Optimizing Outbound Process Lead Times in High-Bay Warehouse Operations

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PREFACE

Completing this master's thesis marks the end of my master's degree in Industrial Engineering and Management at the University of Twente. Throughout this journey, I have gained invaluable knowledge and experience. Moreover, it has been a period of personal growth filled with challenges and accomplishments.

This thesis results from research and analysis and reflects the continuous support and guidance of professors, colleagues, and loved ones. Their guidance has been a constant source of motivation, helping me navigate even the more challenging moments. In particular, I would like to thank my university supervisors for their valuable feedback and guidance throughout this process. Their expertise has been crucial to the success of this project.

Furthermore, I would like to express my gratitude to Euroma for giving me the opportunity to conduct this research. The team's support and willingness to share valuable insights have played a key role in shaping this work. In particular, I would like to thank Jeppe, my supervisor at Euroma, for his continuous support and constructive feedback throughout the research process.

Finally, I want to thank my family and friends for supporting me during this research and my academic journey. As I move on to the next chapter of my life, I do so with anticipation and a sense of readiness for the upcoming challenges and opportunities.

I hope this thesis reflects my dedication and efforts and provides valuable contributions to the company. I appreciate your interest in this work and hope you enjoy reading this thesis.

Ronja Cremer
March 2025

MANAGEMENT SUMMARY

Koninklijke Euroma B.V. (Euroma) is a leader in the production of herbs and spices. To meet increasing demand, Euroma implemented a robotized high-bay warehouse system at its facility in Zwolle. With no capacity for additional buffer spots, timely pallet deliveries are critical to prevent production disruptions and truck waiting times.

Problem Statement

Full outbound pallets must reach their destination within one hour, yet 14% exceed this limit due to inefficiencies in the outbound process. Queueing times are the largest source of variability, influenced by scheduling logic, pipeline threshold configurations, and operator behavior. These delays result in daily costs of up to €1,865 due to production standstills and truck waiting times.

Research Focus and Goal

The main research question is:

How can Euroma optimize the outbound process of its high-bay warehouse to improve on-time delivery performance?

This study identifies strategies and parameter optimizations to enhance the outbound process. The research classifies the high-bay warehouse operations as a Blocking Job Shop Scheduling Problem (BJSSP). Due to system complexity, exact approaches and heuristics are infeasible for real-time decision-making in the dynamic environment at Euroma. Instead, a discrete event simulation is developed to evaluate:

- Dispatching rules (FCFS, R1)
- Pipeline threshold configurations
- Operator behavior affecting pallet retrieval from the outfeed lanes

Current System

The current outbound logic processes outbound pallets in two priority groups: workstation pallets take precedence over full outbound pallets. A first-come-first-served (FCFS) approach is applied within each priority group. Moreover, workstation pallets must strictly adhere to a predefined sequence, preventing retrieval until the preceding pallet has been processed. Pipeline thresholds further limit the number of pallets simultaneously in transit to a destination.

Key Findings

Simulation results indicate that both proposed dispatching rules improve performance:

- The R1 dispatching rule maximizes on-time delivery but increases tardiness.
- The FCFS approach slightly reduces on-time delivery compared to R1 but is less complex and shows advantages in tardiness performance.

Additionally, increasing the pipeline thresholds for outfeed lanes significantly improves performance. Raising the pipeline threshold at the outfeed lane at MP0 by just one unit results in:

- 1.46% increase in on-time delivery
- 5.48-minute reduction in tardiness per delayed pallet, reducing daily tardiness by 7.29 hours

Finally, the simulation results highlight the importance of the operator behavior. Increasing full outbound pallet retrieval times in 5-second increments (up to 300 seconds) leads to on average:

- 0.5% increase in on-time delivery
- 2.37-hour daily reduction in overall tardiness

Conclusions and Recommendations

Euroma's high-bay warehouse operates at full capacity, yet outbound performance remains a bottleneck. The simulation results confirm that adjusting pipeline thresholds and dispatching rules can significantly improve warehouse efficiency. However, it is essential to acknowledge that the simulation model does not fully replicate real-world operations due to missing Warehouse Control System (WCS) logic and limited documentation. Despite this, the findings provide valuable insights into potential improvements.

Key Recommendations:

1. Increase Pipeline Thresholds
   - Raising pipeline thresholds for outfeed lanes improves on-time delivery and tardiness of full outbound pallets without negatively affecting other pallet flows.
   - These changes do not require modifications to the WCS, allowing immediate implementation.
2. Pilot Test of FCFS Logic
   - FCFS eliminates priority distinctions between pallet types, reduces overall tardiness and on-time delivery percentages.
   - Implementing FCFS requires minimal WCS modifications, making it feasible for real-world testing.
   - A controlled trial during week 52 (when production is paused) is recommended to assess feasibility without operational disruptions.
3. Improve Operator Coordination
   - Ensuring timely pallet retrievals from the outfeed lanes minimizes bottlenecks and further enhances warehouse throughput.

This study demonstrates that Euroma's high-bay warehouse can increase outbound pallet flow without negatively impacting other operations, leading to more efficient resource utilization and increased outbound pallet flow.

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Glossary

AMCC Avoid Maximum Current Completion Time. 30, 32

AS/RS Automated Storage and Retrieval System. 2, 4, 5, 7–10, 15, 21–23, 35, 36, 38, 39, 45, 49, 51, 54, 56, 74

BJSSP Blocking Job Shop Scheduling Problem. ii, ix, 27, 30–33, 35–37, 40, 41, 47, 72, 75, 82

compartment double-deep storage location. 8

EDD Earliest Due Date. 28

EP0 first floor of the logistics department, one of the three outbound locations of the high-bay warehouse. 2, 7–10, 12, 13, 15–18, 20, 54, 55, 57, 58, 65, 69, 71, 80, 81, 100, 101, 106–108, 110, 113–118, 120–126, 129–131

EP1 ground floor of the logistics department, one of the three outbound locations of the high-bay warehouse. 2, 7–10, 13–18, 20, 55, 57, 65, 71, 73, 80, 81, 100, 101, 104–108, 110–118, 120–126, 129, 130

FCFS First-Come-First-Served. ii, iii, 13, 28, 50, 51, 56–73, 80, 87, 88, 91, 93, 95, 136–138, 145–147, 159, 160, 164, 167, 177, 178, 182, 185

FDD Flow Due Date. 29

GUROBI software for mathematical optimization. 43

I/O-point In-/Output points of the Automated Storage and Retrieval System or pickup/dropoff point. 7–9, 11, 13, 35, 38, 40, 45, 50, 51, 80, 81, 86, 103–105

IG Iterated Greedy. 30, 32

IT Information Technology. vii, 6, 7, 10, 11

JIFR Job Insertion Feasibility Recovery. 31, 32

JSSP Job Shop Scheduling Problem. 22–25, 27, 29–31, 33, 35, 36, 82

KPI Key Performance Indicator. 5, 11–13, 49, 58, 65–68, 70, 80, 94, 132

LWKR Least Work Remaining. 29

MAE Mean Average Error. 54, 111, 112, 114, 117

MAPE Mean Average Percentage Error. x, 54, 110–114, 117, 119–121, 124

MIP Mixed Integer Program. 27, 28, 32, 33

MP0 ground floor of the mixing department, one of the three outbound locations of the high-bay warehouse. iii, 2, 7–10, 12, 13, 15–19, 55, 57, 65, 66, 70, 71, 73, 80, 81, 95, 100, 102–108, 110–118, 120–126, 129–131

MPSM Managerial Problem-Solving Method. ix, 4–6

MWKR Most Work Remaining. 29

pipeline parameter determining the number of pallets that are on the way toward or waiting at a destination. v, vii, ix, 8, 12–21, 36, 48, 51, 53, 56–58, 65–70, 85

RPT Remaining Processing Time. 29

SA Simulated Annealing. 30, 32, 33, 36

SKU a Stock Keeping Unit is a unique item. 10, 74

SPT Shortest Processing Time. 28

TS Tabu Search. 30–33, 36

WCS Warehouse Control System. iii, 2, 4, 10, 12–14, 17, 49, 69, 71, 73, 74, 80, 86, 87

WINQ Work Content in the Next Queue. 28

WMS Warehouse Management System. 10, 12, 86

1 INTRODUCTION

This chapter overviews the research and situates it within its broader context. Section 1.1 introduces the company Koninklijke Euroma B.V. (Euroma), while Section 1.2 defines and motivates the problem. Finally, Sections 1.3 and 1.4 outline this study's research goal, approach, methodology, and structure.

1.1 Introduction of Euroma

Founded in 1899 by Antonij ten Doesschate, Euroma began producing herbs, spices, and pharmaceutical items in Zwolle. The brand name ”Euroma” was introduced in 1966 and is still being used. In 2001, Euroma received the Royal predicate – an acknowledgment of its national significance and importance in its field (Euroma, 2023d).

In 2018, Euroma strengthened its position in the European and Dutch herb and spice markets by acquiring Intertaste. A year later, a state-of-the-art production facility, shown in Figure 1.1, was opened in Zwolle. This facility boasts a robotized warehouse, fully automated mixers, and automatic guided vehicles (Euroma, 2023d).

Figure 1.1: Production Facility in Zwolle (Euroma, no date).

Following the acquisition, Euroma operated six production facilities. Three of these were gradually integrated into the Zwolle facility, leveraging combined expertise in the dry production of herbs, spices, and sauces (Euroma, 2023a). In addition to the Zwolle facility, Euroma operates two other production sites: one in Nijkerk, specializing in ambient liquid solutions, and another in Schijndel, focusing on the production and packaging of cooled fresh liquid products (Euroma, 2023a).

Euroma is the leader in the Dutch market for herbs and spices and has a top-three position in the European market (Euroma, 2023d). With about 650 employees, Euroma reached a turnover of 230 million euros in 2020 (Euroma, 2021). Euroma continues to pursue its mission of becoming ”Europe's foremost partner of taste, providing food business with a range of spice-based solutions” (Euroma, 2023b).

1.2 Research Motivation

After opening the production facility in Zwolle, Euroma centralized the demand and stock from the three merged facilities at this location. The company installed a 27-meter-tall robotized warehouse system to accommodate increased operational demands with six automatic pallet cranes (Euroma, 2023c). These cranes transport pallets between their storage locations and conveyor belts on either side of the Automated Storage and Retrieval System (AS/RS). The conveyor belts, referred to as MP0, EP0, and EP1, connect the AS/RS with the production site.

The departments within Euroma rely on timely pallet delivery to fulfill customer demand. The high-bay warehouse outbound process involves various individuals and systems handling interconnected tasks. The team leaders initiate the process by requesting goods from the high-bay warehouse. Subsequently, The Warehouse Control System (WCS) assigns the outbound tasks to the cranes, transporting the pallets from storage to the conveyors. Operators retrieve full outbound pallets from the conveyors and move them to buffer spots near their intended destination within the production site. There, they remain until further processing.

This division of tasks presents a challenge. Operators lack insight into the pallets' initial request time, so they do not know the overall duration of the outbound process. Similarly, the team leaders only notice the delays if a pallet fails to arrive at its destination on time. As a result, neither the operators nor the team leaders perceive the typical duration of the retrieval process.

Currently, Euroma anticipates that full outbound pallets will reach their destination within a maximum timeframe of one hour. However, approximately every seventh pallet fails to meet this expectation. Table 1.1 presents the average daily pallet counts and the percentage that exceeds or meets the 60-minute threshold for delivery.

	Average Daily Pallet Quantity			Percentage		
	MP0	EP0	EP1	MP0	EP0	EP1
Total Duration Exceeds Threshold (60 Minutes)	5.58	30.68	6.09	14.12%	18.24%	6.95%
Total Duration Within Threshold (60 Minutes)	33.95	137.52	81.54	85.88%	81.76%	93.05%

Table 1.1: Outbound Duration Analysis: Average Daily Pallet Counts and Percentage Split Above and Within 60-Minute Threshold

On average, 43 pallets per day exceed the one-hour delivery threshold to their outbound destination, accounting for 13.56% of all full outbound requests. Notably, pallets routed through conveyor EP1 demonstrate the highest probability (93.04%) of meeting the desired timeframe, while those utilizing EP0 are slightly less likely to meet the target (81.76%). This results in an average of 31 pallets daily from EP0 and six from EP1 exceeding the threshold.

The untimely arrival of pallets can lead to significant issues, such as truck waiting times, production interruptions, and last-minute schedule adjustments, all of which incur additional costs. Expert consultation estimates the following costs for delays:

- Production standstill: €200 per hour
- Truck waiting time: €72 per hour

Delays at MP0 and EP1 primarily cause production standstills, while those at EP0 result in truck waiting times. On average, these delays amount to daily costs of €902.82 for production standstills and €962.28 for truck waiting times, totaling €1865.10 if all delays lead directly to costs.

Based on the identified issues, we established a problem cluster (Figure 1.2). The cluster highlights the core problem in red as the fundamental cause of the action problem (in grey), while the intermediary green boxes delineate the causal chain.

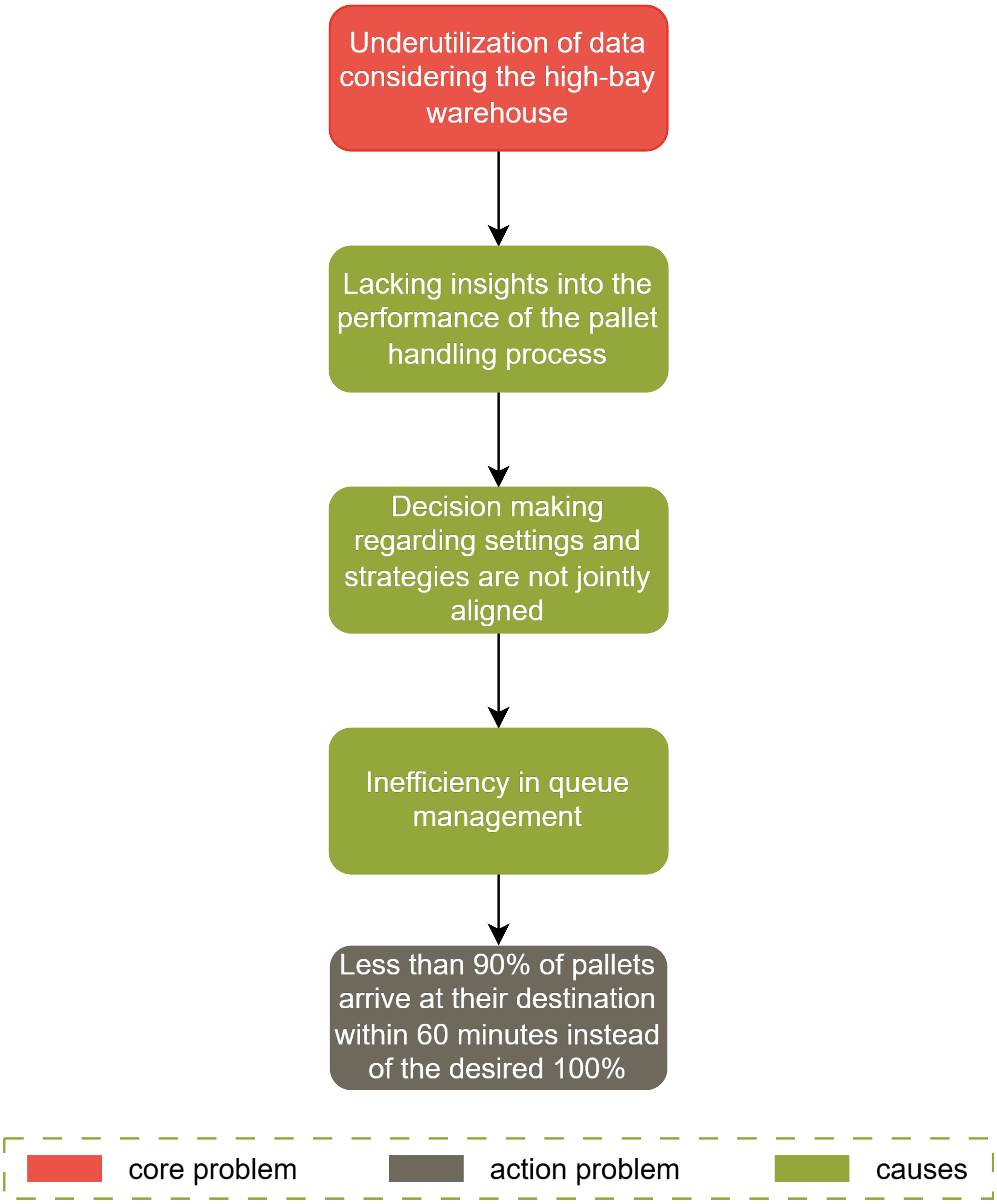


Figure 1.2: Problem Cluster

Although the high-bay warehouse collects substantial operational data, Euroma has not leveraged this information for analysis. Consequently, there is limited insight into the performance of the high-bay warehouse, hindering effective decision-making regarding strategy and parameter optimization for the outbound process. Hence, this research defines the core problem as follows:

"Euroma underutilizes existing data of high-bay warehouse performance, resulting in suboptimal settings and strategy formulation for the outbound process of the high-bay warehouse."

1.3 Research Goal

Euroma aims to enhance its production process, including the performance of the high-bay warehouse. Therefore, this research seeks to optimize strategies and parameter settings that impact the outbound process of the high-bay warehouse. Key areas of improvement include sequencing outbound requests and examining parameters influencing the outbound operations. This research identifies ways to improve the on-time delivery of outbound pallets by conducting a discrete event simulation. While tailored to Euroma's current demands, the study attempts to offer solutions for varying demand scenarios in the future. Therefore, we formulate the research goal as follows:

"Design of a discrete event simulation study that assesses the contribution of strategies and parameter settings to achieving timely delivery of all requested outbound pallets."

Scope and Limitations The complexity of high-bay warehouse processes and the time constraints of a master's thesis make it essential to define the scope and limitations of this thesis. This research includes a historical data analysis aimed at evaluating the current performance of the high-bay warehouse. The analysis uses historical data from 5 August 2023 to 31 December 2023. Specifically, the study focuses on identifying factors contributing to delays in full outbound operations on both the AS/RS and the conveyor system. While the influence of other pallet movements, like the inbound process, is recognized, we will not individually analyze them.

In two phases, the WCS assigns outbound tasks to a crane. This research does not investigate the decision-making process of reserving specific pallets based on product requests. Instead, it concentrates on the subsequent step: assigning reserved outbound pallets to cranes. Additionally, this research focuses on parameters directly influencing the assignment of outbound tasks, while parameters related to the timing and quantity of pallet requests are not within the scope of interest.

Finally, the destinations for full outbound pallets are predetermined and based on the distance from the outfeed lane to the destination on the production side. In contrast, the WCS can assign new orders to any of the available workstations. For the purpose of this study, we assume that the destinations of full outbound pallets are fixed according to historical data and cannot be altered.

1.4 Research Approach

First, we formulate the main research question to meet the research objective in a structured manner. Subsequently, we develop sub-questions and outline the approach to addressing them. The main research question is:

"How can Euroma optimize the outbound process of the high-bay warehouse to increase the on-time delivery performance of pallets?"

The sub-research questions are established by following the Managerial Problem-Solving Method (MPSM) from Herkens and Winden (2017). This approach structures the research into seven

MPSM Approach		Research Approach	
Phase	Description	Chapter	
1	Problem definition	1.2	Introduction of the Problem
2	Formulation of the approach	1.4	Research Approach
3	Analysis of the problem	2	Problem Context
4	Formulation of (alternative) solutions	3	Literature Review
		4	Modelling and Solution Design
5	Choice of a solution	5	Simulation Experiments
6	Implementation of the solution	6	Implementation

Table 1.2: MPSM Approach and Application

phases. This research's scope covers six phases, which impose the report's structure. Table 1.2 summarizes the phases and their mapping to the report structure.

The first group of sub-research questions aims to evaluate the current situation. This evaluation is essential for understanding the current performance and identifying improvement opportunities. Chapter 2 addresses the questions corresponding to phase 3 of the MPSM, using insights based on observations, stakeholder input, and available data.

Phase 3: Analysis of the problem
What are the current control policies and settings for managing high-bay warehouse operations at Euroma?

- Which strategies does Euroma use for inbound and outbound pallet management?
- Which parameters influence warehouse processes?
- What key performance indicators (KPIs) are relevant for evaluating the high-bay warehouse performance?
- How does the current system perform based on KPIs?
- Which specific stages of the outbound process offer potential for optimization?

Following the analysis of the current situation, phase four focuses on classifying and translating the on-time delivery optimization problem into problems proposed in the scientific literature. By analyzing various techniques, we identify similarities and differences. Chapter 3 details the literature review. Afterward, Chapter 4 answers the question regarding the design of the solution approach, where methods to solve the identified problems are developed based on the literature.

Phase 4: Formulation of (alternative) solutions
What does the literature propose for optimizing the on-time delivery in an AS/RS connected to a conveyor system?

- How is the integration of conveyor systems and AS/RS addressed in the literature?
- What are the similarities and differences between Euroma's challenges and problems studied in the literature?
- Which optimization techniques does the literature propose for minimizing lead times in outbound processes?

- What are the advantages and disadvantages of the optimization models proposed in the literature?
- How can discrete event simulation contribute to this study?

How should the solution approach be designed for the on-time delivery problem of Euroma?

- How can the conveyor system's capacity and requirements be incorporated into the solution?
- Which solution approaches can solve the problem instances of Euroma in limited computational time?
- What is the conceptual model for a discrete event simulation study for optimizing the outbound process at Euroma?

In the fifth phase of the MPSM, the focus shifts to evaluating the model's performance. We test their effectiveness across various scenarios after developing and selecting appropriate solution approaches. Chapter 5 presents the result and corresponding experimental setting.

Phase 5: Choice of a solution
Which model configuration performs best compared to the current system under different scenarios?

- What scenarios and experimental setups should we consider?
- What is the impact of demand fluctuations on system performance?
- Which outbound points represent bottlenecks?

The last phase of the MPSM addresses the implementation of the solution approach. Thus, Chapter 6 explores the requirements, possible consequences, and the benefits and drawbacks of the proposed solution.

Phase 6: Implementation of the solution
What are the consequences and requirements of implementing the proposed solution?

- What are the IT requirements for implementation?
- What are the benefits and drawbacks of the changes?

The study concludes with recommendations and suggestions for future research in Chapter 7.

2 PROBLEM CONTEXT

This chapter's main objective is to inform the reader of the current situation by providing a detailed description of the problem and addressing the first research question: What are the current control policies and settings for managing Euroma's high-bay warehouse operations?

First, Section 2.1 presents an overview of the high-bay warehouse, while Section 2.2 focuses on the key IT system in use. Afterward, Section 2.3 outlines the relevant performance measures and gives insight into the outlier analysis. Furthermore, Section 2.4 explains the control rules of the outbound process, followed by an analysis of the current performance. Finally, Section 2.5 summarizes the key findings.

2.1 Overview of the High-Bay Warehouse

Euroma operates an automated high-bay warehouse to store pallets containing raw materials, packaging materials, and finished goods. The central part is the Automated Storage and Retrieval System (AS/RS), which manages the goods' storage and retrieval process and integrates with a conveyor network. The cranes pick up incoming pallets and drop off outgoing ones at in- and output points (I/O-points), linked to the production site by conveyor belts. Figure 2.1 provides a schematical overview of the high-bay warehouse and its systems.

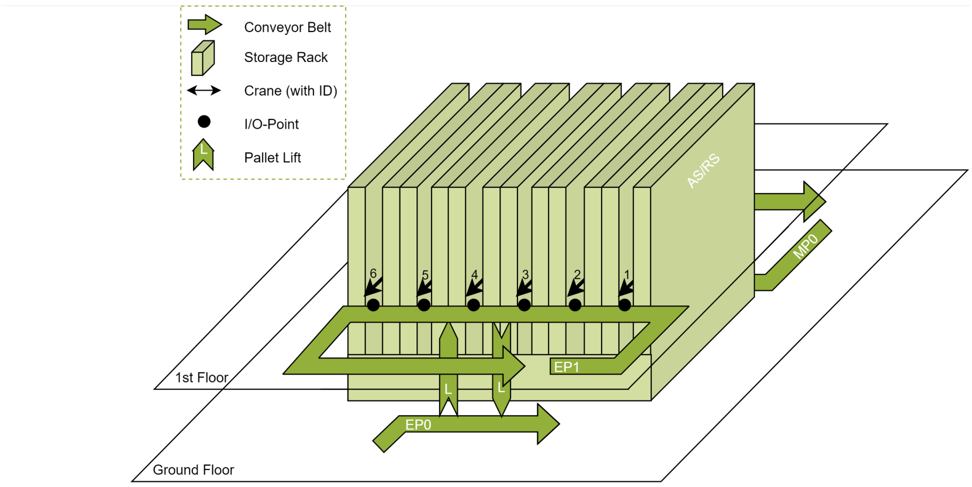


Figure 2.1: 3D Visualization of the High-Bay Warehouse and its Systems. Conveyor belt MP0 and EP1 have a direct connection with the AS/RS over I/O-points while EP0 is connected to the EP1 via pallet lifts. Figure 2.2 presents a detailed representation of the conveyors.

2.1.1 Automated Storage and Retrieval System

The 27-meter high AS/RS consists of six aisles (highlighted in light green in Figure 2.1). Each aisle accommodates an aisle-captive crane operating exclusively within its designated aisle.

Additionally, cranes can move vertically and horizontally simultaneously and are limited to carrying one unit load (pallet) at a time (single shuttle).

The AS/RS employs a double-deep storage configuration. Thus, each compartment has space for two pallets, one in the front and one in the back. It features 18,000 pallet locations and accommodates various pallet heights and widths (Euro and Block pallets).

2.1.2 Conveyor System

Unidirectional conveyors connect the AS/RS with the production side. On the ground floor, the high-bay warehouse features two conveyor belts: MP0 and EP0. A third conveyor belt, EP1, is located on the first floor directly above EP0. As depicted in Figure 2.1, MP0 and EP1 are directly linked to the I/O-points of the AS/RS. Conversely, EP0 is connected to EP1 through pallet lifts, each dedicated to transporting pallets in a single direction. For visual clarity, the detailed layout of these conveyor belts, along with key abbreviations representing significant conveyor spots, is illustrated in Figure 2.2.

All three conveyor belts feature similar configurations, comprising distinct lanes designated for specific functions.

- An infeed lane (green border) for pallets entering the system.
- An outfeed lane (red border) for pallets exiting the system.
- A reject lane (blue border) for pallets requiring review before entering the system.

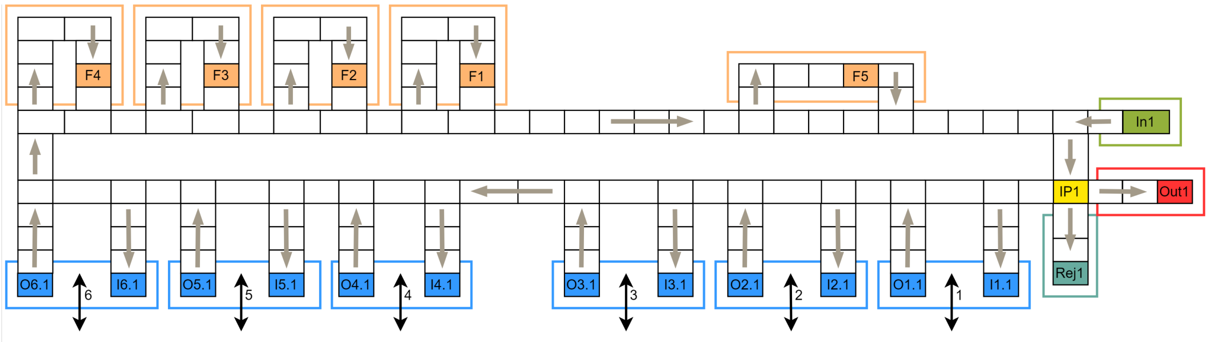
The conveyors MP0 and EP1 fulfill roles beyond mere inbound or outbound pallet transportation. Conveyor spots with an orange border represent workstations. At workstations, operators often require only partial use of pallet contents. Therefore, the pallets subsequently undergo inbound processing. Every outfeed lane and workstation comprises multiple buffer spots. At the last buffer spot, pallets await further handling by operators. Unique IDs identify these spots:

- *Out1* to *Out3* for the outfeed lanes,
- *F1* to *F5* for the workstations at MP0, and
- *P1* to *P2* for the workstations at EP1 (illustrated in Figure 2.2).

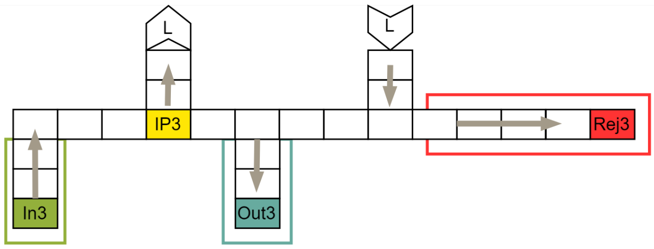
The conveyor system operates unidirectionally, meaning pallets cannot bypass obstructions. Arrows indicate this directional flow in Figure 2.2. Furthermore, each conveyor spot can accommodate one pallet at a time.

The system continuously tracks the location and destination of pallets within the high-bay warehouse, allowing it to monitor the number of pallets currently in transit to each destination. We refer to the maximum number of pallets in transit or awaiting processing at an outfeed lane or workstation as pipeline thresholds. Table 2.1 displays these thresholds.

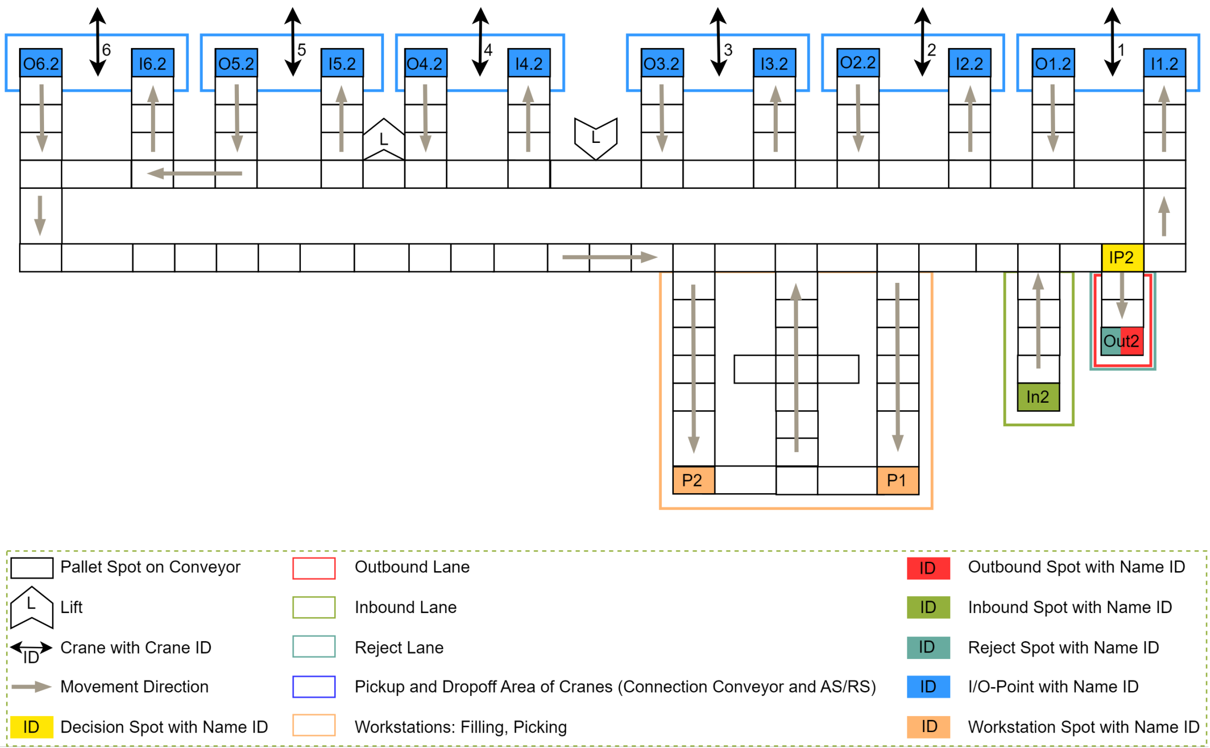
Euroma initially based the pipeline thresholds on the number of available buffer spots. For instance, the outfeed lane at MP0 comprises three buffer spots. Hence, the company set the pipeline threshold to three. This principle extends also to the workstations. In contrast, the pipeline threshold for EP0 and EP1 exceed the available buffer spots due to the control algorithm's ability to handle pallet blockages. If pallets occupy the outfeed lanes, the blocked pallets complete another cycle on conveyor EP1 after a 25-second waiting period, allowing for a higher threshold without causing congestion.



(a) Location Overview of the Conveyor MP0 on the Ground Floor. The six pallet cranes of the AS/RS facilitate pallet movement to and from the conveyor via I/O-points. The conveyor transports pallets between the workstations, inbound or outbound lanes, and the AS/RS.



(b) Location Overview of the Conveyor EP0 on the Ground Floor. Pallet lifts connect the conveyor to EP1.



(c) Location Overview of the Conveyor EP1 on the Ground Floor. The six pallet cranes of the AS/RS facilitate pallet movement to and from the conveyor via I/O-points. The conveyor transports pallets between the workstations, in- or outfeed lanes, and the AS/RS. Additionally, lifts transport pallets to EP0.

Figure 2.2: Location Overview of High-Bay Warehouse Conveyor Belts. An overview of key locations within the warehouse conveyor system is provided, with a focus on connections to the AS/RS, in- and outfeed lanes, and workstations

Pallet Destination	Abbreviation	Pipeline Threshold (N. of Pallets)
Outbound Location at EP0	Out3	10
Outbound Location at EP1	Out2	7
Workstations at EP1	P1 & P2	7
Outbound Location at MP0	Out1	3
Workstations at MP0	F1 - F4	7
	F5	5

Table 2.1: Pipeline Threshold for Pallet Destinations: maximum allowable number of pallets in transit or awaiting processing at designated destination, including outfeed lanes and workstations

2.2 Overview of IT Systems

The automation of warehouses necessitates the development of IT systems designed for managing warehouse operations. For the management of the high-bay warehouse, Euroma utilizes two different IT systems: a Warehouse Management System (WMS) and a Warehouse Control System (WCS). Typically, the WMS focuses on the management of orders and inventory, while the WCS monitors and controls machinery (Son et al., 2016).

The WMS maintains information about the stock levels and pallet location across the production site. In contrast, the WCS manages the processes within the high-bay warehouse. Placing a pallet on the infeed lane initiates an inbound task in the WMS, which then communicates the task details and pallet characteristics to the WCS. Considering the pallet's specifications, the WCS assigns the inbound task to a crane within the AS/RS. Additionally, the WCS monitors the exact location of pallets on the conveyor belt and in the storage rack. Upon completing an inbound task, the WCS updates the WMS with the pallet's status, enabling the WMS to maintain accurate stock information.

Outbound requests also originate from the WMS. Typically, a single order includes multiple pallets. These orders do not necessarily require pallets simultaneously containing the same SKU. Instead, the WMS communicates a specific number of requests for each SKU to the WCS, depending on the availability of buffer spots on the production floor. Euroma designed these buffer spots to store materials sufficient to sustain production for at least one hour. Once an operator uses the first pallet from the buffer, the WMS automatically communicates the following request for the same SKU to the WCS.

Upon receiving the SKU requests, the WCS determines the exact pallet location from which the SKU is to be retrieved and assigns the outbound task to the crane. After completing the outbound process, the WCS informs the WMS about the pallet's transfer to the outfeed conveyor. Any further actions involving the pallet outside the high-bay warehouse are tracked directly by the WMS.

Figure 2.3 visually summarizes the communication flow between these systems. The diagram illustrates the interactions among the IT systems and the material handling equipment, with arrows indicating the direction of communication.

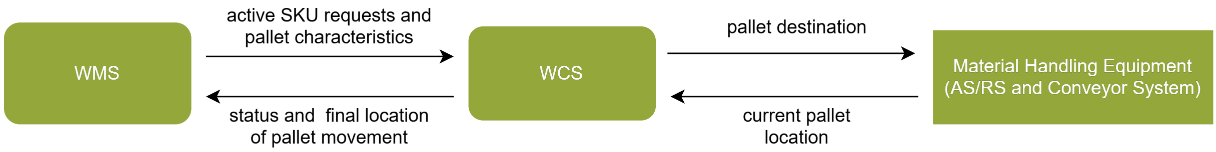


Figure 2.3: Communication of IT Systems. Schematic overview of the communication flow and content between IT systems (oval forms) and material handling equipment (rectangular form) during the outbound process. Arrows indicate the communication direction.

2.3 Assessment

Companies use key performance indicators (KPIs) to measure the performance of activities or processes. Additionally, KPIs assist in planning future activities and identifying areas of improvement (Faveto et al., 2021; Staudt et al., 2015). Thus, establishing a set of KPIs is crucial for evaluating the performance of the warehouse system at Euroma. Currently, the KPIs measured by Euroma reflect the technical availability of cranes and conveyors and the number of pallets stored in each aisle. However, these KPIs are insufficient for thoroughly assessing and monitoring the performance of the high-bay warehouse. Therefore, this section introduces additional KPIs established based on expert opinions, followed by the outlier analysis.

2.3.1 Key Performance Indicators

Full Outbound Tardiness Euroma organizes its production activities to ensure that full outbound pallets delivered within 60 minutes do not cause any disruption in production. We classify pallets that reach the outbound spot on the conveyor within one hour as on-time deliveries and assign a tardiness value of zero. For late pallets, we calculate the tardiness by subtracting the due time (60 minutes after the request time) from the arrival time. The sum of the tardiness of all full outbound pallet requests determines this KPI.

On-Time Delivery Percentage With the full outbound tardiness, the on-time delivery percentage is the most critical KPI as delayed pallet deliveries can cause production standstills and high waiting times for trucks. Outbound pallets with zero tardiness are considered on-time and contribute to the on-time delivery percentage.

Other performance measures, in addition to the tardiness and on-time delivery percentages, are relevant for evaluating the current situation and assessing the impact of potential changes on the system's performance.

Outbound Lead Time The outbound lead time measures the total duration of the outbound process, comprising queueing time, crane, and conveyor travel time. After a pallet request, the pallet has to wait for a crane to initiate the outbound movement by retrieving the pallet from its storage location. This duration marks the queueing time, while crane travel time and conveyor movement time refer to the duration taken by the crane to transport the pallet from its storage position to the I/O-point and the duration taken by the conveyor to transport the pallet from the I/O-point to the outbound location, respectively. Monitoring the outbound lead time is essential for evaluating the possibilities for changes in production processes and demand.

Inbound Queueing Time The queueing time refers to the duration pallets spend waiting for cranes to retrieve them at the I/O-points. Excessive inbound queueing time can lead to conveyor congestion. Therefore, although this research primarily focuses on the outbound process, monitoring inbound queueing times is valuable.

Workstation Tardiness Similar to full outbound tardiness, workstation tardiness monitors delayed pallet arrivals. Euroma expects workstation pallets to arrive at their destination at least when the preceding pallet of the same order finishes processing. The first pallet of a new order is on time if it arrives 20 min after its request.

2.3.2 Outlier Analysis

We use data from August 2023 to December 2023 to analyze the high-bay warehouse's performance according to the KPIs. Before delving into the analysis, we thoroughly checked the dataset for outliers and incomplete data points.

Handling Incomplete Data and Unusual Circumstances First, we exclude incomplete data, such as missing end times of the outbound process, from the analysis. Subsequently, we filter out instances resulting from unusual circumstances. For example, we discard pallet requests made on weekends at EP0, as weekends typically have no scheduled truck arrivals to receive goods. Although occasional requests might occur, they do not represent typical operational patterns and are thus considered outliers. Additionally, we exclude requests made before August 15th for MP0 due to changes in the pipeline threshold, leading to different queueing times. Moreover, we omit data points from week 52 as there is no production during that week.

Identification of Unusual Behavior We identify prolonged outbound lead times resulting from equipment failure. Afterward, we scrutinize days with multiple outbound lead times exceeding five hours for patterns indicative of equipment failure. Next, we visualize the remaining data points using histograms and establish cutoff points in collaboration with experts. Finally, we determine outliers based on the duration of queueing and movement times.

Consequently, outlier removal accounts for 17.18% of full outbound data, 4.97% of inbound data, and 23.38% of workstation pallets, resulting in a final dataset of 117,151 pallet data points. The interconnected pallet movements explain the higher percentage of outliers in the full outbound and workstation pallets. A single instance of unusual behavior can affect all pallets in the system, particularly those destined for the same location. This is due to the inability to overtake on the conveyor, the pipeline restrictions, and the strict sequencing rules for workstations.

2.4 Outbound Process

Following receiving an order from the WMS, the WCS initiates the reservation process. This process involves selecting and reserving pallets containing the requested products. Afterward, the assignment process determines which pallet undergoes retrieval and when. Once these pallets arrive at their designated conveyor destination, operators manually transfer them to their final destination on the production side.

The reservation process is outside the scope of this research. Therefore, this section focuses on the control policy guiding the assignment process. Additionally, subsequent sections evaluate current performance and provide an illustrative example.

2.4.1 Outbound Control Policy

The assignment process can be divided into two procedures: pallets destined for outfeed lanes (full outbound pallets) and pallets assigned to workstations. Figure 2.2, marks the workstations with an orange border at MP0 and EP1 while it highlights outfeed lanes in red. For outbound pallets, the WCS treats the request with the highest priority and oldest timestamp first. Currently, Euroma assigns priority values only for workstation pallets. Thus, the company generally handles outbound tasks in a first-come-first-served (FCFS) manner, except in cases of workstation pallets, which receive higher priority.

Euroma assigns a higher priority to workstation pallets because they must follow a strict sequence. The WCS verifies whether the previous pallet in the sequence has already started its outbound movement. If not, the pallet must remain in the crane queue until a crane initiates the retrieval for the preceding pallet.

Furthermore, the pipeline threshold influences the selection of pallets for both types of outbound tasks. When the number of in-transit pallets for an outfeed lane or a workstation is below the pipeline threshold, the WCS chooses the next pallet based on the outbound control logic and the workstation sequence. The flowchart in Figure 2.4 summarizes the criteria.

Finally, the WCS prioritizes outbound tasks over inbound tasks. Therefore, the crane performs single commands of outbound movements until an inbound pallet is awaiting processing on the I/O-point. At this point, the crane switches to a hybrid command, handling both the outbound and inbound tasks subsequently. For more details on the inbound process, we refer the reader to Appendix A.

2.4.2 Outbound Process Analysis

Three KPIs monitor the performance of the outbound process: full outbound tardiness, on-time delivery percentage, and outbound lead time. Additionally, workstation tardiness is essential, as improving the outbound process cannot deteriorate the workstations' performance.

Full Outbound Lead Time The outbound movement of pallets comprises three main actions:

- Outbound queueing time: The waiting period before the crane begins the outbound movement, specifically the interval between the request and the crane's retrieval from storage.
- Crane movement duration: The time the crane takes to transport the pallet from its storage location to the I/O-point (*O1.1* to *O6.2*).
- Conveyor movement duration: The time required for the pallet to travel from the I/O-point to its retrieval from the outfeed lane.

Table 2.2 summarizes these durations across different outbound locations.

The average and median times of the crane movement remain consistently below one minute, exhibiting minimal variation as indicated by a low standard deviation of seven seconds. Consequently, the crane processing duration constitutes only a minor portion of the lead time. Conversely, the conveyor movement time contributes more significantly to the lead time, with median durations ranging between 8.43 and 9.97 minutes at MP0 and EP0, respectively. Moreover, the conveyor duration displays a positively skewed distribution, with median durations smaller than the averages. The observed fluctuations, averaging between six and 15 minutes, are w.l.o.g. influenced by crane location, operator behavior, and the number of preceding pallets on the

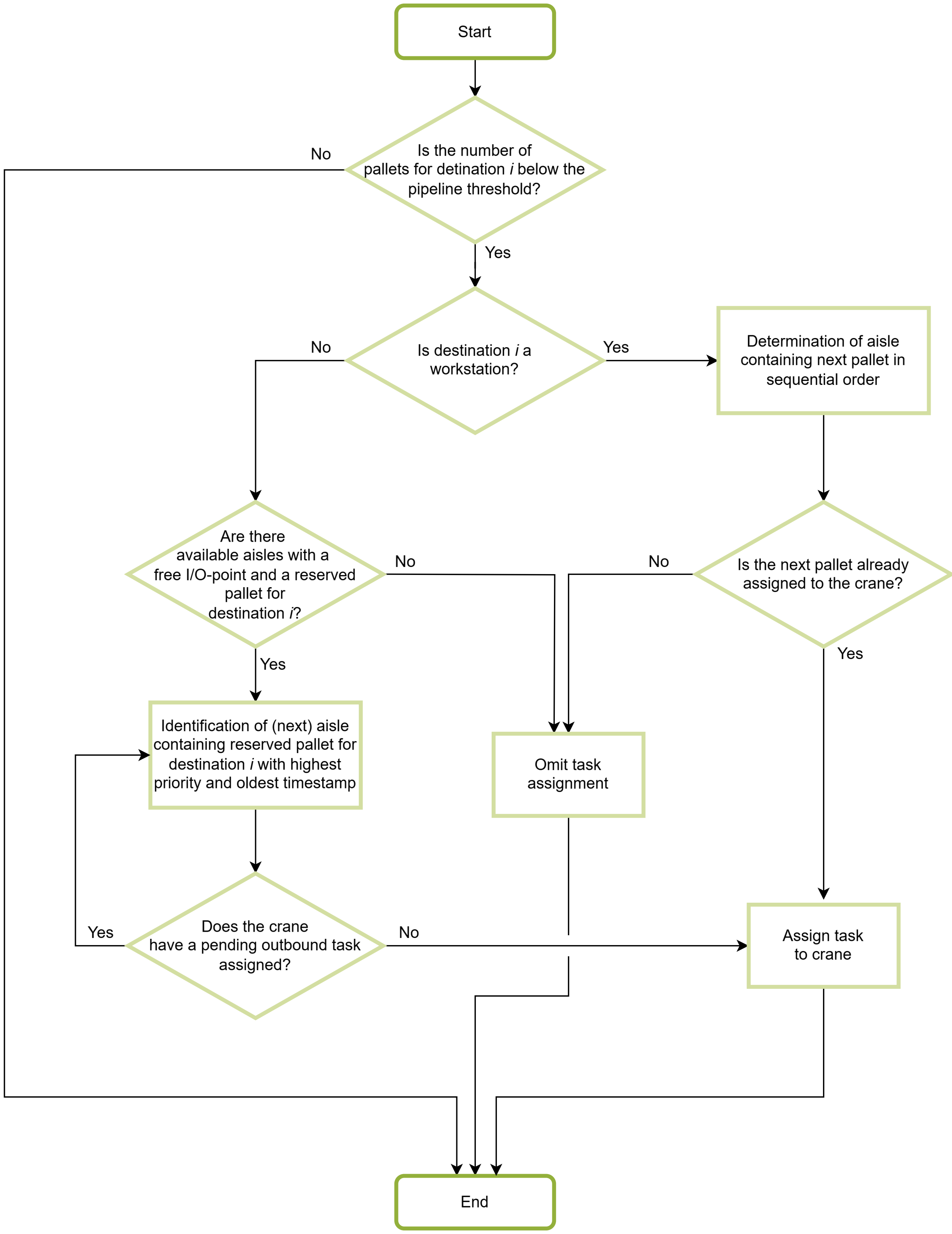


Figure 2.4: Flow Chart of the Assignment Process. This process assigns outbound tasks to a crane when the destination's pipeline falls below the threshold. If the destination is a workstation, the WCS checks whether it has assigned the preceding pallet to a crane before it assigns the task. If the destination is not a workstation, the system checks for an idle crane with a reserved full outbound pallet.

conveyor. Additionally, full outbound pallets destined for the outfeed lane at EP1 (*Out2*) show

		MP0	EP0	EP1
Outbound Queueing Time (min)	Average	18.58	26.67	9.33
	Median	3.18	19.2	2.2
	Standard Deviation	26.72	26.77	13.56
Crane Movement Duration (min)	Average	0.76	0.66	0.69
	Median	0.78	0.65	0.68
	Standard Deviation	0.12	0.12	0.12
Conveyor Movement Duration (min)	Average	10.39	10.40	15.20
	Median	8.43	9.97	9.57
	Standard Deviation	5.93	5.99	14.96

Table 2.2: Average, Median, and Standard Deviation Duration for Outbound Process of Pallets in Minutes. The outbound process is divided into three phases: queueing time, crane movement, and conveyor movement, across the three full outbound locations MP0, EP0, and EP1.

a higher standard deviation due to the high pipeline threshold relative to the number of spots on the outfeed lane, which increases the likelihood of congestion and the need for pallets to re-loop. In the following, we analyze the factors influencing the full outbound lead time.

Factors Influencing Outbound Lead Time: Crane Location The distance pallets travel on the conveyor depends on their storage aisle in the AS/RS. As depicted in Figure 2.2, pallets retrieved by crane six typically cover shorter distances on the conveyors MP0 and EP1. However, if these pallets' destination is the outfeed lane *Out3* at EP0, they must first loop through conveyor EP1 due to the positioning of the lift between cranes three and four.

The average conveyor movement time decreases with increasing crane ID at MP0 and EP1. Conversely, at EP0, pallets from cranes four to six require more time on the conveyor than from one to three. Notably, we observe the most significant time difference at EP0, with crane four averaging 15 minutes, nine minutes longer than pallets from crane three. Figure 2.5 illustrates these varying conveyor movement times.

Factors Influencing Outbound Lead Time: Operator Behavior The duration of conveyor movement is determined by the time a pallet takes to traverse the conveyor until it reaches its designated endpoint. If another pallet obstructs the terminal spot on the conveyor, the subsequent pallet cannot complete its outbound process. This situation also impacts waiting pallets' queuing time if the current pipeline size exceeds its threshold. Although the dataset does not include the operator retrieval time, the duration for a pallet to traverse the last four spots on the conveyor offers insights into this process. An increase in this time suggests that a preceding pallet remained on the destination spot longer than usual.

At conveyor MP0, 50% of the pallets require at most 26 seconds to move across the last four spots of the conveyor. For EP0 and EP1, this time is slightly higher, at 1.5 and 2.23 minutes, respectively. This difference results from the varying request patterns for the outbound locations. Team leaders request about half of the pallets individually at MP0, meaning there is no subsequent request within the next five minutes. Consequently, pallets can move directly to the end location without waiting for an operator to retrieve the previous pallet. At EP1, this occurs for about 40% of the pallets, and at EP0 for just 13%.

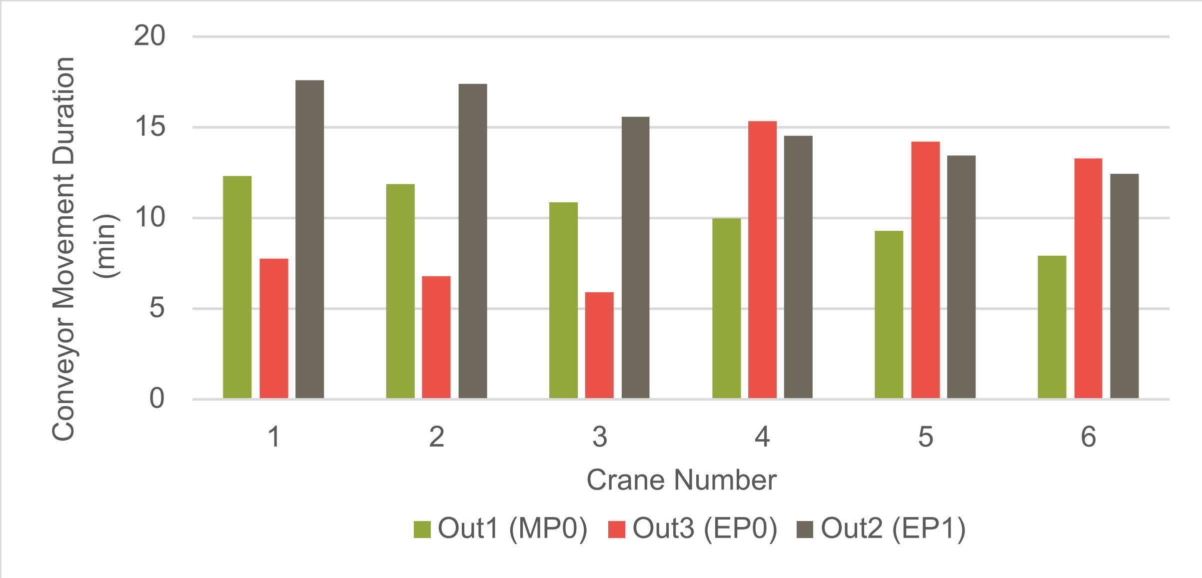


Figure 2.5: Average Conveyor Movement Time per Crane per Outbound Location. The bars represent the average duration, in minutes, pallets spend on the conveyor, starting from the moment a crane drops them on the I/O-point until they reach the end of the outfeed lane at one of the outbound locations MP0, EP0, EP1.

Additionally, we can attribute the shorter time at *Out3* (EP0) compared to *Out2* (EP1) to multiple operators managing pallet retrieval. At *Out1* (MP0) and *Out2* (EP1), Euroma typically assigns a single operator to retrieve pallets from the conveyor, leading to delays when they are unavailable, such as during breaks. In contrast, *Out3* (EP0) benefits from additional operators stepping in to maintain smooth operations. The 90th percentile reflects this impact. Compared to the 50th percentile, MP0 and EP1 show significant increases in duration, exceeding ten and 20 minutes, respectively, indicating slower retrieval. Although pallets reaching the outfeed lane and moving directly to the last spot are more common in the lower percentiles, the increase in duration is also influenced by more prolonged waiting times for retrieval from the end position.

	MP0	EP0	EP1
50th Percentile (min)	0.43	1.50	2.23
70th Percentile (min)	1.53	2.67	5.20
90th Percentile (min)	10.63	5.00	20.10

Table 2.3: Pallet Movement Durations Across the Last Four Conveyor Spots. Durations are presented as the 50th, 70th, and 90th percentile in minutes across the three outbound locations MP0, EP0, and EP1.

Factors Influencing Outbound Lead Time: Request Quantity Figure 2.6 illustrates the correlation between the number of requested pallets and lead time. More requests result in longer queueing times, particularly notable at *Out1* (MP0) due to its lower pipeline threshold. The initial full outbound pallet requested for MP0 within an hour spends an average of nine minutes in the queue. By the fourth request, this time has already more than doubled. While the queueing time increases with the number of requests, the movement time – comprising conveyor and crane movement – remains constant. Moreover, queueing time accounts for most of the total outbound duration, significantly influencing the overall process.

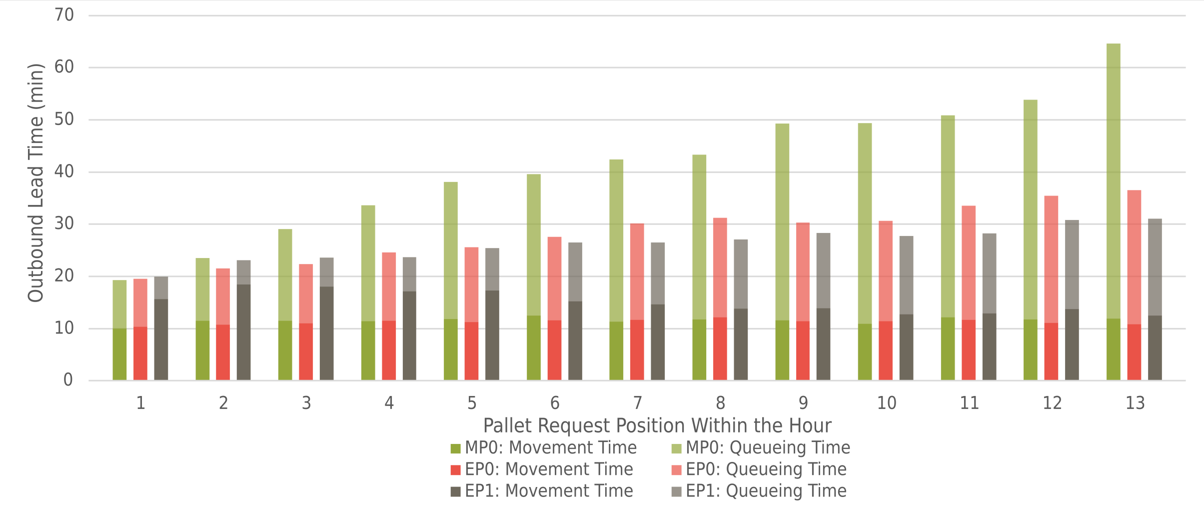


Figure 2.6: Correlation between Lead Time and Number of Pallet Requests. The total lead time (in minutes) is divided into the outbound queueing time and the movement time (crane and conveyor movement). The average durations are displayed per xth request within an hour. Each color represents one of the outbound locations MP0, EP0, and EP1.

Furthermore, Figure 2.7 shows that the hourly request rate at EP0 is generally higher than the request volume at MP0 and EP1. On average, the daily number of full outbound requests at EP0 is approximately six times that of MP0. Together, Figure 2.6 and Figure 2.7 explain the lower tardiness percentage of full outbound pallets at EP1 compared to MP0 and EP0 (Table 1.1). The outbound lead time increases significantly with the number of requests at MP0, causing the 60-minute threshold to be reached with fewer requests per hour. In contrast, the high frequency of requests at EP0 results in more instances where lead times exceed the threshold.

