated through the introduction of independent power producers (IPP). Most reforms involve restructuring, privatization, and sometimes the transfer of ownership.

In 1998, efforts to restructure the sector were initiated through the International Monetary Fund's economic assistance program for Indonesia. In the reform transition process, additional types of efficiency programs were implemented to improve the performance of the power sector (Fujii & Kaneko, 2011). Currently, the need for electrical energy continues to increase in every province this is due to increased industrialization and national prosperity. Including Indonesia, Indonesia's electricity consumption data in Figure 1 continues to increase in 2010-2019 and is projected to continue to increase.

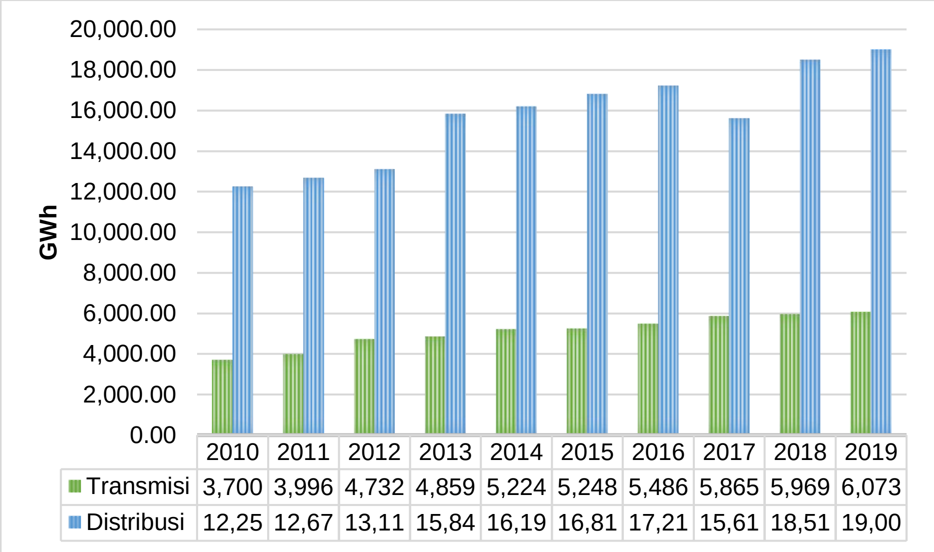
Figure 1. Indonesia's Electricity Consumption



Source: PT.PLN, 2019

Population growth is one of the factors increasing the demand for electrical energy. However, efforts to fulfill electricity needs for the community have been hampered due to inefficient electricity distribution and resulting in electricity losses. Based on Figure 2, blue color indicates distribution loss and green color indicates transmission loss. The electricity loss in Indonesia in 2019 was 9.32%, an increase of 894.06 GWh compared to 2018. While the total electricity loss in 2010–2019 increased by 13395.95 GWh, distribution losses were 6752.82 GWh, and transmission loss of 2373.23. It can be said that the loss of electrical energy is increasing almost every year.

Figure 2. Indonesia's Electric Energy Loss

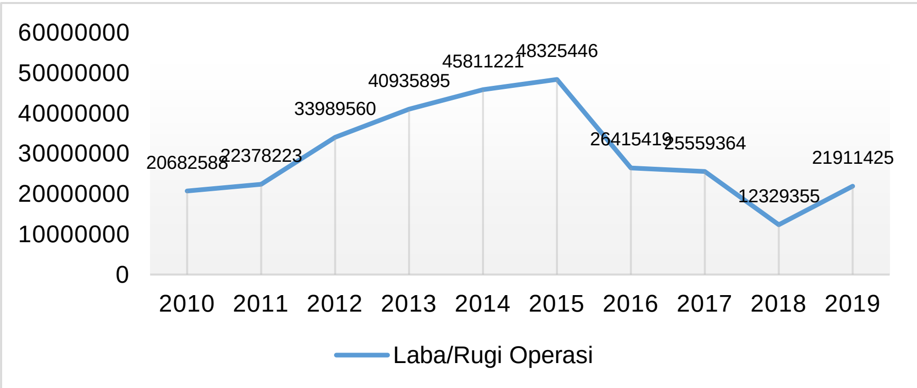


	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Transmisi	3,700	3,996	4,732	4,859	5,224	5,248	5,486	5,865	5,969	6,073
Distribusi	12,25	12,67	13,11	15,84	16,19	16,81	17,21	15,61	18,51	19,00

Source: PT.PLN, 2019

Figure 3 shows the operating profit/loss data in the form of the difference between the total operating income minus operating costs. Electricity income is derived from sales, connection costs, and subsidies, while operating costs come from purchasing electricity, fuel and lubricants, maintenance, staffing, depreciation of fixed assets, and other costs.

