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Optimal Worker Allocation of Food Manufacturing System using Simulation and Data Envelopment Analysis

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ABSTRACT

This study suggests employing simulation and data envelopment analysis to support decision making for determining the optimal worker allocation for a food manufacturing production line. The simulation model for food production is based on a real-world example from the food industry, focusing on a manufacturing company. The challenge faced by the company involves a constrained number of workers allocated to four processes. The imbalance number of workers in each process will affect the productivity of the company. Through simulation modeling of the actual systems, it was discovered that the filling process presents a bottleneck due to its significantly higher average waiting time compared to the other processes. A valid simulation model was subsequently employed to generate potential improvements. Nineteen improvement models were proposed and assessed based on various selection criteria, including average total production time, average number of entities still in the system, total production, and average resource utilization. Among the nineteen improvement models, Improvement Model 11 (IM11) emerged as the best improvement model. The optimal worker allocation alternative involves assigning two workers to each process, leading to anticipated increases in total production and average resource utilization. Utilizing simulation and data envelopment analysis can help the management of the company to make better decisions in determining the optimal worker allocation.

Keywords: simulation, data envelopment analysis, worker allocation

1 INTRODUCTION

There are Small Medium Enterprise (SMEs) industries which still use low level technologies and are often relatively more labour intensive in their operations. Innovative processes and products should be introduced to enhance efficiency. However, this problem may not have a straightforward solution due to the limited organizational capacity and resources of SMEs. They often lack efficient and experienced management, as well as a clear strategic vision and mission.

Furthermore, the development and implementation of innovation can be challenging for these companies because they struggle with resource allocation, resource adjustment, and the acquisition of necessary information and knowledge. The imbalance in the number of workers at each process could interfere with the process flow of the manufacturing system. Hence it will cause bottlenecks in the system. The proposed multi-agent system is attractive and suitable for solving resource allocation problems. However, the resource allocation problem being solved is static problems. Most resource allocation problems are practically dynamic, involving discrete changes over time. The allocation is made based on the current state of the system. This allocation is maintained until a new event occurs.

Therefore, this study is carried out to help the food manufacturing system industries to solve the imbalance number of workers at each process by determining the optimal worker allocation alternative using simulation and data envelopment analysis (DEA).

2 METHODS AND DATA

Food and beverage manufacturing companies are always competing in producing high-quality products. Small food and beverage companies can compete to ensure the production process used is up-to-date and efficient. Therefore, looking at the growth of SMEs in the context of the food manufacturing industry in Malaysia, improvements can be made across the entire supply chain, from agricultural product, food processing, food distribution and finally to consumers. This improvement needs to be made because it has a significant impact on the growth of the food manufacturing industry [1].

Manufacturing industries are facing significant challenges due to the continuous growth in manufacturing technology. These challenges encompass meeting customer satisfaction, accurately forecasting product demand, enhancing manufacturing operations' efficiency, thriving in a competitive market, and adapting to technological advancements. In this landscape, simulation emerges as a valuable tool for replicating real-time outcomes, facilitating measurement of productivity. In the current context, industrial technology has progressed into the fourth stage of industrialization, refer to Industry 4.0 [2]. To remain competitive, a well-optimized manufacturing system plays a crucial role in swiftly manufacturing innovative products and reducing the time the product being ready to sale in the market [3]. A good manufacturing system requires several thoughts, such as production scheduling, production planning and control, the organization of facilities layout, and many others. Therefore, by using simulation, the actual manufacturing system of the food industry will be examined. Subsequently, leveraging the insights gained from this analysis, several improvements can be recommended for the system.

The worker allocation problem is same as the production line problem. This problem is to find the optimal allocation of workers to machines. Either by minimizing the number of machines based on the cycle time or minimizing the cycle time based on the number of machines, taking into account the number of workers constraint. In contrast, in this study the problem differs from the assembly line problem in that it involves allocating workers to machines while ensuring non-crossing walking routes for the workers.