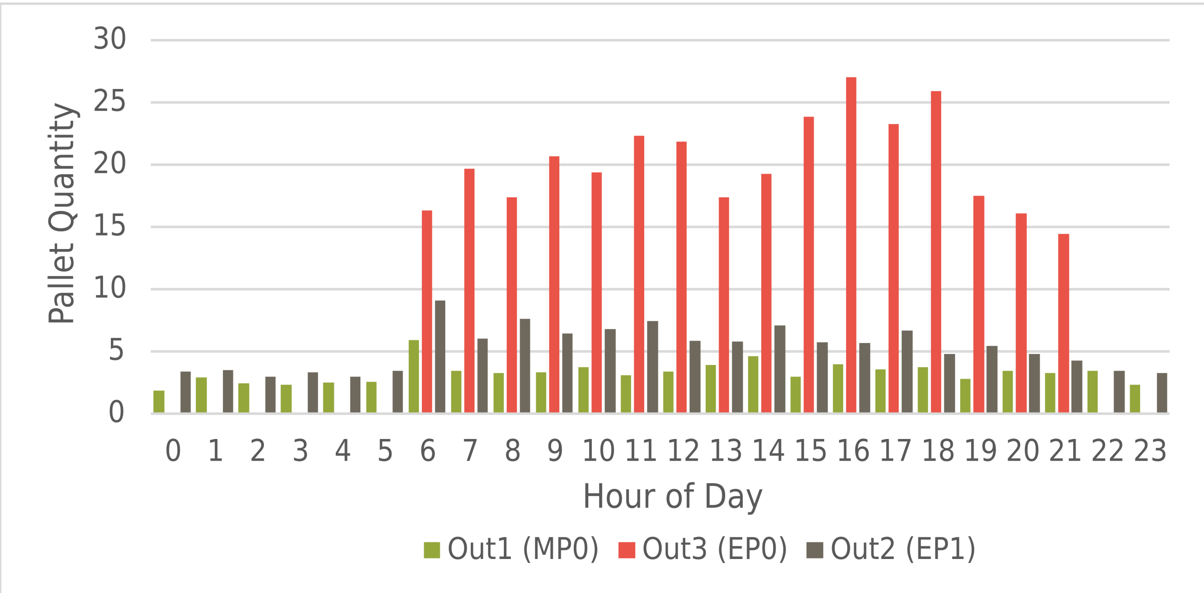


Figure 2.7: Average Outbound Pallet Request Quantity per Hour. Columns represent the average request quantities per hour for the outbound locations: MP0, EP0, EP1.

Factors Influencing Outbound Lead Time: Prioritization Priorities impact queueing times in addition to the request volume and the pipeline size. While most outbound pallets share the same priority, the WCS prioritizes workstation pallet requests over full outbound pallets. The workstations at MP0 handle an average of 220 pallets daily, compared to 68 at EP1. The prioritization increases queueing times for full outbound pallets, particularly at MP0.

Given the discussed factors, the high standard deviation of queueing times, as shown in Table 2.2, is not surprising, reflecting considerable variability in durations. Notably, the standard deviations for *Out1* (MP0) and *Out3* (EP0) reach 27 minutes, indicating significant fluctuation. Furthermore, the average queueing time significantly exceeds the median. While 50% of outbound pallets at conveyor MP0 wait no longer than three minutes, the average waiting time is 19 minutes, suggesting the presence of prolonged queueing durations that increase the average. The patterns for EP0 and EP1 are comparable but less extreme.

Total Tardiness and On-Time Delivery Percentage On average, 42 full outbound pallets exceed their due date of 60 minutes after request each day, representing approximately 14% of all full outbound pallets. For these delayed pallets, the average tardiness varies between 14 minutes at EP1 and 27 minutes at MP0 per pallet. Among the outbound locations, EP0 exhibits the highest tardiness percentage at 18.24%, followed by MP0 at 14.12%. In contrast, EP1 achieves the lowest tardiness rate at 6.95%.

These results align with the analysis of factors contributing to tardiness. At MP0, the low pipeline threshold appears to be a significant driver of delays for full outbound pallets, while the high request volume at EP0 contributes to its increased tardiness. No unique cause stands out for EP1; instead, the factors contributing to tardiness at EP1, such as operator behavior and workstation pallet prioritization, also impact MP0.

While workstation pallets face similar tardiness percentages, their delays are generally shorter. At MP0, 15.12% of workstation pallets are delayed, averaging 8.62 minutes. At EP1, 10.31% workstation pallets are tardy, with an average delay of 18.15 minutes. Table 2.4 shows detailed results for all locations.

	MP0		EP0	EP1	
	Out1	*F1 - F5*	*Out3*	*Out2*	*P1, P2*
On-Time Delivery Percentage	85.88%	84.88%	81.76%	93.05%	89.69%
Tardy Delivery Percentage	14.12%	15.12%	18.24%	6.95%	10.31%
Daily On-Time Pallet Volume	33.95	120.09	137.52	81.54	39.54
Daily Tardy Pallet Volume	5.58	25.54	30.68	6.09	5.63
Pallet Tardiness (min)	26.88	8.62	24.83	13.74	18.15

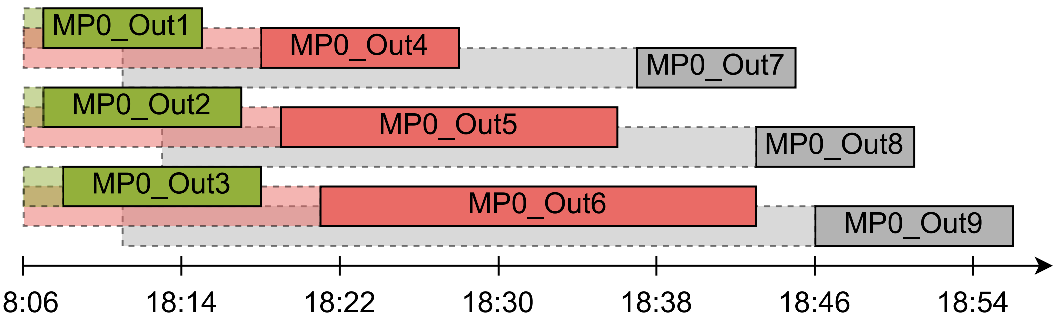
Table 2.4: Total Tardiness and On-Time Delivery Percentage. The pallet volumes represent the average daily pallet volume that is either on time or tardy. Pallet tardiness indicates the average delay, in minutes, for each pallet that exceeds its due date. Data is provided for the three outfeed lanes at MP0, EP0, and EP1, as well as the workstations at MP0 and EP1.

The analysis of the outbound process highlights that queueing times contribute significantly to the lead time variability. Factors such as the pipeline threshold, operator behavior, and request quantity influence the queueing time. Given these insights, the management of the crane queues is a crucial factor in ensuring that full outbound pallets reach their destination within the targeted one-hour timeframe.

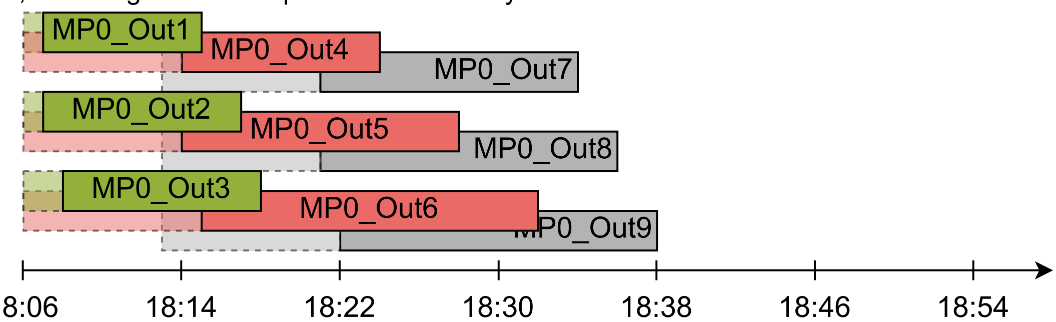
2.4.3 Example Assignment Process

Figure 2.8a illustrates the full outbound process for nine pallets at the outbound location MP0. At 18:06, the team leader requests the first six pallets simultaneously. The first three pallets promptly begin their outbound movement as the cranes retrieve them from their storage locations, while pallets four to six experience delays due to the pipeline threshold. The transparent bars with dashed lines represent the queueing time.

The first pallet arrives at its destination (*Out1*) at 18:15, nine minutes after its request. Once an operator retrieves this pallet, the pipeline resets to two, allowing pallet four to begin its outbound movement. Figure 2.8a illustrates this transition by showing the transparent bar of pallet four becoming solid at 18:19. This process repeats until pallet nine reaches its destination, resulting in an outbound lead time of 45 minutes. Notable, pallet seven starts its outbound movement significantly later than pallet four reaches *Out1*. Additionally, the movement times of pallets five and six are considerably longer than those of the other pallets. These observations suggest that pallet four was not retrieved promptly upon arrival, causing increased queueing and conveyor movement times for the subsequent pallets.



(a) Example of the Current Situation. This demonstration captures the outbound lead time at location MP0, reflecting the current process without any modifications.



(b) Example of Improved Lead Time. The example illustrates a full outbound movement process to reduce total lead time. This approach minimizes queueing time by relaxing the pipeline threshold and limiting the conveyor retrieval time.

Figure 2.8: Example of Outbound Lead Time Analysis. The timeline illustrates nine pallets' full outbound lead times at the *Out1* (MP0) on 16.11.2023. Solid, non-transparent bars represent the movement time, while transparent bars with dashed lines indicate the queueing time.

The improved scenario in Figure 2.8b demonstrates how relaxing the pipeline threshold, thereby allowing pallet movements to overlap, can significantly improve the outbound lead time. Instead of remaining in its storage location until a spot in the outfeed lane becomes available, the pallet restricted by the pipeline threshold begins its movement earlier. This example underscores the importance of constantly retrieving pallets from the conveyor to prevent congestion as successive pallets reach the outfeed lane faster.

2.5 Summary of the Problem

Euroma expects pallets to reach their destination within one hour. But, in 14% of the cases, this expectation is not met. Consequently, Euroma aims to optimize the full outbound process. This section summarizes the problem identified in Chapter 1 and analyzed in Chapter 2.

The full outbound process at Euroma consists of several stages: pallet request, retrieval by the crane, transportation by the conveyor, and retrieval from the conveyor by an operator. As highlighted in Section 1.3, the main focus of this research is on the assignment process determining the retrieval schedule. This process significantly contributes to delays within the full outbound process, as examined in Section 2.4.2.

Pallets traverse multiple material handling resources within the automated retrieval and transport process in a predetermined order. These resources are shared and have the following limitations:

- **Crane Capacity**: Each crane can transport one pallet at a time.
- **Conveyor Capacity**: Each conveyor spot can process one pallet at a time.
- **Lift Capacity**: The lifts connecting EP0 and EP1 can accommodate one pallet at a time. Additionally, each lift is unidirectional, transporting pallets from EP0 to EP1 or vice versa.
- **Workstation Capacity**: Each workstation can process one pallet at a time.
- **Buffer Capacity**:
  - Workstations can buffer up to six pallets simultaneously, except for workstation *F5*, which has four buffer spots.
  - Outfeed lanes have three buffer spots available, except for the outfeed lane at EP0, which has five.
- **Pipeline Threshold**: Derived from the buffer capacity, the pipeline limits the number of pallets in transit to a specific destination.

Consequently, to ensure the timely delivery of pallets, optimizing decisions regarding the order and timing of pallet retrievals is crucial to maximizing the efficiency of shared resources.

3 LITERATURE REVIEW

The main objective of the literature review is to address the second research question: What does the literature propose for optimizing the outbound process in a high-bay warehouse?

This thesis focuses on a complex warehouse system integrating an AS/RS and a conveyor system. These systems are critical to the overall performance of the production facility in Zwolle, where they manage the flow of goods between the storage locations and the production site. Since Euroma already installed the high-bay warehouse, modifications in the hardware components of both the AS/RS and the conveyor system are limited. However, significant potential exists for optimizing the control decisions that govern the AS/RS and conveyor system. This chapter establishes a basis for optimizing the outbound process by reviewing the literature across these interconnected areas.

The review begins with a detailed examination of scheduling problems in Section 3.1. As job shop problems can help model the situation presented in the first two chapters, we subdivide this section into reviews on the machine environment (Section 3.1.1), job characteristics (Section 3.1.2), and optimality criterion (Section 3.1.3). Furthermore, Section 3.1.4 introduces different solution approaches, while Section 3.2 covers the discrete event simulation.

The focus then shifts to the impact of the pipeline thresholds on system performance, focusing on their influence on outbound lead times. Finally, the review concludes with a summary in Section 3.4.

3.1 Scheduling in AS/RS and Conveyor Systems

The performance of an automated warehouse is usually attributed to the AS/RS, assuming it operates independently from the interface system. However, this assumption holds only if a crane can start a new cycle immediately after completing the previous one. In practice, potential delays in the conveyor system can prevent this (Basile et al., 2012). These delays in one subsystem can significantly impact the performance of others, highlighting the interdependence of the AS/RS and conveyor system (Roodbergen and Vis, 2009). Therefore, optimizing these systems in isolation can reduce operational efficiency. Given this interdependence, exploring the scheduling problems within this combined system is crucial.

Scheduling is a decision-making process that aims to optimize a given objective. In scheduling terminology, a sequence refers to the order in which jobs are processed across machines (Pinedo, 2016), while the centering challenge in scheduling problems involves the allocation and timing of limited resources to a set of tasks (Blazewicz et al., 2019). Machine scheduling involves coordinating jobs that need to be processed and machines that facilitate the processing of jobs to optimize one or more performance metrics. Many practical situations require considering additional resources, including transportation devices and buffers. Besides, several job- and resource-related attributes may be considered (Xiong et al., 2022).

To classify these different considerations Graham et al. (1979) introduced a three-field classification scheme $\{\alpha|\beta|\gamma\}$. Here, α describes the machine environment, β the job characteristics, and γ the optimality criteria. This notation serves as the framework for the subsequent sections, followed by the presentation of solution approaches.

3.1.1 Machine Environment

The literature typically classifies machine scheduling problems as single- or multi-stage scheduling problems. In a single-stage problem, each job consists of a single operation. Conversely, jobs in a multi-stage scheduling problem comprise a set of operations (Graham et al., 1979).

Euroma's scheduling problem involves jobs with multiple operations. Therefore, we consider only multi-stage scheduling problems. In an open shop environment, each job requires processing on a set of machines, and the system does not impose any restrictions on the order in which the job's operations are processed. Conversely, flow and job shop environments impose precedence constraints for each job. In flow shop environments, each job follows the same processing order, while job shop scheduling problems require a specific machine order for each job (Blazewicz et al., 2019). As discussed in Section 2.1, three conveyor belts connect the production side to the AS/RS. These belts handle pallets with various destinations. Therefore, the route through the high-bay warehouse depends on each pallet's specific start and endpoints. Consequently, this section focuses on the job shop environment.

The Job Shop Scheduling Problem (JSSP) is one of the most popular combinatorial optimization problems (Xiong et al., 2022). A job shop environment contains m resources, denoted as $\mathcal{R} = \{R_1, R_2, ..., R_m\}$, and n jobs, represented as $\mathcal{J} = \{J_1, J_2, ..., J_n\}$. At Euroma the resources are the cranes, conveyor spots and operators, while the jobs represent the pallet requests. Processing a job on a machine is called an operation. Each job, J_i, consists of a series of operations $\mathcal{O}_i = \{O_{i1}, O_{i2}, ..., O_{in_i}\}$ that have to be processed in a predetermined sequence on machines in $\mathcal{R}$, each with a specified and uninterrupted duration known as the processing time. In this environment, each job can be processed on only one machine at a time, and each machine can handle at most one job at any given time. This constraint necessitates a well-defined processing order for operations that require the same machine (Pranzo and Pacciarelli, 2015).

3.1.2 Job Characteristics

A variety of job and resource characteristics can describe scheduling problems. A problem may thereby involve more than one characteristic. This section discusses key factors relevant to JSSPs.

Release Dates The release date r_i of a job J_i indicates when a job arrives at the system. Consequently, it denotes the earliest time a job can begin processing (Pinedo, 2016). The classical JSSP assumes that all jobs are available at the beginning of the time horizon (Ku and Beck, 2016). Integrating dynamic job arrivals into the JSSP schedules the start time of the first operation O_{i1} of each job $J_i \in \mathcal{J}$ after its release date.

Due Dates Due dates represent the committed completion date for jobs. Although completing a job J_i after its due date d_i is allowed, it is usually associated with a penalty. When meeting a due date is mandatory, we refer to it as a deadline (Pinedo, 2016).

Transportation In the classical JSSP, jobs can be processed immediately on their next machine after completing the previous process, neglecting transportation time between machines. Ignoring the transportation time results in solutions that often do not perform well in real-life applications (Xie and Allen, 2015). Gaiardelli et al. (2024) confirm the crucial role of considering transportation systems. They compare the makespan of schedules with and without considering the transportation system. In their experiments, not accounting for transportation times results in a makespan error of up to 23% compared to the actual outcomes, whereas the schedules considering transportation result in errors less than 5%. Furthermore, schedules that include transportation improve the makespan by up to 14% compared to those that do not.

To the best of our knowledge, most research appears to focus on interface systems involving shuttles or other vehicles. This trend is likely present in the literature on JSSPs with transportation resources. The review by Nouri et al. (2016) classifies JSSPs with transportation resources, focusing solely on vehicles. They define the problem as a combination of two subproblems: job shop scheduling and vehicle scheduling. Similarly, Fontes et al. (2022) focuses on transportation systems comprising vehicles. However, they add the dimension of simultaneously scheduling the cranes of the AS/RS.

Schwenke and Kabitzsch (2017) also observe that most research on transportation systems focuses on vehicles. Their study appears to be the first to investigate integrated scheduling using conveyors between machines in the semiconductor manufacturing context. Instead of using fixed transportation times, which sum up traversing times along the predetermined path between machines, their approach models transport operations similar to machine operations in a JSSP. Furthermore, the authors address transport delays by feeding transport-related delays back into the schedule. This approach is crucial because delays in the target machine cause delays in subsequent transports and machines. This study aims to avoid transport delays resulting from a predetermined machine schedule.

Gaiardelli et al. (2024) consider a flexible job shop scheduling problem where conveyor belts transport the jobs between the machines. As they do not consider buffer spots, the jobs must re-loop on the conveyor if the machine is busy with another job. Therefore, the authors include the transportation time as follows

$$t_{kl} = t_{kl}^0 + t_{kl}^c * n^c \tag{3.1}$$

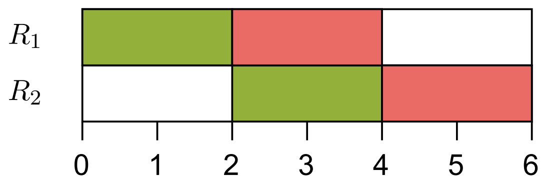
with t_{kl}^0 representing the minimum time to travel from machine k to machine l, t_{kl}^c representing the cycle time in case machine l is unavailable, and n^c the number of extra loops the job has to complete until the machine becomes available.

Blocking Constraint Apart from neglecting transportation times, in its classical form, the JSSP assumes that jobs can move between consecutive operations without restrictions, implying infinite buffer capacity. In practice, many applications face finite buffer capacities (Pranzo and Pacciarelli, 2015), which necessitates including blocking constraints. Blocking situations can arise when there is no or limited storage space between machines. In such cases, a job J_u must remain on the current machine (R_{k-1}) until its next one (R_k) becomes available, preventing it from processing other jobs (Dabah et al., 2019). The blocking constraint ensures that the starting time of the succeeding operation $O_{i,j+1}$ of the preceding job J_i starts at least at the same time as the succeeding operation O_{uv} on the considered machine R_k.

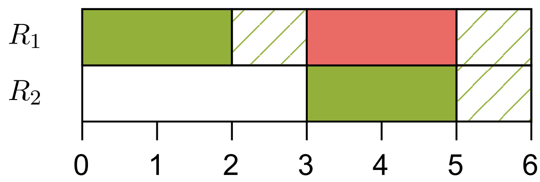
One typical application of the blocking constraint is routing trains on tracks (Hatzack and Nebel, 2001). In this traffic problem, trains travel through a network on predetermined routes, with the trains representing jobs and the track sections representing machines. Due to safety constraints, a train can only move onto the next track section once it is clear, exemplifying the blocking constraint (Liu and Kozan, 2009).

Incorporating blocking constraints into the JSSP requires careful attention to the timing of job transfers between machines (Lange and Werner, 2019b). In train scheduling applications, avoiding frontal collision of trains is critical, making simultaneous interchanges of occupied machines infeasible (Hatzack and Nebel, 2001; Lange and Werner, 2017). Preventing this situation, known as deadlock or no-swap allowed, is essential. Also, the presence of setup times necessitates their exclusion (Lange and Werner, 2019b). In contrast, swaps are feasible in other applications and theoretical studies, such as those by Lange and Werner (2019a) and Lange and Werner (2019b). Therefore, appropriately addressing these constraints allows for successfully modeling various scheduling environments.

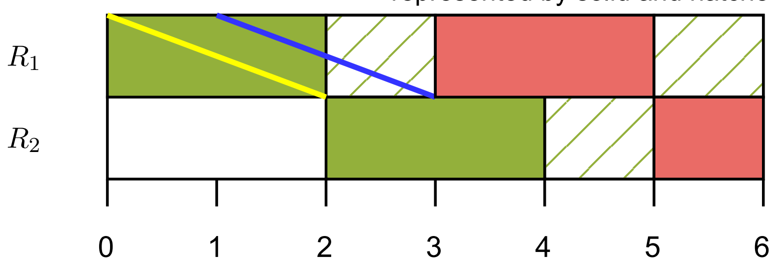
Another essential aspect to consider during machine transfer is the physical job length. Studies by Hatzack and Nebel (2001), Lange and Werner (2019a), and Lange and Werner (2017) assumed that the physical length of the job does not impact the scheduling decisions. However, Liu and Kozan (2009) highlighted the importance of considering train length in scheduling. When a train moves from one section to another, it occupies both sections until its entire length has wholly exited the first section. This simultaneous occupation dramatically affects the performance as visualized in Figure 3.1.



(a) Gant Chart without Considering Train Length. The processing time is measured from when the train head enters the section until the head leaves the section.



(b) Gant Chart Considering Train Length in Processing Time. The processing time spans from the train head entering to the tail leaving the section, represented by solid and hatched bars



(c) Gantt Chart Excluding Train Length from Processing Time. The processing time (solid bars) spans from the train head's (yellow) entry to exit, while the occupying time (hatched bars) accounts for the train tail (blue) remaining on the section.

Figure 3.1: Gantt Charts Demonstrating Different Approaches for Handling Train Length. Green bars represent the preceding train, while red bars represent the succeeding train (Liu and Kozan, 2009).

In Figure 3.1a, the model does not consider the train length. Thus, the subsequent train can start on a section while the previous train's tail is still present, potentially causing collisions. The second case, Figure 3.1b, is feasible in practice but lacks precision compared to the third approach. By excluding the occupying time from the processing time, the start and completion time on section two (R_2) become smaller for the green train, which also influences the succeeding red train.

Setup Times The setup time represents the duration required to prepare a machine to perform a task. The literature classifies it into sequence-independent and -dependent setup times (Sharma and Jain, 2015). Sequence-independent setup times solely depend on the current operation. Conversely, sequence-dependent setup times depend on the current and preceding operation (Sharma and Jain, 2015). Therefore, the setup time o_{ijuv} incurs between the processing of two consecutive operations O_{ij} and O_{uv}.

Preemption In the classical JSSP, jobs need to complete processing before they can leave a machine. Allowing preemption eliminates this requirement, enabling jobs to be interrupted at any point during processing (Pinedo, 2016).

Recirculation JSSPs with recirculation allow jobs to be processed on a machine more than once (Pinedo, 2016). Therefore, $\sum_{M_k \in M} o_{ijk} = 1$ changes to $\sum_{M_k \in M} \sum_{j=1}^{n_i} o_{ijk} \geq 1$ (Lange and Werner, 2017).

No-Wait Constraint In a classical JSSP, the succeeding operation may start after or at the same time as the preceding one finishes. However, the no-wait constraint enforces that jobs cannot wait between two successive machines (Pinedo, 2016). Therefore, the succeeding operation must start as soon as the preceding one finishes.

Real Time Events The classical JSSP assumes that the input parameters are known in advance and fixed. This static environment is unrealistic in many real-world contexts (Z. Wang et al., 2019). Real-time events may happen unavoidably and unpredictably and fall into two categories: resource-related and job-related. Resource-related real-time events involve machine breakdowns and operator illnesses, while job-related events include changes in due dates, priorities, and job arrivals (Ouelhadj and Petrovic, 2008). An extension of the general JSSP, the dynamic JSSP, represents this dynamic behavior (Z. Wang et al., 2019). Moreover, in a stochastic dynamic JSSP, at least one of the job characteristic parameters is probabilistic (Sharma and Jain, 2015).

3.1.3 Optimality Criterion

The scheduling objective is to find a specific route through the machines for each job by optimizing one or multiple performance metrics. Yenisey and Yagmahan (2014) summarize these metrics into different categories: time-based criteria, job-number-based criteria, cost-based criteria, revenue-based criteria, and energy and pro-environment-based criteria.

The most common optimality criterion in the JSSP literature is the makespan, C_{max}, a time-based criterion that minimizes the maximum completion time across all jobs (Xiong et al., 2022). The completion time of any job $J_i \in \mathcal{J}$, C_i, refers to the latest time the job J_i is in the system. Another criterion related to completion time is the total flow time F. This criterion measures the sum of time each job spends in the system, from its release date until completion (Yenisey and Yagmahan, 2014):

$$F_i = \sum_{i \in J} (C_i - r_i) \tag{3.2}$$

Time-based criteria can also consider a job's due date d_i. From this, the lateness of a job, L_i, can be determined (Graham et al., 1979):

$$L_i = C_i - d_i \tag{3.3}$$

Alternatively, the tardiness of a job, T_i, can be calculated. Unlike lateness, tardiness cannot be negative; thus, it does not consider early arrivals:

$$T_i = max\{C_i - d_i; 0\} \tag{3.4}$$

Minimizing the flow time aims to stabilize resource utilization and reduce work in progress, while tardiness-related objectives focus on meeting customer demand (Yenisey and Yagmahan, 2014). Further due date-related optimization criteria include job-number-based measures, like the number of tardy jobs (Xiong et al., 2022), which is equivalent to the percentage of on-time deliveries. Since this criterion does not account for the order in which the jobs miss their due dates, some jobs might experience unacceptably long waiting times. Therefore, this objective is typically not used alone (Pinedo, 2016).

While to the best of our knowledge, most of the literature focuses on single objective optimization, Xiong et al. (2022) and Yenisey and Yagmahan (2014) note that real-world scheduling problems are often inherently multi-objective. Mathematically, an objective function f can be formulated in several ways. Table 3.1 provides an overview of the formulation of objective functions for multi-objective problems similar to the work of Yenisey and Yagmahan (2014), where Z_k is the k-th sub-objective function.

Formulations	Aims	Approach
$f_w(Z_1, Z_2, \ldots, Z_k)$	minimize weighted k objectives	utility approach
$f_p(Z_1 : Z_2 : \ldots : Z_k)$	minimize all objectives	Pareto-optimal approach
$f_L(Z_1, Z_2, \ldots, Z_k)$	minimize all objectives in a lexicographical orders	lexicographical approach
$f_\epsilon(Z_p \vert Z_1, Z_2, \ldots, Z_k)$	minimize the primary objective Z_p and the other k objectives are subject to constraints	ϵ-constraint approach
$f_{gp}(Z_1, Z_2, \ldots, Z_k)$	minimize each objective until their individual goal is reached	goal programming

Table 3.1: Formulations of Multi-Objective Functions

Three main approaches exist for solving multi-objective problems, such as in Table 3.1. These mainly differ in the role of the decision maker (T'kindt and Billaut, 2006; Yenisey and Yagmahan, 2014).

1. In the *a priori approach*, the decision maker seeks a unique solution by providing all necessary information upfront. This approach applies to methods like the weighted and lexicographical approaches. The weighted approach assigns weights to each objective before the optimization. In contrast, the lexicographical approach prioritizes objectives, meaning after minimizing the first objective Z_1, the second objective Z_2 is minimized subject to Z_1.
2. The *a posteriori approach* generates a set of Pareto-optimal solutions from which the decision maker can select. The pareto-optimal approach is applicable in this context.
3. In the *interactive approach*, the decision maker interacts with the solution process by expressing preference information at each step of the solution process.

3.1.4 Solution Approaches

This section aims to explore and identify solutions to the scheduling problem at Euroma.

The literature broadly classifies the scheduling approaches into two main categories: exact and approximate methods. Exact methods, while capable of solving JSSPs optimally, demand substantial computing time (Zhang et al., 2017). Given that JSSPs are typically NP-hard, these methods are often feasible for only small instances due to the dramatic increase in computational time as the problem size grows (Sels et al., 2012). For example, Ku and Beck (2016) compared MIP formulations based on their computation times, showing that small to moderately sized JSSPs can be solved to optimality in a reasonable time. A JSSP with eight machines and eight jobs (8x8) can be solved using the solver GUROBI in less than one second, whereas the computational time increases to 2.5 and 186.5 seconds for a 10x10 and a 12x12, respectively. Consequently, exact scheduling methods are unsuitable for solving large-scale problems due to their computational demands. In contrast, approximate methods can produce good solutions for large problem instances in a reasonable computational time (Shady et al., 2022).

In a job shop environment, blocking constraints add significant complexity, making the blocking job shop scheduling problem (BJSSP) more computationally challenging than JSSPs with unlimited buffers (Mascis and Pacciarelli, 2002). Similarly, Lange and Werner (2019a) reference the BJSSP with total tardiness minimization as one of the most challenging combinatorial problems.

The scheduling problem at Euroma involves over 200 resources, including cranes, lifts, and conveyor locations. While with an average of 0.4 requests per minute, the number of newly arriving jobs is low, the system sees, on average, five instances per day when requests exceed 15 pallets in a single minute. Furthermore, the dynamic nature of this problem further necessitates short computation times while the blocking constraints add additional complexity. Consequently, exact approaches are unsuitable for this scenario. Thus, the remainder of this section focuses on promising approximate solution approaches.

Many solution approaches for JSSPs are based on the concept of the critical path. Therefore, Appendix B briefly overviews graph theory in a job shop environment. For a more detailed explanation, we refer the reader to Mascis and Pacciarelli (2002) and Mogali et al. (2021).

Dynamic Scheduling Strategies and Policies

Dynamic events necessitate the incorporation of uncertainties into scheduling. The literature identifies three types of dynamic scheduling strategies: totally reactive, predictive reactive, and robust pro-active scheduling (Z. Wang et al., 2019). The robust scheduling approach attempts to create a schedule that anticipates potential changes. Its effectiveness depends on the accuracy of the assumptions made to reflect uncertainties and variations in the job shop environment (H. Wang et al., 2023).

Predictive-reactive scheduling also generates an initial schedule; however, it does not account for dynamic events in the pre-schedule. Instead, it allows for real-time adjustments through event-driven or periodic rescheduling (H. Wang et al., 2023). The periodic policy creates schedules regularly, incorporating all available information from the job shop environment. This approach entails that the schedule remains unchanged in response to real-time events until the next predetermined rescheduling interval (Ouelhadj and Petrovic, 2008). Mannino and Mascis (2009) employ this strategy. The authors propose a periodic rescheduling strategy, optimizing the schedule every five seconds to respond to dynamic conditions. Given that the optimization approach is an exact algorithm, the authors note that extending to larger instances is challenging, as incoming jobs substantially increase the complexity.

In the event-driven approach, unexpected events prompt the rescheduling process. Schwenke and Kabitzsch (2017) apply this approach to address scheduling in an automated material handling system. The authors assign jobs to machines using the simulation of dispatching rules to create an initial machine schedule based on ideal transport times. This schedule then serves as a basis for evaluating three different transport scheduling methods. Among these, the MIP-based solving method, which solves small MIPs by grouping related transports subproblems, demonstrates the best performance. When transport delays occur, the initial schedule integrates them, necessitating updates to subsequent operations. The event-driven approach can combine with periodic rescheduling to create a hybrid policy. In the literature, experts often regard the event-driven approach as superior to the periodic rescheduling policy (Ouelhadj and Petrovic, 2008).

Completely reactive scheduling does not generate a schedule in advance. Instead, the system makes decisions in real-time, responding locally to changes as they occur (Ouelhadj and Petrovic, 2008). This approach demands rapid decision-making, similar to the method proposed by Hatzack and Nebel (2001). In their work, the proposed algorithm constructs a feasible solution by recursively inserting the operations into a schedule based on their release dates. When a conflict arises, the algorithm revisits previous decisions to resolve it. When tested against human schedulers, the backtracking algorithm generates solutions with an average delay of 27 more seconds but is about 60 times faster, delivering results within 0.5 seconds. Completely reactive scheduling frequently relies on dispatching rules, which we will examine in the following section.

Constructive Heuristics

This section describes constructive heuristics, which start with an empty solution and gradually build a complete schedule by adding one job at a time. While all constructive heuristics share this strategy, the heuristics differ in complexity and approach (Pinedo, 2016).

Dispatching Rules Dispatching rules determine the next job to process on a machine from a set of awaiting jobs based on job and machine attributes (Ouelhadj and Petrovic, 2008). These rules are computationally efficient, straightforward to implement, and can quickly adapt to dynamic changes (Shady et al., 2022). Consequently, they have been widely adopted in practice even though they generally cannot outperform heuristics and exact methods (Sels et al., 2012). Some of the most popular dispatching rules are w.l.o.g.

- First Come First Serve (FCFS): This rule prioritizes jobs based on their arrival time, giving the highest priority to the job that has been in the queue the longest (Dominic et al., 2003).
- Shortest Processing Time First (SPT): This rule prioritizes jobs by their processing time. Accordingly, the job with the shortest processing time receives the highest priority (Dominic et al., 2003).
- Earliest Due Date First (EDD): This rule prioritizes jobs based on their due date, with the job having the earliest due date receiving the highest priority. It selects the job with the smallest allowance, representing the remaining time until the due date (H. Wang et al., 2023).

These rules only take a single characteristic into account. However, research suggests that incorporating additional criteria and system information could significantly improve the dispatching rules scheduling performance (Ouelhadj and Petrovic, 2008). Examples are:

- Work Content in the Next Queue (WINQ): This rule avoids prioritizing a job that will likely face delays in a congested queue by considering the number of jobs in the job's successive machine queue. (H. Wang et al., 2023)

- Remaining Processing Time (RPT): The remaining work of a job is the sum of the processing times of all its subsequent operations. The job having either the most (MWKR) or the least (LWKR) work remaining is then assigned the highest priority (Dominic et al., 2003; Ferreira et al., 2022).
- Flow Due Date (FDD): This rule determines priority by adding the job's release time to the total processing time until now and gives the highest priority to the job with the lowest resulting value (Sels et al., 2012).

Research by Dominic et al. (2003) demonstrates that despite the variety of dispatching rules available, none have been universally effective across all job shop environments and objectives. Nevertheless, combining effective rules can mitigate this drawback and increase overall performance. This advantage of combined rules has been further validated in simulation studies by Ferreira et al. (2022) and Sels et al. (2012).

Sels et al. (2012) conduct a comparative study of various dispatching rules based on their performance across different objectives. The best-performing dispatching rules for all considered objectives are combined rules. To minimize mean flow time and tardiness, the authors identify a rule combining twice the processing time, LWKR, and FDD, outperforming all other rules. The effectiveness of this rule across both objectives stems from its inclusion of flow time and tardiness-related information. Additionally, this rule demonstrates robust performance. For large problem instances and dynamic job arrivals, the rule remains the most effective for minimizing mean tardiness. When extending the JSSP to include sequence-dependent setup times, the rule is outperformed by several other rules. It regains superiority by incorporating the shortest setup time rule.

By employing machine learning techniques to develop combined rules, the aim is to increase the performance of dispatching rules by focusing on the overall structure of scheduling problems rather than solely on local characteristics (H. Wang et al., 2023). While H. Wang et al. (2023) generates complex results that are challenging to interpret, Ferreira et al. (2022) evaluate the rule's effectiveness on both the complexity of the expression and its performance in minimizing tardiness.

The two best-performing rules identified by Ferreira et al. (2022) are expressed as follows:

- R1: $2 * p_{ij} + \frac{p_{ij} * SL_i^+}{RPT_i} + WINQ_i$
- R2: $\begin{cases} p_{ij} + p_{ij} * CR_i^+ + WINQ_i & \text{if} SL_i > 0 \\ 3 * p_{ij} + WINQ_i - (\frac{WINQ_i}{p_{ij}}) & \text{otherwise} \end{cases}$

In these rules, slack (SL_i) of job J_i is the difference between the remaining work and the job allowance. Furthermore, the critical ratio (CR_i) is between the allowance and the remaining work.

The authors compare the performance of R1 and R2 rules against existing literature under deterministic and stochastic processing times. While R2 generally outperforms R1, R1 is less complex and outperforms most dispatching rules proposed in the literature. Ferreira et al. (2022) notes that under high utilization levels, it may be beneficial to develop specific rules customized for these conditions. Additionally, Shady et al. (2022) propose a rule similar to R1 for the classical JSSP. This rule does not consistently outperform more complex rules based on machine learning but provides less complexity.

Greedy Heuristics Greedy heuristics, like dispatching rules, expand a solution schedule incrementally. However, the heuristics make the locally optimal choice at each step.

Mascis and Pacciarelli (2002) investigate four greedy heuristics based on a similar basic framework. In their study, they model the job shop environment as a graph. Due to blocking constraints, alternative arcs emerge, representing conflicting sequence dependencies. We refer the reader to Appendix B for an introduction to key graph theory concepts.

The greedy heuristics iteratively select among the alternative arcs. For instance, the Avoid Maximum Current Completion Time heuristic (AMCC) chooses the alternative arc to schedule next, preventing the selection that would most significantly increase the current completion time. We refer to Mascis and Pacciarelli (2002) for a comprehensive explanation of these heuristics.

The increasing complexity of BJSSPs compared to general JSSPs, as noted in the introduction of Section 3.1.4, is evident in the computational results of Mascis and Pacciarelli (2002). While the greedy heuristics successfully found feasible solutions for the general JSSP in all test cases, they encounter difficulties when applied to BJSSPs. Although the AMCC outperforms the tested heuristics in the quality of the solution, it fails to find feasible solutions for many test cases of the BJSSP. Even though the other heuristics find feasible solutions more frequently, they do not achieve acceptable results. Thus, the authors concluded that greedy heuristics are inefficient in consistently providing feasible and reasonable quality solutions for the BJSSPs.

Improvement Heuristics

Improvement heuristics differ fundamentally from constructive heuristics as they start with a complete schedule. By modifying the current schedule, these heuristics aim to enhance the solution (Pinedo, 2016).

Iterated Greedy Pranzo and Pacciarelli (2015) build upon the results of Mascis and Pacciarelli (2002) by proposing an iterated greedy heuristic (IG). This algorithm iteratively improves the performance of a greedy heuristic through two main phases. The destruction phase partially destroys the candidate solution by removing components. The subsequent construction phase reconstructs the partial solution into a new, complete solution. In this paper, the reconstruction utilizes the AMCC greedy heuristic, introduced as a constructive heuristic by Mascis and Pacciarelli (2002) in Section 3.1.4.

Once a candidate solution forms, it is evaluated and potentially accepted as a new starting point for the next iteration. The authors propose two acceptance criteria. The first always accepts the new candidate solution, while the second accepts it only if it is not worse than the previous solution or with a certain probability. Finally, the heuristic continues until a specific stopping criterion is reached.

The main advantages of this heuristic are its simplicity and independence from problem-specific properties. Moreover, the experimental results demonstrate that the iterated greedy algorithm outperforms previous algorithms in computation time and solution quality. For the objective of minimizing the makespan, applying the second acceptance criterion and averaging ten independent runs over 60 seconds each yields an average improvement of 2.25% compared to the best-known solutions from the literature at that time, despite a percentage of failures within the construction phase of about 31%. This feasibility problem, as highlighted in previous chapters, will also recur in the following improvement heuristics.

Local search algorithms such as simulated annealing (SA) and tabu search (TS) are highly efficient in solving classical JSSPs (Mati et al., 2001). However, extending these methods to

BJSSPs poses considerable difficulties. The design of the neighborhood structures is a crucial aspect of the efficiency of local search algorithms. Unlike in classical JSSPs, where the feasibility of generated neighbors does not critically impact performance, BJSSPs are significantly affected by this issue (Mogali et al., 2021).

Neighborhood Structures A neighborhood operation transforms a selection S into a different solution S' by reordering operations. The neighborhood structure, which comprises the set of operations that generate candidate solutions, known as neighbors, controls this process (Lange and Werner, 2019b).

Commonly used neighborhood operators in the field of BJSSPs are summarized in Table 3.2, following the categorization by Błażewicz et al. (1996). Additionally, the table includes selected papers that utilize these operators.

Neighborhood	Neighborhood Operator	Papers
N1	Swap two operations on the same machine by replacing an arc on a critical path in S with its alternative arc.	Bürgy (2017), Dabah et al. (2019), Gröflin and Klinkert (2009), Lange and Werner (2019a), Lange and Werner (2019b), and Mati et al. (2001)
N4	Move an operation to the start or end of a block of operations processed on the same machine.	Mogali et al. (2021)
N5	Move the predecessor of the last operation to the end or the successor of the first operation to the beginning of a block of operations processed on the same machine.	Bürgy (2017) and Mogali et al. (2021)

Table 3.2: Overview of Neighborhood Operators, Their Descriptions, and Corresponding Applications in the Literature.

Neighborhood operators often fail to generate feasible neighbors for the BJSSP. Dabah et al. (2019) note that 98% of cases result in infeasible neighbors, while Mogali et al. (2021) report only 40-45% feasibility. Consequently, a recovery algorithm is essential to transform infeasible neighbors into feasible selections. These algorithms aim to restore feasibility without completely altering the structure of the neighbor solution S'. A common approach is to remove all selected alternative arcs associated with a job J_i that includes an operation causing infeasibility, meaning an operation involved in the neighborhood transformation. By maintaining the changes made during the neighborhood transformation, job J_i is reinserted while preserving feasibility, thereby generating a feasible neighborhood $\bar{S}$ (Bürgy, 2017; Mogali et al., 2021). Mogali et al. (2021) call this algorithm job insertion feasibility recovery (JIFR).

Tabu Search The improvement heuristic tabu search (TS) explores the solution space by using memory structures. Starting from an initial solution, TS iteratively moves to the neighbor with the best objective value $G(S')$ (Gröflin and Klinkert, 2009). Incorporating short-term memory through a tabu list thereby refines the search process. The tabu list stores recently visited neighbor solutions and prohibits their selection to prevent cycling and getting trapped in local optima (Mati et al., 2001). If a neighborhood selection contains attributes stored in the tabu list, it can only be accepted if its objective value improves the best solution found so far (Bürgy, 2017).

Additionally, TS can utilize long-term memory to diversify and intensify the exploration of the search space (Mati et al., 2001). For instance, Bürgy (2017) use elite solutions, adding any solution surpassing the current best solution to the set. If the algorithm does not generate a new best solution for a specified number of iterations, it restarts with the most recent elite solution. Moreover, as the TS cannot entirely prevent cyclic behavior, the authors incorporate an evaluation of the sequence of objective values. The algorithm is restarted from an elite solution if a cycle is detected—the heuristic stops based on a stopping criterion, such as a maximum number of iterations.

Mati et al. (2001) apply a N1 neighborhood (Table 3.2), restricting permutations of consecutive operations. Their recovery strategy consolidates jobs within the partial solution into one job and reinserts the removed job using an optimal two-job insertion procedure. Their approach is tested on non-standard instances, making comparison to later work impossible.

Building on this, Bürgy (2017) and Gröflin and Klinkert (2009) utilize the N1 neighborhood operator with a recovery strategy based on the JIFR mechanism. Gröflin and Klinkert (2009)'s concept of closure ensures minimal changes to convert an infeasible neighbor into a feasible selection. Additionally, the authors incorporate a long-term memory to enhance intensification and diversification through elite solutions and cycle detection. Bürgy (2017) expands this by adding parallel computing capabilities, allowing for more extensive search space exploration. Both approaches show improvements in makespan, with Bürgy (2017) outperforming Gröflin and Klinkert (2009) across all benchmark instances. Additionally, Bürgy (2017) achieves better results than the IG of Pranzo and Pacciarelli (2015) in the swapping-based approach. Furthermore, the authors emphasize that most improvements occur early in the computational process, while running the algorithm longer yields further benefits, especially for larger instances.

Dabah et al. (2019) address the computational challenges implied by the recovery strategy by introducing a parallel TS. The results demonstrate that this approach, combined with a JIFR recovery strategy guided by AMCC, achieves a lower makespan than the closure-based approach in BJSSP where swaps are not allowed. Finally, Mogali et al. (2021) further improves the computational efficiency of the TS approach by introducing new theoretical results. These results allow quick infeasibility checks and efficient restoration of feasibility. Unlike earlier studies, their approach utilizes N4 and N5 neighborhoods, with N5 proving more efficient due to its ability to perform more iterations within the same timeframe. This observation aligns with Bürgy (2017), who preferred N5 for the makespan objective. The TS by Mogali et al. (2021) consistently outperforms earlier approaches, setting a new standard in minimizing the makespan for BJSSPs.

Among the reviewed papers, Bürgy (2017) uniquely evaluates the TS performance on objectives beyond makespan, such as total tardiness minimization. Due to the lack of benchmark results for the total tardiness, the author compares the results with MIP solutions. The TS approach demonstrates clear improvements, especially for larger instances. Although their formulation includes setup and transfer times, the authors set them to zero in their experiments. To the best of our knowledge, only one earlier study, Gröflin and Klinkert (2009), considers this generalization of the BJSSP.

Simulated Annealing Similar to TS, the simulated annealing procedure (SA) iteratively explores neighboring solutions, potentially accepting worse solutions until meeting a specific stopping criterion. However, the acceptance criterion is probabilistic. The current neighbor solution S' is thereby always accepted if the value of the objective function of the neighbor solution $F(S')$ is better than the value of the current solution $F(S)$. Worse solutions are also occasionally accepted with a certain probability. This probability depends on the difference between the objective values $F(S)$ and $F(S')$ and decreases over time, allowing the procedure to escape local optima (Pinedo, 2016).

Lange and Werner (2019a) and Lange and Werner (2019b) apply SA to solve the BJSSP with total tardiness minimization. The authors use a neighborhood structure similar to N1 (Table 3.2) but restrict the pairwise interchange to operations without idle time between them. This neighborhood operator is applied in 90% of the iterations, while the remaining 10% involve shifting all tardy job operations randomly to the left. The recovery algorithm constructs a feasible schedule from the initial permutation by adjusting operations to maintain job precedence and machine availability. This approach differs from previous recovery algorithms in that it continually reapplies the repair process after each change in the permutation.

Both Bürgy (2017) and Lange and Werner (2019b) evaluate their heuristics against the Lawrence instances (Lawrence, 1984). However, as these benchmark instances do not provide release and due dates, there are differences in their setups. While Bürgy (2017) releases all jobs at time zero, Lange and Werner (2019b) randomly select release dates between zero and twice the minimal total processing time. Additionally, the due dates in Bürgy (2017) are more lenient, complicating direct performance comparisons.

The TS approach proposed by Bürgy (2017) matches or improves upon the results obtained by their MIP model. In contrast, the results received by the SA from Lange and Werner (2019b) match or surpass their MIP results only in three out of the ten smallest instances.

3.2 Discrete Event Simulation

Simulation is widely used in operations research and management science, gaining popularity for modeling dynamic JSSPs and validating customized scenarios (Law, 2015; H. Wang et al., 2023). Simulation studies generally imitate real-world facility operations or processes to gain insights and identify areas for improvement (Robinson, 2014). This chapter focuses on discrete event simulation, a common approach where a system evolves. Changes in the system's state occur only when specific events happen (Law, 2015).

Advantages and Disadvantages of Simulation Studies Based on the reviewed research, discrete event simulation has been widely utilized to evaluate and analyze the performance of a solution approach, particularly in the testing of dispatching rules. For example, Ferreira et al. (2022) and Shady et al. (2022) use simulation experiments to compare dispatching rules and their combinations. Multiple simulation runs with different parameter settings allow the authors to evaluate the performance and robustness of these rules across various scenarios. These studies exemplify several advantages of simulation studies. Simulation models provide a controlled environment to test the impact of different experimental settings that real systems cannot control. Thus, simulation allows for repeated testing and enables a large set of parameters and settings to be tested in a shorter timeframe than real-life experiments would allow (Robinson, 2014). Schwenke and Kabitzsch (2017) also note the increased comparability due to the decreased influence of random events. Furthermore, as observed in Shady et al. (2022), simulation is a powerful tool for understanding the impact of experimental factors, offering more profound insights into the behavior of dispatching rules than mathematical equations alone can offer.

In addition to evaluating the performance of dispatching rules, simulation models can also be used to assess the effectiveness of heuristics. Gaiardelli et al. (2024) highlight another advantage of simulation studies. The authors compare their approach in three ways: against benchmark instances from the literature, on a real-world production line, and finally, using simulation experiments on a modified version of the real-world case. The simulation allows them to test their proposed algorithm in scenarios that do not exist.

Despite their numerous advantages, simulation studies have certain drawbacks. Firstly, they require considerable expertise and demand significant data. Additionally, the realistic appearance of simulation animations can lead to overconfidence in the results. Therefore, when interpreting the outcomes, it is essential to consider factors such as validity, underlying assumptions, and simplifications made during the simulation process (Law, 2015; Robinson, 2014).

Modeling Processes of Simulation Studies Improper experimentation can lead to incorrect understandings and ineffective improvements. Therefore, verifying and validating the model throughout the modeling development is crucial. Two critical factors in setting up reliable experiments are removing initialization bias and ensuring enough output data (Robinson, 2014).

Both Ferreira et al. (2022) and Shady et al. (2022) address the initialization bias by running their model for a warm-up period to reach a steady state before collecting the data. Specifically, both studies use a warm-up period of 500 jobs, with metrics calculated from the subsequent 2000 jobs. Alternatively, instead of waiting for the model to reach realistic conditions during the run, the model can be initialized in a realistic state from the beginning (Robinson, 2014).

Collecting sufficient output data from the simulation is essential to estimate the model's performance accurately. Achieving this involves simulating for an extended period or conducting multiple replications. While Shady et al. (2022) performs 20 replications for each test configuration, Ferreira et al. (2022) conducts 100 replications for each scenario.

3.3 Pipeline Capacity

The pipeline size of a workstation or outfeed lane refers to the number of pallets that can simultaneously be transported to this destination at any point in time (Haneyah et al., 2013). Therefore, pallets are only sent to the destination if the number of pallets in the pipeline does not exceed the pipeline size, including scheduled retrievals that are not physically in the pipeline yet. Consequently, the pipeline capacity influences pallets' interarrival time and workstations' idle time. As the pipeline parameter controls the material flow in the system and is used to prevent overflows, the size is important to define in the control architecture.

Despite its importance, to the best of our knowledge, this capacity has not been studied much in the literature. While Andriansyah et al. (2014) only refer to pipeline capacity as an experimental factor in their simulation model, Haneyah et al. (2013) provide two ways of determining the parameter. The authors explain that typically, the pipeline size equals the number of locations on the inbound buffer of a workstation. On the other hand, the authors propose the following formula to determine the pipeline size

$$ps_i = cap_i * (t_i + ta) \tag{3.5}$$

where index i represents the workstation or outfeed lane. The pipeline size ps_i of i results from multiplying the capacity cap_i with the sum of the average travel time of a pallet to i, t_i, and the time allowance ta. This time allowance accounts for realistic delays caused by other pallets in the system and scheduled requests not yet in the pipeline (Haneyah et al., 2013).

Haneyah et al. (2013) address the planning and control of automated material handling systems in two industrial sectors: baggage handling and distribution. The authors set the pipeline size for distribution centers as the number of buffer spots at workstations to control flow in a small sorter system and prevent conveyor capacity wastage by looping due to blocked entry. In baggage handling, they determined the Equation 3.5 to maintain a continuous flow of luggage to the workstations. Furthermore, the larger size of this system results in longer travel times for some workstations, leading to a higher pipeline size assigned to these stations.

3.4 Summary of the Literature Review

The scheduling problem at Euroma involves optimizing the outbound process in the high-bay warehouse, which integrates the conveyor system and the AS/RS. Based on the reviewed literature, most research focuses on AS/RS optimization but comparatively little on optimizing the conveyor performance. Given the interdependence between these subsystems, our research builds upon existing scheduling studies while addressing Euroma's specific constraints and challenges.

Section 3.1, reviews JSSPs, involving the allocation of operations to machines in various environments. As highlighted in Section 3.1.2, numerous characteristics can be incorporated to model system features adequately. Based on this review, we identify the problem at Euroma as an extended blocking job shop scheduling problem, incorporating multiple constraints. Using the three-field classification scheme, the problem is formulated as:

$$J_m | r_i, d_i, \text{blocking}, o_{ijuv}, \text{recirulation}, \text{no-wait} | T, F, Q$$

The classification in Table 3.3 shows that the BJSSP literature addresses nearly all characteristics of the system installed at Euroma. However, each existing study covers only a limited range of practical aspects. Our analysis could not identify a scheduling problem in the literature with a set of characteristics identical to our case.

The majority of BJSSP literature model blocking constraints in manufacturing or transportation contexts but rarely consider conveyor-based BJSSPs. Our research explicitly incorporates conveyor movements, where pallets wait if the next spot is occupied, rather than imposing classical no-wait constraints. To the best of our knowledge, no previous study has relaxed the no-wait constraint in this context. Additionally, we integrate AS/RS operations, where crane movements depend on conveyor flow as pallets are not allowed to wait on the cranes (classical no-wait constraint). Therefore, pallets wait in their storage location until the I/O-point becomes available.

All studies summarized in Table 3.3 incorporate blocking constraints, but due dates and release dates are primarily considered in dynamic scheduling problems. Furthermore, based on the literature considered for this thesis, existing research does not address the combination of setup times, recirculation, and no-wait constraints in dynamic environments. Additionally, to the best of our knowledge, none of the reviewed studies involve precedence constraints between jobs. At Euroma this constraint is critical as workstation pallets must adhere to a predetermined sequence.

In Section 3.1.3, we observe that most research in this area concentrates on single objectives. Table 3.3 reflects this observation. While some studies, such as Bürgy (2017), consider multiple objectives, they evaluate them separately rather than simultaneously. The predominant objective in existing studies is makespan minimization, though tardiness is also frequently considered. Our research adopts a multi-objective approach, optimizing tardiness (to increase on-time deliveries) and flow time (to reduce work-in-progress), making it more applicable to real-world warehouse operations. In addition to these objectives, we optimize queueing time to prevent outbound pallets from being unnecessarily delayed in their retrieval, ensuring that any postponement only occurs if it helps maintain the efficiency of other pallet flows.

Section 3.1.4 highlights that BJSSPs are generally NP-hard, with complexity even more significant than that of classical JSSPs. Consequently, exact algorithms cannot solve medium and large problem instances for real-world applications. Therefore, Section 3.1.4 explores constructive and improvement heuristics that can obtain suitable solutions for large problem instances in a reasonable time. The potential of infeasibility due to constructive heuristics and neighborhood operators makes direct adaptations from classical JSSPs challenging. The diversity of BJSSPs further complicates the identification of a universally superior approach. Nevertheless, in static cases, local search methods such as SA and TS are predominant, while dispatching rules are common in dynamic settings. Although dispatching rules offer flexibility and ease of implementation, local search heuristics often yield higher-quality solutions. Additionally, dynamic BJSSPs are frequently analyzed through simulation, as discussed in Section 3.2. However, comparative studies on different dispatching strategies for BJSSPs remain limited. Our research evaluates two alternative dispatching rules against Euroma's current approach using discrete event simulation.

To our knowledge, no study within the BJSSP literature explicitly addresses the pipeline capacity. Although some research, like Schwenke and Kabitzsch (2017), indirectly considered pipeline capacity by modeling the transportation process, no study explicitly evaluated restrictions on the number of jobs in transit. In general, the literature on pipeline capacity is limited, as outlined in Section 3.3. Findings suggest that setting pipeline capacity based on available buffer space prevents inefficient conveyor utilization, while a larger pipeline capacity supports continuous job flow. We analyze different pipeline thresholds and their impact on system performance, which is a novel aspect of our work.

In summary, this research provides a comprehensive and practical approach to scheduling in high-bay warehouses with integrated AS/RS and conveyor systems. It introduces new insights into pipeline management, multi-objective optimization, and dynamic scheduling strategies, addressing key gaps in the existing literature.

	Problem Type	Release Date	Due Date	Setup Time	Recircu-lation	No-Wait	Job Pre-cedence	Pipeline	Optimality Criteria	Solution Approach
Bürgy (2017)	static BJSSP	✓(0 in tests)	✓	✓					makespan, flow time, or tardiness	tabu search
Lange and Werner (2019a)	static BJSSP	✓	✓		✓				tardiness	simulated annealing
Liu and Kozan (2009)	static BJSSP			✓					makespan	local search
Mascis and Pacciarelli (2002)	static BJSSP			✓		✓			makespan	Branch & Bound, Greedy
Haneyah et al. (2013)	dynamic material flow control	✓	✓					✓	throughput	dispatching rules, simulation
Hatzack and Nebel (2001)	dynamic BJSSP	✓							makespan	backtracking, simulation
Schwenke and Kabitzsch (2017)	dynamic BJSSP	✓	✓						delays	dispatching rules, simulation
Our Problem	dynamic BJSSP	✓	✓	✓	✓	✓and relaxed	✓	✓	tardiness, flow time, and queueing time	dispatching rules, simulation

Table 3.3: Framework Literature: This framework presents the most relevant papers on BJSSPs, highlighting the characteristics incorporated in each study. A checkmark indicates the inclusion of a characteristic, with additional details provided where relevant. For example, Bürgy (2017) consider release dates in their model development but assume them to be zero in their experiments.

4 MODELLING AND SOLUTION DESIGN

This chapter addresses the third research question: How should the solution approach be designed for Euroma's lead time reduction problem?

The first part of the chapter focuses on the mathematical model. Section 4.1 provides an overview, followed by the formal mathematical formulation in Section 4.2 and an illustrative example in Section 4.3. Then, the focus shifts to the discrete event simulation. Section 4.4 introduces the conceptual model, while Section 4.5 discusses key assumptions and simplifications. Section 4.6 explores potential improvements in the scheduling strategy before Section 4.7 presents the discrete event simulation framework.

4.1 Model Description

The system under consideration comprises an AS/RS and conveyor modules, involving a set of m resources (machines), $\mathcal{R} = \{R_1, R_2, ..., R_m\}$, used to process a set of n pallet requests (jobs), $\mathcal{J} = \{J_1, J_2, ..., J_n\}$. The jobs compete for the resources, and each resource can handle only one job at a time, which is typical for scheduling problems.

