# Determining the performance levels of SMEs in frozen food manufacturing sector in Selangor

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Frozen convenience food has become a necessity for Malaysian regardless the race, age, gender and income level. The demand of ready-to-eat or ready-to-serve products has increased each year as people need to be more effective in managing time and money. The increasing in demand has required the manufacturers to continuously meet the needs of products. Therefore, the efficiency analysis is conducted to assess the performance of SME frozen food manufacturer firms in Selangor. Through the study of past literature and the availability of data, four input variables; fixed asset, current asset, cost of sales and share capital while total of sales as output variable are identified and are used to measure the efficiency level of each firm. Data Envelopment Analysis approach is used to evaluate the efficiency score and two different approaches are compared to select the suitable model to rank the firms using the efficiency score obtained from CCR-DEA method. DEA methods reveals that from thirteen firms, eight are efficient while another five firms are inefficient. This study discovered that Cross Efficiency is more applicable to provide the complete ranking. The third objective is to suggest improvement to increase the efficiency of inefficient firms. Hence, the progress measure in context dependent DEA is employed to achieve the best efficiency frontier. The firms with higher progress score needs more improvement while the lower progress score indicates less improvement to achieve the best practice frontier. The target inputs are computed by using progress score and presented as the suggestion for improvement for each inefficient DMUs.

## 1. Introduction

Performance measurement system is a course to assist organizations effectively doing business and efficiently accomplishing goals. It is an information system, whereby is used to evaluate both individual and organizational performance. It is generally used by business and company to initiate improvements and to help achieving the objectives and targets by recognizing the inhibiting factors and optimizing the essential resources. For that reason, the first step to be taken is to develop and implement a system in order to improve and achieve a high quality of business. According to [1], performance measurement is as a means to ensure the strategy is well executed, and the execution of the strategy is aligned and fit within the operation planning of the company.

This study focuses on the frozen food manufacturing firms among SMEs in Selangor. Food processing industry in Malaysia is one of the fast growing industry, comprises of nineteen categories. Nowadays, frozen convenience food has become one of necessities amongst urban consumers. With the urbanization taking place in the new generation, the changes in lifestyle and demographics become the reasons the chilled and frozen food industries keep on growing [2]. The auxiliary food products that are easy to be prepared and served are increasing in global demand [3].

A study by [2] reveals that frozen food is in an uprising trend worldwide and investors see great potential in the frozen food sector in Malaysia. However, small and medium food enterprises sector progress is not in parallel with the increasing demand for convenience foods [4]. Malaysian SMEs in general are lacking in aspects of financial management and planning [5] and causes SMEs to fail by the five-year mark. Hence, in consideration of the financial drawback mentioned by [5], the performance efficiency evaluation in this study emphasizes on the financial aspects by assessing the financial variables of the SMEs.

Therefore, in general, this article assists the industry players to improve their performance in respect to other firms in the same industry. This study aimed to evaluate the score of performance efficiency of small and medium food manufacturing firms by using Data Envelopment Analysis. By obtaining the score, the related firms are ranked based on their performance of effectiveness in utilizing the financial resources. Lastly, the least efficient firms are proposed with suggestions of progress needed for them to reach the level of best practice.

## 2. Methodology

### *2.1 Data collection*

This study used secondary data from Small and Medium Enterprise Corporation (SME Corp) and Suruhanjaya Syarikat Malaysia (SSM). The data from thirteen SMEs in frozen food manufacturing in Selangor were used to determine and compare the efficiency scores between the firms. The inputs and output data used in this study are from basic financial statement report from SSM. Therefore, the inputs and output variables chosen are based on the data availability.

By considering the information from previous studies and the limitation on data availability, four inputs and one output are selected to become the criteria in measuring the performance of the firms. The inputs and outputs are chosen by the availability of the data from both SME Corp and SSM. The secondary data from year 2016 to 2017 is comprised of four inputs and one output as shown in Table 1; fixed asset, current asset, capital share and cost of sales as input variables, while total of sales as output variable.

