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# An integrated simulation and data envelopment analysis in improving SME food production system

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**Abstract.** Small and Medium Enterprises (SMEs) food manufacturing sub-sector contributes to the growth of national economy. Food manufacturing has the potential to grow due to increase in human population and changes in living standards and lifestyles. In order to ensure a balance between the growth of food manufacturing and also the quality of food products, the enhancement and improvement of the food manufacturing system need to be done. A case study of the SME food production company is modeled and analyzed in order to improve the performance of the system using simulation. The problems faced by the SME food production system is identified and a template of actions is obtained from the simulation results. Five improvement models are developed with several modifications on the original simulation model. In order to determine the efficient improvement models, Data Envelopment Analysis (DEA) model BCC with output orientation is used. Cross efficiency and Super efficiency- BCC methods is used to rank the improvement models and to select the best improvement model. DEA application in the final step is seen as a complementary approach to strengthen the decision in ranking the improvement models and in selecting the best improvement model.The application methods and the results obtained can assist the management of the company to make better decisions and can provide ideas to other SME companies for enhancing and improving the performance of food manufacturing systems.

**Keywords:** simulation, data envelopment analysis, production, improvement model

## 1 Introduction

In the manufacturing sector of food production industry, Small and Medium Enterprises (SMEs) particularly contribute significantly to the development of a country to meet the needs of food production locally and internationally as well as provide jobs to people. SMEs food manufacturing needs to be more proactive as food demand will increase continuously. It is estimated that global retail sales of food products are expected to grow due to changes in living standards and lifestyles. SMEs should seize this opportunity based on the potential that has been identified in food manufacturing sub-sector, which eventually will create opportunities for investment in food production and marketing development.

There are many categories of food products produced by SMEs in Malaysia that have high demand in the domestic market and also for export which include cocoa based products, prepared cereals, flour-based products, processed seafood, dairy products and others. Another category of food products that has the potential to grow is the snack food products, namely chips. There are various types of chips which are based on cassava, sweet potato and banana. Among those chips, the demand of cassava chips has the potential to increase based on its high nutritional value and taste which is palatable.

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Therefore, to ensure a balance between the growth of cassava-based snack and also the quality of food products, the enhancement and improvement of the food manufacturing system need to be done. In order for the enhancement and improvement in the food manufacturing to be implemented, simulation is applied to model and analyze of this snack food manufacturing system. Simulation is a practical tool to use when modeling and analyzing the food production process in order to understand the behavior of the system. Through simulation, once the cause and effect are identified and understood, improvements can be applied to the system.

Simulation has been widely applied in the modeling of the food manufacturing system, including modeling bakery production line[8], pasta production[12] and juice production[16]. Simulation models are used to improve the performance of bakery production with the aim to reduce the wasted time and energy consumptions[8]. The results of rescheduling the production planning of bakery products reduce the wasted time and energy consumption and help in reducing workers working times. Simulation models are developed in order to analyze and solve supply chain problems faced by pasta manufacturer[12]. The weaknesses of the supply chain network of pasta production are identified. The simulation model of juice production line is developed in a study done by Ur-Rehman et al.[16]. The simulation model is developed to analyze the used of production line and to identify bottlenecks. Two scenarios are proposed. The best scenario is based on the lowest cost contribution and the ability to realize the current and future market demand. In addition, simulation also had been used in improving the efficiency of a food reclamation center operations[11] and harvesting supply chain system[4]. The simulation model of a food reclamation center warehouse is built and analyzed in order to minimize the costs of operations and to maximize the food supply to the needy families[11]. The simulation model of all activities involved in the harvesting supply chain system is developed. Re-configuration of the harvesting supply chain system is suggested in improving the performance[4].

Based on previous studies, simulation is a suitable method to solve problems faced by food manufacturers and improve the performance of the production systems. One of the advantages of simulation compared to other methods is its cost-effective which possible modifications on the model can be done without disturbing the actual system. The effects of changes in variables over many weeks, months or years can be obtained from simulation in a short time. Moreover, in conducting experiments for improvement models, the experiment environment can be controlled and repeated many times to get an accurate result.