Figure 3. Operating Profit/Loss



Source: Statistik PLN, 2019

During 2010-2019 there were no losses during the electrical operation process. However, the net profit received by PLN has decreased since 2015. Although the profit in 2019 managed to increase again, this value is still far below the profit before 2015. Measuring the performance of power distribution companies is considered one of the most important issues for policymakers. Measuring and comparing the relative efficiency between power companies can help policymakers adjust various factors such as price and income (Sadjadi & Omrani, 2008).

Benchmarking techniques can be used to assess the production efficiency of a power distribution company to measure the company's performance and identify potential areas for further improvement (Thakur et al., 2006). The methods that are often used are the Stochastic Frontier Analysis (SFA) parametric model and Data Envelopment Analysis (DEA) nonparametric model which is considered a deterministic function. The deterministic function shows the absence of statistical inference as if the method is lacking in basic statistical applications so it is feared that the estimation results are biased (underestimate or overestimate) (Cooper et al., 2007).

Many studies have been conducted to measure the efficiency of electricity distribution to assess how well the company is performing. For example (Agrell et al., 2014) used 111 Norwegian electric power distribution companies from 1998 to 2002. Çelen (2013) analyzed the efficiency performance of 21 Turkish electricity distribution companies during the period 2002-2009. In Indonesia, for example, research by Fuiji & Kaneko (2011) used 22 electricity companies in 2002-2005. Hardiyan & Wahyudin (2021) studied the efficiency of electricity distribution in DKI Jakarta. However, the study had some limitations. First, mostly using short-term data, it does not fully capture efficiency changes. Second, the method used is deterministic but does not take into account the limitations of the method.

Based on the previous explanation, this study aims to measure the estimated efficiency of electricity distribution in 33 provinces in Indonesia. This study uses two variables as outputs and three inputs. The output used is the number of customers and the amount of electricity distributed, while the input uses the number of workers, installed capacity, and the length of the distribution network. Using a two-stage DEA analysis, first DEA BCC then DEA Bootstrap. DEA Boostrap Based on the procedure of Simar & Wilson (1998, 2000) was calculated to overcome the weakness of the BCC DEA method. It is expected that by using DEA bootstrap the resulting estimation is more efficient and accurate compared to other studies.

2. LITERATURE REVIEW

Efficiency is defined as the comparison between the actual output value obtained against the expected output. This value is a criterion for good and bad resource management to achieve the goals of an activity (Sumanth, 1984). This research will study the efficiency of electricity distribution in Indonesia, for this purpose efficiency will be related to the efficiency of the energy sector and the efficiency of the economic sector.

Energy efficiency is defined as the energy service provided per unit of energy input. Like almost all economic issues, the economics of energy efficiency is at its core a question of the balance of costs and benefits (Patterson, 1996). Energy efficiency can directly affect economic and environmental costs, security, and other costs of supplying and delivering the energy it replaces (Lovins, 2004). But there is not much literature that studies this. While economic efficiency is a term to estimate the results of an economic activity compared to the capital used (Geamănu, 2011).

3. RESEARCH METHODS

3.1 Data Envelopment Analysis (DEA)

Data envelopment analysis (DEA) is a non-parametric performance measurement approach to calculate the efficiency score of a homogeneous set of decision-making units (DMU) with several inputs and outputs (Emrouznejad & Yang, 2018). DEA is a linear programming-based technique to evaluate the relative efficiency of decision-making units, by comparing one DMU with other DMUs that utilize the same resources to produce the same output, where the solution of the model indicates the productivity or efficiency of a unit with other units. (Taylor, 2014). The ultimate goal of DEA is intended as a method for performance evaluation and benchmarking.

