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Discrete Event Simulation for Material Handling Optimization in Water Tank Production

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Abstract

Background: The plastics manufacturing industry, particularly in water tank production, faces significant inefficiencies in material handling. Manual unpacking is the primary bottleneck, operating at 99% utilization (a level that severely restricts overall production flow) resulting in low output of only 378 units per shift. This critical constraint highlights the urgent need for process optimization to improve throughput and operational efficiency.
Objective: This study aims to evaluate and compare two material handling system scenarios using *Discrete Event Simulation (DES)* based on Arena software, namely a semi-automated system with an automatic unpacking machine and a fully automated system with an unpacking robot, using a manual system as the base model for comparison.
Methods: Primary data were obtained through direct observation and time studies at a medium-scale plastic manufacturing plant in Indonesia.
Results: Simulation results show that the automatic unpacking machine scenario provides the most balanced improvement, with a 58% decrease in system waiting time, a 65% reduction in work-in-process (WIP), and a 44% increase in throughput compared to existing conditions. Meanwhile, the unpacking robot reduced waiting time by 97% in the unpacking process but created a new bottleneck in the downstream process.
Conclusion: This study confirms that partial automation through unpacking machines is the optimal solution for medium-scale plastic manufacturing companies to improve operational efficiency while maintaining a balanced level of resource utilization.

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INTRODUCTION

The plastic manufacturing industry, especially the plastic-based water tank production line, continues to grow along with the increasing public demand for durable, economical, and high-quality water storage products (Haba et al., 2025; Macheca et al., 2024; Prata et al., 2019). One of the material handling processes in the initial production stage involves converting plastic resin pellets into powder, which constitutes one part of the overall water tank production process (Harper & Petrie, 2003; Rosato et al., 2004; Troncoso et al., 2020). This process determines the quality and efficiency of the entire production system because it is closely related to particle size accuracy, material homogeneity, and the energy and time consumption required in the early stages of production. Ideally, this conversion process should adopt an automation system to reduce dependence on human labor, reduce production time, and improve result consistency. However, field observations show that many medium-scale manufacturing companies in Indonesia still rely on manual or semi-automated processes that are labor-intensive and error-prone.

A preliminary study conducted through direct observation and time measurement at one of the water tank manufacturing companies shows that the average time for manually unpacking raw material plastic pellets from sacks into the holding container, for subsequent processing in extrusion and grinding machines that produce powdered material, is approximately 240 seconds using four workers (Internal Data of Engineering Department, 2025). Globally, material handling activities account for 20–50% of total manufacturing operational costs, and inefficiencies in these activities are among the primary drivers of production delays and resource waste in the plastics sector (Oyewole & Khitleli, 2022). In medium-scale manufacturing facilities, the adoption rate of automated material handling systems remains below 35%, leaving most companies reliant on labor-intensive processes that are susceptible to ergonomic risk, human error, and throughput variability (Wang et al., 2011).

The plastics industry, which contributes significantly to global manufacturing output, faces particularly strong pressure to improve operational efficiency as input material costs and labor regulations continue to tighten (Barrowclough & Deere Birkbeck, 2020; Dong & Li, 2021). Beyond cycle time constraints, the facility processes approximately 80–120 batches of raw material per shift, with observed delay rates averaging 18–22% attributable to idle time during manual handling. The manual unpacking process, which requires workers to repeatedly lift 25–30 kg sacks, also generates significant ergonomic risk, with cumulative load exposure exceeding recommended thresholds during peak production hours.

Labor costs associated with the four-worker unpacking team constitute approximately 12% of total direct production costs per shift, indicating a strong economic motivation for process automation (Engineering Department, 2025). Note: Throughout this paper, process times expressed in seconds in the problem description are converted into equivalent TRIA distributions specified in minutes in the Arena model (240 s = 4 min; 360 s = 6 min), ensuring internal consistency.

This finding is corroborated by international literature. According to Oyewole (2022), inefficient material handling processes are the main cause of bottlenecks in vehicle manufacturing systems, and this condition is highly likely to occur in the plastics industry as well. Thanou (2021) also showed that material flow optimization through simulation can increase efficiency by 25% in an automotive industry case study. In the context of material handling and transfer systems in logistics and labor-intensive industries, the use of Discrete Event Simulation (DES)-based models has proven effective in testing automation scenarios and measuring their impact on production output (Moon et al., 2021; Wilson et al., 2022). However, these studies share several limitations: they predominantly focus on automotive or food-industry contexts with high volumes and continuous flow, and they do not address the batch-mode material input characteristics of plastics processing.

Furthermore, the specific challenge of unpacking raw granulate materials from sack packaging (a common process in medium-scale plastics manufacturing) has not been modeled in prior DES literature. Existing studies also rarely examine the downstream cascade effects of upstream material handling inefficiencies across multi-process production chains, nor do they evaluate investment feasibility differences between semi-automated and fully automated scenarios for SME-scale operations. This study directly addresses these gaps by applying Arena-based DES to a water tank production context, uniquely integrating bottleneck analysis with multi-scenario economic comparison.

