

Unlocking Landside Efficiency: A Simulation Based Approach to Evaluate Air Cargo Dock and Yard Operations

The background image shows a KLM Cargo aircraft on an airport tarmac. The front cargo door is open, revealing the interior cargo hold. A large yellow cargo loader is positioned in front of the aircraft, with its platform raised to the level of the cargo door. The loader has 'MAG0439' and 'KLM' markings. To the left, a white ground support vehicle is visible. To the right, a white KLM service van is parked. The sky is clear and blue.

A Case Study at KLM Cargo, Amsterdam Airport Schiphol

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Schiphol

by

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Preface

Writing this thesis marks the end of my academic journey in obtaining the MSc Transport, Infrastructure & Logistics at TU Delft. My time at the university has not always been as straightforward as that of a typical TU Delft student. There were moments where things did not go as planned, and I definitely had a few setbacks along the way. Because of that, finishing this thesis is something I am proud of. It feels like a significant milestone, and I am thankful for everyone who helped me get here.

Aviation has been an interest of mine since I was young, so being able to work on a thesis in collaboration with KLM Cargo made this project special. Earlier in my studies, I also did an internship at Fokker under the supervision of Dr. Jaap Vleugel. Being supervised by him again for my thesis felt familiar in a good way. Over the last few months, I have developed not just an academic connection with him but also a more personal one, which I think explains his teaching and mentoring style.

Speaking of, I want to thank my TU Delft supervisors, Dr. Jaap Vleugel and Ir. Mark Duinkerken, for their guidance, feedback, and especially their patience. I am not a simulation expert, and I fear I never will be, however Ir. Duinkerken guided me by challenging me and asking the right questions. My planning was not always perfect, and sometimes not even close, but they continued to support me and kept me moving in the right direction when I needed it.

I am also very grateful to my supervisor at KLM Cargo, Mark van Zijl, and to all my colleagues at KLM. They made me feel welcome from day one and provided valuable insights for this thesis. Working in a friendly and professional environment at KLM Cargo only strengthened my enthusiasm for the aviation industry.

Last but not least, I want to thank my family and friends for always being there for me. Their support and encouragement, especially during the more challenging moments of my studies, meant more than they probably realize.

I hope you enjoy reading this thesis as much as I enjoyed writing it.

*Alex van Wijngaarden
Delft, December 2025*

Summary

This thesis examines how dock & yard performance on the landside an air cargo terminal can be improved. At the moment, the terminal often deals with strong peaks in truck arrivals. During these periods long queues form. This is in contrast with the quieter hours of the day when some docks are even idle. This imbalance is the main issue the research tries to understand and improve.

The study focuses specifically on what happens outside the warehouse, the dock & yard area. This includes truck arrivals, queue formation, unloading at the docks, and the impact these have on the buffer zone, which is inside the warehouse. Processes deeper inside the warehouse, such as build-up and breakdown, storage etc. are not included. As a result, the findings focus on the landside performance rather than the full terminal operation.

To analyze the problem in a structured way, a discrete-event simulation model was built in Enterprise Dynamics. The model is based on 93 days of operational data, covering 9,162 truck arrivals, and recreates realistic patterns of how trucks arrive, wait, and are processed. To do this, it incorporates unloading times, queue formation, dock capacity in the simulation. The model was validated by comparing simulated lead times, waiting times and dock occupancy with real operational data, giving confidence that the scenarios reflect the system accurately enough for this study.

Several improvement ideas were developed based on literature and expert analysis. Some focus on adding or adjusting capacity, for example, by activating unused docks or introducing additional conventional docks. Another focuses on making the arrival pattern more even throughout the day. These ideas were tested through six configurations to understand their effect on performance.

Activating an extra MTD dock had almost no effect, mainly because only a small share of trucks use MTD doors. Replacing the unused MTD dock with a normal dock gave a clearer improvement and nearly halved the waiting time. Increasing the number of normal docks even further, up to a total of six, continued to reduce waiting times and lead times. In the configuration with six docks, waiting times were more than sixty percent lower than in the base case. For Configurations 3-5 the improvement became smaller with each additional dock, and dock occupancy dropped to very low levels. Extra docks also require more staff, and the buffer zone limits how effectively this added capacity can be used during busy periods.