Data Envelopment Analysis (DEA) is a linear programming based technique to measure the relative efficiency of homogenous decision making units (DMUs)[5]. The evaluation is based on inputs used and outputs produced. Many studies used DEA in identifying which DMU is efficient and inefficient. DEA also can be a decision making tool in determining the best decision among possible alternatives or DMUs. The efficient DMUs can be ranked using ranking methods in the context of DEA. There are some literatures that used DEA in the studies to determine the best possible alternatives for examples in identifying the optimal resource allocation alternative in Taiwan's Hospital Emergency Department[17], selecting the best flexible manufacturing system alternative[15] and determining the optimal operator allocation in cell manufacturing system[6]. The above studies used simulation in the first phase to generate inputs and outputs for each alternative or DMU. Then, in the second phase, DEA will be used in determining the best alternative. Normally, by using simulation, the determination of the best alternative is based on the analysis of the impact of the observation if the chosen alternative is implemented. Therefore, the DEA approach in determining the best possible alternative is seen to help the decision maker to make the decision in an efficient and a systematic way.

Realizing the importance of SMEs to the national economy, there is a necessity to help them improve the performance of the production system. Most SMEs use informal, unplanned and not systematic approach in improving the performance of the production system[7]. This will result in low productivity and increase operating costs. In that instance, SMEs will be left behind in their production systems' performance and cannot go further to compete with other companies in the global market.

For that reason, an analysis of operational problems in a representative SME food production system was conducted in order to improve the performance of the system using an integrated simulation and DEA.Recommendations for operational modification are offered that can be implemented in order to improve the performance of the SME food production system. The focus of this paper is to rank the improvement models and to select the best improvement model. With the assistance of simulation, its create flexibility in developing the improvement models. DEA application in the final step is observed as a complementary approach to support the decision in ranking the improvement models and in selecting the best improvement model. This finding will help the management of the company to reach better decisions and can give ideas to other SME companies in enhancing and improving the performance of food manufacturing systems. Fig. 1 presents an overview of the research study.

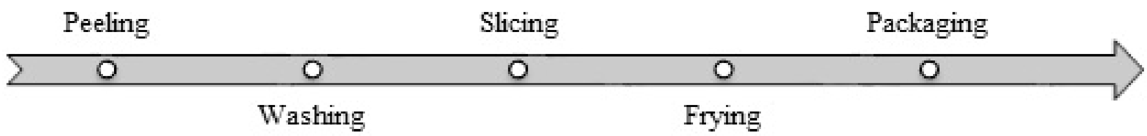


**Fig. 1.** Overview of the research study

The remaining of the paper is organized as follows: Section 2 contains the background information about the food production process, the development of simulation model for food production line and presents the BCC model - output oriented, Cross efficiency model and Super-efficiency BCC model in ranking and selecting the best improvement model. The experimental results are discussed in Section 3. Finally, Section 4 includes conclusions.

## 2 Material and methods

The food production of cassava based snack is chosen in this study due to its potential in current and future market demand. The production line of the cassava chips has been divided into five main processes. The flow diagram of the cassava chip production process is shown in Fig. 2. The first step in producing cassava chips is peeling process which is using cassava hand peeling tools. The next step is to wash peeled tubers. After washing process is done, washed tubers are sliced using slicing machine. Then the sliced tubers are soaked in a brine solution. Sliced tubers are fried using fryer machine. The final step is filling the cassava chips in plastic bags and sealing them using sealer machine.

Currently, the total number of operators involved in the production process is 12. There are six operators assigned to the peeling workstation, two operators at washing and slicing workstation. Operators at washing and slicing operators are the same persons. Two operators are required at frying workstation and the other two operators are assigned at the packaging workstation.

### 2.1 Simulation model

The cassava chips food production line in Fig. 3 is developed using ARENA software package version 14 to visualize the actual operation. The simulation model is based on data collections of daily activities on the production line. Data were collected during four hours of a morning session from 8.00 am to 12.00 pm. The data collected will be analyzed using the input analyzer to determine the appropriate distribution. Tab. 1 shows the distributions of the processing time in cassava chips production line.