In order to achieve specific objectives and comply with all constraints, labor-intensive production systems need to ensure optimal resource allocation. The problem of worker allocation is more about determining who and where workers will be assigned to specific tasks and locations. The objective is to reduce production time, labor costs and overtime, at the same time the quality of production needs to be improved. In practice, managers will usually allocate workers based on work experience. Randomly allocate workers, it may result in a long production period and excessive costs.

Resource allocation is regarded as one of the very important factors because allocation of workers, reduction of cycle time, scheduling of machines, task allocation all acts as resources which are to be optimized. When certain methods are used to solve the problem, then it will provide a very useful contribution. This recognition is intended to appreciate and acknowledge the methods at resolving worker allocation problems.

Due to its significant impact on optimizing cost and productivity, the use of discrete-event simulation has been extensively used in examining operations for the past three decades. Arena software can be used to develop discrete-event simulation models. The advantage of Arena software is its flexibility in developing simulation models across different areas of industries. Meanwhile, data envelopment analysis is an optimization method that is proposed for improving operations with multiple inputs and outputs. The CCR model, a data envelopment analysis model introduced by Charnes et al. [4] was designed to measure the relative efficiency of homogenous decision-making units. Banker et al. [5] then expand the CCR model, and the model is known as BCC model. In this study, BCC model is applied. The main advantage to this method is its ability to handle multiple inputs and outputs. It is also useful because it takes into consideration returns to scale in determining the efficiency scores. Given the multiple inputs and outputs to be analyzed in this study, the combination of simulation and the DEA-BCC model appears to be an ideal method.

In this study, there will be several steps used as the methodology to achieve the objectives. Firstly, the collection of data for each process, followed by analysing the obtained data using the analysing tools. Next, the data will be used to develop a simulation model based on the actual system. The simulation model then must undergo a verification and validation process. Upon successful validation process, the simulation model will be extended to encompass various alternatives (improvement models) to solve the problem. Simulation models corresponding to these improvement models are used to acquire the inputs and outputs which are represents the performance criteria. Next step is to develop the DEA-BCC model, with the improvement models serving as the Decision-Making Units (DMUs). The best improvement model with the best performance criteria will be identified after analysing the results. Figure 1 illustrates the flow of the research framework in brief.

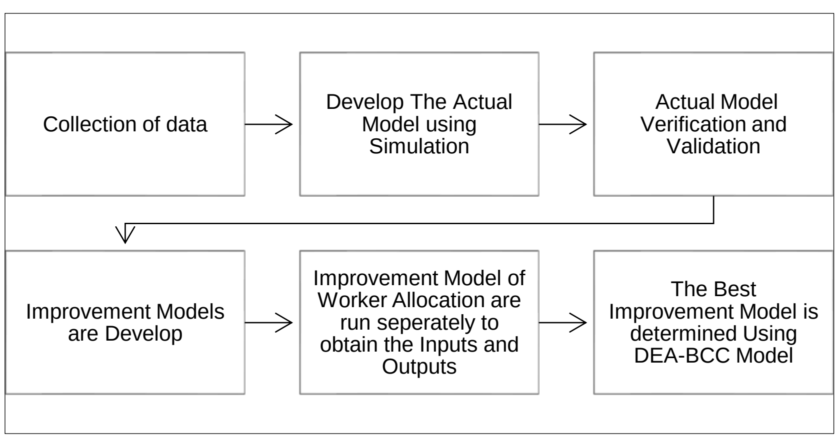

Figure 1: Research Framework

This research will be using secondary data obtained from an SME food manufacturing company located in Penang. This data is related to the food manufacturing system which produces chocolate malt. The manufacturing process for chocolate malt powder involves several stages, resulting in the creation of a high-quality product. The flowchart detailing each process within the system's operation is depicted in Figure 2.

