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OPTIMIZATION OF EGG-TRAY MANUFACTURING PROCESS BY USING DISCRETE-EVENT SIMULATION

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Abstract. *The egg tray industry plays a vital role in global food security by ensuring the safe transport of eggs, a staple in diets worldwide. However, inefficiencies in the manufacturing process, particularly among Small and Medium Enterprises (SMEs), often lead to reduced productivity and higher costs. This study addresses these challenges by employing Discrete Event Simulation (DES) to identify bottlenecks and optimize resource allocation in egg-tray production. A comprehensive DES model is developed using field data, including machine operation times and production rates, to accurately represent current manufacturing practices. The analysis reveals that increasing printing capacity and integrating mechanical drying—thereby reducing dependence on environmental conditions—significantly improves throughput and system resilience. Furthermore, strategic adjustments in resource allocation, such as increasing the number of blenders and egg tray machines, effectively minimized waiting times across production stages. This study underscores the potential of DES to promote sustainable and efficient manufacturing practices, contributing to enhanced food security, reduced economic disparities, and improved productivity in developing regions.*
Keywords: Discrete Event Simulation (DES), Optimization, Egg Tray, Manufacturing, Monte Carlo Simulation

1. **Introduction.** Eggs are a widely consumed commodity worldwide due to their affordability and excellent nutritional value. They play a crucial role in various food industries, including bread-making, mayonnaise production, and as staple ingredients in daily meals [1, 2]. As a result, the demand for eggs and their efficient distribution mechanisms continues to grow. In Indonesia, for example, the egg consumption increases from 5.08 kg/capita/year in 2015 to 17.07 kg/capita/year in 2021 (see Fig. 1) [3]. This significant rise in consumption drives a corresponding increase in production. Between 2015 and 2022, egg production in Indonesia grows from 1,705 kilotons to 6,323 kilotons (see Fig. 1) [4], reflecting the rising demand for egg trays.

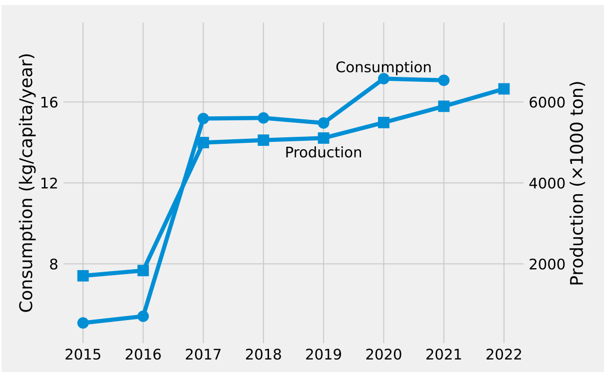


Figure 1. The 2015–2022 Consumption and Production of Eggs in Indonesia [3, 4].

An egg tray is a simple apparatus designed to securely and stably hold eggs [5], counteracting gravitational and other forces. Friction is critical for preventing the eggs from slipping or shifting. To enhance grip and stability, some egg trays are equipped with non-slip layers or rubberized surfaces. The egg-tray role becomes more important during handling and transportation [6].

Egg trays are made from a variety of materials depending on requirements and cost. The three most common are plastic, metal, and paper pulp. Plastic is a popular choice due to its lightweight nature, corrosion resistance, affordability, and versatility in being molded into various shapes and colors [7]. Metals, such as aluminum or stainless steel, are another common choice, valued for their high strength, durability, and elegant appearance. Metal trays are long-lasting and suitable for repeated use. Lastly, paper pulp is an environmentally friendly and cost-effective option. While not as strong as plastic or metal, it provides sufficient stability to safely support eggs [8].

