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Enhancing Order Fulfillment in Electric Motor Gate Manufacturing: A South African Simulation Study

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Abstract

This study investigates the operational efficiency of the production order and picking process in a manufacturing environment. It specifically looks at the process from the Operational Planner's release of a production order to the delivery of materials that have been picked and packed to the production line. Production orders start a sequence of jobs involving various resources and time distributions as they arrive at the stores, which follows an exponential distribution with a mean interval of seven minutes. Material picking, packing into a mini pallet, loading onto an electric stacker for transportation, and bin location verification in SAP system are all part of the entire workflow. An electric stacker, one pallet for packaging, and seven operators with variable duty durations are essential resources. With an emphasis on throughput optimization and delay minimization, we use this study to identify possible bottlenecks, resource utilization rates, and process flow limitations. Based on the outcomes of the simulation, suggestions are made to enhance workflow effectiveness and resource allocation, which will help to streamline production support and enhance operational planning.

Keywords
Arena, Operators, Electric stacker, SAP system

1. Introduction

Maintaining productivity and reducing downtime in manufacturing requires effective operational planning and resource allocation, as evidenced in recent advancements in discrete event simulations to address production bottlenecks and line balancing issues (Guerrero, et al. 2022; Teshome, et al. 224; Kamal and Rahman, 2024) which help shift managers intervene effectively as highlighted by Rocha and Lopes (2022). Meeting production goals and preserving workflow continuity in a production setting depend on materials being delivered to the production line on schedule to support production monitoring and planning as noted by Belli et al. (2019). Coordinating the release of production orders, which in turn triggers store employees to start the picking process, is the responsibility of an operational planner. The total efficiency of material flow is impacted by the various processes, resources, and time distributions involved in this complex operation.

Effective inventory control and material handling are essential elements of every manufacturing system that affect output and total operating expenses, as supported by industry-specific models that prioritize sustainable and technologically advanced material handling (Ferraro et al., 2024). The prompt and precise delivery of goods from the warehouse to the production line guarantees a continuous flow in production and reduces downtime in nowadays manufacturing and production environments (Munro, 2023). To meet production needs, orders are picked, packed, and transferred to the production line in a warehouse setting. The analysis and improvement of this process is the focus of this case study.

Despite widespread application of Discrete event simulation in manufacturing, limited research has focused specifically on electric gate motor production system, within south Africa industrial context. Furthermore, existing studies often lack integration with theory of constraints and lean flow principle, and rarely incorporate queueing-based conceptual models (M/M/C) to explain system behavior. The study bridges this gap by combining these theoretical frameworks with simulation to improve order fulfillment performance

In this case, the Operational Planner creates and releases production orders to start the picking procedure. At an average period of seven minutes, orders come at the stores according to an exponential distribution. Once the order is received, an operator must use SAP to check the Kanban bin's location, which takes varying amounts of time. Variability and possible delays may be introduced by this step in addition to the restricted number of operators available. Operators pick material after verifying the Bins location, and they are subsequently put onto a mini pallet. Operators may have to wait for packing availability if there is only one pallet available for packing. Loading the packed pallet onto an electric stacker is the next step, which is also a resource-constrained process. Specific task timings and the availability of resources, like stackers, packing pallets, and operators, affect each of these phases. These constraints may result in inefficiencies that affect the flow of production, bottlenecks, and queue accumulation.

Analyzing time distributions, queuing patterns, and resource consumption is necessary to comprehend the dynamics of this process to detect and eliminate bottlenecks, maximize throughput, and guarantee resource efficiency. To properly support manufacturing processes, this study aims to investigate these elements through simulation and analysis, offering data-driven insights and suggestions for process improvement.

1.1 Problem Statement

Picking and delivering materials to the production line is a crucial procedure in a production environment, but it is complicated by resource limitations and inconsistent task completion timeframes. A series of actions, including kanban bin location verification, material selection, packaging onto a pallet, and loading into an electric stacker, are triggered by production orders, which arrive at the stores in an unexpected, exponential manner. The number of operators and the single pallet used for packing are two examples of the restricted resource availability and temporal variability that could cause delays and inefficiencies at any stage of this process.

The ability to supply materials to the production line on time is eventually impacted by bottlenecks, longer wait times, and decreased throughput caused by task length unpredictability and resource constraints. This inefficiency impacts overall operational productivity in addition to running the danger of interrupting the production flow. These problems can result in higher operating costs, lower utilization rates, and delays in reaching production goals if proper planning and resource optimization are not implemented.

Therefore, the problem lies in understanding and addressing the impact of time variability and resource constraints on the picking process. This study aims to analyze the current workflow, identify critical bottlenecks, and propose data-driven improvements to optimize resource allocation, reduce delays, and enhance the efficiency of material delivery to the production line.

1.2 Research Aim, Objectives, and Questions

This paper aims to enhance the order fulfillment process in electric motor gate manufacturing by leveraging simulation modeling. Through pinpointing bottlenecks, optimizing resource distribution, and minimizing delays in production order handling and material picking, the study strives to improve operational efficiency and secure timely delivery of materials to the production line.

