International Journal on Advanced Science Engineering Information Technology

Vol.15 (2025) No. 1
ISSN: 2088-5334

Optimization of Lubricant Oil Filling and Packaging Lines: A Simulation-Based Automation Approach

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***Abstract*— This research was conducted to improve the efficiency of lubricating oil filling and packaging lines for 1L and 4L packages in a manufacturing company using the Arena Simulation. The existing system, which involves the handling of goods by operators is semi-automatic, leading to production activities shortage, employee overtime, and additional costs. The validity of the model was tested with Fuzzy Inference System (FIS) and t-test analysis, to achieve average significance values of 0.462 and 0.419 for 1L and 4L packages, with p>0.05 confirming no significant difference between simulation and actual data. This research proposed three improvement scenarios to optimize the production system. The first involved the addition of a robotic system for the packing process, which resulted in 5% time reduction and 6% productivity improvement for 1L packages, and 11% time reduction with 12% productivity increase for 4L packages. The second complemented the first through the introduction of a robotic arm palletizer, achieved a 12% time reduction and 13% productivity improvement for 1L packages, and 14% time reduction with 17% productivity increase for 4L packages. The third scenario, which combined an automatic case packer and robotic arm palletizer, showed the most significant improvements with 14% time reduction and 16% productivity increase for 1L packages, and 19% time reduction with 23% productivity improvement for 4L packages. The optimal third scenario reduced working time from 9.3 to 7.9 hours/day for 1L packages and to 7.53 hours/day for 4L packages.**

***Keywords*—Lubricating oil packaging; manufacturing efficiency; production optimization; palletizer systems; process automation.**

Manuscript received 7 Aug. 2024; revised 11 Sep. 2024; accepted 30 Nov. 2024. Date of publication 28 Feb. 2025.

I. INTRODUCTION

The main objective of businesses is to maximize profits with the least capital [1]. However, various operational costs are unavoidable particularly when running a business. In order to ensure sustainability and prosperity, companies must be capable of identifying opportunities and confronting obstacles in the contemporary industrial era, which focuses on automation. The dynamic and evolving circumstances compelled the industrial sector to adjust in order to sustain global progress [2]. Moreover, industry 4.0 aimed to develop efficient and low-cost production by prioritizing the flexibility of related activities through intelligent manufacturing and system automation [3]–[5].

Several industries currently apply automation to systems and machines to improve effectiveness and efficiency difficult to achieve with human labor. Automation also helps cover shortage of less competent labor [6], [7]. A particular field that prioritized automation is manufacturing which deals with the use of the latest equipment, ranging from industrial machinery to production management controls [8]. Although not a requirement, this mechanization process was essential for the company to remain competitive [9], [10]. Automation enabled the entire process to operate automatically without intervention, handling repetitive tasks beyond human capabilities [11]. The more varied and complicated consumer needs get adaptable and rapid automation becoming comparable to traditional approaches. Automation allows the entire process to run automatically without human assistance, engaging in repetitive activities, or work that humans are unable to perform [8]. The objective was to enhance productivity, precision, and efficiency, to minimize human error [12], [13].

Automation systems consist of components composed by instruction programs and control schemes to form a structured series of processes [14]. In the manufacturing sector, it is combined with a production system programmed with certain logic, resulting in a series of coordinated processes managed by humans. As a result, it becomes essential to schedule system components according to respective working speeds in order to prevent errors caused by process mismatches, including achieving optimal production outcomes [15].

Production systems are the core for manufacturing companies that focus on process optimization to get the best efficiency, in terms of speed, cost reduction, and operational time [16]. Common problems were caused by non-optimal application and allocation of resources, including production planning and scheduling. The production line, as a system, comprised various components that work according to instructions and controls to form series of processes. It includes various processes such as filling and others, starting from incoming materials to finished products [17]. In companies that had not fully adopted automation, some processes adding value to the product may be performed by the same machine or operator. This can create additional burden, reducing work efficiency and overall production time [18].

Several research stated that automation of production systems had been widely implemented globally, although some companies still use conventional methods [19], [20]. Industrial companies, especially those with high production volumes, continue to search for robotic solutions to automate the manufacturing processes. Various sectors consistently depend on labor-intensive manual processes despite widespread belief that these do not contribute economically to the company [21].

Robotic arms are the most widely used, compared to the various types of robots. Moreover, the use of robots is no longer limited to the industrial field, but has also penetrated into other sectors [22], [23]. A robot arm or manipulator is specifically designed to perform tasks that require the manipulation of objects or tools [24], [25]. The usual structure is comprised of a number of joints enabling it to move and bend in a variety of ways [26]. This included picking, moving, and positioning items with a level of precision and accuracy much beyond human possibility. Robotic arms are simple to design and control, and performs a wide range of functions [27]. In the manufacturing industry, these were used for various tasks such as transporting, painting, packaging, and polishing [28].