The egg tray manufacturing process starts with the pulping stage, where raw materials are broken down into a slurry. This is followed by the molding and drying stages, and the process concludes with a detailed inspection to ensure product quality (see Fig. 2). The pulping process in the egg tray manufacturing industry involves converting raw materials, such as carton boxes, into pulp, which is then molded into egg trays. Three primary methods of pulping are used: mechanical, biological, and chemical [9]. Mechanical pulping involves the physical breakdown of carton fibers, using grinding, refining, or crushing to separate the cellulose fibers from the material, retaining both lignin and cellulose fibers, resulting in a high pulp yield. It is cost-effective and energy-efficient [10]. Biological pulping uses environmentally friendly agents, such as white-rot fungi or lignin-degrading enzymes, to pre-treat carton fibers, reducing the reliance on harsh chemicals but taking a longer time. These agents soften and degrade the lignin while preserving the cellulose content of the fibers [10]. Chemical pulping involves treating carton fibers with chemicals in an aqueous solution under high temperatures and pressure, removing hemicellulose and lignin, resulting in high-quality pulp with excellent strength properties. The Kraft process produces strong and durable pulp suitable for various paper products. However, the method is more expensive and less environmentally friendly due to its reliance on hazardous chemicals and high energy consumption. While it produces high-quality pulp, chemical pulping may not be the most cost-effective or sustainable option [11].

Despite its importance, research on optimizing manufacturing processes in the egg tray industry remains limited. Key factors such as productivity, efficiency, and risk management are essential for maintaining optimal production but are largely underexplored [12]. Ref. [13] used DES to optimize egg-tray weekly production and distribution for maximum profit involving multiple distribution centers, incorporating fluctuating costs. Refs. [14, 15] also deployed DES to identify bottlenecks, reorganize production workflows, and optimize equipment usage in manufacturing.

DES has been widely applied across various industries. One study integrated DES with value stream mapping (VSM) to optimize a pharmaceutical warehouse's supply chain, improving lead times and resource utilization [16]. Similarly, DES was used in

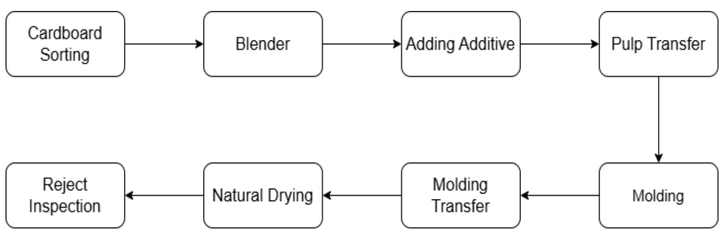


FIGURE 2. The Typical Manufacturing Process of the Egg Tray.

an aluminum brake bracket production facility to identify bottlenecks, resulting in a 6% productivity increase and an 8% reduction in workforce requirements [17]. Another study combined DES with a closed-loop Kaizen system to automate production lines in a Chinese manufacturing company, reducing labor costs by 59% while maintaining productivity [18]. Additionally, DES optimized a flexible manufacturing system (FMS) by internalizing outsourced production phases, reducing cycle time, and enhancing scheduling strategies [19]. The technique also proved valuable in optimizing lean production planning for precast component manufacturing by improving workstation synchronization and reducing bottlenecks [20]. Ref. [15] demonstrates how DES optimizes production lines in the automotive sector by reducing idle times and improving workflow efficiency. Similarly, Ref. [14] applied to the plastic manufacturing industry, achieving significant improvements in equipment utilization and process efficiency.

The method has been applied in facility layout optimization and workflow efficiency. A study on wool harvesting facilities demonstrated that a curved layout significantly improved worker travel distances and fleece throughput compared to a traditional linear arrangement [21]. Another study utilized DES in garment manufacturing by integrating real-time power monitoring systems (PMS), improving simulation accuracy by 19% and facilitating dynamic workload balancing [22]. Furthermore, in an engine manufacturing plant, DES was combined with multi-objective optimization and data mining, reducing storage levels by 31%, lead times by 67%, and batch sizes by over 50%, while leveraging genetic algorithms for enhanced decision-making [23]. Lastly, DES has been applied in sustainability efforts, with one study integrating it with photovoltaic (PV) energy generation, leading to a 36% reduction in energy costs [24]. These studies collectively showcase the versatility of DES in enhancing efficiency, reducing waste, and supporting data-driven decision-making. DES simulation was used to simulate a large-scale production involving selective laser sintering 3D printing to increase the production rate [25]. DES facilitated the study of the complex manufacturing process of electric motors and its interdependencies [26], the development of smart dynamic scheduling of jobshop policy [27], the study of the impact of design complexity in additive manufacturing [28], and the study of the propagation of variability in a manufacturing system [29].