- The primary objective of this study is to identify and examine bottlenecks in the current order fulfillment process of electric motor gate manufacturing, specifically looking at how these inefficiencies impact throughput and overall productivity.
- Additionally, the study evaluates resource utilization, focusing on the roles of operators, pallets, and stackers to reveal areas where overuse or underuse may disrupt workflow balance and contribute to delays.
- Finally, by using simulation modeling, the study explores alternative configurations and process improvements to generate actionable insights that reduce non-value-added time, optimize workflow, and enhance the efficiency of order fulfillment.

Three key research questions guide this study. First, what are the primary bottlenecks in the order fulfillment process, and how do they affect throughput and operational efficiency? Second, how does resource utilization, specifically among operators, pallets, and stackers, impact workflow balance and productivity in the order fulfillment process? Third, what alternative configurations or process changes could improve throughput and reduce delays?

1.3 Study Scope, Limitations and Significance

This study examines the order fulfillment process in a South African electric motor gate production line, focusing on warehouse operations for material picking, packing, and delivery. Through simulation modeling, it assesses resource use and workflow efficiency, identifying bottlenecks and testing alternative setups to improve throughput.

The study was limited by time constraints and relied on historical data, which may add variability as real-time data was unavailable for dynamic tracking of workflow changes. The stores section's picking and delivery procedure has also been a limitation of the study given its case study nature; it does not include the production line's downstream effects. Task timeframes and resource availability may change in the future due to changes in workforce size, technology, or equipment; these factors are not taken into consideration in this analysis, which is based on present resource levels. Therefore, due to the fact this is a case study limited to one company; its findings cannot be generalized.

This study is significant because it helps to enhance the effectiveness of material flow in a critical operational procedure that directly supports production. The study provides useful suggestions for improving the picking and delivery process by identifying bottlenecks and evaluating resource usage, which can result in more efficient production line operations, shorter wait times, and reduced costs. The study's findings offer actionable insights for enhancing production efficiency, reducing delays, and supporting similar facilities in optimizing order fulfillment.

2. Literature Review

2.1 Introduction to Core Theories and Gap Analysis

In production and warehouse management, foundational theories like queuing theory, lean manufacturing, and simulation modeling are essential. Queuing theory helps manage waiting times and resource allocation in high-variability tasks that impact production flow. Lean manufacturing, with its focus on waste reduction and streamlined processes, aligns with this study's goals of optimizing resources and minimizing delays (Sugimori et al., 1977; Hopp and Spearman, 2011). Simulation modeling—particularly discrete-event simulation (DES)—offers a controlled environment for testing process improvements and resource configurations (Banks et al., 2005). Goldsman and Goldsman (2015) DES as a technique in which a system's state changes at defined points due to specific events, such as customer arrivals, machine breakdowns, or departures. The authors go further and explain that DES is particularly useful for studying systems like queues, manufacturing processes, and inventory management, in contrast to continuous-time simulation, which is suited for modeling phenomena through differential equations. Other core theories which have been detailed in Table 1 below include System Dynamics (SD), Agent-Based Modelling (ABM), SIMHeuristics, and Simulation-Optimization have been used in different industries to ensure that operations are optimized and deliver what the customers expect.

Table 1. Core Theories in the Literature

Core Theories	Description	Sources	Location	Industry
Discrete Event Simulations (DES)	Used to model and simulate the production processes to identify bottlenecks and production lines optimization	Agalianos et al. (2020)	Greece	Logistics
		Meissner et al. (2021)	Germany	Aviation
		Atalan (2022)	Turkey	Healthcare
		Le Lay et al (2024)	France	
		Guerrero et al. (2022)	Spain	Automotive
		Kamal and Rahman (2024)	UK	Electronics
System Dynamics (SD)	Focus on time delays, nonlinearities, and system feedback	Selvakkumaran and Ahlgren (2020)	Sweden	Energy
		Alamerew and Brissaud (2020)	France	Electric Car Battery
		Sayyadi and Awasthi (2020)	Canada	Transport
		Keyhanpour et al. (2021)	Iran	Civil Engineering
		Ghadge et al. (2022)	UK	Supply-Chain
		Luo et al. (2023)	China	Textile
Agent-Based Modelling (ABM)	Simulates the behavior of individuals (agents) and their interactions within the system	Daly et al. (2022)	Belgium	Various
		Young and Aguirre (2021)	USA	Fire safety & Evacuation
		Wilson et al. (2023)	USA	Transport
		Sibale and Munthali (2021)	Malawi	Road Traffic
		Vuthi et al. (2022)	Germany	Energy
SIMheuristics	Combination of simulation with heuristics and metaheuristics to solve real-world problems with uncertainty	Rabe et al. (2021)	Germany	Material Trading
		Juan et al. (2023)	Spain/Italy	Logistics
		Bayliss and Panadero (2023)	UK	Healthcare
		Peyman et al. (2024)	Spain	Transport
		Castenada et al. (2022)		
		Gomez et al. (2023)		
		Berkhout (2024)	Netherlands	Cattle Feed Industry
Simulation-Optimization	Using simulation to optimize system performance, reduce costs, and improve efficiency through the identification and elimination of bottlenecks and workload balancing.	Guerrero et al. (2022)	Spain	Automotive
		Tordecilla et al. (2020)	Columbia	Supply-Chain
		Saputro et al. (2023)	Portugal	
		Atabaki et al. (2022)	Iran	Electricity Generation
		Sakki et al. (2022)	Greece	Energy
		Sawik et al. (2022)	Poland	Logistics

While not an exhaustive gap analysis, Table 1 reveals a notable gap in applying simulation and optimization specifically for electric motor gate order fulfilment in manufacturing. While sectors like logistics, energy, and healthcare receive considerable focus, electric motor gate manufacturing remains underexplored, specifically from a South African perspective. This study seeks to fill that gap.