**Table 1.** Summary of inputs and outputs selection.

| | Denotation | Variable |
|---|---|---|
| Input | | |
| | $v_1$ | Fixed Assets |
| | $v_2$ | Current Assets |
| | $v_3$ | Share Capital |
| | $v_4$ | Cost of Sales |
| Output | | |
| | $u_1$ | Total of Sales |

### *2.2 Data Envelopment Analysis*

Data Envelopment Analysis is a non-parametric approach, which was introduced by [6]. It is originally proposed to measure the relative performance of decision making unit (DMU). DEA is recognized as an excellent methodology in modeling and assessing performance evaluation [7]. This study was intended to employ multiple inputs and outputs from financial perspective, therefore DEA is well suited to evaluate their performance efficiency.

There are several assumptions in performing DEA model, therefore a clear purpose and goal of the study is compulsory. The assumption of model orientation and return to scale model need to be verified first before commencing the analysis work in order to obtain a reliable and accurate result. The core drive of this study is to assist the firms to achieve the best performance with the allocated resources, hence, the model used is input-oriented which minimize the inputs while maintaining the output level.

Another important assumption that need to be considered before initiating the efficiency analysis is the return to scale model. According to [1], CCR approach proposes that output change is proportionate to the changes in input variables. It is called constant return to scale (CRS), where the increase in input is relational to the increase in outputs level.

*2.2.1 Stage I: Measure Efficiency Score using Data Envelopment Analysis.*

The classical CCR-DEA model is employed in this study to generate the efficiency score.

$$\text{Max} \quad h_o = \sum_{r=1}^{s} u_r y_{rj_0}$$

Subject to

$$\begin{gathered} \sum_{i=1}^{m} v_i x_{ij_0} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \;\; j = 1, \dots, n \\ u_r, v_i \geq 0, r = 1, \dots, s \\ i = 1, \dots, m, \quad j = 1, \dots, n. \end{gathered} \tag{1}$$

Where,

| | |
|---|---|
| $y_{rj}$ | *value of the* $r^{th}$ *output for the* $j^{th}$ *DMU,* |
| $x_{ij}$ | *value of the* $i^{th}$ *input for the* $j^{th}$*DMU,* |
| $u_r$ | *weight given to the* $r^{th}$ *output,* |
| $v_i$ | *weight given to the* $i^{th}$ *input,* |
| *n* | *number of firms,* |
| *s* | *number of outputs,* |
| *m* | *number of inputs.* |

Model 1 holds the assumption to maximize the sum of weighted outputs with sum of weighted inputs. In Model 1, $h_o$ is the relative efficiency of the DMU under evaluation ($DMU_0$), *j* is the DMU index, *i* is the input index and *r* is the output index. Value of $h_o$ is bounded between 0 and 1, $DMU_0$ is said to be efficient if value of $h_o$ is equal to 1. Otherwise, they are inefficient if $h_o$ is less than 1 ($h_o$<1). The value of $ur$ and $vi$ are set to be greater than or equal to zero, as to prevent inputs and outputs from being ignored by the DMUs.

*2.2.2 Stage II: Compare, Choose the Suitable Approach and Rank the DMUs.*

There is no definite method in assessing performance efficiency as well as the determining factors contribute to the efficiency of a firm [9]. The method of analysis could differ depending on the objectives of research as well as the input and output variables involved in the study.

Thus, two methods are employed to rank the DMUs using their efficiency scores obtained from CCR-DEA model; MCDEA and DEA Cross Efficiency.

i. Multi Criteria DEA (MCDEA)

A combination method of multiple criteria decision making and data envelopment analysis approach is proposed [10]. The objectives of MCDEA are to increase the discriminating power among DMUs and yield appropriate weights. Therefore, three objective functions will be used to properly distinguish the position of the decision making units. The objective functions are minimizing $d_o$, minimizing the maximum deviation (minimax) and minimizing the sum of deviations (minsum) respectively.

$$
\begin{aligned}
&\min \quad d_o \quad \left(or \max h_0 = \textstyle\sum_{r=1}^{s} u_r y_{rj_0}\right) \\
&\min \quad M \\
&\min \quad \textstyle\sum_{j=1}^{n} d_j
\end{aligned} \tag{2}
$$

Subject to

$$
\begin{gathered}
\sum_{i=1}^{m} v_i x_{ij0} = 1 \\
\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \ \ j = 1, \dots, n \\
M - d_j \geq 0, \\
u_r, v_i, d_j \geq 0, \ \ for\ all\ r, i, and\ j.
\end{gathered}
$$

In the above MCDEA model, $d_o$ in the first objective function denotes the measure of inefficiency of $\text{DMU}_0$ which is bounded between [0, 1]. $\text{DMU}_0$ is considered to be relatively efficient if $d_o = 0$. While the constraint $M - d_j \geq 0$ for $j = 1, \dots, n$ is established in order to ensure that $M$ does not alter the feasible region of decision variables.