The present research focused on two main functions of robot manipulator applications, namely case packer and arm palletizer for 1 Liter (1L) and 4 Liter (4L) capacity packaging. These two functions play a significant role in the production and distribution process of lubricant products. Based on preliminary review, it was inferred that the topic of industrial automation had been investigated severally. The focus of previous research covered various aspects, including optimization of manufacturing process design, manufacturing system configuration, system automation scheduling, simulation for decision making, as well as production system improvement scenarios.

Several gaps had remained unaddressed, despite previous research exploring the benefits of automation in manufacturing. First, existing research mainly focused on fully automated systems, with limited attention to the transition from semi to fully automated processes in lubricant packaging. Second, while robotic solutions had been reviewed extensively, the specific application of case packers and arm palletizers in lubricant filling lines lacked comprehensive analysis. Third, most analyses evaluated either production efficiency or worker conditions separately, rather than considering the interdependence in semi-automatic systems.

This research aimed to achieve several important objectives by focusing on the following four main aspects

1. Developing Comprehensive Models Creating a robust simulation model integrating manual and automated processes, validated through dual methods such as Fuzzy Inference System (FIS) and t-tests.
2. Implementing Automation Innovations Introducing specific automation solutions for lubricant packaging, optimizing robotic systems for 1L and 4L packages, including designing integrated configurations for case packers and palletizers.
3. Analyzing Performance Gains Quantifying productivity enhancements resulting from diverse automation scenarios while assessing the impacts on worker conditions, including reduced overtime, and conducting a detailed cost-benefit analysis.
4. Facilitating Industry Transitions Providing a practical framework for gradually automating semi-automatic facilities, offering benchmark data applicable to similar industrial contexts.

The efficiency, productivity, and profits of manufacturing companies had been proven to increase through the implementation of various simulation and optimization models [29], [30]. However, lack of specificity regarding the application of automation to the product filling and packing process in the production line of a lubricating oil manufacturing company with a semi-automatic system is an important drawback. This gap outlined the unexploited potential to enhance efficiency and productivity in the sector.

In order to fill this gap, the proposed research aimed to analyze and develop an appropriate automation solution. The relevant steps included analyzing the existing conditions of the product filling and packing process in the production line of a lubricating oil manufacturing company with a semi-automated system. This was realized using simulation methods to mimic the real system, including creating improvement scenarios through the implementation of automation. Therefore, the main purpose of this research is to ensure the company becomes more efficient, productive, and cost-effective.

II. Material and Methods

The present section described the suggested simulation-based method for analyzing and optimizing filling and packaging processes in the manufacturing industry. The flowchart in Fig. 1, shows a systematic process from problem identification to the end, with a particular focus on simulation modeling and production process optimization analysis.

Field research was conducted at a lubricant manufacturing company to understand the existing production system. The investigation included direct observation of the filling and packaging lines for both 1L and 4L packages. This stage comprised detailed examination of current manufacturing processes, equipment specifications, production flow, operator activities, and existing automation levels. Moreover. observations were made during regular production hours to capture actual operating conditions, namely machine operations, manual processes, quality control procedures, and material handling activities. The field research also included discussions with production supervisors and operators to understand operational challenges and constraints in the current semi-automatic system. This comprehensive field observation provided foundation data for developing the simulation model and identifying potential areas for automation improvement.