Current research predominantly emphasizes production and supply chain optimization, with limited attention to order fulfilment. By using simulation to enhance fulfillment efficiency, this study aims to improve both customer satisfaction and operational performance. Additionally, most existing studies originate from Europe, the UK, and the USA, with minimal representation from South Africa. Conducting this study in South Africa adds valuable regional insights and geographic diversity. Unlike many discrete-event simulation (DES) applications that focus on general production, this research targets resource optimization—covering workers, materials, and equipment—specifically for fulfilling orders. Discrete-event simulation (DES) with software like Arena provides a controlled environment to evaluate workflow efficiency and potential improvements. DES allows for testing various resource allocation scenarios and their effects on throughput (Banks et al., 2021).

2.2 Order Picking and Production Order Efficiency

According to Prunet (2024) order picking is a highly resource-intensive part of warehouse operations, crucial for timely material delivery (Jiang et al., 2024). Research emphasizes optimizing picking strategies and layouts to reduce lead times and avoid bottlenecks (De Koster et al., 2007). Variability in picking and packing times impacts efficiency (Jiang et al., 2024), particularly in high-variability settings where orders arrive at irregular intervals, Koster et al. (2007) point out that picking process optimization can result in significant increases in warehouse efficiency, lead time reductions, and bottleneck minimization.

2.3 Kanban and Lean Manufacturing

The Kanban system, fundamental to lean manufacturing, is designed to control inventory while limiting work-in-progress (WIP). By managing inventory flow and reducing excess stock, Kanban improves visibility and streamlines production (Gross & McInnis, 2003). For instance, integrating digital Kanban with ERP systems, like SAP, enhances tracking and enables just-in-time (JIT) replenishment.

Originating from Toyota's production methodology, the kanban system is a key component of lean manufacturing because it improves material flow to the production line and controls inventory (Sugimori et al., 1977). By limiting work-in-progress (WIP) and emphasizing "just-in-time" principles, kanban helps reduce excess inventory and prevent overloading the system. According to studies by Gross and McInnis (2003), utilizing kanban in production support can improve response times in high-demand settings, reduce waste, and enhance process visibility. Real-time tracking and quick access to location data is made possible by integrating kanban with digital tools like SAP, which is essential for minimizing order picking delays.

2.4 Resource Allocation and Bottleneck Management

Allocating resources effectively is essential to maintaining effective warehouse operations, particularly when managing several manufacturing orders. The use of simulation models to examine resource usage and locate bottlenecks in complex systems is explained by Law and Kelton (2000). Warehouse simulation studies, like those by Gu, Goetschalckx, and McGinnis (2007), demonstrate that resource limitations, including the scarcity of pallets or operators, frequently result in queuing delays that affect throughput. In order eliminate bottlenecks and guarantee balanced workloads and efficient resource use, they promote the strategic deployment of resources. Continuous material flow is supported by this method, which is necessary to support production lines.

2.5 Task Time Variability and its Impact on Process Efficiency

Task time variability, such as that in bin location checks, picking, packing, and loading, is a major problem in warehouse operations that impacts dependability and efficiency. Hopp and Spearman (2008) emphasized that waiting periods and queue formation result from task time variability, which adds unpredictability to processes. To lessen the impact of unpredictability, strategies including resource pooling, buffer allocation, and temporal standardization are recommended. Additionally, Meyer, Näf, and Schwarz (2019) discovered that the application of queuing theory and stochastic modeling can help anticipate possible delays in sequential processes and offer important insights into projected waiting periods.

2.6 Simulation for Process Improvement in Warehouse Operations

According to Banks et al. (2005), simulation modeling is frequently utilized to comprehend and enhance warehouse operations by offering a virtual setting for evaluating process modifications and resource allocation techniques. Arena, a popular simulation program, enables thorough workflow modeling, including task time distributions and resource limitations. According to studies by Rouwenhorst et al. (2000), simulation models can be used to quantitatively assess possible throughput and efficiency gains, test the effects of resource adjustments, and successfully identify areas for improvement. In settings where task time unpredictability and resource constraints are common, simulation enables businesses to make data-driven decisions about workflow optimization.