Figure 2: Operating system flowchart

The initial stage known as the premix process; this process is to formulize the raw materials for making the product which is chocolate malt powder. In this process, only two workers are needed. This process is carried out completely using workers. All raw materials that have been formulated at the premix process are mixed at the mixing process. This process needs two workers and machines. The machines must rotate 20 minutes per 100kg of powder that was formulized at the previous process. The time is set to get good quality chocolate malt. The powder from the mixing process is packed into 1kg packets during the filling process. This process needs two workers and machines. The final stage in the operating system is the packaging process. In this process, only one worker and a machine are needed. This is because the packaging processing time is short compared with the previous three processes. This process is to pack the 1kg packet into boxes. Each box has 12 packets of the 1kg packet of chocolate malt powder.

3 RESULTS AND DISCUSSION

After gathering all the required data and information, the modules were compiled and connected resulting in a flowchart view within the Arena software. Figure 3 shows the simulation model for the manufacturing system using the Arena software.

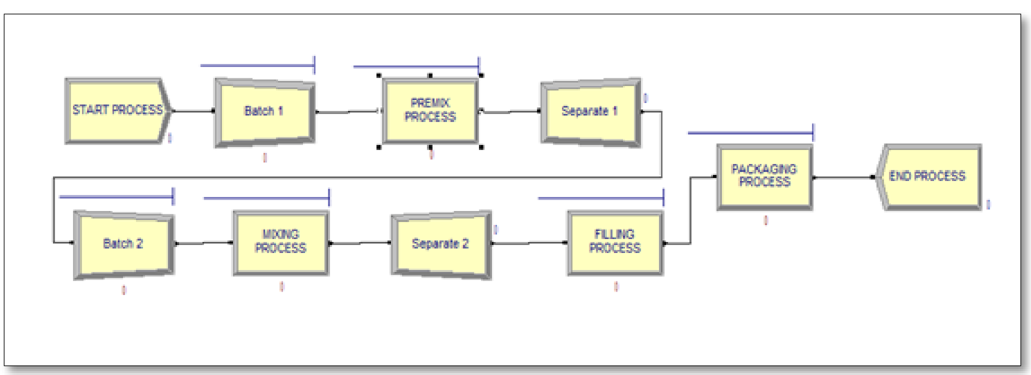

Figure 3: Flowchart view of the simulation model using Arena software

The statistical distribution of the data for the simulation model of the actual manufacturing system is presented in Table 1. Following the development of the simulation model using Arena software, it undergoes a verification and validation process. Model verification is to ensure simulation model is free from logical errors. Model validation, on the other hand, ensures the simulation model can represent the actual system. The processing time for each process was used to validate the simulation model. Number in and number out were also used to validate the simulation model. The calculations of the differences can be found in Table 2.

Table 1**:** The distributions of the process time derived from Arena Input Analyzer

Process	Distribution	Expression
Premix	Exponential	255 + EXPO (46.5)
Mixing	Weibull	1.2e+003 + WEIB (0.468, 0.166)
Filling	LogNormal	3.5 + LOGN (4.82, 4.2)
Packaging	LogNormal	4.5 + LOGN (1.65, 1.35)

Table 2: Differences between simulation output and the actual data for each process

Process	Simulation Output (minutes)	Actual Data (minutes)	Difference (%)
Premix	4.9890	5.0250	0.0072
Mixing	20.0770	21.2500	0.0552
Filling	0.1349	0.1375	0.0189
Packaging	0.1027	0.1015	0.0118
Number in	1995	2000	0.0025
Number out	1894	1800	0.0522

The model is valid if the percentage differences are less than 10%. Since the percentage differences are all less than 10%, then the model is valid [6]. The next step involves identifying 19 improvement models based on assumptions related to the minimum, maximum, and total number of workers. The minimum number of workers is one, the maximum is three, and the total number of workers is eight. Table 3 shows all the improvement models that have been recorded.