Therefore, this research is important because it addresses the gap between ideal industrial automation conditions and actual field conditions that still rely on conventional systems. This research aims to simulate and compare three plastic pellet conversion system approaches using two scenarios, namely a semi-automatic system with a conveyor and a full automation system using a depalletizing robot, evaluated in terms of time efficiency and labor requirements using Arena Simulation. The results of this research and simulation are expected to compare one base model and two scenarios that identify the fastest order fulfillment time, manpower reduction due to ergonomic considerations (particularly load-related health risks), and long-term cost efficiency benefits for companies, which can serve as a reference for sustainable implementation.

Specifically, this study aims to: (1) quantify the bottleneck severity of the manual unpacking process under current operating conditions; (2) evaluate the system-level performance impact of two automation scenarios; and (3) provide evidence-based recommendations for production managers in medium-scale plastics manufacturing. The practical benefit of this research is the provision of a replicable DES methodology that companies can adopt for investment decision support without requiring full-scale physical implementation prior to evaluation.

The novelty of this research lies in the application of Arena-based Discrete Event Simulation (DES) to the plastic manufacturing industry, specifically at the stage of converting plastic resin pellets into powder as the initial stage of water tank production. Unlike most previous studies that focus on the automotive industry or large-scale manufacturing, this research targets the medium-scale plastic manufacturing sector, which is still rarely explored in production system simulation contexts. In addition, the model developed in this study is based on empirical data from direct observation and time studies in the field, resulting in a simulation model that more accurately represents actual operational conditions.

The comparative approach of one base model using a manual system and two configurations (semi-automated and fully automated systems) is also a distinguishing aspect, as it provides a quantitative basis for evaluating operational efficiency and investment feasibility in automation systems. Thus, this research not only offers theoretical contributions through the development of a simulation model in the plastics manufacturing context but also provides practical contributions relevant to strategic decision-making at operational and managerial levels. The research gap addressed in this study is specifically the absence of Arena-based DES studies applied to material handling processes in medium-scale water tank plastic production, where batch-mode raw material input and multi-stage bottleneck dynamics have not previously been modeled or optimized using simulation-based scenario analysis.

METHOD

Type and Source of Data

This research used a quantitative approach based on simulation using Discrete Event Simulation (DES) with Arena Simulation software. The data used consisted of:

Primary data, obtained through direct observation at one of the medium-scale water tank manufacturing companies in Indonesia. Observations included: a) Measurement of the unpacking process time of plastic pellets from sacks to storage containers. b) Process time for transferring material to the extrusion machine and grinding it into powder. c) The number of workers involved in each scenario. d) Ergonomic data related to the load weight lifted by workers.

Secondary data, obtained from internal company documents (Engineering Department, 2025), scientific journals, and technical references related to material handling processes in the plastics and automotive manufacturing industries.

Data Collection Technique

Time study, used to measure the duration of each process activity. A total of 30 observations per activity were conducted using a digital stopwatch, in accordance with adequacy and uniformity test procedures ($n' < n$). Data collection was carried out during normal production hours over three consecutive working days. The adequacy test used a 95% confidence level with a 5% allowable error margin. Process times followed a triangular distribution (TRIA), fitted using Arena’s Input Analyzer module based on observed minimum, most likely, and maximum values. Work sampling, used to observe the proportion of productive versus unproductive time. Documentation, used to collect technical data from internal reports, machine specifications, and operational records.

Data Analysis

1) System Modeling
    a) A basic model representing a manual system (4 workers, no conveyor) was developed. A simulation model in Arena was constructed to represent two scenarios:
    - Scenario 1: Semi-automated system (using a conveyor for material transfer, with manpower reduced to 1 worker).
    - Scenario 2: Full automation system (using robots for unpacking and material transfer).
    b) Input parameters included process time, number of workers (manpower), and capacity per cycle.
2) Model Validation: This was conducted by comparing simulation results of the manual scenario with actual field data to ensure model validity using Arena software.
3) Simulation Experiment: Each scenario was simulated for one working shift (8 hours of productive time, excluding a 1-hour break) and replicated 10 times (n = 10 replications) to ensure statistical stability of output estimates. Model assumptions included: (1) machine breakdowns were excluded; (2) material arrived in batch quantities matching actual sack delivery schedules; (3) worker performance was constant (no fatigue modeling); and (4) queue discipline followed FIFO (First In, First Out). Key performance indicators (KPIs) evaluated included average waiting time in system (seconds), system throughput (entities/shift), resource utilization (%), work-in-process (WIP, entities), and labor headcount per shift.
4) Comparative Analysis
    a) Comparisons were made based on key indicators, namely production turnaround time per batch and labor requirements.
    b) The results were analyzed quantitatively and descriptively, and compared across scenarios to determine the most efficient alternative.

