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APPLICATION OF SIMULATION AND MCDEA IN SME FOOD PROCESSING COMPANY: A CASE STUDY AT A COFFEE PROCESSING FACTORY

(Penggunaan Simulasi dan MCDEA di Syarikat Pemprosesan Makanan PKS: Suatu Kajian Kes di Kilang Pemprosesan Kopi)

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ABSTRACT

Food production in the manufacturing sector contributes significantly to the development of the Malaysian economy. Therefore, the improvement of food manufacturing should be emphasised so that it is possible to ensure its sustained growth. This study focuses on applying a simulation model and Multi-Criteria Data Envelopment Analysis (MCDEA) in the food manufacturing system. A case study on an SME food processing company was modelled and analysed to improve the system's overall performance. In this study, simulation experiments and MCDEA were used to improve the processing system, and several improvement models were suggested. The simulation model of each improvement was used to generate inputs and outputs, while MCDEA was used to determine the most efficient improvement model to minimise waiting time. The result demonstrates that IM7 is the most efficient model as compared to other improvement models. This model suggests adding a worker into the packaging process and reducing processing time at grinding and packaging processes. The methods and the results obtained can assist the management of a factory in making better decisions and can offer insights to other SME companies to help improve the performance of their food processing system.

Keywords: improvement model; MCDEA; simulation; food processing

ABSTRAK

Pengeluaran makanan di sektor perkilangan memberikan sumbangan yang besar kepada perkembangan ekonomi Malaysia. Oleh itu, peningkatan pembuatan makanan harus dititikberatkan agar dapat memastikan perkembangan yang berterusan. Kajian ini memfokuskan pada penggunaan model simulasi dan Analisis Penyampulan Data Pelbagai Kriterium (APDPK) dalam sistem pembuatan makanan. Kajian kes di sebuah syarikat pemprosesan makanan PKS dimodelkan dan dianalisis untuk meningkatkan prestasi keseluruhan sistem. Dalam kajian ini, eksperimen simulasi dan APDPK digunakan untuk menambah baik sistem pemprosesan, dan beberapa model penambahbaikan dicadangkan. Model simulasi bagi setiap penambahbaikan digunakan untuk menghasilkan input dan output, sementara APDPK digunakan untuk menentukan model penambahbaikan yang paling cekap bagi mengurangkan masa menunggu. Hasilnya menunjukkan bahawa IM7 adalah model yang paling cekap berbanding dengan model penambahbaikan yang lain. Cadangan untuk model ini adalah dengan menambah bilangan pekerja di proses pembungkusan dan mengurangkan masa pemprosesan pada proses pengisaran dan pembungkusan. Kaedah dan hasil yang diperoleh dapat membantu pengurusan kilang membuat keputusan yang lebih baik, dan dapat memberikan pandangan kepada syarikat PKS yang lain untuk membantu meningkatkan prestasi sistem pemprosesan makanan mereka.

Kata kunci: model penambahbaikan; MCDEA; simulasi; pemprosesan makanan

1. Introduction

Small and Medium Enterprises (SMEs) in Malaysia were initiated by the Malaysia Government in the early 1970s and play an important role in developing the Malaysia economy. SMEs promote private ownership and entrepreneurial skills. These SMEs are also flexible and can quickly adapt to the market's changing demand and supply conditions. The implementation of development programs for SMEs across all related Ministries and Agencies is being coordinated by SME Corporation Malaysia (SME 2018).

The government announced a new SMEs definition in 2013 that covers all sectors, including services, manufacturing, mining and quarrying, agriculture, and construction. The definition of SMEs is defined based on two criteria: sales turnover and the number of full-time employees. For the manufacturing sector, the sales turnover must not exceed RM50 million, or number the of full-time employees must be less than 200. The sales turnover must not exceed RM20 million for services sector, or the number of employees must be less than 75 (SME 2018).

Based on the Economic Census 2016 (DOSM 2016), there are 907,065 SMEs that represent 98.5% from the total business establishments of 920,065 firms in Malaysia. From among these SMEs, 87.9% of the establishments are from the services sector, while 5.2% are from the manufacturing sector. The construction and agriculture sector make up only 4.3% and 1.1% from the total SMEs, respectively. In the manufacturing sector, food and beverage products are the second highest contributor, after textiles and apparel.