This study will use the DEA method with the BCC model developed by Banker et al. (1984) which is oriented towards the output. This model was chosen because the ratio between the addition of inputs and outputs is not the same (Variable Return to Scale) and the number of output increases every year. Assuming that there are n DMUs $(DMU_j,\ j = 1,2,\dots,n)$ that use m inputs $(x_i, i = 1,2,\dots,m)$ to produce $s\ (y_r, r = 1,2,\dots,s)$ then the output-oriented conventional BCC model can be written according to Banker et al. (1984) is,

$$Min \sum_{i=1}^{m} w_i x_{ij} + u_0$$

$$s.t. \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} w_i x_{ij} + u_0 \leq 0 \qquad j = 1,2,\dots,n$$

$$\sum_{r=1}^{s} u_r y_{rj} = 1$$

$$u_0\ free$$

$$w_i \geq \varepsilon, \quad i = 1,2,\dots,m$$

$$u_r \geq \varepsilon, \quad r = 1,2,\dots,s$$

One of the advantages of the DEA method is that it can determine to benchmark for DMUs that are not yet efficient. Benchmarking is the process of evaluating and imitating the best performing products, services, and organizational processes (Donthu et al., 2005). In addition, using DEA produces values for radial movement and slack movement on the output and input variables. These two values are the difference between the actual value (AV) and projected value (PV) of a variable from each DMU that is not yet efficient.

3.2 Data Envelopment Analysis Bootstrap

Nonparametric efficiency estimates such as data envelopment analysis (DEA) methods generally use linear programming techniques for calculating value estimates and are often characterized as deterministic. This shows that the method is lacking in basic statistical applications. Previous studies using this method have usually also provided estimates of the point of inefficiency, without a measure or even discussion of the uncertainty surrounding the estimate (Cooper et al., 2007).

Thus, a correction is needed in the DEA model so that the weaknesses of the DEA method can be avoided and the results of the analysis are unbiased. Currently, there is a growing set of tools for statistical inference in nonparametric efficiency estimation based on bootstrap methods. Efron (1979) provides an alternative approach to classical inference and hypothesis testing. In the case of DEA estimators with multiple inputs or outputs, bootstrap being a reasonable approach for hypothesis inference and testing, the bootstrap principle can be repeated to increase the confidence interval estimates (Cooper et al., 2007).

The bootstrap procedure used in this study follows (Simar & Wilson, 1998, 2000). The algorithm is as follows:

a. The DEA efficiency score was calculated first using the VRS-DEA.
b. DEA efficiency scores were also calculated using CRS and NIRS (nonincreasing

return to scale) to reflect the nature of returns to scale (RTS) for different operations. RTS is calculated by dividing the bootstrap result from the CRS assumption by the bootstrap result from the NIRS assumption.

c. The bootstrap procedure is then used to generate $\theta_i^* = 1,2,..,n$ by substituting $\hat{\theta}_1, \dots, \hat{\theta}_n$, yielding $\theta_{1b}^*, \theta_{2b}^*, \dots, \theta_{nb}^*$ where b is the iteration of the b from bootstrap.
d. Count bootstrap input, given by $x_{ib}^* = \left(\frac{\hat{\theta}_i}{\theta_{ib}^*}\right) x_i$
e. Using bootstrap input to get a DEA-bootstrap estimate of the efficiency score θ_{ib}^*.
f. Repeat all steps B times to produce a set of approximations $\{\theta_{ib}^*, b = 1, \dots, B\}$.

The mean value of the bootstrap estimator can then be used as an estimate of the DEA estimator. However, it is not bias-free. The bootstrap estimate of the bias of the DEA estimator is given by,

$$\widehat{bias}_i = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{ib}^* - \hat{\theta}_{in}$$

The term on the right represents the mean bootstrap efficiency score, and the second is the original DEA estimate of the efficiency score.

3.3 Research Variables

DEA allows multiple input-outputs to be considered at the same time without assuming data distribution. Several studies have proposed limiting the number of variables relative to the number of DMUs. In general, the number of input and output variables in the DEA model should not be more than one-third the number of DMUs (Sinuany-Stern & Friedman, 1998). The research will use input and output variables that have been widely used by previous studies.