In short, $\text{DMU}_0$ is efficient if and only if $d_o = 0$ for optimizing the first objective function. Next, $\text{DMU}_0$ is minimax efficient if the value of $d_o$ with respect to minimizing the second objective is equal to zero. Lastly, $\text{DMU}_0$ is minsum efficient if the value of $d_o$ with respect to minimizing the third objective in Model 2. Therefore, from the above three definitions, no matter if $\text{DMU}_0$ is efficient or not, its efficiency score is $1 - d_o$. $\text{DMU}_0$ is efficient if and only if the values of $d_o$ of each criteria is equal to zero.

ii. DEA Cross Efficiency

The main idea is to include the peer evaluation in ranking the DMUs rather than to have it work in a pure self-assessment. Therefore, cross efficiency is based on self-assessment and peer assessment and can be calculated in two phases.

The first phase is founded on the self-assessment and is derived from classical DEA model (1), where the score for $\text{DMU}_0$ is $h_o$.The second phase is the peer-evaluation, whereas the score of $\text{DMU}_t$ is generated using the optimal weights $\text{DMU}_0$ produced from model (1). The peer assessment is established by [11] as follows:

$$
\begin{gathered}
E_{pt} = \frac{\sum_{r=1}^{s} u_{rp} y_{rt}}{\sum_{i=1}^{m} v_{ip} x_{it}} \\
p, t = 1, 2, \dots, n
\end{gathered} \tag{3}
$$

$E_{pt}$ is the score for $\text{DMU}_\text{t}$ using the optimal weights selected by $\text{DMU}_\text{p}$. The cross efficiency score for $\text{DMU}_\text{t}$ or the average of all $E_{pt}$ or $\overline{E_t}$ can be calculated as follows:

$$
\overline{E_t} = \frac{1}{n} \sum_{t=1}^{n} E_{pt} \tag{4}
$$

The self-assessment score from model (1), and the peer assessment from model (3) is organized in a matrix form, namely as cross efficiency matrix. From the matrix, the average, $\overline{E_t}$ can be calculated. According to **Error! Reference source not found.**, considering the model of cross efficiency in this study is using the input-oriented models, the score of cross efficiency is not greater than one. While, the DMU with the highest $\overline{E_t}$ is classified as the optimal DMU.

*2.2.3 Stage III: Determine the Improvement Progress for Inefficient DMUs.*

Consequent from efficiency score evaluation in stage I, DMU with score less than 1 ($h_o$<1) is considered as inefficient and have poorer performance than other DMUs whose score, $h_o$ is equal 1. Therefore, in stage III, this study attempts to propose an estimation of improvement progress for DMU with poorer efficiency performance.

In stage III, Context-Dependent DEA model is introduced to cater the idea of DMU may be attractive against a less attractive evaluation context and become less attractive when compared to more attractive alternatives. This approach propose that a relative performance is defined with respect to a particular best practice context, where each evaluation context represents an efficient frontier in a particular performance level [7]. This approach is particularly appealing in that the DMUs are stratified with respect to their efficiency levels.

i. Stratification method

Model (5) below is the stratification DEA method.

$$\theta^*(l,k) = \min_{\lambda_j,\theta(l,k)} \theta(l,k)$$

Subject to

$$\begin{aligned} \sum_{j \in F(J^l)} \lambda_j x_{ij} &\leq \theta(l,k) x_{ik} \\ \sum_{j \in F(J^l)} \lambda_j y_{rj} &\geq y_{rk} \\ \lambda_j \geq 0, \quad & j \in F(J^l) \end{aligned} \tag{5}$$

Where,

| | |
|---|---|
| $\lambda_j$ | *intensity,* |
| $y_{rk}$ | *value of the $r^{th}$ output of $DMU_k$,* |
| $x_{ik}$ | *value of the $i^{th}$ input of $DMU_k$,* |
| $l$ | *level of best practice frontier,* |
| $k$ | *number of observations..* |