Jobs and Resources Following the notation in Section 3.1, each job is represented by the tuple $(r_i, d_i, [o_{ij}, R_k, p_{ij}])$, where

- r_i refers to the earliest release date,
- d_i denotes the due date,
- and $[o_{ij}, R_k, p_{ij}]$ represents the predetermined path through the high-bay warehouse, specifying the operations, corresponding resources, and processing times of job J_i. The processing times p_{ij} depend on each operation's specific resource R_k.

Based on their flow through the high-bay warehouse, we divide the pallet requests into three subsets: inbound pallet requests $\mathcal{J}^{\mathsf{I}}$, full outbound pallet requests $\mathcal{J}^{\mathsf{O}}$, and outbound pallet requests with a workstation as their destination $\mathcal{J}^{\mathsf{W}}$. Since pallet requests are submitted throughout the day, the scheduling problem operates in a dynamic environment. Therefore, each job $J_i \in \mathcal{J}$ is assigned the earliest release date r_i. Additionally, each outbound job $J_i \in \mathcal{J}^{\mathsf{O}} \cup \mathcal{J}^{\mathsf{W}}$ is assigned a due date d_i.

The system comprises several types of resources, as described below:

- Storage Locations (R^{SL}): Double deep storage racks in the AS/RS store pallets. Each storage location buffers pallets until the crane retrieves them.
- Cranes (R^{C}): Each aisle in the AS/RS is served by a single crane. The cranes transport pallets one at a time between the storage locations and I/O-points.
- Operator (R^{O}): Operators process pallets at outbound stations or workstations.

- Main Conveyor (R^{MC}): The conveyor system transports pallets between various resources, with each spot on the conveyor representing a resource that can handle one pallet at a time.
- Buffer Spots (R^{B}): The inbound and outbound buffer spots reduce congestion on the main conveyor by temporarily storing pallets before they reach the main conveyor or destination points.
- Destination Spots (R^{D}): Buffer spots always precede destination spots. Operators serve these resources, marking the final processing point for pallets before they leave the system or move (back) into the AS/RS.
- Entrance Spots (R^{E}): Entrance spots, unlike destination spots, involve processing by operators to initiate the transportation process on the conveyor. Buffer spots succeed these resources.
- Lifts (R^{L}): Lifts transport pallets vertically between different levels, operating only in one direction.

Based on the system structure, the resources R^{MC}, R^{B}, R^{D}, R^{E}, and R^{L} collectively form the conveyor system, while the resources R^{SL} and R^{C} constitute the AS/RS.

Operations and Precedence Each pallet $J_i \in \mathcal{J}$ enters and leaves the system at designated resources $R_k \in \mathcal{R}^{\mathsf{E}} \cup \mathcal{R}^{\mathsf{D}}$. The movement between the entrance and the destinations of each pallet request $J_i \in \mathcal{J}$ is predetermined by an ordered sequence of n_i operations (actions) $(o_{i,1}, o_{i,2}, ..., o_{i,n_i})$. However, if a pallet is processed on a main conveyor spot $R_k \in \mathcal{R}^{\mathsf{MC}}$ and the next operation $o_{i,j+1}$ is scheduled on an occupied buffer spot $R_{k+1} \in \mathcal{R}^{\mathsf{B}}$, the pallet needs to alter its predetermined path. In such case, action $o_{i,j+1}$ occurs on the next main conveyor spot instead of the buffer spot. Consequently, all subsequent actions must be adjusted, resulting in the pallet continuing on the main conveyor until it can enter the buffer spot.

In addition to the precedence constraints within the operations of each pallet, pallets $J_i \in \mathcal{J}^{\mathsf{W}}$ also have precedence constraints among each other. As a result, the first pallet requested for a workstation must arrive before subsequent pallets for the same workstation. If pallets do not meet this condition, they loop on the main conveyor until the preceding pallet arrives at the workstation.

Constraints and Objectives A solution to this scheduling problem must define the exact start time for each pallet's processing while adhering to the following constraints:

- The processing of pallet J_i cannot start before its release date r_i.
- Overtaking on machines is prohibited.
- Pallets J_i must obey any existing precedence relationships between jobs.
- Each job J_i can only be processed by one machine at a time.
- Each resource R_i can only process one job J_i at a time.
- Jobs cannot be interrupted once started.

The objective is to minimize the tardiness of the outbound jobs $J_i \in \mathcal{J}^{\mathsf{O}} \cup \mathcal{J}^{\mathsf{W}}$ while reducing the time spent on the conveyor and in the queue. Therefore, the model minimizes the following objectives in lexicographic order:

1. Tardiness of all outbound jobs $J_i \in \mathcal{J}^{\mathsf{O}} \cup \mathcal{J}^{\mathsf{W}}$: The tardiness T is calculated as

$$T = \sum_{i \in \mathcal{J}^{\mathsf{O}} \cup \mathcal{J}^{\mathsf{W}}} \max\{C_i - d_i; 0\} \tag{4.1}$$

   where C_i represents the completion time and d_i the due date of job J_i.

2. Flow time of all jobs $J_i \in \mathcal{J}$: The flow time F is given by

$$F = \sum_{i \in \mathcal{J}} (C_i - s_i) \tag{4.2}$$

   where s_i denotes the start of the processing time. For inbound pallets, s_i corresponds to the time the pallet is placed on the conveyor, while for outbound pallets, it represents the crane retrieval time. The flow time is adjusted to reflect only the pallet's actual time moving through the system, starting from its initial movement rather than the request time.

3. Queuing time of all jobs $J_i \in \mathcal{J}$: The queueing time is defined as

$$Q = \sum_{i \in \mathcal{J}} Q_i \tag{4.3}$$

   where Q_i represents the queueing time for job J_i. For inbound pallets, Q_i is the time elapsed between the arrival at the I/O-point and crane retrieval. For outbound pallets, it is the time between the request and crane retrieval.

The lexicographic order ensures that the main focus is on minimizing the tardiness of the outbound jobs $J_i \in \mathcal{J}^{\mathsf{O}} \cup \mathcal{J}^{\mathsf{W}}$. At the same time, the secondary objectives prioritize minimizing conveyor and queueing times. This approach prevents congestion on the conveyor, ensures timely pallet retrieval by the crane, and avoids unnecessary delays. For inbound pallets that do not have a due date d_i, the secondary objective ensures their timely retrieval without disrupting outbound operations.

4.2 Mathematical Model

The mathematical formulation of the BJSSP of Euroma extends the classical BJSSP formulation. Additionally, the model incorporates further characteristics and constraints presented in Section 3.1.2. Table 4.1 summarizes the notation introduced in Section 4.1. The goal is to derive an optimal schedule, minimizing tardiness and flow time while respecting various operational constraints.

Objective Function The optimization problem is structured using a lexicographical objective function, stated in Equation 4.4. This function minimizes three objectives – tardiness, flow time, and queueing time – in lexicographical order. Each subsequent objective optimizes the schedule without worsening the optimal value of the preceding objectives. Equation 4.1 and Equation 4.3 define each objective.

$$\min f_L(T, F, Q) \tag{4.4}$$

Tardiness Constraints The first three constraints calculate each job's tardiness based on the completion times and due dates.

$$C_i = s_{i,n_i} + p_{i,n_i} \quad \forall J_i \in \mathcal{J}, n_i = |O_i| \tag{4.5}$$

$$T_i \geq C_i - d_i \quad \forall J_i \in \mathcal{J} \tag{4.6}$$

$$T_i \geq 0 \quad \forall J_i \in \mathcal{J} \tag{4.7}$$

Symbol	Description
	Sets
$\mathcal{R} = \{R_k \mid k = 1, \ldots, m\}$	set of m resources
$\mathcal{J} = \{J_i \mid i = 1, ..., n\}$	set of n jobs
$\mathcal{A} = \{J_i \mid s_i, 1 \geq t\}$	set of active jobs
$\mathcal{O}_i = \{O_{ij} \mid j = 1, \ldots, n_i\}$	set of n_i operations of job J_i
$\mathcal{O} = \cup_{J_i \in \mathcal{J}} O_i$	set of operations
$\mathcal{OR}_k$	set of operations being processed on machine R_k
	Parameters
O_{ij}	j-th operation of job J_i
p_{ij}	processing time of operation O_{ij}
r_i	request time of job J_i
d_i	due date of job J_i
$o_{i,u,k}$	setup time between jobs J_i and J_u on machine R_k
t	current time
M	big-M, large positive constant
	Variables
s_{ij}	starting time of operation O_{ij}
Q_i	queueing time of job J_i $\begin{cases} s_{i,n_i} - s_{i,n_i-1} & \text{if job } J_i \in J^I \\ s_{i,1} - r_i & \text{otherwise} \end{cases}$
C_i	completion time of job J_i
T_i	tardiness of job J_i
	Binary Variables
y_{ijuvk}	$\begin{cases} 1 & \text{if operation } O_{ij} \text{ is scheduled before operation } O_{uv} \text{ on machine } k \\ 0 & \text{otherwise} \end{cases}$
q_{ij}	$\begin{cases} 1 & \text{if at least on job } J_u \in \mathcal{J} \text{ precedes job } J_i \text{ on the machine of operation } O_{ij} \\ 0 & \text{otherwise} \end{cases}$
x_{ijuv}	$\begin{cases} 1 & \text{if operation } O_{ij} \text{ is scheduled immediately before operation } O_{uv} \text{ on machine } k \\ 0 & \text{otherwise} \end{cases}$
z_{ij}	$\begin{cases} 0 & \text{if waiting is required before starting operation } O_{ij} \\ 1 & \text{otherwise} \end{cases}$

Table 4.1: Notation BJSSP. This table summarizes the notation used in the mathematical model of the scheduling problem at Euroma.

Release Date Constraints This set of constraints enforces that jobs cannot start before their release dates or the system's current time.

$$s_{i,1} \geq r_i \quad \forall J_i \in \mathcal{J}^0 \cup \mathcal{J}^W \tag{4.8}$$

$$s_{i,1} \geq t \quad \forall J_i \in \mathcal{J}^0 \cup \mathcal{J}^W \setminus \mathcal{A} \tag{4.9}$$

Precedence Constraints The BJSSP of Euroma includes two types of precedence constraints. The first ensures that operations within a job follow the correct sequence (Equation 4.10). The second enforces adherence to a predefined sequence between jobs at workstations (Equations

4.11 and 4.12).

$$s_{i,j+1} \geq s_{i,j} + p_{i,j} \quad \forall J_i \in \mathcal{J}, j < |O_i| \tag{4.10}$$

$$\begin{aligned} y_{i,n_i,u,n_u} = 1 \quad & \forall J_i, J_u \in \mathcal{J}^W | J_i \neq J_u, n_i = |O_i|, n_u = |O_u|, \\ & O_{i,n_i}, O_{u,n_u} \in \mathcal{OR}_k, \\ & \text{Sequence Position}(J_i) < \text{Sequence Position}(J_u) \end{aligned} \tag{4.11}$$

$$\begin{aligned} y_{u,n_u,i,n_i} = 1 \quad & \forall J_i, J_u \in \mathcal{J}^W | J_i \neq J_u, n_i = |O_i|, n_u = |O_u|, \\ & O_{i,n_i}, O_{u,n_u} \in \mathcal{OR}_k, \\ & \text{Sequence Position}(J_i) > \text{Sequence Position}(J_u) \end{aligned} \tag{4.12}$$

Resource Constraints These constraints ensure that a machine processes only one operation at a time. Together, they manage the start times of a job's operation on resources while considering the availability of resources, processing times, setup times, and precedence of other jobs.

$$\begin{aligned} s_{i,j} \geq s_{u,v} + p_{u,v} + o_{u,i,k} - M * y_{i,j,u,v} \quad & \forall J_i, J_u \in \mathcal{J} | J_i \neq J_u, j \in O_i, v \in O_u, \\ & O_{i,n_i}, O_{u,n_u} \in \mathcal{OR}_k \end{aligned} \tag{4.13}$$

$$\begin{aligned} s_{u,v} \geq s_{i,j} + p_{i,j} + o_{i,u,k} - M * (1 - y_{i,j,u,v}) \quad & \forall J_i, J_u \in \mathcal{J} | J_i \neq J_u, j \in O_i, v \in O_u, \\ & O_{i,n_i}, O_{u,n_u} \in \mathcal{OR}_k \end{aligned} \tag{4.14}$$

Blocking Constraint This constraint ensures that operations cannot proceed until the resource for the subsequent operation becomes available. The resource becomes available only after the succeeding operation of the preceding job starts processing on the succeeding machine and any required setup time has passed.

$$\begin{aligned} s_{u,v} \geq s_{i,j+1} + o_{i,u,k} - M * (1 - y_{i,j,u,v}) \quad & \forall J_i, J_u \in \mathcal{J} | J_i \neq J_u, j \in O_i, v \in O_u, \\ & O_{i,n_i}, O_{u,n_u} \in \mathcal{OR}_k \end{aligned} \tag{4.15}$$

No-Wait Constraints No-wait constraints enforce that jobs cannot wait between two successive machines. In the high-bay warehouse installed at Euroma, this constraint (Equation 4.16) applies to crane resources (R^C). Other resources require a relaxed version of the no-wait constraint. In this relaxed version, jobs must proceed to the next machine if it is available. If the machine is unavailable, the job waits on the preceding machine. Constraints 4.17 to 4.23 enforce this condition.

$$s_{i,j+1} = s_{i,j} + p_{i,j} \quad \forall J_i \in \mathcal{J}, j < |O_i|, O_{i,j} \in \mathcal{OR}_k, R_k \in R^C \tag{4.16}$$

$$\begin{aligned} y_{i,j,u,v} = 0 \quad & \forall J_i, J_u \in \mathcal{J}, j \in O_i, v \in O_u, \\ & O_{i,n_i}, O_{u,n_u} \notin \mathcal{OR}_k \end{aligned} \tag{4.17}$$

$$y_{i,j,u,v} = 0 \quad \forall J_i, J_u \in \mathcal{J} | J_i = J_u, j \in O_i, v \in O_u \tag{4.18}$$

- Constraints 4.17 and 4.18 ensure that the binary variable $y_{i,j,u,v}$ is zero if J_i and J_u are the same job or if operation j of job J_i and operation v of job J_u are not processed on the same machine. Enforcing these constraints is necessary to ensure that machine availability and start times of operations are determined only by jobs preceding J_i on the machine.

$$y_{u,v,i,j} \leq q_{i,j} \quad \forall J_i, J_u \in \mathcal{J}, j \in O_i, v \in O_u \tag{4.19}$$

- Constraint 4.19 ensures that the binary variable $q_{i,j}$ equals one if at least one job $J_u \in \mathcal{J}$ precedes job $J_i \in \mathcal{J}$ on the machine of operation $j \in O_i$.

$$\sum_{J_u \in \mathcal{J}, v \in O_u} (y_{u,v,i,j} * x_{u,v,i,j}) = q_{i,j} \quad \forall J_i \in \mathcal{J}, j \in O_i \tag{4.20}$$

- Equation 4.20 ensures that if there is at least one job J_u that precedes job J_i on their common machine (where operation $j \in O_i$ and $v \in O_u$ are processed) then exactly one binary variable $x_{u,v,i,j}$ must be one.

$$s_{i,j} \leq M * (q_{i,j} + 1 - z_{i,j}) \quad \forall J_i \in \mathcal{J}, j \in O_i \tag{4.21}$$

$$s_{i,j} \leq s_{u,v+1} + o_{u,i,k} + M * (2 - x_{u,v,i,j} - z_{i,j}) \quad \forall J_i, J_u \in \mathcal{J} | J_i \neq J_u, \; j \in O_i, v < |O_u| \tag{4.22}$$

$$s_{i,j} \leq s_{i,j-1} + p_{i,j-1} + M * z_{i,j} \quad \forall J_i \in \mathcal{J}, j \in O_i | j > 1 \tag{4.23}$$

- This set of constraints ensures that operation $j-1$ of job $J_i \in \mathcal{J}$ begins its next operation j as soon as the succeeding machine becomes available. By using binary variables $q_{i,j}$, $x_{i,j,u,v}$, and $z_{i,j}$, the model establishes an upper bound for the start time of operation j of job $J_i \in \mathcal{J}$. Together with the lower bounds from Equation 4.10 and Equation 4.15, these constraints ensure that job $J_i \in \mathcal{J}$ proceeds as soon as the succeeding machine becomes available.

Fixed Start Times Constraint For active jobs, the start times of the first operations are fixed due to system constraints. We consider jobs as active once they begin their movement through the system. In other words, outbound jobs become active when the crane retrieval begins. In contrast, inbound jobs become active when they enter the system, marked by an operator placing the pallet on the conveyor. The start times of these operations are fixed since they have already started in the actual system and, therefore, cannot be modified by the optimization algorithm.

$$s_{i,1} = \text{fixed start}_{i,1} \quad \forall J_i \in \mathcal{A} \tag{4.24}$$

Binary Variable Constraint The binary variables $y_{i,j,u,v}$, q_{ij}, and x_{ijuv} represent precedence relationships between jobs on resources, while z_{ij} determines the necessity of waiting times on the conveyor.

$$q_{i,j} \in \{0,1\} \quad \forall J_i \in \mathcal{J}, j \in O_i \tag{4.25}$$

$$x_{i,j,u,v} \in \{0,1\} \quad \forall J_i, J_u \in \mathcal{J}, j \in O_i, v \in O_u \tag{4.26}$$

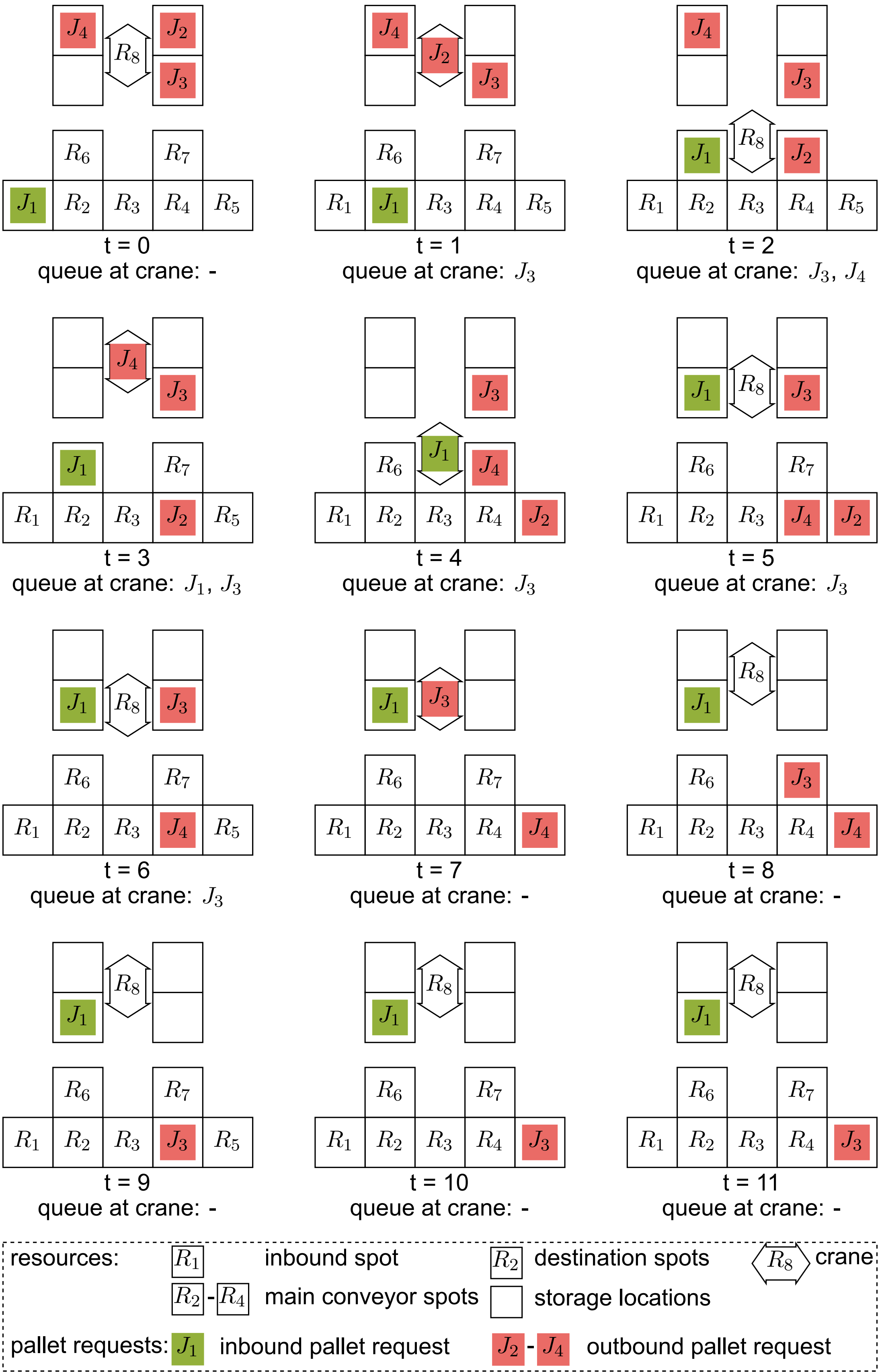
$$y_{i,j,u,v} \in \{0,1\} \quad \forall J_i, J_u \in \mathcal{J}, j \in O_i, v \in O_u \tag{4.27}$$

$$z_{i,j} \in \{0,1\} \quad \forall J_i \in \mathcal{J}, j \in O_i \tag{4.28}$$

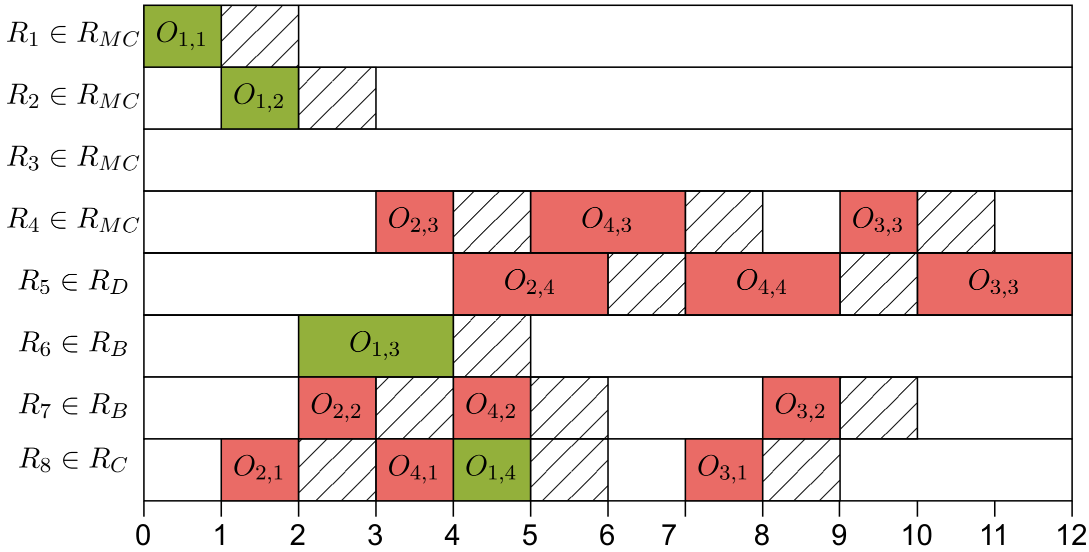
4.3 Illustrative Example

To demonstrate how pallets move through the high-bay warehouse and how the different machines interact, we present an illustrative example with four pallet requests and eight resources. This example highlights the scheduling constraints and dependencies within the system. Figures 4.1a and 4.1b visually represent the warehouse operations, while Table 4.2 details the request times, due dates, setup times, and processing times for each pallet and resource.

To validate the developed mathematical model described in Section 4.2 and assess its applicability, we formulated the problem in Python and solved it using GUROBI. The optimization process yielded an optimal solution within 0.57 seconds. This example not only confirms the solvability of the model but also illustrates how it determines an efficient schedule for pallet movements in the warehouse system.



(a) Illustrative Example: Pallet Movement Over Time. The figure illustrates the warehouse state at each time step, highlighting the movement of outbound (red) and inbound (green) pallets across components. Pallets queued for the crane are also shown per time step.



(b) Illustrative Example: Gantt Chart. This visualization displays the processing and setup times for each pallet on each resource, depicting the sequence in which pallets are handled.

Figure 4.1: Illustrative Example. This figure provides an overview of pallet movements and resource utilization within the warehouse system.

Initial Setup (t = 0) Initially, three outbound pallets ($J_1, J_2, J_3 \in \mathcal{J}^{\mathsf{O}}$) highlighted in red in Figure 4.1 are stored in the AS/RS. Simultaneously, pallet $J_1 \in \mathcal{J}^{\mathsf{I}}$, an inbound pallet highlighted in green, is placed on the conveyor.

First Requests (t = 1) At $t = 1$, pallets J_2^{O} and J_3^{O} are requested. Given the constraint that the crane can only move one pallet at a time, it retrieves pallet J_2^{O} first, as this sequence minimizes tardiness (discussed later). Meanwhile, inbound pallet J_1^{I} moves to the next conveyor spot R_2^{MC}.

Crane Operations (t = 2 - t = 5) After dropping off pallet J_2^{O} at the I/O-point (R_7^{B}) at $t = 2$, the crane moves back to the storage area to retrieve J_4^{O}, which is prioritized over J_3^{O} to minimize total tardiness. The crane does not retrieve pallet J_1^{I} from the buffer spot R_6^{B} at $t = 2$ because J_1^{I} must first complete processing on this spot. This processing time accounts for the duration required for a pallet to traverse a conveyor module. Additionally, since the inbound pallet J_1^{I} lacks a due date and is thus not time-critical, it remains in place until the crane is idle or has completed a retrieval of an outbound pallet. This occurs at $t = 4$ when the crane drops off pallet J_4^{O} at the I/O-point. On its way back to retrieve J_3^{O}, the crane picks up pallet J_1^{I} and stores it, utilizing a dual command operation. This does not incur additional time, as the crane must move from the I/O-point to the storage area.

Buffer and Conveyor Movements (t = 5 - t = 7) At $t = 5$, pallet J_2^{O} reaches its destination R_5^{D} and awaits further processing. Typically, pallets have a processing time of one minute per conveyor module, but at the final destination, they require two minutes, as detailed in Table 4.2. This additional time accounts for waiting for retrieval. By $t = 6$, pallet J_2^{O} leaves the system, allowing space for other pallets to advance. However, due to the setup time of one minute, pallet J_4^{O} cannot immediately proceed to the newly available destination. The setup times reflect the real-life scenario where pallets occupy two conveyor spots simultaneously because they do not transfer instantly from one spot to the next. Figure 4.1b visualizes the required setup time with dashed bars after processing pallets.

	Request Date (r_i)	Due Date (d_i)	Processing Times (p_k)
J_1^{I}	0	-	
J_2^{O}	1	6	
J_3^{O}	1	10	
J_4^{O}	2	9	
R_1^{MC} - R_4^{MC}, R_6^{B}, R_7^{E}, R_8^{C}			1
R_5^{D}			2

(a) Release Dates, Due Dates, and Processing Times. While the first two parameters are job-related, the processing time is resource-related. The times are given in minutes.

job \ resource	R_1^{MC}	R_2^{MC}	R_3^{MC}	R_4^{MC}	R_5^{D}	R_6^{B}	R_7^{E}	R_8^{C}
J_1^{I}, J_2^{O}	1	1	1	1	1	1	1	0
J_1^{I}, J_3^{O}	1	1	1	1	1	1	1	0
J_1^{I}, J_4^{O}	1	1	1	1	1	1	1	0
J_2^{O}, J_1^{I}	1	1	1	1	1	1	1	0
J_2^{O}, J_3^{O}	1	1	1	1	1	1	1	1
J_2^{O}, J_4^{O}	1	1	1	1	1	1	1	1
J_3^{O}, J_1^{I}	1	1	1	1	1	1	1	0
J_3^{O}, J_2^{O}	1	1	1	1	1	1	1	1
J_3^{O}, J_4^{O}	1	1	1	1	1	1	1	1
J_4^{O}, J_1^{I}	1	1	1	1	1	1	1	0
J_4^{O}, J_2^{O}	1	1	1	1	1	1	1	1
J_4^{O}, J_3^{O}	1	1	1	1	1	1	1	1

(b) Setup Time Matix.

Table 4.2: Input Parameter for the Illustrative Example.

Completion (t = 7 - t = 11) At $t = 7$, pallet J_4^{O} starts processing at its destination R_5^{D}, waits for retrieval at $t = 8$ and exits the system at $t = 9$. One time step later, at $t = 10$, the last pallet, J_3^{O}, reaches its destination R_5^{D}.

Schedule Discussion and Objective Calculations Retrieving J_2^{O} first results in lower overall tardiness, as retrieving another pallet first would delay J_2^{O}'s arrival without benefiting the overall schedule. Early arrivals do not provide any scheduling advantage. For a similar reason, J_4^{O} is prioritized over J_3^{O}.

- Sequence 1 ($J_2^{\mathsf{O}} \rightarrow J_4^{\mathsf{O}} \rightarrow J_1^{\mathsf{I}} \rightarrow J_3^{\mathsf{O}}$)
  - Both J_2^{O} and J_4^{O} meet their due date, resulting in a tardiness of zero time steps.
  - J_3^{O} reaches its destination at $t = 12$, resulting in a tardiness calculated as $T_3 = max\{0, 12 - 10\} = 2$.
  - The total tardiness is two time steps.
- Sequence 2 ($J_2^{\mathsf{O}} \rightarrow J_3^{\mathsf{O}} \rightarrow J_1^{\mathsf{I}} \rightarrow J_4^{\mathsf{O}}$)
  - J_2^{O} meets its due date ($T_2 = 0$).

- J_3^{O} meets its due date ($T_3 = max\{0, 9 - 10\} = 0$).
- J_4^{O} reaches its destination at $t = 12$, resulting in a tardiness of three three time steps.
- The total tardiness is three time steps.

Due to the lexicographical approach, optimizing the schedule for the second objective must not worsen the first objective. Therefore, we consider only schedules with a tardiness of two minutes or less. This constraint limits the sequence of outbound pallets: $J_2^{\mathsf{O}} \rightarrow J_4^{\mathsf{O}} \rightarrow J_3^{\mathsf{O}}$. The crane can retrieve inbound pallet J_1 between J_4^{O} and J_3^{O} or at the end without increasing the tardiness.

Minimizing the flow time ensures that pallets do not wait on shared resources unless delaying retrieval prevents increasing tardiness. For example, retrieving pallet J_3^{O} at $t = 7$ instead of earlier prevents unnecessary waiting on the conveyor without increasing its tardiness. Additionally, the second objective prevents the inbound pallet from remaining in the crane queue when the crane is idle. Consequently, the optimal sequence is: $J_2^{\mathsf{O}} \rightarrow J_4^{\mathsf{O}} \rightarrow J_1^{\mathsf{I}} \rightarrow J_3^{\mathsf{O}}$. The third objective, queueing time, does not influence this case, as reducing queueing time would increase flow time due to conveyor congestion.

This example highlights the importance of the relaxed no-wait constraint. If the model applies the traditional no-wait constraint to conveyor resources, it will delay J_4^{O}'s retrieval by at least one time step. As a result, either inbound pallet J_1^{I}'s retrieval would also be delayed – increasing its queueing and flow time – or J_1^{I} would be retrieved before J_4^{O}, increasing J_4^{O}'s queueing time and tardiness by one time step. Conversely, removing the no-wait constraint would allow J_1^{I} to wait at another conveyor spot before entering R_6^{B}, reducing queueing time but creating unrealistic conditions.

In this example, the model optimizes the scheduling process by considering release dates, due dates, processing times, and resource constraints to minimize overall tardiness while ensuring efficient pallet movement. Prioritizing J_2^{O} and J_4^{O} achieves lower tardiness, demonstrating the importance of strategic scheduling. The optimal schedule results in a tardiness of two, a flow time of 21, and a queueing time of eight time steps.

4.4 Conceptual Model of the Simulation

While the mathematical model successfully provides optimal schedules for small instances, its scalability is limited. As the problem size increases, computation time grows rapidly. Table C.1 presents the computation time for varying example sizes. The reader can find the exact input parameters for each scenario in Appendix C. When doubling the number of jobs from the presented example in Section 4.3, the solution time increases to 2.75 seconds – more than double the original 0.57 seconds. Doubling the job count again, the solver could not reach an optimal solution within one hour. Increasing the number of machines to 15 also leads to higher computation times, even for smaller job instances, emphasizing the additional complexity introduced by a larger system configuration. This exponential increase in computation time makes the exact approach impractical for larger, real-world instances.

Euroma's scheduling problem is a dynamic BJSSP, where job arrivals and resource availability change over time. Therefore, it requires rapid decision-making. Most of the literature on dynamic BJSSPs addresses this challenge using dispatching rules. We employ discrete event simulation to evaluate and compare the performance of different dispatching strategies under realistic conditions. This decision is driven by the reviewed studies, which highlight that comparing dispatching rules in a controlled simulation environment is highly effective. Simulation allows for repeated testing with excellent comparability within a short time frame. Therefore,

	Problem Size		Solution Performance	
Inbound Jobs	Outbound Jobs	Machines	Computation Time (sec)	Optimality Gap
1	3	8	0.57	0.00%
1	3	15	1.29	0.00%
2	6	8	2.95	0.00%
2	6	15	6.47	0.00%
4	12	8	3600	5.93%

Table 4.3: Problem Size and Solution Performance: The table presents the computational time and optimality gap for different problem sizes based on the number of inbound and outbound jobs, and the number of machines in the system.

it provides valuable insights into system performance under different conditions. While it does not guarantee optimal solutions, simulation offers flexibility and realistic insights into dynamic scheduling in real-world scenarios.

The following sections focus on the discrete event simulation model and its application to Euroma's scheduling problem. Before developing the simulation model in Siemens Tecnomatix Plant Simulation 16.1, we created a conceptual framework to describe the high-bay warehouse system at Euroma in a non-software-specific manner. Therefore, this section summarizes the information provided by the main problem description in Section 2 in a conceptual model, which serves as the foundation for building the simulation model.

Modeling Objectives Euroma faces challenges in the full outbound process of its high-bay warehouse. Operators and truck drivers frequently report waiting times for pallets. These delays do not result from stock or capacity issues but coordination issues affecting pallet outbound processes. Therefore, Euroma aims to gain insights into the outbound process and identify opportunities for improvement. The primary goal is to ensure that all full outbound pallets achieve a maximum lead time of one hour at any time of the day.

The simulation assesses the effects of potential adjustments on outbound lead times. Additionally, it monitors the entire system's performance, including inbound and workstation processes, to ensure that improvements do not negatively impact other areas.

Inputs and Outputs The input variables represent the experimental factors that can be modified to achieve the model's objectives (Robinson, 2014). At Euroma, these factors include the sequencing policy, the operator behavior when retrieving pallets from the conveyor, and adjustments influencing the pipeline threshold, as detailed in Section 4.6. Additionally, the simulation model relies on constant input parameters across experiments derived from historical data. These parameters include pallet arrival times, processing time distributions at workstations, and crane and conveyor movement times.

The pallet arrival times in the simulation precisely replicate the timing observed in the historical data. Similarly, the crane's processing times for loaded outbound movements strictly follow the historical data. For loaded inbound movements and empty crane travel times – where exact historical data is unavailable – assumptions are made based on loaded outbound movement times and real-system observations. A normal distribution models the crane travel times for loaded inbound movements (time in seconds):

$$\text{Normal}(\mu = 42.26, \sigma = 8.74, \text{lower bound} = 13, \text{upper bound} = 63) \tag{4.29}$$

An additional delay is included for empty single command crane travel times to account for the observed pause before the crane initiates its next task, modeled as a uniform distribution between zero and ten seconds. Furthermore, the empty dual command travel times follow a uniform distribution between 15 and 25 seconds.

We also derive the conveyor speed from historical data and system observations, ranging between 0.12 and 0.2 meters per second. Appendix G provides further explanations and details.

The simulation model provides its results by output parameters to evaluate the system's performance and the effectiveness of the implemented adjustments. The primary output focuses on the percentage of pallets that reach the outfeed within the one-hour threshold and the resulting total tardiness, ensuring the main objective is met. Secondary output KPIs include the inbound queuing time and workstation tardiness. These metrics help to assess the broader system performance, ensuring adjustments do not negatively impact the inbound processes or disrupt production workflows.

We use additional outputs to analyze the factors contributing to the total outbound lead time. These include crane queuing and pallet movement times. By monitoring these aspects, we gain insights into how specific adjustments impact overall system efficiency and identify areas for further improvement. Appendix D, specifically Table D.1, provides a detailed summary of the input and output parameters.

Scope The scope of the simulation model is defined based on the identified objectives and the input and output parameters. It includes the AS/RS, which encompasses the retrieval queue, stacker cranes, and storage racks, as these are critical components of the outbound process. The conveyor system and its retrieval process are also within the scope, as they directly impact pallet movement. Additionally, we include the WCS to capture the coordination and control of the entire system. Appendix D, particularly Table D.2, provides a detailed explanation of the scope and justifications for including and excluding specific elements.

4.5 Modeling Assumptions and Simplifications

This section presents the assumptions and simplifications made in developing the model. These limit the complexity of the model without interfering with the model's ability to provide valuable insights into the scheduling and operational behavior of the high-bay warehouse.

- Dedicated Machines: Although the WCS can assign new orders to any available workstation, we treat this decision as fixed. This simplification is made because the assignment depends on factors beyond the scope of this research.
- Breakdown and Maintenance: We exclude machine breakdowns and maintenance from the model. Given a technical uptime between 98% and 99%, breakdowns are not considered critical. Additionally, Euroma schedules its maintenance, resulting in the assignment of alternative machines to process the pallets. The model's input data reflects this reorganization.
- AS/RS: The simulation models the AS/RS as a black box. Therefore, methods represent the crane movement, logic, and storage aisles. For instance, the crane travel times

implicitly account for varying distances between storage locations and the I/O-points. Additionally, we assume requested jobs are always available for retrieval and transportation without considering misplacement or unavailability. Finally, the model explicitly tracks and stores the crane queue, as its behavior is an essential experimental factor.

- Pallet Dimensions: The pallet size does not affect the crane or conveyor processing time. Additionally, storage assignment rules lay outside the scope of this research. Therefore, we assign all pallets the same dimensions even though Euroma uses two types of pallets.
- Operator Availability: In a real-life situation, operators are not always available to retrieve pallets from the conveyor due to breaks, other tasks, or absenteeism. This research considers operator behavior only if it directly affects pallet retrieval. As such, we can indirectly account for operator availability by including the duration of a pallet on the conveyor waiting for retrieval.

Appendix E visualizes the simulation model we developed based on the information summarized in Sections 4.4 and 4.5.

4.6 Potential Improvements in Scheduling Strategies

As elaborated in Section 3.2, dispatching rules offer a computationally efficient and straightforward method for managing scheduling tasks in dynamic environments. Their simplicity and adaptability make them a practical choice for simulation-based analysis. For this study, we selected two dispatching rules, each chosen for the following reasons.

FCFS Simulation The FCFS rule processes pallets in the order they are requested. In contrast to the scheduling logic currently applied by Euroma (details in Section 2.4.1), this simulation applies FCFS to all pallets, regardless of the destination. This allows us to evaluate how the system would perform without workstation-based pallet prioritization. Additionally, since the due dates of full outbound pallets are derived from their release times, processing pallets in request order naturally aligns with prioritizing those with earlier due dates.

R1 Simulation Ferreira et al. (2022) identified the R1 rule and highlighted it as one of the most effective combined dispatching rules with relatively low implementation complexity. This rule integrates multiple scheduling criteria:

- Current machine's processing time (in this case, the crane)
- Remaining processing time
- Due date
- Workload in the next queue

Research consistently shows that combined rules outperform single-criterion rules. Therefore, we selected the R1 rule to explore the behavior and performance of a combined approach.

The mathematical model explicitly optimizes tardiness, flow time, and queueing time in a lexicographic manner. Conversely, dispatching rules are heuristic approaches approximating these objectives by making real-time scheduling decisions. Therefore, they do not guarantee an optimal solution. We assess their effectiveness based on how well they deliver full outbound pallets on time without worsening the performance of other pallet flows, aligning with the objectives of the mathematical model.

Dispatching rules do not solve the lexicographic objective function directly. Instead, the discrete event simulation helps evaluate their performance. Among the tested rules, R1 more closely reflects the mathematical model's objectives, as it considers slack (which affects tardiness) and queue conditions (which influence flow time). In contrast, FCFS does not explicitly account for these objectives but naturally prioritizes earlier-requested pallets, which may still lead to favorable on-time delivery performance.

A key performance metric when evaluating dispatching rules is the on-time delivery percentage. While this metric is closely related to tardiness, the mathematical model does not directly optimize it. Instead, it minimizes total tardiness, providing a structured way to prioritize and reduce lateness across all pallets. This prevents concentrating excessive lateness on a few jobs. As highlighted by Pinedo (2016) on-time delivery does not account for the severity of delays, which can lead to excessively long waiting times for some pallets. By minimizing tardiness, the mathematical model encourages on-time delivery while ensuring scheduling decisions remain effective in practical applications by minimizing delays balanced across pallets.

In contrast, the discrete event simulation explicitly monitors the on-time delivery percentage when evaluating dispatching rules. In real-world operations, on-time delivery is often the more intuitive measure, as it directly reflects adherence to due dates. Therefore, by assessing both on-time delivery and tardiness, we identify the dispatching rule that maximizes on-time deliveries while preventing excessive delays.

Beyond tardiness, the discrete event simulation also considers the other optimization objectives. Following the lexicographic approach, we analyze dispatching rule performance on these secondary objectives to ensure that improvements in one area do not negatively impact overall system efficiency.

4.7 Discrete Event Simulation

In this research, we use Siemens Tecnomatix Plant Simulation 16.1 for discrete event simulation. The simulation framework follows the logic outlined in the conceptual model (Section 4.4), ensuring an accurate representation of the warehouse processes. This section describes how the warehouse functionality is implemented in the discrete event simulation software.

Figure 4.2 illustrates the general pallet flow in the high-bay warehouse. Inbound pallets move along the conveyor system toward the AS/RS, while outbound pallets follow the reverse process. Next to the logical sequence of operations, the flowchart highlights methods responsible for key simulation decisions. Red boxes indicate these critical decision-making points that guide the scheduling and execution of pallet movements.

In conjunction with the applied dispatching rule, the method *CraneTask* selects the next outbound pallet for retrieval whenever a crane is idle and queueing pallets are available, based on the pipeline size and workstation sequence. The *InboundQueue* method selects the next pallet from the inbound queue when an inbound pallet reaches the I/O-point. The method *HybridCommand* connects both queues by tracking the crane's current position and prioritizing inbound retrieval if a dual command is feasible; otherwise, the crane retrieves the selected outbound pallet. Finally, the *CraneProcessing* method manages empty and loaded crane movements while ensuring precedence constraints between workstation pallets and compliance with no-wait constraints. This method oversees the entire crane processing for inbound and outbound pallet movements. Appendix E provides detailed flowcharts of these methods.

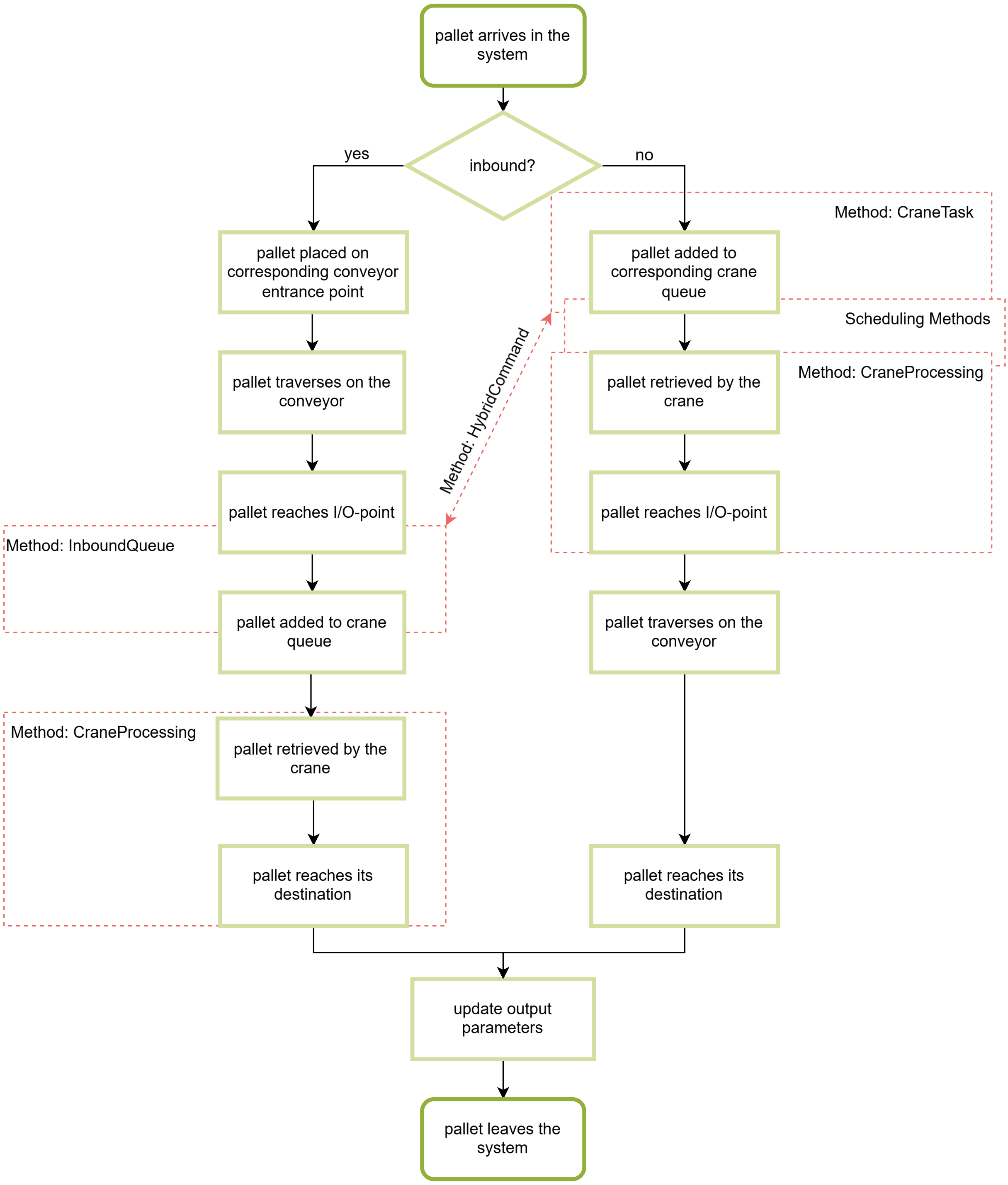


Figure 4.2: Flowchart General Simulation Logic: The flowchart illustrates the pallet flow through the high-bay warehouse and highlights the methods responsible for determining and executing the scheduling logic.

We implement the conveyor system using the conveyor modules available in Siemens Tecnomatix Plant Simulation. These modules inherently manage pallet movements, eliminating the need to explicitly model constraints such as pallet overtaking. Each conveyor spot can hold a single pallet at a time and automatically advances the pallet whenever possible. As a result, the conveyor system in the simulation naturally enforces a relaxed no-wait constraint. This differs from the mathematical model, where such constraints must be explicitly formulated.

5 SIMULATION EXPERIMENTS

This chapter's main goal is to answer the fourth research question: Which model configuration performs best compared to the current system under different scenarios?

First, Section 5.1 presents the validation and verification of the simulation model. Afterward, Section 5.2 outlines the experimental setups, while Section 5.3 explores the results of the conducted experiments. Finally, Section 5.4 summarizes the key findings. In this chapter, an *experiment* refers to a specific set of input configurations. In contrast, a *replication* refers to a single simulation run using a particular stream of random numbers. Multiple replications are conducted by varying the random number streams.

5.1 Verification and Validation

This section focuses on validating the model's performance, ensuring it adequately represents the real-world system, and enabling its confident use as a decision-support tool. We developed the conceptual model (Section 4.4) through expert consultations and direct observations of the real-world system. Validation of the simulation model based on this conceptual framework involves three key steps: verification, operational, and experimental validation.

5.1.1 Verification

Verification is conducted continuously throughout the simulation study to confirm that the implemented model accurately follows the conceptual model (Robinson, 2014). Frequent expert consultations ensure the implemented logic aligns with the conceptual assumptions and structure. We verify this alignment through visual observation of the animated elements in the simulation model and discussions to confirm that the underlying logic reflects real-world constraints. The flowcharts provided in Appendix E help the discussion with experts as they illustrate the simulation methods' logic software independent. Additionally, we perform systematic reviews of the code to detect any syntax and logical errors.

We evaluate three simplified test scenarios to verify the model's logic further. By using fixed durations for crane travel times and operator actions, we remove variability, making it easier to trace the flow of elements through the system. Each test focuses on a specific aspect of the model's logic: adherence to pipeline and workstation sequence requirements, compliance with prioritization rules, and execution of hybrid command requirements.

Finally, we use pallet request data and inbound start times from a one-hour segment of the real dataset to test the model's expected behavior against simulation outcomes. We select this one hour, taken from a day with minimal outliers and including all possible movement directions (both inbound and outbound movements to all locations), to ensure comprehensive testing across scenarios and allow this data segment to serve in operational validation. Based on these criteria, we choose data from December 4, 2023, between 8 and 9 a.m. We calculate each pallet's expected paths and timings and compare them with the simulated results.

Across all four experimental scenarios, the calculations show only minor deviations in the simulated timings. Any observed differences could be explained by pallet interactions on the conveyor, which are not considered in the expected lead time calculations. This confirms that the simulation model accurately reflects the conceptual model and aligns with the logic described by the experts. Appendix F provides detailed datasets for each experimental scenario.

5.1.2 Operational Validation

Operational validation assesses how well the model's outputs align with historical data to ensure accuracy in replicating system performance. In our approach, we compare the model's performance with historical data using the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) as key validation metrics. Furthermore, summary statistics and visual comparisons, such as histograms, provide additional insights into the alignment between the model and historical data.

The primary performance measure is the lead time, representing the duration between the request and destination arrival times. The calculated error for this metric reflects how accurately the model reproduces overall system performance compares to historical data on a per-pallet basis. However, validating only the overall lead time may obscure discrepancies in the individual components contributing to it. Therefore, we also evaluate the subcomponents contributing to the overall lead time. Appendix G presents the detailed results of these comparisons.

While system-wide comparisons confirm that the simulation captures overall performance with reasonable accuracy, deviations remain on a per-pallet basis – particularly in operator behavior and queueing times. The most notable discrepancies appear in outbound movements for EP0 and the workstations.

Several factors contribute to these discrepancies:

1. Limited available documentation and expert insights, resulting in uncertainties regarding specific AS/RS processes, as well as system durations and flows.
2. Limitations in recorded data, such as conveyor retrieval times, which are essential for accurately capturing the full system dynamics.

Historical data analysis reveals discrepancies between the simulation model's outbound logic for workstations and real-world processes. Despite conducting ten additional simulation experiments to adjust the logic, significant differences in queueing time statistics persist. The simulation consistently underestimates queueing times, and multiple modifications fail to resolve these discrepancies. Consequently, we revert to the original logic verified by experts, where cranes can retrieve workstation pallets when the previous pallet in the sequence starts its outbound movement.

The system lacks documentation on two key aspects: the time operators take to retrieve full outbound pallets from the conveyor and the empty crane travel times. Additionally, historical data records inbound pallet crane travel and queueing times as a single timestamp, making it difficult to model these components separately. In contrast, outbound pallet crane movements are well-documented. This allows us to make more precise assumptions for inbound pallets, despite the lack of separate timestamps for their crane travel and queueing times. Histogram comparisons of crane processing and queueing times for inbound pallets confirm that the model accurately captured overall system trends.

Modeling operator behavior proves more challenging. We conduct two experiments using existing data to estimate operator behavior. One method estimates waiting times based on the recorded arrival of the next pallet, as the retrieval of the previous pallet must occur before its arrival. The other approach estimates waiting times by measuring traversal times across the last three conveyor spots and subtracting the minimum required travel time, accounting for potential delays due to preceding pallets. In addition, two expert-opinion-based experiments provide alternative estimates. The expert-based distributions generally produce more realistic operator behavior, except for EP1, where the distribution derived from conveyor traversal durations is more accurate. While the model accurately captures trends for MP0 and EP1, significant deviations remain for EP0, and additional experiments do not resolve these differences.

Following consultations with experts and the analysis in Appendix G, we summarized the agreed-upon input parameters in Table 5.1. For the loaded outbound crane movement and workstation operator behavior, the simulation applies the distributions only when a pallet is identified as an outlier, as we can not use the historical durations for those pallets.

Crane Specifications	Distribution	Distribution Parameters (time in minutes)			
		μ	σ	Lower Bound	Upper Bound
		Operator Behavior: Workstations (in minutes)			
F1 (MP0)	lognormal	11.27	25.40	0.25	60
F2 (MP0)	lognormal	10.03	19.73	0.25	60
F3 (MP0)	lognormal	9.60	18.52	0.25	60
F4 (MP0)	lognormal	9.48	20.07	0.25	60
F5 (MP0)	lognormal	7.87	13.22	0.25	60
P1 (EP1)	lognormal	4.68	8.45	0.25	30
P2 (EP1)	lognormal	4.80	9.52	0.25	30
		Operator Behavior: Full Outbound Locations (in minutes)			
Out1 (MP0)	lognormal	3.50	2.67	0.17	15
Out3 (EP0)	normal	0.33	1.33	0.17	5
Out2 (EP1)	lognormal	29.08	625.67	0.17	8
		Crane Processing Times (in seconds)			
empty, single command	normal	37.26	8.74	13	63
	+ uniform			0	15
empty, dual command	uniform			20	25
loaded, inbound	normal	37.26	8.74	13	63
loaded, outbound	normal	42.26	8.74	13	63

Table 5.1: Input Parameter Distributions for the Simulation Model

5.1.3 Experimental Validation

Before conducting experiments to improve the system performance, obtaining accurate data on the model performance is crucial, thereby avoiding biased and misleading results. Key aspects of this process include mitigating initialization bias and collecting sufficient output data, as emphasized by Robinson (2014).

Initialization Bias Euroma operates on a 24/7 schedule, meaning the system lacks a clear starting point with no work in progress. Therefore, collecting results from the beginning of a simulation run with an initially empty system could produce biased outcomes. Since pallet flow fluctuates and pallets typically influence one another only when their request times are close, moments of an empty system occur naturally but inconsistently. We implement a one-day warm-up period to address this, during which the system does not collect data. This approach records results only after the system reached realistic operating conditions.

We determined the duration of the warm-up period based on Welch's graphical procedure, which identifies the warm-up phase by plotting moving averages of lead times. From approximately 480 pallets onward, the plot stabilizes, indicating the end of the warm-up phase. This number aligns closely with the typical number of pallet requests on a weekend day, reinforcing the choice of a one-day warm-up period. The reader can find further details on this validation process in Appendix H. Additionally, we assume that the AS/RS is fully stocked at the start, containing all pallets that will be requested during the simulation.

Sufficient Output Data Sufficient output data can be obtained by extending the simulation runtime or performing multiple replications. Each replication generates a unique sequence of random events due to the random number streams used. By averaging results across multiple replications, we can estimate the model's performance more reliably (Robinson, 2014).

We assess convergence of results as additional replications are performed, to determine the minimum number of replications. This approach indicates that the simulation requires at least three replications. However, as a general guideline, a simulation should include at least five replications. A common rule of thumb suggests that the simulation run length should be at least ten times the warm-up period (Robinson, 2014). Based on these guidelines, we set the run length to two weeks and the number of replications to five. Appendix H.2 provides further details and supporting calculations for these choices.

5.2 Experimental Setup

The simulation experiments evaluate different scheduling logics and analyze the impact of operational factors. The Baseline simulation is based on the validated and verified model and represents the current system at Euroma. In this scenario, scheduling follows Euroma's existing approach: a FCFS strategy with workstation prioritization and pipeline thresholds, as detailed in Table 2.1. Section 5.3.1 compares the Baseline simulation's performance with the historical data.

Section 5.3.2 investigates the potential impact of scheduling improvements outlined in Section 4.6. We compare the FCFS approach and R1 logic against the Baseline simulation to ensure that observed performance differences result from actual changes rather than modeling simplifications or assumptions. By comparing against the Baseline simulation, we ensure consistency in the analysis, as both sets of results are based on the same assumptions and simplifications.

Beyond scheduling logic, the experiments explore variations in pipeline configurations, operator behavior, and pallet demand to assess the system's robustness. Table 5.2 provides an overview of the experimental setup.

Operator time, defined as the time required to retrieve pallets from the conveyor or process them at a workstation, is a key experimental factor for two reasons:

Parameter		Description/Value		
		Scheduling Logic		
Baseline		A modified FCFS approach where pallets requested for a workstation are prioritized. This is the current prioritization rule applied by Euroma.		
FCFS		A pure first-come-first-served rule without any additional prioritization.		
R1		A dispatching rules combining multiple scheduling criteria, identified by Ferreira et al. (2022).		
		Operator Time		
		Exp. 3		
Full Outbound Pallets		[-10, 300]		
Workstation Pallets		–		
		Pipeline Configurations		
		Exp. 4a	Exp. 4b	Exp. 4c
Outfeed Lanes	*Out1* (MP0):	[3, 4, 5]	[5]	[7, 8]
	Out3 (EP0):	[10, 11, 12]	[10, 11, 12]	[24, 25, 26, 27, 28]
	Out2 (EP1):	[5, 6, 7]	[7]	[9, 10, 11]
Workstations	*F1 - F4* (MP0):	[7]	[3, 4, 5, 6]	[7]
	F5 (MP0):	[5]	[3, 4]	[5]
	P1, P2 (EP1):	[7]	[3, 4, 5, 6]	[7]
		Looping Configurations		
		Exp. 4a	Exp. 4b	Exp. 4c
Looping Behavior	*Out1* (MP0):	no	yes	yes
	Out3 (EP0):	yes	yes	yes
	Out2 (EP1):	yes	yes	yes
		Demand Configurations		
		Exp. 5		
Demand Increase Factors		[5%, 10%, 15%, 20%, 25%, 30%]		
		Experimental Settings		
Number of Replications		5		
Length of Warmup Period		1 day		
Run Length		14 days		

Table 5.2: Overview of Experimental Factors in the Simulation Study. The table presents the experimental factors used in the simulation study to analyze the impact of scheduling logic, operator time, and pipeline configurations.