To develop a simulation model, the actual production system should be studied and investigated. It is also to understand the whole system and all the processes involved. After all the data and information are gathered and transformed into appropriate distributions, the modules must be compiled and linked in a form of flow chart view (simulation model) in the model window. A simulation model of the cassava chips production line is shown in Fig. 3. The simulation model is run for 100 replications. The entities that are used in the production process are baskets of cassava. On average, it consists of 15 pieces of cassava, which in turn can produce a pack of 3 kg cassava chips.

Model verification and model validation are done to make sure that the simulation model can represent the actual production system. Verification refers to the process of ensuring that the model is free from logical

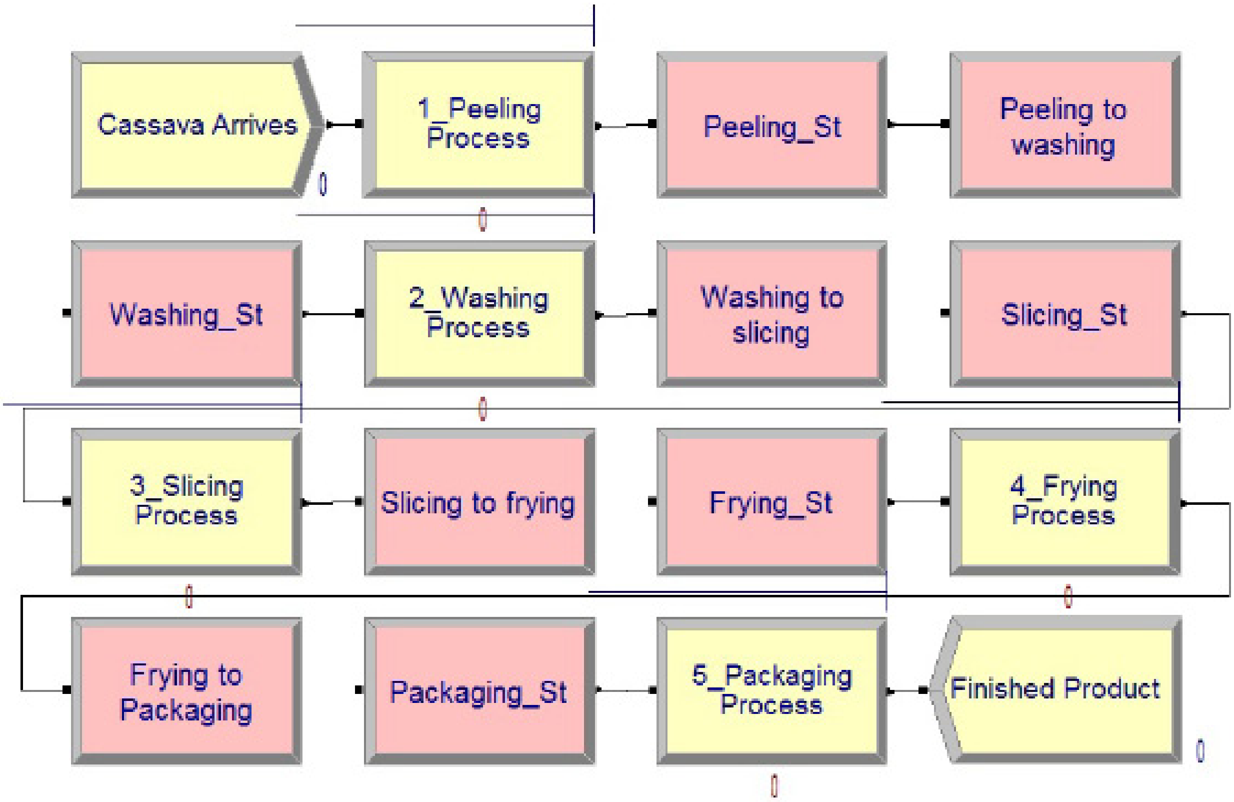


**Fig. 2.** Cassava chip production process

**Table 1.** Distributions of the process in cassava chips production line

| Process | Distribution | Expression Value |
|---|---|---|
| Peeling | Exponential | 60 + EXPO(105) |
| Washing | Beta | 4 + 9 * BETA(0.519, 0.917) |
| Slicing | Triangular | TRIA(15, 40.7, 90) |
| Frying | Erlang | 132 + ERLA(14.5, 1) |
| Packaging | Lognormal | 42.5 + LOGN(14.7, 45.6) |

errors. In order to ensure the model is free from logical error, Little's formula is used in this study. Little's formula is as the following [1]:

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

Where, $\bar{N}$ is the average number of entities in the system, $\bar{W}$ is average time an entity spends in the system and $\lambda$ is the average rate of arrivals enter to the system. From the results of the simulation model, the average number of baskets in the system is 22.5130 baskets $(\bar{N})$. The average time a basket of cassava spends in the system is 24.6080 minutes $(\bar{W})$ and the average rate of arrivals enter into the system is 0.93 $(\lambda)$. $\lambda\bar{W}$ is 22.8916. Once the Little's formula based on Eq. (1) is complied, the simulation model is considered verified.

According to Sargent [13], model validation is defined as ensuring that the simulation model and animation develop and its implementation is accurate, by using the correct data and able to represent the actual production system. The difference between simulation output and actual data is calculated using the following formula:

$$\text{Difference}(\%) = \frac{|\text{ Simulation output-ActualData }|}{\text{ActualData}} \times 100\%. \tag{2}$$

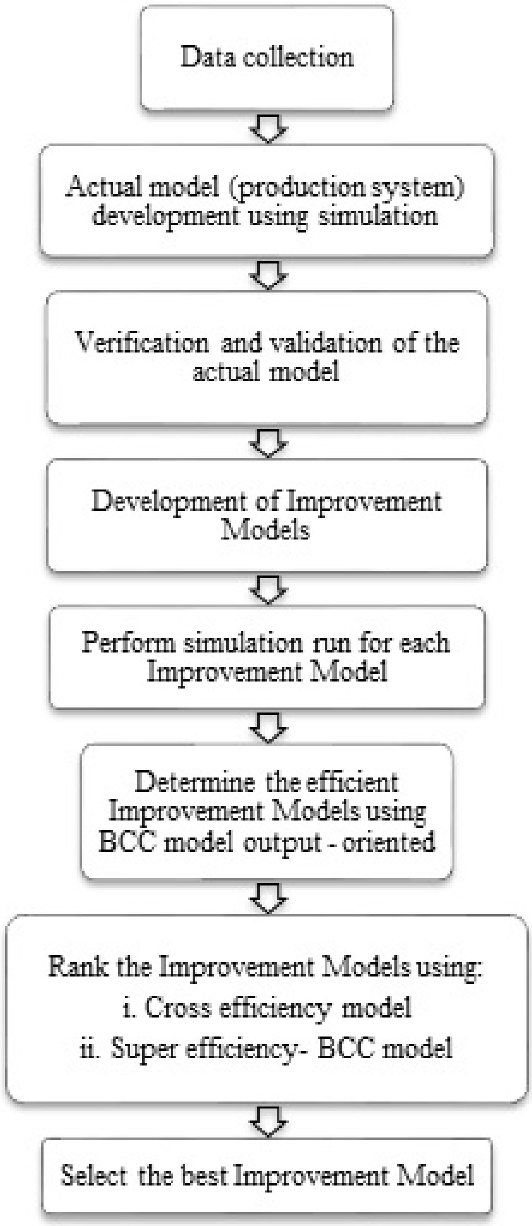


**Fig. 3.** Simulation model of cassava chips production line

Based on the Eq. (2), simulation output refers to data obtained from simulation model and actual data refers to data obtained from the actual production system. The difference between simulated data and actual data must not be more than 10% to arrive at the level of sufficient accuracy[2].

Tab. 2 displays the difference between simulated process time and actual processing time for each process and Tab. 3 displays the difference between simulated and actual data on the total entities enter into the system and total production using Eq. (3).

All differences between simulated process time and actual processing time of each process are less than 10%. The actual total entities enter into the system is 216 units and actual total production is 180 units whereas the simulated total entities enter into the system and total production are 223 units and 188 units, respectively. The difference between simulated and actual data on the total entities enter into the system is 3.241% and total production is 4.444%. All different values are not more than 10%. Therefore, it shows that the simulation model is valid.