$J^l$ is defined as the set of all DMUs and $El$ is the set of efficient DMUs in $J^l$. $J^{l+1} = J^l - E^l$ where $E^l = \{DMU_k \in J^l | \theta^*(l,k) = 1\}$, and $\theta^*(l,k)$ is the optimal value to the input oriented CRS model when $DMUk$ is under evaluation. The first level of stratification DEA method would be the efficient DMUs. When $l$ =1, then first level is defined as $E^1$, next when $l$ =2, model (5) give the second level efficient frontier with omission of the first level efficient DMUs. By excluding the second level efficient frontier, a third level of efficient frontier will be made. The process is continued until no DMU is remained inefficient.

ii. Progress Measure

The score of progress measure portrays the distance between an observation and the frontier of the lower efficiency level. It shows the extent of improvement in productivity needed by the inefficient DMU to achieve a higher level of efficiency [9].Progress measure is evaluated with respect to the preceding level of efficient frontier, whereas the DMUs exhibit better performance are chosen as the evaluation context.

$$G^*{}_q(g) = min\, G_q(g)$$

Subject to

$$\sum_{j \in F(E^{l_0-g})} \lambda_j\, x_j \leq G_q(\beta) x_q$$
$$\sum_{j \in F(E^{l_0-g})} \lambda_j\, y_j \geq y_q \qquad (6)$$
$$\lambda_j \geq 0, \quad j \in F\left(E^{l_0-g}\right), \quad g = 1, \dots, l_0 - 1$$

Model 6 shows that for a specific $\mathrm{DMU_q} \in \mathrm{E}^{\mathrm{l_0}}, l_0 \in \{2, \dots, l\}$,

(i) $G^*{}_q(g) < 1$ for each $\mathrm{g} = 1, \dots, l_0 - 1$

(ii) $G^*{}_q(g+1) < G^*{}_q(g)$

$$M^*{}_q(g) = {}^1\!/_{G^*{}_q(g)} \qquad (7)$$

As $M^*{}_q(g) > 1$, the larger value of $M^*{}_q(g)$, more progress is anticipated. A high progress depicts that the DMU need to improve substantially [7]. Next, the value of g-degree progress of $\mathrm{DMU_q}$, $M^*{}_q(g)$ will be used in the layer improvement of DMUs, so that the improvement approaches can be designed and presented.

iii. Layer Improvement of DMUs

The improvement is designed for each DMU by taking the progress score into account in order to attain better performance of each inefficient DMU and this approach is done step by step to achieve efficiency frontier or the best level.

Note that according to [14] the extent of improvement is measured by layer improvement of DMUs in respect to each preceding frontier level. In short, it is level-by-level improvement process. This method proposes to choose the nearest accessible level, $\mathrm{E}^{\mathrm{l_0}-1}$ as the starting point to improve the performance. Then, the inputs and outputs level will be altered in order to achieve that efficiency level. The changes in inputs and outputs are as follows:

$$S^-(g) = G^*{}_q(g) x_q - \sum_{j \in F\left(E^{l_0-g}\right)} \lambda_j\, x_j$$
$$S^+(g) = \sum_{j \in F\left(E^{l_0-g}\right)} \lambda_j\, x_j - y_q \qquad (8)$$
$$S^+(g), S^-(g) \geq 0,$$
$$\lambda_j \geq 0, \quad j \in F\left(E^{l_0-g}\right)$$

where $S^-(g)$ is the input slack, while $S^+(g)$ is the output slack.

The target input of each DMU will be obtained from Model 8 by using the score of progress measure and the multiplier of each input for each DMU. The target input is acquired from the changes in inputs and output by considering the degree of progress needed by the DMU. Therefore, the DMUs can improve its efficiency level step by step.

## 3 Result And Discussion

### *3.1 Efficiency Score Measure*

In correspondence to the first objective of this study, this section describes the efficiency analysis of SME frozen food manufacturers in Selangor. LINGO software version 12 is employed in this study to generate the efficiency score for each related firms.

The $\mathrm{DMU}_0$ is said to be efficient if the efficiency score is 1, ($h_o = 1$), meanwhile if the value of $h_o < 1$, it is considered as inefficient.