Food production in the manufacturing sector contributes significantly to the development of the Malaysia economy. The government has made various fundamental steps to enhance the growth of SMEs. However, SMEs are still facing many challenges that prevent them from expanding their businesses. These problems may lead to unsatisfied customers towards the available companies. Therefore, the improvement of processing systems in the manufacturing sector should be taken into consideration. Simulation experiments were applied to model and analyse a processing system with the intention of improving it. Computer simulations are among the most useful methods to analyse and understand the behaviour of a food processing system. Simulations can be used to measure and improve the performance of the considered food processing system (Zahraee *et al.* 2014). Improvements can be made to the system through simulation modelling to avoid interrupting the real system processes. This makes simulations a cost-effective method as compared to other methods. Other than that, researchers can run the simulation model and improvement models repeatedly to obtain more accurate and reliable results. If the list of improvement models is too large, it is hard to choose the best improvement model. In this case, additional methods can be used to support the decision made, such as Data Envelopment Analysis (DEA), Scoring model or other Multi-Criteria Decision-Making methods to rank the improvement models. Wan Malissa *et al.* (2016) and Nazhatul Sahima *et al.* (2018) had integrated simulation model and DEA-BCC model in determining the best improvement model. The combination of simulation model and Scoring model also had been used in deciding the best improvement model for the food manufacturing system (Siti Nur Shahirah & Ruzanita 2020).

DEA is a linear programming approach for measuring the relative efficiency and productivity of homogeneous decision making units (DMUs) based on their multiple inputs and outputs. Many studies used DEA to identify the efficiency of DMUs, which can be a decision-making tool to determine the best decision among the available alternatives. Many works in the literature used DEA to determine the best alternative (Zerafat *et al.* 2009).

Since SME is considered the lifeblood of modern economies that give a significant contribution to the Malaysia economy, there is a necessity in helping them to improve the performance of the processing system. This study focuses on a coffee processing factory, an

SME company in the food manufacturing sector. In this study, simulation model was used to develop the actual system and to design possible improvement models. Then, the MCDEA was employed to determine the best improvement model from all the available models.

2. Materials and Methods

The coffee processing factory considered for this case study is in Yan, Kedah. This factory produces a pre-mixed coffee powder. There are six main processes involved to produce pre-mixed coffee powder. The process initiates with a roasting process, followed by cooking process. The coffee mixture is then cooled down for several minutes before being grounded. Next, the grounded coffee is transferred to the filling process. In the filling process, the pre-mixed coffee powder is filled in packets. In the final step, the packets of pre-mixed coffee powder are in a 20-packet box. Figure 1 shows the layout of the production system.

