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Optimizing Food Manufacturing using Hybrid DES-DEA techniques: A Case Study at a Bean Curd Puff Factory

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Abstract The competitiveness and expansion of small and medium-sized business (SMEs) engaged in food manufacturing is restricted by ineffective food production systems. This paper applied discrete event simulation to construct and simulate a representation of a food production line which enables better management and performance enhancement. The simulation results inform three improvement models (IMs) designed to reduce bottlenecks by adjusting operator allocation and soybean entry intervals. Data Envelopment Analysis (DEA) with the Banker, Charnes, and Cooper (BCC) output-oriented model is employed to determine the efficiency score of each improvement scenario. Additionally, Cross efficiency and Super efficiency BCC methods are used to rank these strategies, aiding in the selection of the best improvement model to maximise total production and average resource utilisation. This study found that IM1 which involves Operator 1 managing the grinding and coagulation process, Operator 2 handling the filtering and moulding process, and Operator 5 being assigned to the cutting process with a 15-minute interval between soybean entries selected as the most effective improvement model. IM1 significantly reduces the average cycle time by 30.25%, increases total production output from 144 kg to 198 kg and achieves a modest increase of 5.91% in average resource utilisation. This study demonstrates the value of discrete event simulation and DEA in operational decision-making by providing strategies that help in identifying and eliminating bottlenecks and optimise the food production process. The findings contribute to improve the competitiveness of SMEs by providing a reproducible framework for optimising production efficiency and resource usage in food manufacturing systems.

Keywords Discrete event simulation; food manufacturing; data envelopment analysis; improvement model.

Mathematics Subject Classification 90B22, 68M20.

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1 Introduction

The food manufacturing industry transforms raw agricultural ingredients into safe, high-quality and nutritious food products that satisfy demands and preferences of consumers. Food production is highly dependent on specialist machinery, equipment and operators to ensure efficiency and quality. Small and medium-sized businesses (SMEs) contribute significantly to a nation's industrial economic growth [1]. Despite government support, SMEs frequently encounter obstacles to growth. As a result, focusing on better processing systems is critical for dealing with these limits and increasing overall operational effectiveness.

Discrete event simulation (DES) is a computational modelling technique that allows creation of virtual representations of real-world production lines for analysing and optimising complex food manufacturing processes. As Kelton et al. [2] highlights that DES allows for thorough analysis and optimisation without disrupting existing business operations. It helps informed decision-making by enabling the exploration of various production scenarios and identifying inefficiencies within the production line.

The objectives of this study are to identify the food production process limitations, evaluate the relative efficiency of various improvement strategies and select the best improvement model in order to enhance the operational effectiveness. This research aims to answer the following questions. Firstly, how can discrete event simulation (DES) be applied to model and analyse the production line to identify inefficiencies? Then, how does Data Envelopment Analysis (DEA) rank improvement strategies for food manufacturing production lines based on their performance in a simulated environment, with a focus on maximizing production output and resource utilization? Therefore, a simulation model was developed using Arena software to simulate the processes of the bean curd puff production which enables bottlenecks identification in the production process. Data Envelopment Analysis (DEA) can differentiate and rank various improvement strategies to provide valuable guidance in selecting the most impactful strategies for optimising the bean curd puff production line in terms of maximising the total production output and average resource utilisation.

2 Literature Review

Discrete event simulation used to study systems by representing them as a sequence of distinct events that happen at specific times. Entities move through a sequence of activities, in between which they wait in queues. Each entity can be assigned unique characteristics that influence its behaviour within the system. The time durations for these activities are generated by sampling from probability distribution functions [3].