**Table 2.** The difference between simulated process time and actual processing time for each process

| Process | Simulation Output (minutes) | Actual Data (minutes) | Difference (%) |
|---|---|---|---|
| Peeling | 2.7394 | 2.7462 | 0.248 |
| Washing | 0.1221 | 0.1208 | 1.076 |
| Slicing | 0.8117 | 0.8095 | 0.272 |
| Frying | 2.4378 | 2.4333 | 0.185 |
| Packaging | 0.9508 | 0.8966 | 6.045 |

**Table 3.** The difference between simulated and actual data on total entities enter into the system (number in) and total production (number out)

| Phase | Simulation Output (unit) | Actual Data (unit) | Difference (%) |
|---|---|---|---|
| Number in (per basket) | 223 | 216 | 3.241 |
| Number out (per packet) | 188 | 180 | 4.444 |

The simulation model of production system is verified and validated, recommendations for improvement model can be made to solve the problems that have been detected. Suggestions for improvement model involves several modifications to the original simulation model.

## 2.2 Data envelopment analysis

Data Envelopment Analysis (DEA) is a linear programming based technique to measure the relative efficiency of homogeneous decision making units (DMUs). It was introduced by Charnes, Cooper, and Rhodes [5] and is used to measure DMUs relative efficiency based on selected inputs and outputs. CCR model is under the assumption of constant return to scale. Constant return to scale (CRS) is based on the assumption that an increase in all inputs at a certain rate will cause an increase in output at the same rate. Banker, Charnes and Cooper [3] then expand the CCR model and the model is known as BCC model. BCC model is under the assumption of variable return to scale (VRS). The proportional change between inputs and outputs is not at the same rate either increase, constant or decrease. There are two model orientations in DEA which are input-oriented and output-oriented. Input-oriented objective is to reach a minimum level of input to the given output while output oriented objective is to reach a maximum level of output to the given input. Based on the company's objective, BCC model output -oriented is used. Below is the BCC model output-oriented (multiplier model):

$$\theta_0 = \min \sum_{i=1}^{m} v_i x_{ij_0} - v_0$$

$$\text{s.t.} \begin{cases} \sum\limits_{r=1}^{s} u_r y_{rj_0} = 1 \\ \sum\limits_{r=1}^{s} u_r y_{rj_0} - \sum\limits_{i=1}^{m} v_i x_{ij_0} + v_0 \leq 0 \\ \sum\limits_{r=1}^{s} u_r y_{rj} - \sum\limits_{i=1}^{m} v_i x_{ij} + v_0 \leq 0 \\ v_0 \text{ free}, u_r, v_i \geq \varepsilon, r = 1, \cdots, s_i = 1, \cdots, m_j = 1, \cdots, n \end{cases} \tag{3}$$

Where $\theta_0$ is the relative efficiency of $DMU_0$, i.e. the DMU under evaluation, *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, $v_i$ is the weight given to the $i^{th}$ input and is arbitrarily small positive number. *DMU*$_0$ is efficient (best in practice) if $\theta_0 = 1$. On the other hand, if $\frac{1}{\theta_0} < 1$, the DMU is inefficient. However, when using DEA, it may occur that there are more than one DMUs which are efficient. In order to choose the best DMU, Cross efficiency and Super efficiency-BCC will be used to rank the efficient DMUs.

