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A Discrete Event Simulation Model for Simulating and Analyzing Soy Sauce Production Processes

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Abstract. Various factors, such as process bottlenecks, un-optimized production schedules and imbalance employees' working time, can complicate production processes and operations. These factors, however, have rarely been considered in previous discrete event simulation studies, which typically analyses the impact of available resource capacities on system throughput. By considering the factors, this paper models and analyses the production processes of a soy sauce manufacturing company. The flow of the processes and their processing time were first observed and collected from the real system. The flow logic and behavior were simulated using Arena software. The model was run, verified and validated to measure the current performance of the system, especially on the utilization of available resources. Various 'what-if' scenarios were then analyzed to propose strategies to improve the processes. The analyses show that bottlenecks occur at the *moromi* and *koji* processes, imposing the company to extend their operation hours to satisfy the demand of the product. The model helps the company identify the pain point in the production flow and analyze potential actions and its impact on production throughput.

INTRODUCTION

Manufacturing systems are systems producing physical valuable goods in large quantities using raw materials and relevant resources, such as machines and labor [1, 2]. The goods are produced or transformed through a series of manufacturing processes, beginning with product design and material specification [3]. The goods can either be sold to other manufacturers for further producing more complex products (e.g., automobiles and aircraft) or distributed through the tertiary industries (e.g., wholesalers or retailers) to end users and consumers. Among the most important manufacturing industries are electronics, automobiles, heavy machinery and furniture.

Manufacturing industries play an important role in the economic development of a country. In case of Malaysia, manufacturing is a major component of its economy strength and contributed about 20% to its GDP in 2021 (Department of Statistics Malaysia). In addition, Malaysia's manufacturing sector has been dominated by small and medium enterprises (SMEs). The existence of the SMEs has offered many benefits. These include reducing unemployment and poverty by providing jobs, minimizing regional disparities and helping earn foreign exchange [4, 5]. However, SME manufacturing companies throughout the world have been facing many challenges in their production lines, such as the lack of the latest technological tools, little or no access to any funds to upgrade their existing technologies or to support research to improve their performance [6, 7]. As a result, their businesses need to be run manually and require a lot of human participation in the productions processes. This may eventually lead to a lot of manufacturing problems, such as poor working systems and production schedules. Additionally, SME industries have now been hit harder by the volatility of market demand especially during this COVID-19 pandemic [8].

To mitigate the problems, running a factory overtime has been the easiest approach. However, the decision to have overtime or not should rely upon certain reasons, e.g., increased demand or understaffing. Overtime normally emerges at a production line since it is the place where expanded hours of labors are mostly required. At this line, a

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great deal of waste, such as bottlenecks and work in progress, will typically occur that may prompt wasteful production processes. Without identifying such waste prior to running overtime, SME businesses may face a deeper financial problem. Thus, a study needs to be carried out before implementing scheduled and unscheduled overtime to fulfill customer orders and to comprehend at which zones most time is wasted. The paper develops a discrete event simulation (DES) [9-12] model for simulating the production flow of a soy sauce manufacturing company in Malaysia. The model was then used to analyze the current production flow performance, identify the stations having bottlenecks and recommend strategies to improve the current production processes.

The rest of this paper is organized as follows. Section 2 provides literature reviews on overtime, bottlenecks and DES. Section 3 discusses the research methodology, especially the essential steps that for designing and developing the DES model. Section 4 describes the development of the model, how its outputs were analyzed and some recommendations to be considered to improve the system performance. Finally, conclusions with a summary of our contributions are outlined in Section 5.

LITERATURE REVIEW

Financial sustainability of a country is significantly dependent on the economy of its nation. The economy can be contributed by various sectors. One of the sectors is industry, which can include manufacturing, technology, food and airline industries [13]. Each industry has its own complexities and challenges determining its survival and the competencies in the market. To encourage economic growth and sustainability, the existence of competitive market is very important. The competitive market is mainly navigated by two main factors: demand and supply [14, 15]. Demand refers to consumers' willingness to purchase specific goods and services with a ranges of price. Supply, meanwhile, refers to the willingness and ability of producers to provide goods and services to the market. The availability of demand is significant for the economy, since it impacts the prices of consumer goods and services. However, it become a nightmare to industries if production of products is not managed effectively [16].

