Journal of Engineering Science and Technology
Vol. 14, No. 1 (2019) 479 - 488

DATA ENVELOPMENT ANALYSIS: THE EFFICIENCY STUDY OF FOOD INDUSTRY IN INDONESIA

AMIR MACHMUD[1,*], EENG AHMAN[1], PUSPO DEWI DIRGANTARI[1], IKAPUTERA WASPADA[1], ASEP BAYU DANI NANDIYANTO[2]

[1]Faculty of Business and Economic Education, Universitas Pendidikan Indonesia, Jl. Dr. Setiabudi no 229, Bandung 40154, Indonesia
[2]Departemen Kimia, Universitas Pendidikan Indonesia, Jl. Dr. Setiabudi no 229, Bandung 40154, Indonesia
*Corresponding Author: amir@upi.edu

Abstract

This study aimed to determining and analyse the level of efficiency of the food industry in Indonesia using Data Envelopment Analysis (DEA). This study was motivated because there is a suboptimal condition in the food industry in Indonesia. The research method used an analytical descriptive method, which employed data collection techniques through interviews, questionnaires, and literature studies. Data were obtained from the leading food industry players in Indonesia (about 16 companies). Data were collected and analysed using DEA through Constant Return to Scale (CRS) and Variable Return to Scale (VRS) models. The study results showed that the use of food industry production factors in Indonesia is not yet optimum, confirmed by the VRS and CRS values of less than one. The main reason for the suboptimal production is due to the condition of raw materials and labour, giving ideas for the consideration careful improving the efficiency in the production are This finding implies that creating efficiency with the Data Envelopment Analysis method needs to optimize the use of raw materials and labour.

Keywords: Constant return to scale (CRS), Data envelopment analysis efficiency (DEA), Food industry, Variable return to scale (VRS).

1. Introduction

The general, obstacle faced by food industry entrepreneurs in Indonesia is the price of production factors, either directly or indirectly. This condition has an impact on the high cost of production, which eventually raises the price of output in the market. This condition certainly decreases the company income and forces some entrepreneurs to stop the production process because of inefficiency [1]. Debreau [2] and Koopmans [3] were first introduced this definition of efficiency. Farell [4] explained that then, the definition has been widely used in the production rate and efficiency [4].

Efficiency is an important indicator in measuring the overall performance of a company's activities. Data Envelopment Analysis (DEA) is a tool to measure the efficiency level that measures the operational efficiency of an industry based on each company in an industry. Charnes et al. [5] presented the model when DEA was introduced over 40 years ago, where they can resize the overall efficiency into a linear programming model. DEA empirical applications are found in many sectors including education [6], bank-related [7-9], manufactures [10], logistics [11], telecommunications [12], healthcare-related [13], and even sport [14, 15].

This DEA is a non-parametric approach. Therefore, it does not require an initial assumption of a production function. It can identify the units used as a reference for inefficient units. There are two models often used in this approach, namely Constant Return to Scale (CRS) and Variable Return to Scale (VRS). DEA is a mathematical program for optimizing the measurement of the technical efficiency of an economic activity unit (UKE). Then, it compares to other UKEs [5, 16, 17].

2. Food Industry in Indonesia

Food and beverage industry in 2015 continued to show positive performance and grown to 9.82% (or Rp. 192.69 trillion). The industries that contributed to fulfilling the people's living needs are required to implement good food safety management and management systems starting from raw material selection, processing, packaging, distribution, and trade. The food and beverage industry also has an important role in the development of the industrial sector, which is shown in Fig. 1.