The electrical energy sector around the world has undergone major reforms to increase efficiency and productivity. Especially seen in the distribution of electricity. The number of units of energy distributed is considered to be the main cost driver in the electric power system (Santos et al., 2011). The amount of electricity distributed is used as an output variable for service quality indicators, measuring the continuity of supply to customers. Distributed electricity is defined as the amount of electrical energy distributed by PLN to customers through the distribution system (GWh).

The output of electricity distribution relates to the services provided to customers, relations with the authorities, and their impact on the environment and society. According to Neuberg (1977) to determine the variable and total cost functions can be used variable output number of consumers and electricity distributed to customers. These two variables describe the elements of the electricity distribution service, network connection, and electricity supply.

The same result is shown by Jamasb and Pollitt (2000), using 20 benchmarking studies showing that the most widely used output variables are distributed electricity and the number of customers. In addition, research by Growitsch et al. (2009), Fillipini and Wetzel (2014), Bobde et al. (2018), Çelen 2013), Yang & Lu (2006), and Chen (2002) use the number of customers and the amount of electricity distributed as output in the DEA analysis of electricity distribution companies.

The number of customers is an important output to assess the efficiency of public service provision. Helping the delivery of high-quality services to customers and being one measure of the goodness of performance (Santos et al., 2011). The more electricity demand, the more electricity sold. This means that the income received by PLN is also getting bigger and optimizing the electricity that has been produced. Electricity is an indicator of economic and technological progress, an increase in the number of customers is the government's target to improve the welfare of the population.

Table 1. Operational Definition of Variables

No	Variables	Source	Definition
1.	Number of Customers	Growitsch *et al.* (2009) Bobde *et al.* (2018) Çelen *et al.* (2013) Chen (2002) Fillipini dan Wetzel (2014) Yang dan Lu (2006)	A customer is someone who uses products produced by a company. For jada companies, the customer is a person who uses services at the company.
2.	The amount of electricity distributed to customers	Growitsch *et al.* (2009) Agrell *et al.* (2014) Bobde *et al.* (2018) Çelen *et al.* (2013) Chen(2002) Fillipini dan Wetzel (2014) Fillipini dan Wild (2001) Kinnunen (2005) Yang dan Lu (2006) Korhonen dan Syrjänen (2003) Santos *et al.* (2011)	The amount of electrical energy distributed by PLN to customers through the distribution system
3.	Number of Labor	Agrell *et al.* (2014) Yang dan Lu (2006) Filipini dan Wild (2001)	Labor is a society that is in working age (15-64), or a society that is able to provide labor and participate in activities to produce output in the form of goods and services of a company.
4.	Installed capacity	Çelen *et al.* (2013) Chen (2002) Bobde *et al.* (2018) Santos *et al.* (2011) Yang dan Lu (2006)	The designed output amount can be generated by a facility or capacity registered with the relevant authority
5.	Distribution network length	Bobde *et al.* (2018) Çelen *et al.* (2013) Santos *et al.* (2011) Yang dan Lu (2006)	The length of the distribution network is the total of the medium voltage network (JTM) and the low voltage network (JTR)

Table 1 shows the operational definitions of output and input variableswhich were used in this study. Inputs are variables used by industry to produce output (Korhonen & Syrjänen, 2003). According to Jamasb and Pollitt (2000), three input variables that are most widely used in research, such as the labor, installed capacity, and operational expenses. In addition, the length of the distribution network is also found as an input variable that is often used in research. For example used by Bobde & Tanaka (2018), Çelen (2013), Santos et al. (2011), and Yang & Lu (2006). The length of the distribution network (JTM and JTR) is considered a cost variable because it represents one of the assets owned by the company

Efficiency and productivity in electricity generation are largely determined by technological factors, but in the electricity distribution sector, these are mainly determined by efficient management and use of labor (Kumbhakar & Hjalmarsson, 1998). Because general expenditures are most easily controlled by distribution managers, the amount of labor used represents general costs as an input variable. Labor represents all the people involved in turning resources into goods or services that can be purchased. It is therefore important that the workforce is properly educated and trained to ensure that they can produce the highest quality and efficiency outputs. When labor productivity increases, it is expected to produce more output for the same relative amount of work.