Production problems may occur before, during and after manufacturing processes. The problems are mainly caused by waste [17, 18] , improper production and resource schedules [19, 20], and inconsistent demand [21, 22]. Wastes are activities that do not add values or benefits to manufacturing processes, which hinder them from operating at their optimized levels. Wastes exist at various manufacturing stages, such as transportation, processes and inventory. Wastes should be eliminated to better utilize resources, reduce the required time for performing processes and improve company competitiveness in the market. One way to eliminate wastes is by eliminating bottlenecks.

A bottleneck is a common issue in a production or assembly system [23, 24]. It is a point of congestion or an area where work is held up. It can be triggered by many factors, such as poor production schedule, lack of human and equipment resources, and equipment breakdown. These factors can interrupt particular processes and delay the entire production processes. For this reason, a bottleneck is also known as a workstation limiting production productivity and efficiency. A bottleneck at a particular process is always contributed by a high usage of relevant machines, which eventually contributes to a high potential of failure. How to detect and analyze bottleneck in manufacturing systems has been discussed in literature [e.g., 24, 25, 26]. Bottlenecks can be eliminated using several ways. These include eliminating non-value activities, adding more resources or introducing overtime to bottleneck operations and minimizing machine downtime.

Overtime is extended working hours of the total planned working time [27]. Overtime issues have widely been discussed in many studies [e.g., 28, 29]. Overtime becomes a nature especially when the manufacturing processes are running inefficiently or the target production of goods has not been achieved. Overtime is frequently implemented in various phases of cost management and staff planning [27]. Thus, overtime and the number of staff are highly correlated [30]. A smaller number of hired staff may lead to a higher number of overtime to fulfill staffing requirement. There are two types of overtime: scheduled overtime and unscheduled overtime [31]. Scheduled overtime is extra working time planned to complete tasks or support ongoing operations. In contrast, unscheduled overtime is extra working time activated as a reactive strategy to overcome operation disturbance. The requirement for overtime must consider many factors, e.g., machine maintenance, labor cost and utility cost.

Bottlenecks, overtime and resource schedules affect production processes and operations. These factors should be considered in modelling a manufacturing or production system. How the factors affect the production of products in a manufacturing environment, especially in a complex multi-product assembling plant, can be modelled and analyzed using DES [32-34]. In fact, DES has been used to measure and improve the performance of various types of systems, including service [35], traffic [36] and people evacuation [37-39]. By considering the factors, this paper uses DES to analyze the production processes of a soy sauce manufacturing company. This allows the company to consider actions to be taken to improve its production without interrupting the current operations.

METHODOLOGY

To develop the model, we adopted a DES framework proposed by Banks, Carson, Nelson and Nicol [9]. The framework consists of important steps for conducting a DES study as shown in Figure 1.

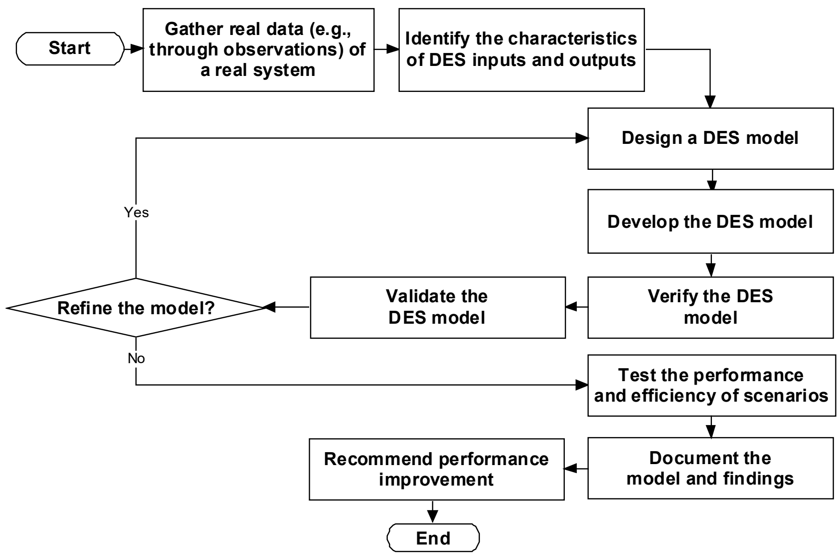

FIGURE 1. DES framework

Data Sources

This study used both data observed from the real manufacturing processes and information gathered from interviews with the company's experts, including the owner of the company and the manufacturing managers in its operations department. Observation was conducted to collect all information about available processes and the flow logic of the system. Examples of data include arrival time of soybeans and wheat, the processing time of each available process and resource schedule. A series of interview sessions was held to get information about how the current operations work.