There is a large volume of published studies describing the applications of discrete event simulation in the manufacturing industry. Rani et al. [4] integrated simulation and the DEA-BCC model to analyse the efficiency of a cassava chip production line. The study was based on data collected over a four-hour period and applied Cross efficiency and Super efficiency methods due to multiple Decision Making Units (DMUs) with an efficiency score of 1. Their model increased production output from 188 to 213 packets, reduced waiting and production times, and improved operator utilisation by 0.5%. While the study showcases the potential of simulation and DEA in enhancing production efficiency, its short data collection period limits the generalizability of the findings. Additionally, the improvement model focuses on adding operators to bottleneck areas, reallocating operators, and process improvement, without considering adjustments to the time arrival of entities, which may impact overall system performance. Liong et al. [5] employed simulation to optimise resource allocation in chilli sauce production. The findings revealed that the most effective course of action not only increased chilli sauce production but also reduced resource costs. However, this study primarily focuses on resource allocation without considering long-term sustainability. Subrata et al. [6] used simulation to model a bottle production line, identifying a bottleneck at the capping station. They proposed replacing it with an automated machine, reducing waiting times and increasing overall output. Additionally, they conducted a breakeven analysis to determine the time required to recover the cost of the new machine. Despite these contributions, the authors investigated limitations including the lack of consideration for worker fatigue and machine breakdowns. Moreover, the use of average cost and revenue values which may not accurately represent real-world conditions.

Krishnan et al. [7] studied discrete event simulation in a tyre manufacturing plant to identify the presence of bottleneck. They also utilised Pareto analysis to confirm the bottleneck simulation analysis result and cause-effect diagram to determine the root causes that lead to the problems detected. Based on their findings, they suggested modifying the calendering machine and implementing a pyrometer to avoid waste from under heating or overheating and save time. They also proposed future research to analyse productivity by automating transport systems between processes within the plant. Edirisinghe and Karunarathne [8] employed a combination of simulation, Pareto analysis and cause-and-effect diagrams to identify and address limitations in a solid tire manufacturing sector. Their findings pointed to inadequately maintained outdated machines and frequent power failures as key issues and recommended upgrading machines and adopting new technologies. For future studies, they suggested conducting an extensive analysis of the entire tire production process, including resilience, press-on band, and flap tire-building processes, and employing different productivity improvement techniques.

Wogiye [9] conducted a discrete event simulation study on line balancing in shoemaking. The research identified disruptions in stitching assembly and lasting and finishing lines. By simulating different scenarios, the study achieved improved line and production efficiencies, increased output and reduced waiting times in these critical areas. Dereje et al. [10] addressed challenges in a mineral water production line facing low throughput, long cycle times and equipment failures issues. Their simulation model successfully identified bottlenecks and eliminated bottlenecks. The result shows that there is a significant improvement in throughput and cycle time with the effectiveness of implementing a preventive maintenance strategy.

Zaibidi et al. [11] leveraged simulation modelling to assess the performance of a shrimp paste production system. Their investigation successfully identified a bottleneck within the packaging process and underutilised resources. By adding an additional packaging station, they achieved a reduction in total waiting time. Sinem and Merve [12] investigated production lines in a meat processing industry to improve their production lines and meet the increasing demand of customers. Through simulation modelling, they developed four scenarios to enhance final product output while maintaining the existing working time by evaluating the utilisation rate of machines. The analysis identified the scenario by changing delicatessen production plan, increasing freezer speed for sliced salami group and adding printer that yielded the highest production increase while fulfilling the company's production goals. Teshome et al. [13] applied discrete event simulation to analyse a polo shirt production line. Their study identified areas for improvement and proposed alternative line arrangements. There were four proposed line balancing scenarios while the fourth scenario with merging similar operations and resource adjustment brought the resulted in significant gains in output, capacity utilisation, and reduced waiting times. Additionally, the study highlighted cost savings through reduced labour cost and increased revenue potential.

3 Methodology

The research methodology involves data collection from the existing system, developing a simulation model using Arena, validating the data once the simulation model is constructed, proposing improvement models, applying Data Envelopment Analysis (DEA) with the BCC model, and ranking and selecting the improvement models based on their efficiency scores, as shown in Figure 1.