Despite its broad applications, gaps remain in the use of DES for small-to-medium-sized industries, including egg tray manufacturing. Most existing research focuses on large-scale or highly automated industries, leaving smaller sectors largely underexplored. This study aims to address these gaps by developing a customized DES model for the egg tray industry, with an emphasis on production planning and resource optimization. Thus, the current objectives are to identify inefficiencies and suboptimal sections in the current egg tray manufacturing process, design an efficient manufacturing system that achieves desired performance targets, and determine the optimal case for an improved manufacturing process using DES.

The manuscript is organized as follows. Section 2, Research Method, describes the research procedure and a relevant statistical method. Section 3, Results and Discussion, discusses the developed DES models for a reference and for improvement scenarios. At the section end, the performances of the scenarios are compared. Section 4, Conclusions, provides a concluding remarks including a recommendation for the future study.

2. **Research Method.** The study begins with extensive data collection, during which field data are gathered from the current manufacturing process (Fig. 3). The key data include machine cycle times, production rates, and resource allocation at various stages. The collected data are subsequently used to develop a DES model that replicates current operations, providing a comprehensive representation of the existing manufacturing case.

Once the DES model is constructed, we perform a rigorous analysis to identify potential bottlenecks and inefficiencies within the system. In addition to pinpointing bottlenecks,

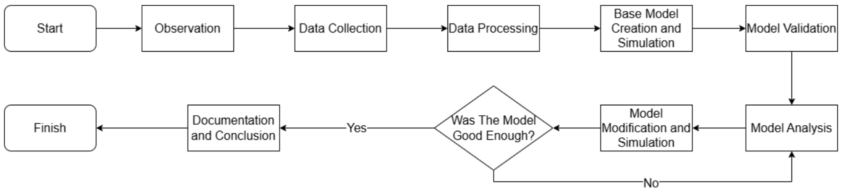


FIGURE 3. The Research Flowchart.

the analysis also focuses on evaluating the system's overall throughput—essentially, how efficiently the production line can produce egg trays over a specified period.

After identifying bottlenecks and throughput, the next phase involves developing alternative DES models to explore potential optimization strategies. These changes include adjustments to resource allocation, machine scheduling, and the sequencing of production stages. Each alternative model is simulated under the same conditions as the base model to ensure valid comparisons. The performance of these optimized models is evaluated based on key performance indicators, such as reduced cycle times, increased throughput, and improved resource utilization.

The main input data for any DES model are probability distribution functions describing the involved processes. The function is established by collecting the relevant data, developing a histogram to visualize the data distribution, selecting a potential probability distribution function, and finally, computing the relevant statistics, with the χ^2-statistic.

To validate the assumption, a χ^2-goodness-of-fit test is conducted by comparing the observed frequencies of process durations with the expected frequencies under a uniform distribution hypothesis [30]. The test statistic is computed by summing the squared differences between observed and expected counts, normalized by expected frequencies, and is mathematically written as: $\chi^2 = \sum(O_i - E_i)^2/E_i$, where O_i represents the observed frequency in category i and E_i represents the expected frequency.

Finally, we compare the optimized DES models to the initial model. By quantifying improvements in efficiency, throughput, and bottleneck reduction, the research identifies the most effective strategies for optimizing the egg tray manufacturing process. Ultimately, the study demonstrates how simulation-based analysis can be a powerful tool for enhancing production efficiency in industrial settings.

3. **Results and Discussion.** This section presents the results of applying DES to optimize the egg tray manufacturing process.