Model Design

Based on the processes and information, a DES model was developed using Arena software. The model was first verified to ensure that it performs as intended and validated to ensure that it accurately replicates all the processes and mimics the behavior of the real system. It can then be used as a platform for performance analysis.

MODEL DEVELOPMENT AND ANALYSIS

The processes involved in the soy sauce manufacturing are shown in Figure 2. Soy sauce uses three main ingredients: soybeans, wheat and salt. The soy sauce manufacturing processes start with the arrival of soybeans and wheat. Soybeans are first steamed, while wheat is roasted. Both of them are mixed for making *koji*. *Koji* is then mixed with salt water. This mixture is known as *moromi*. *Moromi* is transferred to a tank to be fermented. Matured *moromi* is then compressed by a machine to get a liquid form, called raw soy sauce. The soy sauce is filtered through cloths, heated and refined. They are then inspected before being bottled for delivery.

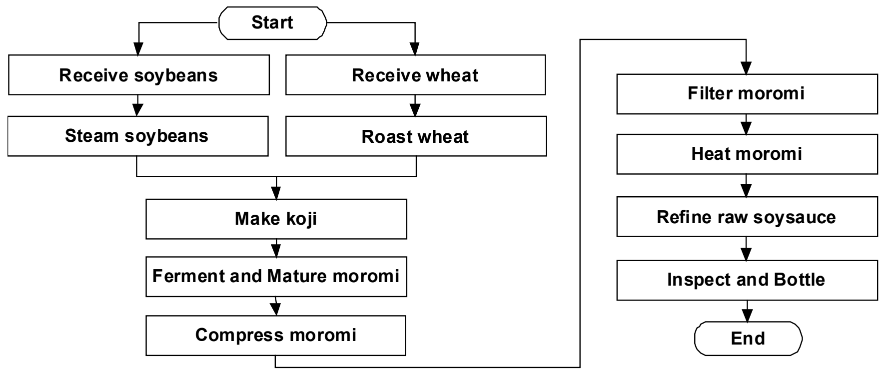

FIGURE 2. Manufacturing processes of soy sauce

Input Data and Parameters

The collected data were first input into the Input Analyzer package in Arena to find the best distribution for each process. The information is shown in Table 1. The detail explanations of the various types of the distributions can be found in most of simulation textbooks [e.g., 40, 41].

TABLE 1. Input data for the soy sauce manufacturing processes

Process	Expression	Units
Steam soybeans	2.47 + 1.02 * BETA(2.54, 2.53)	Days
Roast wheat	2.47 + 1.02 * BETA(2.54, 2.53)	Days
Make *koji*	4 + WEIB(1.05, 2.6)	Days
Ferment and mature *moromi*	TRIA(90, 93.4, 94.8)	Days
Compress *moromi*	8.19 + WEIB(0.952, 2.62)	Hours
Filter *moromi*	1 + 1.97 * BETA(2.28, 2.38)	Hours
Heat *moromi*	TRIA(1, 2.1, 3)	Hours
Bottle soy sauce	1 + 2 * BETA(2.21, 2.28)	Hours

Translating the Processes to a DES Model

The model used various Arena modules. The modules used to model the first four processes of the system is shown in Figure 3. A *Create* module generates the arrival of entities at the system, i.e., soybeans and wheat. A *Process* module simulates a process in the system, such as *steam soybeans*, *roast wheat*, *make koji* and *bottle soy sauce*. All these processes require a resource to operate. For example, the *make koji* process is performed by a *koji machine*. The time taken for a resource to operate the entities at a particular process is shown in Table 1. The resource can be attached with other resources. For example, a machine can be attached with operators to operate the machine. In addition, all resources can be scheduled to simulate overtime. An *Assign* module was used to assign relevant attributes to the entities to logically flow them throughout the model. A *Record* module was utilized to collect relevant statistics in the model, such as the number of bottles produced. A *Dispose* module destroys the generated entities to reclaim computer memory that has been reserved for the entities before.