1. The validation identifies deviations in operator times at full outbound locations, which rely on significant assumptions due to a lack of historical data.
2. As analyzed in Section 2.4.2, delays at the end location can significantly affect conveyor movement times and the queueing times of subsequent pallets. Additionally, examining performance under varying operator times accounts for potential human variability.

Section 5.3.3 assesses the impact of the operator duration on the performance of the three considered dispatching rules. Therefore, we modify the mean (μ) of the lognormal distribution representing operator behavior at full outbound locations. Since the μ for *Out3* (EP0) is 20 seconds with a lower bound of ten seconds, the maximum reduction applied to the μ is ten seconds. Additionally, we increase μ by up to 300 seconds in steps of five seconds to analyze the impact of extended operator behavior.

Experiments 4a to 4c in Section 5.3.4 analyze the pipeline configurations, which define the number of pallets allowed in transit or at a destination. We assess how different configurations influence outbound efficiency by increasing and decreasing the pipeline unit. Pipelines can restrict or enhance flow efficiency, making it a critical factor in system performance.

Finally, Section 5.3.5 evaluates the robustness of scheduling rules and pipeline configurations for fluctuating pallet volumes. The demand increases ranging from 5% to 30%.

The primary performance indicators – total tardiness and tardiness ratio – measure the adjustments' effectiveness in reducing delays for full outbound pallets. Additional output parameters assess the influence on workstation and inbound pallet flows. Sections 2.3.1 and 4.4 discuss the KPIs used in the analysis in more detail.

5.3 Results

The experiments provide insights into the performance of the three dispatching rules – Current Prioritization (Baseline), FCFS, and R1 – under various scenarios involving different operator times and pipeline configurations. We compare and analyze the results based on the KPIs determined in Section 2.3.1, primarily focusing on improving the on-time delivery percentage and reducing tardiness for full outbound pallets. Workstation and inbound pallet flows are secondary measures to ensure their performance remains stable. Appendix K provides the detailed results in tables for all experiments.

Computation Time The computation time for each replication solely depends on the used dispatching rule because all other methods work the same (regardless of the dispatching rule). Table 5.3 provides the computation time among the three dispatching rules. The average decision time indicates that FCFS and the Baseline logic determine the next retrieval pallet faster than R1. As a result, the average run time of a replication for R1 takes 13 seconds longer than the FCFS simulation.

	Average Run Time (sec)	Average Decision Time (sec)
Baseline	125.50	0.000026
FCFS	115.99	0.000022
R1	129.09	0.000126

Table 5.3: Comparison of Computational Time Among Dispatching Rules. The average runtime represents the total time for a single simulation replication, while the average decision time reflects the time to determine the next crane task. Both metrics, reported in seconds, highlight differences in computational efficiency.

5.3.1 Experiment 1: Comparison Historical Data with Baseline Simulation

On-Time Delivery Percentage The Baseline simulation generally outperforms the real system regarding on-time delivery percentage. Without altering the validated and verified parameters determined in Section 5.1, the Baseline logic achieves an 86.28% on-time delivery rate, which is approximately 1.10% higher than the historical data analysis reveals.

Notable differences emerge when distinguishing the on-time delivery percentage between pallet types. As shown in Table 5.4, full outbound pallets in the Baseline simulation reach their destination on time about 4% more often than in the real system. In contrast, workstation pallets in the Baseline simulation show a 2% decrease in on-time delivery performance.

Tardiness When evaluating average pallet tardiness, the Baseline simulation underperforms. The actual system has a lower average tardiness per tardy pallet for both types. These findings align with the results from the validation (Section 5.1 and Appendix G). Lead times for full outbound pallets in the Baseline simulation are generally shorter than those in the historical dataset, contributing to increased on-time delivery. While workstation pallet lead times are also lower, this does not improve on-time delivery; instead, it leads to more tardy workstation pallets. Two potential explanations for this discrepancy include:

- The due dates of workstation pallets depend on the processing times of preceding pallets. A shorter lead time for a preceding pallet also necessitates a shorter lead time for the succeeding pallet to maintain on-time delivery.
- Uncertainty in the logic governing workstation outbound pallet processing may contribute to the observed differences.

	All Outbound Pallets	Full Outbound Pallets	Workstation Pallets
		On-Time Delivery Percentage	
Baseline Simulation	86.28%	90.78%	81.34%
Historical Data	85.18%	86.44%	83.46%
		Pallet Tardiness (min)	
Baseline Simulation	21.06	55.08	2.65
Historical Data	12.41	23.11	0.41

Table 5.4: Results Experiment 1: Comparison Historical Data with Baseline Simulation. The table presents the on-time delivery percentage and average tardiness for outbound pallet flows based on historical data and the Baseline simulation. The observed differences reflect the deviations identified during validation.

Table 5.5 highlights that the Baseline simulation produces shorter durations for all queueing and movement durations than the real system, especially for workstation pallets. This reinforces the notion that the logic for processing workstation outbound pallets in the Baseline simulation does not accurately replicate the real system.

5.3.2 Experiment 2: Comparison of Dispatching Rules

The second experiment compares the performance of the three dispatching rules – Baseline, FCFS, and R1 – under the same conditions established in Section 5.1. While the Baseline simulation and FCFS exhibit similar performances, the R1 logic stands out with notable differences. Table 5.5 summarizes the detailed results.

On-Time Delivery Percentage				
	Historical Data	Baseline Simulation	FCFS Simulation	R1 Simulation
All Outbound Pallets	85.18%	86.28%	86.39%	86.67%
Full Outbound Pallets	86.44%	90.78%	90.90%	91.35%
Workstation Pallets	83.46%	81.34%	81.45%	81.53%
Pallet Tardiness (min)				
	Historical Data	Baseline Simulation	FCFS Simulation	R1 Simulation
All Outbound Pallets	12.41	21.06	21.27	22.14
Full Outbound Pallets	23.11	55.08	55.83	60.08
Workstation Pallets	0.41	2.65	2.66	2.73
Maximum Pallet Tardiness (h)				
	Historical Data	Baseline Simulation	FCFS Simulation	R1 Simulation
Full Outbound Pallets	1.58	3.72	3.72	6.60
Workstation Pallets	0.29	0.52	0.56	0.55
Full Outbound Pallet Volume Exceeding Threshold				
	Historical Data	Baseline Simulation	FCFS Simulation	R1 Simulation
> 30 min Tardiness	4.63%	4.83%	4.92%	4.07%
> 60 min Tardiness	0.91%	2.92%	2.93%	2.44%
> 120 min Tardiness	0.00%	1.38%	1.44%	1.13%
Queueing and Movement Durations (min)				
	Historical Data	Baseline Simulation	FCFS Simulation	R1 Simulation
Inbound Queueing Time	1.04	0.90	0.90	0.90
Full Outbound Queueing Time	19.22	17.24	17.17	17.24
Workstation Outbound Queueing Time	41.36	6.15	6.38	6.25
Full Outbound Conveyor Time	12.12	17.40	17.30	17.30
Full Outbound Lead Time	32.03	27.77	27.62	27.66
Workstation Outbound Lead Time	129.33	40.51	40.61	40.48

Table 5.5: Results Experiment 2: Comparison of Three Dispatching Rules

Although the primary focus is on full outbound pallets, we include workstation pallet performance in the figures to provide a more comprehensive view of the system's behavior under different dispatching rules. This experiment focuses on the comparison of the dispatching rules. Since workstation pallets share resources with full outbound pallets, changes in scheduling logic can affect their performance. Including both pallet types allows us to assess whether optimizing full outbound pallet performance comes at the expense of workstation pallet efficiency or if certain rules improve both simultaneously.

On-Time Delivery Percentage Among the three dispatching rules, the R1 scheduling logic achieves the highest on-time delivery percentage for both pallet types: 91.35% for full outbound pallets and 81.53% for workstation pallets. Compared to the Baseline logic, this results in approximately 21 more full outbound pallets and six more workstation pallets delivered on time over two weeks – equivalent to about two additional pallets per day. FCFS performs second best, improving on-time deliveries by about one pallet per day compared to the Baseline logic. Figure 5.1 visualizes the comparison between the three dispatching rules. Additionally, the performance of the real system is shown, underscoring the findings discussed in Experiment 1.

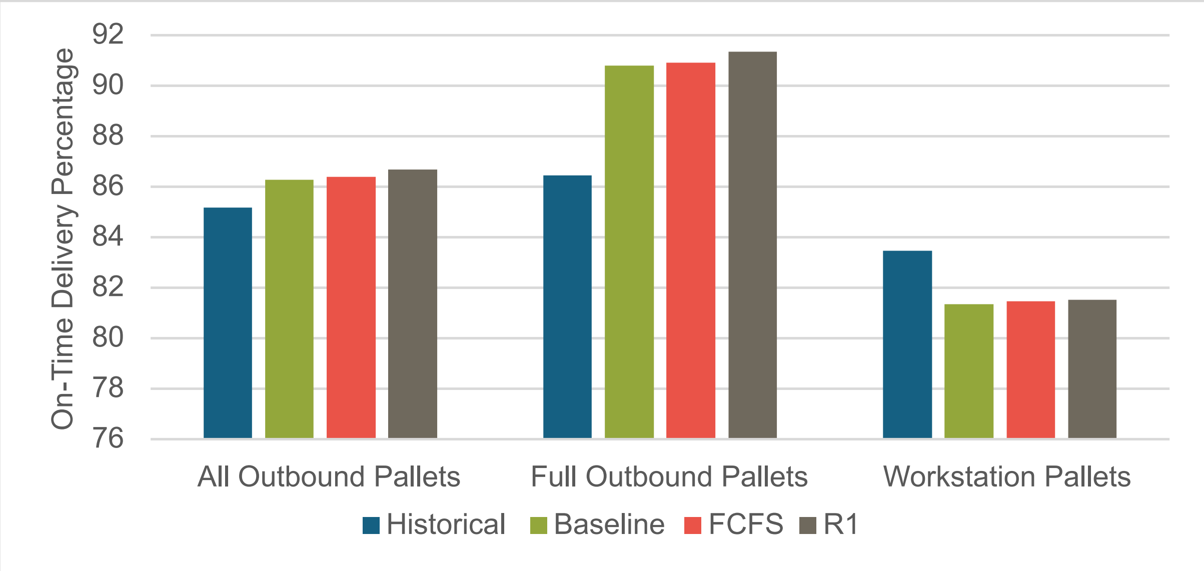
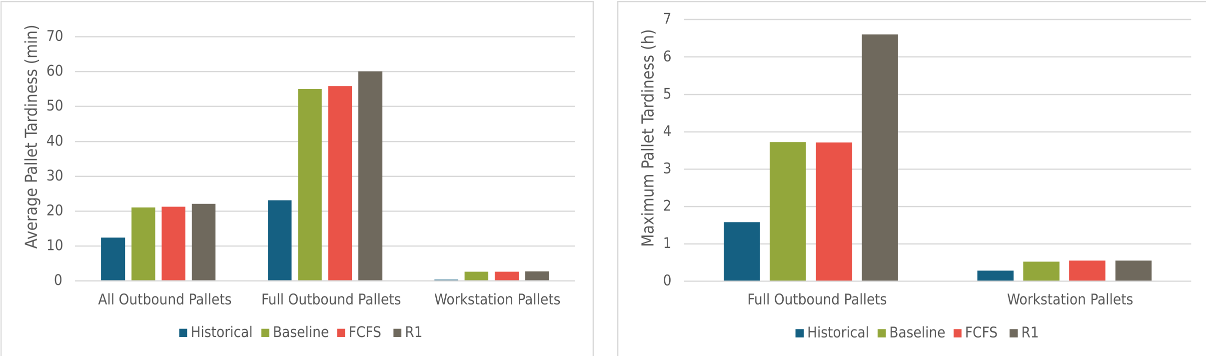


Figure 5.1: Comparison of On-Time Delivery Percentage between Dispatching Rules. The chart distinguishes the dispatching rules by color and groups them by pallet type. The real system's performance, derived from historical data analysis, is included for reference.

Tardiness While R1 improves on-time delivery percentages, it results in higher average tardiness for full outbound pallets. Figure 5.2a shows that R1 exceeds FCFS by an average of five minutes per tardy pallet. For workstation pallets, tardiness differences between the rules are minimal, with a maximum variation of five seconds per pallet.

Figure 5.2b depicts a similar trend for maximum pallet tardiness. While the maximum workstation pallet tardiness remains comparable across all three rules, R1 results in a maximum full outbound pallet tardiness that is about three hours longer than for the other two dispatching rules. The high maximum tardiness for R1's full outbound pallets suggests that only a few pallets disproportionately increase the average tardiness. The distribution of tardy pallets exceeding the thresholds of 30, 60 and 120 minutes supports this observation. In these categories, R1 consistently shows the lowest volume of tardy pallets, as presented in Table 5.5.

Queueing and Movement Times The three dispatching rules show no significant differences in queueing and movement times. As expected, the inbound queueing time remains consistent across all three dispatching rules since they all follow the same hybrid command strategy. The Baseline simulation exhibits the shortest queueing times for workstation pallets, while FCFS achieves the lowest queueing times for full outbound pallets. However, the differences between the dispatching rules are minimal, with a maximum variation of 14 seconds.



(a) Pallet Tardiness (b) Maximum Pallet Tardiness

Figure 5.2: Comparison of Maximum and Average Tardiness per Tardy Outbound Pallet between Dispatching Rules. The charts distinguish the dispatching rules by color and group them by pallet type. The real system's performance, derived from historical data analysis, is included for reference. The average tardiness is given in minutes, while the maximum tardiness is represented in hours.

5.3.3 Experiment 3: Impact of Operator Durations

Operator times significantly influence system performance. As shown in Figure 5.3 and Figure 5.4, shorter operator times generally improve on-time delivery percentages and reduce tardiness. In contrast, longer operator times have the opposite effect. The x-axis of the graphs represents adjustments to the mean (μ) of the lognormal distribution for full outbound pallet retrieval times (operator time) from Table 5.1.

On-Time Delivery Percentage The on-time delivery percentage for full outbound pallets across the three dispatching rules remains relatively similar for shorter operator times. Among them, the R1 scheduling logic generally achieves the highest on-time delivery percentage. The Baseline logic and FCFS perform slightly worse by an average of 0.4%. As the operator time increases, the difference between the dispatching rules becomes more significant.

From the point where we increase the mean (μ) of the lognormal distribution by 135 seconds, R1 consistently outperforms both the Baseline logic and FCFS by at least 2% in on-time delivery percentage. The maximum observed difference amounts to 6.7%. Meanwhile, the performance gap between FCFS and the Baseline logic remains negligible. Furthermore, Figure 5.3 illustrates a critical threshold where on-time delivery percentages decline significantly. Increasing μ by up to 95 seconds causes only minor decreases across all dispatching rules. Beyond this point, on-time delivery percentages decline sharply, with reductions of up to 1.71% when adding just five seconds to μ (FCFS from 110 to 115 seconds). After an additional increase of 120 seconds to μ, the decline flattens out, indicating a stabilization in the on-time delivery percentage.

The on-time delivery percentage of workstation pallets fluctuates across all three dispatching rules between 81% and 82% without a clear pattern. Given this stability and the primary focus on full outbound pallet performance, we excluded it from the figure. While small variation in on-time delivery can have significant impacts, the lack of a trend suggests that changes in operator time do not significantly affect workstation pallet performance. We attribute this fluctuating behavior to the dependency of workstation pallet due dates on the processing times of preceding pallets, which are not directly influenced by changes to full outbound operator times. However, increases and decreases in retrieval time of full outbound pallets may provoke changes to the shared resource sequences. As workstation pallets must strictly adhere to their given sequence, these adjustments can result in small changes in crane operations. For instance, when the next workstation pallet in sequence is ready to start, a previously idle crane may now be occupied, or vice versa. Such changes can lead to variations in queueing times and conveyor times for workstation pallets. The average workstation pallet tardiness is only about 2.6 minutes, so these small changes can significantly impact the on-time delivery percentage.

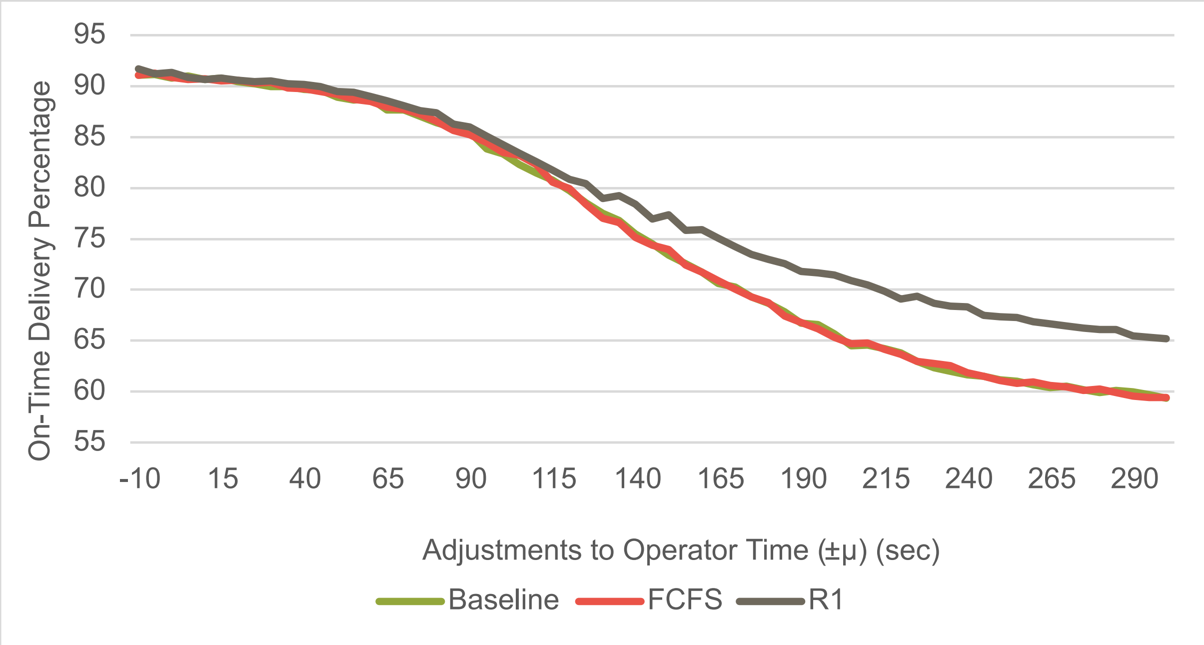


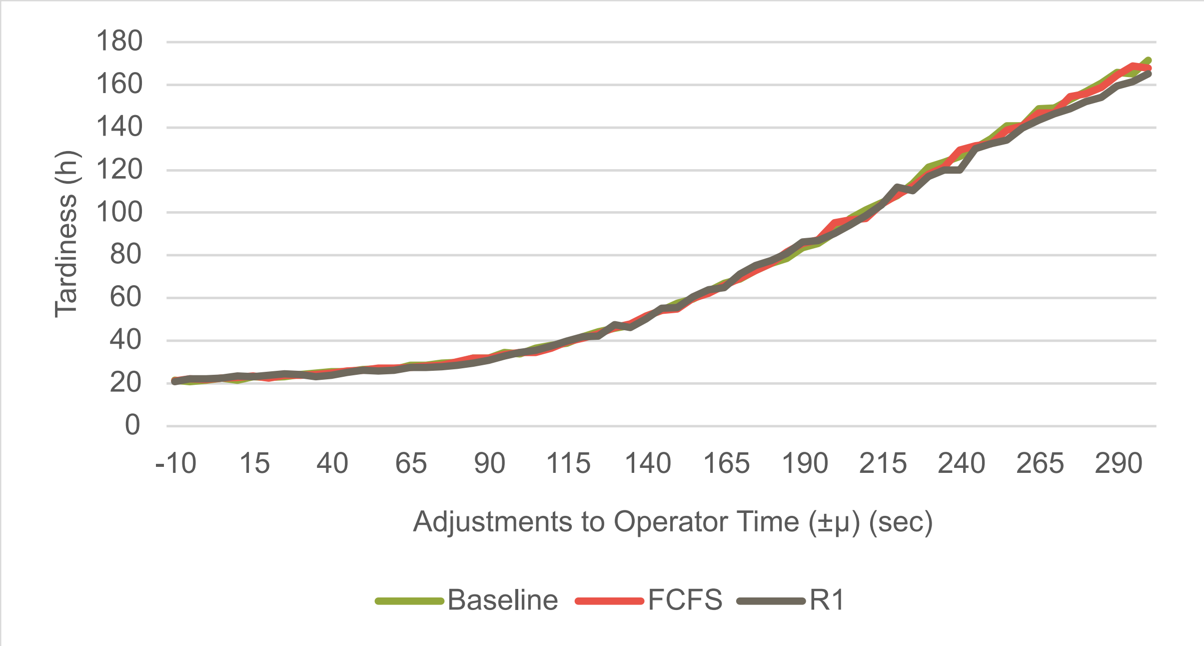
Figure 5.3: Comparison of Full Outbound On-Time Delivery Percentages between Dispatching Rules under Different Operator Times. The chart distinguishes the dispatching rules by color. The x-axis represents the adjustment to the operator time, where the value indicates the addition or subtraction to μ from the lognormal distribution.

Tardiness The average daily tardiness follows a similar trend as the on-time delivery percentage. Increasing the full outbound operator time worsens the daily tardiness of full outbound pallets. This trend is evident in Figure 5.4a. However, due to the relatively similar performance across dispatching rules and the more significant impact of operator time adjustments, Figure 5.4a does not highlight variations between individual rules.

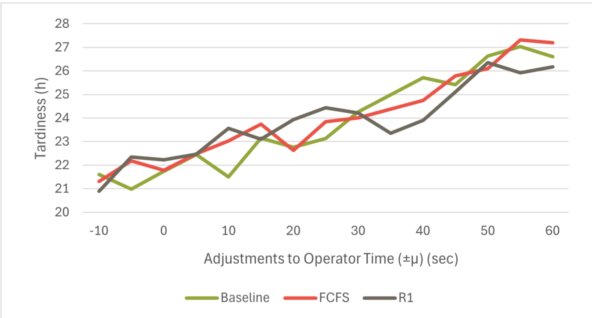
To provide a clearer view of these differences, Figure 5.4b and Figure 5.4c present a more focused comparison at different operator time levels. At lower operator times, the Baseline and FCFS scheduling logic generally perform slightly better. As the operator time increases, no single dispatching rule consistently outperforms the others. Notably, from an increase of μ by 225 seconds onward, R1 consistently achieves lower average daily tardiness compared to FCFS and the Baseline scheduling logic.

Much like their on-time delivery percentage, the daily tardiness of workstation pallets exhibits fluctuating behavior without a clear pattern. We attribute this variability again to the dependency on their due dates and changes in the utilization of shared resources.

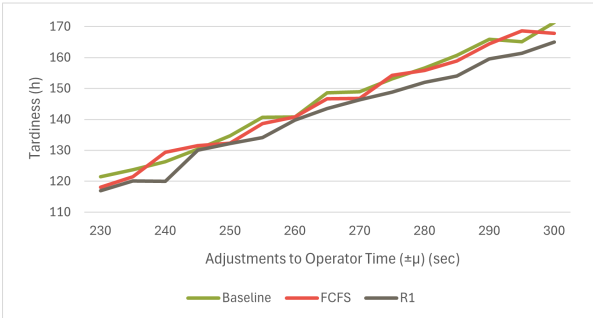
Queueing and Movement Times The inbound and workstation queueing times remain largely unaffected by adjustments to the full outbound operator times. While the inbound queueing time decreases slightly – by up to 1.31 seconds as operator time increases – the workstation pallet



(a) Daily tardiness of Full Outbound Pallets Over the Entire Range of Operator Time Adjustments



(b) Zoomed-In View of Daily Tardiness for Operator Time Adjustments up to +60 Seconds



(c) Zoomed-In View of Daily Tardiness for Operator Time Adjustments from +225 Seconds onward

Figure 5.4: Comparison of Average Daily Tardiness of Full Outbound Pallets between Dispatching Rules under Different Full Outbound Operator Times. The charts distinguish the dispatching rules by color. The x-axis represents the adjustment to the operator time, where the value indicates the addition or subtraction to μ from the lognormal distribution.

queueing times fluctuate between 6.08 and 6.55 minutes without any identifiable pattern. In contrast, the queueing time for full outbound pallets changes significantly. As expected, shorter operator times result in lower queueing times, whereas longer operator times increase them. The lowest observed queueing time averages around 17 minutes (at $\mu - 10$), while the highest queueing time approaches 60 minutes (at $\mu + 300$). Even though the R1 scheduling logic tends to achieve lower queueing times, the differences among the three dispatching rules are minimal for shorter operator times. As operator times increase, the gap between R1 and the other two rules becomes more pronounced.

The lead times show a similar trend. Notably, the average lead time surpasses the 60-minute threshold for on-time delivery when increasing μ by 220 seconds for FCFS and the Baseline logic, and by 230 seconds for R1. Similarly, an increase in operator time increases the conveyor time. Unlike the queueing and lead times, the conveyor time increases proportionally with the operator time, suggesting that the increased operator times do not cause additional congestion on the conveyor but results in longer retrieval waiting times at the last spot on the outfeed lanes.

5.3.4 Experiment 4: Impact of Pipeline Configurations

Experiment 4 investigates how changes to the pipeline threshold influence pallet flow performance. Table 2.1 in Section 2.1.2 presents the current configurations Euroma applies for the pipeline threshold. We structure the analysis of Experiment 4 into three parts. First, Experiment 4a explores the effects of increasing or decreasing the pipeline threshold for full outbound pallets. Next, Experiment 4b shifts the focus to workstation pallets, examining how their pipeline threshold influences workstation and full outbound pallet performance. Finally, Experiment 4c uses the methodology introduced by Haneyah et al. (2013) to determine the appropriate pipeline threshold for full outbound pallets.

Experiment 4a: Impact of Pipeline Configurations – Adjustments in Full Outbound Destination Configurations The impact of pipeline adjustments varies depending on the dispatching rule, type of pallet, and KPI. Generally, increasing the pipeline improves on-time delivery percentages while reducing tardiness, particularly for full outbound pallets. In this experiment, we increase the pipeline thresholds for *Out1* (MP0) and *Out3* (EP0), whereas the threshold for *Out2* (EP1) is decreased. We base this decision on their original configurations: Euroma set the threshold for *Out1* (three) according to its available outfeed lane spots, whereas the thresholds for *Out2* (seven) and *Out3* (ten) exceeded their outfeed lane capacity. As illustrated in Figure 2.2b, the original threshold of *Out3* allows all waiting pallets to remain on the conveyor without obstructing other pallets. In contrast, the threshold for *Out2* exceeded the number of pallets that could queue on the outfeed lane without causing congestion on the conveyor. We do not adjust the pipeline threshold for workstation pallets.

On-Time Delivery Percentage Figure 5.5 shows how different pipeline threshold settings affect on-time delivery for full outbound pallets. The x-axis represents different pipeline configurations, with *Out1* at the top, *Out2* in the middle, and *Out3* at the bottom. To analyze the impact of adjusting one threshold, one can observe performance variations for different values of that outfeed lane while keeping the other two thresholds constant.

We observe the most distinct effect of pipeline threshold adjustments for *Out1* (MP0). Increasing the pipeline threshold from three to five improves the on-time delivery percentage for full outbound pallets by about 1.70% for R1 and FCFS and 1.51% for the Baseline scheduling logic. In contrast, increasing the threshold for *Out3* (EP0) leads to a maximum improvement of only 0.30% (FCFS) and even a small reduction of 0.18% for R1. Decreasing the threshold for *Out2* (EP1) follows the same trend, reducing the on-time delivery percentage across all three dispatching rules. We observe the highest on-time delivery percentages for R1 (93.02%) at the pipeline configuration *Out1* = 5, *Out2* = 7, *Out3* = 10, whereas FCFS achieves its best performance (92.68%) at *Out1* = 5, *Out2* = 7, *Out3* = 11.

Adjusting the pipeline thresholds for full outbound pallets has little effect on the on-time delivery percentage of workstation pallets. The on-time delivery percentage for workstation pallets fluctuates between 81% and 82% with no clear pattern indicating whether an increase or decrease improves performance.

Tardiness Average pallet tardiness follows the same trend as the on-time delivery percentage: a higher pipeline threshold generally reduces tardiness. Increasing the threshold for *Out1* results in the most significant improvement, reducing full outbound pallet tardiness by an average of approximately 15 minutes for all three dispatching rules. In comparison, increasing the pipeline threshold for *Out2* and *Out3* reduces tardiness by a maximum of four minutes. Table 5.6 also presents this trend for the average daily tardiness. Increasing the *Out1* threshold

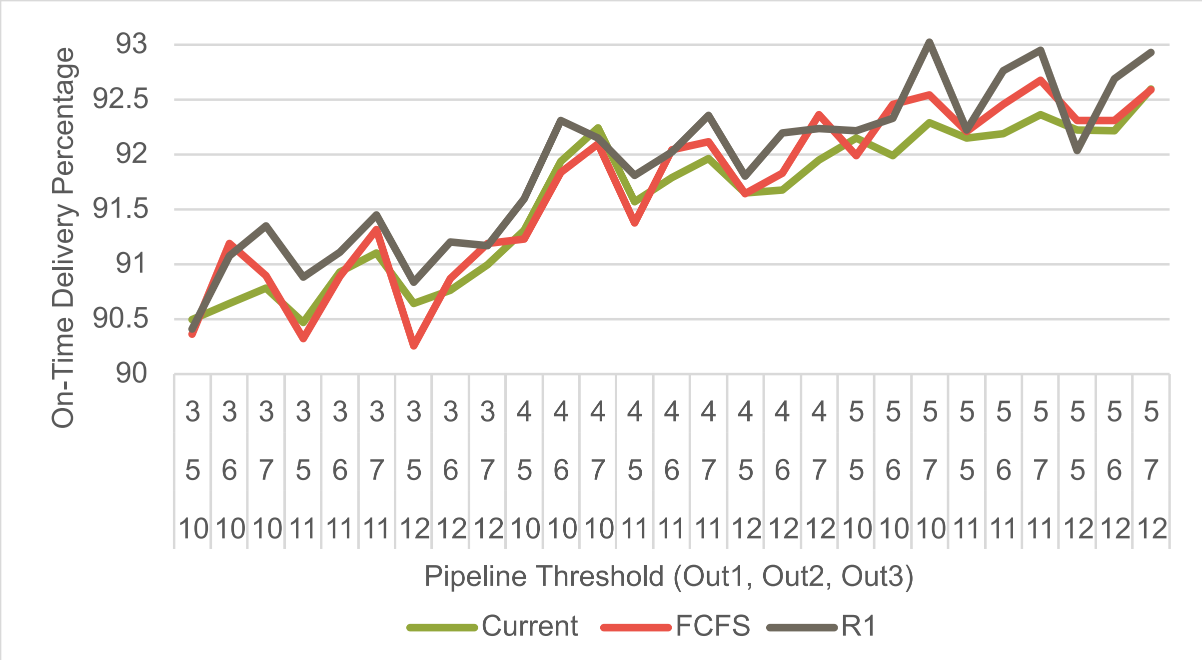


Figure 5.5: Comparison of On-Time Delivery Percentage between Dispatching Rules and Different Pipeline Configurations for Full Outbound Pallets. The chart distinguishes the dispatching rules by color. The x-axis indicates the pipeline threshold, i.e. the maximum number of pallets simultaneously in transit to an outfeed lane. The first row corresponds to *Out1*, the second to *Out2*, and the third to *Out3*.

from three to five reduces daily average tardiness by almost nine hours for FCFS and R1, while adjustments to the other pipeline thresholds result in reductions by a maximum of 90 minutes. Workstation tardiness shows no clear pattern, fluctuating by a maximum of ten seconds in average pallet tardiness.

Tardiness KPI (h)	Baseline Simulation		FCFS Simulation		R1 Simulation	
	[3, 7, 10]	[5, 7, 12]	[3, 7, 10]	[5, 7, 11]	[3, 7, 10]	[5, 7, 10]
Daily	23.67	19.2	23.71	14.98	24.19	15.57
Pallet	0.35	0.24	0.35	0.24	0.37	0.25
Maximum	3.72	2.76	3.72	2.67	6.60	4.48

Table 5.6: Results Experiment 4a: Tardiness Comparison Between High Pipeline Thresholds and Original Settings. This experiment compares full outbound tardiness values under the original pipeline thresholds with those best performing in Experiment 4a. The original thresholds are set at 3 for *Out1*, 7 for *Out2*, and 10 for *Out3*. Tardiness values are measured in hours.

Queueing and Movement Times The inbound and workstation queueing times remain largely unaffected by adjustments to the full outbound pipeline thresholds. While increasing the pipeline threshold slightly increases inbound queueing time (by up to one second), workstation pallet queueing times fluctuate between six and 6.5 minutes without an identifiable trend. In contrast, full outbound pallet queueing times show more significant changes. The FCFS logic produces by an average of 1.8 minutes the highest reduction when increasing the pipeline thresholds by one unit. In terms of outfeed lanes, *Out1* (MP0) shows the highest reduction with an average of 3.22 minutes. The configuration yielding the best performance results in substantial improvements compared to the original pipeline configurations, with a reduction in the queueing time of full outbound pallets of approximately four minutes across all dispatching rules. Specifically, the configuration *Out1* = 5, *Out2* = 7, *Out3* = 12, results in average queueing times of 13.02 minutes for R1, 13.06 minutes for FCFS, and 13.30 minutes for the Baseline logic.

The full outbound lead times follow a similar trend, decreasing by approximately one minute across all dispatching rules (to an average lead time of 25 minutes across all pipeline configurations) as the pipeline threshold increases. Similar to the full outbound queueing times, FCFS and *Out1* show the highest reductions. In contrast, the conveyor times increase slightly (up to 30 seconds) with higher pipeline thresholds. This minor increase indicates that a higher pipeline threshold only slightly impacts conveyor congestion.

Experiment 4b: Impact of Pipeline Configurations – Adjustments in Workstation Configurations Experiment 4a focuses solely on adjusting the pipeline threshold for full outbound pallets. The best settings identified for each dispatching rule in that experiment serve as the basis for Experiment 4b. Here, we adjust workstation pipeline thresholds and analyze their impact on workstation performance and full outbound pallet performance.

Unlike Experiment 4a, which primarily impacts full outbound pallet KPIs, Experiment 4b significantly affects workstation KPIs. We assumed that reducing workstation pipeline thresholds has a limited effect on their on-time delivery since due dates depend on the lead times of preceding pallets. However, the results show that reducing workstation pipeline thresholds decreases on-time delivery percentages by up to 9.5% to a minimum of 71%.

The three dispatching rules perform similarly, with no clear advantage for any specific rule. Even though the on-time delivery percentage of full outbound pallets remains largely unaffected, we observe a slight trend: reducing workstation pipeline thresholds leads to a marginal increase in the full outbound on-time delivery percentage. As the on-time delivery percentage remains within a range of 92% to 93%, we can not observe a clear improvement compared to Experiment 4a. Specifically, by decreasing the workstation pipeline threshold, the best-performing configuration for each dispatching rule increases the full outbound on-time delivery percentage by an average of 0.39% while simultaneously decreasing the workstation on-time delivery percentage by an average of 5.64%.

Reducing the workstation pipeline thresholds to three decreases the average conveyor movement duration of full outbound pallets by approximately four minutes. This result suggests that workstation pallets on the conveyor significantly influence the travel duration of full outbound pallets.

Experiment 4c: Impact of Pipeline Configurations – Pipeline Calculation Experiments 4a and 4b adjust pipeline thresholds by increasing or decreasing their original values. In contrast, Experiment 4c applies the pipeline calculation introduced by Haneyah et al. (2013) in Chapter 3.3. Using Equation 3.5, we calculate pipeline thresholds under different time allowance (ta) values, ranging from zero to one minute. These calculations result in increased pipeline thresholds across all full outbound locations compared to Experiment 4a. Since the threshold for *Out1* significantly exceeds the available buffer spots, we introduce a looping mechanism similar to those for *Out2* and *Out3*. Appendix I details the pipeline threshold calculations.

Experiment 4c confirms previous findings: increasing pipeline thresholds improves on-time delivery percentages, though the improvement is less pronounced than in Experiment 4a. The highest observed on-time delivery percentage for full outbound pallets is 93.62%, achieved using outbound logic R1 with pipeline configurations of 7 (*Out1*), 11 (*Out2*), and 25 (*Out3*). This represents only a 0.60% improvement compared to the best configuration in Experiment 4a (5, 7, 10). Similarly, for FCFS and the Baseline simulation, the on-time delivery percentage increases by just 0.5%, while the maximum workstation on-time delivery percentage even decreases by 0.3% for R1 and the Baseline simulation (while increasing by only 0.03% for FCFS).

We observe a similar trend for tardiness-related KPIs. Table 5.7 shows slight reductions in daily, pallet, and maximum tardiness in Experiment 4c compared to Experiment 4a. Given the pipeline adjustments, the improvements remain relatively small. The best-performing configuration in Experiment 4c reduces daily tardiness by approximately two hours across all dispatching rules. Reductions in average pallet tardiness are less pronounced, and the maximum tardiness values remain largely unchanged. Table 5.7 provides the corresponding pipeline thresholds for each experiment above the tardiness values.

Tardiness KPI (h)	Baseline Simulation		FCFS Simulation		R1 Simulation	
	Exp. 4a	Exp. 4c	Exp. 4a	Exp. 4c	Exp. 4a	Exp. 4c
Daily	[5, 6, 10]	[8, 10, 28]	[5, 7, 12]	[8, 10, 26]	[5, 7, 12]	[7, 9, 28]
	14.95	12.56	14.51	12.32	14.51	12.56
Pallet	[5, 6, 12]	[8, 10, 25]	[5, 5, 10]	[8, 10, 26]	[5, 5, 10]	[7, 11, 24]
	2.65	2.52	2.43	2.38	4.36	4.00
Maximum	[5, 6, 10]	[8, 10, 28]	[5, 7, 12]	[8, 10, 26]	[5, 7, 12]	[8, 9, 28]
	0.23	0.20	0.23	0.20	0.23	0.21

Table 5.7: Results Experiment 4c: Tardiness Comparison Between Various Pipeline Thresholds. This experiment compares best tardiness values under the thresholds in Experiment 4a with those from Experiment 4c. The corresponding threshold values are provided above the tardiness values in the following format [*Out1*, *Out2*, *Out3*]. Tardiness values are measured in hours.

The differences in the queueing and movement times are more significant. Experiment 4c shows an increase in conveyor movement times, fluctuating between 19 and 20 minutes. This represents an increase of on average 2.4 minutes. We attribute this increase to the higher pallet volume on the conveyor, resulting in:

- more frequent waiting times as pallets queue behind each other before processing,
- and increased looping, as more pallets in transit result in more pallets potentially congesting the outfeed lanes.

Even though the conveyor movement time increases, the lead time decreases, attributed to the significant decrease in queueing time (average of seven minutes) across all dispatching rules.

5.3.5 Experiment 5: Impact of Increased Demand

Euroma aims for long-term growth. Therefore, it is essential to analyze the impact of increased demand and how different dispatching rules respond to these changes. To address this, we conduct experiments simulating demand increases ranging from 5% to 30%. Appendix J outlines the methodology for adjusting demand levels. We perform these experiments under three different pipeline threshold configurations [*Out1*, *Out2*, *Out3*]:

- the currently applied threshold: [3, 7, 10]

- and two of the best performing thresholds from Experiment 4a and 4c: [5, 7, 11] and [7, 11, 27]

As expected, performance deteriorates when demand increases. While R1 generally achieves the highest on-time delivery rate for full outbound pallets under lower demand conditions, its advantage diminishes when demand increases beyond 10%. Beyond this point, the performance of R1 aligns with the performance of the other two dispatching rules. When demand increases by 30%, on-time delivery rates decrease by approximately 2% across all dispatching rules and pipeline threshold configurations compared to historical demand levels.

Beyond on-time delivery rates, increased demand also negatively impacts movement and queuing times. Specifically, the queueing time for full outbound pallets increases by approximately three minutes across all dispatching rules when demand rises by 30% for lower dispatching rules ([3, 7, 10] and [5, 7, 11]). For the highest threshold ([7, 11, 27]), the queuing time increases by up to 2.25 minutes. Similarly, conveyor travel times also rise with increased demand. However, unlike queuing times, the most significant increase occurs at the highest pipeline threshold rather than the lower thresholds. This effect is likely due to more frequent pallet interactions on the conveyor for higher pipeline thresholds. As a result, the lead time for full outbound pallets increases for all pipeline configurations, leading to higher tardiness levels.

The effects of increased demand are not limited to full outbound pallets but also impact workstation and inbound pallets. Similar to full outbound pallets, their performance declines. However, as observed in previous experiments, pipeline thresholds have only a marginal influence on workstation and inbound pallets.

5.4 Summary of Experimental Results

This chapter aims to find the best-performing model configurations for the situation at Euroma. Therefore, we began by verifying and validating the created simulation model in Section 5.1. The verification confirms that the model follows the conceptual design through controlled test scenarios and real-data experiments. However, validation reveals discrepancies between historical data and simulation results, particularly regarding workstation and operator behavior at EP0. These deviations align with limitations in recorded data and WCS documentation, necessitating expert-based assumptions.

Despite these limitations, the experimental phase provids valuable insights into warehouse performance. In general, the Baseline simulation results in a better performance than the historical data of the real system. Despite the discrepancies, the simulation captures the trend that the full outbound delivery percentage and tardiness of full outbound pallets is higher compared to the workstation pallets. In the remainder of the experiments, we tested the three proposed dispatching rules – Baseline, FCFS, and R1 – under varying operator behavior, pipeline thresholds, and demand levels.

The R1 logic achieves the highest on-time delivery percentages across the conducted experiments. Simultaneously, this logic results in the highest average tardiness values among the tested dispatching rules, driven by a small number of significantly delayed pallets. Therefore, R1 effectively prioritizes most pallets to maximize on-time delivery at the cost of a few extreme queueing times.

Generally, the difference to other dispatching rules is not that distinct; however, when increasing the pipeline and operator time, the R1 logic shows its advantages as the difference to the other considered rules gets more distinct.

FCFS performs slightly below R1 in on-time delivery but demonstrated less complexity and lower average tardiness. Across all pipeline configurations, FCFS reduces daily tardiness by an average of 23 minutes compared to R1, with significantly lower maximum tardiness. Generally, FCFS results in the lowest tardiness related KPIs and while performing close to the Baseline simulation's performance, FCFS performs slightly better in most KPIs with less complexity as the prioritization applied in the Baseline simulation is removed here.

Moreover, an increase in demand and operator time results in reduced high-bay warehouse performance. Additionally, decreasing the pipeline threshold for workstations worsens the performance of workstation pallets significantly while only marginally improving the full outbound pallet performance. In contrast, increasing the full outbound pallet threshold improves the on-time delivery percentage and tardiness for full outbound pallets without significantly worsening the performance for workstation and inbound pallets. Especially, increasing the threshold for *Out1* (MP0) leads to significant improvements. While higher pipeline thresholds increase the time pallets spend on the conveyor, it reduces queueing times, ultimately decreasing lead times.

Table 5.8 summarizes the best-performing pipeline configurations across the three dispatching rules with their corresponding on-time delivery percentage and average pallet tardiness. The deviations in parentheses behind the KPI values show the possible increase (+) or decrease (-) the best pipeline configuration shows for this logic. The R1 logic with pipeline configuration [7, 11, 25] achieves the highest on-time delivery (93.62%), resulting in an increase of 2.84% compared to the settings currently applied at Euroma. However, this configuration increases average tardiness by one minute per tardy pallet compared to FCFS. The lowest recorded tardiness using FCFS is compared to R1 2.52 minutes lower per tardy pallet, further highlighting the trade-off between on-time delivery percentage and tardiness.

Dispatching Rules	On-Time Delivery Percentage		Tardiness (min)	
	Full Outbound Pallets	Workstation Pallets	Full Outbound Pallets	Workstation Pallets
	pipeline Configuration *Out1* = 5, *Out2* = 7, *Out3* = 11			
Baseline	92.37% (+0.23%)	81.22% (+0.64%)	40.03 (-2.08)	2.70 (-0.08)
FCFS	92.68% ($\pm$ 0.00%)	81.33% (+0.52%)	41.35 (-2.44)	2.70 (-0.08)
R1	92.95% (+0.07%)	81.97% ($\pm$0.00%)	44.95 (-3.77)	2.72 (-0.08)
	pipeline Configuration *Out1* = 7, *Out2* = 11, *Out3* = 25			
Baseline	93.12% ($\pm$ 0.00%)	81.47% (+0.13%)	38.40 (-3.55)	2.71 (-0.03)
FCFS	93.18% (+0.02)	81.52% (+0.37%)	39.55 (-4.30)	2.80 (-0.11)
R1	93.62% ($\pm$ 0.00%)	81.12% (+0.52)	40.43 (-2.66)	2.75 (-0.10)

Table 5.8: Results Best Performing Configurations. This table summarizes the on-time delivery percentage and average pallet tardiness performance of the three dispatching rules for two of the best-performing pipeline configurations under the historical demand pattern. The values in parentheses indicate the possible increase (+) or decrease (-) in performance compared to the best pipeline configuration for each logic.

6 IMPLEMENTATION

This chapter outlines the necessary steps for implementing the evaluated improvement opportunities within the WCS. The proposed changes focus on three key areas: dispatching rules, pipeline configurations, and looping mechanisms. It discusses the implementation feasibility and requirements.

Implementation of Dispatching Rules The WCS manages the internal processes within the high-bay warehouse, including sequencing reserved pallets for crane retrieval. Therefore, implementing new dispatching rules requires adjustments to the WCS logic. The implementation of the FCFS requires minimal changes to the existing system. All pallets must be assigned the same priority to ensure retrieval occurs in the order of arrival. Since the WCS already tracks pallet arrival times, this modification can be implemented by adjusting priority assignment rules in the system's logic.

The implementation of the R1 rule is more complex, as it requires additional calculations within the WCS. Even though the necessary parameters can be pre-calculated or are already recorded by the WCS, modifications to the WCS logic are necessary to integrate these factors into the dispatching decision process.

Pipeline Configuration Adjustments The WCS already tracks the pipeline size and applies a predetermined pipeline threshold. Since this threshold is integrated into the user interface, Euroma can make adjustments without requiring changes to the underlying WCS logic.

Implementation of Looping Mechanisms Currently, full outbound pallets at EP0 and EP1 can loop when outfeed lanes are obstructed. Since the possible reloop conveyor spot at MP0 (*IP1* in Figure 2.2) is the same model type as the one at EP1 (*IP2*), implementing a looping mechanism at MP0 is technically feasible. The necessary adjustments require modifications to the WCS logic, similar to those implemented for EP1.

In summary, Euroma can adjust pipeline configurations immediately using the existing WCS functionalities. In contrast, implementing new dispatching rules and looping mechanisms requires expertise in the WCS logic.

7 CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusions of the research. First, Section 7.1 addresses the main research question by summarizing the key findings. Subsequently, Section 7.2 presents recommendations to Euroma. Next, Section 7.3 outlines this research's limitations and provides directions for further research. Finally, Section 7.4 discusses the study's contribution to theory and practice.

7.1 Conclusions

Euroma's facility in Zwolle is operating at full capacity, with nearly every available square meter utilized. Nevertheless, the facility struggles to meet internal and external pallet demand on time. Additionally, Euroma aims to increase production further in the future. A critical bottleneck in this process is the high-bay warehouse, where delays in the outbound process can cause delays in production and order fulfillment. An analysis of the current system indicates that less than 90% of the full outbound pallets arrive at their destination on time. This leads to the main research question:

How can Euroma optimize the outbound process of the high-bay warehouse to increase the on-time delivery performance of pallets?

We modeled this problem as a BJSSP, incorporating several constraints, such as setup times, looping possibilities, and job precedence constraints. The model aims to generate a feasible schedule that optimizes retrieval times for pallet requests. Due to the complexity of the problem and the need for real-time adjustments, we chose dispatching rules over more advanced heuristics. Therefore, we proposed two alternative rules – FCFS and R1 – in addition to the currently used dispatching rule.

We conducted a series of experiments in a simulation environment to evaluate these dispatching rules. Next to the dispatching rules, the experiments analyzed different pipeline configurations, operator behaviors, and demand scenarios. These various scenarios account for real-world fluctuations and potential future conditions.

The results demonstrate that both proposed dispatching rules outperform the current one. In particular, R1 shows significant advantages as the pipeline threshold increases, leading to a maximum full outbound on-time delivery percentage of 93.62%, an improvement of 2.84% compared to the baseline configurations. FCFS performs slightly below R1 (by 0.42%) but yields significantly lower tardiness values.

A difference of 0.40% in on-time delivery translates to approximately one additional pallet arriving on time per day. While this may seem marginal, historical data suggests that a delayed pallet incurs an average tardiness of 23.11 minutes, leading to estimated costs of €27.73 for truck waiting times (€72 per hour) or €77.03 for production standstills (€200 per hour). Over a week, this amounts to €388.35 or €1,078.47, depending on the pallets' destination.

On average, FCFS reduces tardiness per delayed pallet by 1.5 minutes compared to R1 across all pipeline configurations. This equals to cost savings of approximately €1.80 per tardy pallet for truck waiting times and €5.00 per tardy pallet for production standstills. Additionally, the maximum full outbound tardiness for a delayed pallet under R1 is, on average, two hours longer than under FCFS. Given the estimated delay costs, a single pallet with an additional two-hour tardiness could result in €144.96 for truck waiting times and €402.66 for production standstills.

Moreover, increasing the pipeline threshold alone – without modifying the dispatching rules – already leads to noticeable improvements without negatively impacting the other pallet flows. In particular, increasing the threshold of the outfeed lanes at MP0 and EP1 each by two already improves the full outbound on-time delivery percentage by 1.82% and the daily tardiness by 8.59 hours.

7.2 Recommendations

After evaluating the proposed dispatching rules and pipeline modifications, we recommend that Euroma increase the pipeline threshold for the outfeed lanes. This adjustment enhances the performance of full outbound pallets without significantly affecting workstation and inbound pallet operations.

It is essential to acknowledge that the simulation model does not accurately model the real-world system. Validation reveals notable discrepancies, though multiple experiments confirmed that the model behaves as expected based on expert understanding. This strengthens confidence in insights gained by the simulation but also highlights the need to address deviations from reality. Therefore, before implementing significant changes to the real-world system, we recommend enhancing data collection and verifying the expert's understanding of the system logic to improve model accuracy.

Pipeline adjustments do not require modifications to the WCS logic and can immediately be implemented. Therefore, we suggest testing the real system's performance under slightly increased pipeline thresholds. In particular, the simulation already showed significant improvements when raising the pipeline threshold for *Out1* (MP0) by one unit. Since the historical data analysis indicates that full outbound pallets for MP0 experience long queuing times, and the simulation results consistently demonstrate that a higher pipeline threshold reduces these delays, we are confident that this improvement will translate effectively to the real-world system.

Additionally, we propose a controlled test phase for the FCFS dispatching rule. Implementing FCFS requires minimal modifications to the WCS, as it simply removes priority distinctions between pallet types. The simulation results indicate that this logic improves on-time delivery and tardiness performance.

Although the simulation does not accurately replicate real-world dynamics, several factors suggest that FCFS is unlikely to disrupt workstation pallet retrieval significantly. First, pipeline thresholds limit the number of full outbound pallets a crane can retrieve before a workstation pallet. Additionally, the average crane retrieval time of 42 seconds suggests that workstation pallet delays due to FCFS would be minimal. Although sequence dependencies could theoretically cause a chain reaction of delays, simulation results do not support this concern. To further minimize potential disruptions, we recommend scheduling initial trials under realistic demand patterns during week 52 when Euroma's production is paused. This approach allows Euroma to evaluate the impact without affecting ongoing operations.

While the R1 dispatching rule achieves the highest on-time delivery percentage, we do not recommend testing it in the real system at this stage. The primary reason is the significantly higher tardiness of delayed pallets, which could lead to severe disruptions in production and logistics. Additionally, implementing R1 requires more substantial changes to the WCS, likely requiring specialized expertise. Nevertheless, simulation results suggest that under optimized system configurations – particularly with increased pipeline thresholds – R1 can mitigate these drawbacks. To further explore its potential, we recommend refining the discrete event simulation with more accurate input parameters. This would provide greater certainty regarding R1's feasibility and potential trade-offs.

Finally, the simulation results highlight the significant impact of operator behavior on warehouse performance. Therefore, we strongly recommend that Euroma emphasize the importance of timely retrieval of full outbound pallets from the outfeed lane to optimize system efficiency further.

7.3 Limitations and Future Research

The study's scope is limited to processes within the high-bay warehouse. Therefore, we did not consider processes outside this system. The analysis reveals that high demand for one outbound destination increases lead times and tardiness. In this study, we addressed this issue by increasing pipeline thresholds. Another potential approach could focus on the root cause – the pallet request pattern. Developing a production schedule that incorporates the constraints of the high-bay warehouse could distribute the demand for a single outfeed lane more evenly. Additionally, enabling the WCS to select the optimal outfeed lane dynamically – potentially applying a penalty for choosing a suboptimal outfeed lane – could further enhance the high-bay warehouse's performance.

Furthermore, this study does not encompass storage assignment policies. Our analysis shows that retrieval times can vary by up to nine minutes, depending on the storage aisle's location. While increasing the pipeline threshold mitigates this issue, optimizing storage assignment to minimize conveyor transport times could improve pallet flow without requiring increased pipeline thresholds.

Moreover, we only investigated possibilities for totally reactive scheduling, as this is the approach Euroma currently uses. This focus prevents us from exploring more computationally intensive scheduling methods, like tabu search. Thus, considering alternative dynamic scheduling strategies, such as predictive-reactive scheduling, could have allowed the application of heuristics that may generate a schedule closer to optimal than dispatching rules. Further research could explore the feasibility of predicting pallet requests based on a predetermined production schedule. However, such an approach would also require incorporating the reservation process into the model, as multiple pallets with the same SKU are stored across different aisles of the AS/RS.

Finally, it is important to acknowledge data availability and reliability limitations. While Euroma collects a significant amount of data, some necessary data points are missing. As a result, we relied heavily on expert opinions and established assumptions. Although several verification experiments confirm that the simulation model adheres to the rules described by experts, the model does not fully align with real-world observations. Notably, the workstation outbound logic does not match historical data, and accurately modeling operator behavior proved challenging. This discrepancy raises concerns about how well the simulation results translate to the real-world system. Future work should focus on refining the model by incorporating additional details, such as actual retrieval times for full outbound pallets and the precise logic used for outbounding workstation pallets.

7.4 Contribution to Theory and Practice

First, as discussed in Section 3.1.4, existing studies on BJSSPs typically incorporate only a limited set of practical constraints. Our research extends the literature by developing a mathematical formulation with a broad and unique set of real-world constraints. Notably, our formulation accounts for queuing on conveyor resources when necessary. To the best of our knowledge, this aspect is not addressed in prior studies, which either impose strict no-wait constraints or do not consider such limitations at all.

Moreover, our research evaluates the performance of well-known dispatching rules within a unique operational environment. In this study, key constraints limit the ability of dispatching rules to influence system performance. First, workstation pallet sequences are predefined, preventing dispatching rules from dynamically adjusting their retrieval order. Additionally, pipeline thresholds impose further restrictions by defining a maximum number of pallets in transit. As a result, even if a dispatching rule prioritizes a specific pallet, it may need to select an alternative option when the preferred choice is not feasible. To the best of our knowledge, no previous research has examined the effectiveness of dispatching rules under these practical constraints.

From a practical perspective, this research provides Euroma with a comprehensive analysis of the processes and flows within the high-bay warehouse. Additionally, it delivers the first performance evaluation of the warehouse based on historical data, offering valuable insights into its efficiency. Furthermore, the study offers educated improvement recommendations for operational enhancements and future optimization strategies. Finally, the developed simulation model serves as a foundational tool for Euroma, enabling further experimentation and a deeper understanding of warehouse dynamics.

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A INBOUND PROCESS

The process of storing pallets in the high-bay warehouse is not the center of this research. However, the inbound process requires available spots on the conveyor belt and the cranes. While the conveyor belts can accommodate multiple pallets simultaneously, each crane is limited to one active in- or outbound task. Additionally, incoming products need to be stored in a reasonable time to avoid obstruction on the conveyor. Therefore, the inbound process is connected to the performance of the outbound process of the high-bay warehouse. Consequently, the inbound process is discussed in this appendix to provide additional context without shifting the main focus of the analysis. This chapter provides an overview of the inbound control policy and the performance of the inbound process.

A.1 Inbound Control Policy

The loading docks on the ground floor serve as the primary delivery access point to Euroma. Upon arrival, operators assign incoming products a unique pallet ID. Afterward, the pallets are directed to storage within the high-bay warehouse, utilizing the infeed lane at EP0 (*In3*). Placing a pallet on the infeed lane triggers the creation of an inbound task. Additionally, internally produced products, materials, and ingredients not fully utilized during production can trigger inbound tasks. These types of inbound processes mainly occur through the infeed lanes at MP0 (*In1*) and EP1 (*In2*).

After creating an inbound task, the WCS assigns a storage location. Upon the arrival of a pallet at the I/O-point, the assigned crane performs the inbound in a FCFS manner if either of the two conditions holds:

1. The crane executes an outbound task on the same side where the inbound pallet awaits processing.
2. The crane has no outbound tasks in progress and thus is idle.

Under these conditions, the cranes follow a single cycle of outbound tasks until an inbound pallet is on the same side as an ongoing outbound task. At this point, the crane transitions into a dual cycle, handling both inbound and outbound tasks.

A.2 Inbound Process Analysis

In this research, the performance of the inbound process is monitored by the KPI *Inbound Queueing Time*. Obtaining this KPI directly from the data is not feasible. Instead, estimating a pallet's inbound queueing time involves calculating the duration between the arrival at the I/O-point and the arrival at the storage location, with an additional deduction for the estimated crane travel time.

According to the information provided in Table 2.2 in Section 2.4.2, it takes an average of 42 seconds for a crane to transfer a pallet from its storage location to the I/O-point. We assume the same duration applies to the reverse movement to determine the average inbound queueing time. Table A.1 displays the average and median time incoming pallets spend waiting in the crane queue and being transported by the crane. After accounting for the average crane travel time, the adjusted average queueing time is approximately 1.5 minutes. It is essential to note that the queueing time specifically refers to the period during which a pallet waits at the I/O-point (*I1.1* to *I6.2*, excluding the time spent on the conveyor segment leading to the crane's pickup spot. Moreover, the slight difference between the median and average suggests that the inbound queueing time is subject to minor fluctuations, and cranes consistently pick up pallets from the I/O-points at regular intervals.