2.7 Impact of Order Arrival Patterns on Queue Management

An element of unpredictability introduced by the arrival pattern of production orders, especially when represented by an exponential distribution, can make scheduling and resource planning more difficult. According to research by Silver, Pyke, and Peterson (1998), workload irregularities caused by exponential order arrival patterns can result in resource demand fluctuation. Effective queue management techniques are necessary to prevent order backlogs and preserve a constant flow in light of this fluctuation. It is advised to use strategies like buffer management, priority queuing, and dynamic staffing to effectively handle high order arrival unpredictability, lower the chance of bottlenecks, and facilitate easier task transitions.

The research emphasizes that optimizing production support operations requires smart resource allocation, effective kanban system utilization, and efficient order picking. To avoid bottlenecks and guarantee timely material flow, it is crucial to manage unexpected order arrival rates and address task time variability. A powerful tool for examining intricate workflows, simulation modelling makes it possible to pinpoint areas in need of development and support data-driven process modifications. This study aims to boost the production order selection procedure by utilizing these insights, guaranteeing dependable material delivery and increased operational effectiveness in the production support environment.

2.8 Theory of constraints

This study is grounded in the Theory of Constraints (TOC), which emphasizes identifying and optimizing system bottlenecks to improve overall throughput. By focusing on the most constrained resources, the system can achieve significant performance improvements with minimal changes. Additionally, Lean flow theory is applied to eliminate non-value-adding activities such as waiting, excess motion, and overproduction. Hopp, W. J., & Spearman, M. L. (2022) The integration of Lean principles ensures smoother process flow and reduced cycle times. From a modeling perspective, the production system is conceptualized as an M/M/c queueing system, where arrivals follow a Poisson distribution and service times are exponentially distributed across multiple servers. This framework supports analytical understanding of queue lengths, waiting times, and system utilization, complementing the simulation model.

3. Methods

3.1 Introduction

This methodology section outlines the research approach used to evaluate and optimize the order fulfillment process in electric motor gate manufacturing. Simulation modeling serves as the primary tool for analyzing resource allocation, pinpointing bottlenecks, and testing potential improvements to enhance operational efficiency. By simulating both current workflows and alternative configurations, the study aims to generate actionable insights for optimizing order fulfillment.

3.2 Research Design

Simulation modeling was chosen for its ability to replicate complex systems and analyze various "what-if" scenarios in a controlled environment as noted by Niloofar et al (2021). Discrete-event simulation (DES) was selected as the specific model type due to its suitability for modeling systems where state changes occur at discrete points in time, such as the arrival of production orders and completion of tasks as supported by Al-Hawari et al (2022). Arena software was used for this study, as it is a powerful tool allowing for designing and evaluating manufacturing systems with detailed modeling of resource constraints capabilities, task durations, and process flow variations critical to understanding and improving order fulfillment operations at low cost, low risk, and the ability to provide meaningful insights (Mouritz et al., 2014).

A Discrete-Event Simulation created with Arena software is the model type utilized in this investigation. When processes follow a series of events, where entities go through stages or tasks in response to time-driven events, DES models work effectively. In this study, discrete events—like production orders arriving, kanban bin locations being checked, picking, packing, and loading onto a stacker—occur at predetermined intervals and are impacted by job durations and resource availability. Because of its capacity to manage resource limitations, handle complicated workflows, and capture time variability—all of which enable precise modeling of each process step and its dependencies—Arena software was selected. The process depicted in Figure 1 as reported by Maria (1997), then most recently followed by Tau et al. (2022) and Zulkepli et a.l (2017) was followed to model the stores (warehouse) process of picking and packing of material for production line.

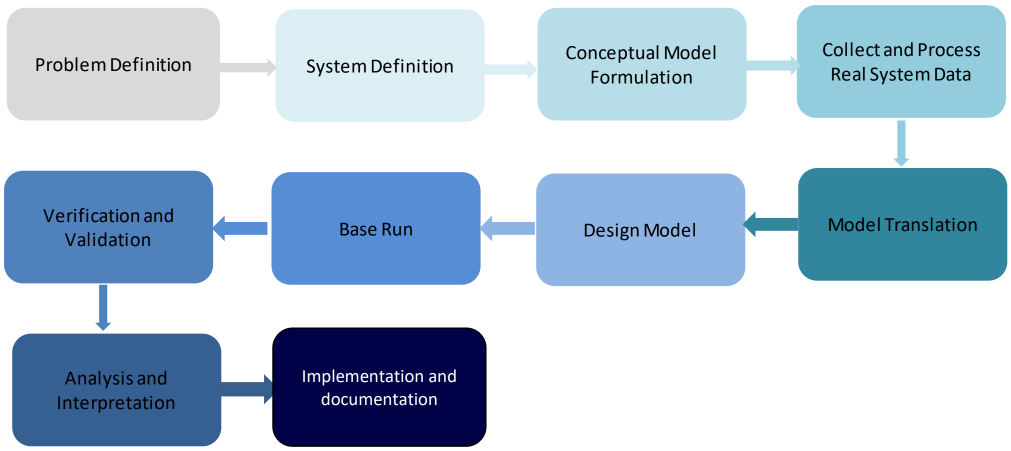

Figure 1: Modeling framework

3.3 Data Collection

Data was collected from historical records and observations within the manufacturing facility, with key variables including task durations, order arrival rates, and resource availability. The arrival of production orders follows an exponential distribution with a mean interval of seven minutes. Additional data was collected on task times for checking bin locations, material picking, packing, and loading onto stackers. Assumptions were made regarding task durations and resource availability based on standard operational conditions to ensure the model's representativeness.