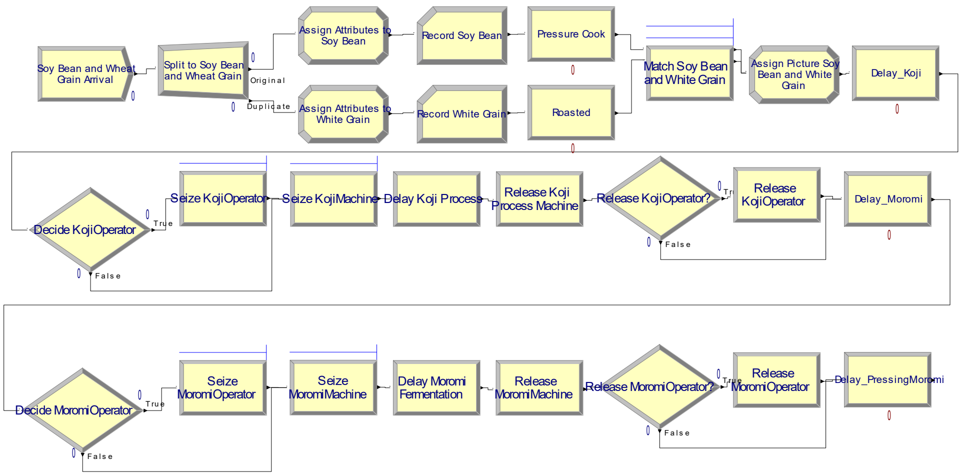

FIGURE 3. A snapshot of the DES model

Model Validation

For the validation purpose, the model was run for 360 days (to represent one year of operations) with 30 replications (to reduce variability in experimental results). Its performance outputs based on the setting were then compared with the actual performance of the system. The performance comparison is shown in Table 2. Total cycle time refers to the time taken from the processes of *compress moromi* until *bottle soy sauce.*

TABLE 2. Model validation

Performance Measure	Real Output	Simulation Output	Difference (%)
Total production per day	600 bottles	627 bottles	4.5 %
Total cycle time	14 hours	15 hours	7.1 %

Resource Analysis

Each process uses two types of resources: machine and operator. The model reported that the utilization of most of the resources is below than 5%. There are only two operations having a long queue and high utilization: *make koji* (99%) and *ferment and mature moromi* (81%). *Make koji* is the first process after the two entities are combined to be one entity. *Ferment and mature moromi* is the process right after the *make koji* process. The high utilization reflects that there is an overwhelming operations happening at these two processes, causing their resources to be fully utilized. In addition, the two processes require long processing time, making the downstream processes have very low utilization. This situation is called bottleneck. Thus, the bottlenecks in the soy sauce manufacturing have been identified.

Resource Capacity Analysis

The resource capacities at the two processes should be expanded to improve the overall manufacturing performance. Thus, the two processes were the target for the resource capacity expansion experiments and analyses. The first experiment was analyzing the optimal capacity for the *koji* machine, where the first bottleneck starts. Currently, the capacity for the *koji* machine is only one, representing one closed area with one machine for fermentation culture. The simulation analysis showed that the *koji* machine should be expanded to 40 to optimally improve the system performance. However, improving the flow at the *make koji* process would create congestion at the *Ferment and mature moromi* process. Thus, the second experiment was performed to find the optimal capacity of the *moromi* machine. The simulation analysis showed that the *moromi* machine should be increased from one capacity to 10 capacities to improve the entire process. Increasing the capacities of both machines will improve the flow of entities to all downstream processes in the soy sauce manufacturing. Table 3 shows the performance comparison if such recommendation is implemented.

TABLE 3. Overall performance comparison

Performance measure	Comparison		
	Actual	Simulation	Improved
Total Output (bottle)	600	627	8,303
Cycle Time (hours)	14	15	11

CONCLUSION AND FUTURE WORKS

This paper models and analyzes the production processes of a soy sauce using a DES approach. The DES model provides a holistic view of the performance of the system. Using the DES model, various strategies to improve the performance can be carried out using *what-if* analysis. Such analysis assists the soy sauce production company identify bottlenecks disrupting the system performance, which slow down the entire manufacturing processes. Overcoming the bottlenecks enables them compete in the competitive market. The results show that the bottlenecks occur at two processes: *moromi* and *koji*. Adding more resources at these two processes will improve the system performance. For future work, the DES model will be animated to visually demonstrate the production of soy sauce at each stage of the processes. The animation allows the company visualize the impact of various changes in model structures and logic and experiment potential alternatives to determine the best approach to optimizing the performance. Additionally, data envelopment analysis (DEA) [42, 43] can be used to measure the efficiency of various input configurations to improve the performance of the system.

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