	MP0	EP0	EP1
Average Response Time (min)	1.69	1.83	1.68
Median Response Time (min)	1.53	1.53	1.42
Average Inbound Queuing Time (min)	1.00	1.14	0.99

Table A.1: Inbound Queuing Time. Average and median response time, including the queueing time added to crane travel time, alongside the average queuing time calculated by subtracting the average crane travel time. The times are provided in minutes.

B GRAPH REPRESENTATION

This appendix introduces key graph theory concepts relevant to a job shop environment, as many solution approaches for JSSPs rely on the critical path concept. Particular emphasis is placed on alternative graphs, which are essential for BJSSPs.

Representing a JSSP as a graph involves associating each operation with a node and each precedence relationship with an arc. The literature categorizes these precedence relationships into fixed and alternative sets. Fixed precedence relationships occur between consecutive operations of the same job and have arcs with weights corresponding to the processing time. Conversely, alternative arcs link operations of different jobs sharing the same resources and have an arc weight of zero. These alternative relationships are paired, reflecting the constraint that each machine can handle only one operation at a time (Mascis and Pacciarelli, 2002). Consequently, there is a direct correspondence between pairs of operations requiring the same machine and pairs of alternative arcs.

An alternative graph $G = (V, F, A)$ for the BJSSP is defined by the set of nodes V, the set of fixed directed arcs F, and the set of directed alternative arc pairs A (Mogali et al., 2021). The alternative arcs represent blocking constraints for a BJSSP. Therefore, for each pair of operations sharing common resources, the job successor of each of the two operations is connected to the machine successor of each. Figure B.1 exemplifies this situation. Different colors represent each machine, with alternative arcs represented by dashed lines and fixed sequence dependencies by solid lines. It clearly illustrates the characteristic of blocking constraints: machines become available only after the job moves on to the next operation.

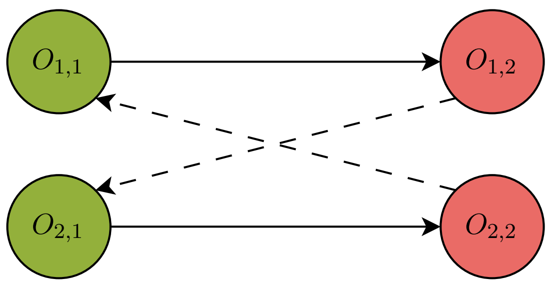


Figure B.1: Segment of an Alternative Graph. Machines are shown in different colors, with dashed arrows for alternative arcs and solid lines for fixed sequence dependencies.

In a selection $S \subset A$, at most, one arc of each alternative arc pair in A can be selected, meaning either job J_1 starts its second operation before job J_2 starts its first or vice versa. A selection S is complete if it includes precisely one arc from each alternative arc pair. Furthermore, a selection S is consistent if the graph $G(V, F \cup S)$, which includes only fixed arcs and the selected subset of alternative arcs, is acyclic. A feasible selection is complete and consistent. A schedule can be generated from a feasible selection S by determining the longest path on the graph $G(V, F \cup S)$. The length of this path corresponds to the makespan of S. Any of the longest paths is called a critical path (Mascis and Pacciarelli, 2002; Mogali et al., 2021).

C INPUT PARAMETERS FOR COMPUTATIONAL EXPERIMENTS

This appendix provides the input parameters for the computational experiments that analyze the scalability of the mathematical model. Table C.1 summarizes the scenarios, including varying numbers of inbound jobs, outbound jobs, and machines. Additionally, the table lists the first and last machine IDs, as well as the release and due dates for each scenario. All other parameters follow the definitions provided in Section 4.3, except for the scenario with 15 machines, where the machine layout is illustrated in Figure C.1.

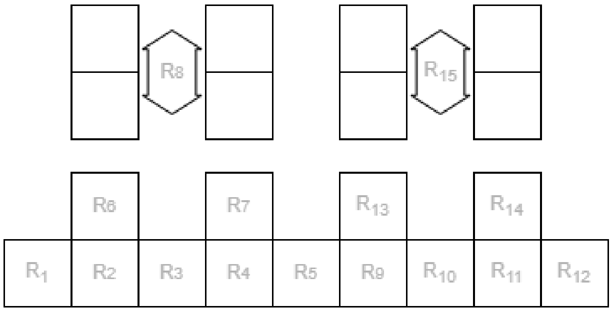


Figure C.1: Machine Configuration for the 15-Machine Scenario. This figure illustrates the machine setup for the scenario with 15 machines, which differs from the standard configuration described in Section 4.3.

	First Machine	Destination Machine	Request Time	Due Date
		Scenario 1: 8 machines		
J_1^I	1	8	0	-
J_2^O	8	5	1	6
J_3^O	8	5	1	10
J_4^O	8	5	2	9
		Scenario 2: 15 machines		
J_1^I	1	8	0	-
J_2^O	8	12	1	6
J_3^O	8	12	1	10
J_4^O	15	12	2	9
		Scenario 3: 8 machines		
J_1^I	1	8	0	-
J_5^I	1	8	2	-
J_2^O	8	5	1	6
J_3^O	8	5	1	10
J_4^O	8	5	2	9
J_6^O	8	5	3	11
J_7^O	8	5	4	12
J_8^O	8	5	5	12
		Scenario 4: 15 machines		
J_1^I	1	8	0	-
J_5^I	1	15	2	-
J_2^O	8	12	1	6
J_3^O	8	12	1	10
J_4^O	15	12	2	9
J_6^O	15	12	3	11
J_7^O	8	12	4	12
J_8^O	8	12	5	12
		Scenario 5: 8 machines (Scenario 3 jobs + additional jobs		
J_9^I	1	8	4	-
J_1^I0	1	8	6	-
J_1^O1	8	5	7	14
J_1^O2	8	5	7	15
J_1^O3	8	5	9	17
J_1^O4	8	5	10	17
J_1^O5	8	5	10	20
J^O16	8	5	12	20

Table C.1: Input Parameters for Computational Experiments: This table presents the input parameters for different problem sizes used to evaluate computation time.

D CONCEPTUAL MODEL

Conceptual modeling is a crucial step in a simulation study as it outlines the important aspects of the real world to be modeled. Table D.2 summarizes the conceptual model for the simulation study at Euroma as a component list. Key aspects involve developing a thorough understanding, formulating modeling objectives, and designing the conceptual model by identifying inputs, outputs, scope, and the level of detail (Robinson, 2014). The tables presented in this appendix follow the conceptual model description in Section 4.4.

Table D.1 summarizes the input and output parameters discussed in Section 4.4. The inputs are categorized into experimental factors and constant parameters, while the output parameters are divided into those used to evaluate the achievement of the objectives and those that help identify underlying causes.

Experimental Factors
pipeline threshold
conveyor retrieval time (operator behavior)
sequencing policy
Constant Parameters
system arrival time
workstation processing time (operator behavior)
crane processing time
conveyor speed

(a) Inputs of the Simulation Study

Responses (determination of achievement of objectives)
on-time delivery ratio
total tardiness
inbound queueing time
Responses (identification of reasons for failure to meet objectives)
outbound queueing time
conveyor movement time
crane movement time
lead time

(b) Outputs of the Simulation Study

Table D.1: Inputs and Outputs of the Conceptual Model

Table D.2 provides an overview of the scope and assumptions defined for the simulation study, as outlined in Sections 4.4 and 4.5. The tables are organized by components, specifying whether each component is included or excluded from the simulation. Table D.2a explains the rationale behind these decisions, while Table D.2b delves into the details of the included components, highlighting the specific assumptions and simplifications applied.

Component	Incl./Excl.	Justification
Pallets	include	flow through high-bay warehouse
Staff	include	required for conveyor retrieval and workstation tasks
Storage Racks	include	required for holding the stock
Stacker Cranes	include	contribution to outbound lead time
Conveyor	include	contribution to outbound lead time
Workstations	include	required for measuring achievement of objective
Crane Retrieval Queueus	include	required for determination of total outbound lead time and sequencing policy
Storage Queues at Infeed	exclude	queues outside high-bay warehouse not related to outbound lead time
Storage Queues at I/O-points	include	required for measuring achievement of objective
WCS	include	required for decision making and strategy formulation
WMS	exclude	movements outside the high-bay warehouse not relevant

(a) Scope of the Simulation Study

Component	Detail	Incl./Excl.	Comment
Pallets	system arrival time	include	time stamps of real data collected at Euroma
	order size	exclude	does not influence speed of outbound lead time
	dimensions	include	dimensions of Euro pallet, block pallet dimensions excluded
	storage location	include	inclusion of crane assignment (based on historical data), exact storage location not included
Staff	retrieval time	include	full outbound pallets remain on their destination for a duration following an assumed distribution (operator behavior)
	transportation time	exclude	assumed distribution for conveyor retrieval time (operator behavior) includes assumptions on transportation time
	breaks	exclude	not explicitly modeled but could be represented by increasing retrieval time
	absenteeism	exclude	not explicitly modeled but could be represented by increasing retrieval time
Storage Racks	dimensions	exclude	storage racks modeled as black box
Stacker Crane	speed	include	historical data
	capacity	include	unit load
	failure	exclude	technical uptime above 98%
Conveyor	speed	include	speed based on historical data analysis and real-system observations
	capacity	include	one pallet per conveyor spot
	size	include	based on data from manufacturer
	failure	exclude	technical uptime above 99%
Workstations	processing time	include	historical data
	failure	exclude	workstations are not main objective
Retrieval Queue	queueing	include	required for crane queueing time and queue size response (sequencing policy)
	capacity	exclude	no effective limit
	behaviour	include	experimental factor
Storage Queue	queueing	include	output measurement
	behaviour	include	FCFS
WCS	pallet assignment policy	exclude	historical data
	task assignment policy	include	experimental factor

(b) Level of Detail of the Simulation Study

Table D.2: Conceptual Model of the Simulation Study. Representation of the content of the conceptual model with the help of the component lists.

E SIMULATION MODEL DESIGN

This appendix outlines the simulation model designed to analyze Euroma's high-bay warehouse operations, primarily focusing on outbound processes. First, we visualize the general logic governing pallet flow through the high-bay warehouse as implemented in the simulation. Subsequently, we introduce detailed flowcharts to illustrate the simulation model's logic, highlighting critical decision points and the key constraints embedded in the system. The chapter concludes with an overview of the simulation dashboard.

E.1 Flow Charts

Section 4.7 presents an overview of the general pallet flow and introduces the key methods utilized in the discrete event simulation model. This appendix expands on the introduction by offering a detailed explanation of the structure and operation of these methods, along with their corresponding flowcharts.

Method: CraneTask Together with the considered scheduling logic, the *CraneTask* method determines the next outbound pallet for retrieval by the crane. This method is invoked whenever a new outbound request enters the queue, or the crane completes its current task. If the crane is idle and there is at least one pallet in the outbound queue, the method identifies the next task based on the scheduling rules (refer to Figure E.5).

Figure E.1 outlines this decision-making process in two stages. When the queue contains a single outbound pallet, the crane retrieves it directly, as no scheduling method is required. However, if multiple pallets are waiting, the scheduling method is applied to determine which pallet should be retrieved next.

Before executing the outbound task, the *HybridCommand* method ensures proper coordination between the inbound and outbound queues. This method enforces the rules governing both queues and is also triggered when the crane finishes a task but finds no pallets waiting in the outbound buffer. This ensures that inbound pallets in the buffer are considered, maintaining an efficient workflow.

Method: InboundQueue Similar to the *CraneTask* method, the *InboundQueue* method determines the next inbound pallet to be retrieved by the crane. Since the inbound queue operates in a FCFS manner, and the *HybridCommand* method dictates when the next inbound pallet is retrieved, the primary task of the *InboundQueue* method is to maintain the queue in the correct order for each inbound side. This process is visually represented in Figure E.2.

Method: HybridCommand The *HybridCommand* method manages the coordination between inbound and outbound queues by tracking the crane's current position and state. If a dual command is feasible, the method prioritizes retrieving an inbound pallet by invoking the *CraneProcessing* method before handling the assigned outbound pallet determined by *CraneTask*. When

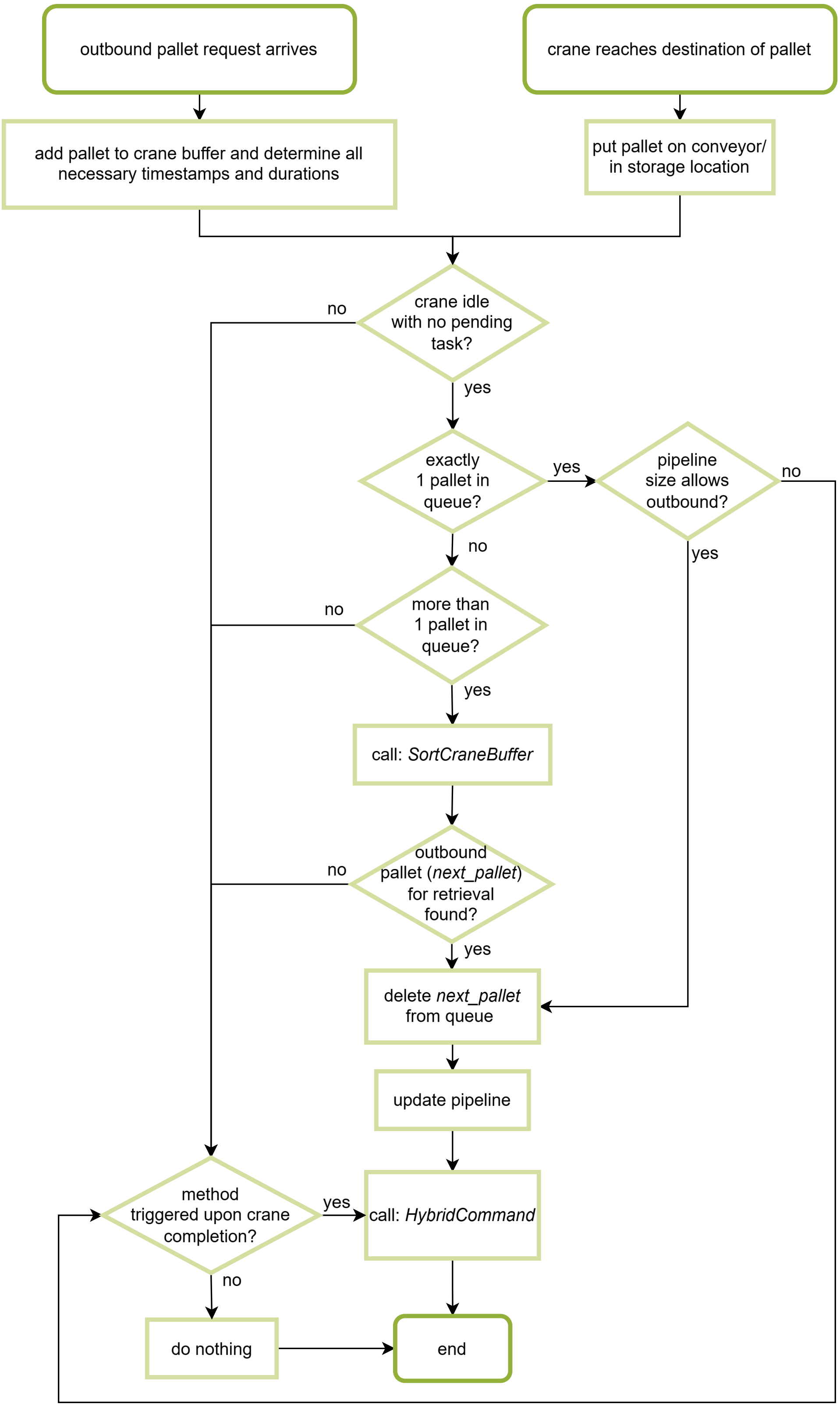


Figure E.1: Flowchart Method CraneTask: The flowchart depicts the method CraneTask, which initializes a new task assignment for the crane whenever it is idle.

a dual command is impossible, the crane initiates the next single command cycle, also triggered through the *CraneProcessing* method. Figure E.3 visualizes this decision-making process, with key decision points leading to either dual or single command cycles highlighted in red boxes.

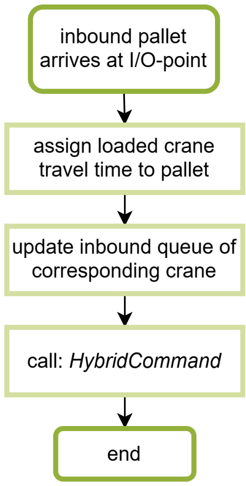


Figure E.2: Flowchart Method InboundQueue: The flowchart illustrates the InboundQueue method, which updates the queue of inbound pallets assigned to their respective cranes.

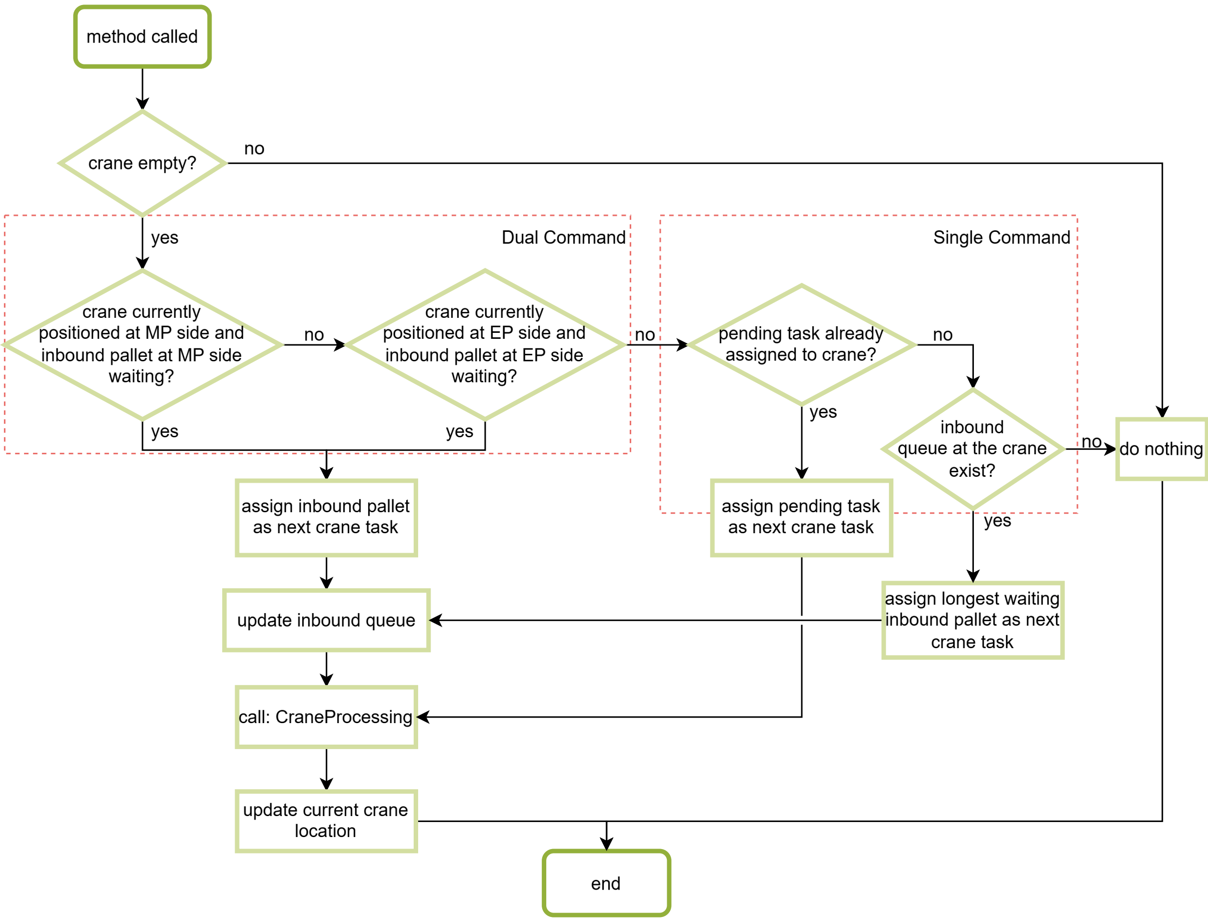


Figure E.3: Flowchart Method HybridCommand: The flowchart illustrates the HybridCommand method, which coordinates inbound and outbound queues based on the crane's current position and state. When a dual command is feasible, the method prioritizes retrieving an inbound pallet. Otherwise, the crane proceeds with the next single command cycle.

Method: CraneProcessing The *CraneProcessing* method simulates the crane's operations, including both empty and loaded movement times, to represent its handling durations realistically. These key activities are marked in red within Figure E.4.

The method incorporates an additional step for pallets destined for workstations: verifying whether the next pallet in the workstation sequence is ready to begin its crane movement. This check calls via method *SortCraneBuffer* the applied scheduling rules (see Figures E.5a to E.5c).

Scheduling Rules The simulation offers three distinct scheduling methods. These methods are triggered whenever the *SortCraneBuffer* method is called.

Method: CurrentScheduling The *CurrentScheduling* method is executed in two key scenarios. First, when a crane completes its current task, it must determine the next task to process. Second, when the pipeline size decreases (due to a pallet leaving the system), the method is called to assess which pallet is next for the corresponding location. The pallets eligible for processing based on location or crane availability are then sorted. Workstation pallets receive a higher prioritization value of 1, while all other pallets are assigned a prioritization value of 50. In cases where multiple pallets share the same prioritization, the pallet with the earliest request time is selected. As illustrated in Figure E.5a, a pallet can only be selected if the corresponding crane is idle and the pipeline size is below a set threshold.

Method: FCFSScheduling As shown in Figure E.5b, the *FCFSScheduling* method functions similarly to the *CurrentScheduling* method, with one key distinction: no prioritization is applied to specific pallet types or movements. Instead, all pallets are processed based solely on their system arrival time.

Method: R1Scheduling The *R1Scheduling* method, illustrated in Figure E.5c, is more complex and involves additional steps. First, the remaining processing time for a pallet is calculated by accounting for the conveyor spots the pallet must traverse to reach its destination and the crane's travel time. Additionally, the waiting time, estimated by the expected arrival time of in-transit pallets, contributes to the remaining processing time. Furthermore, the pipeline position indicates the remaining work in the next queue. This is determined by multiplying the number of pallets in the pipeline by the expected time each pallet spends at its destination. In this method, a smaller R1-value is preferred, as it indicates that the pallet is closer to its due date and has fewer pallets already in the pipeline, ensuring it is handled promptly.

The due date for full outbound pallets is aligned with the goal of full outbound pallets reaching their destination within one hour, making the due date one hour. For workstation pallets, due dates depend on the following criteria:

- If a pallet is the first in an order, it should arrive at the workstation within 20 minutes.
- All other workstation pallets are due at the expected workstation arrival time of the preceding pallet in the sequence.

Since the specific order to which each pallet belongs is unknown, any pallet with a sequence number of one or succeeding pallets whose request times exceed the expected workstation arrival time of their preceding pallet in the sequence are treated as initiating a new order and are assigned a 20-minute due date. The expected workstation arrival time is calculated by summing the pallet's remaining processing time (crane and conveyor) and the remaining work in the queue.

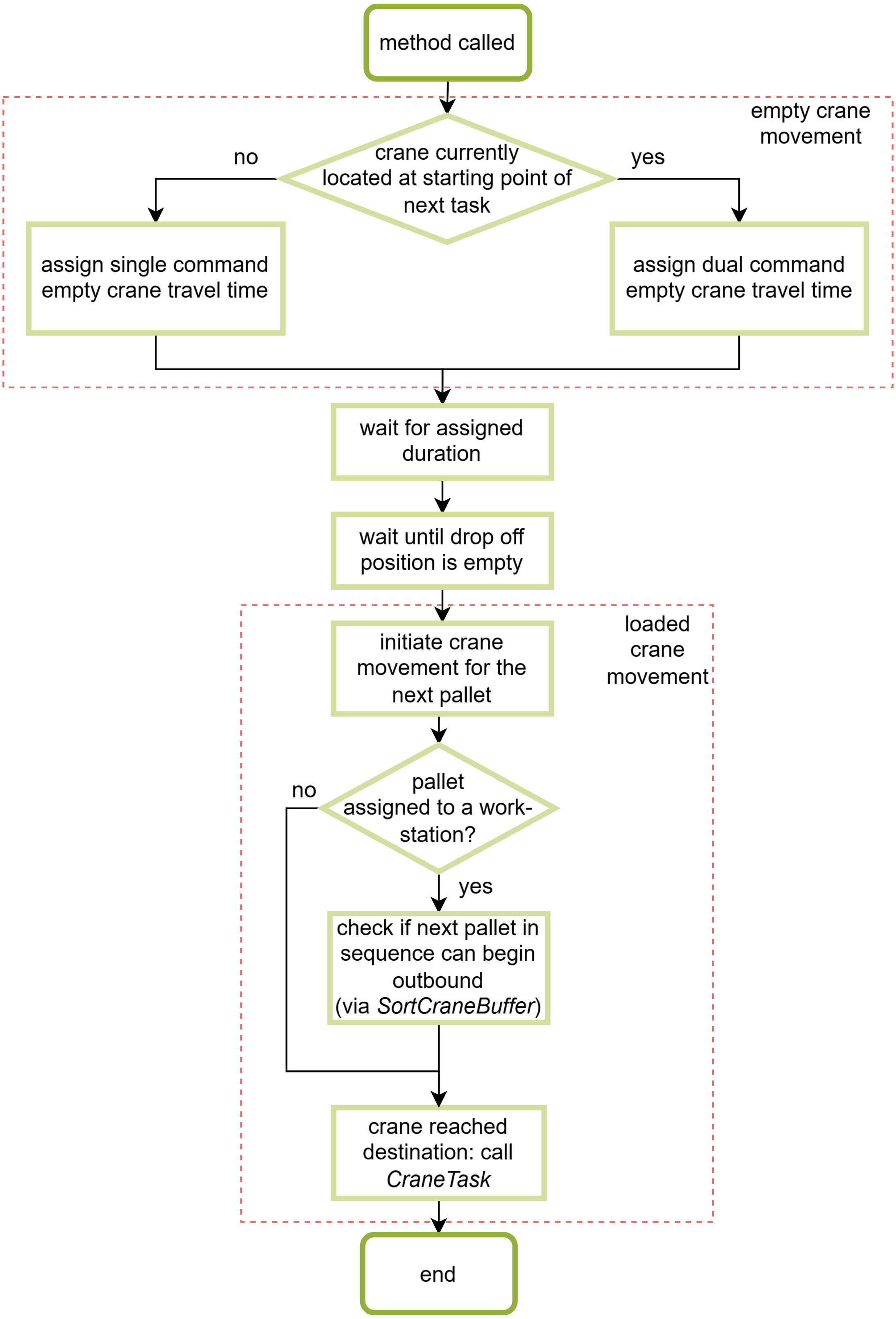
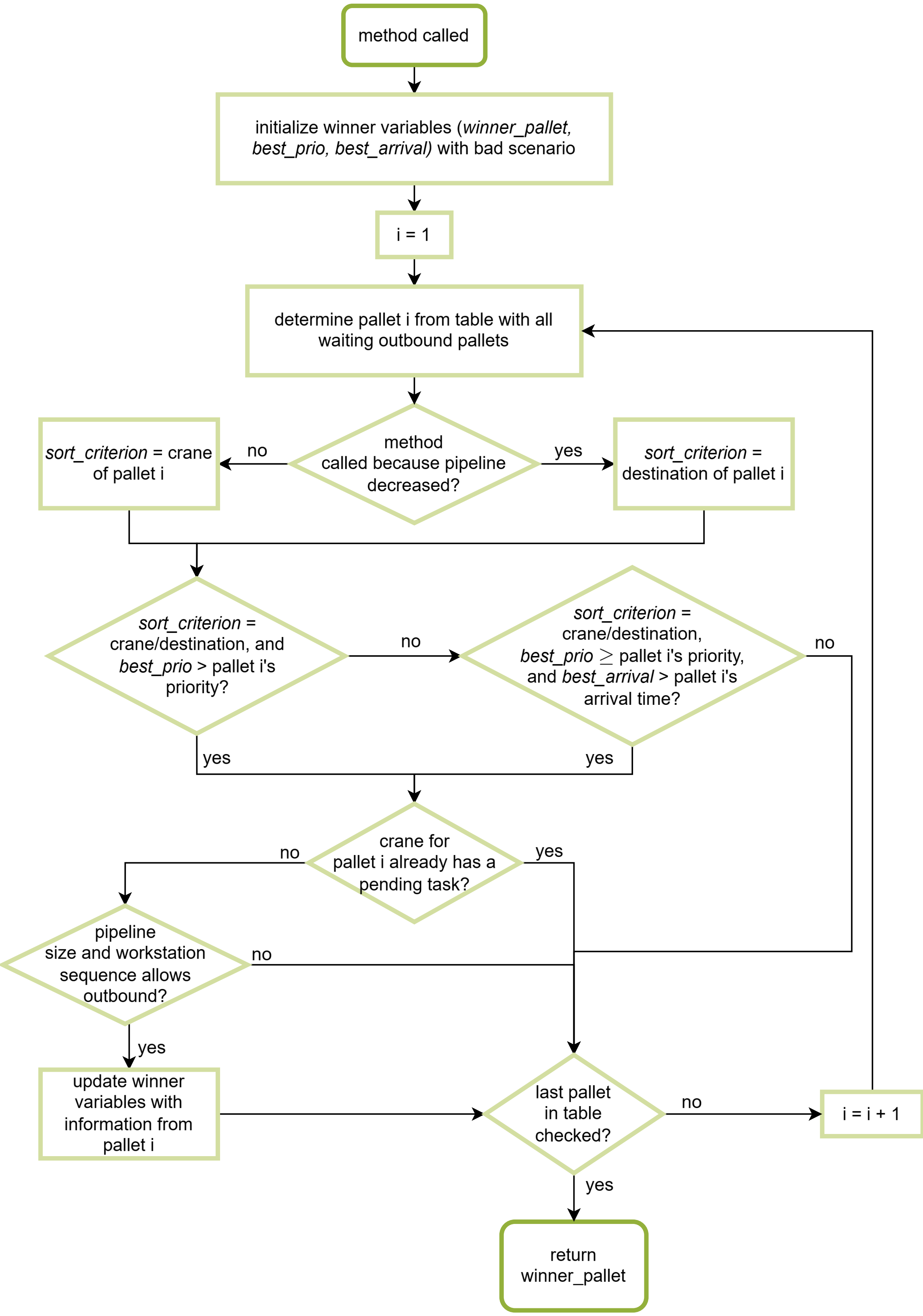


Figure E.4: Flowchart Method CraneProcessing: The flowchart represents the CraneProcessing method, which simulates the crane's travel and retrieval operations, covering both empty and loaded movements.



(a) Flowchart Method CurrentPrioritization: The flowchart depicts the CurrentPrioritization method, which determines the next pallet for the crane to process. This method reflects the scheduling logic currently applied by Euroma. Generally, pallets are assigned the same priority value, except for workstation outbound pallets, which are prioritized. Within each priority group, pallets are scheduled in a FCFS manner.

E.2 Simulation Dashboard

Figure E.6 presents the dashboard of the developed simulation model. The dashboard is organized into distinct sections to provide a structured overview and facilitate user interaction with the simulation.

High-Bay Warehouse The section labeled *High-Bay Warehouse* contains a frame that represents the high-bay warehouse, including conveyor modules and crane locations. This frame allows the user to visually track pallet movements along the conveyors. Additionally, it incorporates a black-box model of the cranes, as described in Figure 4.2.

Event Control The *Event Control* section includes all necessary methods managing a simulation run. Before starting a replication, the *Reset* method clears all tables and variables to ensure consistent initial conditions. The methods *Init* and *FirstTimeInitialization* handle the initialization of the simulation run, while the *endSim* method computes KPIs before terminating a replication. In contrast to methods, which operate at the beginning or end of a replication, the *StartOfDay* method executed daily to update the current date variable within the *Settings & Experimental Factors* section.

Warehouse Control The *Warehouse Control* section encompasses all parameters and methods required for pallet movements within the high-bay warehouse. The *Schedules* frame stores request schedules and pallet destinations based on historical data, while the *SetAttributesMUs* method assigns relevant attributes such as destination and due date to each pallet.

Conveyor modules in the *HighBayWarehouse* frame generally function without additional methods. However, at the merge points before an outfeed lane, the *MergePoints* method implements the required logic, including the possible looping condition. Additionally, this method ensures that workstation sequences are followed correctly by verifying whether the previous pallet has entered the workstation. The *BufferEntrance* method updates the last workstation pallet entering the buffer.

Pipeline constraints are enforced using several methods. First, method *UpdateEnRoute* tracks pallets entering or exiting transit, updating the corresponding pipeline count. The variables under this method show the updated number of in-transit pallets. Second, method *CheckEnRoute* determines whether a pallet can begin movement based on the pipeline threshold and, for workstation pallets, ensures the preceding pallet has already moved.

Method *SortCraneBuffer* determines which dispatching rule to apply for managing the crane queue. The methods *CurrentPrioritization*, *FCFSPrioritization*, and *R1Prioritization* implement the respective scheduling policies, as detailed in Flowcharts E.5a to E.5c. These methods interact with table *SortRequests* as this table stores all pallet requests in crane queues. Tables *RemSpots* and *ExpectedDestinationTimes* solely support the R1 logic. The first of these tables records the number of conveyor positions a pallet must pass before reaching its destination, while the second one stores the estimated arrival times for in-transit pallets.

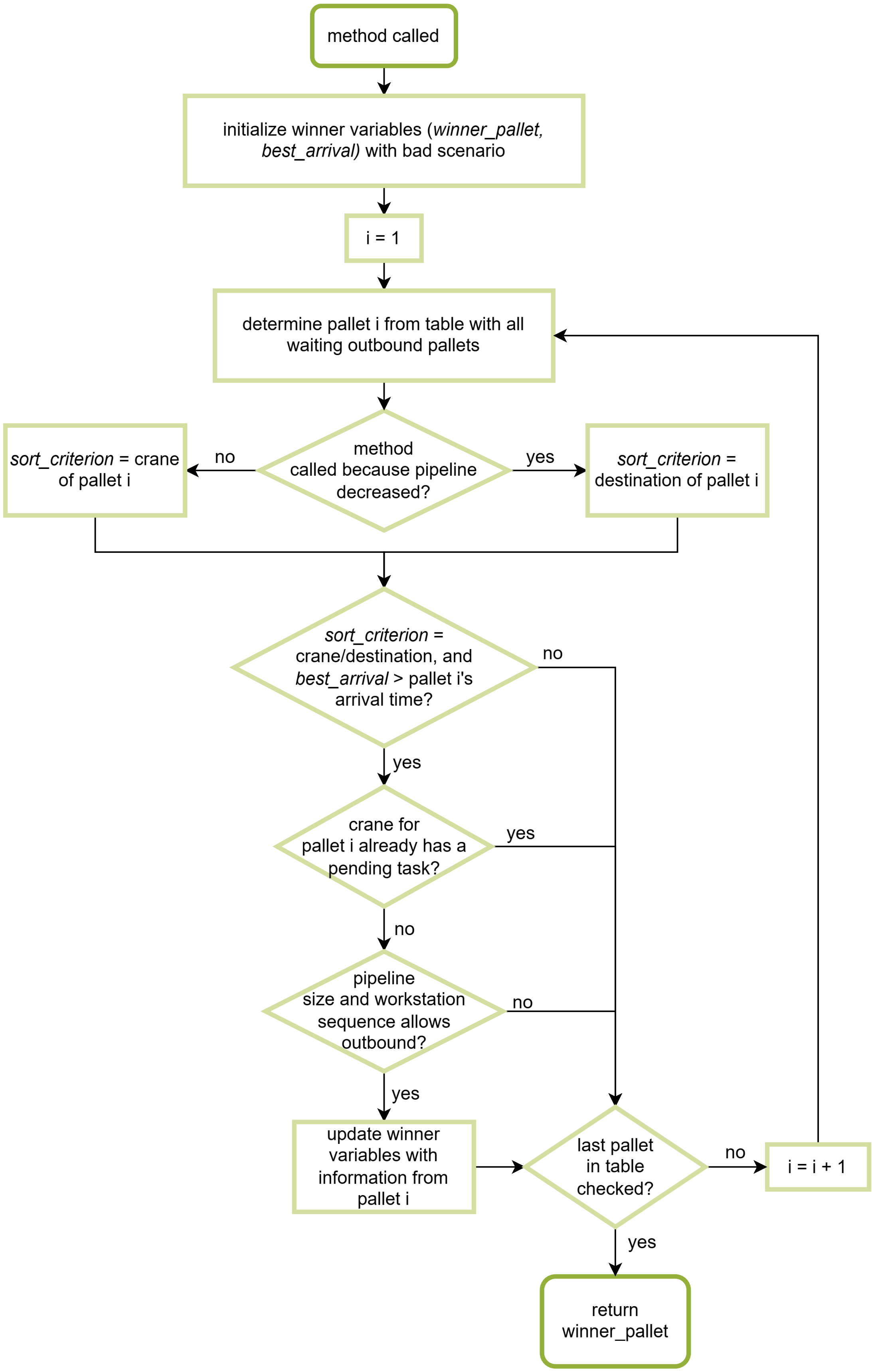
Performance Measurements The performance data is recorded in two key tables. Table *PalletPerformance* stores performance metrics per pallet, including lead-time components and looping behavior. To reduce computation time, the *UpdatePerformance* method performs the necessary calculations only if the *singlePalletInfo* variable is set to *true*. Additionally, table *PerformancePerRun* stores average KPIs for each experiment per replication.

Historical Data The tables in section *Historical Data* contain historical records used to derive operator and crane processing times.

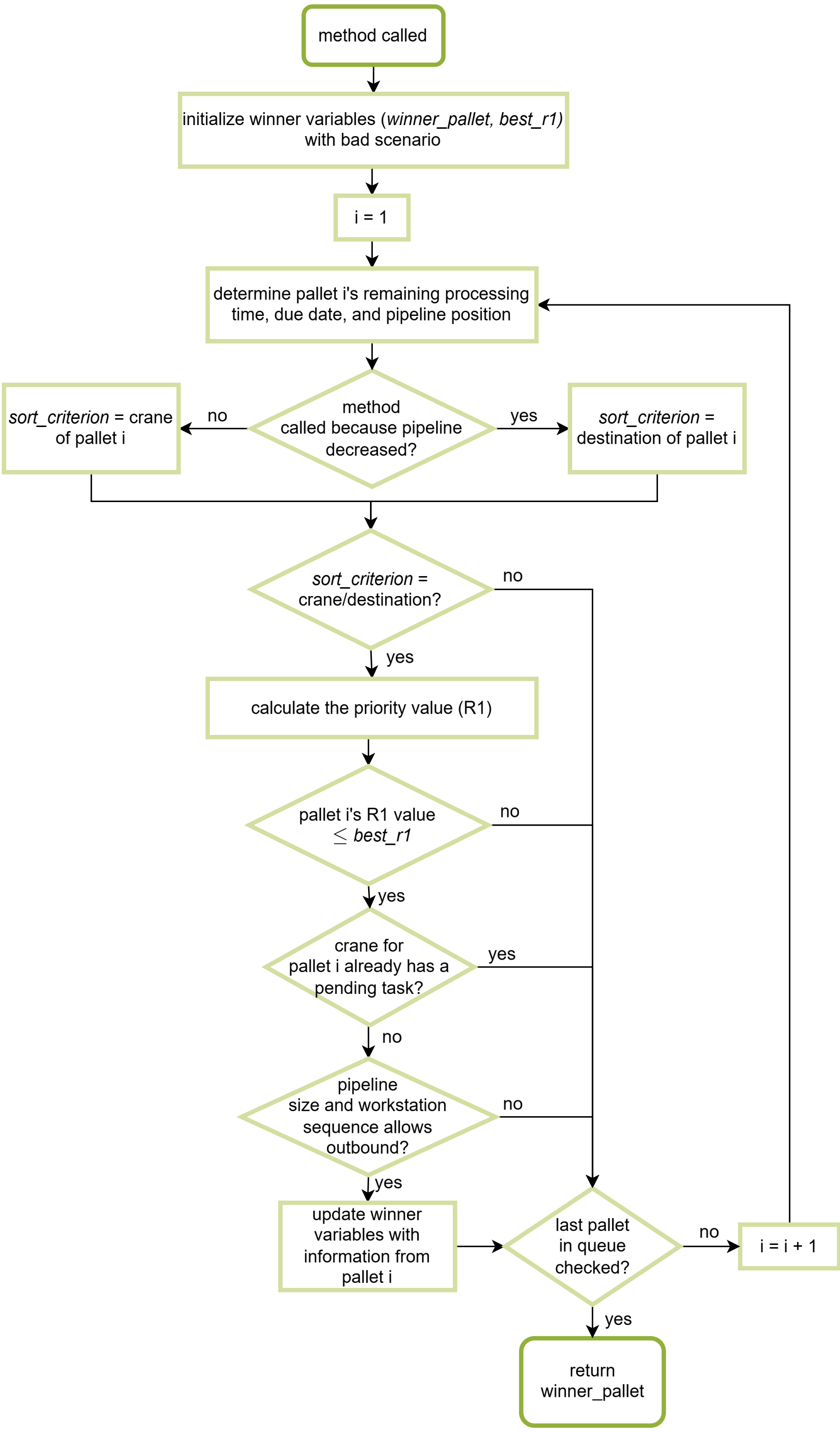
Settings & Experimental Factors Section *Settings & Experimental Factors* displays user-relevant parameters, including

- the current pipeline threshold (variable name in Figure E.6 is *enRoute_Threshold*),
- the selected prioritization rule
  - 0 represents the Baseline Simulation
  - 1 represents the FCFS Simulation
  - 2 represents the R1 Simulation
- the reloop strategy for full outbound pallets requested for *Out1* (MP0)
  - if variable *reloop_MP0* is true, full outbound pallets are allowed to loop on conveyor MP0
  - otherwise, they must wait until a spot on the outfeed lane becomes available

Experiment Control The *StartExperiments* method initiates the experiments. It serves as both a trigger button and a function that populates the *ExperimentalSettings* table with the specified experimental configurations. It also calls methods from the *Event Control* section to initialize the simulation. Furthermore, the user can modify the parameters *nrReplications* and *totalExp* to define the number of replications and experiments. Additionally, three status variables dynamically update during the simulation to indicate the current replication and experiment progress.



(b) Flowchart Method FCFSPrioritization: The flowchart illustrates the FCFSPrioritization method, which determines the next pallet for the crane to process. The method sorts outbound requests by request time and prioritizes the pallet with the earliest request time.



(c) Flowchart Method R1Prioritization: The flowchart visualizes the R1Prioritization method, which determines the next pallet for the crane to process. The method evaluates each outbound request using multiple criteria: crane processing time, remaining processing time to the destination, due date, and workload in the next queue.

Figure E.5: Flowcharts Scheduling Methods

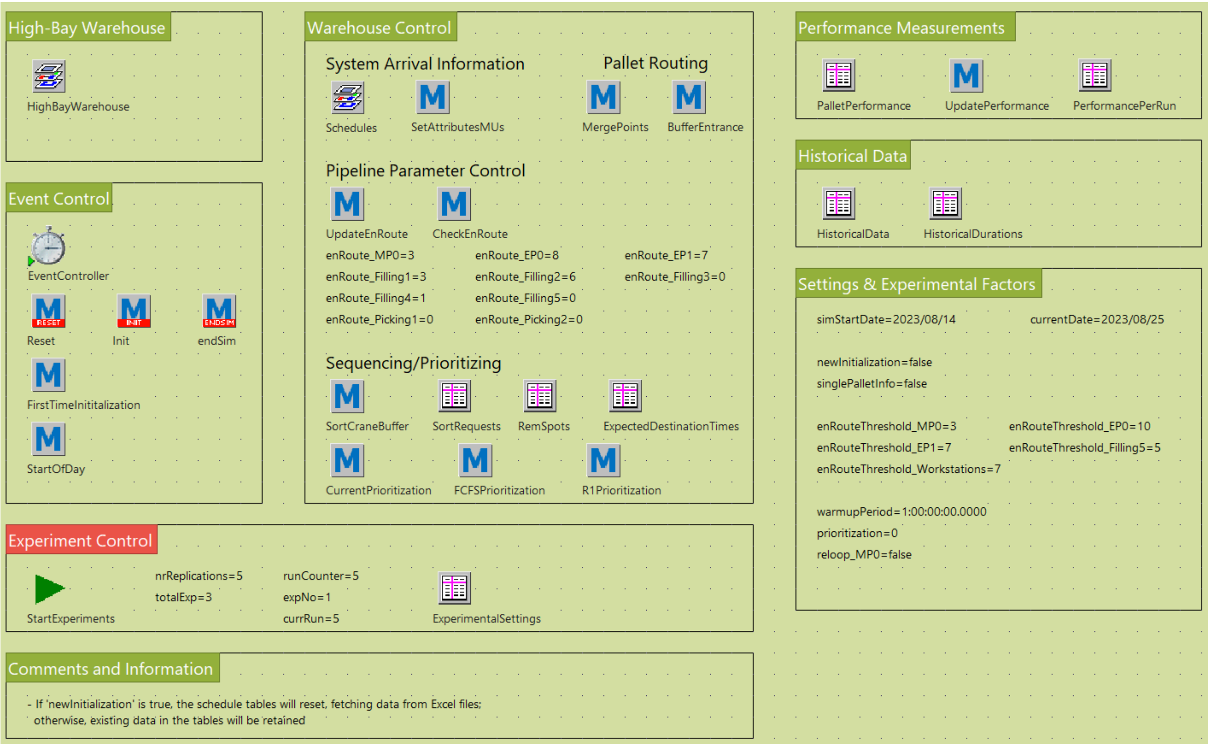


Figure E.6: Simulation Dashboard

F VERIFICATION

Verification ensures that the implemented simulation model accurately represents the conceptual model. We evaluate three simplified test scenarios and one one-hour segment from the historical dataset to confirm the model's logic. By using fixed durations, we eliminate variability, enabling precise calculations of the expected system behavior. This appendix details the datasets, verification results, and additional explanations.

The following input parameters remain consistent across all verification experiments:

- crane movement durations
  - empty travel time (single command): 45 seconds
  - empty travel time (dual command): 15 seconds
  - loaded travel time: 45 seconds
- conveyor specifications
  - conveyor speed: 0.15 meters per second
  - conveyor dimensions: 1.5 meters long and 1.1 meters wide
- lift movement durations
  - empty travel time: 25 seconds
  - loaded travel time: 35 seconds
- operator duration
  - 5 minutes

F.1 Test Scenario 1: Pipeline and Workstation Sequence

The first verification experiment assesses whether the simulation model correctly enforces pipeline and workstation sequence requirements. The pipeline thresholds, as outlined in Table 2.1, ensure that the number of pallets moving to an outbound location does not exceed its allowable capacity. Additionally, workstation pallets must follow their assigned sequence, meaning they must arrive at the workstations in order. To enforce this, the current outbound control logic permits a crane to retrieve a pallet destined for a workstation only after the preceding pallet in the sequence has been retrieved.

To validate compliance, we design a controlled test where pallets for each outbound location are requested on separate days. This setup ensures that pallets bound for different destinations do not interfere with each other, isolating the behavior of pallets moving to the same location.

The results, presented in Table F.1, confirm adherence to pipeline constraints for the outbound locations *Out1* (MP0), *Out3* (EP0), and *Out2* (EP1). For example, pallet MP0WA1_3 is retrieved immediately after its request:

- request time: 00:00:27
- empty crane travel time (single command): 45 seconds
- retrieval time: 00:01:12

However, pallet *MP0WA1_4* cannot be retrieved immediately after its request because the pipeline has already reached its maximum capacity of three pallets. Thus, crane 4 retrieves *MP0WA1_4* only after the first pallet is retrieved from the conveyor. The sequence of events is as follows:

- arrival of the first pallet (*MP0WA1_3*) at the outbound location: 00:10:03
- operator processing time: 5 minutes
- conveyor retrieval time of pallet *MP0WA1_3*: 00:15:03
- empty crane travel time (single command): 45 seconds
- retrieval time of pallet *MP0WA1_4*: 00:15:48

A similar analysis confirms pipeline adherence at *Out3* (EP0) and *Out2* (EP1).

Pallet ID	**System Arrival**		**Crane Movement**	**Destination**	
	Location	**Time**	**Pickup Time**	**Location**	**Time**
MP0WA1_1	Crane 1	00:00:25	00:01:10	*Out1* (MP0)	00:20:03
MP0WA1_2	Crane 2	00:00:26	00:01:11	*Out1* (MP0)	00:15:03
MP0WA1_3	Crane 3	00:00:27	00:01:12	*Out1* (MP0)	00:10:03
MP0WA1_4	Crane 4	00:00:28	00:15:48	*Out1* (MP0)	00:25:03
MP0WA1_5	Crane 5	00:00:29	00:20:48	*Out1* (MP0)	00:30:03

(a) Test Scenario 1: Outbound Data *Out1* (MP0).

For workstation-bound pallets, results show that the model correctly enforces sequence constraints. As seen in Tables F.1d to F.1j, pallets reach their destinations in the order of their arrival in the system. If a pallet arrives at a workstation before its designated predecessor, it loops on the conveyor until its sequence number permits entry.

For instance, pallet *MP0K0X_1*, enters the workstation before pallet *MP0K0X_2*, even though *MP0K0X_2* has a shorter travel distance (as seen in Figure 2.2a). Since *MP0K0X_2* arrives before its predecessor, it must loop on the conveyor, delaying its entry.

These observations confirm that the model correctly enforces both pipeline capacity limits and workstation sequence requirements.

F.2 Test Scenario 2: Prioritization Rules

This experiment verifies whether the simulation model correctly applies prioritization rules. As described in Section 2.4.1, workstation pallets have higher priority than full outbound pallets. In Table F.2, full outbound pallets are assigned a prioritization value of 50, ensuring they are

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	**Time**	**Pickup Time**	**Location**	**Time**
EP0WA1_1	Crane 1	00:00:25	00:01:10	*Out3* (EP0)	00:14:28
EP0WA1_2	Crane 2	00:00:26	00:01:11	*Out3* (EP0)	00:09:28
EP0WA1_3	Crane 3	00:00:27	00:01:12	*Out3* (EP0)	00:04:28
EP0WA1_4	Crane 4	00:00:28	00:01:13	*Out3* (EP0)	00:44:28
EP0WA1_5	Crane 5	00:00:29	00:01:14	*Out3* (EP0)	00:39:28
EP0WA1_6	Crane 6	00:00:30	00:01:15	*Out3* (EP0)	00:34:28
EP0WA1_7	Crane 1	00:00:31	00:02:40	*Out3* (EP0)	00:29:28
EP0WA1_8	Crane 2	00:00:32	00:02:41	*Out3* (EP0)	00:24:28
EP0WA1_9	Crane 3	00:00:33	00:02:42	*Out3* (EP0)	00:19:28
EP0WA1_10	Crane 4	00:00:34	00:02:43	*Out3* (EP0)	00:49:28
EP0WA1_11	Crane 5	00:00:35	00:10:13	*Out3* (EP0)	00:54:28
EP0WA1_12	Crane 6	00:00:36	00:15:13	*Out3* (EP0)	00:59:28

(b) Test Scenario 1: Outbound Data *Out3* (EP0)

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	**Time**	**Pickup Time**	**Location**	**Time**
EP1WA1_1	Crane 1	00:00:25	00:01:10	*Out2* (EP1)	00:21:56
EP1WA1_2	Crane 2	00:00:26	00:01:11	*Out2* (EP1)	00:36:56
EP1WA1_3	Crane 3	00:00:27	00:01:12	*Out2* (EP1)	00:26:56
EP1WA1_4	Crane 4	00:00:28	00:01:13	*Out2* (EP1)	00:16:56
EP1WA1_5	Crane 5	00:00:29	00:01:14	*Out2* (EP1)	00:11:56
EP1WA1_6	Crane 6	00:00:30	00:01:15	*Out2* (EP1)	00:06:56
EP1WA1_7	Crane 1	00:00:31	00:02:40	*Out2* (EP1)	00:31:56
EP1WA1_8	Crane 2	00:00:32	00:12:41	*Out2* (EP1)	01:01:56
EP1WA1_9	Crane 3	00:00:33	00:17:41	*Out2* (EP1)	00:51:56
EP1WA1_10	Crane 4	00:00:34	00:22:41	*Out2* (EP1)	00:56:56
EP1WA1_11	Crane 5	00:00:35	00:27:41	*Out2* (EP1)	00:41:56
EP1WA1_12	Crane 6	00:00:36	00:32:41	*Out2* (EP1)	00:56:56

(c) Test Scenario 1: Outbound Data *Out2* (EP1)

treated with lower priority.

The results, sorted by the crane pickup time, confirm that the retrieval sequence adheres to the prioritization rules. Key observations include:

- Crane 1 retrieves pallet *MP0WA1_1* first, as it is the earliest request. While the crane is en route, additional requests are made. The requests of these pallets cannot influence the retrieval of *MP0WA1_1*. Despite its earlier request, *MP0WA1_2* is retrieved after *MP0K0X_1* and *MP0K0X_2* because workstation pallets have priority.
- The behavior of cranes 4 and 6 confirms that prioritization rules are localized and oper-

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	Time	Pickup Time	Location	Time
MP0K0X_1	Crane 1	00:00:25	00:01:10	*F1* (MP0)	00:08:33
MP0K0X_2	Crane 2	00:00:26	00:01:11	*F1* (MP0)	00:17:03
MP0K0X_3	Crane 3	00:00:27	00:01:12	*F1* (MP0)	00:25:34
MP0K0X_4	Crane 4	00:00:28	00:01:13	*F1* (MP0)	00:33:54
MP0K0X_5	Crane 5	00:00:29	00:01:14	*F1* (MP0)	00:42:24
MP0K0X_6	Crane 6	00:00:30	00:01:15	*F1* (MP0)	00:50:55
MP0K0X_7	Crane 1	00:00:31	00:02:40	*F1* (MP0)	00:55:55
MP0K0X_8	Crane 2	00:00:32	00:14:18	*F1* (MP0)	01:00:55
MP0K0X_9	Crane 3	00:00:33	00:22:48	*F1* (MP0)	01:05:55
MP0K0X_10	Crane 4	00:00:34	00:31:19	*F1* (MP0)	01:13:09
MP0K0X_11	Crane 5	00:00:35	00:39:39	*F1* (MP0)	01:20:49
MP0K0X_12	Crane 6	00:00:36	00:48:09	*F1* (MP0)	01:28:40

(d) Verification Test Scenario 1: Outbound Data Filling 1 (MP0)

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	Time	Pickup Time	Location	Time
MP0K0X_13	Crane 1	00:00:25	00:01:10	*F2* (MP0)	00:08:03
MP0K0X_14	Crane 2	00:00:26	00:01:11	*F2* (MP0)	00:16:33
MP0K0X_15	Crane 3	00:00:27	00:01:12	*F2* (MP0)	00:25:04
MP0K0X_16	Crane 4	00:00:28	00:01:13	*F2* (MP0)	00:33:24
MP0K0X_17	Crane 5	00:00:29	00:01:14	*F2* (MP0)	00:41:54
MP0K0X_18	Crane 6	00:00:30	00:01:15	*F2* (MP0)	00:50:25
MP0K0X_19	Crane 1	00:00:31	00:02:40	*F2* (MP0)	00:55:25
MP0K0X_20	Crane 2	00:00:32	00:13:48	*F2* (MP0)	01:00:25
MP0K0X_21	Crane 3	00:00:33	00:22:18	*F2* (MP0)	01:05:25
MP0K0X_22	Crane 4	00:00:34	00:30:49	*F2* (MP0)	01:12:09
MP0K0X_23	Crane 5	00:00:35	00:39:09	*F2* (MP0)	01:19:53
MP0K0X_24	Crane 6	00:00:36	00:47:39	*F2* (MP0)	01:27:40

(e) Verification Test Scenario 1: Outbound Data Filling 2 (MP0)

ate independently for each crane. For example, pallets *EP0WA1_1* and *EP1K0X_2* are retrieved immediately after their respective requests, unaffected by the activities at other cranes.

- If two pallets share the same priority, the one with the earliest request timestamp is retrieved first. This is evident in the retrieval order of pallets *MP0WA1_6* and *EP0WA1_2*.

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	Time	Pickup Time	Location	Time
MP0K0X_25	Crane 1	00:00:25	00:01:10	*F3* (MP0)	00:07:33
MP0K0X_26	Crane 2	00:00:26	00:01:11	*F3* (MP0)	00:16:03
MP0K0X_27	Crane 3	00:00:27	00:01:12	*F3* (MP0)	00:24:34
MP0K0X_28	Crane 4	00:00:28	00:01:13	*F3* (MP0)	00:32:54
MP0K0X_29	Crane 5	00:00:29	00:01:14	*F3* (MP0)	00:41:24
MP0K0X_30	Crane 6	00:00:30	00:01:15	*F3* (MP0)	00:49:55
MP0K0X_31	Crane 1	00:00:31	00:02:40	*F3* (MP0)	00:54:55
MP0K0X_32	Crane 2	00:00:32	00:13:18	*F3* (MP0)	00:59:55
MP0K0X_33	Crane 3	00:00:33	00:21:48	*F3* (MP0)	01:04:55
MP0K0X_34	Crane 4	00:00:34	00:30:19	*F3* (MP0)	01:11:09
MP0K0X_35	Crane 5	00:00:35	00:38:39	*F3* (MP0)	01:18:49
MP0K0X_36	Crane 6	00:00:36	00:47:09	*F3* (MP0)	01:26:50

(f) Verification Test Scenario 1: Outbound Data Filling 3 (MP0)

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	Time	Pickup Time	Location	Time
MP0K0X_37	Crane 1	00:00:25	00:01:10	*F4* (MP0)	00:07:03
MP0K0X_38	Crane 2	00:00:26	00:01:11	*F4* (MP0)	00:15:33
MP0K0X_39	Crane 3	00:00:27	00:01:12	*F4* (MP0)	00:24:04
MP0K0X_40	Crane 4	00:00:28	00:01:13	*F4* (MP0)	00:32:24
MP0K0X_41	Crane 5	00:00:29	00:01:14	*F4* (MP0)	00:40:54
MP0K0X_42	Crane 6	00:00:30	00:01:15	*F4* (MP0)	00:49:25
MP0K0X_43	Crane 1	00:00:31	00:02:40	*F4* (MP0)	00:54:25
MP0K0X_44	Crane 2	00:00:32	00:12:48	*F4* (MP0)	00:59:25
MP0K0X_45	Crane 3	00:00:33	00:21:18	*F4* (MP0)	01:04:25
MP0K0X_46	Crane 4	00:00:34	00:29:49	*F4* (MP0)	01:10:09
MP0K0X_47	Crane 5	00:00:35	00:38:09	*F4* (MP0)	01:17:50
MP0K0X_48	Crane 6	00:00:36	00:46:39	*F4* (MP0)	01:25:40

(g) Verification Test Scenario 1: Outbound Data Filling 4 (MP0)

F.3 Test Scenario 3: Hybrid Command

The third verification experiment evaluates whether the simulation model correctly executes the hybrid command logic. As described in Section A.1, cranes operate single command cycles for outbound tasks until an inbound request appears on the same side as an ongoing outbound task. At this point, the crane transitions into a dual cycle, handling both inbound and outbound tasks.