**Table 2.** Efficiency scores derived from CCR-DEA model.

| DMU | Input | | | | Output | Efficiency |
|---|---|---|---|---|---|---|
| | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $u_1$ | |
| 1 | 0.082 | 16.516 | 2.000 | 64.237 | 65.914 | 1.000 |
| 2 | 0.932 | 0.174 | 0.100 | 0.036 | 0.085 | 0.862 |
| 3 | 12.716 | 6.245 | 1.000 | 9.366 | 14.650 | 0.935 |
| 4 | 3.050 | 11.924 | 3.000 | 21.671 | 29.795 | 0.994 |
| 5 | 16.126 | 2.922 | 2.000 | 59.112 | 62.512 | 1.000 |
| 6 | 0.206 | 1.324 | 0.200 | 2.605 | 3.221 | 0.963 |
| 7 | 0.005 | 0.187 | 0.025 | 0.405 | 0.504 | 1.000 |
| 8 | 3.718 | 4.152 | 1.250 | 8.803 | 9.777 | 0.788 |
| 9 | 1.580 | 1.891 | 0.100 | 1.173 | 2.432 | 1.000 |
| 10 | 0.782 | 1.574 | 2.500 | 1.122 | 3.042 | 1.000 |
| 11 | 0.039 | 0.314 | 0.100 | 0.325 | 0.567 | 1.000 |
| 12 | 2.279 | 0.593 | 0.100 | 1.550 | 2.383 | 1.000 |
| 13 | 0.001 | 0.757 | 0.100 | 1.696 | 2.052 | 1.000 |

The results shown in Table 2 shows that eight out of thirteen DMUs obtain efficiency score of 1,( $h_o$=1) and the remaining five DMUs obtain scores of less than 1, ($h_o$<1). ). It means that eight DMUs are efficient compared to other DMUs. In the meantime, the other five DMUs, namely $\mathrm{DMU}_2$, $\mathrm{DMU}_3$, $\mathrm{DMU}_4$, $\mathrm{DMU}_6$ and $\mathrm{DMU}_8$ acquire efficiency score of 0.862, 0.935, 0.994, 0.963 and 0.788 respectively. As their efficiency score are less than 1, the latter five DMUs are classified as inefficient in using inputs to produce certain level of total sales.

*3.2 Rank the Efficiency Score of DMUs*

The DMUs involved in this section are the DMUs who appear to be efficient in CCR-DEA model only as shown in Table 2. Two methods; MCDEA and DEA Cross Efficiency are applied and compared to choose the suitable model. Later, the suitable model will be used to rank the DMUs.

i. Multi Criteria DEA (MCDEA) Model

**Table 3.** Efficiency score and ranks derived from MCDEA model.

| DMU | min $d_0$ | | minsum | | minmax | | Overall MCDEA |
|---|---|---|---|---|---|---|---|
| | Score | Rank | Score | Rank | Score | Rank | Rank |
| 1 | 1.000 | 1 | 1.000 | 1 | 0.980 | 4 | 3 |
| 5 | 1.000 | 1 | 1.000 | 1 | 1.000 | 1 | 1 |
| 7 | 1.000 | 1 | 1.000 | 1 | 1.000 | 1 | 1 |
| 9 | 1.000 | 1 | 0.577 | 8 | 0.674 | 8 | 8 |
| 10 | 1.000 | 1 | 0.232 | 7 | 0.721 | 6 | 7 |
| 11 | 1.000 | 1 | 0.940 | 5 | 0.934 | 5 | 5 |
| 12 | 1.000 | 1 | 0.625 | 6 | 0.717 | 7 | 6 |
| 13 | 1.000 | 1 | 0.993 | 4 | 0.996 | 3 | 4 |

The minsum objective function in Table 3 shows that the number of efficient DMUs have substantially decreased to three DMUs compared to the first objective function, minimizing the $d_0$.

While, the third objective function, minmax shows that efficient DMUs has reduced to only two DMUs. From the results in Table 3, clearly shown that all three objective functions are incapable to provide the whole complete ranking of DMUs.

ii. DEA Cross Efficiency Model

The score of self-assessment and peer assessment is organized in a form of matrix. The value of $E_{pt}$ is calculated.