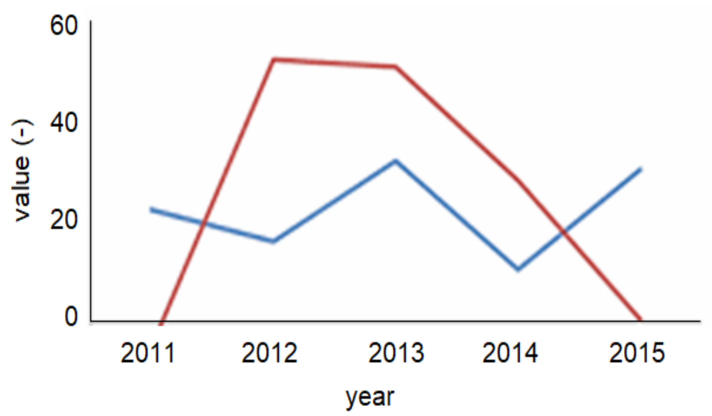

Fig. 1. Growth of the food industry in Indonesia.

The contribution of the food Industry in Indonesia to Gross Domestic Product (GDP) of the non-oil and gas industry was the largest compared to other subsectors, reaching 33.6% in 2016. The growth reached 9.82%, informing that the food industry supported the growth of non-oil and gas industry with 4.71% of GDP.

Meanwhile, the contribution of export value of food and beverage products including palm oil in January-September 2016 reached USD 17, 86 billion. This achievement makes the trade balance to have positive value (compared to the value of imports in the same period of USD 6, 81 billion). Viewed from the realization of investment in the food industry sector in 2016, it amounted to Rp. 24 trillion (USD 1, 6 billion). The profile of the contribution of the food industry in Indonesia is presented in Fig. 2.

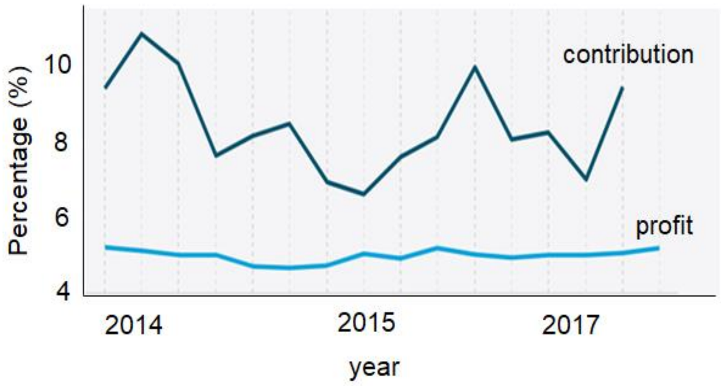

Fig. 2. Contribution of the food industry in Indonesia to GDP.

In facing these challenges, the government continues to create an investment climate and provide support in the development of the food and beverage industry. According to Andika and Valentina [18] and Nandiyanto [19], the strategic supports include providing investment incentives, facilitation of raw materials supply, and infrastructure development in supporting connectivity to improve effectiveness and efficiency of the distribution of raw materials and products.

3. Basic DEA Model

The basic efficiency measurement utilized by DEA is calculated using the ratio of output to input. This measurement is good, but it is applicable only to some cases for a single input and output. In 1957, Farrell [4] implemented this basic concept. This report developed the efficiency frontier analysis. The analysis using Farrell's method [4] requires two-dimensional data where all data are plotted on a two-axis graph.

Charnes et al. [5] invented the first calculation model. This model introduces an efficient measurement for each Division Making Unit (DMU). The model calculated the maximum ratio between the weighted output and the weighted input. Each weight value is determined by the specific condition, in which, the same ratio for each DMU must have a value less than or equal to one. The size of the DMU efficiency can be calculated by solving the following mathematical programming problems:

$$\max_{u,v} h_0(u,v) = \frac{\sum_{r=1}^{s} u_r y_{r0j}}{\sum_{i=1}^{s} v_i x_{i0j}} \text{ subject to } \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1,2,3 \ldots, jo, \ldots, n$$

$$u_r \geq 0, r = 1,2, \ldots, s;\ v_i \geq 0, i = 1,2, \ldots, m$$

By x_{ij} a is the input value observed by the$i$ of the DMU to $j$and ;x_{ij} > 0 for $i = 1,2,3, \ldots .m$ and $j = 1,2, \ldots .n$. Likewise with condition, which, y_{rj} is the output value observed with type - i from DMU to $y_{rj} > 0 = 1,2, \ldots m$; for and. $j = 1,2, \ldots .n$, the correlation can be written as the variable of *u* and *v*. The variables of u_r and v_i are the weight values for determining the above programming problems. By following Charnes-Cooper transformation, the solution can be chosen. The solution (u, v) can be representative with condition:

$$\sum v_i x_i = 1$$

Thus, the linear programming is obtained, which is equivalent to a linear fractional programming problem. The divisor in the above efficiency measure is made equal to that of the transformed linear matter. It can be written by

$$\max{}_{z_0} = \sum u_r y_{r0} \text{ ; subject to } \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij}$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$u_r \geq 0, r = 1,2, \ldots, s;\ v_i \geq 0, i = 1,2, \ldots, m$$

The above linear programming problems are often called CCR models with output-oriented outputs. Maximization is done by selecting virtual multiplication (i.e., weight values) of u and v that produce the greatest rate virtual Output / virtual Input". The problem can be written for each DMU0 as:

$$\min_{\lambda} = \Theta_0 \text{ ; subject to } \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0,} r = 1,2, \ldots, s$$

$$\Theta_0 X_{i0} - \sum_{j=1}^{n} \lambda_j y_{rj} \geq 0\ i = 1,2, \ldots, m$$

$$\lambda_j \geq 0, j = 1,2, \ldots, n$$

The above linear programming problem obtains the optimal solution $\Theta_0 *$, which is the value of efficiency, also known as the technical efficiency or efficiency of the CCR, for a particular DMU_0. Efficiency value for all DMUs obtained by repeating the above process for each DMU_j, $j = 1,2, \ldots n$. The values are always smaller or equal to one. For DMUs obtaining $\Theta_0 * = 1$ is called relatif efficiency, where the combination of "virtual" input and output lies in the efficient frontier. For scalable return variables, it is necessary to add convexity conditions on the values of weights and λ, i.e., by entering in the model above the following limits:

$$\sum_{j=1}^{n} \lambda_j = 1$$

The result of the DEA model that provides the scalable return variable is called the BCC model [16]. The BCC model with input-output oriented for DMU0 can be written by:

$$\min_{\lambda} = \ \Theta_0 \ ; \text{ subject to } \sum_{j=1}^{n} \lambda_j y_{rj} \ \geq \ y_{r0,} r = 1,2, \dots , s$$

$$\Theta_0 X_{i0} - \sum_{j=1}^{n} \lambda_j y_{rj} \ \geq \ 0 \ i = 1,2, \dots , m$$

$$\sum_{j=1}^{n} \lambda_j = 1 \ ; \ \lambda_j \geq 0 \ j = 1,2, \dots , n$$

BCC efficiency values are obtained by running the above model for each DMU. The performance efficiency measures of BCC are called pure technical efficiency, which related to the values obtained from the model that allows scalable return variables. Thus, the scale can be eliminated. If we have obtained the value of pure technical efficiency, the scale efficiency can be calculated. The calculation can be written by:

SE = Technical Efficiency/Pure Technical Efficiency

In the DEA, the model or commonly known as a constant value as a return value, the ratio of output and input values is constant. The addition of input and output values are compared. In the DEA, the BCC model is also known as the variable return to scale. The increases in input and output are not in the same proportion. Increasing the proportion of “increasing return to scale” (IRS) or “Decreasing Return to Scale” (DRS) can be described in Fig. 3. Cooper et al. [20] presented the performance measurements with DEA, CCR and BCC models, with input and output orientation, which are accomplished with the help of DEA Solver Learning Version software.

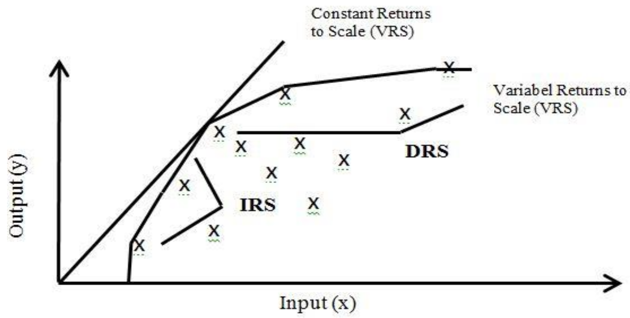

Fig. 3. Comparison of CCR and BCC model was adopted from literature [2].