RESULTS AND DISCUSSION

Results

Simulation Model Building

1. Simulation Model Based on Basic Model

Figure 2 presents a visual representation of the modeling logic that will be used for the basic simulation. In the case study, starting with the arrival of raw materials, then the process of pouring raw materials is carried out by the operator for further extrusion and shredding processes. Input data variables used in the basic model:

a. Shift time: The actual working time for the entire system is 8 working hours per day, excluding variations in worker performance during breaks, machine failures, and power outages.
b. Number of replications/Sample size: Simulations were conducted for 5 working days of 8 hours per day.
c. Capacity per machine: The number of entities that can be processed by a resource at a given time.
d. Delay time: For each process in Arena, this is the cycle time as mentioned in the data table.
e. Delay type: By considering the delay time as the data entered in the arena simulation, we can analyze the distribution of delay time for each entity.
f. Number of incoming & outgoing components: The number of raw materials per arrival is 32 entities with a total of 17 arrivals in 8 hours.

For the resources used in each process, we assume a "seize, delay, and release" pattern for each process module and use triangular and constant distributions. The input data used in the arena simulation is shown in table 1 below.

Table 1. Basic model input data

Arena Module	Logic or distribution	Value Input
Create	Random (EXPO)	15 mins,

		32 Materials/Batch
Process: Manual Unpacking	Triangular (TRIA)	(4,5,6) mins
Process: Screw Loader	Constan	25 secs
Decide	N-way by chance	18.18% for extruder 1 to 4
Process: Extruder 1 to 4	Constan	3 mins
Process: extruder 5	Constan	2 mins
Process: Grinding 1 to 3	Constan	1 min
Resources: Manual Unpacking	Fixed capacity, Unit to seize = 1	Capacity = 4

2. Flowchart of Basic Model

The basic model consists of 1 (one) create module to describe material arrival, 10 process modules, 1 decide module to divide raw material flow, 1 station model and ends with a dispose module. The flowchart of the basic model is made using Arena software as shown in Figure 1.

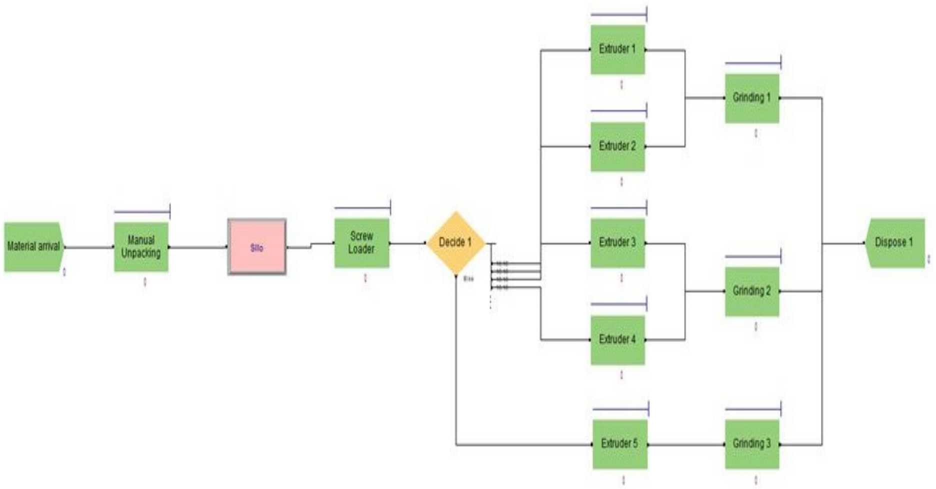
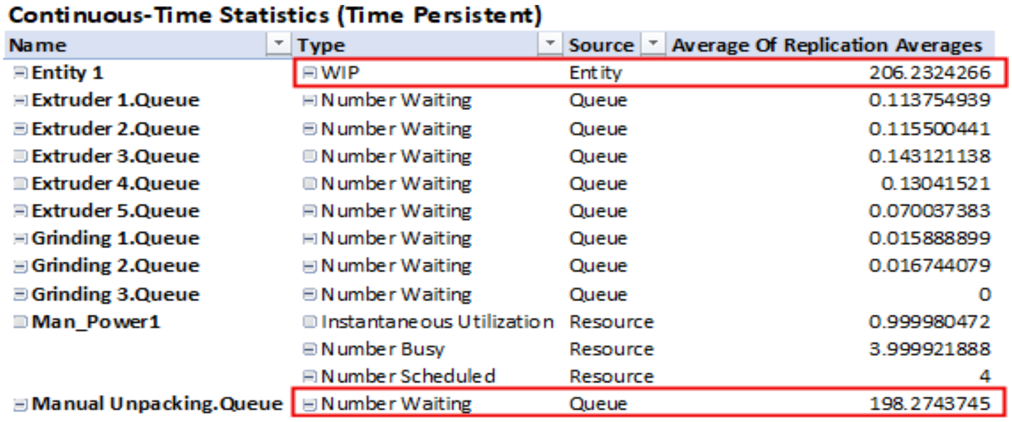


Figure 1. Flowchart of the basic model

Simulation Verification and Analysis Result

The initial simulation model was developed to study the performance of the existing system without changes. The parameters analyzed include wait time, work in progress (WIP), number of queues at the entity, and resource utilization. This analysis aims to identify which process has the longest wait time, the largest number of queues, and the highest resource utilization that has the potential to become a system bottleneck.