3.1. **The Base Model.** Egg tray production is a complex manufacturing process, requiring coordination of multiple stages to ensure efficiency and product quality (see Fig. 4). From raw material preparation to final inspection, each stage is critical in determining overall throughput and minimizing waste. In this study, a DES model is developed to replicate the real-world production process of egg trays, focusing on key manufacturing variables such as batch processing, resource allocation, weather conditions, and quality control. The manufacturing process starts with the arrival of the cardboard as the raw material. The material is then blended, molded, dried, and inspected. The material is transferred from one process to another, and the transfer process is also modelled.

The simulation runs over 18 days, 5 h per day, following the process outlined in Fig. 5. The simulation begins with the arrival of cardboard (top-left block), the primary raw material for the manufacturing process. Cardboard is sorted and batched for processing with an inter-arrival time of 14 min, and each arrival containing 12 entities, where 1 entity corresponds to 1 kg of cardboard (Blender Process block). Approximately 240 entities are processed daily, allowing for a maximum of 360 arrivals over the 18-day simulation period.

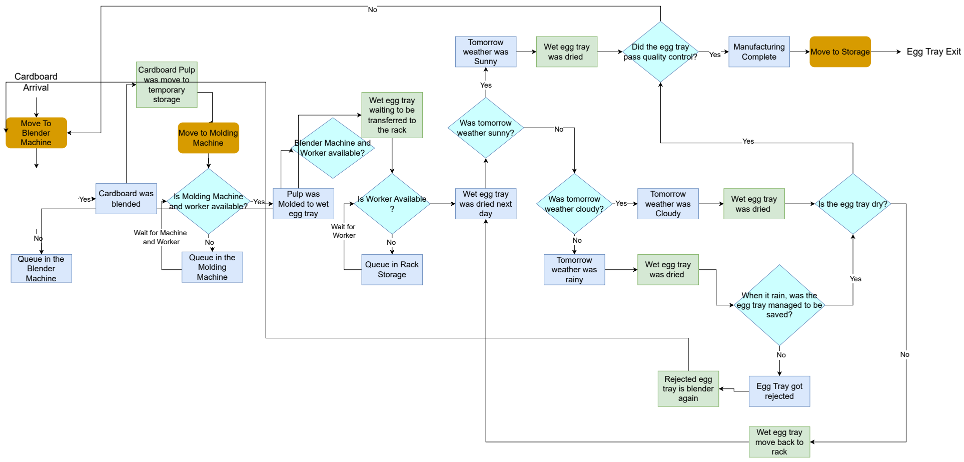


FIGURE 4. The Flowchart of Manufacturing Process of Egg-Tray.

To maintain operational efficiency, a hold condition is implemented, pausing processing whenever the number of egg trays stored in the drying rack exceeds 4,000 units.

The first stage of active processing is the blender operation, where cardboard is converted into pulp. The stage consists of three subprocesses: blending, adding additives, and blender transfer. These subprocesses operate in batches of 12 cardboard entities at a time, utilizing one blender machine and one worker as resources. During the blending process, the sorted cardboard is broken down into pulp. Additives, such as tapioca, are then mixed into the pulp to enhance its structural integrity. Finally, the pulp is transferred from the blender machine to a temporary storage area. The process times for these subprocesses are defined using probability distribution functions to incorporate variability that reflects real-world conditions. Each batch of 12 cardboard entities produces 120 egg trays, which are subsequently sent to the molding stage.

The process times for the blending, adding additive, and blender transfer operations are modeled using a uniform distribution, reflecting the observed range of durations. The