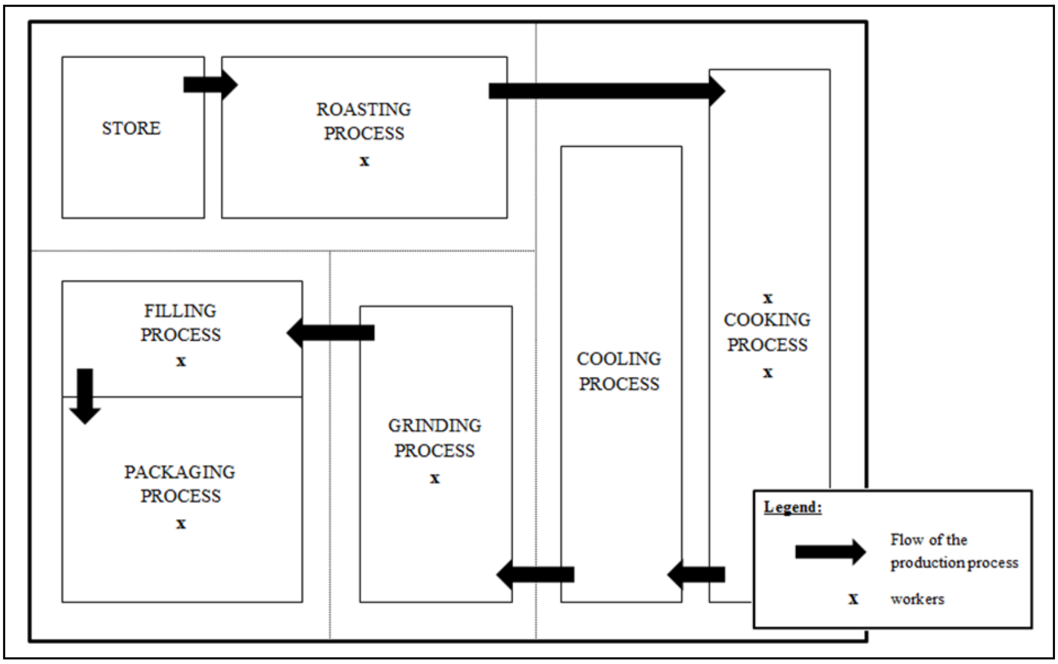

Figure 1: Layout of the pre-mixed coffee production system

The company currently has 20 workers at the factory, but only six workers are in the production line. There are two workers assigned to the cooking process, and one worker at each other process; roasting, grinding, filling, and packaging. No worker is assigned at the cooling process. In this simulation model, a packet of coffee beans is the entity for the pre-mixed coffee production. A packet of coffee beans of approximately 120g can produce a packet of pre-mixed coffee powder. The factory can produce approximately 250 packets of pre-mixed coffee powder per day.

2.1. *Simulation model*

This study used a two-phase methodology. The first phase involves developing a simulation model of the actual system and the improvement models. The simulation model of the actual system was visualized using Arena software version 14.0. The simulation model was developed based on the data collection of daily activities at the factory, from 8am to 5pm (9 hours). For this study, the data was collected using face to face interviews and the observation method. Data collected were analysed using an input analyzer to determine the appropriate probability distribution. Input analyzer is one of the tools in Arena software that allows to process the related data and fit it into the suitable probability distribution (Mat Desa *et al.* 2015). Table 1 shows the probability distribution of each process involved for the actual system.

Table 1: Distribution of the process in pre-mix coffee powder

Process	Distribution	Expression	Unit
Roasting	Normal	NORM(17.6, 1.57)	
Cooking	Beta	14.5 + 6 * BETA(1.31, 1.14)	minutes
Cooling	Uniform	UNIF(5, 10)	
Grinding	Beta	120 + 11 * BETA(1.41, 1.71)	
Filling	Constant	2.4	seconds
Packaging	Weibull	40 + WEIB(2.09, 1.68)	

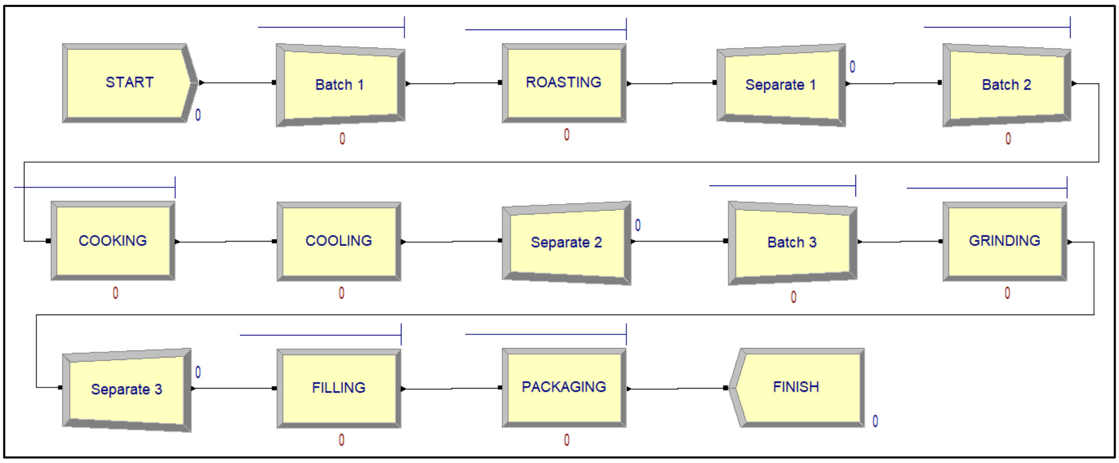

Figure 2: Pre-mixed coffee powder production process

The probability distribution was then used to develop the simulation model. The modules were compiled and connected in the form of flow charts in Arena software, as shown in Figure 2. The simulation model was run for 10 replications.