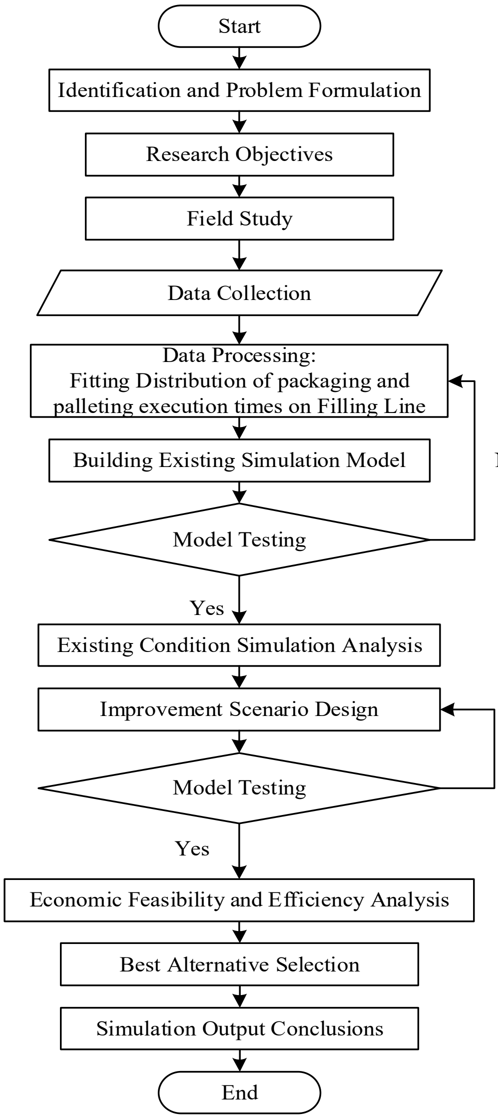

Fig. 1 Research flowchart

The filling and packing line process flow in Fig. 2, shows the detailed sequence of operations from input to output. The line is divided into two interconnected main work stations, namely the filling and packing work station. This process diagram shows how these two stations were integrated into a single unit, connected by a conveyor system. Data was collected through systematic observation and recording of the production system operation. The first dataset comprised production performance indicators collected over nine weeks, such as defect percentages, preparation hours, daily overtime, hourly production rates, and line uptime efficiency as shown in Table 1. The second dataset covered detailed process timing measurements for each production stage in Table 2, comprising preparation time, filling rates, assembly speeds, as well as operation durations for both 1L and 4L packaging lines. These measurements were taken during normal production operations using standard time research methods to ensure data accuracy and reliability. Data collection also included machine specifications, system constraints, and quality control parameters necessary for developing an accurate simulation model.

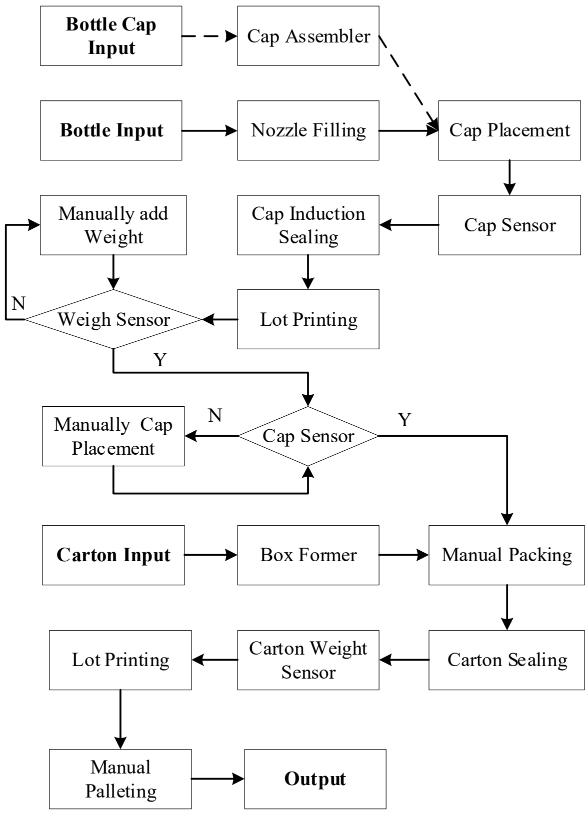

Fig. 2 Process Diagram for Line Filling and Packing

Based on this, data processing focused on fitting distribution analysis of packaging and palletizing execution times in the filling line. The collected timing data from production operations were subjected to statistical distribution fitting. This was aimed to determine the most appropriate probability distribution for use in the simulation model [31], [32]. Additionally, the process included analyzing the variability in execution times for both 1L and 4L packaging operations. The distribution fitting helped capture the natural variation in process times, enabling more accurate representation in the simulation environment. In line with this, the processing steps comprised outlier detection, normality testing, and selection of best-fit probability distributions for each process timing dataset. These fitted distributions served as major inputs for the simulation model development.

The research adopted Arena Simulation Software for modeling and analyzing the production system, selected for the robust capabilities in discrete event simulation, particularly in manufacturing systems. The software provided comprehensive features through an extensive modeling environment essential for research requirements. Furthermore, specialized modules including Basic and Advanced Processes, as well as Packaging enabled detailed process flow modeling, supporting complex manufacturing simulations. Built-in statistical tools also facilitate distribution fitting for process timing data, ensuring precise representation of operational dynamics. The advanced analysis capabilities enabled comprehensive system performance evaluation, while integrated animation features support critical model verification processes. The model development adopted the graphical user interface of the software, systematically incorporating production stages from filling to palletizing operations. Meanwhile, process logic and timing data were implemented using precise modeling constructs, with built-in statistical tools employed for comprehensive output analysis and scenario comparison.