The slot-booking scenario proved to be the most effective option without changing the physical layout. By spreading arrivals more evenly across the day, peak congestion became much lighter. Average waiting time fell to about 12 minutes and lead time to around 37 minutes, which is slightly even slightly better than the 6 dock scenario. These findings support the air cargo terminals plan to introduce a slot-booking system partially, and this research forms one of the inputs for that decision.

The overall conclusion is that capacity expansion and arrival smoothing can improve performance, but in different ways. Adding docks reduce delays but comes with decreasing returns and a higher number of employees needed to operate, which results in higher costs. Smoothing the arrival pattern uses the existing capacity much more effectively, without very large investments needed. The study therefore recommends that the air cargo terminal prioritizes improvements in arrival management and coordination with forwarders. When doing so, it should consider physical expansions only when they are realistic and cost-effective within the current hall layout.

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Nomenclature

Abbreviations

Abbreviation	Definition
AWB	Air Waybill
DES	Discrete Event Simulation
DSR	Design Science Research
FB1 / FB2 / FB3	Freight Building 1 / 2 / 3
FCFS	First Come First Served
FW	Freight Forwarder
GH	Ground Handler
IMPEX	Import/Export
KPI	Key Performance Indicator
LAT	Latest Acceptance Time
LIFO	Last In First Out
MCDA	Multi-Criteria Decision Analysis
MTD	Motorized Transfer Dolly
ULD	Unit Load Device

1

Introduction

This chapter introduces the case context of KLM Cargo at Schiphol, which serves as the empirical setting for this research. It outlines the role of KLM Cargo within the global air cargo supply chain and describes the current state of its landside operations, with a focus on dock and yard processes at Freight Building 3 (FB3). The chapter discusses the research problem of increasing congestion during peak hours, defines the scope of the study, and formulates the research objective. It further presents the research questions and the methodological approach applied, based on the Design Science Research framework. By combining literature insights with operational data and expert input, this chapter establishes the foundation for developing and evaluating interventions to improve dock throughput and reduce yard congestion.

1.1. Air Cargo Logistics

Air cargo volumes have grown significantly over the past years. Besides a dip during the COVID-19 pandemic, the industry grew by 21% post pandemic and is expected to grow at 4.1% annually through 2041 [7]. This growth strains the capacity of existing cargo terminals to handle trucks and shipments [42]. Landside operations, like truck dock and yard areas at air cargo warehouses, often become bottlenecks. This leads to congestion and delays. To meet rising demand and avoid costly queues, airports and operators are exploring strategies to increase overall air cargo operations [49].

Air cargo facilities often face high landside congestion during peak hours. Major air cargo hubs have seen trucks delayed and warehouses overwhelmed due to an increase in freight volume. In 2021, for example, cargo congestion at Chicago O'Hare forced importers to wait days for shipments [26]. These bottlenecks form a critical challenge in air cargo logistics: The efficiency of dock and yard operations at freight terminals. As global airfreight demand grows and becomes more demanding in total, improving operations at cargo docks and reducing yard congestion is essential for the industries reliability.

1.2. Case Introduction

KLM Cargo, officially Air France KLM Marinair Cargo, is the air cargo division of KLM Royal Dutch Airlines. It operates as a key carrier at Schiphol. Every day, worldwide shipments ranging from perishables to pharmaceuticals are handled at its facilities. To handle this flow, a large volume of vehicles pass by every day: cargo trucks, delivery vans, and other support vehicles. During peak periods, this can amount to a lot of vehicle movements per day, pressuring its operational infrastructure.

As an airline's cargo division, it is responsible for transporting goods on KLM- and partner aircraft. In order to do this, it handles landside operations like loading, unloading and storage at Schiphol, next to its airside operations.

Operating within what is known as the air cargo supply chain, KLM Cargo plays a key role in connecting

the world. However, multiple stakeholders make up this complex process from *shipper* to *consignee*. Figure 1.1 shows a schematic illustration of all stakeholders involved. The chain starts when the *shipper*, either a consumer or a company, contracts a *forwarder* (FW) to ship a product. The *FW* at origin is a logistics intermediary, responsible for arranging transportation from the shipper to the airport. It prepares cargo for safe transportation, prepares export documentation and ensures customs clearance, ultimately delivering the cargo to the *airline*. KLM Cargo is an *airline* and its responsible for preparing cargo for air transportation and flying it. This ultimately makes it what is called a *Ground Handler* (GH). The cargo is first built into standardized loading units known as ULD's (Unit Load Devices). The cargo on every ULD is selected based on size, weight and vulnerability in order to achieve maximum efficiency. Finally, the cargo is secured with nets or straps and positioned to optimize space and maintain weight balance while flying. The cargo is unloaded after arriving at the destination airport and is passed on to the *FW* at destination, which clears customs and arranges final delivery to the *consignee*.