**Cross efficiency method**

Cross efficiency method was introduced by Sexton et al.[14]. Cross efficiency score can be calculated based on input and output weights of efficient DMUs. Each efficient DMU uses input and output weights from other efficient DMUs. The cross efficiency score can be calculated using the following equation:

$$E_{pt} = \frac{\sum\limits_{r=1}^{s} u_{rp} y_{rt}}{\sum\limits_{i=1}^{m} v_{ip} x_{it}} p, t = 1, 2, \cdots, n. \tag{4}$$

Where, $E_{pt}$ is the score for $DMU_t$ using the optimal weights selected by $DMU_p$, $y_{rt}$ the value of the $r^{th}$ output for $DMU_t$, $x_{it}$ the value of the $i^{th}$ input for $DMU_t$, $u_{rp}$ the weight given to the $r^{th}$ output for $DMU_p$ and $v_{ip}$ the weight given to the $i^{th}$ input for $DMU_p$. The average of all $E_{pt}$ can be calculated using the following equation:

$$\bar{E}_t = \frac{1}{n} \sum_{p=1}^{n} E_{pt}. \tag{5}$$

Efficient DMU with the highest $\bar{E}_t$ is considered as the best DMU among the efficient DMUs.

**Super efficiency-BCC technique**

Super efficiency-BCC technique was introduced by Seiford and Zhu[9]. This technique modifies the BCC model in Eq. (3). The $DMU_0(j_0)$ constraint is removed from BCC model. The Super efficiency-BCC model is as the following:

$$\begin{aligned} &\varphi_0 = \min \sum_{i=1}^{m} v_{ik} x_{ij_0} - v_0 \\ &\text{s.t.} \begin{cases} \sum\limits_{r=1}^{s} u_r y_{rj_0} = 1 \\ \sum\limits_{r=1}^{s} u_r y_{rj} - \sum\limits_{i=1}^{m} v_{ik} x_{ij} + v_0 \leq 0 \\ v_0 \text{ free}, u_r, v_i \geq \varepsilon, r = 1, \cdots, s_i = 1, \cdots, m_j = 1, \cdots, n \end{cases} \end{aligned} \tag{6}$$

The Super efficiency-BCC score should be obtained from

$$\left( \frac{1}{\varphi_0} > 1 \right).$$

Otherwise, it will result in no feasible solution exists[10]. The highest Super efficiency-BCC score is considered as the best DMU.

## 3 Results and discussion

Cassava chip production involves five main processes that need to be carried out in order by entities. The first process is the process of peeling, followed by washing process then the next process is slicing process. After the slicing process is done, the entities then are moved to frying process and the final process which is packaging.

From the simulation results, the total production time for a basket of cassava is 24.6080 minutes on average. A basket of cassava total waits to move to the next process is 15.8839 minutes on average. This means

**Table 4.** Simulation results of each process at each workstation

| Workstation | Average processing time (minutes) | Average waiting time (minutes) | Average total processing time(minutes) |
|---|---|---|---|
| 1_Peeling | 2.7394 | 0.2352 | 2.9726 |
| 2_Washing | 0.1221 | 0.1512 | 0.2733 |
| 3_Slicing | 0.8117 | 0.1439 | 0.9555 |
| 4_Frying | 2.4378 | 15.5303 | 17.8475 |
| 5_Packaging | 0.9508 | 0.0116 | 0.9624 |

that, 64.5% of total production time is the waiting time for a basket of cassava to be processed. From Tab. 4, the results of simulation model show that the highest waiting time is at frying workstation, which is 15.5303 minutes on average. It is about 97% of total average waiting time for a basket of cassava to be processed. The average processing time at peeling workstation is 2.7394 minutes. According to the information from company's management, processing time for peeling a basket of cassava can be done up to 2.5 minutes for each operator because all operators involved in the process of peeling are skilled and have been trained accordingly. Based on simulation results, during four hours of production time, 188 packets of cassava chips could be produced and 23 baskets of cassava remained in the production system. Regularly, a total of 12 operators involved in the production system .

**Table 5.** The average operator utilization for each process at each workstation

| Workstation | Operator | Average operator utilization (%) |
|---|---|---|
| 1_Peeling | Operator_1 | 42.35 |
| | Operator_2 | 42.19 |
| | Operator_3 | 42.30 |
| | Operator_4 | 42.35 |
| | Operator_5 | 42.21 |
| | Operator_6 | 42.66 |
| 2_Washing & 3_Slicing | Operator_7 | 42.62 |
| | Operator_8 | 42.53 |
| 4_Frying | Operator_9 | 96.64 |
| | Operator_10 | 96.49 |
| 5_Packaging | Operator_11 | 37.66 |
| | Operator_12 | 37.08 |
| Total average | | 50.59 |

As shown in Tab. 5, it can be seen that the use of operator is unbalanced. Operators involved at frying workstation are almost fully utilized compared to other workstations such as packaging workstation where the average operator utilization is the lowest.