The subsequent subject of investigation is the filling and packaging line, comprising numerous critical processes, as shown in Fig. 2. The process diagram was adopted from previous research in manufacturing automation [15], production monitoring systems [33], and production line scheduling [20], [32]. This method was selected due to the effectiveness in visualizing complex semi-automatic systems and supporting the identification of automation opportunities while clearly showing quality control points and decision flows. The process starts with assembling the packaging cap and the filling of the liquid through the nozzle. Sensors were used to verify the quality of the closure after the packaging lid had been installed. The packaging is then run through the sealer equipment, as well as weighed and labeled alongside the cartons. The packets were manually transferred into the cartons, designed using a box former. After filling, these were sealed, weighed, and lot-labeled , while the cartons were manually arranged on pallets. A combination of automated and manual steps, such as quality checks and operator intervention when necessary, were adopted throughout the entire process guaranteeing that the final product satisfied the established standards.

The next step after the completion of the data collection stage included constructing the simulation model. It was designed using Arena Simulation software, which replicated the logical operations of the actual system to accurately represent real processes within the simulation environment. Preprocessed data was input into this model. In addition, the development process was divided into several subprocesses to ensure smooth operation of the model, reflecting the complexity of the actual system.

The dataset used was collected from a lubricant manufacturing company over a nine-week observation period. Data was collected through two main methods, namely (1) direct observation of the production line to gather process timing data for each stage of the filling and packaging operations, (2) compilation of production performance records from the production department of the company. The process timing data comprised detailed measurements of 15 major processes, from preparation to palletizing, with specific timing for both 1L and 4L package variants. Production performance data consisted of five main performance indicators, namely defect percentage, average preparation hours, and daily overtime, pieces produced per hour, as well as line uptime percentage. All measurements were conducted during normal production operations to ensure data validity and reliability. Meanwhile, the data collection process adhered to standard industrial engineering measurement practices, with multiple observations taken for each process to account for variations in operating conditions.

The next step after constructing the model focused on testing the simulation model. During this process, the actual system was compared to the built model to verify the application chain, identifying possible mistakes [34], [35]. This verification was achieved using the capabilities provided by Arena Simulation software, which helped avoid modeling difficulties.

In this research, Fig. 3 proposed working diagrams for three improvement scenarios, each with different features. Scenario 1 introduced a Robotic Packaging System that replaced manual type with an automated solution while maintaining palletizing at the end of the line. This approach aimed to reduce human intervention in the packaging process, targeting 5 to 11% reduction and a 6 to 12% increase in time and productivity, respectively. Based on this foundation, Scenario 2 incorporated a robotic arm palletizer, eliminating the need for performing the process manually, palletizing and automating the packaging operations. This scenario led to the realization of a more significant time reduction and productivity increase of 12 to 14% and 13 to 17%. Finally, Scenario 3 implemented a fully automated case packing system that integrated a robotic arm palletizer, offering complete automation for both processes. This scenario was designed to maximize efficiency, with projected time reductions and productivity improvements, ranging from 14 to 19% and 16 to 23%.

The outlined method offered a systematic framework for analyzing and improving the lubricant oil filling and packaging line through simulation-based automation. The entire process started with comprehensive data collection from field observations and production records, followed by detailed model development adopting Arena Simulation software. The validity of the model was rigorously tested using statistical methods and FIS analysis to ensure an accurate representation of the actual production system. Based on the validated model, three progressive automation scenarios were designed, each building upon the previous one to address the identified production challenges. Evaluation and discussion regarding the effectiveness of these scenarios in improving production efficiency while reducing manual intervention was analyzed in the following section. This also included the potential impact on working hours and productivity metrics for both 1L and 4L packaging lines.