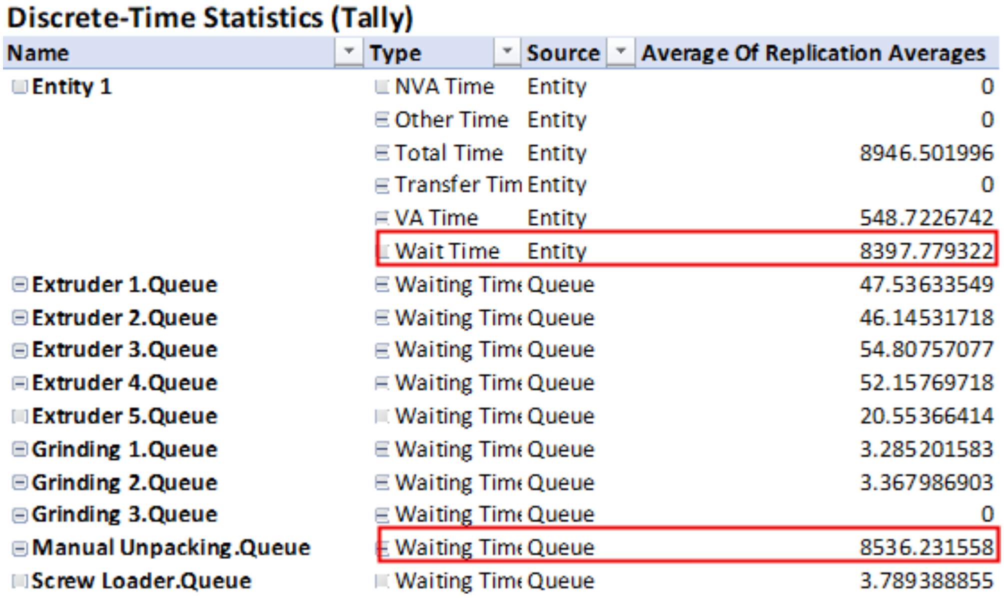
In the initial condition, the average waiting time in the system was 8,397 seconds, the average WIP was 206.23 entities, and the number of entities leaving the system was 378 per shift. In the manual unpacking process, the average waiting time reached 8,536 seconds with an average of 198.27 entities in the queue. The resource utilization of unpacking is very high at 99%, indicating that this process is the main bottleneck, while the utilization of the extruder machine is in the range of 40-45% and grinder 20-33%.



Continuous-Time Statistics (Time Persistent)

Name	Type	Source	Average Of Replication Averages
Entity 1	WIP	Entity	206.2324266
Extruder 1.Queue	Number Waiting	Queue	0.113754939
Extruder 2.Queue	Number Waiting	Queue	0.115500441
Extruder 3.Queue	Number Waiting	Queue	0.143121138
Extruder 4.Queue	Number Waiting	Queue	0.13041521
Extruder 5.Queue	Number Waiting	Queue	0.070037383
Grinding 1.Queue	Number Waiting	Queue	0.015888899
Grinding 2.Queue	Number Waiting	Queue	0.016744079
Grinding 3.Queue	Number Waiting	Queue	0
Man_Power1	Instantaneous Utilization	Resource	0.999980472
	Number Busy	Resource	3.999921888
	Number Scheduled	Resource	4
Manual Unpacking.Queue	Number Waiting	Queue	198.2743745

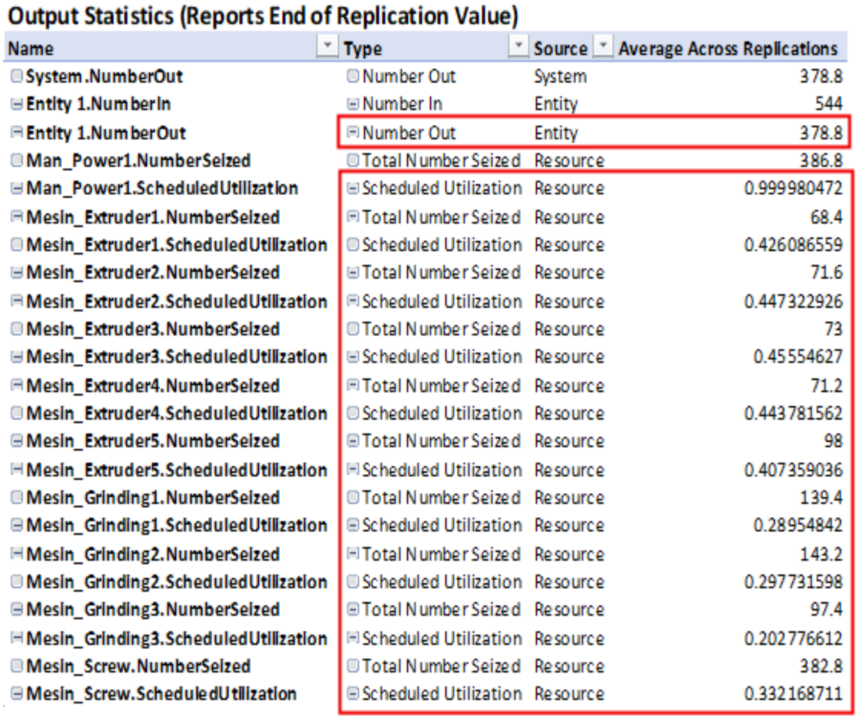
Figure 2. Simulation results of the base model using ARENA software