3.4 Simulation Model and Scenario Development

The simulation model was developed in several stages, representing the current order fulfillment process. The main entities included production orders and pallets, while resources included operators, an electric stacker, and a mini pallet for packing. Key processes modeled in the simulation included:

- **Order Arrival**: Production orders arrive at the warehouse following an exponential distribution.
- **Kanban Bin Location Check**: Operators check bin locations in SAP, a task taking between 3 to 9 minutes.
- **Picking Materials**: Operators pick materials based on the production order, taking around 10 minutes per order.
- **Packing on Mini Pallet**: The items are packed on a single mini pallet, a resource constraint that introduces bottlenecks in the workflow.
- **Loading on Electric Stacker**: Packed pallets are loaded onto an electric stacker for transportation to the production line.
- The replications length for simulation of 10 independent simulation runs were conducted to ensure statistical reliability

This model, depicted in Figure 2 below, captures resource constraints and task variability, offering insights into potential bottlenecks and inefficiencies.

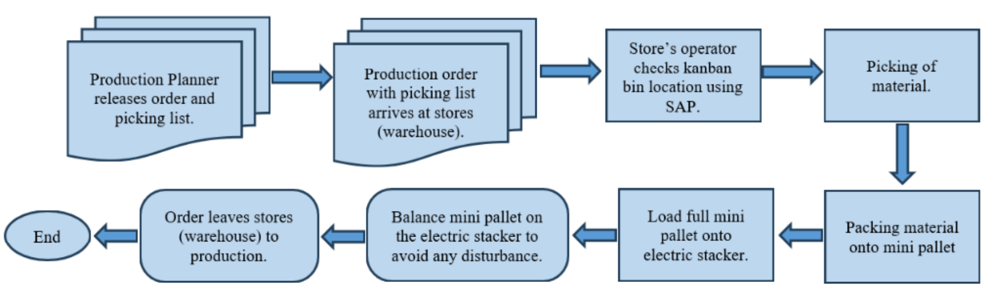

Figure 2. Performance study steps

The operational planner initiates production by releasing a production order, which is sent to the warehouse for materials collection. Each order, along with a picking list, arrives at the warehouse about every 7 minutes. Upon receiving the order, a store operator uses SAP to check kanban bin locations for all required parts, a step that generally takes 5 minutes but can vary from 3 to 9 minutes. With seven operators available, they move on to the picking stage, spending around 10 minutes gathering all listed items. After picking, items are packed onto a mini pallet, a process that takes between 4 and 7 minutes. Once the pallet is full, an operator loads it onto an electric stacker, which takes 5 to 7 minutes. Finally, the pallet is balanced for secure transport, with this final step taking roughly 2 minutes to ensure stability during transit.

Based on the gathered data, a simulation model is created using Arena software. The following stages are included in the model, which depicts the manufacturing order picking process as it is currently occurring. In this system, the main entities are the Production Order, representing each order needing materials for production, and the Pallet, used to pack these materials post-picking. With only one pallet available, it may become a bottleneck. Essential resources include the operator, mini pallet, and electric stacker to fulfill each order. The workflow encompasses several critical steps: order arrival, kanban bin location checks, material picking, packing onto the mini pallet, loading onto the electric stacker, and pallet balancing for transport security. Key attributes tracked throughout this process include order arrival time, part number lists, bin check time, picking and packing completion times, loading time, and balancing time.

To assess potential workflow improvements, two scenarios were tested: a baseline scenario and an improved scenario, following the recommendations by Tellis et al. (2021): In the baseline scenario, operators work standard 8-hour shifts with a single mini pallet available for packing. Under these conditions, bottlenecks arise during high-demand periods due to limited shift duration and pallet availability, resulting in potential delays and queue build-ups, especially in the packing stage. The improved scenario incorporates two modifications: (1) Extended Working Hours and an (2) Additional Pallet for Packing. Here, operator shifts are extended from 8 to 12 hours, providing a longer, more continuous workflow that reduces delays associated with operator unavailability. The addition of a second mini pallet allows two orders to be packed simultaneously, addressing the packing bottleneck and reducing queue times. These adjustments collectively enhance process continuity, efficiency, and overall system productivity, enabling the system to better manage higher demand.

3.6 Data Analysis

The data analysis cantered on three core performance metrics—throughput, queue lengths, and resource utilization—to evaluate the efficiency of the production order picking and delivery process. These measures provide a clear picture of production volume, congestion points, and resource effectiveness within the system. Statistical methods were applied to ensure the accuracy and reliability of simulation results.