**Table 4.** DEA Cross-Efficiency matrix.

| DMU | 1 | 5 | 7 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|
| 1 | 1.000 | 0.985 | 1.008 | 0.710 | 0.391 | 0.807 | 0.716 | 1.000 |
| 5 | 0.978 | 1.000 | 1.005 | 0.693 | 0.721 | 0.940 | 0.736 | 0.995 |
| 7 | 0.961 | 1.000 | 1.000 | 0.708 | 1.000 | 1.000 | 0.763 | 0.989 |
| 9 | 0.888 | 0.805 | 0.945 | 1.000 | 0.485 | 0.999 | 0.740 | 1.000 |
| 10 | 0.961 | 1.000 | 1.000 | 0.708 | 1.000 | 1.000 | 0.763 | 0.989 |
| 11 | 0.886 | 0.798 | 1.017 | 1.000 | 0.480 | 1.000 | 0.731 | 1.000 |
| 12 | 0.928 | 0.980 | 0.989 | 1.000 | 0.653 | 1.000 | 1.000 | 0.993 |
| 13 | 0.888 | 0.804 | 1.017 | 1.000 | 0.484 | 1.000 | 0.738 | 1.000 |
| $\overline{E_t}$ | 0.936 | 0.921 | 0.998 | 0.852 | 0.652 | 0.968 | 0.774 | 0.996 |
| Rank | 4 | 5 | 1 | 6 | 8 | 3 | 7 | 2 |

Table 4 shows the value of $E_{pt}$ from cross efficiency matrix. The DMU with the highest score of cross efficiency, $\overline{E_t}$ is considered as the first in ranking. $DMU_7$ is in the first rank, obtains a value of 0.998, followed by $DMU_{13}$, the second in rank with a value of 0.996 for the cross efficiency score. Meanwhile, $DMU_{10}$ acquire the lowest score of cross efficiency which is 0.652, and is in the bottom rank.

Table 5 below displays the combination of Table 3 and Table 4 to acquire a clear view of ranking of DMUs generated by MCDEA model and cross efficiency model.

**Table 5.** Overall ranking for MCDEA and cross efficiency model.

| DMU | Overall MCDEA | Cross Efficiency |
|---|---|---|
| | Rank | Rank |
| 1 | 3 | 4 |
| 5 | 1 | 5 |
| 7 | 1 | 1 |
| 9 | 8 | 6 |
| 10 | 7 | 8 |
| 11 | 5 | 3 |
| 12 | 6 | 7 |
| 13 | 4 | 2 |

Cross efficiency model is evidently chosen as the suitable approach to rank the DMUs in this study. There are a few reason which support the choice of cross efficiency model. The first indication is cross efficiency model produce a unique solution, whereas there is only one DMU in the first rank. Even though MCDEA has a better discriminating power to differentiate the DMUs with the two additional objective functions proposed in the model, the ranking produced by MCDEA is not unique as there are two DMUs in the first rank.

The second reason is, the results display in Table 4 show that the weight of sum of input and output variables by cross efficiency model is distributed more evenly compared to MCDEA model. It is undeniable that MCDEA has the minmax and minsum objective functions generally to minimize the deviations in weighted sum of inputs and outputs variables but for this study, cross efficiency has done better work in distributing the sum of weighted inputs and output variables. Thus, the produced efficiency score is better estimated.

### *3.3 Improvement Measure for Inefficient DMUs*

Earlier in Section 3.1, there are five DMUs who are considered as inefficient which obtain the score of $h_o$ less than 1, namely $\mathrm{DMU}_2$, $\mathrm{DMU}_3$, $\mathrm{DMU}_4$, $\mathrm{DMU}_6$ and $\mathrm{DMU}_8$. In order to improve the performance of inefficient DMUs, the model measure the progress needed for an inefficient DMU to reach the efficient frontier.

#### *3.3.1 Context-Dependent DEA Model.*

The stratification method divides the set of DMUs into different frontier levels characterized by $E^l, (l = 1, \dots, \mathrm{L})$. By using the stratification method shown in Equation 5, three levels of efficient frontier are found. There are shown in Table 6. It can be seen from the original CCR-DEA model in Section 3.1, Table 2 shows that there are eight DMUs who are efficient, therefore they are placed in the first level of efficient frontier, $E^1$. This is supported by [15] who state that the original input-oriented CCR model becomes the first level ($l$ =1), $E^1$ = {$\mathrm{DMU_j}$ | j = 1, 5, 7, 9, 10, 11, 12, 13}.