Electricity distribution costs are usually broken down into capital costs and operating costs which include maintenance costs. In this study, installed capacity is used as a proxy for capital stock. Even in the short term installed capacity is a variable that is considered an environmental factor because there is evidence in the data that distribution companies can control it (Santos et al., 2011).

About operating costs, the installed capacity was chosen because it provides more reliable use of inputs, some distributors outsource some of their services. The capital stock for the variable cost function model is defined as the maximum distribution transformer demand in megawatts. This definition represents a measure of the capacity of the stock of capital and reflects the maximum output that a particular network can handle at one point in time (Filippini, 1996).

Installed capacity is important considering the government's goal to increase national electricity consumption. Installed capacity is related to electricity demand and the amount of electricity supplied. The demand for electricity that is smaller than the installed capacity will cause losses because it incurs high load costs such as system operating costs, employee salaries, fuel, and electricity maintenance. Optimal installed capacity also shows an increase in electricity distributed by PLN. Electricity is not stored as inventory but is used by customers so that PLN can increase revenue. Therefore, the installed capacity is suitable to be used as input for the output of the number of customers and distributed electricity

In addition to installed capacity, the length of the distribution is also used as a proxy for capital stock. This input variable is not considered a factor that can be controlled by the company, even in the short term (Santos et al., 2011). The length of the network is used as an indicator of the geographical spread of the subscriber. Network length can describe the actual distance to each subscriber. The higher geographic spread of subscribers is assumed to lead to higher costs due to the longer cable length required. The distribution network is concerned with the quality of the power of electricity that is distributed to customers.

Data on the workforce and length of the distribution network increases as the number of customers increases. These two variables become a measure of direct service to customers. The more customers, the demand/need for electricity also increases, to provide these needs, PLN requires more manpower. The workforce is a resource for maintaining power generating equipment, providing services to the community, repairing networks, controlling electrical performance, electricity management, etc.

The length of the network is a measure of the geographical spread of the customer, the closer the distance to the customer, the lower the distribution network shrinkage. A large number of customers causes the distance between the network and the load to be close and can reduce losses and increase the efficiency of electricity distribution.

4. FINDINGS

4.1 DEA BCC Result

The electricity distribution process is related to the activity of distributing electricity from the generator to the consumer through the distribution network. The closer the distance between the customer and the distribution network reduces the possibility of shrinkage. This means that the distance decreases, and the shrinkage increases over a large conducting area.

The results of the analysis show that the average efficiency of electricity distribution in 2010-2019 is 74.9%. Almost all provinces in Java were efficient in that year. The average efficiency in Java is 98.9%. Sumatra Island 73.4%, Sulawesi Island 69.2%. NTT 51.5%, Bali 79.1%, NTB 96.9%. Kalimantan Island 59.4%. Papua Island 66.9%, and Maluku Island 65.1%. It can be seen that the efficiency of Java Island is better than Other Islands.

4.2 DEA Bootstrap Result

DEA has many advantages, especially its ability to accommodate many inputs and outputs without determining the distribution of data, DEA does not consider the nature of random data sampling but tends to overestimate the actual efficiency value. DEA bootstrap helps overcome these shortcomings by maintaining the advantages of conventional DEA methods. In addition, it provides a confidence interval and allows hypothesis testing of power distribution performance (Nguyen et al., 2016).

To overcome the weakness of the DEA method, the estimation results obtained will be re-analyzed using DEA Bootstrap with 3000 repetitions. The results of the analysis are in Table 2, the average DEA value is greater than the bootstrap DEA confidence interval. This shows that DEA estimates the overestimated electricity distribution compared to the actual efficiency value. In addition, the average standard deviation of the bootstrap DEA in 2010 was 0.1396, indicating a significant variation in the bootstrap DEA, which was smaller than the average DEA standard deviation of 0.1951.