Throughput assesses productivity by tracking the number of completed manufacturing orders within a given timeframe, offering a measure of system capacity under both baseline and alternative scenarios. Higher throughput indicates improved efficiency, often achieved through added resources or extended shifts that help eliminate bottlenecks. Queue lengths reflect the average number of orders waiting at each stage (such as kanban checks, picking, and packing), pinpointing bottlenecks that arise from limited resources or slow processing times. Tracking these queues allows for analysis of scenario impacts on wait times, with shorter queues signifying reduced bottlenecks. Finally, resource utilization measures the active working time of resources—such as operators, pallets, and stackers—as a percentage of their total availability. High utilization rates signal efficient resource use, though values near 100% can indicate resource strain. Ideally, utilization should be balanced to ensure effective resource deployment without bottlenecks or excessive idle time.

4. Results and Discussion

4.1 Summarized Time Studies

Time studies were conducted to capture the duration of each task in the production order process, covering steps like kanban location verification, material picking, packing, loading onto the electric stacker, and pallet balancing. Table 2 summarizes these findings, displaying both the actual cycle time per part number and the standard time for each task. For example, checking kanban locations on SAP averages 4.46 minutes per part, aligning closely with the standard 5 minutes. Material picking takes 8.92 minutes compared to a standard of 10 minutes, while packing and loading onto the stacker take 4.91 and 5.35 minutes, respectively—both near their standards of 5.5 and 6 minutes. Pallet balancing before dispatch averages 1.78 minutes, within the 2-minute standard. These time distributions provide accurate data for modeling and analysis.

Table 2. Conducted and Summarized Time Studies

Process	**Cycle time/part number (minutes)**	**Standard time (minutes)**
Checking kanban location on SAP	4,46	5
Picking material	8,92	10
Packing material	4,91	5,5
Loading to electric stacker	5,35	6
Balance pallet to electric stacker	1,78	2
Order leaves to production	N/A	N/A

Additionally, resource availability was carefully documented to mirror actual constraints. The system operates with a single mini pallet, creating a potential packing bottleneck, and relies on seven operators for task handling. This setup allows simulations and evaluations to accurately reflect real-world resource limitations. In terms of resource availability, it is important to indicate that the quantity of resources (such as pallets and operators) is recorded to accurately replicate resource allocation limitations. One little pallet is used for packing, and there are seven operators.

4.2 Simulation Results – 8-hour Shift vs. 12-hour Shift

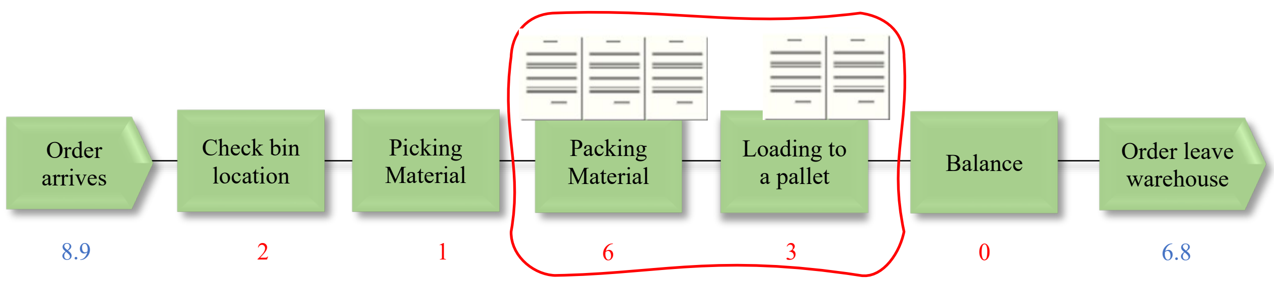

Figure 3. Simulation of the current 8-hours store operations.

The simulation of 8 hours store operations in Arena was conducted and Figure 3 depicts the model results. According to the result obtained from the Arena simulation, it is evident that the critical bottleneck is on packing and loading process as highlighted in red in Figure 3. This delays the production and the picking process for the next order. However, when adding an extra resource such as one mini pallet for packing station and an extra operator for loading pallets onto the electric stacker, the scenario shows improvement as depicted in Figure 4.

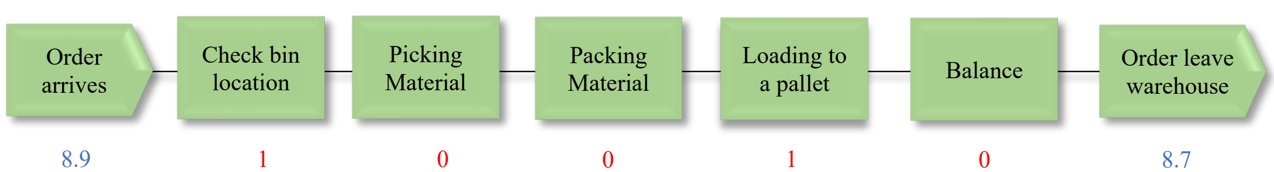

Figure 4. Simulation of the extended 12-hour store operations.

Table 3 below shows data from the number of orders out in the 8-hour shift (C*) and the 12-hour shift (E*).