4. Method

This study used descriptive analytics with a saturated sample technique. The population in this study were 16 food industries in West Java, Indonesia. Data collection was done through observational studies, interviews, questionnaires, and literature studies. The data collected were then analyzed by DEA through a non-parametric frontier approach. This study used 2 models, namely CRS (Constant Return to Scale) and VRS (Variable Return to Scale). Detailed information is shown in the following

- Model Charnes, Cooper, Rhodes (CCR). The model developed by Charnes et al. [5], which used the assumption of CRS, in which, the ratio of inputs and outputs of a company is the same.
- Model Banker Charnes Cooper (BCC). Banker et al. [16] introduced the model, which was developed in 1984, is a continuation of the CRS DEA model, the Return to Scale (VRS) variable and is only applicable if all firms operate at optimal scales.

The CCR (CRS) model reflects (multiplication) technical efficiency and scale efficiency, while the BCC (VRS) model reflects the technical efficiency only. Thus, the relative scale efficiency is the ratio of the efficiency of the CCR (CRS) model and the BBC (VRS) model. The correlation is shown as [8]

$Sk = qk$, CCR/qk, BCC

If the value of $S = 1$, the value is operated at the best scale efficiency measure. If the S value is less than 1, there is still scale inefficiency in the UPK. Thus, the value (1-S) indicates the level of scale inefficiency of the UPK. This is because the UPK is technically efficient. Thus, the existing inefficiency comes from the scale [8].

By comparing the assumption of CRS with VRS, the calculation can be done. If the operational size of a work unit is reduced or enlarged, its efficiency value will still decrease. Work units on the Efficiency Scale are work units that operate on optimal returns to scale. There are three conditions of Returns to Scale (RTS) [20]: Decreasing returns to scale, Constant returns to scale, and Increasing returns to scale.

5. Results and Discussion

5.1. Description of the technical efficiency of food industry in Indonesia

To measure and analyze the efficiency of the food industry in Indonesia, there are two models (i.e., CRS and VRS). This technical efficiency resulted in the value of technical efficiency among the units of economic activity (UKE) under study. The UKE, which has a maximum efficiency of 100, indicates that the UKE is suited to an efficient condition. If the UKE has a value of less than 100, the UKE is not yet in an efficient position. Based on the results of calculations using DEA, the result can be written in Table 1.

Table 1 shows that efficiency of the technique resulted from the calculation using DEA method with the assumption of CRS from respondents in Indonesia is still at the level of less than 100% (inefficient) with the number of 10 respondents or about 63,5%. The average technical efficiency level of the whole food industry in Indonesia from the calculation with the assumption of CRS is about 84.6% (inefficient).

Table 2 presents the calculation used the VRS model to determine the level of efficiency using the VRS model in the food industry. Table 2 shows that the efficiency resulting from the calculation using the DEA method with the assumption of VRS with 16 respondents of food entrepreneurs in Indonesia is at less than 100% (inefficient) with 3 respondents or 18.75 of the overall respondents. Food industry land is at 100% (efficient) level of 81.25% or about employers. The average technical efficiency level of all food industries in Indonesia using VRS assumption calculation is about 97.7% (inefficient).

Table 1. Efficiency technique in the food industry in Indonesia with CRSE model.

Technical facility (%)	Frequency	Percentage (%)
0-99	10	63.50
100	6	37.50
Total	16	100.00
Average		**84.60**

Table 2. Efficiency rate in the malfunctioning food industry in Indonesia with VRS efficiency.

Technical efficiency (%)	Frequency	Percentage (%)
0-99	3	18.75
100	13	81.25
Total	16	100.00
Average		**97.70**

5.2. Level of efficiency achievement and input target calculation in food industry

In this study, efficiency improvements in the inefficient food industry were done with a table of target values obtained from calculations using DEAP software. The average calculation is available in Table 3.