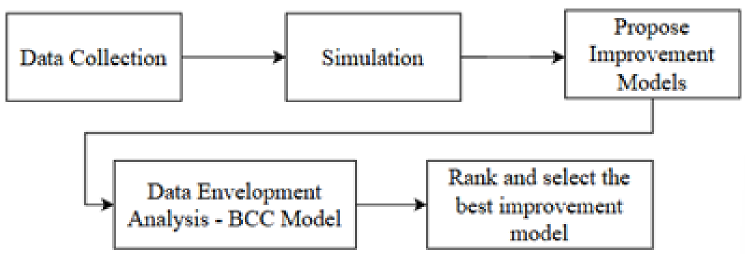

Figure 1: Process Flow Diagram

In this study, the simulation is designed to focus on the system's maximum capacity by excluding resource downtime, such as operator breaks or machine breakdowns. In addition, the inter-arrival time for soybeans is assumed to be consistent rather than random or following a specific distribution pattern to ensure the system's performance is evaluated under controlled condition. Furthermore, the simulation assumes that there are no "re-work" activities which refers to any pre-processed soybean that were rejected in the middle of the production process since the rejection rate is very low.

3.1 Data Collection

All data for the model were gathered through direct observation with the details on operator and machine counts, processing time for each stage of production and operator assignments using a stopwatch. Since the factory's operations follow a repetitive daily cycle without high fluctuations in workload, observations were conducted over four operating days, from 6:00 a.m. to 1:00 p.m. Four days observation period was chosen to enhance the reliability of the data and result of the system's overall performance. The collected data was analysed using Arena's input analyser. Input analyser helps to determine appropriate probability distributions for each process to improve the validity and reliability of the simulation model. Table 1 shows the resulting expression distribution values for each process time.

Table 1: Distribution of the process in bean curd puff production

Process	Distribution	Expression value
Grinding	Beta	3.15 + 1.5 * BETA (1.31,1.98)
Filtering	Beta	9 + 3 * BETA (0.954,1.07)
Cooking	Exponential	8 + EXPO (3.34)
Coagulation	Beta	9 + 11 * BETA (1.52, 1.4)
Moulding	Normal	NORM (4.57, 0.537)
Pressing	Beta	8 + 15 * BETA (1.29, 1.15)
Pressing with machine	Erlang	31 + ERLA (0.784, 4)
Cutting	Triangular	TRIA (8.38, 13.6, 15)
Frying	Erlang	17.2 + ERLA (0.196, 3)

3.2 Simulation Model

The bean curd puff production process was modelled and visualised using Arena software version 16.2 as shown in Figure 2.

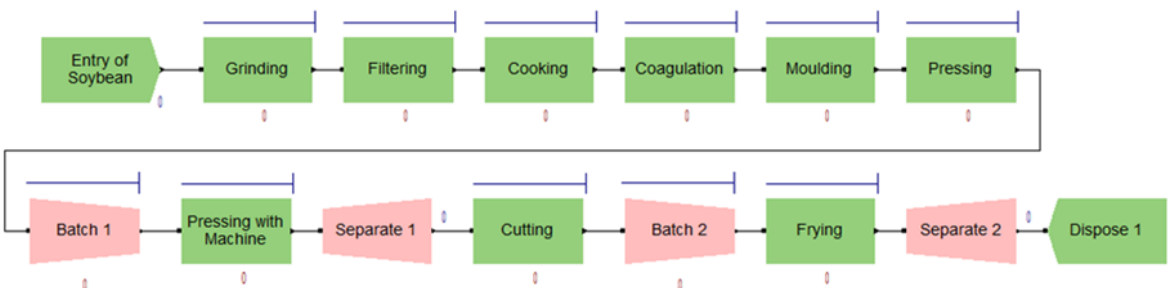

Figure 2: Simulation model in Arena software

The production of bean curd puff involves nine main processes. It begins by grinding softened soybeans into a slurry using a grinding machine. This slurry is mixed with hot water to create soybean milk and then filtered to separate it from the dregs using a filtering machine. After that, the soybean milk is cooked with a steam boiler. Coagulants are added to form curds which are subsequently shaped in moulds, compressed, and sliced into squares. Finally, these squares are fried until they become crispy and golden brown.

Currently, five operators are involved in the bean curd puff production process, with a 15-minute interval between each soybean input. The details of the operator assignments shown in Table 2. However, the roles of operators for coagulation, moulding and cutting can shift depending on availability.