Table 3. Number of Orders Processed in 8-hour shift vs. 12-hour shift

Name	Type	Source	Average Across Replications		Half-Width	
			(C*)	(E*)	(C*)	(E*)
System.NumberOut	Number Out	System	65,4	103,5	6,00	7,03
Entity 1.NumberIn	Number In	Entity	73,6	106	7,02	6,82
Entity 1.NumberOut	Number Out	Entity	65,4	103,5	6,00	7,03
Balancing operator.NumberSeized	Total Number Seized	Resource	65,9	103,8	6,03	7,06
Balancing operator.ScheduledUtilization	Scheduled Utilization	Resource	0,27	0,29	0,03	0,02
Packing operator.NumberSeized	Total Number Seized	Resource	69	29,91	6,91	2,01
Packing operator.ScheduledUtilization	Scheduled Utilization	Resource	0,78	0,23	0,08	0,02
SAP operator.NumberSeized	Total Number Seized	Resource	10,51	15,14	1,00	0,97
SAP operator.ScheduledUtilization	Scheduled Utilization	Resource	0,12	0,12	0,01	0,01
loading operator.NumberSeized	Total Number Seized	Resource	66,7	29,86	6,19	1,96
loading operator.ScheduledUtilization	Scheduled Utilization	Resource	0,83	0,25	0,08	0,02

As displayed in Table 3, the 12-hour shift substantially boosts throughput, with notable increases in both input and output orders processed compared to the 8-hour shift. Resource utilization for tasks like balancing, packing, and loading shows moderate increases under the extended shift but remains relatively low overall, suggesting that resources are not overstrained despite the higher processing volume. Half-width values indicate some variability, particularly in larger metrics, but the system efficiently handles the additional workload enabled by the extended shift.

Table 4 compares Value-Added (VA), Non-Value-Added (NVA) and Waiting Times for orders processed in 8-hour (C*) and 12-hour (I*) shifts.

Table 4. Value Added, Non-Value-Added and Waiting Times for Orders Processed in 8-hour shift vs. 12-hour shift

Name	Type	Source	Average of Replication Averages		Observed = Requested	
			(C*)	(I*)	(C*)	(I*)
Entity 1	NVA Time	Entity	0	0	Yes	Yes
	Other Time	Entity	0	0	Yes	Yes
	Total Time	Entity	45,46	29,50	Yes	Yes
	Transfer Time	Entity	0	0	Yes	Yes
	VA Time	Entity	29,18	29,09	Yes	Yes
	Wait Time	Entity	16,27	0,41	Yes	Yes
Balancing pallet.Queue	Waiting Time	Queue	0	0,29	Yes	Yes
Check bins location.Queue	Waiting Time	Queue	0	0	Yes	Yes
Loading pallet.Queue	Waiting Time	Queue	6,86	0,05	Yes	Yes
Packing.Queue	Waiting Time	Queue	9,66	0,07	Yes	Yes

From the above Table 4, the 12-hour shift results in a marked reduction in waiting times across entities and queues, with notable improvements in Wait Time for Entity 1 and waiting times in various queues. Additionally, Total Time for Entity 1 decreases, while VA Time remains consistent across shifts. The observed values align with the requested processing time requirements in both scenarios, indicating that the system operates more efficiently under the 12-hour shift.

With regards to the resource utilization during the 8-hour shift vs. the 12-hour shift, Figure 5 shows that in the 12-hour shift, Loading and Packing operators exhibit notably reduced utilization, reflecting a more balanced workload over the extended shift. Meanwhile, SAP and Balancing operators maintain similar utilization levels across both shift durations. The half-width values, which measure variability, remain minimal for all operators and show slight reductions in the 12-hour shift. This indicates consistent performance and improved stability in resource usage with the extended shift duration.

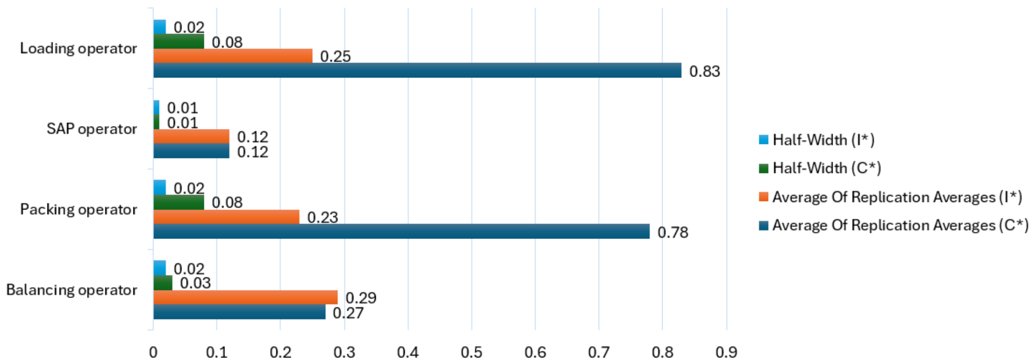

Figure 5. Resource Utilization in 8-hour (C*) Shift vs. 12-hour Shift (I*) (numerical values in minutes).