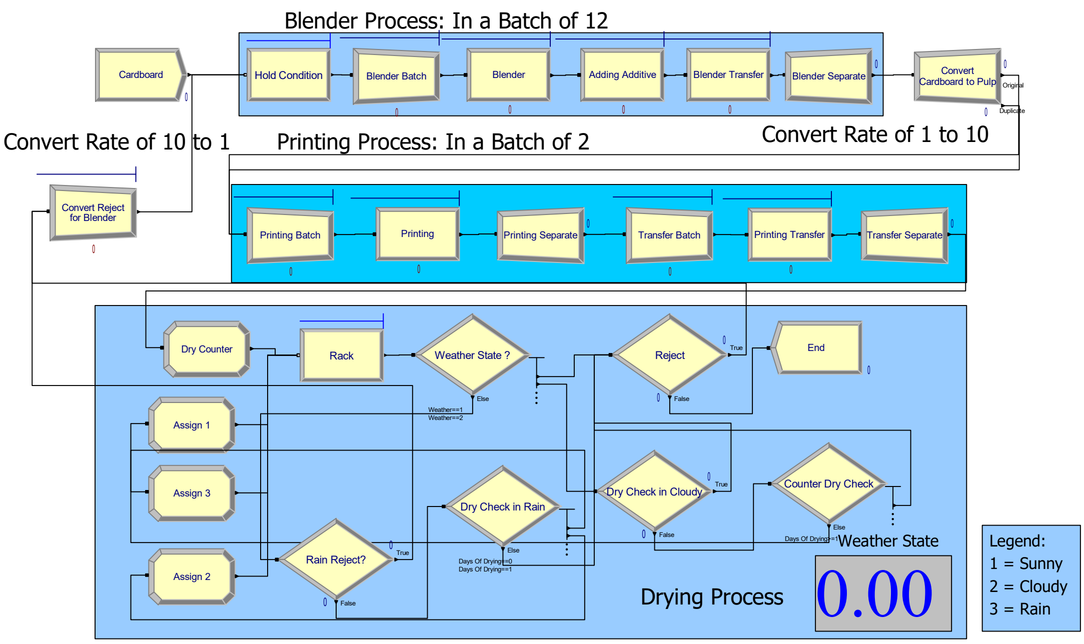


FIGURE 5. Discrete Event Simulation Model of the Egg Tray Manufacturing Process.

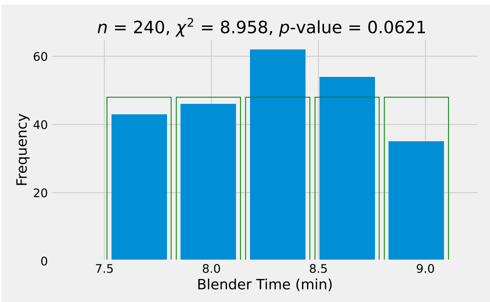
histogram of blending data, as well as the results of the fitness test, shows a relatively even spread of values across time intervals, with minor fluctuations (see Fig. 6(a)).

Similarly, the duration for adding additives and blender transfer exhibits an almost uniform frequency distribution across time intervals (Fig. 6(b) and Fig. 6(c)). The absence of a distinct peak or concentration in any specific interval supports the assumption that all time ranges are approximately equally likely. The even distribution makes the uniform distribution a logical choice for representing these process durations in the simulation.

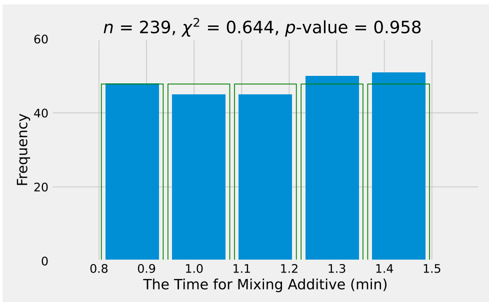
The molding operation comprises two subprocesses: molding and molding transfer, both of which process batches of two entities (Molding Process block). In the molding stage, the pulp is shaped into wet egg trays using one molding machine and one worker. Subsequently, the molding transfer stage involves moving the molded wet trays to storage racks, a task carried out by a single worker.

The uniform distribution is selected for the molding transfer data as it effectively captures the range of variability observed in the process. The evidence confirms that the uniform distribution accurately represents the variability in the molding transfer stage (Fig. 6(d)). In a summary, as shown in Table 1, the χ^2-goodness-of-fit tests for all four processes confirm the validity of the uniform distributions.