The results in Table F.3, organized by crane pickup time, confirm this behavior:

- If a crane is idle when an inbound request arrives at the I/O-point, it immediately retrieves

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	**Time**	**Pickup Time**	**Location**	**Time**
MP0K0X_49	Crane 1	00:00:25	00:01:10	*F5* (MP0)	00:09:51
MP0K0X_50	Crane 2	00:00:26	00:01:11	*F5* (MP0)	00:18:21
MP0K0X_51	Crane 3	00:00:27	00:01:12	*F5* (MP0)	00:26:52
MP0K0X_52	Crane 4	00:00:28	00:01:13	*F5* (MP0)	00:35:12
MP0K0X_53	Crane 5	00:00:29	00:01:14	*F5* (MP0)	00:43:42
MP0K0X_54	Crane 6	00:00:30	00:15:36	*F5* (MP0)	00:48:42
MP0K0X_55	Crane 1	00:00:31	00:24:06	*F5* (MP0)	00:53:42
MP0K0X_56	Crane 2	00:00:32	00:32:37	*F5* (MP0)	00:59:08
MP0K0X_57	Crane 3	00:00:33	00:40:57	*F5* (MP0)	01:06:52
MP0K0X_58	Crane 4	00:00:34	00:49:27	*F5* (MP0)	01:14:17
MP0K0X_59	Crane 5	00:00:35	00:54:27	*F5* (MP0)	01:19:17
MP0K0X_10	Crane 6	00:00:36	00:49:27	*F5* (MP0)	01:24:17

(h) Verification Test Scenario 1: Outbound Data Filling 5 (MP0)

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	**Time**	**Pickup Time**	**Location**	**Time**
EP1K0X_1	Crane 1	00:00:25	00:01:10	*P1* (EP1)	00:09:50
EP1K0X_2	Crane 2	00:00:26	00:01:11	*P1* (EP1)	00:17:31
EP1K0X_3	Crane 3	00:00:27	00:01:12	*P1* (EP1)	00:24:51
EP1K0X_4	Crane 4	00:00:28	00:01:13	*P1* (EP1)	00:32:36
EP1K0X_5	Crane 5	00:00:29	00:01:14	*P1* (EP1)	00:39:52
EP1K0X_6	Crane 6	00:00:30	00:01:15	*P1* (EP1)	00:47:32
EP1K0X_7	Crane 1	00:00:31	00:02:40	*P1* (EP1)	00:52:32
EP1K0X_8	Crane 2	00:00:32	00:15:35	*P1* (EP1)	00:57:32
EP1K0X_9	Crane 3	00:00:33	00:23:16	*P1* (EP1)	01:03:22
EP1K0X_10	Crane 4	00:00:34	00:30:36	*P1* (EP1)	01:09:54
EP1K0X_11	Crane 5	00:00:35	00:38:21	*P1* (EP1)	01:16:59
EP1K0X_12	Crane 6	00:00:36	00:45:37	*P1* (EP1)	01:23:34

(i) Verification Test Scenario 1: Outbound Data Picking 1 (EP1)

the inbound pallet. For instance, when *MP0WE1_1* arrives at the I/O-point of crane 1, the crane promptly retrieves it, as shown in the following timeline:

- I/O-point arrival time: 00:01:56
- empty crane travel time (single command): 45 seconds
- retrieval time: 00:02:41

- If a crane is occupied, inbound pallets must wait until the crane either completes its current task or a dual command cycle is possible. For example, *MP0WE1_2* arrives at the I/O-point while crane 1 is handling the outbound request *MP0WA1_1*. Since the outbound location is on the same side, the crane performs a dual command:

Pallet ID	System Arrival		Crane Movement	Destination	
	Location	Time	Pickup Time	Location	Time
EP1K0X_13	Crane 1	00:00:25	00:01:10	*P2* (EP1)	00:08:03
EP1K0X_14	Crane 2	00:00:26	00:01:11	*P2* (EP1)	00:16:33
EP1K0X_15	Crane 3	00:00:27	00:01:12	*P2* (EP1)	00:25:04
EP1K0X_16	Crane 4	00:00:28	00:01:13	*P2* (EP1)	00:33:24
EP1K0X_17	Crane 5	00:00:29	00:01:14	*P2* (EP1)	00:41:54
EP1K0X_18	Crane 6	00:00:30	00:01:15	*P2* (EP1)	00:50:25
EP1K0X_19	Crane 1	00:00:31	00:02:40	*P2* (EP1)	00:55:25
EP1K0X_20	Crane 2	00:00:32	00:14:55	*P2* (EP1)	01:00:25
EP1K0X_21	Crane 3	00:00:33	00:22:26	*P2* (EP1)	01:05:25
EP1K0X_22	Crane 4	00:00:34	00:30:05	*P2* (EP1)	01:12:09
EP1K0X_23	Crane 5	00:00:35	00:38:21	*P2* (EP1)	01:19:53
EP1K0X_24	Crane 6	00:00:36	00:45:37	*P2* (EP1)	01:27:40

(j) Verification Test Scenario 1: Outbound Data Picking 2 (EP1)

Table F.1: Verification: Test Scenario 1. The tables present the timestamps for key events in the simulation: system arrival time, crane retrieval time, and destination arrival time. These timestamps align with the calculated values for each respective event.

- I/O-point arrival time (*MP0WE1_2*): 00:02:47
- retrieval time (*MP0WA1_1*): 00:04:11
- loaded crane travel time (single command): 45 seconds
- empty crane travel time (dual command): 15 seconds
- retrieval time: 00:05:11

F.4 Test Scenario 4: Comprehensive Testing

The final verification experiment evaluates a one-hour segment from the historical dataset. The results in Table F.4 confirm that the previously verified logic is maintained in a real-world scenario.

- Workstation pallets loop if they arrive before their predecessor, as seen with the longer conveyor movement time of pallet *MP0K0X_26701*. Similarly, full outbound pallets unable to enter their designated outbound buffer areas due to occupied buffer spots also loop on the conveyor.
- Minor discrepancies between expected and simulated lead times result from rounding in calculations. Additionally, most pallets with an identical flow path through the high-bay warehouse presented similar errors (e.g., 0.01 minute differences for inbound pallets from *In2* (EP1)).
- Larger differences arise from pallet interactions on the conveyor, which were not explicitly factored into expected lead times. For instance, pallet *MP0WE1_27560* experienced delays due to other pallets traversing the conveyor while moving from the inbound area at MP0 to the main conveyor.

Pallet ID	System Arrival		Crane Movement		Destination	Prioritization
	Location	Time	Pickup	Dropoff	Location	
MP0WA1_1	Crane 1	00:00:25	00:01:10	00:01:55	*Out1* (MP0)	50
MP0K0X_1	Crane 1	00:00:27	00:02:40	00:03:25	*F1* (MP0)	1
MP0K0X_2	Crane 1	00:00:35	00:04:10	00:04:55	*F2* (MP0)	1
MP0WA1_2	Crane 1	00:00:26	00:05:40	00:06:25	*Out1* (MP0)	50
EP1K0X_1	Crane 3	00:16:40	00:17:25	00:18:10	*P1* (EP1)	1
EP1K0X_2	Crane 4	00:16:45	00:17:30	00:18:15	*P2* (EP1)	1
EP0WA1_1	Crane 6	00:16:55	00:17:40	00:18:25	*Out3* (EP0)	50
MP0K0X_3	Crane 5	00:17:20	00:18:05	00:18:50	*F3* (MP0)	1
EP1K0X_3	Crane 3	00:17:10	00:18:55	00:19:40	*P1* (EP1)	1
MP0WA1_5	Crane 5	00:17:40	00:19:35	00:20:20	*Out1* (MP0)	50
EP1WA1_1	Crane 3	00:16:50	00:20:25	00:21:10	*Out2* (EP1)	50
EP1WA1_2	Crane 5	00:33:35	00:34:20	00:35:05	*Out2* (EP1)	50
MP0K0X_4	Crane 5	00:33:50	00:35:50	00:36:35	*F4* (MP0)	1
EP1K0X_4	Crane 5	00:33:55	00:38:20	00:39:05	*P2* (EP1)	1
MP0K0X_5	Crane 5	00:34:00	00:39:50	00:40:35	*F5* (MP0)	1
MP0WA1_6	Crane 5	00:33:40	00:41:20	00:42:05	*Out1* (MP0)	50
EP0WA1_2	Crane 5	00:33:45	00:42:50	00:43:35	*Out3* (EP0)	50

Table F.2: Verification: Test Scenario 2. The table presents the timestamps for key events in the simulation: system arrival time, crane retrieval time, start of the conveyor movement time, and destination arrival time. These timestamps align with the calculated values for each respective event. Additionally, the priority value is provided, with 1 representing a higher priority than 50.

While Table F.4 presents the calculated expectation for the full lead time duration alongside the simulation results, the expected durations of the lead time components are not explicitly shown. However, these divided parts were compared to the corresponding simulation results during the verification process. This comparison helped explain discrepancies between the expected and simulated lead times.

Pallet ID	System Arrival		Crane Movement		Destination	
	Location	Time	Pickup	I/O-point	Location	Time
MP0WE1_1	*In1* (MP0)	00:00:25	00:02:41	00:01:56	Crane 1	00:03:26
MP0WA1_1	Crane 1	00:02:00	00:04:11	00:04:56	*Out3* (MP0)	00:14:22
MP0WE1_2	*In1* (MP0)	00:00:40	00:05:11	00:02:47	Crane 1	00:05:56
EP1WA1_1	Crane 1	00:02:10	00:06:41	00:07:26	*Out2* (EP1)	00:15:42
EP0WA1_1	Crane 1	00:02:20	00:08:11	00:08:56	*Out3* (EP0)	00:12:47
MP0WA1_2	Crane 1	00:02:30	00:09:41	00:10:26	*Out3* (MP0)	00:19:52
EP1WA1_2	Crane 2	00:18:40	00:19:25	00:20:10	Out EP0	00:27:46
MP0WA1_3	Crane 2	00:19:00	00:20:55	00:21:40	*Out3* (MP0)	00:30:26
MP0WA1_4	Crane 2	00:21:30	00:22:25	00:23:10	*Out3* (MP0)	00:35:26
EP0WA1_2	Crane 2	00:22:30	00:23:55	00:24:40	*Out3* (EP0)	00:27:51
EP1WE1_2	*In2* (EP1)	00:18:40	00:24:55	00:21:17	Crane 2	00:25:40
MP0K0X_1	Crane 4	00:30:50	00:31:35	00:32:20	*F3* (MP0)	00:35:48
MP0K0X_2	Crane 4	00:43:20	00:44:05	00:44:50	*F4* (MP0)	00:47:48
EP1K0X_1	Crane 4	00:44:10	00:45:35	00:46:20	*P1* (EP1)	00:52:15
EP0WE1_1	*In3* (EP0)	00:33:20	00:46:35	00:43:24	Crane 4	00:47:20
MP0K0X_3	Crane 4	00:45:50	00:48:05	00:48:50	*F2* (MP0)	00:52:48
MP0K0X_1	*F3* (MP0)	00:40:48	00:49:05	00:48:06	Crane 4	00:49:50
EP1WA1_3	Crane 4	00:46:40	00:50:35	00:51:20	*Out2* (EP1)	00:57:36
EP0WE1_2	*In3* (EP0)	00:33:40	00:51:35	00:46:42	Crane 4	00:52:50
MP0K0X_2	*F4* (MP0)	00:52:48	01:01:21	01:00:36	Crane 4	01:02:06
EP1K0X_1	*P1* (EP1)	00:57:15	01:03:22	01:02:37	Crane 4	01:04:07
MP0K0X_3	*F2* (MP0)	00:57:48	01:05:21	01:04:36	Crane 4	01:06:06

Table F.3: Verification: Test Scenario 3. The table presents the timestamps for key events in the simulation: system arrival time, crane retrieval time, start of the conveyor movement time, and destination arrival time. These timestamps align with the calculated values for each respective event.

Pallet ID	System Arrival		Destination	Duration (in minutes)					
				Simulation					Expectation
	Location	Time	Location	Queue-ing	Crane	Con-veyor	Work-sta-tion	Lead Time	Lead Time
EP0WE1_16977	*In3* (EP0)	08:01:35	Crane 5	1.18	0.75	2.58		4.52	4.52
MP0WE1_27662	*In1* (MP0)	08:04:16	Crane 6	0.75	0.75	5.17		6.67	6.52
EP0WE1_18972	*In3* (EP0)	08:02:42	Crane 1	0.75	0.75	8.07		9.57	9.58
MP0K0X_26878	Crane 1	08:03:05	*F4* (MP0)	0.75	0.75	5.13	5	11.63	11.63
MP0K0X_26905	Crane 2	08:05:57	*F1* (MP0)	0.92	0.75	5.97	5	12.63	12.63
MP0K0X_26701	Crane 5	08:03:06	*F4* (MP0)	0.75	0.75	11.46	5	17.96	17.95
MP0K0X_26905	*F1* (MP0)	08:18:35	*Rej1* (MP0)					3.57	3.57
MP0K0X_26719	Crane 2	08:03:07	*F4* (MP0)	0.75	0.75	16.44	5	22.94	22.94
MP0K0X_26701	*F4* (MP0)	08:21:03	Crane 1	0.75	0.75	5.63		7.13	7.14
MP0K0X_26818	Crane 2	08:03:08	*F4* (MP0)	2.23	0.75	19.94	5	27.92	27.92
EP1WE1_10115	*In2* (EP1)	08:27:47	Crane 3	0.75	0.75	3.29		4.79	4.80
EP1WA1_12391	Crane 4	08:25:25	*Out2* (EP1)	0.75	0.75	6.27		7.77	7.77
MP0K0X_26719	*F4* (MP0)	08:26:03	Crane 2	0.45	0.75	6.3		7.50	7.50
EP1WE1_10189	*In2* (EP1)	08:28:56	Crane 4	0.75	0.75	3.96		5.46	5.47
EP1K0X_6013	Crane 2	08:22:03	*P1* (EP1)	0.75	0.75	7.26	5	13.76	13.75
MP0K0X_26704	Crane 4	08:03:09	*F4* (MP0)	2.97	0.75	24.19	5	32.91	32.90
EP1WE1_10111	*In2* (EP1)	08:32:11	Crane 3	0.75	0.75	3.29		4.79	4.80
EP1WE1_10114	*In2* (EP1)	08:34:22	Crane 1	0.75	0.75	1.96		3.46	3.47
EP1K0X_6013	*P1* (EP1)	08:35:48	*Out2* (EP1)					2.72	2.72
EP1WE1_10116	*In2* (EP1)	08:36:10	Crane 2	0.75	0.75	2.62		4.12	4.13
MP0K0X_26818	*F4* (MP0)	08:31:03	Crane 4	0.75	0.75	7.80		9.30	9.31
EP1K0X_6012	Crane 1	08:22:05	*P1* (EP1)	1.22	0.75	11.75	5	18.72	18.72
MP0WA1_6034	Crane 6	08:32:58	*Out1* (MP0)	1.27	0.75	5.93		7.95	7.95
MP0K0X_26690	Crane 3	08:03:10	*F4* (MP0)	3.7	0.75	28.44	5	37.89	37.89
MP0K0X_26704	*F4* (MP0)	08:36:03	*Rej1* (MP0)					5.37	5.07
MP0K0X_26855	Crane 6	08:31:59	*F1* (MP0)	0.75	0.75	3.13	5	9.63	9.63
EP1K0X_6012	*P1* (EP1)	08:40:48	Rej EP1					2.72	2.72
EP1WE1_10112	*In2* (EP1)	08:40:21	Crane 2	0.75	0.75	2.62		4.12	4.13
EP1K0X_6020	Crane 1	08:31:21	*P2* (EP1)	0.75	0.75	7.26	5	13.76	13.75
MP0K0X_26855	*F1* (MP0)	08:41:37	*Rej1* (MP0)					3.57	3.57
EP1K0X_6028	Crane 1	08:22:06	*P1* (EP1)	2.71	0.75	15.25	5	23.71	23.70
MP0K0X_26717	Crane 5	08:03:10	*F4* (MP0)	4.45	0.75	32.69	5	42.89	42.89
MP0WE1_27487	*In1* (MP0)	08:41:57	Crane 3	0.75	0.75	2.84		4.34	4.36
MP0K0X_26868	Crane 1	08:32:00	*F1* (MP0)	1.6	0.75	7.27	5	14.62	14.62
MP0WE1_27560	*In1* (MP0)	08:40:36	Crane 6	0.25	0.75	5.15		6.15	6.02

Table F.4: Verification: Test Scenario 4. The table presents the timestamps for key events in the simulation and the expected lead time based on calculations.

G VALIDATION

The simulation model, like the real-world system it replicates, is a complex construct with multiple interdependent components. The behavior of each component impacts and is influenced by the others. The process is divided into several targeted experiments to ensure a comprehensive validation. The methodology and outcomes of these validation experiments are detailed in the following sections.

Most experiments are conducted using data from 01.12.2023 to 04.12.2023. This specific timeframe is selected because it contains the fewest outliers across consecutive days, thereby minimizing the impact of influences on subsequent pallets. A shift in pallet behavior can influence other pallets in the system. For instance, if a workstation pallet finishes processing earlier than expected, even if only by a few seconds, it clears space in the conveyor pipeline sooner. This allows the next workstation pallet to move forward earlier, prioritizing it over other pallets assigned to the same crane.

As a result, an outbound pallet might be delayed by the time the crane spends moving loaded and empty to retrieve the workstation pallet. If the pipeline for the outbound pallet drops below its threshold while the crane is occupied, the delay can be even longer. In such cases, the next pallet destined for the outbound location is processed first. This sequence increases the queueing time of the initially delayed outbound pallet by the time needed to reduce the pipeline again. Meanwhile, the advanced outbound pallet benefits from a reduced queueing time due to the adjusted behavior of the workstation pallet.

To mitigate these effects, exact historical durations are incorporated as input data for the simulation in specific experiments. The input data used for each experiment is provided in their respective sections.

In addition, experiments are conducted with a larger dataset spanning two months (15.08.2023 to 15.10.2023). This extended dataset allows for a more reliable evaluation of pallet behavior over a longer period. It confirms that the patterns observed in the smaller dataset hold under broader operational conditions. These additional experiments further validate the observations from the smaller dataset, ensuring consistency across varying timeframes. We run the experiments of both datasets over 10 replications.

G.1 Initial Validation (4-Day Dataset)

Workstation Outbound Logic In collaboration with domain experts, the logic governing outbound flows for workstation requests was established. The first validation experiment evaluats this logic, presented in Table G.1b. According to the implemented rules, cranes retrieve pallets only after the preceding pallet in the sequence has been retrieved. This logic primarily affects the queueing time of workstation pallets, making queueing time a key metric for evaluation. The results shown in Table G.1b are based on the settings and operator behavior distributions outlined in Table G.1a.

The initial validation reveals significant discrepancies between the simulation and historical data. Specifically, the MAPE for queueing times is 74.50% for workstations on the MP0 side and 64.24% for those on the EP1 side. Analysis of the historical data reveals instances where workstation-bound pallets experience longer queueing times than the logic in Experiment 1 would predict. Significantly, this behavior could not be attributed solely to crane unavailability, as workstation pallets are prioritized over full outbound pallets. Despite an extensive analysis, no clear pattern emerged to explain the delays.

To address this, Experiments 2 through 6 tested alternative logics, where a pallet could be retrieved when the pallet with a sequence number $(n - X)$ – with X ranging from 1 to 5 – reached the entrance of the workstation buffer. For example, if $X = 1$, retrieval occurs when the pallet two positions earlier in the sequence reaches the buffer entrance (see Experiment 2 in Table G.1b).

Experiments 7 through 11 explore a different approach: retrieval is permitted once the pallet with sequence number $(n - X)$ reaches the last spot on the crane's outbound conveyor. For instance, as depicted in Figure 2.2a, a pallet retrieved by crane five occupies this position as the third spot after *O5.1*.

Outbound Location	**Distribution**	**Distribution Parameters (time in minutes)**			
		μ	σ	**Lower Bound**	**Upper Bound**
	Operator Distributions				
Out1 (MP0)	lognormal	3.50	2.67	0.17	15
Out3 (EP0)	normal	0.33	1.33	0.17	5
Out2 (EP1)	lognormal	29.08	624.97	0.17	8
F1-F5 (MP0)	exact historical durations				
P1, P2 (EP1)	exact historical durations				
	Crane Distributions				
empty, single command	normal	37.26	8.74	13	63
	+ uniform			0	15
empty, dual command	uniform			20	25
loaded, inbound	normal	37.26	8.74	13	63
loaded, outbound	exact historical durations				

(a) Validation Workstation Outbound Logic: Experimental Settings. The table presents the distributions used to model operator times at each outbound destination and workstation across the experiments conducted to validate the workstation outbound logic.

Despite testing these alternative logics, the high error values persist across all eleven experiments, indicating that the simulation does not closely replicate the historical data per-pallet basis. Consequently, an additional evaluation is conducted to assess the system's overall behavior. This second approach compares summary statistics and histograms, rather than individual pallet queueing times, to validate whether the simulation captures broader trends and variability.

Table G.2 and Figure G.1 summarize and visualize the results of this approach, comparing the queueing times observed in the historical data with those predicted by the simulation. Table G.2 provides the summary statistics for both datasets, including the average, median, stan-

Exp.	Workstation Logic Description	Workstation	Queueing Error	
			MAE (minutes)	MAPE
Exp 1	Next workstation pallet can be retrieved as soon as the crane picks up the previous pallet in the sequence.	*F1-F5* (MP0)	39.88	74.50%
		P1, P2 (EP1)	11.21	64.24%
Exp 2	Next workstation pallet can be retrieved once the previous pallet two sequence positions earlier reaches the workstation buffer.	*F1-F5* (MP0)	38.56	104.10%
		P1, P2 (EP1)	12.39	118.95%
Exp 3	Next workstation pallet can be retrieved once the previous pallet three sequence positions earlier reaches the workstation buffer.	*F1-F5* (MP0)	39.19	85.43%
		P1, P2 (EP1)	10.35	76.62%
Exp 4	Next workstation pallet can be retrieved once the previous pallet four sequence positions earlier reaches the workstation buffer.	*F1-F5* (MP0)	39.28	77.33%
		P1, P2 (EP1)	10.11	61.10%
Exp 5	Next workstation pallet can be retrieved once the previous pallet five sequence positions earlier reaches the workstation buffer.	*F1-F5* (MP0)	39.59	74.44%
		P1, P2 (EP1)	10.64	61.95%
Exp 6	Next workstation pallet can be retrieved once the previous pallet six sequence positions earlier reaches the workstation buffer.	*F1-F5* (MP0)	39.88	74.39%
		P1, P2 (EP1)	10.93	61.33%
Exp 7	Next workstation pallet can be retrieved once the previous pallet two sequence positions earlier reaches the last crane spot.	*F1-F5* (MP0)	39.34	82.04%
		P1, P2 (EP1)	10.48	70.55%
Exp 8	Next workstation pallet can be retrieved once the previous pallet three sequence positions earlier reaches the last crane spot.	*F1-F5* (MP0)	39.45	73.06%
		P1, P2 (EP1)	10.86	66.42%
Exp 9	Next workstation pallet can be retrieved once the previous pallet four sequence positions earlier reaches the last crane spot.	*F1-F5* (MP0)	39.78	73.69%
		P1, P2 (EP1)	11.02	62.87%
Exp 10	Next workstation pallet can be retrieved once the previous pallet five sequence positions earlier reaches the last crane spot.	*F1-F5* (MP0)	39.83	74.13%
		P1, P2 (EP1)	11.10	64.64%
Exp 11	Next workstation pallet can be retrieved once the previous pallet six sequence positions earlier reaches the last crane spot.	*F1-F5* (MP0)	39.89	74.54%
		P1, P2 (EP1)	11.21	63.95%

(b) Validation Workstation Outbound Logic: Results. The table presents the MAE and MAPE for the workstations at MP0 and EP1 across eleven experiments conducted to validate the workstation outbound logic. Queueing time is used as the key performance measure.

Table G.1: Validation Workstation Outbound Logic

dard deviation, minimum, and maximum queueing times for the workstations in MP0 and EP1. Figure G.1 illustrates the distribution of queueing times as histograms, comparing the historical data with the simulation results for the first experiment. Separate comparisons are shown for workstations on MP0 and EP1, highlighting differences in frequency across time bins.

The findings suggest that the overall trends are captured to a reasonable extent. Both datasets display a high frequency of pallets experiencing shorter queueing times (represented by the first bin) and a long tail for extended queueing times. However, some discrepancies are evident:

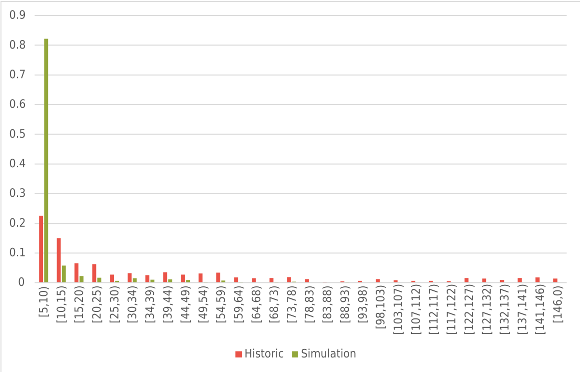
- The minimum queueing times of the simulation align closely with the historical data, with differences ranging from 0.2 to 3.85 seconds for workstations at MP0 and 0.28 to 4.85 seconds for EP1 workstations. This alignment suggests that the simulation captures the lower bounds of queueing times. The maximum queueing times show more variations, particularly for MP0, where differences extend to 106 minutes. This discrepancy points to the simulation's limitations in replicating extreme cases, likely due to differences in the applied workstation logic in the simulation compared to the real system's logic.

- The simulation's average and median queueing times are consistently lower than the historical data for both *F1 - F5* (MP0)and *P1*, *P2* (EP1) – the histogram comparisons further support this underestimation. At *F1 - F5* (MP0), for example, Figure G.1a reveals that the simulation predicts a higher frequency of pallets in the first bin than the historical data. Similar trends are evident for the workstations at EP1(Figure G.1b).

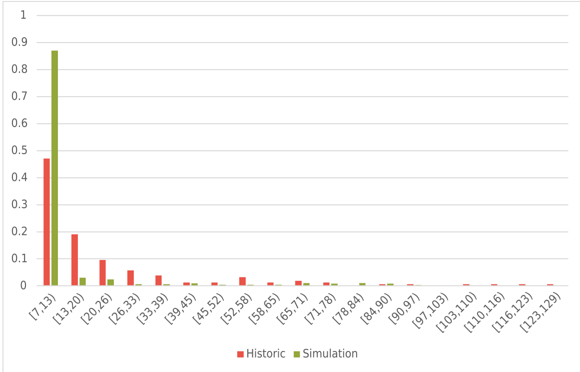
Exp.	**Workstation Locations**	**Queueing Time (in minutes)**				
		Average	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
				Historical Data		
	F1-F5 (MP0)	45.57	18.67	54.78	0.23	239.10
	P1, P2 (EP1)	16.36	7.28	22.59	0.33	116.25
				Simulation Results		
Exp. 1	*F1-F5* (MP0)	5.77	1.47	12.85	0.30	133.63
	P1, P2 (EP1)	6.48	1.97	15.19	0.30	88.32
Exp. 2	*F1-F5* (MP0)	12.49	5.95	15.99	0.24	133.33
	P1, P2 (EP1)	16.76	10.98	19.72	0.25	101.96
Exp. 3	*F1-F5* (MP0)	9.07	1.99	14.42	0.29	133.38
	P1, P2 (EP1)	10.88	3.30	16.50	0.28	99.44
Exp. 4	*F1-F5* (MP0)	7.71	1.65	14.00	0.26	148.99
	P1, P2 (EP1)	8.74	2.62	15.55	0.34	94.32
Exp. 5	*F1-F5* (MP0)	6.59	1.53	13.39	0.24	147.62
	P1, P2 (EP1)	7.53	2.26	15.16	0.27	89.40
Exp. 6	*F1-F5* (MP0)	5.94	1.42	12.78	0.23	133.25
	P1, P2 (EP1)	6.65	2.08	14.51	0.33	94.79
Exp. 7	*F1-F5* (MP0)	8.38	2.41	13.57	0.26	147.18
	P1, P2 (EP1)	7.93	2.78	15.15	0.32	97.60
Exp. 8	*F1-F5* (MP0)	6.62	2.68	13.08	0.22	134.16
	P1, P2 (EP1)	6.50	2.12	13.91	0.26	89.11
Exp. 9	*F1-F5* (MP0)	5.96	1.48	12.70	0.26	133.15
	P1, P2 (EP1)	6.51	2.07	14.82	0.35	97.93
Exp. 10	*F1-F5* (MP0)	5.81	1.45	12.87	0.25	133.01
	P1, P2 (EP1)	6.34	2.02	14.42	0.30	91.84
Exp. 11	*F1-F5* (MP0)	5.76	1.47	12.83	0.30	133.63
	P1, P2 (EP1)	6.47	1.97	15.20	0.30	88.32

Table G.2: Validation Workstation Outbound Logic: Summary Statistics. The table presents summary statistics for the workstations at MP0 and EP1 across eleven experiments conducted to validate the workstation outbound logic. Queueing time is used as the key performance measure.

Despite these efforts, neither approach demonstrates consistent improvements for all workstations. As a result, it remains unclear whether the high MAPE and MAE values are inherently due to the workstation logic tested or other factors, such as limitations in the assumed distributions for durations not covered by historical data.



(a) Validation Workstation Outbound Logic: Queueing Time Workstations at MP0



(b) Validation Workstation Outbound Logic: Queueing Time Workstations at EP1

Figure G.1: Histogram of Queueing Times for Workstation Outbound Pallets. Each figure compares the queueing times of workstation outbound pallets with historical data (red) as a reference and simulation results (green) based on the settings from Experiment 1. The x-axis represents time bins in minutes, while the y-axis indicates the frequency.

Given that the logic tested in Experiment 1 was developed in consultation with domain experts and reflects their understanding of the system, this logic will be used as the baseline for subsequent validation experiments. Future efforts will focus on refining the assumed input distributions and incorporating additional real-world data to improve model accuracy further.

Conveyor Specifications The conveyor dimensions and speeds are determined based on real-world observations, measurements at specific conveyor spots, and technical documentation of the conveyor system. Most conveyor spots have dimensions of 1.5 meters in length and 1.1 meters in width. However, some places have longer lengths, between 1.7 meters and 3 meters. The general conveyor speed is assumed to be 0.2 meters per second. Specific spots where pallets can move in different directions have a reduced speed of 0.15 meters per second due to the need for pallet scanning. Additionally, conveyor spots where the pallet's position is adjusted or its direction of movement changes require special handling, reducing the speed further to 0.12 meters per second.

The conveyor specifications are validated using the experimental setup described in Table G.1. Since historical data reliably captures conveyor durations only for full outbound pallets, these durations are used for validation. Conveyor times for workstation pallets and inbound pallets are excluded because their measurements are directly influenced by operator and crane activities. For workstation pallets, the conveyor time includes queueing time on the workstation buffer, while for inbound pallets, the conveyor time encompasses crane movement and waiting time.

For full outbound pallets destined for MP0, the MAPE across all 12 experimental setups is approximately 5%. For pallets destined for EP0 and EP1, the MAPE is about 11% and 7%, respectively. The higher errors for EP0 and EP1 compared to MP0 can be attributed to the potential for looping behavior on these conveyors. When the outbound buffer is occupied, pallets at EP0 and EP1 may loop, waiting 25 seconds before continuing. This can cause small jams on the conveyor. Furthermore, pallets for EP0 are frequently requested in large numbers simultaneously, increasing the likelihood of interaction between pallets.

An additional experiment is conducted to minimize the influence of interactions between pallets, operators, and cranes. This experiment only considers pallets requested for their respective outbound location without any other requests for that side within the same hour. For example, for MP0, the full outbound pallet has to be the only request for MP0 (excluding other full outbound or workstation pallets) within that hour. Due to the limited number of applicable data points, the dataset is extended to include data from 15.08.2023 to 02.10.2023. Even with the extended dataset, insufficient data points are found for EP0, as these pallets are often requested simultaneously in large quantities.

This experiment yields a notable reduction in MAPE. For MP0 and EP1, the error is reduced to below 2%, demonstrating improved accuracy under controlled conditions.

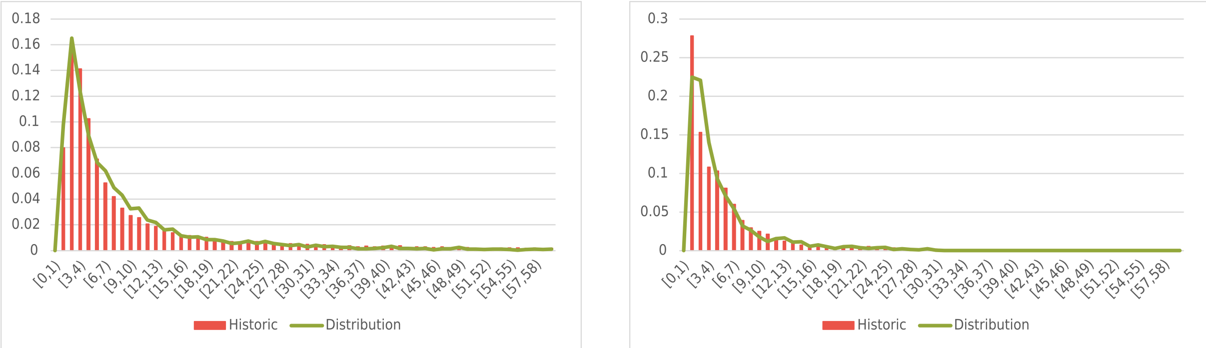
Operator Behavior Historical data provides information on pallets' arrival and departure times at their respective workstations, which serve as input for the simulation model. For pallets identified as outliers, the operator behavior at workstations follows the distribution fitted to the durations at each workstation, as shown in Table G.3a. Additionally, Figure G.2 illustrates the fit of the distribution compared to the historical durations. As shown, the green line, representing the fitted distribution, closely follows the shape of the histogram of historical durations. Plotted as percentages, these graphs show how often each value occurs within each bin. The good fit is further validated by comparing the simulation results to historical durations, where the MAPE and MAE are close to zero.

Outbound Location	**Distribution**	**Distribution Parameters (time in minutes)**			
		μ	σ	**Lower Bound**	**Upper Bound**
F1 (MP0)	lognormal	11.27	25.40	0.25	60
F2 (MP0)	lognormal	10.03	19.73	0.25	60
F3 (MP0)	lognormal	9.60	18.52	0.25	60
F4 (MP0)	lognormal	9.48	20.07	0.25	60
F5 (MP0)	lognormal	7.87	13.22	0.25	60
P1 (EP1)	lognormal	4.68	8.45	0.25	30
P2 (EP1)	lognormal	4.80	9.52	0.25	30

(a) Validation Operator Behavior: Workstation Distributions. The table presents the distributions used to model operator times at each workstation across the experiments conducted to validate the operator behavior. These distributions apply to pallets identified as outliers, while non-outlier pallets follow their historical duration.

For full outbound pallets, the last recorded timestamp corresponds to their arrival at the destination, with no timestamp available for their retrieval from the conveyor. As a result, estimating operator processing times directly is not feasible. Instead, the destination arrival time of the succeeding pallet is considered. However, not all pallets are retrieved from the conveyor directly before the succeeding pallet reaches its destination, requiring the exclusion of certain data points. Specifically, pallets that take more than 30 seconds to traverse the outbound buffer area are included, as this delay likely indicates that the pallet waited for a preceding pallet to clear the subsequent conveyor spot.

The filtered data points are plotted as a histogram and outliers are removed. The upper bound for the retained data, shown in Table G.4, serves as the cutoff for excessively long durations. A distribution is fitted to the remaining data and Table G.4 summarizes the obtained parameter values.



(a) Distribution of Operator Behavior at Workstations at MP0

(b) Distribution of Operator Behavior at Workstations at EP1

Figure G.2: Distributions of Operator Behavior at the Workstations. Each figure compares the historical operator time distributions (red) with the fitted distributions used for outlier pallets (green). The x-axis represents time bins in minutes, while the y-axis indicates the frequency

Additionally, simulation results are evaluated for distributions similar to the fitted ones, with adjustments of two intervals of 20 seconds to account for the assumptions underlying the fitted distribution. However, these adjusted distributions do not produce a good fit. Specifically, the operator behavior at the outbound locations EP0 and EP1 show significant deviations, as measured by the histogram-based absolute error. This metric is calculated by dividing the duration range into discrete bins and summing the absolute differences between the frequency distributions of historical and simulated durations for each bin. The minimum errors for the original fitted and adjusted distributions are 1.02 and 0.46, respectively.

Another estimation approach involves calculating the time pallets traverse the last three conveyor spots before reaching their destination and subtracting the minimal duration for the first two spots. The parameters of the fitted distribution for this approach are provided in Table G.4.

The expected behavior based on expert opinions is tested as a further validation option. Experts suggested two scenarios outlined in Table G.4. The primary difference between these scenarios lies in the underlying distributions: the first uses a lognormal distribution consistent with the options based on historical data. In contrast, the second employs a normal distribution.

The distributions fitted from historical data or based on expert opinion are tested alongside similar distributions. The additional tests included variations of the original distributions, ranging from two minutes less to two minutes more than the parameters provided in Table G.4.

Despite these efforts, high error values persist across all experiments, indicating that the simulation does not closely replicate historical data on a per-pallet basis. Consequently, the overall system behavior is evaluated. This assessment suggested that distributions based on expert opinion generally best represent operator behavior. However, the operator behavior for retrieving full outbound pallets from the conveyor at EP1 is more accurately captured by the distribution derived from the traversal durations of the last three conveyor spots.

Figure G.3 displays histograms of simulation results based on the best-fitted distribution (shown in green) alongside the historical data (orange). Table G.5 provides the exact parameters of these distributions.

From a system-wide perspective, the retrieval durations for full outbound pallets at MP0 and EP1 are well-represented, with histogram-based absolute errors of 0.13 and 0.24, respectively.

Outbound Location	Distribution	Distribution Parameters (time in minutes)			
		μ	σ	Lower Bound	Upper Bound
based arrival time of succeeding pallet					
Out1 (MP0)	lognormal	8.10	14.50	0.17	45
Out3 (EP0)	lognormal	2.33	2.45	0.17	15
Out2 (EP1)	lognormal	7.40	18.97	0.17	60
based on traversal duration of last three spots					
Out1 (MP0)	lognormal	6.18	110.90	0.17	15
Out3 (EP0)	lognormal	2.07	2.48	0.17	5
Out2 (EP1)	lognormal	28.58	624.47	0.17	8
based on expert opinion					
Out1 (MP0)	lognormal	3.00	1.67	0.17	15
Out3 (EP0)	lognormal	0.67	0.83	0.17	5
Out2 (EP1)	lognormal	0.67	1.17	0.17	8
based on expert opinion					
Out1 (MP0)	normal	6.50	4.33	0.17	15
Out3 (EP0)	normal	1.50	1.33	0.17	5
Out2 (EP1)	normal	3.00	2.17	0.17	8

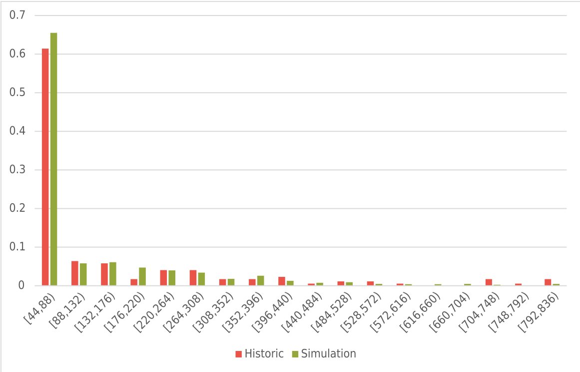
Table G.4: Validation Operator Behavior: Experimental Settings. The table presents four scenarios and their corresponding initial distributions for each outbound location. These scenarios serve as the basis for experiments aimed at identifying the most representative distributions of operator behavior for full outbound pallets.

Outbound Location	Distribution	Distribution Parameters (time in minutes)			
		μ	σ	Lower Bound	Upper Bound
Out1 (MP0)	lognormal	3.50	2.67	0.17	15
Out3 (EP0)	normal	0.33	1.33	0.17	5
Out2 (EP1)	lognormal	29.08	624.97	0.17	8

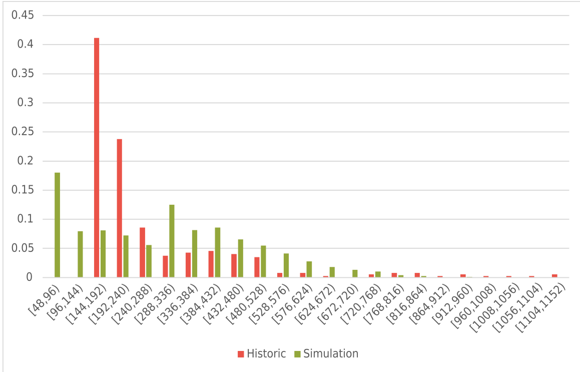
Table G.5: Validation Operator Behavior: Best Distribution. Based on the conducted experiments, the table presents the distribution identified as best fitted for modeling operator behavior for full outbound pallets at each outbound location.

However, operator behavior at outbound location EP0 is less accurate, with a histogram-based absolute error of 0.97. These pallets must traverse the EP1 conveyor before entering the lift and reaching the EP0 conveyor, making them more affected by interactions with other system components.

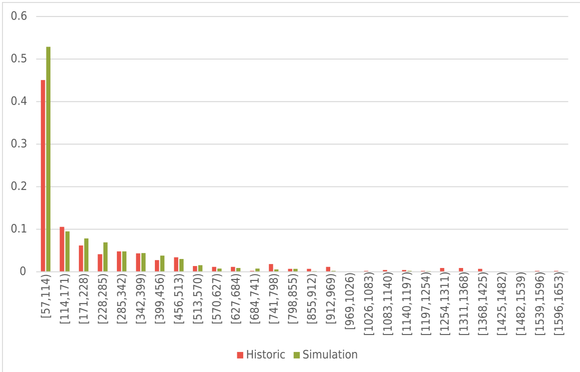
Additional experiments are conducted for full outbound pallets destined for EP0 to address the significant deviations. These experiments refine the current best distributions and test similar distributions around the identified parameters. Despite these efforts, only marginal improvements are achieved, reducing the absolute error to 0.967.



(a) Operator Behavior *Out1* (MP0)



(b) Operator Behavior *Out3* (EP0)



(c) Operator Behavior *Out2* (EP1)

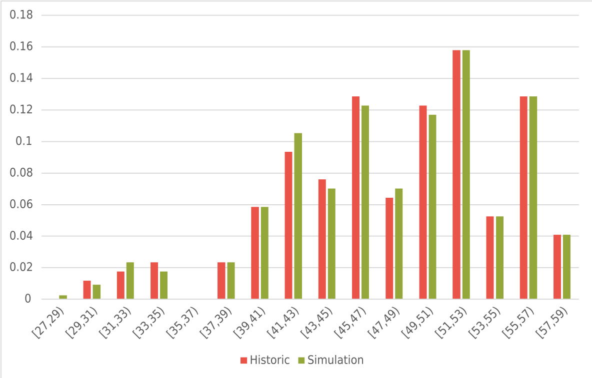
Figure G.3: Histogram of Operator Behavior for Full Outbound Pallets. Each figure compares the retrieval times (operator behavior) of full outbound pallets, with the historical data represented in orange and the simulation results in green

Crane Processing Times The analysis of the historical data reveals distinct durations for the loaded crane movement times; however, it lacks the durations for the empty crane processing times. Additionally, the historical data reliably captures crane movement times only for outgoing pallets because the durations for inbound pallets encompass the queueing times. Therefore, we use only the outbound crane processing times as input for the simulation.

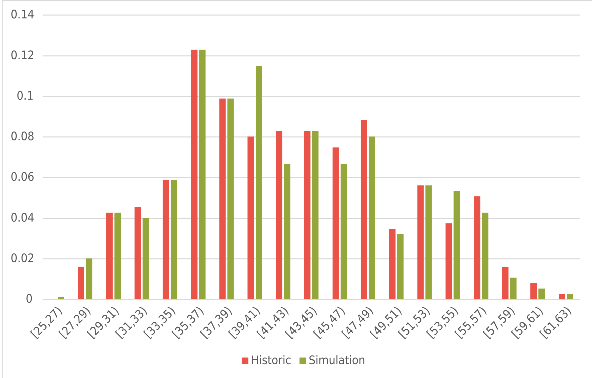
We validate the crane processing times using the experimental setup described in Table G.1 and the operator behavior as described in Table G.3a and Table G.5. As shown in Figure G.4, the simulation's outbound crane processing times follow the same pattern as the historical data. Also, on a per-pallet basis, the correct use of the historical processing times in the simulation is validated, represented by an MAE and MAPE of close to zero. This is expected as the direct measurements from the historical data are given as input.

In contrast to the loaded movement time, the historical data lacks timestamps for the empty crane travel time, making precise estimation of its distribution challenging. Additionally, the historical data combines the queuing and crane travel time for inbound movements, further complicating an accurate estimation. Nevertheless, we assume that the crane typically covers a similar distance for both inbound and outbound movements, whether loaded or empty, except for dual commands. In these cases, the crane travels a shorter distance. To address these assumptions:

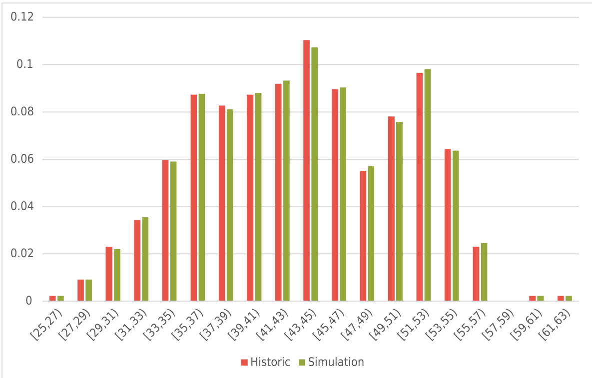
- We model the empty single-command crane travel time and the loaded inbound crane travel time using the same distribution derived from historical durations for the loaded outbound crane travel times.



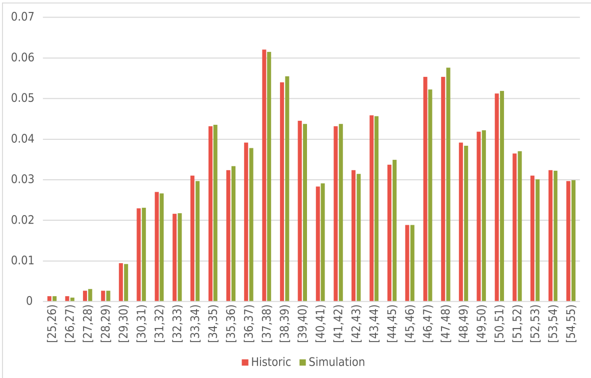
(a) Validation Crane Processing Time: Full Outbound MP0



(b) Validation Crane Processing Time: Full Outbound EP0



(c) Validation Crane Processing Time: Full Outbound EP1



(d) Validation Crane Processing Time: Workstation Outbound MP0

(e) Validation Crane Processing Time: Workstation Outbound EP1

Figure G.4: Validation Crane Processing Time: Outbound Pallets. The histograms compare the loaded crane movement time for outbound pallets based on historical data (red) and simulation results (green). The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.

- The empty crane travel time is combined with a uniform distribution to account for the additional processing time observed before the crane initiates its next task, which varies between zero and ten seconds.
- The dual-command empty crane travel time follows a uniform distribution ranging from 15 to 25 seconds based on the crane's observed physical behavior and its known speed in the z-direction when unloaded and loaded.

Table G.6 summarizes these assumed distributions. To account for underlying assumptions, experiments are conducted with similar distributions varying by ± 10 seconds from the originally assumed values. Given the lack of detailed historical durations for empty and loaded inbound crane movements, these distributions are compared to the combined queuing and crane processing time for inbound pallets.

Crane Specifications	**Distribution**	**Distribution Parameters (time in minutes)**			
		μ	σ	**Lower Bound**	**Upper Bound**
empty, single command	normal	42.26	8.74	13	63
	+ uniform			0	10
empty, dual command	uniform			15	25
loaded, inbound	normal	42.26	8.74	13	63

Table G.6: Validation of Crane Processing Time: Experimental Settings. The table summarizes the initial distributions for empty crane travel time and loaded inbound crane travel time, derived from historical data on outbound loaded crane travel time. These distributions serve as the baseline for experiments aimed at identifying the best-fitting distributions for empty and loaded inbound crane travel times.

The best settings, as outlined in Table G.7, result in a mean absolute error of 0.2 across all full inbound and workstation locations based on histogram comparisons. This low mean absolute error indicates that the histograms exhibit similar patterns for both the simulation results (green) and the historical durations (red), as illustrated in Figure G.5.

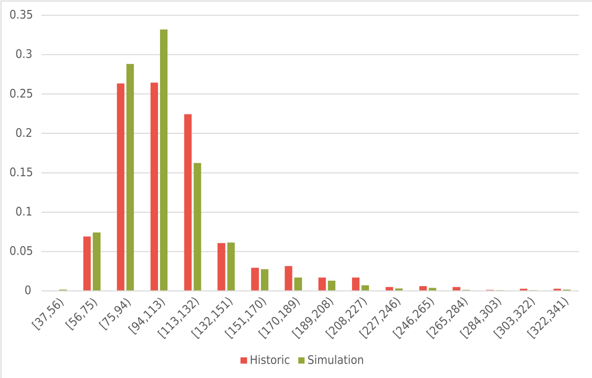
Crane Specifications	**Distribution**	**Distribution Parameters (time in minutes)**			
		μ	σ	**Lower Bound**	**Upper Bound**
empty, single command	normal	37.26	8.74	13	63
	+ uniform			0	15
empty, dual command	uniform			20	25
loaded, inbound	normal	37.26	8.74	13	63

Table G.7: Validation of Crane Processing Time: Best Settings. The table provides the distributions identified as the best-fitting representations for empty crane travel time and loaded inbound crane travel time based on experimental results.

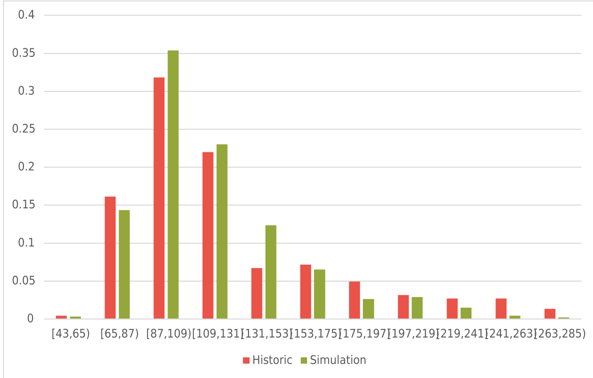
Lead Time The lead time encompasses the previously discussed time components. Errors and comparisons are based on the best distributions determined through the experiments for each sub-component of the lead time.

Table G.8 presents the MAPEs for inbound and outbound movements at each location. As shown, inbound movements generally exhibit lower MAPEs than outbound movements. For outbound movements, the queuing and operator times display particularly high MAPEs. This aligns with the findings summarized in Table G.1b, where the queuing time for workstation outbound pallets shows significant errors during per-pallet comparisons. Similarly, the queuing time for full outbound pallets also demonstrates high MAPEs.

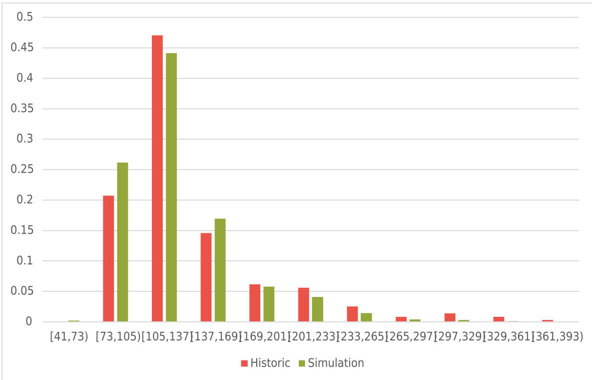
However, not only do queuing and operator times exhibit high MAPEs, but other durations also show substantial errors, indicating that the simulation struggles to accurately model pallet flow



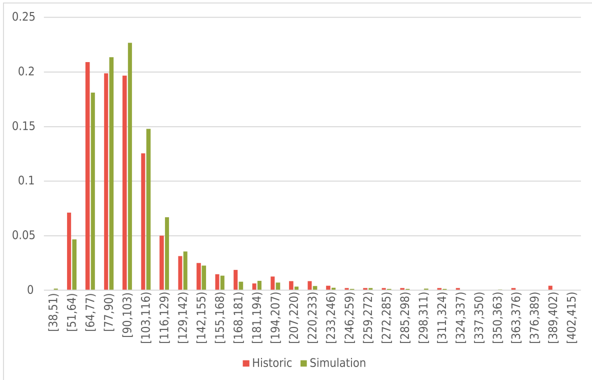
(a) Crane Validation *In1* (MP0)



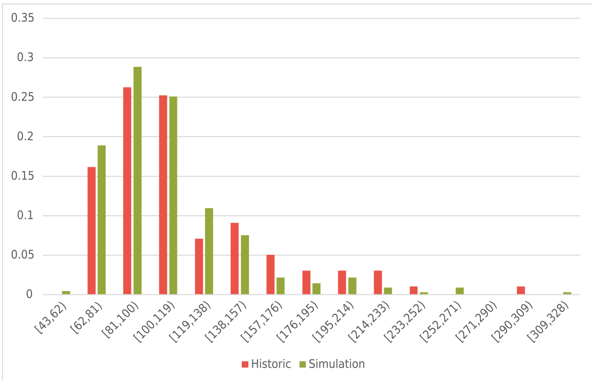
(b) Crane Validation *In3* (EP0)



(c) Crane Validation *In2* (EP1)



(d) Crane Validation *F1-F5* (MP0)



(e) Crane Validation *P1, P2* (EP1)

Figure G.5: Validation Crane Processing Time: Inbound Pallets. The histograms compare the loaded crane movement time for inbound pallets based on historical data (red) and simulation results (green). Since the historical data does not separately record crane travel time for inbound pallets, the measured time includes both queueing and crane processing time. The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.

on a per-pallet basis when durations rely on distributions. When durations are primarily based on historical data, the MAPE is nearly zero.

A different perspective emerges when considering system-wide comparisons. Inbound lead times are better captured than outbound lead times; however, the lead times are generally well-represented, as illustrated in Figure G.6 and Figure G.7. Notable deviations occur at EP0 and the workstations. Comparing the frequency distributions of historical data with simulation results, the absolute error is 0.62 for full outbound pallets at EP0 (Figure G.7b), 1.38 for workstation pallets on the MP0 side (Figure G.7d), and 0.61 for workstation pallets on the EP1 side

Location	MAPE				
	Crane Processing	**Queueing**	**Conveyor**	**Operator**	**Lead Time**
	Inbound Movement				
In1 (MP0)	26.40%				12.55%
In3 (EP0)	35.41%				21.97%
In2 (EP1)	32.44%				14.70%
F1-F5 (MP0)	32.64%				15.57%
P1, P2 (EP0)	38.75%				14.17%
	Outbound Movement				
Out1 (MP0)	0.06%	123.44%	4.86%	135.25%	29.51%
Out3 (EP0)	0.08%	68.12%	8.57%	89.49%	43.64%
Out2 (EP1)	0.00%	82.40%	5.88%	223.88%	53.64%
F1-F5 (MP0)	0.00%	74.50%		0.00%	65.86%
P1, P2 (EP1)	0.00%	64.24%		0.14%	37.95%

Table G.8: Validation Lead Time: MAPE. The table presents the MAPE for each component contributing to the lead time, along with the overall MAPE for the lead time. Each MAPE value is provided separately for each inbound and outbound movement type.

(Figure G.7e).
These findings reflect earlier observations. Deviations in workstation lead times primarily result from discrepancies in queuing times, likely attributable to the workstation outbound logic. Meanwhile, deviations for full outbound pallets at EP0 mirror inaccuracies in modeling operator behavior, which tend to underestimate durations.

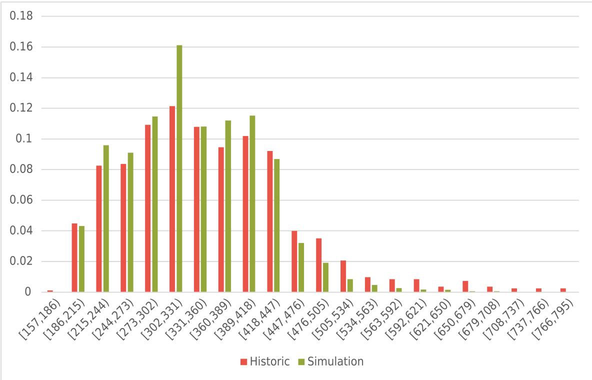
G.2 Expanded Validation (2-Month Dataset)

The expanded validation, covering two months (15.08.2023 – 15.10.2023), generally confirms the findings of the four-day validation.