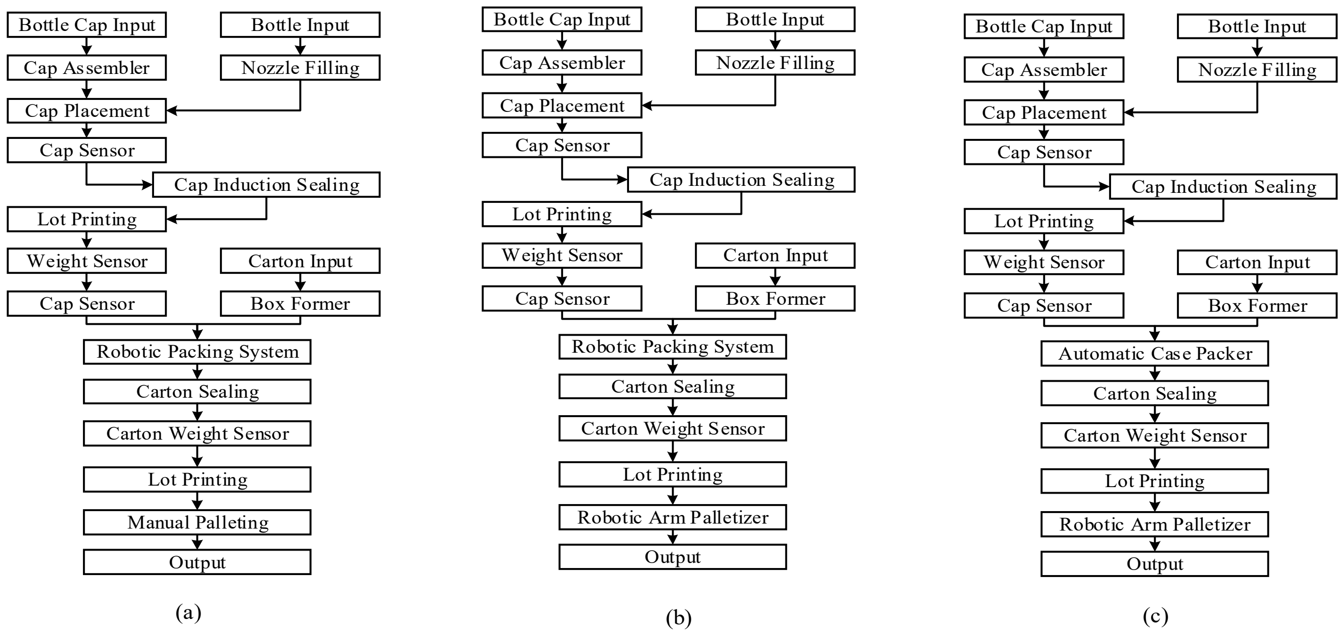

Fig. 3 Working diagrams for the three improvement scenarios: (a) Robotic Packing System, (b) Robotic Packing with Palletizer, and (c) Automatic Case Packer with Palletizer.

Model validation started with replication analysis, where the number of replications was calculated with a confidence level > 95% to enhance accuracy [36]. This ensured sufficient statistical power in the results of the simulation, providing a robust foundation for further analysis. Meanwhile, statistical validation, was conducted by adopting paired t-test analysis to compare simulation outputs with actual production data using 95% confidence level (α = 0.05). This quantitative method examined whether there were significant differences between simulated and actual results, providing rigorous statistical validation of the accuracy of the model.

Further validation adopted fuzzy logic analysis using FIS to assess the discrepancies between simulated outputs and actual system performance. This system incorporated membership functions for the percentage difference and significance as input and output, respectively with fuzzy rules linking the two. The process included calculating the significance value for each replication of the simulation results, which yielded an average significance for comprehensive interpretation.

The validation process used FIS to evaluate the accuracy of the simulation model. Input variables were defined by the percentage difference between simulated and actual data, characterized by three membership functions, namely Small (0 to 10%), Medium (5 to 25%), and Large differences (over 15%). The output variable represented significance levels through membership functions Not Significant implied high model accuracy, Moderately Significant reflected acceptable deviation, and Highly Significant suggested the need for model adjustment.

The system processed these variables through IF-THEN rules to establish relationships between input and output values. When the difference is Small, the system depicts Not Significant results, Medium and Large differences yielded Moderately, and Highly Significant results, respectively. The analysis process included calculating percentage differences between simulation and actual outputs, which were further processed through FIS membership functions and fuzzy rules to determine significance levels. These results were then defuzzified to obtain final significance values, with the average across replications determining the overall model validity. This method provided the basis for the analysis shown in Fig. 5 and Fig. 6, where lower significance values depicted better association between the simulation model and actual system performance.

The main objective of this investigation is to develop various enhancement scenarios based on an analysis of output data from the existing system conditions. The improvements tend to focus on the final components to optimize processes and shorten working time. However, the final component is not always improved because each process has a different level of difficulty. This led to the need for research to carefully design multiple improvement scenarios including offering realistic and applicable solutions.

III. Result and Discussion

The preliminary outcome of this research focused on analyzing the performance of the production line over a nine-week period. Table 1 shows a summary of the main performance indicators (KPIs) of the production line. The standard employee working time was set at eight hours per day with five working days per week. The collected data was further analyzed using the distribution fitting method. This was aimed to determine the most suitable distribution to be used in the simulation process.

Performance indicators served as a common evaluation method in the manufacturing industry used to assess production systems. The indicators comprised various aspects of process performance, focusing on specific target values. This approach facilitated process control to achieve the expected cost and efficiency targets. In this research, performance indicators from the filling and packing line were used as a basis of comparison to identify problems. The standard working time of employees in the line became the benchmark for analyzing the issue of overtime encountered.