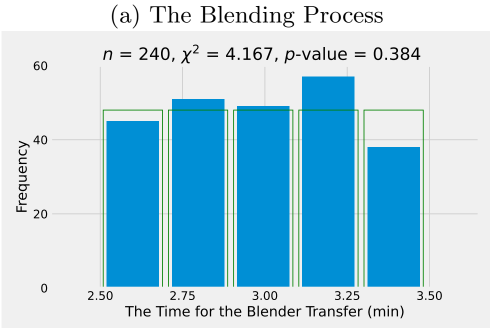
Drying is the most weather-dependent stage of the process, relying heavily on external environmental conditions to dry wet egg trays. The model incorporates three weather states: sunny, cloudy, and rainy (see Fig. 7). Observational data collected during the 18-day simulation period indicate probabilities of 83.3% for sunny days, 11.1% for rainy days, and 5.6% for cloudy days (Table 2). On sunny days, trays dry completely within a single day. On cloudy days, trays may only partially dry, requiring an additional day to



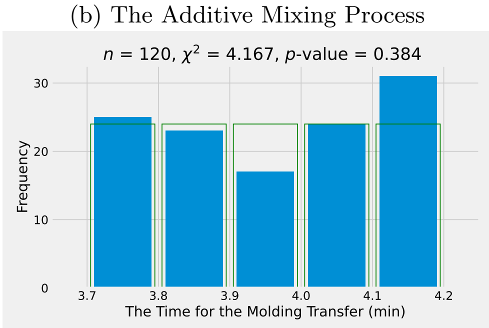
(a) The Blending Process



(b) The Additive Mixing Process



(c) The Blender Transfer Process



(d) The Molding Transfer Process

FIGURE 6. The Distributions of the Duration Required by Number of Processes and Comparisons to Uniform Distributions.

TABLE 1. The Chi-Square Goodness-of-fit Test For Each Process.

Process	df	χ^2	p-value	Decision
Blender	4	8.958	0.062	Do Not Reject H_0
Adding Additive	4	0.644	0.958	Do Not Reject H_0
Blender Transfer	4	4.167	0.384	Do Not Reject H_0
Molding Transfer	4	4.167	0.384	Do Not Reject H_0

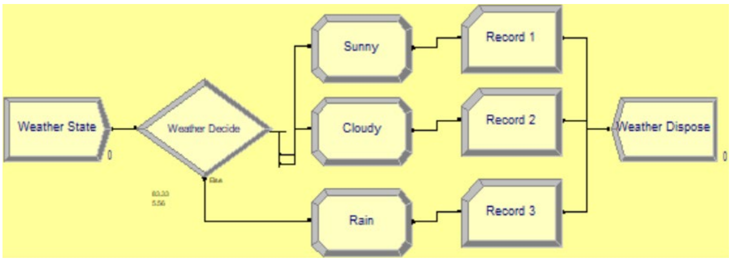


Figure 7. The Discrete-Event Simulation Model of the Weather State.

Table 2. The Probability Distribution of the Weather States.

Weather	Duration (day)	Probability	Drying Time (day)
Sunny	15	0.833	1
Cloudy	1	0.056	2
Rainy	2	0.111	3

reach full dryness. Rainy days present the greatest challenge, as prolonged exposure to moisture increases the risk of tray rejection.

By incorporating factors such as batch sizes, resource availability, and weather variability, the model offers valuable insights into the efficiency and bottlenecks of the manufacturing process. Detailed information is in Table 2.

After developing the base model, validation was conducted to ensure its accuracy by comparing the simulated throughput of egg trays with the collected data (Fig. 8). Both datasets exhibit similar trends, with consistent throughput on sunny days, moderate decreases on cloudy days, and significant drops during rainy weather. It validates that the simulation model effectively captures the key dynamics and variability of the real-world manufacturing process, particularly in weather-dependent stages like drying.