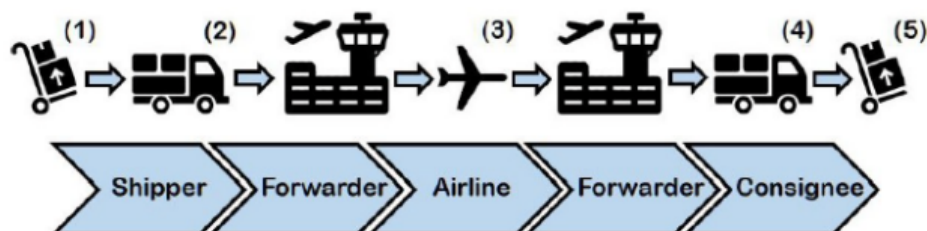


Figure 1.1: Air Cargo Supply Chain

1.3. Research Scope and Current Situation

The air cargo terminal facility can be divided into three main areas: Landside, Cargo Service Area, and Airside. Figure 1.2 shows a bird eye view of the cargo terrain, illustrating the overall layout of the facility between the Landside, Cargo Service Area, and Airside. The Landside functions as the area where all trucks arrive and park before proceeding to a dock to unload their cargo. The Cargo Service Area contains FB1 (yellow), FB2 (green), and FB3 (blue), while the Airside is the area where cargo is loaded and unloaded into aircraft.

FB1 and FB2 handle import and other streams such as express and valuable goods, whereas FB3 is dedicated to export. The terrain is accessed via the security lodge located at the main entrance of the site. All trucks entering the area are registered here and directed to the appropriate freight building. Trucks destined for export follow the yard past FB2 towards FB3, where three active docks are available.

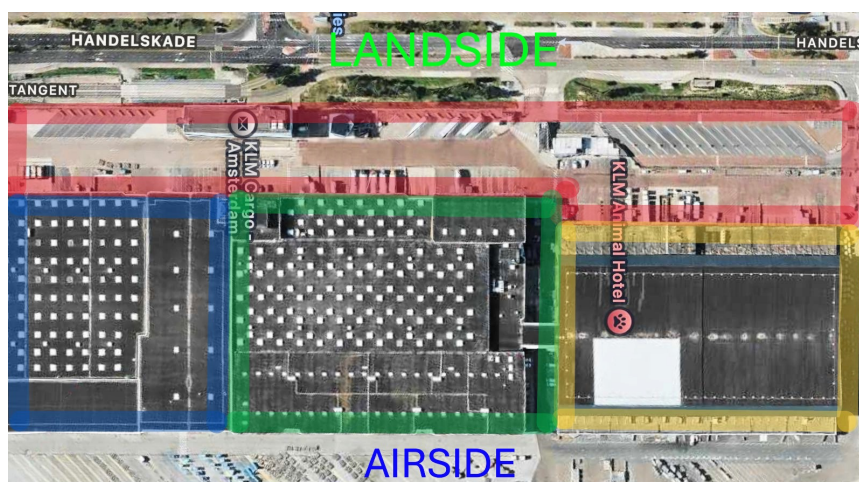


Figure 1.2: KLM Cargo's terrain

This research focuses on the landside export logistics of air cargo operations at the terminal. While FB3 is the main location for export handling and experiences significant congestion during peak hours, FB2 may offer additional capacity. FB2 officially closes every day at 22:00, which means it could potentially provide more capacity during night time peaks. Therefore, this study looks into infrastructural and operational interventions involving both FB2 and FB3 to improve dock & yard operations.

This studies scope focuses specifically on export handling within the Landside area, particularly the operations in and around FB3. Export takes place in FB3 (Figure 1.3), which has three operational docks. Trucks enter the terrain through the security lodge, as shown in Figure 1.4. From the lodge, trucks transporting export goods are directed toward FB3, passing FB2 and the head office on the way (Figure 1.5). Further elaboration on the research scope and boundaries is given in Chapter 2.