TABLE I
KEY PERFORMANCE INDICATOR OF PRODUCTION LINE

Measurable	Measurable Report Line/Week (W)									
	W1	W2	W3	W4	W5	W6	W7	W8	W9	Average
Defect %	2.42	1.48	2.78	1.73	1.59	1.31	1.66	1.43	2.27	2
Average Preparation Hours	2.9	3.5	3.3	4.0	3.8	3.9	4.2	2.9	3.5	3.5
Average Overtime/Day (hours)	1.1	1.5	1.7	1.0	1.2	1.1	0.8	2.1	1.5	1.3
Piece Produce Average/Hours	1191	2751	2093	1413	1845	3352	2043	1864	786	1926
Line Uptime % (Average/Production)	98.4	98.2	98.1	97.5	98.2	98.7	98.8	98.1	97.8	98

In Fig. 2, the filling and packing line is divided into two interconnected main workstations. This included the filling and packaging workstations. The two stations were integrated into a single unit, connected by a conveyor system. The packaging workstation has numerous and complex components compared to the filling station, comprising tasks such as package closing, labeling, sealing, packing into cartons, and the arrangement into pallets for shipment to the finished product storage warehouse. This division was designed to facilitate more detailed analysis and ease data input into the simulation software. Table 2 shows the time information relating to each process in this filling and packing line, providing a comprehensive overview of the duration of each production stage. Based on this data, a simulation model was constructed to replicate the entire set of activities, from the entity entering the system to the one leaving.

The subsequent step included the development of a simulation model using Arena software, as shown in Fig. 4. The process sequence is depicted in detail, starting with the movement of the packaging toward the conveyor and ending with the palletizing process. The filling and packing lines of the company were rendered in an integrated manner through the construction of the model, exhibiting the entire process flow. Furthermore, the complexity of the actual system was reflected in the synthesis of the Packaging, Basic, and Advanced Process modules in the model. The three modules were integrated based on a variety of factors, namely (1) The actual system is a blend of automated and manual processes, requiring the specific features of each module. (2) The current production system is characterized by distinct factors, including preparation time, errors, downtime, and other variables. Consequently, the modules were selected based on compatibility with the existing system. (3) Accurate estimation of processing time was realized by the adaptability of the packaging module.

The integration of three modules (Packaging, Basic, and Advanced Processes) in the Arena simulation model was designed to handle the complexity of the actual production system. The Packaging module specifically managed packaging operations timing and flow, while the Basic Process module handled core production processes and resource allocation. The Advanced Process module was responsible for controlling complex decision logic and quality checks. These modules work together to address both manual and automated operations, with the Basic and Advanced Process modules managing manual, and automated operations, respectively. The Packaging module focused on specific packaging operations. The model also managed various production variables, with preparation time and downtime handled by the Basic Process module, while error handling and quality checks were controlled by the Advanced Process, and packaging rates managed by the Packaging module. For data integration, the Packaging module focused on processing time estimation, with resource usage, and system performance metrics regulated by the Basic and Advanced Process modules. This integration resulted in a flexible system where the Packaging, Basic and Advanced Process modules handled the package-specific parameters, core operation flows, and complex decision logic. However, through this comprehensive integration, the model accurately represented the actual system while maintaining the flexibility needed for scenario testing.

TABLE II
PRODUCT PROCESSING TIME ON EACH MACHINE

No	Process	Time
1	Preparation	90 – 120 min
2	Filling	1L = 1600 bottle/hour
		4L = 625 bottle/hour
3	Cap Assembler	120 unit/min
4	Capping	1L = 240 bottle/min
		4L = 120 bottle/min
5	Cap Sensor	60 unit/min
6	Cap Induction Sealing	60 unit/min
7	Lot Printing	60 unit/min
8	Weight Sensor	60 unit/min
9	Cap Sensor	60 unit/min
10	Rework	± 30s/bottle
11	Manual Packing	1L = ± 50 s/box
		4L = ± 60 s/box
12	Carton Sealing	20 box/min
13	Carton Weight Sensor	20 unit/min
14	Lot Printing	20 unit/min
15	Manual Palletizing	1L = ± 30s/box
		4L = ± 30s/box