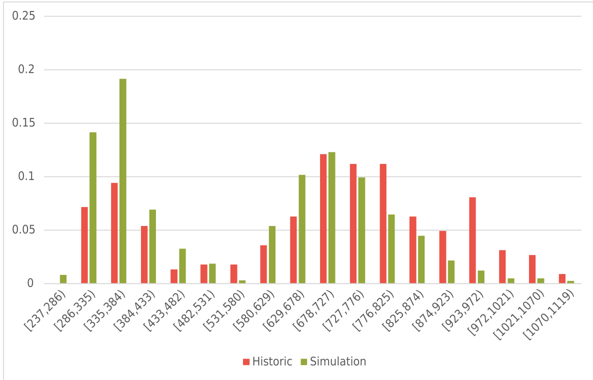
Inbound movement durations exhibit lower MAPEs than outbound movements, as summarized in Table G.9. Additionally, crane processing times and conveyor movements show consistently low MAPEs. These results reinforce the conclusion from the four-day validation that deviations primarily stem from the outbound logic and missing data on operator behavior for handling full outbound pallets.

The histograms of the two-month validation (Figure G.8 and Figure G.9) align with the trends observed in the four-day validation (Figure G.6 and Figure G.7). Inbound movements are again better represented than outbound movements. Notably, workstation pallet outbound movements diverge the most from historical data, which is expected given the significant deviations in queueing time.

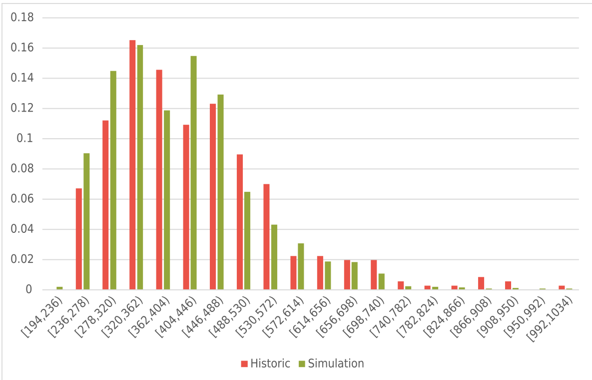
Overall, the two-month validation supports the results of the four-day validation, indicating that the conclusions remain valid over a longer time frame.



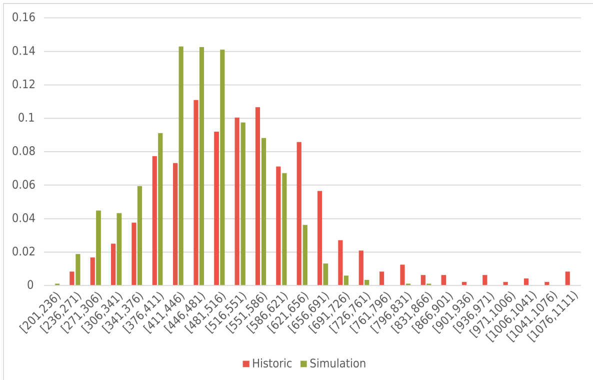
(a) Lead Time Validation *In1* (MP0)



(b) Lead Time Validation *In3* (EP0)



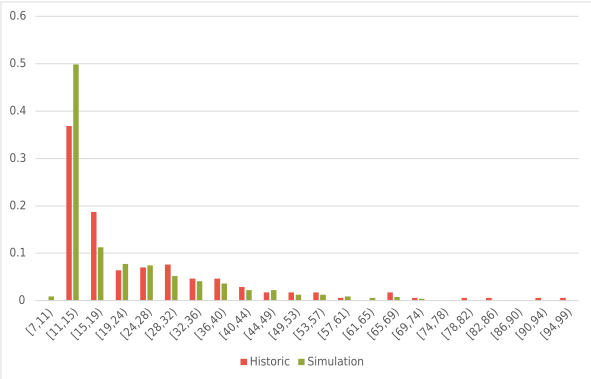
(c) Lead Time Validation *In2* (EP1)



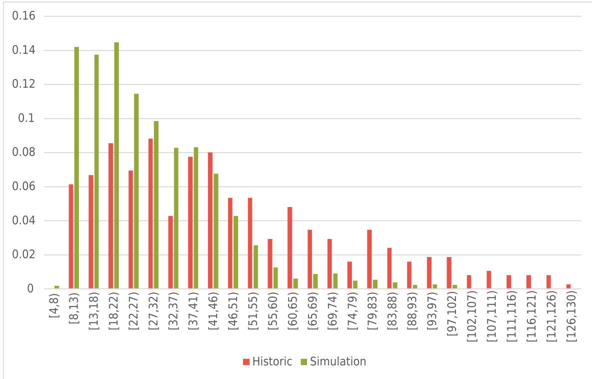
(d) Lead Time Validation *F1 - F5* (MP0)

(e) Lead Time Validation *P1, P2* (EP1)

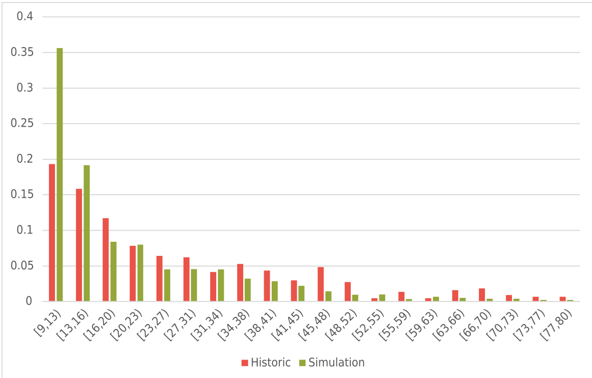
Figure G.6: Validation Lead Time: Inbound Pallets. The histograms compare the lead time for inbound pallets based on historical data (red) and simulation results (green). The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.



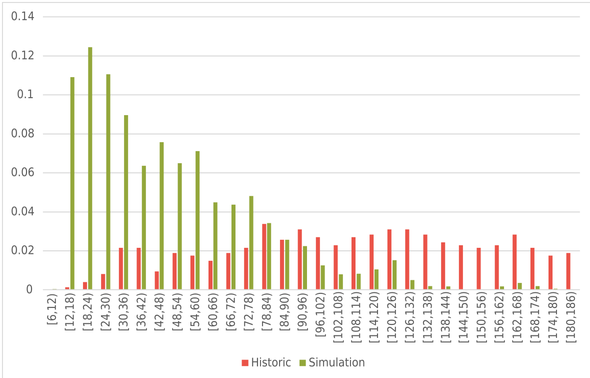
(a) Lead Time Validation *Out1* (MP0)



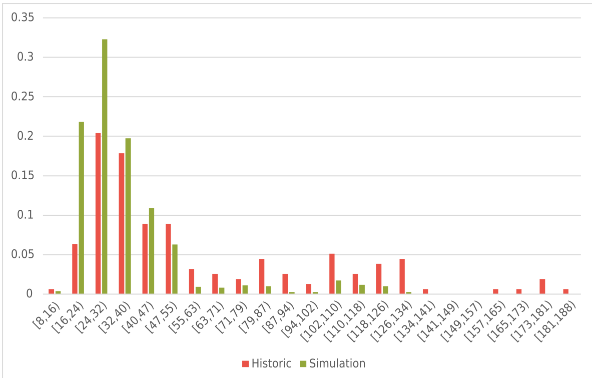
(b) Lead Time Validation *Out3* (EP0)



(c) Lead Time Validation *Out2* (EP1)



(d) Lead Time Validation *F1 - F5* (MP0)

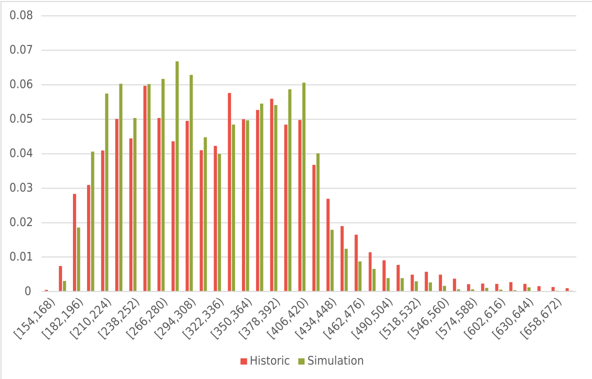


(e) Lead Time Validation *P1, P2* (EP1)

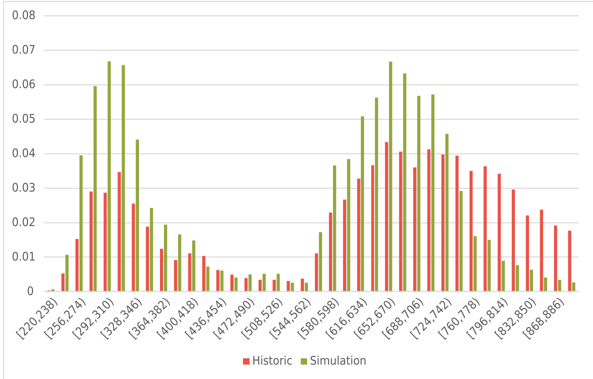
Figure G.7: Validation Lead Time: Outbound Pallets. The histograms compare the lead time for outbound pallets based on historical data (red) and simulation results (green). The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.

Location	MAPE				
	Crane Processing	**Queueing**	**Conveyor**	**Operator**	**Lead Time**
Inbound Movement					
In1 (MP0)	25.73%				12.47%
In3 (EP0)	31.38%				21.94%
In2 (EP1)	30.04%				12.75%
F1-F5 (MP0)	33.80%				17.64%
P1, P2 (EP0)	37.67%				15.68%
Outbound Movement					
Out1 (MP0)	0.06%	104.83%	4.56%	155.79%	37.12%
Out3 (EP0)	0.07%	73.53%	10.03%	68.18%	41.37%
Out2 (EP1)	0.00%	76.48%	6.32%	172.94%	45.18%
F1-F5 (MP0)	0.00%	72.83%		0.16%	59.12%
P1, P2 (EP1)	0.00%	73.53%		1.19%	56.25%

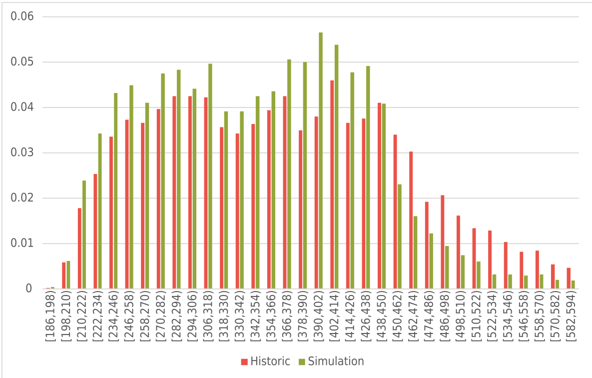
Table G.9: Expanded Validation: MAPE. The table presents the MAPE for each component contributing to the lead time, along with the overall MAPE for the lead time. Each MAPE value is provided separately for each inbound and outbound movement type.



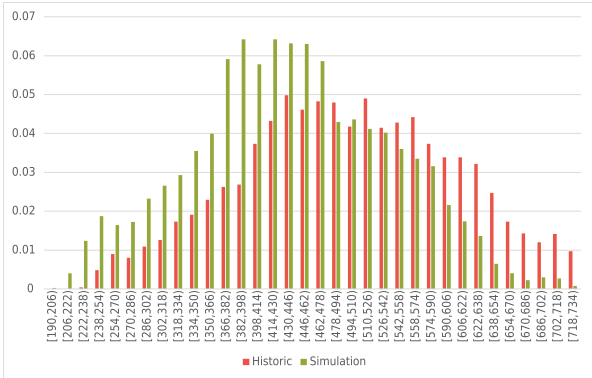
(a) Lead Time Expanded Validation *In1* (MP0)



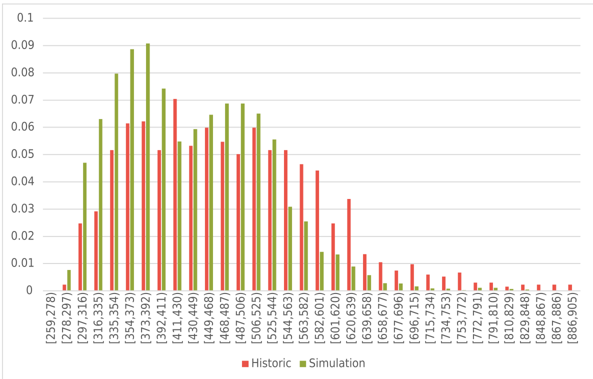
(b) Lead Time Expanded Validation *In3* (EP0)



(c) Lead Time Expanded Validation *In2* (EP1)

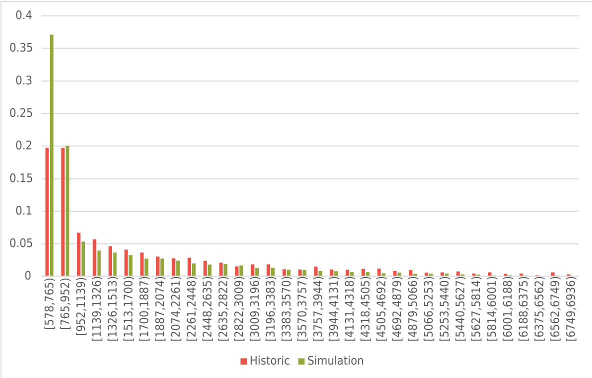


(d) Lead Time Expanded Validation *F1 - F5* (MP0)

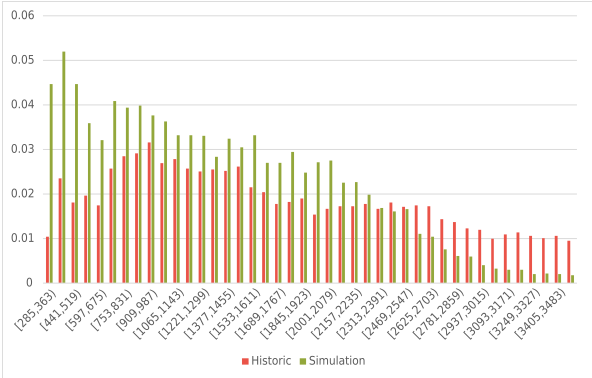


(e) Lead Time Expanded Validation *P1, P2* (EP1)

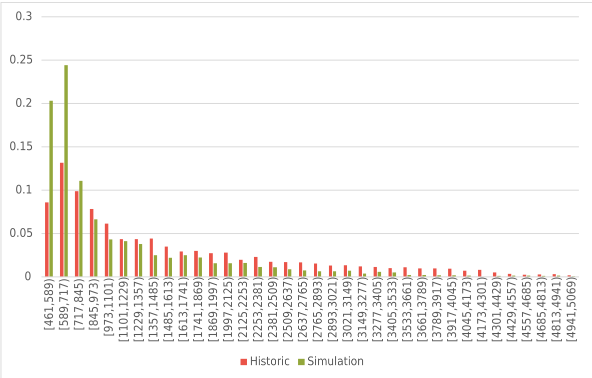
Figure G.8: Expanded Validation Lead Time: Inbound Pallets. The histograms compare the lead time for inbound pallets based on historical data (red) and simulation results (green) over a period of two months. The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.



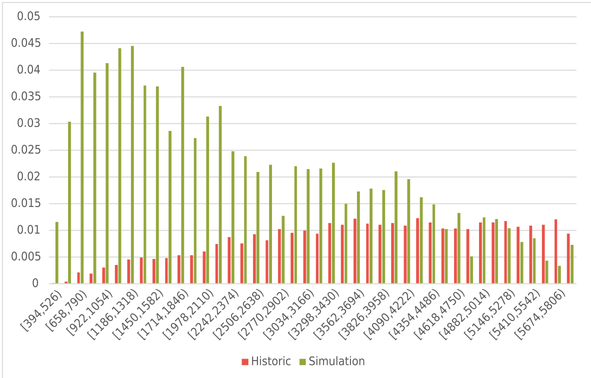
(a) Lead Time Expanded Validation *Out1* (MP0)



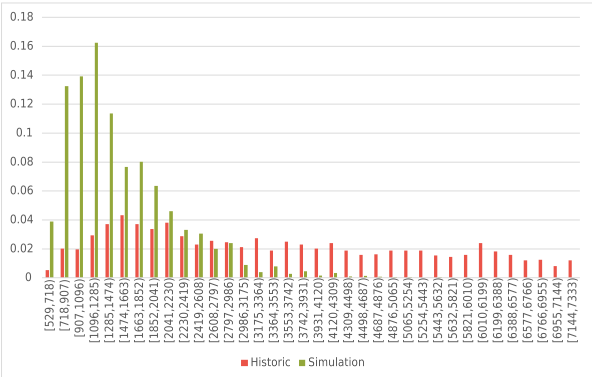
(b) Lead Time Expanded Validation *Out3* (EP0)



(c) Lead Time Expanded Validation *Out2* (EP1)



(d) Lead Time Expanded Validation *F1 - F5* (MP0)



(e) Lead Time Expanded Validation *P1, P2* (EP1)

Figure G.9: Expanded Validation Lead Time: Outbound Pallets. The histograms compare the lead time for outbound pallets based on historical data (red) and simulation results (green) over a period of two months. The x-axis represents time bins in seconds, while the y-axis shows the frequency of occurrences.

H EXPERIMENTAL VALIDATION

Obtaining reliable data on model performance is crucial. Therefore, key experimental factors are carefully considered to capture system variability, minimize initialization bias, and ensure sufficient output data collection. This appendix details the determination of these factors, including the warm-up period, number of replications, and simulation run length.

H.1 Warm-Up Period

Welch's method identifies the necessary warm-up period in a simulation by calculating moving averages over the observed data. For this study, the simulation is run for a two-month timeframe with ten replications. The lead times of the pallets from these runs are used to calculate moving averages with varying window sizes ranging from 50 to 500. The results for different window sizes are shown in Figure H.1, with each window size represented by a distinct color.

The moving averages are calculated using the formula below (Robinson, 2014):

$$\overline{Y}_i(w) = \begin{cases} \frac{\sum_{s=-(i-1)}^{i-1} \overline{Y}_{i+s}}{2i-1}, & \text{if } i = 1, \cdots, w, \\ \frac{\sum_{s=-w}^{w} \overline{Y}_{i+s}}{2w+1}, & \text{if } i = w+1, \cdots, m-w. \end{cases} \tag{H.1}$$

where $\overline{Y_i}(w)$ is the moving average of window size w, $\overline{Y_i}$ is the mean of the lead times of the replications, i is the period number, and m is the number of periods in the simulation run.

The results in Figure H.1 show that even with a window size of $w = 250$, fluctuations remain due to the inherent variability in pallet flow. Additionally, pallets primarily influence one another when their request times are close. Consequently, lead times vary throughout the day, and moments when the system is empty occur naturally but inconsistently.

The analysis reveals that considering the first 2800 observations with larger window size ($w = 500$) is sufficient to detect a warm-up length of approximately 480 pallets. After 480 observations, the graph levels off, showing minimal fluctuations.

The number of pallets processed daily varies depending on the day of the week. On average, weekdays (excluding Thursdays due to planned maintenance) process 1426 pallets, while Thursdays handle 1126 pallets. Weekends see approximately half the weekday average, with 781 pallets per day. For simplicity, and since the warm-up length aligns with the daily average of weekend pallet flow, the warm-up period is set to one day.

H.2 Number of Replications

The number of replications and the run length together ensure that enough outbound data is obtained for reliable simulation results. According to a general rule of thumb, the run length should be at least ten times longer than the warm-up period (Robinson, 2014), suggesting a run

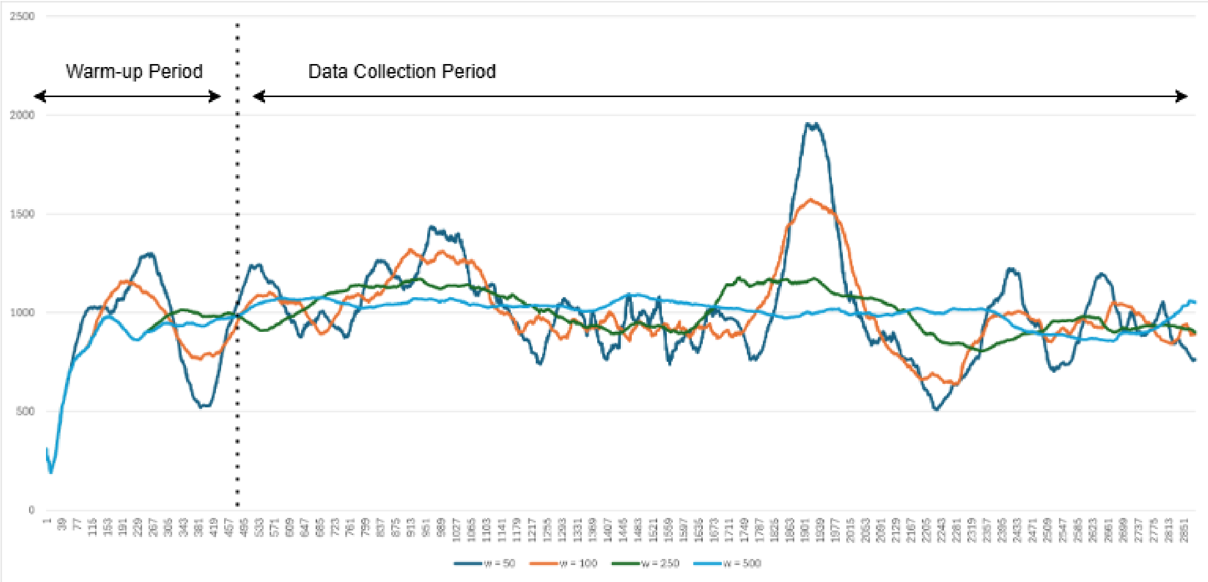


Figure H.1: Warm-Up Period Identification: Welch's Method. The figure illustrates the moving averages of lead times for various window sizes ($w = 50$ to 500), with each window size represented by a different color. The x-axis denotes the number of pallets, while the y-axis shows the corresponding moving average of lead times. A dashed line marks the point where the moving average for $w = 500$ stabilizes, indicating the end of the warm-up period.

length of ten days. However, due to fluctuating pallet flow caused by variations in production demand, a run length of two weeks is chosen to better capture the system's variability over the different weekdays.

To determine the minimum number of replications required for achieving the desired level of confidence in the simulation results, we use a sequential approach. In this approach, the average lead time for each of the ten replications is collected, and moving averages and variances are calculated to assess the convergence of results as more replications were performed. The error is then computed using the t-value from the Student's t-distribution. Table H.1 summarizes the calculation results for the first five replications.

Replication	**Average Lead Time**	**Moving Average**	**Moving Variance**	**T-Value**	**Error**
1	1036.57				
2	1048.27	1042.42	68.44	12.71	0.07
3	1065.09	1049.97	205.51	4.30	0.03
4	1025.30	1043.81	289.24	3.18	0.03
5	1037.87	1042.62	223.96	2.78	0.02

Table H.1: Number of Replications

The minimum number of replications is determined when the error meets the desired tolerance level. This is achieved after three replications, where the error value (0.03) is smaller than the threshold of $\gamma' = \gamma/(1+\gamma) = 0.05/(1+0.05) = 0.05$. However, performing at least five replications is recommended to ensure sufficient accuracy. Therefore, five replications are chosen for this simulation.

I PIPELINE CALCULATIONS

Pipeline thresholds influence the outbound flow simulated in this thesis. Experiments 4a to 4c in Chapter 5.3.4 analyze the impact of different pipeline threshold configurations. In Chapter 3.3, we introduced a formula (Equation 3.5) proposed by Haneyah et al. (2013) to determine the appropriate threshold. This chapter details the calculation of the pipeline threshold based on Equation 3.5 and the specifications of Euroma's high-bay warehouse.

Capacity Calculations The buffer capacity is expressed in pallets per minute. Therefore, we divide the available buffer spots by the average operator processing time. The resulting capacities for each outfeed lane are as follows:

- *Out1* (MP0): $cap_i = 3/3.35 = 0.89$
- *Out2* (EP1): $cap_i = 3/2.15 = 1.40$
- *Out3* (EP0): $cap_i = 5/1.29 = 3.87$

Average Travel Time Calculations We calculate the travel time from each crane to each outfeed lane based on the cumulative processing time of the conveyor spots along the route. Next, we average the travel time from each crane location for all three outfeed lanes. The resulting average travel times are:

- *Out1* (MP0): $t_i = 7.16$
- *Out2* (EP1): $t_i = 6.23$
- *Out3* (EP0): $t_i = 6.09$

Time Allowance Calculations We incorporate a time allowance into the calculation to account for realistic delays. Therefore, we subtract the average travel time t_i from the corresponding historical average. The historical data reflects real-world variations due to interactions with other pallets. The resulting time allowances are:

- *Out1* (MP0): $ta = 0.87$
- *Out2* (EP1): $ta = 1.06$
- *Out3* (EP0): $ta = 1.07$

Pipeline Size Finally, the pipeline size is calculated based on Equation 3.5:

$$ps_i = cap_i * (t_i + ta)$$

Since fractional pipeline sizes are not feasible, we round up to the nearest integer. As Haneyah et al. (2013) do not provide a definitive method for determining the time allowance, relying instead on experimental adjustments, we also calculate pipeline thresholds for additional time allowances ranging from zero to one minute. Table I.1 presents the pipeline thresholds based on these varying allowances.

Time Allowance	Pipeline Threshold		
	Out1 (MP0)	*Out2* (EP1)	*Out3* (EP0)
0.87, 1.06, 1.07	8	28	11
0	7	24	9
0.2	7	25	9
0.4	7	26	10
0.6	7	26	10
0.8	8	27	10
1	8	28	11

Table I.1: Configurations of the Calculated Pipeline Thresholds

J INCREASING DEMAND

The simulation model used in this thesis relies on historical data as input for pallet requests. As Euroma aims for long-term growth, testing solution approaches under increased demand patterns is essential to ensure their applicability for future needs. This appendix outlines the method for generating input data for experiments based on historical records when higher demand scenarios are required.

To simulate increased demand, we compress the time intervals between pallet requests. This ensures that interdependencies between orders and pallet requests remain intact, as their relative timing is maintained. The increased demand pattern is implemented through the following steps:

1. Select a reference time, for example the starting time of the simulation.
2. Calculate the difference from each request's original time to the reference time:
   $\Delta =$ request time $-$ reference time
3. Compress the time interval by determining an adjusted delta (Δ_{adj}) by reducing Δ with the desired factor ($0 \leq \alpha \leq 1$):
   $\Delta_{\text{adj}} = \Delta * (1 - \alpha)$
4. Update each request's request time based on the adjusted delta: new request time $=$ reference time $+ \Delta_{\text{adj}}$

For illustration purposes, we provide an example calculation in Table J.1. The two full outbound pallet requests for MP0 and EP0 were originally scheduled for August 14th at 06:25:24 and 06:41:03, respectively. With an α value of 0.2, indicating a 20% increase in demand, the new pallet request times are adjusted to 05:08:24 and 05:20:50, respectively.

Original Data		Increasing Demand Data		
Pallet ID	Request Time	Delta (Δ)	adjusted Delta (Δ_{adj})	New Request Time
MP0WA1_377	14-08-2023 06:25:42	0.2678	0.2143	14-08-2023 05:08:34
EP1WA1_698	14-08-2023 06:41:03	0.2785	0.2228	14-08-2023 05:20:50

Table J.1: Example for Generation of Increased Demand

K RESULTS OF IMPROVEMENT EXPERIMENTS

This appendix presents the detailed experimental results. The appendix is organized based on the conducted experiments in Chapter 5.3. The tables summarize the results for the on-time delivery and tardiness related KPIs and the movement and queueing times for each experiment. Each dispatching rule presents the result in a separate table.

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
-10	91.65%	80.19%	19.35	2.00	0.90	0.04	3.32	0.14
-5	91.80%	79.93%	19.16	2.05	0.91	0.04	3.37	0.15
0	91.87%	80.35%	20.92	2.01	1.00	0.04	3.72	0.14
5	91.39%	80.13%	21.13	2.05	0.95	0.04	3.72	0.14
10	91.45%	79.72%	21.35	2.10	0.97	0.04	3.86	0.15
15	91.44%	79.96%	20.91	2.05	0.95	0.04	3.53	0.14
20	91.62%	80.51%	21.40	2.01	0.99	0.04	3.74	0.14
25	91.33%	80.08%	22.86	2.05	1.03	0.04	3.81	0.15
30	91.52%	79.96%	22.31	2.03	1.02	0.04	3.68	0.14
35	91.15%	80.23%	23.04	2.01	1.01	0.04	3.85	0.14
40	91.18%	80.80%	23.36	1.96	1.03	0.04	3.97	0.14
45	91.33%	80.72%	22.70	1.98	1.02	0.04	3.91	0.14
50	90.97%	80.10%	25.01	2.02	1.08	0.04	4.08	0.14
55	90.85%	80.20%	23.74	2.05	1.01	0.04	3.92	0.14
60	90.67%	80.17%	25.40	2.01	1.06	0.04	4.23	0.14
65	90.76%	79.98%	25.16	2.05	1.06	0.04	4.05	0.14
70	90.39%	79.69%	25.80	2.10	1.05	0.04	4.18	0.14
75	90.04%	80.34%	26.11	1.97	1.02	0.04	4.14	0.14
80	90.03%	80.02%	25.80	2.01	1.01	0.04	4.49	0.14
85	89.48%	80.06%	27.77	2.06	1.03	0.04	4.40	0.15
90	88.98%	79.96%	28.50	2.06	1.01	0.04	4.45	0.15
95	88.48%	79.99%	28.68	1.99	0.97	0.04	4.33	0.14
100	87.24%	80.23%	30.59	1.99	0.94	0.04	4.54	0.14

(a) Results Experiment 3: Baseline Simulation

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
105	86.61%	80.16%	30.98	2.01	0.90	0.04	4.52	0.14
110	85.98%	80.58%	31.77	1.94	0.88	0.04	4.76	0.14
115	85.58%	80.40%	33.17	2.04	0.90	0.04	4.74	0.14
120	83.86%	80.04%	34.84	2.01	0.84	0.04	4.50	0.15
125	83.05%	80.45%	35.15	1.99	0.81	0.04	4.63	0.15
130	81.67%	80.22%	38.05	2.00	0.81	0.04	4.87	0.14
135	80.25%	79.55%	39.59	2.07	0.78	0.04	4.86	0.15
140	78.98%	79.93%	42.48	2.04	0.79	0.04	4.97	0.14
145	77.46%	80.28%	45.42	2.04	0.79	0.04	5.01	0.15
150	76.35%	79.97%	48.67	2.00	0.80	0.04	5.01	0.14
155	75.17%	80.57%	50.96	1.98	0.80	0.04	5.04	0.15
160	73.83%	80.36%	55.46	2.01	0.83	0.04	5.17	0.15
165	72.89%	79.65%	57.99	2.06	0.84	0.04	5.25	0.14
170	71.62%	80.22%	63.18	2.02	0.87	0.04	5.44	0.14
175	70.67%	79.97%	66.70	2.07	0.89	0.04	5.51	0.15
180	69.39%	80.39%	72.61	1.99	0.93	0.04	5.46	0.15
185	68.63%	80.42%	76.46	1.96	0.96	0.04	5.77	0.14
190	67.65%	80.50%	78.82	1.99	0.96	0.04	5.47	0.14
195	67.04%	80.05%	84.63	2.05	1.01	0.04	5.81	0.14
200	66.15%	79.90%	89.22	2.06	1.04	0.04	5.94	0.14

(b) Results Experiment 3: Baseline Simulation (continued)

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
205	65.35%	80.04%	93.02	2.08	1.06	0.04	5.87	0.14
210	64.87%	80.61%	98.20	1.97	1.10	0.04	6.03	0.15
215	64.16%	79.94%	104.78	2.02	1.15	0.04	5.80	0.14
220	63.17%	80.53%	110.05	1.99	1.18	0.04	6.10	0.15
225	63.01%	80.72%	114.21	1.98	1.22	0.04	5.91	0.14
230	62.70%	80.51%	119.76	2.01	1.27	0.04	6.02	0.15
235	61.95%	80.37%	125.70	1.98	1.31	0.04	6.25	0.15
240	61.43%	79.92%	129.86	2.04	1.33	0.04	6.34	0.14
245	61.60%	80.37%	135.35	1.96	1.40	0.04	6.47	0.14
250	60.87%	80.24%	141.35	2.02	1.43	0.04	6.48	0.15
255	60.73%	80.37%	146.15	2.01	1.48	0.04	6.56	0.16
260	60.49%	80.28%	150.61	2.01	1.51	0.04	6.57	0.14
265	60.12%	80.31%	154.93	1.99	1.54	0.04	6.64	0.14
270	60.06%	80.04%	160.29	1.99	1.59	0.04	6.62	0.14
275	60.00%	79.88%	164.48	2.05	1.63	0.04	6.64	0.14
280	59.82%	80.31%	165.71	2.04	1.64	0.04	6.64	0.14
285	59.52%	80.09%	173.22	2.05	1.70	0.04	6.67	0.14
290	59.42%	80.01%	176.13	2.08	1.73	0.04	6.64	0.15
295	59.40%	79.81%	179.99	2.01	1.77	0.04	6.58	0.14
300	59.09%	79.91%	183.14	2.05	1.78	0.04	6.60	0.14

(c) Results Experiment 3: Baseline Simulation (continued)

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
-10	91.64%	80.33%	19.01	2.01	0.89	0.04	3.34	0.15
-5	91.61%	80.17%	20.50	2.05	0.95	0.04	3.57	0.15
0	91.54%	80.52%	21.08	2.02	0.97	0.04	3.69	0.15
5	91.42%	80.27%	20.69	2.04	0.94	0.04	3.50	0.14
10	91.64%	80.15%	20.79	2.03	0.97	0.04	3.65	0.15
15	91.58%	80.05%	21.55	2.06	1.00	0.04	3.68	0.15
20	91.11%	79.81%	21.47	2.06	0.94	0.04	3.59	0.15
25	91.17%	80.63%	22.29	1.98	0.98	0.04	3.56	0.16
30	91.10%	80.58%	23.99	1.99	1.05	0.04	3.84	0.14
35	91.18%	80.54%	23.00	1.97	1.01	0.04	3.72	0.14
40	91.23%	80.83%	23.50	1.92	1.04	0.04	3.75	0.14
45	91.13%	80.39%	23.69	1.99	1.04	0.04	3.89	0.15
50	91.02%	81.00%	23.86	1.96	1.03	0.04	3.83	0.14
55	90.78%	79.61%	24.72	2.09	1.04	0.04	3.87	0.14
60	90.59%	80.34%	25.27	2.02	1.05	0.04	4.10	0.16
65	90.20%	80.32%	24.75	2.01	0.98	0.04	3.86	0.15
70	90.31%	80.52%	25.62	2.01	1.03	0.04	4.29	0.14
75	90.02%	80.51%	25.76	1.99	1.01	0.04	4.19	0.15
80	89.76%	80.41%	26.35	2.01	1.00	0.04	4.26	0.14
85	89.99%	80.62%	26.96	1.98	1.05	0.04	4.35	0.15
90	88.48%	80.15%	27.88	1.99	0.95	0.04	4.64	0.15
95	88.19%	80.14%	28.32	2.04	0.94	0.04	4.33	0.14
100	87.78%	80.61%	29.40	1.99	0.94	0.04	4.59	0.14

(d) Results Experiment 3: FCFS Simulation

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
105	86.80%	80.46%	30.70	1.98	0.91	0.04	4.51	0.15
110	86.01%	80.63%	31.94	1.96	0.89	0.04	4.57	0.14
115	84.92%	80.60%	33.26	1.95	0.86	0.04	4.71	0.15
120	84.42%	80.28%	34.55	1.99	0.87	0.04	4.78	0.15
125	82.72%	80.45%	36.75	1.95	0.83	0.04	4.62	0.14
130	81.38%	80.67%	38.52	1.96	0.81	0.04	4.76	0.15
135	80.53%	80.56%	39.24	1.97	0.79	0.04	5.02	0.14
140	79.29%	80.38%	42.69	1.97	0.81	0.04	4.86	0.14
145	77.30%	79.88%	45.65	2.01	0.79	0.04	4.94	0.16
150	76.63%	80.62%	48.04	1.97	0.80	0.04	5.05	0.14
155	75.45%	80.21%	51.00	2.05	0.81	0.04	5.15	0.15
160	74.31%	80.61%	54.48	1.95	0.83	0.04	5.19	0.16
165	72.77%	80.53%	58.88	1.96	0.85	0.04	5.10	0.14
170	71.86%	80.53%	62.36	2.02	0.87	0.04	5.39	0.15
175	70.80%	80.52%	66.01	2.01	0.88	0.04	5.32	0.15
180	70.01%	80.50%	68.38	2.03	0.89	0.04	5.52	0.14
185	68.59%	80.18%	75.20	2.04	0.94	0.04	5.49	0.15
190	67.55%	80.54%	79.83	1.97	0.97	0.04	5.83	0.15
195	67.29%	80.47%	82.43	2.01	0.99	0.04	6.13	0.16
200	66.52%	80.48%	88.06	1.99	1.03	0.04	5.68	0.15

(e) Results Experiment 3: FCFS Simulation (continued)

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
205	65.38%	80.34%	94.01	1.97	1.07	0.04	5.89	0.14
210	64.83%	80.52%	98.33	1.99	1.10	0.04	5.93	0.15
215	63.92%	80.52%	103.71	1.97	1.13	0.04	5.89	0.14
220	63.61%	80.50%	109.67	2.00	1.19	0.04	6.00	0.14
225	62.92%	80.21%	115.50	1.99	1.23	0.04	6.03	0.15
230	62.08%	80.05%	120.41	2.01	1.25	0.04	6.23	0.15
235	62.09%	80.36%	123.90	2.01	1.29	0.04	6.21	0.15
240	61.21%	80.41%	129.99	2.02	1.33	0.04	6.34	0.15
245	61.26%	80.36%	135.05	1.97	1.38	0.04	6.31	0.14
250	60.71%	80.06%	143.04	2.06	1.44	0.04	6.34	0.15
255	60.73%	80.40%	145.37	1.95	1.47	0.04	6.45	0.15
260	60.43%	80.49%	151.22	1.97	1.52	0.04	6.62	0.14
265	60.54%	80.46%	154.83	1.99	1.56	0.04	6.55	0.15
270	59.93%	80.01%	159.27	2.04	1.58	0.04	6.61	0.14
275	59.92%	80.50%	165.56	1.97	1.64	0.04	6.64	0.14
280	59.66%	80.35%	167.58	1.99	1.65	0.04	6.62	0.15
285	59.73%	79.96%	172.84	2.01	1.71	0.04	6.65	0.15
290	59.47%	80.67%	175.51	1.96	1.72	0.04	6.61	0.15
295	59.27%	80.48%	180.47	2.00	1.77	0.04	6.62	0.14
300	58.93%	80.10%	182.53	2.03	1.77	0.04	6.65	0.14

(f) Results Experiment 3: FCFS Simulation (continued)

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
-10	91.94%	81.42%	20.59	1.95	0.99	0.04	6.23	0.56
-5	91.92%	81.64%	21.57	1.92	1.04	0.04	6.64	0.51
0	91.88%	81.68%	21.92	1.94	1.05	0.05	6.50	0.56
5	91.24%	81.74%	22.77	1.96	1.01	0.05	6.64	0.51
10	91.46%	81.70%	22.22	1.92	1.01	0.04	6.60	0.53
15	91.54%	81.05%	22.89	1.99	1.05	0.04	6.57	0.54
20	91.45%	81.27%	22.30	1.92	1.01	0.04	6.69	0.52
25	91.89%	81.33%	21.99	1.97	1.06	0.05	6.76	0.57
30	91.51%	81.72%	22.77	1.93	1.04	0.05	6.68	0.57
35	91.32%	81.76%	22.80	1.93	1.02	0.05	6.57	0.55
40	91.33%	81.48%	23.54	1.94	1.06	0.04	6.70	0.55
45	91.14%	81.99%	23.80	1.92	1.05	0.05	6.67	0.56
50	91.00%	81.15%	24.24	1.97	1.05	0.04	6.71	0.49
55	91.10%	81.98%	24.64	1.93	1.08	0.05	6.74	0.55
60	90.78%	81.92%	23.77	1.89	1.00	0.04	6.66	0.52
65	90.46%	81.47%	25.15	1.92	1.03	0.04	6.73	0.52
70	90.76%	82.27%	24.08	1.86	1.02	0.04	6.65	0.58
75	90.34%	81.45%	24.99	1.99	1.01	0.05	6.62	0.56
80	89.98%	81.42%	25.56	1.95	0.99	0.04	6.71	0.56
85	89.58%	81.51%	26.10	1.94	0.98	0.05	6.69	0.52
90	88.95%	81.82%	28.24	1.89	1.00	0.04	6.66	0.57
95	88.46%	81.66%	27.83	1.93	0.94	0.05	6.71	0.51
100	87.77%	81.28%	28.92	1.98	0.92	0.05	6.69	0.56

(g) Results Experiment 3: R1 Simulation

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
105	86.92%	81.80%	29.96	1.91	0.89	0.05	6.67	0.55
110	85.95%	81.65%	31.63	1.88	0.88	0.04	6.65	0.52
115	85.39%	81.53%	33.10	1.95	0.88	0.05	6.68	0.55
120	84.28%	81.70%	34.38	1.96	0.85	0.05	6.75	0.56
125	83.30%	81.93%	35.69	1.93	0.84	0.05	6.53	0.55
130	82.43%	81.57%	38.34	1.96	0.85	0.05	6.74	0.52
135	81.72%	81.62%	39.83	1.94	0.85	0.05	6.67	0.52
140	80.47%	81.32%	44.67	1.93	0.89	0.04	6.72	0.52
145	79.94%	81.96%	45.56	1.90	0.89	0.05	6.72	0.57
150	78.52%	81.37%	49.15	2.00	0.90	0.05	6.60	0.56
155	78.01%	81.91%	53.40	1.92	0.95	0.05	6.65	0.56
160	77.06%	81.67%	56.48	1.92	0.96	0.04	6.71	0.56
165	76.43%	81.90%	59.87	1.91	0.99	0.05	6.69	0.56
170	75.51%	82.05%	64.86	1.93	1.04	0.05	6.65	0.57
175	74.51%	81.53%	68.81	1.89	1.06	0.04	6.62	0.52
180	73.95%	81.17%	71.84	1.98	1.08	0.05	6.52	0.52
185	73.42%	81.78%	75.68	1.95	1.12	0.05	6.61	0.55
190	72.71%	81.50%	79.96	1.94	1.15	0.04	6.61	0.55
195	72.30%	81.60%	82.96	1.96	1.18	0.05	6.65	0.57
200	71.73%	81.81%	86.89	1.95	1.21	0.05	6.66	0.57

(h) Results Experiment 3: R1 Simulation (continued)

Operator Behavior ($\pm\mu$)	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
205	70.94%	81.75%	93.84	1.91	1.27	0.05	6.69	0.55
210	70.70%	81.98%	95.52	1.89	1.29	0.05	6.71	0.55
215	70.06%	81.68%	101.80	1.91	1.34	0.05	9.55	0.55
220	69.23%	81.60%	110.31	1.91	1.42	0.04	10.36	0.56
225	68.94%	81.87%	111.09	1.88	1.41	0.04	10.84	0.55
230	68.86%	81.94%	115.80	1.89	1.47	0.05	12.23	0.55
235	68.07%	81.94%	124.71	1.91	1.54	0.05	12.31	0.56
240	67.85%	81.31%	127.01	1.97	1.56	0.05	12.80	0.55
245	67.11%	81.24%	132.71	1.96	1.60	0.05	13.13	0.53
250	67.17%	81.70%	137.00	1.93	1.65	0.05	13.16	0.55
255	67.06%	81.38%	139.79	1.96	1.68	0.05	13.27	0.55
260	66.47%	81.14%	146.10	1.97	1.73	0.05	13.62	0.55
265	65.72%	81.42%	152.52	1.96	1.77	0.05	13.93	0.56
270	65.75%	81.66%	154.51	1.92	1.79	0.05	13.95	0.55
275	65.72%	81.61%	160.26	1.93	1.86	0.05	14.16	0.55
280	65.40%	81.44%	162.64	1.96	1.87	0.05	14.14	0.52
285	65.36%	81.14%	166.02	1.99	1.91	0.05	14.39	0.57
290	64.80%	81.19%	170.35	1.97	1.93	0.05	14.50	0.55
295	64.40%	81.42%	175.63	1.95	1.97	0.05	14.72	0.58
300	64.49%	81.89%	180.05	1.95	2.02	0.05	14.78	0.52

(i) Results Experiment 3: R1 Simulation (continued)

Table K.1: Results Experiment 3: Comparison of Tardiness and On-Time Delivery Performance Metrics Under Different Operator Behaviors

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
-10	6.62	27.39	40.43	0.89	17.02	6.21	17.27
-5	6.61	27.24	40.66	0.89	16.86	6.29	17.34
0	6.62	27.77	40.51	0.90	17.24	6.15	17.40
5	6.61	28.05	40.40	0.89	17.43	6.24	17.38
10	6.61	27.77	40.50	0.89	17.18	6.21	17.41
15	6.61	28.44	40.32	0.89	17.68	6.18	17.44
20	6.61	28.70	40.68	0.89	17.78	6.31	17.62
25	6.61	28.97	40.72	0.89	17.98	6.34	17.64
30	6.61	29.43	40.58	0.89	18.40	6.24	17.67
35	6.62	29.75	40.76	0.89	18.58	6.35	17.76
40	6.61	30.08	40.60	0.89	18.83	6.30	17.76
45	6.62	30.16	40.89	0.89	18.79	6.42	17.88
50	6.61	31.08	40.67	0.89	19.41	6.27	18.02
55	6.61	31.41	40.71	0.89	19.66	6.32	18.06
60	6.62	31.22	40.38	0.89	19.45	6.27	17.96
65	6.62	32.41	40.70	0.89	20.39	6.37	18.17
70	6.62	32.44	40.69	0.90	20.36	6.31	18.24
75	6.62	33.20	40.75	0.89	20.84	6.38	18.38
80	6.62	33.67	40.61	0.89	21.11	6.17	18.49
85	6.62	34.52	40.63	0.89	21.78	6.32	18.55
90	6.62	34.68	40.73	0.89	21.84	6.25	18.67
95	6.61	35.92	40.46	0.89	22.79	6.15	18.77
100	6.61	36.12	40.64	0.89	22.81	6.27	18.88

(a) Results Experiment 3: Baseline Simulation

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
105	6.61	37.12	40.64	0.89	23.57	6.33	18.97
110	6.60	37.76	40.74	0.89	23.97	6.27	19.17
115	6.61	38.33	40.42	0.89	24.37	6.19	19.14
120	6.61	39.37	40.59	0.89	25.15	6.31	19.31
125	6.61	40.25	40.78	0.89	25.96	6.31	19.42
130	6.60	41.15	40.61	0.89	26.51	6.28	19.55
135	6.61	41.56	40.86	0.89	26.89	6.29	19.66
140	6.60	43.04	40.68	0.89	28.08	6.34	19.74
145	6.60	44.04	40.41	0.89	28.74	6.24	19.84
150	6.61	45.26	40.67	0.89	29.77	6.34	19.99
155	6.62	45.90	40.61	0.89	30.21	6.26	20.12
160	6.61	46.94	40.73	0.89	31.12	6.29	20.21
165	6.61	48.16	40.83	0.89	32.02	6.30	20.43
170	6.61	48.75	40.75	0.89	32.43	6.30	20.48
175	6.61	50.04	40.59	0.89	33.48	6.31	20.52
180	6.61	51.07	40.92	0.89	34.30	6.30	20.76
185	6.60	51.72	40.61	0.89	34.91	6.25	20.71
190	6.61	53.47	40.91	0.89	36.22	6.36	21.01
195	6.60	53.83	40.45	0.89	36.51	6.25	20.91
200	6.61	55.36	40.64	0.89	37.73	6.27	21.13

(b) Results Experiment 3: Baseline Simulation (continued)

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
205	6.60	57.32	40.53	0.88	39.39	6.23	21.26
210	6.61	58.27	40.56	0.89	40.16	6.33	21.34
215	6.60	59.21	40.66	0.89	40.90	6.33	21.49
220	6.60	60.13	40.57	0.88	41.70	6.19	21.56
225	6.60	61.67	40.52	0.89	43.03	6.32	21.61
230	6.60	63.76	40.52	0.88	44.83	6.28	21.79
235	6.60	64.31	40.72	0.88	45.32	6.31	21.88
240	6.60	64.99	40.49	0.89	45.90	6.27	21.87
245	6.60	66.08	40.67	0.89	46.89	6.30	21.97
250	6.60	67.14	40.53	0.88	47.74	6.25	22.03
255	6.60	68.73	40.40	0.88	49.18	6.23	22.08
260	6.60	68.93	40.64	0.88	49.16	6.30	22.26
265	6.60	70.93	40.81	0.88	51.03	6.36	22.38
270	6.60	70.99	40.71	0.88	50.95	6.25	22.43
275	6.59	71.97	40.56	0.88	51.87	6.34	22.38
280	6.60	72.95	40.44	0.88	52.64	6.29	22.46
285	6.59	73.92	40.34	0.88	53.50	6.25	22.50
290	6.60	75.32	40.71	0.88	54.75	6.38	22.68
295	6.60	75.13	40.81	0.88	54.51	6.43	22.73
300	6.59	76.91	40.46	0.88	56.10	6.23	22.76

(c) Results Experiment 3: Baseline Simulation

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
-10	6.63	27.23	40.74	0.90	16.86	6.28	17.36
-5	6.63	27.58	40.54	0.90	17.16	6.28	17.31
0	6.62	27.62	40.61	0.90	17.17	6.38	17.30
5	6.62	27.96	40.51	0.90	17.38	6.19	17.40
10	6.61	28.38	40.62	0.89	17.74	6.15	17.50
15	6.62	28.84	40.57	0.90	17.99	6.29	17.54
20	6.62	28.51	40.45	0.90	17.69	6.08	17.55
25	6.62	29.13	40.87	0.90	18.16	6.40	17.68
30	6.62	29.17	40.52	0.90	18.17	6.23	17.63
35	6.62	29.46	40.94	0.89	18.33	6.32	17.83
40	6.62	29.99	40.81	0.90	18.67	6.35	17.87
45	6.62	30.33	40.73	0.90	19.01	6.34	17.84
50	6.62	30.83	40.56	0.90	19.26	6.27	17.94
55	6.62	31.34	40.73	0.90	19.65	6.32	18.04
60	6.62	31.52	40.48	0.90	19.74	6.25	18.01
65	6.62	31.97	40.86	0.90	20.00	6.37	18.21
70	6.62	32.46	40.79	0.90	20.32	6.26	18.34
75	6.62	32.83	40.66	0.90	20.53	6.30	18.32
80	6.63	33.72	40.73	0.90	21.17	6.24	18.50
85	6.62	34.63	40.37	0.89	21.84	6.19	18.53
90	6.62	34.77	40.76	0.90	21.89	6.22	18.71
95	6.62	35.62	40.73	0.90	22.49	6.28	18.81
100	6.61	36.07	40.68	0.89	22.76	6.22	18.90

(d) Results Experiment 3: FCFS Simulation

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
105	6.61	36.27	40.78	0.89	22.88	6.25	18.97
110	6.62	37.14	40.45	0.90	23.53	6.23	18.97
115	6.61	38.56	40.81	0.89	24.63	6.34	19.23
120	6.61	39.16	40.56	0.89	25.05	6.26	19.26
125	6.61	40.21	40.45	0.89	25.81	6.30	19.35
130	6.61	41.36	40.70	0.89	26.66	6.37	19.59
135	6.61	41.99	40.50	0.89	27.16	6.24	19.60
140	6.61	43.17	40.70	0.89	28.11	6.26	19.81
145	6.61	44.20	40.46	0.89	28.92	6.18	19.88
150	6.61	44.50	40.70	0.89	29.19	6.35	19.91
155	6.62	45.89	40.89	0.89	30.25	6.41	20.15
160	6.62	46.75	40.55	0.89	30.91	6.19	20.18
165	6.62	47.87	40.57	0.89	31.70	6.25	20.36
170	6.61	48.74	40.87	0.89	32.48	6.28	20.51
175	6.61	50.00	41.08	0.89	33.42	6.25	20.77
180	6.62	51.14	40.56	0.89	34.31	6.29	20.68
185	6.61	52.62	40.58	0.89	35.58	6.26	20.81
190	6.61	53.81	40.45	0.89	36.55	6.14	20.92
195	6.60	54.48	40.61	0.89	37.06	6.24	21.04
200	6.61	56.53	40.64	0.89	38.74	6.19	21.27

(e) Results Experiment 3: FCFS Simulation (continued)

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
205	6.61	57.11	40.70	0.89	39.24	6.24	21.30
210	6.61	57.21	40.44	0.89	39.24	6.15	21.28
215	6.61	59.05	40.52	0.89	40.81	6.26	21.44
220	6.60	60.28	40.59	0.89	41.83	6.23	21.56
225	6.60	61.33	40.55	0.89	42.35	6.23	21.68
230	6.60	62.99	40.58	0.89	43.52	6.20	21.80
235	6.60	63.94	40.42	0.89	44.23	6.31	21.97
240	6.60	64.76	40.52	0.89	44.70	6.26	22.07
245	6.60	66.41	40.81	0.89	47.14	6.32	22.05
250	6.61	66.80	41.07	0.89	47.39	6.40	22.18
255	6.60	68.30	40.25	0.89	48.77	6.23	22.01
260	6.61	68.88	40.72	0.89	49.19	6.28	22.26
265	6.60	70.39	40.90	0.88	50.57	6.34	22.38
270	6.60	70.47	40.60	0.89	50.51	6.38	22.32
275	6.60	72.37	40.59	0.88	52.18	6.32	22.45
280	6.61	72.81	40.57	0.89	52.54	6.29	22.51
285	6.61	73.57	40.73	0.88	53.20	6.41	22.58
290	6.60	75.09	40.59	0.88	54.48	6.25	22.69
295	6.60	76.15	40.72	0.89	55.42	6.32	22.76
300	6.61	75.88	40.36	0.89	55.15	6.16	22.71

(f) Results Experiment 3: FCFS Simulation (continued)

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
-10	6.63	27.23	40.69	0.90	16.80	6.42	17.30
-5	6.63	27.66	40.67	0.90	17.22	6.32	17.36
0	6.62	27.66	40.48	0.90	17.24	6.25	17.30
5	6.62	28.26	40.47	0.90	17.58	6.22	17.43
10	6.62	28.51	40.81	0.90	17.86	6.38	17.50
15	6.62	28.43	40.77	0.90	17.76	6.31	17.51
20	6.62	28.96	40.47	0.90	18.10	6.35	17.48
25	6.62	29.28	40.46	0.90	18.24	6.28	17.60
30	6.62	29.35	40.48	0.90	18.27	6.20	17.66
35	6.63	29.38	41.05	0.90	18.18	6.55	17.82
40	6.62	29.53	40.70	0.90	18.28	6.33	17.79
45	6.62	30.22	40.75	0.90	18.77	6.30	17.92
50	6.62	30.73	40.54	0.90	19.25	6.29	17.86
55	6.62	30.63	40.89	0.90	19.02	6.31	18.04
60	6.62	31.24	40.73	0.90	19.37	6.36	18.11
65	6.61	31.83	40.56	0.90	19.80	6.23	18.17
70	6.61	31.91	40.62	0.90	19.89	6.26	18.18
75	6.62	32.38	40.28	0.90	20.13	6.17	18.21
80	6.62	32.74	40.42	0.90	20.35	6.27	18.30
85	6.62	33.79	40.75	0.90	21.02	6.29	18.62
90	6.61	34.09	40.70	0.89	21.26	6.27	18.64
95	6.61	35.10	40.48	0.90	22.04	6.23	18.70
100	6.62	35.76	40.65	0.90	22.49	6.30	18.85

(g) Results Experiment 3: R1 Simulation

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
105	6.61	36.32	40.90	0.89	22.88	6.35	19.01
110	6.61	37.09	40.55	0.89	23.44	6.24	19.04
115	6.61	38.17	40.63	0.89	24.18	6.25	19.24
120	6.61	38.83	40.70	0.89	24.72	6.33	19.30
125	6.61	39.14	41.00	0.89	24.86	6.33	19.50
130	6.61	40.98	40.55	0.89	26.35	6.27	19.53
135	6.62	40.54	40.76	0.90	25.82	6.36	19.63
140	6.61	41.79	40.75	0.89	26.85	6.27	19.77
145	6.60	43.41	40.54	0.89	28.13	6.20	19.89
150	6.62	43.51	40.62	0.89	28.15	6.17	19.98
155	6.60	45.23	40.43	0.88	29.55	6.20	20.06
160	6.61	45.85	40.55	0.89	30.05	6.36	20.11
165	6.61	46.41	40.60	0.89	30.40	6.28	20.26
170	6.60	48.29	40.77	0.89	31.93	6.24	20.54
175	6.61	49.64	40.87	0.89	33.02	6.33	20.68
180	6.61	50.40	40.63	0.89	33.57	6.16	20.75
185	6.60	51.24	40.82	0.89	34.20	6.32	20.88
190	6.61	52.84	40.67	0.89	35.54	6.34	20.95
195	6.60	53.01	40.61	0.88	35.65	6.20	21.01
200	6.61	53.91	40.64	0.89	36.35	6.26	21.09

(h) Results Experiment 3: R1 Simulation (continued)

Operator Behavior ($\pm\mu$)	Lead Time (min)			Queueing Time (min)			Conveyor Duration
	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
205	6.59	55.08	40.32	0.88	37.21	6.14	21.19
210	6.60	56.45	40.40	0.89	38.39	6.18	21.31
215	6.60	57.90	40.45	0.89	39.56	6.17	21.46
220	6.60	59.96	40.84	0.88	41.40	6.34	21.70
225	6.60	59.60	40.60	0.89	41.02	6.24	21.64
230	6.60	61.37	40.49	0.89	42.63	6.16	21.71
235	6.61	62.19	40.48	0.89	43.29	6.29	21.75
240	6.60	62.33	40.64	0.88	43.22	6.30	21.93
245	6.61	64.91	40.54	0.89	45.61	6.25	22.01
250	6.60	65.46	40.92	0.88	46.05	6.33	22.16
255	6.60	65.97	40.88	0.89	46.41	6.35	22.22
260	6.60	67.52	40.78	0.88	47.78	6.36	22.27
265	6.60	68.61	40.66	0.88	48.64	6.24	22.39
270	6.60	69.22	40.83	0.88	49.21	6.27	22.47
275	6.60	69.87	40.54	0.88	49.78	6.25	22.41
280	6.60	70.74	40.41	0.88	50.46	6.19	22.48
285	6.60	71.26	40.47	0.88	50.88	6.20	22.56
290	6.60	72.88	40.80	0.88	52.30	6.32	22.74
295	6.60	73.41	40.42	0.88	52.75	6.14	22.70
300	6.60	74.29	40.60	0.88	53.54	6.16	22.81