Table 2. DEA BCC and DEA Bootstrap Average 2010-2019

Year	DEA BCC	SD DEA BCC	DEA Bootstrap	SD DEA Bootstrap	Bias	Lower Limit	Upper Limit
2010	0,735	0,195	0,630	0,140	-5,518	0,549	0,725
2011	0,728	0,186	0,620	0,133	-5,049	0,545	0,717
2012	0,783	0,181	0,685	0,135	-6,384	0,601	0,774
2013	0,783	0,171	0,680	0,122	-5,878	0,598	0,774
2014	0,755	0,203	0,646	0,154	-5,126	0,559	0,745
2015	0,753	0,218	0,642	0,165	-5,197	0,551	0,743

Year	DEA BCC	SD DEA BCC	DEA Bootsrap	SD DEA Bootstrap	Bias	Lower Limit	Upper Limit
2016	0,749	0,219	0,635	0,163	-4,971	0,545	0,740
2017	0,737	0,217	0,619	0,153	-4,608	0,532	0,726
2018	0,736	0,223	0,618	0,164	-4,536	0,528	0,726
2019	0,729	0,221	0,610	0,158	-4,465	0,523	0,718

The average electricity distribution efficiency in Sumatra is 62.1%, Kalimantan is 53.9%, Sulawesi is 59.4%, Maluku is 58.6%, Papua is 59.3%, Bali is 69%, and Nusa Tenggara is 67.4%. It can be seen that the average efficiency of electricity generated is smaller than using DEA BCC. The conclusion that conventional DEA tends to overestimate the actual efficiency is also obtained in research (Andor & Hesse, 2013; Chen & Wang, 2020; Liu et al., 2013; Nguyen et al. al., 2016).

Overestimation of the efficiency of DEA can affect the rationality of targeting, and may even invalidate this method in targeting (Chen, 2020). Therefore bootstrap DEA is better to use because the resulting efficiency estimates are consistent, unbiased, and insensitive to sample size, provide a confidence interval for efficiency scores and allow testing of firm performance hypotheses (Nguyen et al., 2016).

The analysis using DEA BCC and DEA Bootstrap gives the same conclusion that the Provinces in Java Island have better average efficiency and are above the average total efficiency value. The proximity between the power source and the customer is one of the conveniences of the electricity distribution process and reduces the possibility of losses. Statistical data shows that the number of customers and electricity distributed is still dominated by the provinces in Java. In addition, the variables of labor input, installed capacity, and network length were also found to be the most abundant in this region.

Shows geographical advantages to reduce the shrinkage of the electricity distribution network compared to other provinces. The high number of customers is proportional to the high demand for electricity, and in the end, it will maximize the electricity produced and installed capacity by the company. The length of the distribution network describes the geographical distribution of customers, because customers are concentrated in this area, the distance between the network and customers is small. Optimizing the length of the network in the electricity distribution process.

The workforce used by each province also depends on the electricity needs of each province. The higher the electricity demand, the more labor there is. These workers are needed to provide the best possible service to customers. From these results, it can be seen that the input of labor, installed capacity, and network length will adjust to the needs of the customer's electricity demand as a component of the process of distributing electricity from the generator to the consumer. The closer the subscriber and the cable are, the less likely it is to lose the network.

4.3 DMU Optimization

For inefficient provinces, it will produce radial movement or slack movement values in output and input variables, the value is the difference between actual value (AV) and projected value (PV). As shows at Table 3, the output of the number of customers and electricity distributed experienced inefficiency during 2010-2019. The results of the overall analysis show the excess use of labor and installed capacity. While the variable length of the distribution network is only an obstacle in the provinces of Aceh, Bengkulu, Jambi, West Sumatra, and North Sumatra.

Table 3. DMU Optimization

		Year									
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Y1	RM	211182	266117	212423	253007	315444	365303	371421	457148	432188	485660
	SM	856	5498	1117	0	12564	2993	8282	13945	15703	13790
	PV	1413989	1576681	1714112	1880384	2081569	2211881	2281058	2755248	2617507	2783605
Y2	RM	527	599	505	623	782	880	875	881	822	1079
	SM	206	3017	298	331	495	277	200	347	513	194
	PV	4343	7645	6086	6656	7308	7347	7759	8005	8293	8774
X1	RM	0	0	0	0	0	0	0	0	0	0
	SM	-230	-159	-85	-74	-108	-123	-155	-160	-360	-453
	PV	965	1056	1439	1484	1451	1483	1442	1578	1375	1394
X2	RM	0	0	0	0	0	0	0	0	0	0
	SM	-188	-232	-12	-58	-291	-176	-117	-227	-373	-367
	PV	688	727	1178	1159	1119	1255	1560	1532	1547	1662
X3	RM	0	0	0	0	0	0	0	0	0	0
	SM	-52	-92	-131	0	-1795	-444	-643	-173	-276	-103
	PV	19190	19689	21932	23595	25415	26910	25784	28582	28480	29590