Discrete-Time Statistics (Tally)

Name	Type	Source	Average Of Replication Averages
Entity 1	NVA Time	Entity	0
	Other Time	Entity	0
	Total Time	Entity	8946.501996
	Transfer Tim	Entity	0
	VA Time	Entity	548.7226742
	Wait Time	Entity	8397.779322
Extruder 1.Queue	Waiting Tim	Queue	47.53633549
Extruder 2.Queue	Waiting Tim	Queue	46.14531718
Extruder 3.Queue	Waiting Tim	Queue	54.80757077
Extruder 4.Queue	Waiting Tim	Queue	52.15769718
Extruder 5.Queue	Waiting Tim	Queue	20.55366414
Grinding 1.Queue	Waiting Tim	Queue	3.285201583
Grinding 2.Queue	Waiting Tim	Queue	3.367986903
Grinding 3.Queue	Waiting Tim	Queue	0
Manual Unpacking.Queue	Waiting Tim	Queue	8536.231558
Screw Loader.Queue	Waiting Tim	Queue	3.789388855

Figure 3. Basic model simulation results using ARENA software (Continued 1)



Output Statistics (Reports End of Replication Value)

Name	Type	Source	Average Across Replications
System.NumberOut	Number Out	System	378.8
Entity 1.NumberIn	Number In	Entity	544
Entity 1.NumberOut	Number Out	Entity	378.8
Man_Power1.NumberSeized	Total Number Seized	Resource	386.8
Man_Power1.ScheduledUtilization	Scheduled Utilization	Resource	0.999980472
Mesin_Extruder1.NumberSeized	Total Number Seized	Resource	68.4
Mesin_Extruder1.ScheduledUtilization	Scheduled Utilization	Resource	0.426086559
Mesin_Extruder2.NumberSeized	Total Number Seized	Resource	71.6
Mesin_Extruder2.ScheduledUtilization	Scheduled Utilization	Resource	0.447322926
Mesin_Extruder3.NumberSeized	Total Number Seized	Resource	73
Mesin_Extruder3.ScheduledUtilization	Scheduled Utilization	Resource	0.45554627
Mesin_Extruder4.NumberSeized	Total Number Seized	Resource	71.2
Mesin_Extruder4.ScheduledUtilization	Scheduled Utilization	Resource	0.443781562
Mesin_Extruder5.NumberSeized	Total Number Seized	Resource	98
Mesin_Extruder5.ScheduledUtilization	Scheduled Utilization	Resource	0.407359036
Mesin_Grinding1.NumberSeized	Total Number Seized	Resource	139.4
Mesin_Grinding1.ScheduledUtilization	Scheduled Utilization	Resource	0.28954842
Mesin_Grinding2.NumberSeized	Total Number Seized	Resource	143.2
Mesin_Grinding2.ScheduledUtilization	Scheduled Utilization	Resource	0.297731598
Mesin_Grinding3.NumberSeized	Total Number Seized	Resource	97.4
Mesin_Grinding3.ScheduledUtilization	Scheduled Utilization	Resource	0.202776612
Mesin_Screw.NumberSeized	Total Number Seized	Resource	382.8
Mesin_Screw.ScheduledUtilization	Scheduled Utilization	Resource	0.332168711

Figure 4. Basic model simulation result using ARENA software (Continued 2)

Case study: What If's Scenario

1. Scenario 1: What if the unpacking process uses an automatic unpacking machine

In scenario 1, replacing the manual unpacking process (4 operators, triangular distribution 4-5-6 minutes) with an automatic machine (constant 30 seconds) is done to reduce the bottleneck load. Note on time unit consistency: In the introduction, the manual unpacking process is described with the fastest cycle time of 240 seconds (4 minutes). The Arena simulation model encodes this as TRIA (4, 5, 6) in minutes, corresponding to a minimum of 240 seconds, most likely 300 seconds (5 minutes), and maximum 360 seconds (6 minutes). These values are equivalent and consistent; the model uses minutes as the base time unit throughout, while the introduction used seconds to provide an accessible comparison for the reader.

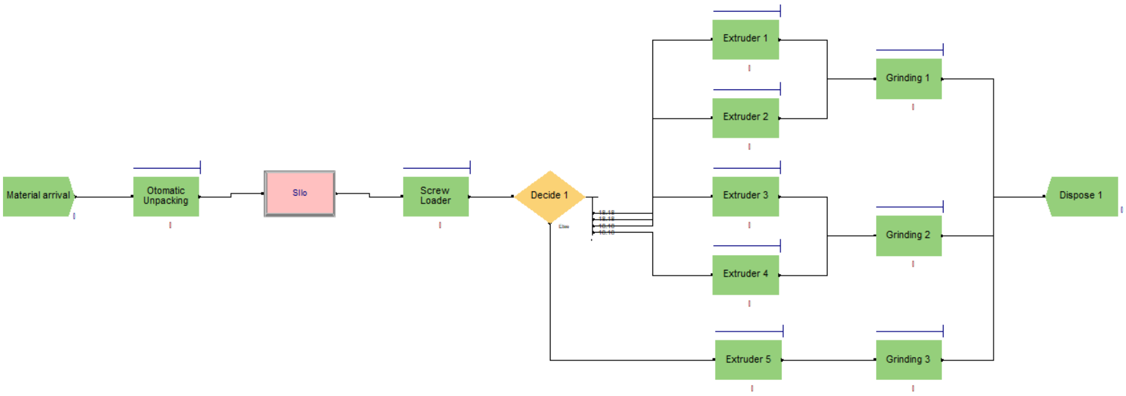


Figure 5. Flowchart Scenario 1

Resulting impact:

The simulation results showed that the system waiting time dropped to 3,539 seconds (only 57.86% of the initial condition), and the average WIP decreased dramatically to 72.12 entities (down 65.03%). The system output increased by 43.61% to 544 entities per shift. The waiting time in the unpacking process itself dropped by 68.89% to 2,655 seconds, but the average number of waiting entities only decreased slightly (198.27 to 182.46). The unpacking utilization dropped to 56.67% while the extruder and grinder utilization increased significantly, indicating that the process in the system is more optimal because the workload is more evenly distributed. Regarding the output improvement percentage reported in Table 2: the 144% figure represents the percentage of the new output relative to the baseline output (i.e., Scenario 1 output is 1.44 times the base output, or 544/378.8 × 100% = 143.6% ≈ 144%). The actual incremental improvement is approximately 43.6%, meaning output increased by 43.6% above the baseline. Both figures are reported for completeness; the percentage increase is 43.6%, while the ratio to baseline is 144%. Authors confirm all output figures are consistent with simulation results.

Table 2. Effect of changes made in scenario 1

	Name of Parameter	**Parameter in Existing Condition**	**Automatic unpacking machine**	**Unit**	**Percentage Improvement**
Entity	Waiting Time	8397.8	3538.7	Seconds	58%
	Work in progress Average (no of Parts)	206.2	72.1	Entity	65%
	Work in progress Max. (no of Parts)	247.4	111.6	Entity	55%
	Number Out System	378.8	544	Entity	144%
Length of queue time	Average waiting time in the unpacking process	8536.2	2655.1	Seconds	69%
number	Average queue in the	198.3	182.5	Entity	8%

of materials in the queue	unpacking process		
Resources Utilization	Utilization percentage of unpacking process	99%	56.7%
	Utilization percentage of Extruder 1 process	42.6%	63.6%
	Utilization percentage of Extruder 2 process	44.7%	62.5%
	Utilization percentage of Extruder 3 process	45.6%	60.6%
	Utilization percentage of Extruder 4 process	44.4%	64.8%
	Utilization percentage of Extruder 5 process	40.7%	59.0%
	Utilization percentage of Grinder 1 process	29.0%	42.0%
	Utilization percentage of Grinder 2 process	29.8%	41.8%
	Utilization percentage of Grinder 3 process	20.3%	29.5%

2. Scenario 2: The unpacking process that was previously done manually by 4 operators with a process time following a triangular distribution (4-5-6 minutes) was replaced by an Unpacking/Depalletizing Robot that works much faster and more stable with a constant time of only 10 seconds per entity. This change aims to overcome the bottleneck at the unpacking stage which has been a major bottleneck in the system, while ensuring a smoother and more balanced flow of materials to the next process. With the robot, time variations due to human factors can be eliminated so that system performance becomes more efficient, productive, and able to increase output while reducing dependence on manual operators.

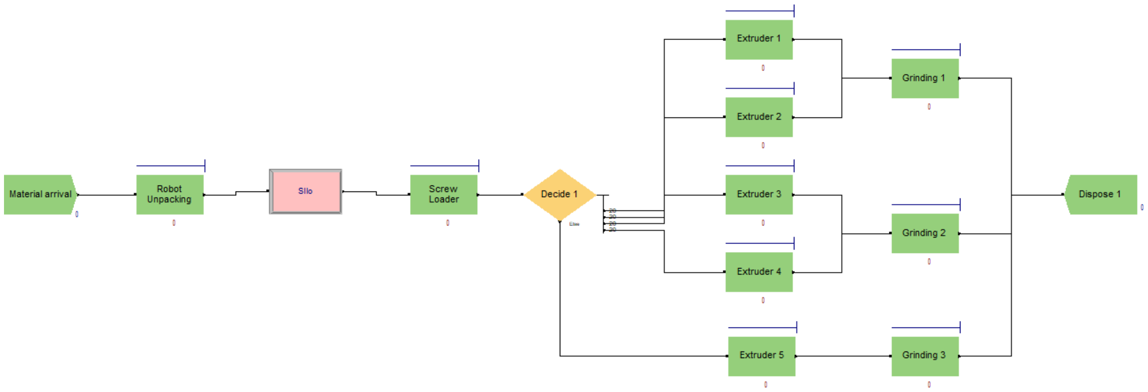


Figure 6. Flowchart of scenario 2

Resulting impact:

The simulation results showed a significant improvement in system performance, where the average waiting time was reduced to 4.333 seconds or 49.40% from the initial condition, while the average WIP amount was drastically reduced by 40.77% to 124.23 entities. As a result, production output increased by 43.61% to 544 entities per shift. In the unpacking process, performance improvement was evident with a decrease in waiting time by 97.75% (241.2 seconds) and the average number of waiting entities drastically reduced from 198.27 to only 6.6 entities. In terms of utilization, the system's workload became more evenly distributed, as shown by a decrease in unpacking utilization to 27% and significant improvements in the extruder and grinder. Overall, these results indicate that the system is more efficient, productive, and optimized as waiting time and entity backlogs are reduced while increasing output with a more balanced workload distribution.