Table 2: Operator assignments

Process	Number of operators	Operator assigned
Grinding	1	Operator 1
Filtering	1	Operator 2
Cooking	-	-
Coagulation	2	Operator 3, Operator 5
Moulding	2	Operator 1, Operator 3
Pressing	-	-
Pressing with machine	-	-
Cutting	2	Operator 2, Operator 4
Frying	1	Operator 4

Once the simulation is complete, a data validation process will be conducted. Sargent [14] discussed a methodology used to assess the validity of a model by measuring the differences between the simulation output and actual data. The following formula is applied to ensure that the model accurately represents the real-world system.

$$\text{Difference}\,(\%) = \frac{|\text{simulation data} - \text{actual data}|}{\text{actual data}} \times 100. \tag{1}$$

The difference (%) between the simulated data and actual data must equal or not exceed 10% to declare the model is valid using Equation (1).

3.3 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a nonparametric, "data-oriented" technique developed by Charnes, Cooper, and Rhodes [15]. It employed linear programming to assess the relative efficiency of comparable entities known as decision-making units (DMUs) which transform various inputs into outputs. By constructing an efficient frontier based on the best-performing DMUs, DEA facilitates a data-driven comparison of each unit's performance. A DMU is considered fully efficient (score of 1) based on the available evidence if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

There are two primary DEA models which are Charnes, Cooper, and Rhodes (CCR) model and Banker, Charnes, and Cooper (BCC) model where CCR model assumes constant return to scale (CRS) while BCC model under assumption of variable returns to scale (VRS). Furthermore, DEA models can be oriented towards either inputs or outputs. Input-oriented models aim to minimise the number of inputs while maintaining the same level of outputs. Conversely, output-oriented models aim to maximise the number of outputs while using the same level of inputs. By employing these different models and orientations, DEA provides a comprehensive analysis of a DMU's efficiency, allowing for targeted improvement strategies. In this study, a BCC output-oriented model is used as the factory aims to increase their total production output and resource utilisation. The BCC output-oriented model is shown below:

$$\text{Min } q = \sum_{i=1}^{m} v_i x_{ij_0} - v_0 \tag{2}$$

$$\text{subject to} \sum_{r=1}^{s} u_r y_{rj_0} - \sum_{i=1}^{m} v_i x_{ij_0} + v_0 \leq 0 \tag{3}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + v_0 \leq 0 \tag{4}$$

$$\sum_{r=1}^{s} u_r y_{rj_0} = 1, \quad v_0 \text{ free}, u_r, v_i \geq \varepsilon \tag{5}$$

where

- j = DMU index
- i = input index
- r = output index
- y_{rj} = the value of the r^{th} output for the j^{th} DMU
- x_{ij} = the value of he i^{th} input for the j^{th} DMU
- u_r = the weight given to the r^{th} output
- v_i = the weight given to the i^{th} input

3.3.1 Cross Efficiency

Traditional DEA models assign an efficiency score of 1 to units on the efficient frontier, indicating they are using resources optimally to produce outputs. However, this approach can lead to the issue of multiple DMUs being classified as equally efficient, even if their performance differs [16]. Cross efficiency method was developed as a DEA extension to rank DMUs with the main idea being to use DEA to do peer evaluation, rather than to have it operate in a pure self-evaluation mode [17]. Each efficient DMU uses input and output weights from other efficient DMUs. The Cross efficiency score can be calculated using the following equation:

$$E_{pt} = \frac{\sum_{r=1}^{s} u_{rp} y_{rt}}{\sum_{i=1}^{m} v_{ip} x_{it}}, \quad \text{where } p, t = 1, 2, \ldots, n \tag{6}$$

where

- E_{pt} = the score for DMU_t using the optimal weights selected by DMU_p
- u_{rp} = the weight given to the r^{th} output for the DMU_p

- y_{rt} = the value of the r^{th} output for the DMU_t
- v_{ip} = the weight given to the i^{th} input for DMU_p
- x_{it} = the value of the i^{th} input for DMU_t

The Cross efficiency refers to the average defined in Equation (7), not the individual score defined in Equation (6).