Based on Table 3, the average target value and achieved input variable CRS model has not reached optimum efficiency. Calculation of the average table of target values with the VRS model as seen in Table 4. Based on Table 4, the average target value and achieved input variables VRS model has not reached optimum efficiency. The results are in line with previous research [11-14].

Table 3. Average calculation of table of target values of food industry entrepreneurs inefficient CRS model.

Input	Average		
	Actual	Target	Achieved (%)
Capital	70,249,387	17,079,343	47.05
Labor	1,372,241	961,389	72.12
Raw material	5,868,708	4,229,283	73.08
Fuel	970,845	511,347	60.31
Helper material	353,475	149,668	55.43

Table 4. Calculation of average table of target values of food industry in Indonesia.

Input	Average		
	Actual	Target	Achieved (%)
Capital	2,770,972	1,328,982	61.80
Labor	1,710,278	1,496,183	87.80
Raw material	5,617,500	4,890,101	87.80
Fuel	963,652	757,200	80.57
Helper material	531,000	175,194	59.70

5.3. Food production scale screening in Indonesia

The calculation of efficiency through the relative efficiency of the food industry in Indonesia is in Table 5. Based on Table 5, the relative scale of the food industry in Indonesia is 0.868. This means that the *S* value is still less than one with a difference of 0.132. This shows that the food entrepreneurs in Indonesia have not been on an optimum efficiency scale yet. It is due to some inputs that have not been optimum including auxiliary materials, capital, fuel, and labour in both the CRS and VRS models. From DEA model, using CRS approach, some inputs are in inefficient condition, whereas in VRS model the input is an inefficient condition. Thus, efficient UKE with CCR model also means efficient scale, while efficient UKE with BCC model but inefficient with CCR model means having scale inefficiency.

Table 5. Results calculation of efficiency through relative scale efficiency.

UKE (Economic Activity Unit)	Average efficiency (%)
Rate production food industry (CRS)	84.60
Rate production food industry (VRS)	97.70
Relative scale level	0.87

This is because the UKE of technique is efficient. Thus, the inefficient condition comes from scale. The result of the calculation of the relative scale shows that the industry still has not reached optimum efficiency. This can be seen from the results of technical efficiency analysis using CRS and VRS assumptions. This is confirmed from the calculation of two assumptions. Firstly, based on the assumption of CRS, it was found that 10 entrepreneurs were inefficient and 6 entrepreneurs were in an efficient condition with an average technical efficiency of 84.6%. Secondly, based on the VRS assumption, three entrepreneurs are in inefficient condition and 13 entrepreneurs are the inefficient condition for the food industry with a mean of technical efficiency equal to 97.70%. In terms of scale, production of the food industry in Indonesia using the DEA approach is in Decreasing Return to Scale stage [4, 5, 9, 20].

According to the result of analysis about production scale based on a non-parametric approach with the DEA method through research of relative scale, the level scale of the food industry obtained a value equal to 0.868. This indicates that the scale of the food industry business in Indonesia is in the Decreasing of Return to Scale. Thus, it can be interpreted that the proportion of additional factors of production will result in additional production, which is smaller. This scale implies that with the addition of each factor of production of one unit, it will increase the output of 0.868 units. It means that input should be reduced in order to meet the optimum output.

6. Conclusion

Based on the results of research and discussion, the use of production factor in the food industry in Indonesia using the DEA method has not reached optimum efficiency. This is evidenced by the result of the calculation assuming CRS, which found that about 10 entrepreneurs are in inefficient condition and six entrepreneurs are the inefficient condition. As for the VRS model, about three entrepreneurs are in inefficient condition and 13 entrepreneurs are in an efficient state. The scale of industrial production of food in Indonesia with the DEA method is in the production stage decreasing returns to scale. This indicates that the scale of the food industry in Indonesia is at Decreasing scale return to scale. In this sense, it means that the proportion of the additional factor of production will produce additional production, which is smaller. This finding implies that in order to create a company that has not yet achieved efficiency, the optimal allocation of production factors is needed. This can be done by increasing competency capabilities through technical and product training.