Figure 1.3: Freight Building 3



Figure 1.4: View on Yard from Security Lodge



Figure 1.5: Corridor from FB2 to FB3

1.4. Research Problem

Previous research has provided valuable insights into the performance of FB3. The time needed to unload a truck depends on two things: The ground staff and the driver's skill. A consistent peak is observed on Friday afternoons between 16:00 and 00:00, with an average of 78 trucks arriving during this period. Unloading one pallet takes around 40–60 seconds, resulting in 95% of trucks being unloaded within 35 minutes. Based on these findings, a slot management system was proposed using 36-minute time slots. Under this system, 95% of trucks could unload within their assigned slot. However, over a six-month period, approximately 1,000 trucks still missed their allocated slots, leading to operational delays. Furthermore, it was found that assigning 36-minute slots resulted in an average dock occupancy rate of 83.17% throughout the week. Table 1.1 presents the performance of the proposed slot management system. The results indicate that, given an average of 78 trucks during peak hours, a

minimum of six docks would be required to ensure stable operations. Nevertheless, expanding to six docks alone would not resolve the underlying issues, highlighting the need for further research.

However, expanding to six docks alone would not resolve all structural constraints. A key limitation is the capacity of the buffer zone, which is where the cargo is placed after unloading. During arrival peaks this space is emptied too slow, causing freight to build up faster than it can be moved into the warehouse. As a result, operations remain limited even when sufficient dock capacity is available. This issue cannot be solved within the current hall layout and long-term improvements would need additional hall capacity or a redesign of the terminal's interior.

Doors open	Timeslots per hour	Timeslots (16:00–00:00)
3	5.00	39.98
4	6.66	53.31
5	8.33	66.64
6	10.00	79.96
7	11.66	93.29

Table 1.1: Results of the proposed slot management system

The results show that the current infrastructure is not able to deal with the volumes of cargo handled at the facility. Despite previous efforts, congestion still happens during peak hours, leading to high waiting times and reduced operational efficiency.

The research problem can therefore be summarized as follows: the current dock & yard infrastructure cannot handle the increasing number of trucks during peak periods, resulting in delays, inefficiencies, and missed flights. Measures such as the proposed slot management system, have improved are insufficient to create stable operations. To improve the dock & yard performance, both infrastructural and operational adjustments are required. However, their combined effects on capacity, efficiency, and feasibility remain are yet unknown.

For this reason, this research aims to identify, model, and evaluate potential interventions that can improve overall landside logistics.

1.5. Research Gap & Questions

Reviewing the state of the art has revealed that air cargo dock & yard operations are underrepresented in current research. Existing studies provide valuable insights: they confirm that dock capacity is often the major bottleneck in operations, that truck arrivals tend to cluster at peak times, and that technologies such as dock scheduling systems can improve performance. However, these insights are fragmented and often conclusions are drawn based on other sectors. Also, they are often case bound and not yet tailored to the air cargo industry. Moreover, the expert interviews have revealed that congestion is not just a result of limited dock capacity but also of infrastructural constraints, arrival patterns, and administrative inefficiencies. These factors have also been underrepresented in literature.

Therefore, the research gap can be summarized as follows: Although dock and yard congestion in air cargo is a well-known problem, there are still little practical, data-based models to test how different infrastructural and operational changes would affect overall system performance. This gap will be addressed through DES and thereby contribute both academically and practically. Accordingly, the study is guided by the following main research question:

How can landside air cargo terminal operations be optimized to increase dock & yard performance?

The main research question is supported by the following sub questions:

1. What are the main causes of dock & yard congestion in air cargo logistics?
2. Which methods can be applied to improve dock & yard performance in air cargo operations?

3. How can a model be designed and developed to evaluate the identified improvement methods for dock and yard operations?
4. To what extent do the proposed configurations increase dock & yard performance?

1.6. Research Objective

This research aims to contribute both academically and practically to improving landside logistics in air cargo terminals. The section distinguishes between the academic goal, the practical goal, and a set of specific objectives that will be used later in the evaluation phase.