$$\overline{E}_t = \frac{1}{n}\sum_{p=1}^{n} E_{pt}. \tag{7}$$

3.3.2 Super Efficiency

The Super efficiency BCC technique, introduced by Seiford and Zhu [18], is employed to assess efficiency while accounting for variable returns to scale (VRS). The Super efficiency BCC model is as the following:

$$\phi_0 = \min \sum_{i=1}^{m} v_{ik} x_{ij_o} - v_0 \tag{8}$$

$$\text{subject to} \sum_{r=1}^{s} u_r y_{rj_0} = 1 \tag{9}$$

$$\begin{aligned} &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} + v_0 \leq 0, \\ &v_0 \text{free}, u_i, v_i \geq \varepsilon, r = 1, \ldots, s_i = 1, \ldots, m_j = 1, \ldots, n \end{aligned} \tag{10}$$

The Super efficiency BCC score should be obtained from

$$\frac{1}{\phi_0} > 1 \tag{11}$$

and calculated by comparing each DMU's performance to this virtual best practice unit. Scores exceeding 1 indicate a level of efficiency surpassing all observed units, providing a clear ranking system even among previously indistinguishable efficient DMUs. The highest Super efficiency-BCC score is considered as the best DMU.

4 Results and Discussion

4.1 Simulation Model

According to the simulation results in Table 3, the average total production time for a cycle time of bean curd puff is 312.9807 minutes accompanied by an average waiting time of 184.9586 minutes. Bottlenecks occurred in filtering, coagulation, moulding, pressing and cutting processes with the average total waiting time of 41.7692 minutes, 18.6186 minutes, 46.6501 minutes, 26.6617 minutes and 17.7464 minutes respectively. The moulding process stands out with the highest waiting time. In addition, the average resource utilisation for each operator and machine were shown in Table 4. The average resource utilization for operator 1 is the lowest compared to others at less than 50%, leading to an imbalance in resource utilization.

Table 3: Results of the simulation model

Process	Average processing time (minutes)	Average total waiting time (minutes)	Average cycle time (minutes)
Grinding	03.7109	01.8509	05.5619
Filtering	10.2598	41.7692	52.0291
Cooking	11.8022	03.0828	14.8850
Coagulation	14.9504	18.6186	33.5690
Moulding	04.3693	46.6501	51.0194
Pressing	16.9519	26.6617	43.6136
Batch 1 (before pressing)	-	12.5756	12.5756
Pressing with machine	34.9260	03.7614	38.6874
Cutting	13.1006	17.7464	30.8470
Batch 2 (before frying)	-	06.7048	06.7048
Frying	17.9510	05.5368	23.4879
Total	128.0222	184.9586	312.9807

Table 4: Resources utilisation of the existing system

Resources	Task	Average Resource utilisation (%)
Operator 1	Grinding, Moulding	41.49
Operator 2	Filtering, Cutting	86.72
Operator 3	Coagulation, Moulding	85.28
Operator 4	Cutting, Frying	58.74
Operator 5	Coagulation	67.41
Steam Boiler	-	57.23
Pressing Barrel	-	61.03
Pressing Machine	-	58.20

4.2 Data Validation

After simulating the production process, Equation (1) was used to validate the accuracy of the simulation model in representing actual production as shown in Table 5. The simulation data is fairly accurate but has slight discrepancies when compared to actual data where the simulation tends to overestimate slightly for the pressing, pressing with machine and cutting processes which show the highest difference between the actual and simulated values among all production processes. Overall, the differences between the simulated and actual data for the processing time in each stage of the production process and the total production time are less than 10% indicating that the simulation model is validated.