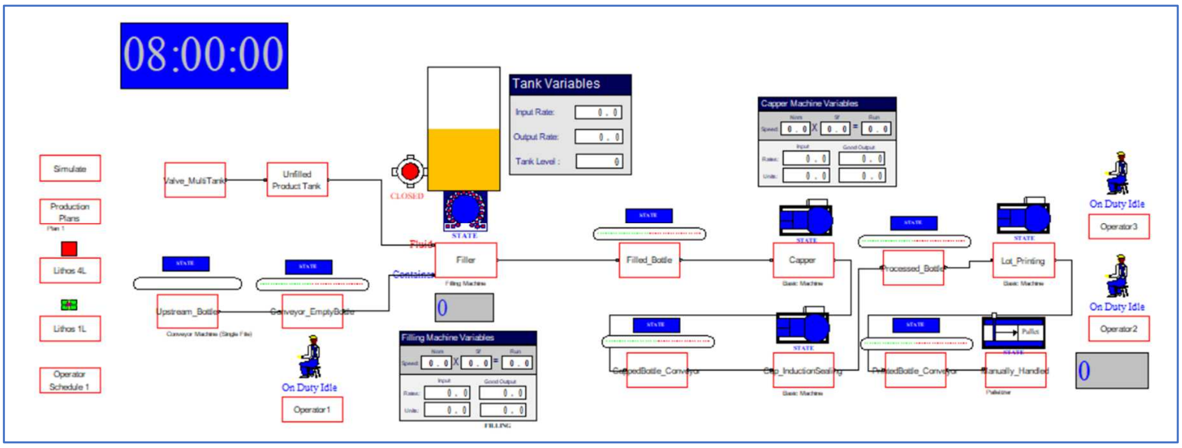

Fig. 4 Existing Filling Model

The working time parameterization of each machine in the simulation model was adapted to the actual system uptime and downtime rates. Based on operational data obtained from the production department, the machine uptime value was set within the range of 85% to 90%. This value reflected the real performance of the actual system. The integration of these parameters, enabled the developed simulation model to provide an accurate and comprehensive representation of the process flow occurring in the manufacturing filling and packing lines of the company.

The comparative results in Table 3 were generated through multiple replications using Arena Simulation software. The model incorporated actual production parameters including standard working hours, machine capacities, and operating conditions documented during field observation. For validation purposes, 10 replications were performed for 1L packaging and four for 4L packaging, each representing a complete production run. The simulation outputs were systematically compared against actual production data collected over the nine-week observation period. These comparative data sets formed the basis for model validation using both FIS and statistical t-test analysis.

TABLE III
PERFORMANCE COMPARISON OF SIMULATION AND ACTUAL SYSTEM PRODUCTION OUTPUT RESULTS

Replication	Simulation Output	Actual Production Output
	1 L	
1	5206	4608
2	5415	4984
3	5251	6080
4	6078	5772
5	4995	6230
6	4817	4758
7	5246	4664
8	5046	6288
9	5690	4984
10	5214	5772
	4 L	
Replication	Simulation Output	Actual Production Output
1	3060	2900
2	3084	3172
3	3180	2920
4	-	3000

A replication process was used to test the approximate range of the obtained simulation model for validation. During software simulation, the replication process included using a variety of random numbers to observe the outcomes and errors that occurred in the system. This research compared several replication results in Table 3, using it to facilitate analysis of the best values.

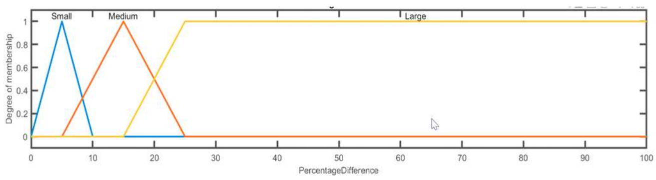

Fig. 5 Percentage difference analysis using Fuzzy

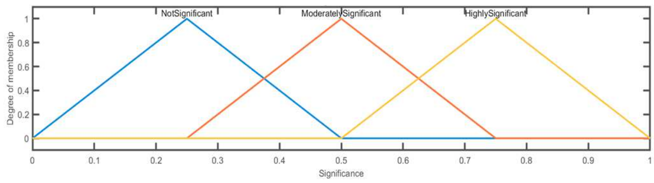

Fig. 6 Output significance analysis using Fuzzy

TABLE IV
ANALYSIS OF THE SIGNIFICANCE OF SYSTEM PRODUCTION OUTPUT

Replication	Difference (%)	Significance
	1 L	
1	12.98	0.5
2	8.65	0.3936
3	13.63	0.5
4	5.3	0.2609
5	19.82	0.6215
6	1.24	0.25
7	12.48	0.5
8	19.75	0.62
9	14.17	0.5
10	9.67	0.4689
	4 L	
Replication	Difference (%)	Significance
1	5.52	0.268
2	2.77	0.250
3	8.90	0.410
4	10.0	0.750

The significance analysis was conducted using two complementary methods FIS and statistical t-test analysis.

In the FIS analysis, as shown in Fig. 5, the percentage difference between simulated output and real system was evaluated using three membership functions Small (0-10%), Medium (5-25%), and Large (>15%). The significance output used three levels (Not Significant, Moderately Significant, Highly Significant) as shown in Fig. 6. The results in Table 4 show average significance values of 0.462 and 0.419 for 1L and 4L packaging, respectively. The t-test analysis provided additional statistical validation, for 1L packages (n=10), the comparison between average simulation output (5,296 units) and actual production (5,414 units) yielded $p>0.05$. Similarly, 4L packages (n=4) showed no significant difference (simulation 3,108 units, actual 2,998 units, $p>0.05$). Both FIS and t-test results confirmed the validity of the model.