3.2. **Optimization.** To evaluate the optimization potential of the egg tray manufacturing process, multiple cases are tested using the ARENA Process Analyzer. Table 3 presents seven cases with variations in three control variables: the number of Blender Machines, Molding Machines, and Workers. The primary goal of this analysis is to determine the case that minimizes queue waiting times throughout the process.

In the baseline model, which includes 1 Blender Machine, 1 Molding Machine, and 3 Workers, the results show minimal waiting times in the early stages of production. The Blender Queue, Adding Additive Queue, and Blender Transfer Queue all have waiting times of 0.01 h, while the Molding Queue Waiting Time is 0.87 h. There is no waiting time in the Molding Transfer Queue. These results highlight that while the blender and additive stages operate efficiently, the molding stage presents a bottleneck.

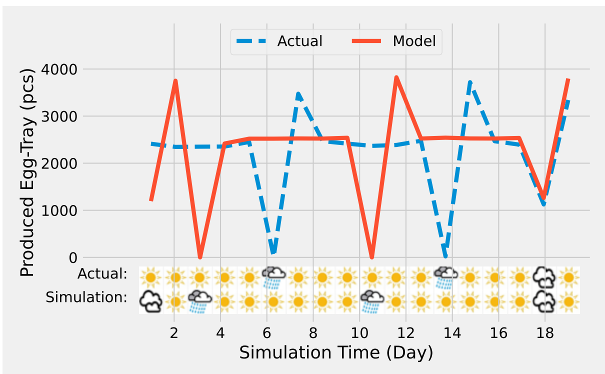


Figure 8. Validation: A Comparison of Model Output and Actual Data.

In the second case, the number of workers is reduced to 2, while the number of machines remains constant. It increases waiting times across all stages of production. The Blender Queue Waiting Time rises to 1.25 h, the Adding Additive Queue Waiting Time increases to 1.32 h, and the Blender Transfer Queue Waiting Time reaches 1.31 h. The Molding Queue Waiting Time also increases to 1.44 h, and the Molding Transfer Queue Waiting Time rises to 1.28 h. These results demonstrate that reducing the number of workers negatively affects efficiency and creates bottlenecks throughout the process.

In the third case, the workforce increases to 4, while the number of machines remains the same. However, this change does not lead to any significant improvement in efficiency compared to the baseline model. The waiting times in the Blender Queue, Adding Additive Queue, and Blender Transfer Queue remain at 0.01 h, while the Molding Queue Waiting Time stays at 0.87 h, with no waiting time in the Molding Transfer Queue. This indicates that increasing the workforce beyond 3 workers does not enhance productivity, as machine capacity remains the limiting factor.

The fourth case examines the impact of increasing the number of Blender Machines from 1 to 2, while maintaining 1 Molding Machine and 3 Workers. Surprisingly, this adjustment worsens queue times in most stages. The Blender Queue Waiting Time rises slightly to 0.13 h, and the Adding Additive Queue Waiting Time increases to 0.15 h. However, the most significant issue occurs in the Molding Queue, where the waiting time surges to 5.72 h, far exceeding the baseline value of 0.87 h. This indicates that adding a second Blender Machine overwhelms the Molding Machine, creating a severe bottleneck in later stages of production. Thus, increasing Blender Machines without addressing Molding capacity is not a viable optimization strategy.

In the fifth case, the number of Molding Machines is increased from 1 to 2, while keeping 1 Blender Machine and 3 Workers. The results reveal a Blender Queue Waiting Time of 1.25 h, an Adding Additive Queue Waiting Time of 1.31 h, and a Blender Transfer Queue Waiting Time of 1.24 h. However, the Molding Queue Waiting Time is significantly reduced to 0.12 h, and the Molding Transfer Queue Waiting Time is 0.12 h. This suggests that increasing Molding Machines primarily alleviates bottlenecks in the later stages of production but does not improve efficiency in earlier stages.

The sixth case explores the effect of increasing both Blender Machines and Molding Machines from 1 to 2, while maintaining 3 Workers. This adjustment results in a more balanced process but still leaves relatively high waiting times. The Blender Queue Waiting Time rises to 0.18 h, and the Adding Additive Queue Waiting Time increases to 0.18 h, while the Molding Queue Waiting Time drops to 0.25 h. This case demonstrates a better balance than case 4 or 5 alone, but it still fails to minimize waiting times as effectively as expected.