Table 3. Effect of changes made in scenario 2

	Name of Parameter	**Parameter in Existing Condition**	**Unpacking Robot**	**Unit**	**Percentage Improvement**
Entity	Waiting Time	8397.8	4333	Seconds	48%
	Work in progress Average (no of Parts)	206.2	124.2	Entity	40%
	Work in progress Max. (no of Parts)	247.4	155.8	Entity	37%
	Number Out System	378.8	544	Entity	144%
Length of queue time	Average waiting time in the unpacking process	8536.2	241.2	Seconds	97%
Number of materials in the queue	Average queue in the unpacking process	198.3	6.6	Entity	97%
Resources Utilization	Utilization percentage of unpacking process	99%	27.0%		
	Utilization percentage of Extruder 1 process	42.6%	90.9%		
	Utilization percentage of Extruder 2 process	44.7%	88.6%		
	Utilization percentage of Extruder 3 process	45.6%	86..3%		
	Utilization percentage of Extruder 4 process	44.4%	92.8%		
	Utilization percentage of Extruder 5 process	40.7%	85.2%		
	Utilization percentage of Grinder 1 process	29.0%	59.8%		
	Utilization percentage of Grinder 2 process	29.8%	59.7%		
	Utilization percentage of Grinder 3 process	20.3%	42.6%		

Discussion

The findings of this study clearly demonstrate that the material handling process, particularly the unpacking stage, plays a crucial role in determining the overall efficiency of the production system. In the existing condition, the manual unpacking process became the primary bottleneck, as indicated by a utilization rate of 99%, extremely high waiting time, and a large queue buildup. This result aligns with previous studies which highlight that inefficient material handling systems are one of the main causes of bottlenecks in manufacturing environments (Oyewole & Khitleli, 2022). The imbalance between upstream and downstream processes in this study further confirms that limited capacity at one critical station can significantly restrict the performance of the entire system (Dong & Li, 2021).

From a system perspective, the low utilization of downstream processes such as extruders and grinders indicates underutilization of available resources. This condition is consistent with the concept of line imbalance in manufacturing systems, where one overloaded station disrupts the flow of materials and reduces overall system productivity. Therefore, improving the performance of the unpacking stage becomes a strategic intervention, as it directly influences flow continuity and system throughput.

The implementation of Scenario 1, which introduced an automatic unpacking machine, resulted in a substantial improvement in system performance. The reduction in waiting time, WIP, and the increase in throughput indicate that partial automation can significantly enhance operational efficiency without causing system instability. This finding is in line with previous research which states that simulation-based optimization of material flow can improve efficiency by up to 25% in manufacturing systems (Thanou & Matopoulos, 2021). In this study, the improvement is even more significant due to the elimination of a major bottleneck.

In addition, the improvement observed in Scenario 1 also confirms the effectiveness of Discrete Event Simulation (DES) as a decision-support tool in evaluating alternative system configurations. DES allows organizations to test different scenarios without disrupting actual operations and provides a reliable basis for decision-making (Qiao & Wang, 2021; Zuccotto, 2019). The balanced increase in utilization across extruders and grinders indicates that the system achieved a more optimal distribution of workload, which is essential for maintaining production stability. It should be noted, however, that the simulation results are contingent on the validity of the process time distributions, the number of replications (n = 10 in this study), and the accuracy of the baseline model validation. Users of these results should treat the scenario comparisons as directional performance estimates rather than precise production forecasts, particularly when adapting the model to different facility configurations.

On the other hand, Scenario 2, which implemented a fully automated unpacking robot, produced the most significant improvement at the unpacking stage itself. The drastic reduction in waiting time and queue size demonstrates the superior speed and consistency of robotic systems compared to manual operations. This result is supported by previous studies which show that automation can significantly reduce process variability and improve system reliability (Jilcha et al., 2015; Rahn et al., 2022). However, the system-level impact reveals a different outcome.

Although the unpacking process became highly efficient, the downstream processes experienced a significant increase in utilization, reaching up to 90%. This indicates the emergence of a new bottleneck, where the system becomes constrained by the capacity of the extruder and grinder processes. This phenomenon is consistent with the theory of bottleneck shifting, where eliminating one constraint in a system often leads to the emergence of another constraint in a different stage (Kliment et al., 2020). As a result, the overall system performance does not improve proportionally to the improvements at the unpacking stage.