Table 5: Difference between actual value and simulated value

Process	Actual value (minutes)	Simulated value (minutes)	Difference (Simulated - Actual)	Difference (%)
Grinding	03.7460	03.7109	- 0.0351	0.9370
Filtering	10.4145	10.2598	- 0.1547	1.4854
Cooking	11.3385	11.8022	- 0.4637	4.0896
Coagulation	14.7180	14.9504	- 0.2324	1.5790
Moulding	04.5670	04.3693	- 0.1977	4.3289
Pressing	15.8610	16.9519	- 1.0909	6.8779
Pressing with machine	34.1345	34.9260	- 0.7915	2.3188
Cutting	12.3200	13.1006	- 0.7806	6.3360
Frying	17.7890	17.9511	- 0.1621	0.9112
Total	124.8885	128.0222	03.1337	2.5092

4.3 Improvement Model

Based on the results from the simulation model in Table 3, improvement models involving operator reallocation and soybean entry arrival time adjustment will be suggested to eliminate detected bottlenecks within the production line and optimise the production flow. Three improvement models (IM) are as follows:

- IM1: Operator 1 manages the grinding and coagulation process, operator 2 handles the filtering and moulding process and operator 5 are assigned to the cutting process.
- IM2: Operator 1 manages the grinding and cutting process, operator 2 handles the filtering and coagulation process and operator 5 is assigned to the moulding process. The time interval between soybean entries adjust to 25 minutes.
- IM3: Combination of IM1 and the time interval between soybean entries adjust to 35 minutes.

According to Table 6, the operator reallocation strategies focus on the coagulation, moulding and cutting processes since these stages have higher waiting times and require direct operator involvement. On the other hand, the assignments for operator 3 and operator 4 remain unchanged. These stages are the bottlenecks in the production line and reallocating operators to these areas aims to reduce idle times and enhance process efficiency. Operator 1, 2, and 5 are considered more proficient in the production processes. Therefore, they are suitable for role adjustments that better balance the workload across the production processes. In addition, adjusting the time interval between soybean entries help to reduce machine and operator idle time. Long intervals may lead to accumulated downtime and wasted capacity, while short interval may cause bottlenecks. This adjustment addresses timing issues that can disrupt the smooth transition between stages and provides better control over the production rate.

Table 6: Details of each improvement models

Improvement Model	Operator	Task	Time between soybean arrivals
IM1	1	Grinding, Coagulation	15 minutes
	2	Filtering, Moulding	
	5	Cutting	
IM2	1	Grinding, Cutting	25 minutes
	2	Filtering, Coagulation	
	5	Moulding	
IM3	1	Grinding, Coagulation	35 minutes
	2	Filtering, Moulding	
	5	Cutting	

Table 7 shows the result for all the three improvement models with their average cycle time, average total waiting time, total production and average waiting time for each production process with the bottleneck. All of these results of improvement models are obtained from simulation models through Arena version 16.2.

Table 7: Comparison of each improvement models

Improvement Model	IM1	IM2	IM3
Average cycle time (minutes)	218.2897	222.9891	184.7159
Average total waiting time (minutes)	93.7843	99.1054	59.4719
Total production (kg)	198.0000	180.0000	180.0000
Average waiting time at filtering process (minutes)	9.0090	26.6687	4.8975
Average waiting time at coagulation process (minutes)	12.9651	3.6485	4.7202
Average waiting time at moulding process (minutes)	17.7815	15.8074	10.5543
Average waiting time at pressing process (minutes)	9.1126	8.7967	6.2043
Average waiting time at cutting process (minutes)	11.2452	15.4416	7.0701

Table 8 compares the result of three improvement models (IM1, IM2, and IM3). IM1 prioritizes high production and efficient resource use, while IM3 excels in reducing waiting and cycle times but at the lower production and resource utilisation. In order to reach the company's objective of maximising the total production output and resource utilisation with given inputs, BCC output-oriented model has been applied with the help of determining the best intervention. Before applying the BCC output-oriented model, the average total waiting time, average cycle time and total operator are serving as inputs, while the total production and average utilisation as outputs.

Table 8: Input and output for each improvement models

Improvement model	Input			Output	
	Average total waiting time	Average cycle time	Total operator	Total production	Average resource utilisation
IM1	93.7843	218.2897	5	198	68.33
IM2	99.1054	222.9891	5	180	57.98
IM3	59.4719	184.7159	5	180	55.07

Based on the result in Table 9, IM1 and IM3 emerge as the top-performing models with an efficiency score of 1. A score of 1 indicates that the model operates at maximum efficiency which produces the maximum output for the given inputs. Since there are two models that achieved an efficiency score of 1, both Cross efficiency and Super efficiency methods have been utilised to determine the superior improvement model between them.