The results of the analysis also show that there is an excess of the installed capacity variable. Installed capacity is related to electricity demand. The demand for electricity that is smaller than the installed capacity will cause losses because it incurs high costs such as system operating costs, employee salaries, fuel, and electricity maintenance.

Several things that PLN can do to optimize the installed capacity that has been produced are by increasing the demand for electricity by encouraging the use of cars and electric stoves. Prediction of electricity demand is also important. In addition, another PLN strategy to overcome excess installed electricity capacity is to export electricity to ASEAN countries through the ASEAN Power Grid program. ASEAN Power Grid is a form of regional electric power interconnection cooperation between ASEAN countries.

4.4 Benchmarking

In addition to efficiency estimates, the DEA method also produces benchmarking for the identification of peer groups from each province (DMU). Based on the analysis that has been done, there are a maximum of four peer groups. Peers with the largest Lambda value will be used as potential DMUs, and become a means of improvement in the service and implementation of electric power distribution (Thakur et al., 2006).

4.5 Discussion

The fulfillment of electrical energy needs is hampered due to inefficiencies in distribution and resulting in losses. Analysis using conventional DEA and DEA Bootstrap gives the same conclusion that the proximity between the power source and the customer becomes one of the conveniences of the electricity distribution process and reduces the possibility of losses. The length of the distribution network describes the geographical distribution of customers, because customers are centralized in this region, the network distance and small load end up reducing the possibility of shrinkage.

The results also showed that there was an excess of labor and installed capacity.

Downsizing is a strategy that can be carried out by PLN to overcome excess manpower. However, this reduction in labor can have a negative impact on all parties. Such as loss of key workers, reduced trust in the company, increased workload, lack of concentration, and reduced job satisfaction (Farel & Mavondo, 2004).

Rather than downsizing, some organizations have adopted a reorientation approach strategy (Mishra and Mishra, 1994). Reorientation becomes part of an ongoing process for continuous improvement, and theoretically synchronized with business strategy (Mone, 1997). However, managers pursuing a reorientation strategy, must necessarily engage in a much more difficult intellectual task to decide how to reorient the organization, combined with the challenges associated with building support, generating commitment and developing a shared vision. The result of such a strategy may not be noticeable at first, meaning that the manager needs confidence, and a puzzle, of qualities that are not always abundant.

Target setting is an important reason the DEA is widely applied to analyzing efficiency. However, it is often common when analyzing using conventional DEA, so it is recommended to use a bootstrap DEA to overcome the shortcomings of conventional DEA. The efficiency estimates produced by the bootstrap DEA are consistent, unbiased, and insensitive to sample size (Nguyen, 2016). DEA analysis depends on the selection of input and output variables used, further research is expected to use certain analytical methods to select input and output variables, such as backward regression.

5. CONCLUSION(S)

During 2010-2019, there was an excess of the variable number of workers and installed capacity. The suboptimal use of these two variables causes inefficiency in electricity distribution. The surplus of labor can be overcome by reorienting the company, while the installed capacity by encouraging electricity demand through electric stoves and cars, as well as exporting electricity to ASEAN countries through the ASEAN Power Grid program.

The length of the distribution network shows the geographical distribution of customers, the closer the distance to the customer, the easier it is to distribute electricity and reduce the possibility of losses. The length of the network is efficient for the efficiency of electricity distribution. The variable input of labor and installed capacity adjusts to the needs of customer electricity demand as a component of the process of distributing electricity and quality of service to customers.

The estimation results using DEA bootstrap show that none of the provinces are efficient during 2010-2019. Efficiency estimation using DEA BCC tends to overestimate the actual efficiency value (overestimate). So the analysis using DEA bootstrap is better to use. And in general, the results of the efficiency performance analysis in Java are better than in other provinces.

6. REFERENCES

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