The simulation model needs to be verified and validated to ensure the model and its results are 'correct' for its use (Sargent 2013; Low & Liong 2015). A verification process is needed to ensure the model behaves as intended by the software, while validation is important to ensure that the model acts the same way as the real system (Banks *et al.* 2010). The verification of the simulation model in this study was done by using Little's Formula (Altiok & Melamed 2007), which is defined as follows:

$$\bar{N} = \lambda \bar{W} \tag{1}$$

where $\bar{N}$ is the average number of entities in the system, $\bar{W}$ is the average time an entity spends in the system, and λ is the average rate of arrivals entering into the system. From the simulation model's result, $\bar{N}$ is the average number of entities in the system, which is 65.1977 packets of coffee beans. The average time a packet of coffee beans spends in the system is 138.9600 minutes ($\bar{W}$), and the average rate of arrivals entering the system is 0.4741 (λ). Hence, $\lambda\bar{W}$ is 65.8810 packets of coffee beans. Once Little's Formula is fulfilled according to Eq. (1), the simulation model is considered verified. Sargent (2013) discussed some practical approaches to verification and validation of simulation models. In clarifying the model's validity, the differences between the simulation output and actual data using the following formula are calculated:

$$Difference\ (\%) = \frac{|simulation\ output - actual\ data|}{actual\ data} \times 100 \tag{2}$$

The simulation output refers to the data obtained from the simulation model, while the actual data refers to the data obtained from the actual system or the existing system. The differences between the actual and simulated values must equal to or not more than 10% (Razman 2006). Farah and Liong (2014) and Norazura *et al*. (2017) used Eq. (2) to check the validity level of the simulation model. The average processing time for each process, number in and number out of entities were used to validate the simulation model. The difference between the actual value and the simulated value was computed using Eq. (2).

The differences between the simulation output and actual data on the average processing time are summarized in Table 2. The differences between the simulation output and actual data on total entities entering the system and total production are summarized in Table 3.

The actual processing time for roasting is 17.5890 minutes and the simulated processing time is 17.7528 minutes. The actual entities entering the system is 250 packets, and actual value of total production is 249 packets. The simulated entities entering the system is 256 packets, and simulated value of total production is 255 packets. The difference between the actual and simulated values on the roasting processing time, total entities entering the system and total production are 5.16%, 2.40% and 2.41%, respectively. Hence, the simulation model is valid since all the difference values are not more than 10%.

Table 2: Average processing time for each process

Process	Average processing time (minutes)		Difference (%)
	Actual value	Simulated value	
Roasting	17.5890	17.7258	5.16
Cooking	17.7050	18.1514	2.52
Cooling	7.3309	7.4249	1.28
Grinding	2.0739	2.0834	0.46
Filling	0.0400	0.0400	0.00
Packaging	0.6979	0.6970	0.13

Table 3: Total entities entering the system (number in) and total production (number out)

Phase	Actual value (packet)	Simulated value (packet)	Difference (%)
Number in	250	256	2.40
Number out	249	255	2.41

After the simulation model was verified and validated, recommendations for the improvement model can be made. Several modifications were made to the simulation model so as to suggest improvement models.

2.2. *Data envelopment analysis*

In the second phase, one of the Data envelopment analysis (DEA) models is used to determine the most efficient improvement model. DEA is used to measure the relative efficiency of homogeneous decision making units (DMUs) when the production process presents a structure of multiple inputs and outputs. DEA is a non-parametric mathematical programming technique that acts as a tool in determining the best decision from among the possible improvement models available. The basic DEA model is known as the Charnes-Cooper-Rhodes (CCR) model by Charnes *et al.* (1978) and is treated as a single-stage DEA model where only inputs are supplied to, and the outputs produced is considered. Otherwise, the operation and interdependence of internal processes are ignored. The DEA-CCR model, also known as a multiplier model, is under the assumption of constant return to scale. Constant return to scale refers to the same proportional change for both input and output.

From the DEA-CCR model, Banker *et al.* (1984) proposed the Banker-Charnes-Cooper (BCC) model follows the assumption of variable return to scale, with the addition of a free variable to the objective function and to the constraint. DEA-BCC is variable return to scale that assumes that the proportional changes for input and output are not the same. DEA models can be represented in the form of input-oriented or output-oriented.