Table 9: Efficiency score for each improvement model with inputs and outputs weights

Improvement model	Efficiency score	Average total waiting time	Average cycle time	Total operator	Total production	Average resource utilisation
IM1	1.0000	0.0057	< 0.001	0.0939	< 0.001	0.0146
IM2	0.9091	< 0.001	< 0.001	0.2200	0.0056	< 0.001
IM3	1.0000	< 0.001	0.0054	< 0.001	0.0056	< 0.001

The results of Cross efficiency in Table 10 indicate that IM1 is a better improvement model compared to IM3 as it obtained a higher average score. The diagonal values of 1 represent each Decision Making Unit (DMU)s efficiency score when evaluated against itself which indicates perfect efficiency according to its own inputs and outputs under the model's assumptions. This implies that the DMU achieves the optimal balance between inputs and outputs as defined by the DEA model based on its own performance metrics. On the other hand, non-diagonal values represent peer evaluations that highlight differences in performance and Zhu [19] mentioned that the Cross efficiency scores can be greater than 1 under the output-oriented model. A Cross efficiency score less than one indicates less efficiency, while a Cross efficiency score more than one indicates that a DMU is performing more effectively relative to its peers as it produces more outputs for the same level of inputs in a output oriented model.

Table 10: Cross efficiency matrix

Improvement model	IM1	IM3
IM1	1.0000	0.9945
IM3	1.0094	1.0000
Average score, $\overline{E}_t$	1.0047	0.9973

IM1 obtained the highest average score in the Super efficiency BCC model, whereas IM3 has no feasible solution as shown in Table 11. When the Super efficiency BCC model produces infeasible results, it means that the model cannot find a valid set of weights for inputs and outputs that satisfies the conditions of the model while maximising the efficiency score beyond what is achieved by the most efficient DMUs. According to Equation (11), the scores of the improvement models will exceed 1 and the highest score will be considered the best improvement model. Given that IM3 is infeasible, IM1 is the optimal solution that achieving the objectives of maximising output production and average resource utilisation.

Table 11: Super efficiency of BCC

Improvement model	ϕ	$\frac{1}{\phi}$
IM1	0.8428	1.1865
IM3	Infeasible	-

This study finds that IM1 selected as the most effective improvement model as IM1 significantly reduces the average cycle time by 30.25% (from 312.9807 minutes to 218.2897 minutes) and bottlenecks in in filtering, coagulation, moulding, pressing, and cutting process had been reduced. It also increases total production output from 144 kg to 198 kg and boosts average resource utilisation from 64.52% to 68.33%, representing a modest increase of 5.91%. More details are shown in Table 12.

Table 12: Difference between simulation model and IM1

Model	Average cycle time (minutes)	Average waiting time (minutes)	Total operators	Total production (kg)	Average Resource utilisation (%)
Simulation model	312.9807	184.9586	5	144	064.52
IM1	218.2897	093.7843	5	198	068.33
Difference (%)	030.2546	049.2944	0	37.5	5.9051

5 Conclusion

This paper optimised a bean curd puff production line by identifying bottlenecks using Arena simulation modelling and recommending the most effective solution using Data Envelopment Analysis (DEA) with BCC output-oriented model, Cross efficiency and Super efficiency BCC model. Three improvement models involving operator reallocation and process adjustments were proposed, IM1 selected as the best improvement model which significantly reduces the cycle time by 30.25% (from 312.9807 minutes to 218.2897 minutes), increases total production output from 144 kg to 198 kg and boosts average resource utilisation from 64.52% to 68.33%, representing a modest increase of 5.91%. By integrating these techniques, the study assists the management in making informed decisions that address bottlenecks within the production process, maximise output and optimise resource utilisation. However, the external factors that could influence the production process such as maintenance costs, machine breakdowns, and other operational disruptions were not considered. Future investigations could be focus on incorporating multiple objectives into the optimisation process and conducting sensitivity analyses to evaluate the impact of assumptions on the optimisation results.

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