The significance analysis in Table 4 showed the validation results realized by comparing simulation outputs with actual production data. For 1L packaging, ten replications represented significance values ranging from 0.25 to 0.6215, with percentage differences varying between 1.24% to 19.82%. The most accurate replication occurred in simulation six, with a difference of only 1.24% and a low significance value of 0.25. Meanwhile, the largest deviation was observed in replication five with a difference and significance of 19.82% and 0.6215, respectively. For 4L packaging, four replications exhibited tighter significance ranging from 0.250 to 0.750, with percentage differences within 2.77% and 10.0%. The 4L simulation had better consistency, particularly in replication two with only 2.77% difference and 0.250 significance value. The overall average significance values of 0.462 and 0.419 for 1L and 4L packages, respectively depicted good model validity, as values less than 0.5 suggested acceptable simulation accuracy. This analysis confirmed that the model effectively represented the actual production system, with slightly better accuracy for 4L packaging processes.

In accordance with this validated model, three improvement scenarios were developed, as shown in Table 5. The first scenario integrated a robotic packing system into the existing production line. This was enhanced by the second scenario through the incorporation of a robotic arm palletizer for faster work completion. The third scenario combined both automatic case packer and robotic arm palletizer into a comprehensive automation solution. Each scenario was designed with specific targets to optimize productivity and reduce processing time, in respect to increasing levels of automation and integration across the production line.

TABLE V

SUMMARY OF IMPROVEMENT SCENARIO CALCULATION RESULTS

Measurements	Scenario 1		Scenario 2		Scenario 3	
	1L	4L	1L	4L	1L	4L
Time Reduction	5%	11%	12%	14%	14%	19%
Production Increased	6%	12%	13%	17%	16%	23%

Based on the results of the scenario improvement analysis, the third scenario that combined automatic case packer and robotic arm palletizer showed the most significant efficiency improvement. For 1L packaging, there was a reduction in working time per day from 9.3 hours to 7.9 hours. This calculation depended on the conversion of normal working time (eight hours) and average worker overtime (1.3 hours). The initial total working time is 9.3 hours (eight hours + 1.3 hours), therefore, the reduction in working time was calculated using the formula 9.3 hours - (9.3 hours * 14%) = 7.9 hours. The 4L packaging also showed a reduction in working time per day to 7.53 hours. The calculation used the same formula as 1L packaging, with the conversion of normal working time (eight hours) and average overtime (1.3 hours) amounting to a total of 9.3 hours. The reduction in working time was calculated by the formula 9.3 hours - (9.3 hours * 19%) = 7.53 hours. These results showed that automation of the packing and palletizing process significantly improved production efficiency, including the potential to reduce employee workload by minimizing the need for overtime, making the scenario an optimal solution for production system improvement.

A comprehensive benchmarking analysis was conducted to evaluate the improvement scenarios against industry standards and best practices in lubricant manufacturing. Current standards showed typical working times of eight to 8.5 hours per day, while best-in-class facilities achieved seven to 7.5 hours per day. Leading manufacturers reported automation-driven productivity improvements and overtime reductions of 15-20% and 60-70% following automation implementation. As a result, the third scenario supported these benchmarks, achieving working times of 7.9 hours and 7.53 hours for 1L and 4L packaging, respectively. The productivity improvements of 16% and 23% for the 1L and 24L lines, along with an approximate overtime reduction of 65%, showed that the proposed automation solutions met or exceeded industry standards, particularly in the performance of the 4L packaging line. The strategy if adopting automatic case packers and robotic arm palletizers reflected the current best practices in lubricant manufacturing automation. While these results are promising, there remains potential for further optimization to reach the industry benchmark of seven hours per day working time through additional refinement processes and the adoption of more advanced automation technologies.

IV. CONCLUSION

In conclusion, this research investigated the possibility of optimization in the filling and packing lines of 1L and 4L of lubricating oil at a manufacturing company. This led to the assessment of three enhancement scenarios using Arena simulation to improve the constraints of the current semi-automated system. The scenarios were evaluated to overcome the limitations of the existing semi-automated system. Moreover, the third scenario, which combined an automatic case packer and robotic arm palletizer, proved to be the most efficient. The process reduced the working time per day from 9.3 hours to 7.9 hours and 7.53 hours for 1L and 4L packs, respectively. This improvement reduced the need for overtime, thereby increasing productivity. The use of an FIS ensured the accuracy and reliability of the simulation model. Therefore, automation in the packing and palletizing processes, improved operational efficiency. This led to the need for further analysis of the investment return period before implementation.

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