For the second efficient frontier level which is $l$ = 2, the eight DMUs with the efficiency score of one are omitted from $J^1$ and the second level efficient frontier, $J^2$ is formed. By applying Model 5 to the second level $J^2$, it turns out that $\mathrm{DMU}_2$, $\mathrm{DMU}_3$, $\mathrm{DMU}_4$, and $\mathrm{DMU}_6$ acquire the perfect efficiency score of 1, while $\mathrm{DMU}_8$ obtains the score of 0.942. Hence, four DMUs are on the second level efficient frontier, $E^2$ = {$\mathrm{DMU_j}$ | j = 2, 3, 4, 6}.

Since there is only one DMU left namely $\mathrm{DMU}_8$ , automatically, $\mathrm{DMU}_8$ forms the third level efficient frontier, $E^3$ = {$\mathrm{DMU_j}$ | j = 8}after omitting the four DMUs who are in second efficient frontier.

**Table 6.** Efficiency score for each frontier levels.

| Level | $\mathrm{DMU}_j$ | Evaluation context | | |
|---|---|---|---|---|
| | | $E^1$ | $E^2$ | $E^3$ |
| 1 | 1 | 1.000 | ----- | ----- |
| | 5 | 1.000 | ----- | ----- |
| | 7 | 1.000 | ----- | ----- |
| | 9 | 1.000 | ----- | ----- |
| | 10 | 1.000 | ----- | ----- |
| | 11 | 1.000 | ----- | ----- |
| | 12 | 1.000 | ----- | ----- |
| | 13 | 1.000 | ----- | ----- |
| 2 | 2 | 0.862 | 1.000 | ----- |
| | 3 | 0.935 | 1.000 | ----- |
| | 4 | 0.994 | 1.000 | ----- |
| | 6 | 0.963 | 1.000 | ----- |
| 3 | 8 | 0.788 | 0.942 | 1.000 |

i. Progress Measure

The progress measure of the five DMUs is evaluated when different efficient frontiers are chosen as evaluation context. These measure are obtained by considering the efficient frontier of the lower order.

**Table 7.** Progress measure scores of the DMUs.

| | Evaluation context | |
|---|---|---|
| Second Level Efficient Frontier, $E^2$ | First Level, $E^1$<br>1st degree | |
| 2 | 1.153 | |
| 3 | 1.066 | |
| 4 | 1.007 | |
| 6 | 1.046 | |
| Third Level Efficient Frontier, $E^3$ | First Level, $E^1$<br>1st Degree | Second Level, $E^2$<br>2nd Degree |
| 8 | 1.269 | 1.061 |

As shown in Table 7, by changing the evaluation context in measuring the progress, the score also changes. It denotes that the improvement needed by the DMUs to achieve that certain level of efficient frontier is differed to each other, it also depends on the evaluation background and what level do they want to achieve.

The progress score in Table 7 reveals that $\mathrm{DMU}_2$ has the highest number of score with 1.153, followed by $\mathrm{DMU}_3$ with 1.066, $\mathrm{DMU}_6$ with 1.046 and the lowest scale is $\mathrm{DMU}_4$ with 1.007. According to [7], the higher score obtained in progress measure, the bigger improvement needed in order to achieve the efficient frontier. For instance in case of $\mathrm{DMU}_8$ since it is in third level of efficient frontier, the progress can be measured for two different evaluation contexts. The first degree denotes that progress measure of DMU8 is evaluated relative to the first efficient frontier, $E^1 = \{\mathrm{DMU_j} \mid \mathrm{j} = 1, 5, 7, 9, 10, 11, 12, 13\}$. While the progress score for second degree obtained is respect to the second level efficient frontier, $E^2 = \{\mathrm{DMU_j} \mid \mathrm{j} = 2, 3, 4, 6, 8\}$. The table reveals that $\mathrm{DMU}_2$ is the worst in the second level due to its progress score, which require the highest percentages of improvement as it obtain the highest progress score among the DMUs in $E^2$.

ii. Layer Improvement of DMUs

The scores of progress are then applied Model 8 which is the layer improvement model. The target inputs are obtained by considering the changes needed for inputs in order to achieve nearest efficiency frontier. The method suggests that $\mathrm{DMU}_2$, $\mathrm{DMU}_3$, $\mathrm{DMU}_4$, and $\mathrm{DMU}_6$ to choose layer $E^1$ as the initial step for improving, while $\mathrm{DMU}_8$ has to choose $E^2$ as the preliminary improvement.