The simulation results for the 8-hour (C*) and 12-hour shifts (I*) highlight significant enhancements in the production process with the extended shift and additional resources. In the 8-hour shift, referring to Table 3, *65.4 orders* were processed (Number Out) out of *73.6 orders* entered (Number In), leaving *8.2 orders* pending in the system by the end of the shift. Referring to Table 4, it is evident that queue times were particularly high, averaging *9.66 minutes* for packing and *6.86 minutes* for loading, revealing bottlenecks caused by limited resources, specifically the single pallet. Again, referring to Table 3, the 12-hour shift, by contrast, processed *104 orders* out of *106 entered*, leaving only *2 orders* pending at the end of the shift. Queue times saw a dramatic reduction, with negligible delays of *0.07 minutes* for packing and *0.05 minutes* for loading (see Table 4). The extended shift supported a higher order volume while facilitating smoother operations and significantly reducing waiting times at bottleneck stages.

As detailed in Table 4, the results show that the 12-hour shift, bolstered by the addition of a second pallet, led to increased throughput, reduced queue times, and more balanced resource utilization. Resource usage remained stable, avoiding overload while accommodating the higher workload. This demonstrates that extending shifts and adding resources effectively streamline production, minimize bottlenecks, and enhance overall system performance.

4.3 Verification and Validation

A two-step verification and validation procedure were used to guarantee the simulation model's accuracy and reliability:

- Verification: To ensure that each process operates as anticipated based on the input distributions and sequence logic, the model undergoes extensive testing. Each operation was observed separately using dummy data inputs to look for problems such as unplanned delays, resource misallocation, and logical mistakes in the sequence.
- Validation: Actual historical performance metrics from the system were compared with the model's output data. To make sure the model's output matched actual operations, key performance metrics including average throughput time and resource usage were examined.

Additionally, simplified mathematical calculations of a store's product line were performed in order to validate simulation results. Like this, the following simplified calculations can be used to estimate the total number of orders that could possibly be selected and delivered to the production line in eight hours:

$$\text{Process} = \frac{\textit{Available stores working hours}}{\textit{Total time required to process order}}$$

Total time required to process order = Order arrival + check kanban bins location + Picking + Packing + Loading onto electric stacker + Balancing pallet

Total time required to process the order = 7 + 5.6 + 10 + 5.5 + 6 + 2 = 36.1

<u>8-hour shift</u>

- Process = $\frac{8 \times 60}{36.1}$ = 13
- Therefore, 1 operator can process 13 orders/8-hr. shift
- Orders that will be processed by 7 operators = 13 × 7 or 93 orders in 8-hour shift

<u>12-hour shift</u>

- Process = $\frac{12 \times 60}{36.1}$ = 19
- Therefore, 1 operator can process 19 orders/ 12-hr. shift
- Orders that will be processed by 7 operators = 19 × 7 0r 133 orders in 12-hour shift.

5. Conclusion and Recommendations

The goal of this study was to identify and fix major inefficiencies and bottlenecks that impact workflow continuity and resource usage by analyzing the production order picking and delivery process. By building a simulation model that mimics the actual system, it was feasible to evaluate how task variability, resource limitations, and process delays affected the order fulfilment cycle's total productivity.

Key findings showed that delays in the production support process are mostly caused by bottlenecks in the packing stage, excessive variability in the kanban bin position check timings and resource limitations like restricted pallet availability and stacker access. Additional pallets, adding working hours shift by extra 4 hours to make it be 12 hours working shift, better operator assignments, and the installation of real-time tracking systems were among the suggestions put forth for solving these problems. By streamlining job flows, decreasing wait times, and optimizing resource use, these changes could eventually boost throughput and productivity.

The study highlights the importance of simulation modeling in intricate operational situations and offers a useful and adaptable methodology for process optimization. These results show how simulation may support well-informed, data-driven decision-making in dynamic, resource-intensive processes, laying the groundwork for further study and continuous improvement in production management.

By creating and examining a discrete-event simulation model of the manufacturing order picking and delivery process, this study effectively achieved all its goals while offering crucial insights into system performance in a range of operating circumstances. The study analyzed resource limitations, found bottlenecks, and assessed the effects of various interventions, including more operators, pallets, stackers, and better shift scheduling, using in-depth modelling in Arena software.

To further enhance order fulfillment and production efficiency in electric motor gate manufacturing, future research should aim to address the limitations of this study. Integrating real-time tracking could provide dynamic insights into workflow fluctuations, enabling more precise identification of bottlenecks and optimization of resource usage. Expanding the scope to include downstream production effects would offer a broader perspective on how picking and delivery processes influence overall production outcomes.

Potential areas for future exploration include optimizing inventory storage layouts, assessing the role of automation in order fulfillment, and improving workplace ergonomics to boost worker productivity. Additionally, leveraging predictive analytics for demand forecasting and enhancing dispatch efficiency could further streamline operations. Conducting multi-facility studies would improve generalizability and help identify industry best practices, building on this study's findings to drive further advancements in operational efficiency.

From a cost–benefit perspective, the proposed improvements require minimal capital investment while delivering substantial operational gains. Increased throughput leads to higher revenue potential, while reduced waiting times and inefficiencies lower operational costs. The simulation model serves as a low-cost decision-support tool, enabling continuous improvement and long-term competitiveness

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