Finally, Case 7 tests the impact of increasing both Molding Machines (from 1 to 2) and Workers (from 3 to 4), while keeping 1 Blender Machine. This case delivers the best overall improvements, significantly reducing waiting times across all processes. The Blender Queue Waiting Time drops to 0.15 h, the Adding Additive Queue Waiting Time to 0.17 h, and the Blender Transfer Queue Waiting Time to 0.15 h. The Molding Queue

Table 3. The System Performance for Various Improvement cases.

Case	Controls			Average Queue Time Responses (h)				
	#Blender	#Molding	#Worker	Blender	Additive	Blender Trsf	Molding	Molding Trsf
1	1	1	3	0.01	0.01	0.01	0.87	0.00
2	1	1	2	1.25	1.32	1.31	1.44	1.28
3	1	1	4	0.01	0.01	0.01	0.87	0.00
4	2	1	3	0.13	0.15	0.11	5.72	0.06
5	1	2	3	1.25	1.31	1.24	0.12	0.12
6	2	2	3	0.18	0.18	0.16	0.25	0.20
7	1	2	4	0.15	0.17	0.15	0.07	0.00

Waiting Time is reduced to just 0.07 h, a substantial improvement compared to the baseline value of 0.87 h. Additionally, the Molding Transfer Queue Waiting Time remains at 0.00 h, effectively eliminating bottlenecks in this stage.

These results demonstrate that Case 7 is the most effective, minimizing waiting times without introducing bottleneck. Key findings are: (a) reducing workers leads to significant delays, (b) increasing workers alone does not improve efficiency, (c) increasing only Blender Machines exacerbates bottlenecks, and (d) increasing only Molding Machines benefits later stages but not earlier ones. Case 6 achieves a better balance but is still less effective than Case 7, which provides the most comprehensive improvements.

3.3. **Suggested Model.** From the analysis conducted, increasing the number of workers does not improve waiting times in any of the five processes. Conversely, decreasing the number of workers significantly increases waiting times across all processes, rendering Case 2 highly unfavorable. Since Case 3 offers no measurable improvement and Case 2 causes substantial delays, neither case is considered viable for further simulation.

In contrast, Cases 4–7 present more promising options for optimization. Case 4 is expected to reduce waiting times, exacerbating the bottleneck in the Molding Queue, making it an ineffective solution. Case 5, which increases the number of Molding Machines, significantly reduces waiting times in the Molding and Printing processes, but its limited impact on earlier stages makes it a partial solution.

Case 6 attempts to balance the system by increasing both Blender and Molding Machines, resulting in moderate improvements across all stages. However, it leaves some inefficiencies and requires higher resource costs compared to Case 5. Finally, Case 7 provides the best overall improvement, minimizing waiting times across all five processes without introducing new bottlenecks. Although it requires additional resources, the resulting efficiency gains justify the cost, making Case 7 the most effective and recommended optimization strategy.

4. **Conclusions.** The study demonstrates the applications of DES in optimizing the egg tray manufacturing process. The study identifies key bottlenecks, particularly in the molding and drying stages, which constrain efficiency and throughput. Case testing allowed for the evaluation of various improvement strategies, including adjustments in resource allocation. Increasing the number of molding machines while maintaining the current blender capacity proved to significantly reduce waiting times and production delays. Furthermore, increasing both molding machines and workers delivered the most effective optimization, achieving a balanced workflow without introducing new bottlenecks.

These findings underscore DES as a powerful tool for diagnosing inefficiencies and evaluating optimization strategies in a virtual environment before physical implementation. The insights gained from this research offer practical recommendations for industry stakeholders, reaffirming the importance of DES in improving productivity and resource utilization. Future studies could expand on this work by exploring further automation in the drying process and material handling systems to maximize overall efficiency.

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