Table 3: Alternatives of Improvement Models for operator allocation at each process

Improvement Model	Premix	Mixing	Filling	Packaging
IM1	1	1	3	3
IM2	1	2	2	3
IM3	1	2	3	2
IM4	1	3	1	3
IM5	1	3	2	2
IM6	1	3	3	1
IM7	2	1	2	3
IM8	2	1	3	2
IM9	2	2	1	3
IM10	2	2	2	2
IM11	2	2	3	1
IM12	2	3	1	2
IM13 (Actual system)	2	3	2	1
IM14	3	1	1	3
IM15	3	1	2	2
IM16	3	1	3	1
IM17	3	2	1	2
IM18	3	2	2	1
IM19	3	3	1	1

Simulation model of each improvement model is developed. Simulation models of improvement models are run using Arena software to obtain the inputs and outputs. The inputs were the average total production time (v1) and average number of entities in the system (v2). while the outputs were the total production (u1) and average worker utilization (u2). The inputs and outputs are shown in Table 4 and these inputs and outputs were employed in the next stage to conclude the decision of optimal worker allocation alternative.

The efficiency scores are evaluated using the DEA-BCC model. The model is output oriented to measure the efficiency scores to accomplish a maximum level of outputs to the given inputs and solved using Lingo 12.0. Thus, the output-oriented BCC-DEA model results as shown in Table 4.

Table 4: Inputs, Outputs and Efficiency Score of each alternative

Improvement Model	Average total production time (minutes)	Average number of entities in the system (packets)	Total production (packets)	Average resource (worker) utilization	Efficiency score
IM1	86.5040	445.76	2317.00	0.5729	0.5530
IM2	96.6377	407.48	2001.00	0.4479	0.4740
IM3	57.5842	240.96	1894.00	0.3876	0.7091
IM4	63.6954	261.36	1876.00	0.4243	0.6976
IM5	73.3378	356.18	2341.00	0.4662	0.5907
IM6	61.7028	217.44	1530.00	0.3344	0.6658
IM7	45.1423	171.78	1890.00	0.3801	0.9667
IM8	89.0462	414.86	1908.00	0.4157	0.4432
IM9	46.0712	193.40	1923.00	0.3845	0.8809
IM10	40.3834	209.18	1854.00	0.3587	0.7968
IM11	40.3318	207.11	2516.00	0.4410	1.0000
IM12	41.4403	153.44	1789.00	0.3223	0.9393
IM13 (Actual system)	37.4070	145.45	1894.00	0.3217	1.0000
IM14	348.0200	1012.87	585.00	0.3597	0.1390

IM15	69.9596	265.51	1890.00	0.3810	0.6265
IM16	215.0300	875.37	1676.00	0.4491	0.2132
IM17	48.5188	287.68	2349.00	0.4189	0.7840
IM18	40.1747	182.94	2209.00	0.3837	0.9692
IM19	46.7037	273.28	1884.00	0.4302	0.7948

This study has proposed that Improvement Model 11 (IM11) is the best improvement model to be compared with the actual system as it has an efficiency score of one. Table 6 shows the comparison between the actual system and the IM11.

Table 6: Inputs and Outputs of each alternative

Model	Average total production time (minutes)	Average number of entities in the system (packets)	Total production (packets)	Average resource (worker) utilization
Actual System	37.4070	145.45	1894.00	0.3217
IM11	40.3318	207.11	2516.00	0.4410

Table 6 illustrates that both the total production and the average resource utilization of IM11 increase when compared to the results of the actual system. Specifically, the total production and the average worker utilization show increments by 622 packets and 0.1193, respectively. Moreover, there are increases in both the average total production time and the average number of entities in the system also increases as compared to the actual system. Notably, while the average total production time increases, the total production also experiences an increase. As a result of this study, the optimal operator allocation is IM11 as the proposed modification can improve the actual system's efficiency and productivity.

4 CONCLUSION

In this study, nineteen improvement models for worker allocation were proposed. Utilizing the DEA-BCC model, each improvement model's efficiency was analyzed to identify the optimal solution for enhancing worker allocation within the company's manufacturing system. The results indicated that only Improvement Model 11 is efficient, achieving an efficiency score of one. Consequently, IM11 has been chosen as the best improvement model. Consistent with the simulation results, IM11 has the potential to increase both total production and average worker utilization.

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