(i) Results Experiment 3: R1 Simulation (continued)

Table K.2: Results Experiment 3: Comparison of Queuing and Movement Performance Metrics Under Different Operator Behaviors

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
3;5;10	90.50%	80.95%	22.92	1.97	0.94	0.04	3.65	0.55
3;6;10	90.64%	81.06%	22.73	1.97	0.94	0.04	3.79	0.55
3;7;10	90.78%	81.34%	21.73	1.93	0.92	0.04	3.72	0.52
3;5;11	90.47%	80.91%	23.27	2.00	0.95	0.04	3.90	0.52
3;6;11	90.93%	81.55%	22.10	1.98	0.95	0.05	3.92	0.53
3;7;11	91.10%	81.86%	21.17	1.88	0.93	0.04	3.54	0.53
3;5;12	90.65%	81.56%	23.43	1.90	0.98	0.04	3.66	0.48
3;6;12	90.76%	81.37%	22.29	1.94	0.94	0.04	3.64	0.52
3;7;12	91.00%	81.51%	22.98	1.97	0.99	0.05	3.91	0.52
4;5;10	91.31%	81.45%	16.44	1.97	0.74	0.05	2.92	0.55
4;6;10	91.94%	81.13%	14.91	1.96	0.72	0.04	2.94	0.58
4;7;10	92.25%	81.84%	14.44	1.93	0.72	0.05	2.77	0.54
4;5;11	91.57%	81.53%	15.70	1.97	0.72	0.05	2.90	0.57
4;6;11	91.79%	81.51%	15.56	1.96	0.74	0.05	2.88	0.56
4;7;11	91.97%	81.34%	14.65	1.91	0.71	0.04	2.92	0.56
4;5;12	91.65%	81.39%	16.04	1.99	0.75	0.05	2.92	0.58
4;6;12	91.68%	81.70%	16.03	1.93	0.75	0.05	2.86	0.56
4;7;12	91.95%	81.66%	16.18	1.91	0.78	0.04	2.93	0.56

(a) Results Experiment 4a: Baseline Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
5;5;10	92.15%	81.81%	14.72	1.90	0.73	0.04	2.87	0.53
5;6;10	91.99%	81.49%	13.99	1.96	0.63	0.05	2.73	0.52
5;7;10	92.29%	80.77%	13.85	2.03	0.70	0.05	2.76	0.55
5;5;11	92.15%	81.08%	14.20	2.02	0.70	0.05	2.85	0.56
5;6;11	92.19%	81.15%	13.63	1.99	0.68	0.05	2.76	0.55
5;7;11	92.37%	81.22%	13.06	1.98	0.67	0.05	2.66	0.56
5;5;12	92.23%	81.86%	13.94	1.90	0.70	0.05	2.74	0.52
5;6;12	92.22%	81.61%	13.41	2.00	0.67	0.05	2.65	0.57
5;7;12	92.60%	81.62%	13.15	1.99	0.69	0.05	2.76	0.56

(b) Results Experiment 4a: Baseline Simulation (continued)

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
3;5;10	90.37%	80.93%	23.13	2.02	0.94	0.05	3.59	0.52
3;6;10	91.19%	80.82%	22.74	2.01	1.00	0.04	3.80	0.52
3;7;10	90.90%	81.45%	21.78	1.93	0.93	0.04	3.72	0.56
3;5;11	90.33%	81.37%	22.63	1.98	0.91	0.05	3.47	0.56
3;6;11	90.89%	81.85%	22.30	1.91	0.95	0.05	3.80	0.54
3;7;11	91.32%	81.51%	21.21	1.97	0.95	0.05	3.65	0.53
3;5;12	90.26%	81.50%	23.48	1.92	0.94	0.04	3.57	0.56
3;6;12	90.87%	81.29%	22.38	2.02	0.95	0.05	3.74	0.58
3;7;12	91.19%	81.28%	21.58	1.97	0.95	0.04	3.68	0.55
4;5;10	91.23%	81.55%	17.18	1.93	0.76	0.04	2.82	0.52
4;6;10	91.84%	81.41%	16.19	1.99	0.77	0.05	2.87	0.57
4;7;10	92.10%	81.30%	15.12	1.92	0.75	0.04	2.74	0.56
4;5;11	91.38%	81.33%	16.73	2.00	0.75	0.05	2.75	0.52
4;6;11	92.04%	81.59%	15.15	1.92	0.74	0.04	2.70	0.56
4;7;11	92.12%	81.54%	14.35	1.93	0.71	0.05	2.64	0.53
4;5;12	91.65%	81.10%	16.04	2.01	0.75	0.05	2.74	0.56
4;6;12	91.83%	80.88%	15.73	2.01	0.75	0.05	2.86	0.59
4;7;12	92.36%	81.57%	15.27	1.92	0.78	0.04	2.82	0.54

(c) Results Experiment 4a: FCFS Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
5;5;10	91.99%	81.17%	14.01	1.99	0.68	0.05	2.43	0.56
5;6;10	92.46%	81.02%	13.13	1.97	0.68	0.04	2.60	0.56
5;7;10	92.55%	80.98%	12.82	2.01	0.67	0.05	2.57	0.53
5;5;11	92.21%	81.33%	14.23	1.96	0.71	0.05	2.65	0.56
5;6;11	92.46%	81.24%	13.59	1.97	0.70	0.05	2.60	0.57
5;7;11	92.68%	81.33%	13.01	1.97	0.69	0.05	2.67	0.55
5;5;12	92.31%	81.50%	13.94	1.97	0.70	0.05	2.53	0.57
5;6;12	92.31%	81.21%	12.85	2.03	0.65	0.05	2.54	0.57
5;7;12	92.59%	80.92%	12.46	2.05	0.65	0.05	2.48	0.55

(d) Results Experiment 4a: FCFS Simulation (continued)

Pipeline Threshold [*Out1*,*Out2*, *Out3*]	On-Time Delivery Percentage Full Outbound	On-Time Delivery Percentage Workstation	Average Daily Tardiness (h) Full Outbound	Average Daily Tardiness (h) Workstation	Average Pallet Tardiness (h) Full Outbound	Average Pallet Tardiness (h) Workstation	Maximum Pallet Tardiness (h) Full Outbound	Maximum Pallet Tardiness (h) Workstation
3;10;5	90.41%	81.46%	23.13	1.96	0.94	0.05	6.56	0.53
3;10;6	91.08%	81.26%	22.80	2.01	0.99	0.05	6.47	0.51
3;10;7	91.35%	81.53%	22.22	1.97	1.00	0.05	6.60	0.55
3;11;5	90.88%	81.06%	23.13	1.99	0.99	0.05	6.56	0.54
3;11;6	91.11%	81.45%	22.04	1.93	0.97	0.04	6.43	0.53
3;11;7	91.45%	81.57%	21.65	1.92	0.99	0.04	6.36	0.55
3;12;5	90.84%	81.29%	22.89	1.97	0.97	0.05	6.26	0.55
3;12;6	91.20%	81.44%	22.21	1.94	0.98	0.05	6.51	0.53
3;12;7	91.17%	81.20%	23.18	1.96	1.02	0.05	6.63	0.55
4;10;5	91.60%	81.54%	17.17	1.97	0.79	0.05	4.96	0.56
4;10;6	92.31%	81.46%	16.57	1.94	0.84	0.05	5.06	0.52
4;10;7	92.15%	81.26%	15.69	1.98	0.78	0.05	5.03	0.55
4;11;5	91.81%	81.58%	16.42	1.94	0.78	0.05	4.82	0.49
4;11;6	92.03%	81.22%	16.25	1.99	0.79	0.05	5.03	0.54
4;11;7	92.36%	81.17%	15.57	1.96	0.79	0.04	4.97	0.55
4;12;5	91.80%	81.33%	16.61	1.98	0.79	0.05	5.02	0.55
4;12;6	92.20%	81.53%	16.09	1.90	0.80	0.04	5.15	0.48
4;12;7	92.24%	81.67%	17.09	1.92	0.86	0.05	5.09	0.51

(e) Results Experiment 4a: R1 Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
5;5;10	92.22%	81.34%	14.40	1.98	0.72	0.05	4.36	0.55
5;6;10	92.33%	81.04%	15.24	2.01	0.77	0.05	4.41	0.51
5;7;10	93.02%	81.41%	13.60	1.98	0.76	0.05	4.48	0.55
5;5;11	92.22%	81.54%	13.89	1.96	0.70	0.05	4.40	0.56
5;6;11	92.77%	81.65%	13.37	1.95	0.72	0.05	4.38	0.55
5;7;11	92.95%	81.97%	13.57	1.92	0.75	0.05	4.63	0.57
5;5;12	92.04%	81.29%	14.64	2.03	0.71	0.05	4.52	0.55
5;6;12	92.69%	81.56%	14.36	1.97	0.76	0.05	4.56	0.57
5;7;12	92.93%	80.83%	12.49	2.02	0.69	0.05	4.46	0.54

(f) Results Experiment 4a: R1 Simulation (continued)

Table K.3: Results Experiment 4a: Comparison of Tardiness and On-Time Performance Metrics Under Different Pipeline Threshold Configurations

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
3;5;10	6.60	28.30	40.41	0.89	18.27	6.25	17.07
3;5;6	6.61	28.14	40.54	0.89	17.85	6.32	17.23
3;5;7	6.62	27.77	40.51	0.90	17.24	6.15	17.40
3;6;5	6.61	28.36	40.37	0.89	18.03	6.21	17.22
3;6;11	6.61	27.77	40.48	0.89	17.21	6.17	17.40
3;7;5	6.62	27.37	40.49	0.90	16.56	6.24	17.51
3;7;6	6.61	28.14	40.44	0.89	17.56	6.13	17.41
3;8;5	6.62	27.80	40.57	0.89	16.96	6.18	17.57
3;9;7	6.62	27.69	40.65	0.90	16.63	6.22	17.71
4;5;10	6.62	26.46	40.74	0.90	16.23	6.23	17.31
4;5;6	6.62	25.74	40.70	0.89	15.29	6.27	17.40
4;5;7	6.63	25.38	40.53	0.90	14.73	6.23	17.44
4;6;10	6.62	26.12	40.82	0.90	15.60	6.38	17.43
4;6;7	6.63	25.70	40.61	0.89	14.96	6.25	17.52
4;7;10	6.63	25.51	40.70	0.90	14.47	6.25	17.72
4;7;5	6.62	26.18	40.78	0.89	15.32	6.40	17.58
4;8;5	6.63	25.85	40.85	0.90	14.77	6.32	17.74
4;9;7	6.62	25.81	40.58	0.89	14.45	6.29	17.81

(a) Results Experiment 4a: Baseline Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
5;5;10	6.66	25.55	40.62	0.89	15.16	6.16	17.35
5;6;10	6.65	25.25	40.75	0.89	14.50	6.26	17.57
5;7;10	6.66	25.24	40.52	0.89	14.26	6.21	17.62
5;5;11	6.65	25.40	40.78	0.89	14.64	6.24	17.59
5;6;11	6.66	25.13	40.31	0.90	14.13	6.13	17.59
5;7;11	6.67	24.72	40.26	0.90	13.49	6.19	17.67
5;5;12	6.66	25.26	40.81	0.89	14.25	6.30	17.71
5;6;12	6.66	24.97	40.49	0.90	13.69	6.24	17.74
5;7;12	6.66	24.86	40.54	0.90	13.30	6.30	17.89

(b) Results Experiment 4a: Baseline Simulation (continued)

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
3;5;10	6.61	28.48	40.57	0.89	18.42	6.23	17.15
3;6;10	6.62	27.81	40.34	0.90	17.53	6.24	17.18
3;7;10	6.62	27.62	40.61	0.90	17.17	6.38	17.30
3;5;11	6.62	28.22	40.56	0.90	17.91	6.22	17.27
3;6;11	6.63	27.86	40.91	0.90	17.27	6.38	17.51
3;7;11	6.62	27.35	40.89	0.89	16.56	6.34	17.61
3;5;12	6.63	28.31	40.66	0.90	17.80	6.22	17.42
3;6;12	6.62	27.81	40.73	0.90	16.98	6.31	17.59
3;7;12	6.63	27.32	40.35	0.90	16.28	6.19	17.59
4;5;10	6.63	26.68	40.92	0.90	16.46	6.24	17.36
4;6;10	6.63	26.02	40.59	0.90	15.56	6.26	17.36
4;7;10	6.63	25.57	40.36	0.90	14.87	6.21	17.43
4;5;11	6.64	26.23	40.63	0.90	15.70	6.22	17.42
4;6;11	6.63	25.66	40.53	0.90	14.93	6.35	17.44
4;7;11	6.63	25.32	40.84	0.90	14.36	6.45	17.63
4;5;12	6.63	25.98	40.36	0.90	15.25	6.26	17.41
4;6;12	6.63	25.72	40.48	0.90	14.68	6.18	17.63
4;7;12	6.63	25.31	40.79	0.90	14.10	6.38	17.76

(c) Results Experiment 4a: FCFS Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
5;5;10	6.66	25.66	40.78	0.90	15.15	6.33	17.41
5;6;10	6.65	25.02	40.45	0.90	14.36	6.24	17.42
5;7;10	6.67	25.00	40.89	0.90	13.99	6.28	17.75
5;5;11	6.68	25.56	40.62	0.91	14.77	6.36	17.50
5;6;11	6.67	25.12	40.51	0.90	14.09	6.31	17.59
5;7;11	6.68	24.77	40.61	0.90	13.46	6.28	17.79
5;5;12	6.66	25.34	40.70	0.90	14.34	6.36	17.65
5;6;12	6.67	24.90	40.86	0.90	13.59	6.34	17.88
5;7;12	6.68	24.59	40.44	0.90	13.06	6.25	17.87

(d) Results Experiment 4a: FCFS Simulation (continued)

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
3;5;10	6.62	28.57	40.67	0.90	18.54	6.29	17.14
3;6;10	6.62	28.13	40.54	0.90	17.86	6.22	17.25
3;7;10	6.62	27.66	40.48	0.90	17.24	6.25	17.30
3;5;11	6.61	28.27	40.62	0.90	17.93	6.27	17.29
3;6;11	6.61	27.91	40.60	0.90	17.30	6.37	17.39
3;7;11	6.63	27.42	40.67	0.90	16.64	6.40	17.50
3;5;12	6.63	28.15	40.53	0.90	17.54	6.29	17.39
3;6;12	6.63	27.78	40.70	0.90	16.91	6.20	17.63
3;7;12	6.63	27.95	40.69	0.90	16.81	6.32	17.73
4;5;10	6.64	26.68	40.64	0.90	16.40	6.31	17.26
4;6;10	6.63	26.24	40.29	0.90	15.69	6.26	17.28
4;7;10	6.63	25.86	40.60	0.90	15.13	6.30	17.48
4;5;11	6.63	26.38	40.91	0.90	15.81	6.41	17.48
4;6;11	6.63	25.98	41.02	0.90	15.22	6.52	17.59
4;7;11	6.64	25.75	40.55	0.90	14.66	6.34	17.65
4;5;12	6.63	26.33	40.61	0.90	15.49	6.31	17.54
4;6;12	6.63	25.71	40.58	0.90	14.69	6.25	17.65
4;7;12	6.64	26.03	40.94	0.90	14.70	6.49	17.84

(e) Results Experiment 4a: R1 Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
5;5;10	6.67	25.75	40.56	0.90	15.27	6.29	17.35
6;5;10	6.66	25.69	40.67	0.90	14.89	6.28	17.56
7;5;10	6.66	25.01	40.65	0.90	14.01	6.34	17.63
5;5;11	6.66	25.45	40.64	0.90	14.71	6.31	17.49
6;5;11	6.66	24.96	40.48	0.90	13.92	6.27	17.61
7;5;11	6.66	24.87	40.74	0.90	13.63	6.40	17.76
5;5;12	6.67	25.59	40.78	0.91	14.54	6.49	17.64
6;5;12	6.67	25.11	40.54	0.90	13.79	6.30	17.77
7;5;12	6.67	24.50	40.39	0.90	13.02	6.33	17.80

(f) Results Experiment 4a: R1 Simulation

Table K.4: Results Experiment 4a: Comparison of Queuing and Movement Performance Metrics Under Different Pipeline Threshold Configurations

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Workstations*, *F5*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
6;4;10	92.46%	80.19%	12.61	2.08	0.65	0.04	2.68	0.56
6;3;10	92.35%	78.62%	13.18	2.27	0.67	0.05	2.66	0.56
5;4;10	92.23%	79.29%	13.77	2.14	0.69	0.04	2.76	0.58
5;3;10	92.15%	77.66%	14.92	2.41	0.74	0.05	2.87	0.58
4;4;10	92.20%	77.38%	14.34	2.40	0.71	0.05	2.81	0.49
4;3;10	92.92%	76.56%	11.13	2.51	0.61	0.05	2.52	0.53
3;4;10	92.42%	73.62%	13.03	2.96	0.67	0.05	2.69	0.56
3;3;10	92.46%	71.43%	13.59	3.12	0.70	0.05	2.91	0.56
6;4;11	92.45%	80.22%	13.64	2.04	0.70	0.04	2.66	0.56
6;3;11	92.45%	78.90%	13.77	2.27	0.71	0.05	2.76	0.52
5;4;11	92.57%	79.57%	12.21	2.11	0.64	0.04	2.64	0.49
5;3;11	92.58%	77.92%	13.41	2.29	0.70	0.04	2.58	0.57
4;4;11	92.54%	78.10%	13.78	2.33	0.72	0.05	2.68	0.56
4;3;11	92.49%	75.99%	13.13	2.63	0.68	0.05	2.78	0.56
3;4;11	92.32%	73.71%	14.55	2.85	0.74	0.05	2.89	0.52
3;3;11	92.21%	71.49%	14.94	3.10	0.75	0.05	2.87	0.52
6;4;12	92.56%	80.26%	13.32	2.08	0.70	0.04	2.67	0.51
6;3;12	92.60%	78.63%	13.43	2.29	0.71	0.05	2.70	0.56
5;4;12	92.24%	79.82%	14.34	2.15	0.72	0.05	2.91	0.58
5;3;12	92.45%	77.71%	13.47	2.37	0.70	0.05	2.80	0.56
4;4;12	92.34%	77.72%	13.57	2.34	0.69	0.04	2.76	0.54
4;3;12	92.61%	75.92%	12.41	2.56	0.65	0.05	2.62	0.55
3;4;12	92.22%	73.71%	13.14	2.87	0.66	0.05	2.71	0.56
3;3;12	92.80%	71.69%	13.22	3.10	0.71	0.05	2.69	0.52

(a) Results Experiment 4b: Baseline Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Workstations*, *F5*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
6;4;10	92.20%	80.49%	13.53	2.04	0.68	0.04	2.66	0.56
6;3;10	92.49%	78.67%	12.90	2.27	0.67	0.05	2.48	0.52
5;4;10	92.30%	79.88%	13.36	2.09	0.67	0.04	2.51	0.57
5;3;10	92.54%	78.03%	12.69	2.31	0.66	0.05	2.54	0.53
4;4;10	92.59%	77.84%	12.99	2.37	0.68	0.05	2.53	0.56
4;3;10	92.55%	76.25%	12.91	2.56	0.67	0.05	2.41	0.56
3;4;10	92.45%	73.78%	13.69	2.87	0.71	0.05	2.59	0.57
3;3;10	92.56%	71.45%	13.54	3.11	0.71	0.05	2.62	0.56
6;4;11	92.62%	80.46%	12.88	2.00	0.68	0.04	2.38	0.56
6;3;11	92.61%	78.63%	14.11	2.26	0.74	0.05	2.65	0.56
5;4;11	92.16%	79.30%	14.27	2.19	0.71	0.05	2.65	0.51
5;3;11	92.48%	77.86%	13.43	2.38	0.69	0.05	2.57	0.57
4;4;11	92.49%	78.09%	13.57	2.35	0.70	0.05	2.69	0.55
4;3;11	92.31%	76.71%	12.36	2.53	0.63	0.05	2.37	0.50
3;4;11	92.53%	73.54%	13.51	2.94	0.70	0.05	2.65	0.56
3;3;11	92.49%	71.34%	13.25	3.14	0.69	0.05	2.50	0.56
6;4;12	92.43%	80.42%	13.80	2.03	0.71	0.04	2.77	0.59
6;3;12	92.51%	78.54%	14.96	2.27	0.78	0.05	2.88	0.52
5;4;12	92.37%	79.57%	13.31	2.17	0.68	0.05	2.54	0.49
5;3;12	92.48%	78.05%	11.51	2.36	0.59	0.05	2.30	0.56
4;4;12	92.75%	77.96%	12.70	2.37	0.68	0.05	2.48	0.56
4;3;12	92.54%	75.94%	13.84	2.57	0.72	0.05	2.73	0.52
3;4;12	92.60%	74.12%	12.81	2.85	0.67	0.05	2.60	0.56
3;3;12	92.99%	71.45%	12.93	3.14	0.72	0.05	2.68	0.57

(b) Results Experiment 4b: FCFS Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Workstations*, *F5*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
6;4;10	92.46%	80.33%	13.94	2.07	0.72	0.04	4.69	0.55
6;3;10	92.55%	78.54%	14.35	2.29	0.75	0.05	4.55	0.57
5;4;10	92.45%	79.56%	13.45	2.18	0.69	0.05	4.57	0.58
5;3;10	92.63%	77.21%	14.03	2.41	0.74	0.05	4.74	0.53
4;4;10	92.58%	78.00%	15.01	2.34	0.79	0.05	4.75	0.55
4;3;10	92.78%	76.60%	13.58	2.51	0.73	0.05	4.40	0.56
3;4;10	92.91%	73.25%	13.80	2.93	0.76	0.05	4.65	0.57
3;3;10	92.65%	71.68%	14.41	3.15	0.76	0.05	4.68	0.55
6;4;11	92.95%	80.20%	13.48	2.06	0.74	0.04	4.51	0.52
6;3;11	93.11%	78.72%	13.91	2.24	0.78	0.05	4.68	0.52
5;4;11	92.47%	79.89%	13.90	2.11	0.72	0.05	4.52	0.56
5;3;11	92.72%	77.75%	14.65	2.40	0.78	0.05	4.67	0.54
4;4;11	92.64%	77.82%	14.29	2.37	0.75	0.05	4.70	0.55
4;3;11	92.94%	76.03%	13.77	2.57	0.76	0.05	4.54	0.55
3;4;11	92.95%	73.11%	14.19	2.93	0.77	0.05	4.81	0.55
3;3;11	92.72%	71.17%	14.19	3.18	0.76	0.05	4.86	0.55
6;4;12	92.47%	80.58%	14.90	2.05	0.77	0.05	4.63	0.55
6;3;12	92.52%	78.84%	14.55	2.26	0.76	0.05	4.80	0.55
5;4;12	92.66%	79.56%	13.97	2.15	0.74	0.05	4.65	0.56
5;3;12	92.58%	78.15%	13.73	2.32	0.72	0.05	4.78	0.57
4;4;12	92.73%	77.41%	13.80	2.38	0.74	0.05	4.60	0.55
4;3;12	92.43%	76.26%	14.84	2.54	0.76	0.05	4.79	0.52
3;4;12	92.85%	73.81%	14.01	2.86	0.76	0.05	4.60	0.56
3;3;12	92.75%	71.21%	14.28	3.20	0.77	0.05	4.80	0.56

(c) Results Experiment 4b: R1 Simulation

Table K.5: Results Experiment 4b: Comparison of Tardiness and On-Time Delivery Performance Metrics Under Different Pipeline Threshold Configurations

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Workstations*, *F5*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
6;4;10	0.90	13.95	8.57	6.62	24.86	40.94	16.63
6;3;10	0.90	14.14	9.89	6.62	25.18	41.18	16.22
5;4;10	0.89	14.14	10.83	6.61	25.19	41.08	15.72
5;3;10	0.90	14.48	12.02	6.61	25.54	41.57	15.36
4;4;10	0.89	14.29	13.70	6.61	25.32	41.31	14.45
4;3;10	0.89	13.43	15.20	6.61	24.32	42.00	13.98
3;4;10	0.89	14.02	17.79	6.60	24.99	42.08	12.84
3;3;10	0.89	14.10	19.18	6.60	25.14	42.50	12.42
6;4;11	0.90	13.69	8.46	6.62	24.94	40.68	16.75
6;3;11	0.90	13.80	10.12	6.63	25.14	41.39	16.36
5;4;11	0.89	13.43	10.63	6.62	24.63	40.91	15.80
5;3;11	0.89	13.65	11.95	6.61	25.00	41.22	15.41
4;4;11	0.89	13.85	13.76	6.61	25.25	41.47	14.67
4;3;11	0.89	13.58	15.48	6.61	24.85	42.28	14.18
3;4;11	0.89	14.03	17.71	6.61	25.36	42.05	13.02
3;3;11	0.89	14.01	19.25	6.60	25.33	42.70	12.60
6;4;12	0.90	13.34	8.60	6.63	24.91	41.01	17.00
6;3;12	0.90	13.31	9.84	6.62	24.86	41.11	16.47
5;4;12	0.90	13.58	10.84	6.62	25.17	41.12	16.03
5;3;12	0.90	13.32	12.18	6.62	24.86	41.67	15.60
4;4;12	0.89	13.38	13.70	6.61	24.88	41.44	14.74
4;3;12	0.89	13.11	15.00	6.61	24.72	41.71	14.34
3;4;12	0.89	13.27	17.60	6.61	24.87	41.86	13.14
3;3;12	0.89	13.10	18.96	6.60	24.60	42.29	12.66

(a) Results Experiment 4b: Baseline Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Workstations*, *F5*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
6;4;10	0.90	14.30	8.69	6.63	25.36	40.82	16.62
6;3;10	0.90	14.01	9.96	6.63	25.04	41.18	16.18
5;4;10	0.90	14.05	10.59	6.62	25.03	40.64	15.62
5;3;10	0.90	13.84	12.04	6.62	24.79	41.49	15.25
4;4;10	0.90	13.92	13.81	6.62	24.87	41.42	14.40
4;3;10	0.89	13.89	15.06	6.61	24.86	41.67	13.97
3;4;10	0.89	14.18	17.90	6.60	25.19	42.28	12.87
3;3;10	0.90	14.07	18.96	6.61	25.05	42.29	12.38
6;4;11	0.90	13.50	8.62	6.63	24.78	40.96	16.82
6;3;11	0.90	13.78	10.06	6.62	25.13	41.09	16.27
5;4;11	0.90	13.83	10.78	6.62	25.09	41.18	15.86
5;3;11	0.90	13.62	12.13	6.62	24.89	41.66	15.46
4;4;11	0.90	13.74	13.74	6.62	25.04	41.51	14.63
4;3;11	0.89	13.47	15.11	6.62	24.75	41.90	14.18
3;4;11	0.89	13.69	17.72	6.61	24.97	41.87	12.96
3;3;11	0.89	13.62	19.32	6.61	24.87	42.80	12.57
6;4;12	0.90	13.40	8.61	6.64	24.97	40.88	16.95
6;3;12	0.91	13.63	10.22	6.64	25.16	41.61	16.52
5;4;12	0.90	13.33	10.92	6.62	24.86	41.06	15.93
5;3;12	0.90	12.86	12.25	6.63	24.41	41.75	15.60
4;4;12	0.90	13.12	13.90	6.62	24.68	41.59	14.75
4;3;12	0.89	13.47	15.33	6.62	25.02	42.12	14.32
3;4;12	0.90	13.14	17.83	6.61	24.68	42.23	13.16
3;3;12	0.89	13.00	19.19	6.61	24.50	42.68	12.70

(b) Results Experiment 4b: FCFS Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Workstations*, *F5*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
6;4;10	0.90	14.28	8.59	6.63	25.33	40.79	16.65
6;3;10	0.90	14.28	10.19	6.63	25.29	41.46	16.17
5;4;10	0.90	14.21	10.67	6.62	25.20	40.79	15.64
5;3;10	0.90	14.29	11.90	6.62	25.34	41.07	15.22
4;4;10	0.90	14.51	13.78	6.62	25.56	41.32	14.43
4;3;10	0.90	14.11	15.14	6.62	25.09	41.94	14.03
3;4;10	0.89	14.19	17.97	6.60	25.18	42.37	12.87
3;3;10	0.89	14.31	18.95	6.60	25.38	42.23	12.42
6;4;11	0.90	13.65	8.58	6.63	24.88	40.87	16.77
6;3;11	0.90	13.64	10.16	6.63	24.91	41.43	16.31
5;4;11	0.90	13.83	10.59	6.62	25.14	40.84	15.85
5;3;11	0.90	13.94	12.10	6.62	25.30	41.49	15.47
4;4;11	0.90	13.92	13.63	6.61	25.24	41.16	14.59
4;3;11	0.90	13.76	15.12	6.62	25.09	41.81	14.18
3;4;11	0.90	13.75	17.67	6.62	24.97	41.92	12.94
3;3;11	0.90	13.76	19.06	6.61	25.00	42.33	12.52
6;4;12	0.90	13.62	8.55	6.63	25.28	40.77	16.97
6;3;12	0.91	13.59	9.82	6.64	25.19	41.09	16.49
5;4;12	0.90	13.47	10.65	6.63	25.05	40.82	15.96
5;3;12	0.90	13.33	12.13	6.64	24.91	41.50	15.56
4;4;12	0.90	13.44	13.76	6.63	25.13	41.36	14.80
4;3;12	0.90	13.75	15.20	6.62	25.46	42.03	14.42
3;4;12	0.90	13.36	17.87	6.61	24.95	42.32	13.19
3;3;12	0.90	13.49	19.19	6.61	24.98	42.73	12.71

(c) Results Experiment 4b: R1 Simulation

Table K.6: Results Experiment 4b: Comparison of Queuing and Movement Performance Metrics Under Different Pipeline Threshold Configurations

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
7;9;24	92.99%	81.33%	10.65	1.98	0.59	0.05	2.62	0.52
7;10;24	92.71%	81.42%	13.34	1.98	0.71	0.05	2.84	0.57
7;11;24	93.04%	80.87%	11.50	2.05	0.64	0.05	2.83	0.52
7;9;25	92.50%	81.24%	11.92	2.04	0.62	0.05	2.70	0.56
7;10;25	92.82%	81.15%	11.80	2.00	0.64	0.05	2.70	0.56
7;11;25	93.12%	81.47%	11.31	1.96	0.64	0.05	2.58	0.56
7;9;26	92.40%	80.97%	12.24	2.04	0.63	0.05	2.64	0.57
7;10;26	93.07%	81.16%	11.78	2.03	0.66	0.05	2.65	0.56
7;11;26	92.73%	80.95%	11.73	2.01	0.63	0.05	2.69	0.56
7;9;27	92.97%	81.17%	11.48	2.02	0.63	0.05	2.79	0.56
7;10;27	93.03%	81.32%	12.09	2.00	0.67	0.05	2.79	0.54
7;11;27	92.71%	81.20%	12.12	2.00	0.65	0.05	2.60	0.52
7;9;28	92.87%	81.48%	11.62	1.98	0.64	0.05	2.82	0.56
7;10;28	92.85%	81.36%	13.55	2.02	0.74	0.05	3.01	0.50
7;11;28	93.04%	81.38%	11.06	1.95	0.62	0.04	2.58	0.53

(a) Results Experiment 4c: Baseline Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
8;9;24	92.50%	80.95%	11.99	2.04	0.62	0.05	2.70	0.56
8;10;24	92.84%	80.95%	12.62	2.03	0.69	0.05	3.23	0.51
8;11;24	93.06%	81.60%	11.57	1.97	0.65	0.05	2.80	0.57
8;9;25	92.97%	81.46%	10.95	1.99	0.61	0.05	2.70	0.56
8;10;25	92.87%	81.09%	11.50	1.99	0.63	0.04	2.52	0.54
8;11;25	93.01%	81.58%	11.62	1.95	0.65	0.05	2.90	0.54
8;9;26	92.48%	81.37%	13.05	1.98	0.67	0.05	2.86	0.56
8;10;26	92.57%	81.10%	11.96	2.00	0.63	0.05	2.80	0.56
8;11;26	92.81%	81.24%	11.21	2.00	0.61	0.05	2.71	0.56
8;9;27	92.79%	81.50%	11.86	1.99	0.64	0.05	2.90	0.55
8;10;27	92.70%	80.90%	11.81	2.04	0.63	0.05	2.88	0.57
8;11;27	92.68%	81.14%	11.04	1.98	0.59	0.04	2.91	0.57

(b) Results Experiment 4c: Baseline Simulation (continued)

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
7;9;24	93.01%	81.33%	12.27	2.01	0.68	0.05	2.64	0.46
7;10;24	92.57%	81.42%	12.23	2.02	0.64	0.05	2.63	0.53
7;11;24	93.04%	81.35%	11.90	2.00	0.67	0.05	2.59	0.53
7;9;25	92.95%	81.76%	11.82	1.95	0.65	0.05	2.50	0.51
7;10;25	92.91%	81.88%	12.07	1.93	0.66	0.05	2.71	0.52
7;11;25	93.18%	81.52%	11.57	2.02	0.66	0.05	2.65	0.56
7;9;26	92.73%	80.50%	12.21	2.09	0.65	0.05	2.49	0.52
7;10;26	93.13%	81.60%	11.88	1.98	0.67	0.05	2.87	0.54
7;11;26	92.59%	81.56%	11.48	2.01	0.60	0.05	2.66	0.56
7;9;27	92.91%	80.94%	11.18	2.06	0.61	0.05	2.48	0.55
7;10;27	92.90%	81.20%	11.51	2.03	0.63	0.05	2.56	0.52
7;11;27	92.83%	81.71%	12.15	1.99	0.66	0.05	2.70	0.57
7;9;28	92.96%	80.89%	11.83	2.01	0.65	0.05	2.48	0.49
7;10;28	92.96%	81.65%	11.15	2.02	0.62	0.05	2.44	0.56
7;11;28	93.07%	81.26%	10.88	2.03	0.61	0.05	2.60	0.52

(c) Results Experiment 4c: FCFS Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
8;9;24	92.79%	81.28%	11.97	2.04	0.65	0.05	2.64	0.53
8;10;24	92.73%	81.33%	13.19	1.99	0.70	0.05	2.77	0.52
8;11;24	92.90%	81.42%	12.57	2.01	0.69	0.05	2.59	0.55
8;9;25	92.91%	81.22%	12.02	2.02	0.66	0.05	2.57	0.52
8;10;25	92.90%	81.14%	11.90	2.01	0.66	0.05	2.61	0.52
8;11;25	92.83%	81.73%	11.89	2.02	0.64	0.05	2.64	0.56
8;9;26	92.68%	81.62%	11.67	2.05	0.62	0.05	2.69	0.56
8;10;26	93.20%	81.62%	10.29	2.03	0.59	0.05	2.38	0.56
8;11;26	93.09%	81.25%	11.56	2.05	0.65	0.05	2.53	0.53
8;9;27	92.69%	81.30%	12.59	2.04	0.67	0.05	2.75	0.56
8;10;27	92.84%	81.33%	11.64	2.05	0.63	0.05	2.42	0.55
8;11;27	92.67%	81.36%	12.58	2.01	0.67	0.05	2.60	0.56

(d) Results Experiment 4c: FCFS Simulation (continued)

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
7;9;24	93.27%	81.00%	12.43	1.97	0.72	0.04	4.29	0.57
7;10;24	93.27%	81.39%	12.40	1.99	0.72	0.05	4.36	0.54
7;11;24	93.53%	81.32%	11.30	2.02	0.68	0.05	4.00	0.57
7;9;25	93.44%	81.50%	11.18	2.00	0.66	0.05	4.16	0.56
7;10;25	93.54%	81.54%	11.72	1.96	0.71	0.05	4.33	0.56
7;11;25	93.62%	81.12%	11.10	2.03	0.67	0.05	4.21	0.52
7;9;26	93.53%	81.37%	11.11	2.02	0.67	0.05	4.14	0.56
7;10;26	92.87%	81.26%	13.48	2.02	0.74	0.05	4.63	0.56
7;11;26	93.40%	81.53%	12.28	2.00	0.73	0.05	4.38	0.56
7;9;27	93.44%	81.34%	11.08	2.04	0.66	0.05	4.01	0.57
7;10;27	92.95%	81.09%	12.83	2.03	0.71	0.05	4.48	0.57
7;11;27	93.62%	81.64%	11.42	2.00	0.69	0.05	4.08	0.52
7;9;28	93.52%	81.25%	10.54	2.02	0.63	0.05	4.01	0.56
7;10;28	93.24%	80.87%	12.40	2.03	0.71	0.05	4.45	0.56
7;11;28	93.42%	81.20%	12.28	1.99	0.73	0.05	4.38	0.52

(e) Results Experiment 4c: R1 Simulation

Pipeline Threshold	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
[*Out1*,*Out2*, *Out3*]	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
8;9;24	92.95%	81.07%	11.88	2.06	0.66	0.05	4.19	0.52
8;10;24	93.23%	81.24%	12.99	1.98	0.75	0.05	4.66	0.53
8;11;24	92.90%	81.47%	13.54	1.99	0.74	0.05	4.60	0.56
8;9;25	93.37%	81.38%	11.44	2.02	0.67	0.05	4.17	0.56
8;10;25	93.32%	81.17%	12.46	2.02	0.73	0.05	4.23	0.57
8;11;25	93.01%	81.20%	12.29	2.06	0.68	0.05	4.42	0.57
8;9;26	93.17%	81.61%	12.31	1.97	0.70	0.05	4.50	0.56
8;10;26	93.29%	81.26%	12.68	2.01	0.73	0.05	4.37	0.53
8;11;26	93.11%	81.11%	13.55	2.02	0.76	0.05	4.68	0.58
8;9;27	93.16%	81.48%	12.10	1.99	0.69	0.05	4.37	0.56
8;10;27	93.09%	81.09%	13.14	2.05	0.74	0.05	4.64	0.56
8;11;27	93.33%	81.53%	11.92	1.96	0.70	0.05	4.33	0.56

(f) Results Experiment 4c: R1 Simulation (continued)

Table K.7: Results Experiment 4c: Comparison of Tardiness and On-Time Delivery Performance Metrics Under Different Pipeline Threshold Configurations

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
7;9;24	0.92	9.15	6.27	6.71	24.02	40.53	19.65
7;10;24	0.92	9.50	6.32	6.72	24.52	40.88	19.84
7;11;24	0.92	8.86	6.30	6.72	23.93	40.75	19.82
7;9;25	0.92	9.39	6.28	6.73	24.43	40.74	19.81
7;10;25	0.92	9.06	6.30	6.72	24.07	40.62	19.73
7;11;25	0.92	8.78	6.25	6.73	24.02	40.62	19.88
7;9;26	0.92	9.36	6.19	6.72	24.41	40.57	19.78
7;10;26	0.92	8.89	6.38	6.72	23.99	40.95	19.87
7;11;26	0.93	8.82	6.29	6.74	24.11	40.63	19.89
7;9;27	0.92	9.03	6.17	6.73	24.08	40.31	19.69
7;10;27	0.93	8.95	6.30	6.74	24.06	40.68	19.82
7;11;27	0.93	8.78	6.24	6.75	24.34	40.63	20.05
7;9;28	0.92	9.09	6.16	6.74	24.24	40.47	19.81
7;10;28	0.92	9.27	6.29	6.74	24.51	40.61	19.86
7;11;28	0.93	8.51	6.32	6.75	24.07	40.83	20.09

(a) Results Experiment 4c: Baseline Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
8;9;24	0.92	9.11	6.24	6.71	24.12	40.31	19.64
8;10;24	0.92	8.99	6.18	6.73	24.29	40.34	19.83
8;11;24	0.92	8.62	6.13	6.73	24.04	40.47	19.95
8;9;25	0.92	8.80	6.23	6.73	23.93	40.47	19.76
8;10;25	0.92	8.73	6.16	6.72	24.05	40.45	19.88
8;11;25	0.92	8.53	6.21	6.73	24.13	40.50	20.02
8;9;26	0.92	9.17	6.24	6.73	24.37	40.62	19.86
8;10;26	0.92	8.87	6.24	6.73	24.37	40.57	20.00
8;11;26	0.93	8.42	6.17	6.75	24.14	40.57	20.13
8;9;27	0.92	8.86	6.25	6.74	24.23	40.53	19.90
8;10;27	0.93	8.73	6.16	6.74	24.34	40.50	20.05
8;11;27	0.93	8.31	6.19	6.75	24.06	40.49	20.11
8;9;28	0.92	9.17	6.23	6.75	24.55	40.39	19.87
8;10;28	0.93	8.35	6.24	6.74	23.79	40.71	20.02
8;11;28	0.93	8.55	6.28	6.75	24.35	40.60	20.15

(b) Results Experiment 4c: Baseline Simulation (continued)

Pipeline Threshold		Lead Time (min)			Queueing Time (min)		Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
7;9;24	0.93	9.37	6.22	6.72	24.21	40.58	19.66
7;10;24	0.92	9.30	6.31	6.73	24.49	40.69	19.85
7;11;24	0.92	8.87	6.33	6.73	24.13	40.83	19.93
7;9;25	0.93	9.15	6.29	6.73	23.99	40.74	19.68
7;10;25	0.93	9.11	6.43	6.74	24.16	40.86	19.79
7;11;25	0.93	8.76	6.27	6.74	24.01	40.60	19.86
7;9;26	0.93	9.38	6.32	6.75	24.41	40.70	19.76
7;10;26	0.93	8.91	6.36	6.75	24.05	40.67	19.80
7;11;26	0.93	8.74	6.35	6.74	24.17	40.94	20.06
7;9;27	0.93	8.99	6.34	6.74	23.93	40.59	19.66
7;10;27	0.93	8.87	6.35	6.75	24.07	40.66	19.83
7;11;27	0.93	8.82	6.37	6.76	24.30	40.83	20.03
7;9;28	0.93	9.04	6.29	6.76	24.25	40.63	19.84
7;10;28	0.93	8.70	6.31	6.75	23.95	40.59	19.86
7;11;28	0.93	8.51	6.29	6.76	23.94	40.77	20.01

(c) Results Experiment 4c: FCFS Simulation

Pipeline Threshold [*Out1*,*Out2*, *Out3*]	Lead Time (min) Inbound	Full Outbound	Workstation	Queueing Time (min) Inbound	Full Outbound	Workstation	Conveyor Duration Full Outbound
8;9;24	0.93	9.08	6.24	6.73	24.24	40.57	19.83
8;10;24	0.93	9.13	6.30	6.73	24.40	40.63	19.87
8;11;24	0.93	8.69	6.37	6.74	24.15	40.82	20.03
8;9;25	0.92	8.96	6.26	6.73	24.25	40.56	19.87
8;10;25	0.93	8.75	6.43	6.74	24.13	40.93	20.00
8;11;25	0.93	8.63	6.40	6.75	24.22	41.05	20.17
8;9;26	0.93	8.95	6.42	6.74	24.42	40.90	20.03
8;10;26	0.93	8.29	6.38	6.74	23.62	40.86	19.96
8;11;26	0.93	8.41	6.47	6.75	23.97	40.89	20.06
8;9;27	0.93	9.01	6.41	6.75	24.61	40.77	20.06
8;10;27	0.93	8.57	6.36	6.75	24.12	40.62	19.99
8;11;27	0.93	8.56	6.35	6.76	24.37	40.89	20.24
8;9;28	0.93	8.89	6.37	6.76	24.48	40.89	20.11
8;10;28	0.94	8.55	6.40	6.77	24.25	40.66	20.08
8;11;28	0.93	8.35	6.53	6.76	24.17	41.21	20.32

(d) Results Experiment 4c: FCFS Simulation (continued)

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
7;9;24	0.92	9.32	6.21	6.71	24.00	40.58	19.58
7;10;24	0.92	9.10	6.37	6.72	24.13	40.97	19.84
7;11;24	0.92	8.72	6.32	6.73	23.89	40.67	19.85
7;9;25	0.93	8.98	6.29	6.73	23.83	40.68	19.68
7;10;25	0.92	8.82	6.26	6.72	23.84	40.48	19.71
7;11;25	0.92	8.47	6.30	6.73	23.54	40.51	19.73
7;9;26	0.92	8.83	6.27	6.72	23.72	40.67	19.69
7;10;26	0.92	9.22	6.41	6.72	24.41	40.72	19.83
7;11;26	0.93	8.74	6.37	6.73	24.01	40.71	19.88
7;9;27	0.92	8.77	6.26	6.73	23.71	40.52	19.67
7;10;27	0.93	9.09	6.43	6.74	24.31	41.00	19.95
7;11;27	0.92	8.43	6.37	6.74	23.80	40.83	19.97
7;9;28	0.92	8.53	6.31	6.74	23.52	40.64	19.72
7;10;28	0.93	8.97	6.37	6.74	24.20	40.81	19.90
7;11;28	0.93	8.64	6.32	6.75	24.05	40.85	20.02

(e) Results Experiment 4c: R1 Simulation

Pipeline Threshold	Lead Time (min)			Queueing Time (min)			Conveyor Duration
[*Out1*,*Out2*, *Out3*]	Inbound	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Full Outbound
8;9;24	0.92	9.04	6.23	6.71	24.15	40.62	19.83
8;10;24	0.92	8.98	6.23	6.72	24.32	40.46	19.86
8;11;24	0.93	8.88	6.35	6.73	24.47	40.85	20.10
8;9;25	0.92	8.74	6.31	6.73	23.99	40.67	19.89
8;10;25	0.93	8.80	6.25	6.73	24.18	40.65	19.96
8;11;25	0.93	8.58	6.43	6.74	24.18	40.68	20.02
8;9;26	0.92	8.91	6.19	6.73	24.15	40.33	19.79
8;10;26	0.92	8.78	6.33	6.73	24.25	40.64	19.97
8;11;26	0.92	8.75	6.35	6.74	24.47	40.88	20.18
8;9;27	0.92	8.85	6.24	6.73	24.11	40.55	19.86
8;10;27	0.93	8.85	6.22	6.74	24.38	40.34	19.93
8;11;27	0.93	8.36	6.26	6.74	24.04	40.55	20.06
8;9;28	0.93	8.94	6.29	6.74	24.27	40.58	19.88
8;10;28	0.93	8.56	6.25	6.74	24.01	40.29	19.87
8;11;28	0.93	8.37	6.24	6.75	24.24	40.63	20.22

(f) Results Experiment 4c: R1 Simulation (continued)

Table K.8: Results Experiment 4c: Comparison of Queuing and Movement Performance Metrics Under Different Pipeline Threshold Configurations

Demand Δ	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
Pipeline Threshold Configurations: [3, 7, 10]								
5%	90.23%	82.15%	25.88	1.99	0.95	0.04	3.83	0.57
10%	89.57%	81.56%	29.82	2.18	0.98	0.04	4.05	0.55
15%	89.78%	81.65%	31.90	2.26	1.00	0.05	3.82	0.57
20%	89.32%	81.63%	35.89	2.39	0.97	0.05	4.20	0.56
25%	89.04%	81.37%	35.39	2.55	0.94	0.05	4.18	0.60
30%	88.79%	82.14%	39.03	2.58	0.99	0.04	4.45	0.60
Pipeline Threshold Configurations: [5, 7, 11]								
5%	92.08%	82.06%	15.59	2.01	0.70	0.05	2.90	0.57
10%	91.27%	81.89%	18.76	2.19	0.74	0.05	2.80	0.56
15%	91.07%	81.58%	21.76	2.25	0.78	0.04	2.91	0.58
20%	91.02%	81.76%	23.72	2.36	0.76	0.04	3.09	0.56
25%	90.81%	81.61%	22.18	2.51	0.70	0.04	2.98	0.60
30%	90.40%	82.30%	26.52	2.56	0.78	0.04	3.10	0.60
Pipeline Threshold Configurations: [7, 11, 27]								
5%	92.15%	81.79%	15.83	2.05	0.72	0.05	2.88	0.56
10%	91.58%	81.45%	16.78	2.25	0.68	0.05	2.64	0.59
15%	91.82%	80.94%	18.48	2.45	0.72	0.05	2.58	0.58
20%	91.83%	80.92%	19.92	2.61	0.70	0.05	2.70	0.57
25%	91.15%	80.87%	21.58	2.72	0.71	0.05	2.95	0.59
30%	90.73%	82.04%	24.58	2.76	0.75	0.05	3.03	0.60

(a) Results Experiment 5: Baseline Simulation

Demand Δ	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
Pipeline Threshold Configurations: [3, 7, 10]								
5%	90.13%	81.65%	25.63	2.00	0.93	0.04	3.80	0.53
10%	89.75%	82.31%	27.76	2.18	0.93	0.05	3.83	0.59
15%	89.88%	81.31%	32.17	2.38	1.02	0.05	4.09	0.56
20%	89.54%	81.64%	34.69	2.42	0.96	0.05	4.06	0.57
25%	89.29%	81.23%	34.57	2.58	0.94	0.05	4.13	0.60
30%	88.79%	82.55%	39.03	2.52	0.99	0.04	4.60	0.59
Pipeline Threshold Configurations: [5, 7, 11]								
5%	91.81%	82.02%	15.46	2.01	0.68	0.05	2.60	0.57
10%	91.41%	82.41%	18.77	2.10	0.75	0.05	2.71	0.54
15%	91.10%	81.77%	20.88	2.30	0.75	0.05	2.55	0.57
20%	90.83%	81.43%	23.99	2.49	0.75	0.05	2.86	0.58
25%	90.82%	81.22%	23.47	2.54	0.74	0.04	3.07	0.59
30%	90.25%	82.47%	29.28	2.55	0.85	0.04	3.00	0.61
Pipeline Threshold Configurations: [7, 11, 27]								
5%	92.26%	81.74%	13.06	2.07	0.60	0.05	2.35	0.54
10%	91.86%	81.68%	17.11	2.21	0.72	0.05	2.68	0.55
15%	91.72%	81.10%	18.48	2.41	0.71	0.05	2.73	0.58
20%	91.80%	81.52%	19.93	2.54	0.70	0.05	2.73	0.55
25%	91.32%	81.45%	21.82	2.68	0.73	0.05	2.86	0.61
30%	91.36%	81.81%	21.24	2.77	0.70	0.05	2.62	0.60

(b) Results Experiment 5: FCFS Simulation

Demand ∆	On-Time Delivery Percentage		Average Daily Tardiness (h)		Average Pallet Tardiness (h)		Maximum Pallet Tardiness (h)	
	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation	Full Outbound	Workstation
				Pipeline Threshold Configurations: [3, 7, 10]				
5%	90.54%	81.74%	26.82	2.06	1.02	0.05	6.81	0.57
10%	90.03%	81.96%	28.54	2.12	0.98	0.04	6.44	0.58
15%	89.80%	81.52%	32.16	2.32	1.01	0.05	6.98	0.57
20%	89.43%	81.82%	37.15	2.41	1.01	0.05	7.21	0.56
25%	89.20%	81.56%	36.90	2.49	1.00	0.04	7.00	0.59
30%	88.99%	82.39%	39.40	2.62	1.01	0.05	6.98	0.60
				Pipeline Threshold Configurations: [5, 7, 11]				
5%	91.98%	81.86%	17.34	2.02	0.77	0.04	4.76	0.56
10%	91.19%	81.90%	20.05	2.18	0.78	0.05	4.42	0.59
15%	91.30%	81.52%	21.65	2.28	0.80	0.05	4.87	0.55
20%	90.94%	81.47%	25.20	2.47	0.80	0.05	4.89	0.57
25%	91.23%	81.26%	23.78	2.53	0.79	0.04	5.00	0.59
30%	90.56%	82.17%	27.26	2.67	0.82	0.05	4.73	0.60
				Pipeline Threshold Configurations: [7, 11, 27]				
5%	92.61%	82.39%	16.03	1.94	0.77	0.04	4.52	0.56
10%	91.91%	82.25%	17.52	2.15	0.74	0.05	4.52	0.60
15%	91.96%	81.13%	19.68	2.36	0.78	0.05	4.39	0.56
20%	91.95%	81.21%	21.27	2.60	0.76	0.05	4.62	0.57
25%	91.72%	81.13%	22.09	2.71	0.78	0.05	4.79	0.59
30%	91.38%	81.56%	24.77	2.82	0.82	0.05	5.08	0.61

(c) Results Experiment 5: R1 Simulation

Table K.9: Results Experiment 5: Comparison of Tardiness and On-Time Delivery Performance Metrics Under Different Demand Patterns and Pipeline Threshold Configurations

Demand Δ	Lead Time (min)			Queueing Time (min)			Conveyor Duration (min)
	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Inbound	Full Outbound
Pipeline Threshold Configurations: [3, 7, 10]							
0%	27.77	40.51	6.62	17.24	6.15	0.90	17.40
5%	28.77	41.29	6.66	17.90	6.48	0.92	17.66
10%	29.53	41.92	6.71	18.69	6.93	0.94	17.82
15%	29.97	42.64	6.84	18.88	7.37	0.96	17.99
20%	30.64	43.89	6.95	19.38	7.89	0.98	18.18
25%	30.57	45.01	7.03	19.26	8.70	1.00	18.62
Pipeline Threshold Configurations: [5, 7, 11]							
0%	24.72	40.26	6.67	13.49	6.19	0.90	17.67
5%	25.58	41.58	6.67	14.13	6.57	0.92	18.02
10%	26.54	42.30	6.72	14.91	6.94	0.94	18.37
15%	27.33	42.95	6.85	15.46	7.52	0.96	18.46
20%	27.60	43.84	6.96	15.66	8.00	0.98	18.48
25%	27.42	45.74	7.03	15.39	9.00	1.00	19.16
Pipeline Threshold Configurations: [7, 11, 27]							
0%	24.34	40.63	6.75	8.78	6.24	0.93	20.05
5%	25.36	41.39	6.81	9.62	6.50	0.95	20.25
10%	25.59	42.05	6.86	9.71	6.94	0.97	20.52
15%	25.98	42.70	7.03	9.84	7.36	0.99	20.73
20%	26.47	43.56	7.13	10.10	7.75	1.01	20.90
25%	26.75	45.08	7.22	10.34	8.61	1.03	21.40
30%	27.17	47.72	7.32	10.68	10.12	1.04	22.10

(a) Results Experiment 5: Baseline Simulation

Demand Δ	Lead Time (min)			Queueing Time (min)			Conveyor Duration (min)
	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Inbound	Full Outbound
				Pipeline Threshold Configurations: [3, 7, 10]			
0%	27.62	40.61	6.62	17.17	6.38	0.90	17.30
5%	28.70	40.97	6.67	17.93	6.47	0.92	17.50
10%	29.23	42.47	6.72	18.41	7.14	0.94	17.94
15%	29.93	42.62	6.86	18.90	7.32	0.96	17.98
20%	30.35	44.00	6.96	19.13	7.91	0.99	18.19
25%	30.43	45.31	7.03	19.12	8.74	1.00	18.72
				Pipeline Threshold Configurations: [5, 7, 11]			
0%	24.77	40.61	6.68	13.46	6.28	0.90	17.79
5%	25.79	41.05	6.67	14.27	6.41	0.92	17.92
10%	26.39	42.43	6.72	14.91	7.04	0.94	18.29
15%	27.22	42.58	6.86	15.35	7.31	0.97	18.41
20%	27.58	43.30	6.97	15.75	7.75	0.99	18.33
25%	27.62	45.16	7.05	15.57	8.89	1.01	19.00
				Pipeline Threshold Configurations: [7, 11, 27]			
0%	24.30	40.83	6.76	8.82	6.37	0.93	20.03
5%	24.60	41.46	6.82	8.93	6.59	0.95	20.22
10%	25.61	42.33	6.89	9.74	7.06	0.98	20.58
15%	26.08	42.88	7.03	9.90	7.56	1.00	20.75
20%	26.47	43.35	7.14	10.06	8.15	1.02	21.07
25%	26.84	45.47	7.23	10.39	8.90	1.03	21.45
30%	27.17	47.35	7.32	10.27	9.94	1.05	22.03

(a) Results Experiment 5: FCFS Simulation

Demand Δ	Lead Time (min)			Queueing Time (min)			Conveyor Duration (min)
	Full Outbound	Workstation	Inbound	Full Outbound	Workstation	Inbound	Full Outbound
Pipeline Threshold Configurations: [3, 7, 10]							
0%	27.66	40.48	6.62	17.24	6.25	0.90	17.30
5%	29.13	40.93	6.67	18.29	6.42	0.92	17.52
10%	29.41	42.48	6.73	18.51	7.08	0.95	17.99
15%	30.12	42.87	6.86	19.09	7.51	0.97	18.00
20%	30.91	44.02	6.96	19.63	7.93	0.99	18.21
25%	30.95	44.97	7.03	19.63	8.62	1.01	18.63
Pipeline Threshold Configurations: [5, 7, 11]							
0%	24.87	40.74	6.66	13.63	6.40	0.90	17.76
5%	26.11	41.04	6.68	14.52	6.46	0.93	17.95
10%	26.85	42.44	6.73	15.21	7.15	0.94	18.35
15%	27.30	42.29	6.86	15.44	7.26	0.97	18.31
20%	27.92	44.14	6.98	15.92	8.25	0.99	18.54
25%	27.54	45.31	7.03	15.55	8.82	1.01	19.04
Pipeline Threshold Configurations: [7, 11, 27]							
0%	23.80	40.83	6.74	8.43	6.37	0.92	19.97
5%	25.22	41.12	6.81	9.44	6.53	0.96	20.16
10%	25.64	42.67	6.88	9.69	7.22	0.98	20.67
15%	25.98	42.92	7.02	9.93	7.35	0.99	20.85
20%	26.47	43.93	7.14	10.06	8.04	1.01	20.96
25%	26.67	45.40	7.23	10.24	8.95	1.03	21.40
30%	27.17	47.71	7.32	10.68	10.12	1.04	22.10

(a) Results Experiment 5: R1 Simulation

Table K.12: Results Experiment 5: Comparison of Queuing and Movement Performance Metrics Under Different Demand Patterns and Pipeline Threshold Configurations