**Table 8.** Target input of improvement needed by DMU.

| Variable | | 1st Degree | | | | 2nd Degree |
|---|---|---|---|---|---|---|
| | | $\mathrm{DMU}_2$ | $\mathrm{DMU}_3$ | $\mathrm{DMU}_4$ | $\mathrm{DMU}_6$ | $\mathrm{DMU}_8$ |
| Fixed Asset | Target Input | 0.290 | 11.423 | 2.511 | 0.321 | 2.985 |
| | Actual Input | 0.932 | 12.716 | 3.050 | 0.206 | 3.718 |
| | Difference | -0.641 | -1.293 | -0.539 | 0.116 | -0.733 |
| Current Asset | Target Input | 0.850 | 5.346 | 11.323 | 0.748 | 3.393 |
| | Actual Input | 0.174 | 6.245 | 11.924 | 1.324 | 4.152 |
| | Difference | 0.676 | -0.899 | -0.601 | -0.576 | -0.758 |
| Share Capital | Target Input | 0.040 | 0.421 | 2.461 | 0.326 | 0.660 |
| | Actual Input | 0.100 | 1.000 | 3.000 | 0.200 | 1.250 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Difference | -0.060 | -0.579 | -0.539 | 0.126 | -0.590 |
| Cost of Sales | Target Input | 3.325 | 8.277 | 21.002 | 1.973 | 7.775 |
| | Actual Input | 0.036 | 9.366 | 21.671 | 2.605 | 8.803 |
| | Difference | 3.289 | -1.089 | -0.669 | -0.632 | -1.028 |

The target inputs are the optimal solution for the inefficient DMU to achieve the level of best practice. Table 8 shows the target inputs as the improvement approaches for each inefficient DMU. $\mathrm{DMU}_6$ should reduce the current asset and cost of sales inputs while increasing the value of fixed asset and capital in order to gain the optimum total sales. The target for fixed asset input for $\mathrm{DMU}_6$ is RM321,000 which increase by 56% from RM206,000. In the meantime, the cost of sales should be cut by 24% from RM2.605 million to RM1.973 million as a means to increase the performance efficiency.

As for $\mathrm{DMU}_8$, this particular DMU is in the third level of efficient frontier, $E^3$. Hence, this particular DMU has $\mathrm{E}^2$ for the nearest accessible layer and it needs to alter and improve the inputs level to reach the second efficient frontier as for the first step. By taking the progress score of 0.942 into account, the target for all inputs generated are smaller than the actual value. For the suggestion of improvement approach, the fixed asset and current asset inputs are suggested to be reduced by 20% and 19% respectively. The cost of sales also is recommended to be decreased by 12% and cut to RM7.8 million.

## 4 Conclusions

Performance evaluation is an important process for every organization and company to ensure their operations and management are on the right track to strive for long term success. The small and medium food manufacturing firms have to work efficiently and effectively in order to continuously provide the increasing demand of frozen food products, which the products have been acknowledged as one of the necessities in Malaysian lifestyle.

Employing DEA to measure the efficiency score of performance as to analyze the current financial situation by using financial variables, the related firms have the knowledge of their present position within the industry. Two different methods; Cross Efficiency and Multi Criteria DEA are compared to choose a suitable method for this study. Cross efficiency model is evidently chosen for its fairly weight distribution and produce a complete ranking which qualifies the model as suitable to be used to rank the firms. By ranking the firms based on the score of performance efficiency, the more efficient firms display the standard of top notch performance among all thirteen evaluated small and medium frozen food manufacturers in Selangor.

On the other hand, in the case of inefficient firms, the study suggests improvement using context dependent DEA model by measuring the target inputs needed by the firms to achieve the efficient frontier or to deliver a better quality performance. The efficient frontier is chosen as the evaluation context in order to evaluate improvement needed by the inefficient firms to achieve the target of efficient frontier.

This study provides a clear mechanism in measuring the performance, rank the firms based on the performance efficiency as well as provides suggestion to increase the competency of the firms. The research framework of this study can be used by industry players other than food manufacturing as a guidance in assessing and improving their performance levels.

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