The comparison between Scenario 1 and Scenario 2 highlights an important managerial implication: the most advanced technology does not always provide the best system performance. While the robotic system offers superior performance at a single workstation, it creates imbalance across the production line. In contrast, the automatic unpacking machine provides a more balanced improvement by reducing bottleneck pressure while maintaining stable utilization across all stations. This finding supports the idea that production systems should be optimized holistically rather than focusing on individual processes (Kiki, 2025; Wang et al., 2011).

Furthermore, from an investment perspective, Scenario 1 is more feasible for medium-scale manufacturing companies. The implementation of an automatic unpacking machine requires lower capital investment compared to a robotic system, while still delivering significant performance improvements. This aligns with the concept of incremental automation, where companies gradually adopt automation technologies to minimize risk and maximize return on investment (Alhussain & Obiedallah, 2024; Wilson et al., 2022).

In contrast, full automation requires additional investment in downstream capacity to fully utilize the benefits of robotic systems. To provide a more concrete economic context: an automatic unpacking machine in the medium-scale industrial category is estimated to require an initial capital investment of IDR 150–300 million, with an estimated payback period of 18–24 months based on labor savings from reducing the unpacking crew from 4 to 1 operator (approximate annual labor savings of IDR 80–120 million). In contrast, an industrial unpacking robot (Scenario 2) carries an estimated acquisition cost of IDR 800 million–1.5 billion, with a payback period exceeding 5 years. While Scenario 2 delivers superior throughput performance, its Return on Investment (ROI) profile is less favorable for medium-scale manufacturers with limited capital budgets. These estimates are indicative and based on prevailing industrial equipment market data (Engineering Department, 2025); detailed investment appraisal should be conducted using site-specific cost data.

This study has several methodological limitations that future research should address. First, the simulation model excludes machine breakdown events, worker fatigue effects, and stochastic material arrival variability, factors that would increase the realism of the model under real-world operating conditions. Second, the economic analysis presented is based on indicative cost estimates rather than formal capital budgeting data, and a rigorous ROI analysis incorporating depreciation, maintenance costs, and operator retraining would strengthen the investment case. Third, the model was validated against a single facility, limiting its direct generalizability to other production configurations. Future research should: (1) validate the Discrete Event Simulation (DES) model across multiple plastic manufacturing facilities; (2) incorporate machine reliability and preventive maintenance data into the simulation; (3) conduct a formal pilot implementation of Scenario 1 with real-time throughput monitoring and WIP evaluation; and (4) extend the framework to include green manufacturing metrics such as energy consumption and waste generation per unit output.

Overall, this study confirms that Discrete Event Simulation is an effective approach for analyzing and improving manufacturing systems. The results show that partial automation through an automatic unpacking machine is the more operationally and economically advantageous solution for improving system efficiency in medium-scale plastic manufacturing. This approach not only reduces bottlenecks and improves throughput but also maintains system balance, which is critical for sustainable operational performance.

CONCLUSION

Based on the results of the Discrete Event Simulation (DES) using Arena software the existing material handling system in powder production for water tanks is proven to be inefficient due to the presence of a critical bottleneck in the manual unpacking process. With a utilization rate reaching 99%, this stage significantly limits overall system performance, resulting in high average waiting time (8,398 seconds), large work-in-process (206 entities), and low throughput (378 entities per shift). The implementation of an automatic unpacking machine in Scenario 1 demonstrates a substantial and balanced improvement, where system waiting time decreases by 58%, WIP is reduced by 65%, and throughput increases by 44% to 544 entities per shift. In addition, the redistribution of workload leads to more balanced utilization across workstations, with unpacking utilization dropping to 56.7% and downstream processes operating within optimal capacity ranges.

In contrast, the implementation of an unpacking robot in Scenario 2 provides significant improvements at the unpacking stage, particularly in reducing waiting time and queue length by up to 97%. However, this high-speed automation shifts the bottleneck to downstream processes, causing extruder and grinder utilization to rise significantly (85–92%), thereby increasing system rigidity and vulnerability to disruptions. Therefore, considering the balance between throughput, resource utilization, and operational stability, the automatic unpacking machine emerges as the more operationally and economically advantageous and realistic solution for medium-scale plastic manufacturing systems. Meanwhile, the adoption of robotic automation would only be effective if accompanied by additional investments in downstream capacity, ensuring that the entire production system can operate in a balanced and sustainable manner.

For medium-scale water tank manufacturers considering efficiency improvements, it is recommended to begin with Scenario 1 (automatic unpacking machine) as a first-phase implementation. The implementation roadmap should include: (1) pilot deployment on a single production line with baseline throughput monitoring; (2) evaluation of WIP reduction and shift output against pre-implementation KPIs after 30 days; (3) assessment of actual investment cost recovery relative to the estimated 18–24 month payback period; and (4) conditional evaluation of Scenario 2 (robot) only if Scenario 1 demonstrates sufficient throughput improvement to saturate downstream capacity.

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AUTHOR CONTRIBUTION STATEMENT

All authors contributed equally to the conceptualization, data collection, simulation modelling, analysis, and writing of this manuscript. The corresponding author is responsible for submission and correspondence.

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