Li and Reeves (1999) then introduced Multi-Criteria Data Envelopment Analysis (MCDEA) to avoid two inter-related problems occurring in the classical DEA, which are weak discriminating power and unrealistic weight distribution. Weak discriminating power occurs when the number of DMUs under evaluation is not large enough compared to the total number of inputs and outputs, which leads to too many efficient DMUs identified by the classical DEA. The MCDEA model has three objectives that are analysed individually, with no order preference, which are minimizing d_0 (min d_0), minimizing the maximum deviation M (minmax), and minimizing the sum (minsum).

$$
\begin{aligned}
& min \quad d_0 \quad (or \quad max \quad h_0 = \sum_{r=1}^{s} u_r\, y_{rj_0}) \\
& min \quad M \\
& min \quad \sum_{j=1}^{n} d_j \\
& subject \quad to \\
& \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} + d_j = 0, \quad j = 1, \dots, n, \\
& M - d_j \geq 0, \\
& u_r, v_i, d_j \geq 0, for \quad all \quad r, i \quad and \quad j.
\end{aligned} \tag{3}
$$

where h_0 is the relative efficiency score of DMU_0, d_0 is the deviation variable for DMU_0 and d_j is the deviation variable for the DMU_j. M represents the maximum quantity among all deviation variables d_j. j is the DMU index, r is the output index, i is the input index, y_{rj} is the value of the r^{th} output for the j^{th} DMU, x_{ij} is the value of the i^{th} input for the j^{th} DMU, u_r is the weight given to the r^{th} output and v_i is the weight given to the i^{th} input. Suppose there are n DMUs, each unit has s output and m input. Based on Eq. (3), DMU_0 is efficient if and only if the value of d_0 is equal to zero. DMU_0 is the selected improvement model when $h_0 = 1 - d_0$. The efficiency score for DMU_0 is calculated as $1 - d_0$.

3. Results and Discussion

In the first phase, the simulation model of the existing system is developed. Table 4 shows the results of simulation model (average processing time, average waiting time and average total processing time) of the existing system at each batch module and each process module.

Table 4: Results of simulation model of the existing system

Batch module /Process module	Average processing time (minutes)	Average waiting time (minutes)	Average total processing time (minutes)
Batch 1 (before Roasting)	-	7.3646	7.3646
Roasting	17.7258	0	17.7258
Batch 2 (before Cooking)	-	0	0
Cooking	18.1514	0	18.1514
Cooling	7.4249	-	7.4249
Batch 2 (before Grinding)	-	0.3297	0.3297
Grinding	2.0834	1.1777	3.2612
Filling	0.0400	2.6489	2.6889
Packaging	0.6970	81.2992	81.9962

The average total processing time equals to the average processing time plus the average waiting time. Based on the results of simulation model, the average total processing time for a packet of pre-mixed coffee powder is 138.9600 minutes. The average waiting time for a packet is 92.8437 minutes. This means that 66.81% of the total production time for a packet of pre-mixed coffee powder is waiting time. Based on Table 4, the highest waiting time occurs during the packaging process, which is on average 81.2992 minutes. The packaging process is conducted by a worker. Therefore, the management of the factory is advised to reduce the waiting time at the packaging process.

Then, suggestions for improvements are made to address the detected problem. The suggestions for improvement involve some modifications to the simulation model. Suggestions are based on the discussion and agreement with the manager of the factory. The seven proposed improvement models are as follows:

(i) IM1: Add one additional worker to the packaging process.
(ii) IM2: The processing time in the cooling process is reduced to 5 minutes.
(iii) IM3: The processing time in the grinding process is reduced to 2 minutes.
(iv) IM4: The processing time in the packaging process is reduced by 10 seconds.
(v) IM5: The processing time in the cooling process is reduced to 5 minutes, and transfer one worker from the cooking process to the packaging process.

(vi) IM6: The processing time in the packaging process is reduced by 10 seconds and the processing time in the grinding process is reduced to 2 minutes. The arrival time is reduced from 15 minutes to 10 minutes.

(vii) IM7: The processing time in the grinding process is reduced to 2 minutes and in the packaging process is reduced by 10 seconds. Add one worker to the packaging process.

All the proposed improvement models are run for 10 replications with the purpose of obtaining accurate and reliable results. Next, comparisons between the improvement models' results is made. Table 5 shows the simulation results of seven improvement models.