In conclusion, it can be seen that the bottleneck occurs primarily at frying workstation which causes baskets of cassava waiting to move to the next process. In addition, the average processing time at peeling workstation should also be improved in order to achieve the company's target. However, washing workstation, slicing workstation and packaging workstation do not experience critical problems.

**Improvement Models**

Several modifications to the original simulation model are suggested. For example, adding operators at bottleneck area, reallocating operators and improving process time at suggested workstation. From this modification, five improvement models have been developed. The cause and effect of the modifications to the original simulation model are analyzed in order to obtain the best improvement model. Five Improvement Models (IM) are as the following:

IM1 - One of the operators at peeling workstation is transferred to the frying workstation. This is equal to five operators at peeling workstation and three operators at frying workstation.

IM2 - One operator at frying workstation is added which gives a total of three operators there.

IM3 - The processing time of peeling process is set to be not more than 2.5 minutes upon request by company's management.

IM4 - Three operators at the frying workstation and the processing time of peeling process is set not to be more than 2.5 minutes at the same time.

IM5 - Five operators at peeling workstation and three operators at frying workstation. The processing time of peeling process is set not to be more than 2.5 minutes.

All improvement models are run for 100 replications in order to get accurate results. Comparisons between improvement models are made. Between five improvement models, the results from Tab. 6 indicate that the average operator utilization for IM1 is the highest with the total production of 213 units. Twelve operators involved in IM1 and at any point in time the number of entities in the system is 10 units. The average total production time is 10.8658 minutes and it is among the lowest.

In order to determine the best improvement model, DEA BCC model with output orientation is used. The selection of this model is based on the company's objective. In this study, Decision Making Units (DMUs) are Improvement Models (IM1, IM2, IM3, IM4 and IM5). The average total production time, average number of entities in the system and total operators are chosen as inputs. Outputs are total production and average operator utilization. The company's objective is to maximize total production and the average operator utilization with the given average total production time, average number of entities in the system and total operators.

**Table 6.** Simulation results of five improvement models

| Improvement Model (IM) | Average total production time (minutes) | Average number of entities in the system (units) | Total operators (person) | Total production (units) | Average operator utilization (%) |
|---|---|---|---|---|---|
| IM1 | 10.8658 | 10 | 12 | 213 | 53.22 |
| IM2 | 10.8716 | 10 | 13 | 213 | 49.43 |
| IM3 | 26.3019 | 25 | 12 | 188 | 43.41 |
| IM4 | 10.4691 | 10 | 13 | 217 | 43.19 |
| IM5 | 10.3405 | 10 | 12 | 215 | 46.36 |

The total production should be maximized to increase the production performance. In that case, the market demand can be expanded locally as well as internationally. At the same time, the company needs to use their operators working hours fully. The maximization of average operator utilization should be achieved to avoid operators' idle time or non-productive time. The DEA BCC results from Eq.(3) are solved using LINGO software and presented in Tab. 7. The efficiency scores show that IM1, IM4 and IM5 are the efficient DMUs.

These three improvement models are among the best ones. Therefore, to identify the best improvement model Cross efficiency and Super efficiency-BCC will be used. Cross efficiency method will rank the efficient DMUs. The cross efficiency score can be calculated using Eq. (4) and Eq. (5). Based on cross efficiency matrix in Tab. 8, the average score of IM1 is the highest. It means that IM1 is in the first rank followed by IM5 and IM4. In this case, IM1 becomes the best improvement model.