Acknowledgements

RISTEK DIKTI (grant-in-aid Penelitian Dasar Unggulan Perguruan Tinggi (PTUPT) and Penelitian Unggulan Strategis Nasional (PUSN)) is acknowledged

References

1. Machmud, A; Nandiyanto A.B.D; and Dirgantari, P.D. (2018). Technical efficiency chemical industry in Indonesia: Stochastic Frontier Analysis (SFA) approach. *Pertanika Journal of Science and Technology*, 26(3), 1453-1464.
2. Debreau, G. (1951). The coefficient of resource utilization. *Econometrica* 19, 273-290.
3. Koopmans, T.C. (1951). An analysis of production as an efficient combination of activities. *Activity Analysis of Production and Allocation*. Cowles Commission for Research in Economics, Monograph No. 13, Wiley, New York.
4. Farrell, M.J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3), 253-290.
5. Charnes, A.; Cooper, W.W.; and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.
6. Bessent, A.; Bessent, W.; Kennington, J.; and Reagan B. (1982). An application of mathematical programming to assess productivity in the Houston independent school district. *Management Science*, 28(12), 1355-1367
7. Thanassoulis, E. (1999). Data envelopment analysis and its use in banking. *Interfaces*, 29(3), 1-13.
8. Machmud, A.; and Rukmana. (2010). *Bank syariah teori, kebijakan dan studi empiris di Indonesia*. Jakarta Timur, Indonesia: PT. Penerbit Erlangga.
9. Ebrahimnejad, A.; Tavana M.; Lotfi, F.H.; Shahverdi, R.; and Yousefpour, M. (2014). A three-stage data envelopment analysis model with application to banking industry. *Measurement*, 49, 308-319.

10. Wahab, M.I.M.; Wu, D.; and Lee, C.-G. (2008). A generic approach to measuring the machine flexibility of manufacturing systems. *European Journal of Operational Research* 186(1), 137-149.
11. Xu, J.: Li, B.; and Wu, D. (2009). Rough data envelopment analysis and its application to supply chain performance evaluation. *International Journal of Production Economics*, 122(2), 628-638.
12. Cooper, W.W.; Park, K.S.; and Yu, G. (2001). An illustrative application of IDEA (imprecise data envelopment analysis) to a Korean mobile telecommunication company. *Operations Research*, 49(6), 807-820.
13. Jacobs, R. (2001). Alternative methods to examine hospital efficiency: Data envelopment analysis and stochastic frontier analysis. *Health Care Management Science* 4(2), 103-115.
14. Cooper, W.W.; Ruiz, J.L.; and Sirvent, I. (2009). Selecting non-zero weights to evaluate effectiveness of basketball players with DEA. *European Journal of Operational Research*, 195(2), 563-574.
15. Sexton, T.R.; and Lewis, H.F. (2003). Two-stage DEA: An application to major league baseball. *Journal of Productivity Analysis*, 19(2/3), 227-249.
16. Banker, R.D.; Charnes, A.; and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
17. Rusydiana, A.S.; and Smart, T. (2013). *Mengukur tingkat efisiensi dengan Data Envelopment Analysis (DEA): Teori dan aplikasi.* Bogor, Indonesia: SMART Publishing.
18. Andika, R.; and Valentina, V. (2016). Techno-economic assessment of coal to SNG Power Plant in Kalimantan. *Indonesian Journal of Science and Technology* 1(2), 156-169.
19. Nandiyanto, A.B.D. (2018). Cost analysis and economic evaluation for the fabrication of activated carbon and silica particles from rice straw waste. *Journal of Engineering Science and Technology* (*JESTEC*), 13(6), 1523-1539.
20. Cooper, W.W.; Seiford, L.M.; and Tone, K. (2002). *Data envelopment analysis.* A comprehensive text with models, applications, references and DEA-solver software. Dordrecht, The Netherlands: Kluwer Academic Publishers.