Table 5: Simulation results for seven improvement models

Improvement model (IM)	Inputs			Outputs	Average waiting time at the packaging process (minutes)	Total workers (person)
	Average total processing time (minutes)	Average number of entities in the system (packets)	Average waiting time (minutes)	Average total production (packets)		
IM1	95.5990	45.2024	49.4797	255	37.9327	7
IM2	136.4600	64.0310	92.7564	255	81.4221	6
IM3	138.8700	65.1534	92.8330	255	81.2926	6
IM4	118.1100	55.5812	72.1653	255	60.6166	6
IM5	93.3921	44.2025	49.6928	255	27.7005	6
IM6	115.5700	54.4197	69.7036	255	60.6260	6
IM7	85.0465	40.3357	39.1780	255	27.6377	7

In the second phase, Multi-Criteria Data Envelopment Analysis (MCDEA) was used to determine the best improvement model and solved using LINGO 13.0 software. The improvement model in this study is known as the decision making unit (DMU), which comprises IM1, IM2, IM3, IM4, IM5, IM6 and IM7. The average total processing time, the average number of entities in the system and the average waiting time are the inputs, while the average total production is the output. The average waiting time at the packaging process and total workers in Table 5 are used for comparison purposes. The efficiency scores obtained from MCDEA were used to rank the DMUs. Table 6 shows the efficiency score of each DMU using MCDEA.

Based on the efficiency scores, Improvement Model 7 (IM7) is in the first rank and was selected as the best improvement model. According to IM7, the production system should add one worker to the packaging process and reduce processing time at the packaging and grinding processes. The total number of workers in the packaging process is two. The processing time at the packaging process was advised to be reduced by ten seconds, and the processing time at the grinding process was reduced to two minutes. Table 7 shows a comparison of the results between the existing system and IM7.

If IM7 is implemented, the average total processing time will be reduced to 85.0465 minutes, and the average waiting time will be reduced to 39.1780 minutes. The actual average total processing time and the actual average waiting time are 138.9600 minutes and 92.8437 minutes, respectively. Besides, the average waiting time at the packaging process can be reduced to 27.6377 minutes from 81.2992 minutes if IM7 is implemented.

In terms of the average processing time, the average waiting time, the average total processing time, and the average number of entities in the system of IM7 are the lowest compared to the existing system. However, based on the average total production, it seems like the value is identical to the existing system. This is because for IM7, the amount of coffee beans per production or the amount of raw ingredient is the same as the existing system, which is 30kg. In the future, if the factory plans to implement IM7, the factory should increase the amount of coffee beans per production so that the average total production will be increased accordingly. In conclusion, IM7 was selected as the best improvement model compared to other improvement models since the suggestion improved the existing system.

Table 6: Efficiency score using MCDEA

Alternative (DMU)	Min d_0		Minmax		Minsum	
	Score	Rank	Score	Rank	Score	Rank
IM1	0.8923	3	0.8923	3	0.8923	3
IM2	0.6299	6	0.6124	7	0.6124	7
IM3	0.6191	7	0.6191	6	0.6191	6
IM4	0.7257	5	0.7257	5	0.7257	5
IM5	0.9125	2	0.9125	2	0.9125	2
IM6	0.7412	4	0.7412	4	0.7412	4
IM7	1.0000	1	1.0000	1	1.0000	1

Table 7: Comparison of results between simulation model of the existing system and IM7

Model	Existing System	IM7	Difference
Average processing time (minutes)	46.1186	45.8685	0.2501
Average waiting time (minutes)	92.8437	39.1780	53.6657
Average total processing time (minutes)	138.96	85.0465	53.9135
Average total production (packets)	255	255	-
Average number of entities in the system (packets)	65	40	25

4. Conclusions

This study developed a simulation model of the coffee processing system and identified the process with the highest average waiting time per entity. Then, seven improvement models were suggested. Finally, MCDEA was used to determine the best improvement model by obtaining the efficiency score for each improvement model. In conclusion, IM7 was selected as the best improvement model compared to other improvement models since the suggestion improved the existing system. The suggestion for this model is adding a worker into the packaging process and reducing processing time at the packaging and grinding processes. The methods and the results obtained can assist the management of a factory to make better decisions and can offer insights to other SME companies to help improve the performance of their food processing systems.

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