**Table 7.** Efficiency score for each improvement model with inputs and outputs weights

| Improvement Model (DMU) | Efficiency score | Input weights | | | Output weights | |
|---|---|---|---|---|---|---|
| | | Average total production time (minutes) | Average number of entities in the system (units) | Total operators (person) | Total production (units) | Average operator utilization(%) |
| | | $v_1$ | $v_2$ | $v_3$ | $u_1$ | $u_2$ |
| IM1 | 1.0000 | 0.0000 | 0.0000 | 0.0833 | 0.0000 | 0.0188 |
| IM2 | 0.9935 | 0.0000 | 0.1006 | 0.0000 | 0.0043 | 0.0017 |
| IM3 | 0.8781 | 0.0000 | 0.0000 | 0.0949 | 0.0050 | 0.0015 |
| IM4 | 1.0000 | 0.0717 | 0.0250 | 0.0000 | 0.0046 | 0.0000 |
| IM5 | 1.0000 | 0.0967 | 0.0000 | 0.0000 | 0.0029 | 0.0082 |

**Table 8.** Cross efficiency matrix

| Improvement model (DMU) | IM1 | IM4 | IM5 |
|---|---|---|---|
| IM1 | 1.0000 | 0.7498 | 0.8719 |
| IM4 | 0.9521 | 1.0000 | 0.9976 |
| IM5 | 1.0032 | 0.9714 | 1.0000 |
| Average score, $\bar{E}_t$ | 0.9851 | 0.9071 | 0.9565 |

As can be seen in Tab. 9, the results of the Super efficiency-BCC based on Eq.(6) show that IM1 again in the first rank followed by IM4. Using Super-efficiency-BCC technique, there is no feasible solution exist for IM5.

**Table 9.** Results of Super efficiency-BCC

| Improvement Model (DMU) | $\varphi_0$ | $\frac{1}{\varphi_0}$ |
|---|---|---|
| IM1 | 0.8711 | 1.1480 |
| IM4 | 0.9908 | 1.0093 |
| IM5 | Infeasible | |

All in all, based on what-if analysis of Cross efficiency and Super efficiency-BCC, the IM1 is selected as the best improvement model by referring to the average total production time, average number of entities in the system, total operators, total production and average operator utilization. Reallocation of operators is implemented because of the bottleneck that occurs at frying workstation. As a result, five operators are assigned to peeling process and three operators to frying workstation. The company's management can reduce the cost of hiring additional operators by adopting this improvement. Furthermore, the average operator utilization is reduced at the frying workstation from 96.57% on average (original simulation model) to 72.0% on average (IM1). IM1 is also recorded as the highest on average operator utilization.

This study suggests IM1 as the best improvement model. IM1 can produce 213 packets of cassava chips with 10 baskets of cassava still in the system compared to the original simulation model that only can produce 188 packets of cassava chips with 23 baskets of cassava still in the system during 4 hours of operation.

Tab. 10 shows that the average processing time, the average waiting time and the average total production time of IM1 are declining compared to the original simulation model. IM1 shows an increase of 13% in the total production and it also succeeds in reducing the number of entities that are still in the system by 57%. The average operator utilization is increased by 0.5% which is due to the reallocation of operators to the bottleneck

**Table 10.** Comparison of the best improvement model selection and the original simulation model

| Model | Average processing time (minutes) | Average waiting time (minutes) | Average total production time (minutes) | Average total entities number out (units) | Average number of entities in the system(units) | Total operators (person) | Average operator utilization (%) |
|---|---|---|---|---|---|---|---|
| Original simulation model | 7.0575 | 15.8839 | 24.6080 | 188 | 23 | 12 | 50.59 |
| IM1 | 7.0514 | 2.1477 | 10.8658 | 213 | 10 | 12 | 53.22 |
| Difference (%) | 0 | 86 | 56 | 13 | 57 | 0 | 0.5 |

area. In conclusion, IM1 is chosen as the best improvement model since the modifications can improve the original simulation model or actual production system to be more efficient.

## 4 Conclusions

This paper presents an integrated simulation and Data Envelopment Analysis (DEA) in improving the performance of the SME food production system.The combination of these two methods is to assist the management of the company to make better decisions in deciding which improvement model is the best ones. The simulation approach gives more flexibility in designing the improvement models without interfering the actual production system and DEA is effective and contributes in supporting the decision regarding the best improvement model to be implemented in the food production system. This will be a useful information and can give ideas for SMEs food production companies in order to strengthen and increase the efficiency of the production system as a preparation to compete in the global market.

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