From an academic point of view, this study expands the limited research on dock and yard logistics within air cargo terminals. While many studies have focused on airside operations or warehouse processes, landside operations have received far less attention. By analysing congestion and testing improvement strategies through discrete-event simulation (DES), this study provides new insights into how air cargo terminals can improve performance during busy periods. The model and results therefore add both theoretical and methodological value to the study of air cargo logistics.

At the practical level, the research focuses on finding effective ways for KLM Cargo to make its dock and yard operations more efficient and reliable. The study concentrates on Freight Building 3 (FB3) as the main area of interest and tests different layout and scheduling strategies. These alternatives are evaluated based on their effect on key performance indicators (KPIs) while also taking into account realistic factors such as available infrastructure and staff capacity. The ultimate aim is to create clear, data-driven recommendations that help KLM Cargo reduce congestion and handle increasing volumes more efficiently.

To make the purpose of this research clear and measurable, five specific objectives are defined. These objectives also form the benchmark that will be used in Chapters 5 and 6 to evaluate the results of the study.

1. System analysis: Describe the current landside processes and identify the main causes of dock and yard congestion.
2. Model development: Build and validate a discrete-event simulation model that represents the dock & yard system at FB3.
3. Scenario testing: Simulate and compare alternative infrastructural and operational improvements to study their impact on system performance.
4. Performance evaluation: Measure and compare the outcomes of each scenario based on the main KPIs.
5. Recommendations: Develop clear, practical recommendations for KLM Cargo based on the simulation results.

Together, these objectives translate the general research problem into concrete and measurable steps. They also form the base for evaluating whether the developed model and proposed improvements achieve the intended impact.

1.7. Research Approach and Methodology

To structure the design process for this study, several methodological frameworks could be considered. A common approach for practice-oriented research is Design Science Research (DSR). DSR is especially suited for situations where both understanding and improving complex systems are central goals. Rather than merely describing or evaluating an existing situation, DSR aims to create and test new, purposeful solutions to address real-world problems [12]. It is applied in logistics, information systems, and operations research to develop innovative methods, tools, and processes.

DSR methodology is structured around five iterative phases: awareness, suggestion, development, evaluation, and conclusion. These phases ensure that design interventions are both theoretically grounded and practically validated. In this study, the context of landside logistics at KLM Cargo presents

an ideal setting for DSR: a complex, constrained system where interventions must be explored through simulation before implementation.

It is not feasible to experiment directly within the real system. The consequences of congestion, infrastructure limitations, and the desire for future slot-based systems make live testing risky and impractical. This is because the operations are ongoing 24 hours per day. Therefore, DSR is used to coordinate this research that enables evaluation in a controlled matter.

Each phase of the DSR cycle contributes to answering a research question, as outlined below:

- **Awareness:** Identify the principal causes of dock and yard congestion through system analysis, stakeholder insights, and literature. *Supports Sub-question 1.*
- **Suggestion:** Translate the identified causes into design objectives and propose interventions grounded in literature and expert input. *Supports Sub-question 2.*
- **Development:** Develop and validate a simulation model that represents dock and yard operations and incorporates the proposed interventions. *Supports Sub-question 3.*
- **Evaluation:** Execute baseline and intervention scenarios in the simulation and assess performance using predefined KPIs. *Supports Sub-question 4.*
- **Conclusion:** Synthesize the results, formulate recommendations, and discuss implications and limitations. *Supports main research question.*

To define the system and understand the causes of congestion in landside air cargo operations, both a literature review and expert interviews are conducted. To structure this part of the research, the analysis is divided into two components: the System Analysis, which describes the operational processes, actors, and performance indicators of a typical air cargo terminals; and the Theoretical Framework, which reviews relevant literature to identify conceptual and methodological foundations for the study. In addition, interviews with industry experts provide operational insights that help validate and refine the problem definition. This way, the awareness phase contributes to answering sub-question 1.

Building on the identified causes of congestion, the next phase focuses on suggesting potential improvements and conceptual solutions. Based on insights from the literature and expert interviews, several design alternatives are proposed to enhance dock throughput and yard performance. The theory of these interventions is further explored in their applicability in air cargo terminals. This suggestion phase contributes to answering sub-question 2.

The next phase focuses on the development of a discrete-event simulation (DES) model that simulates the operational process. This model captures interactions in the scope, allowing the effects of different design alternatives to be tested. The conceptual model, developed from the system analysis and stakeholder insights, is translated into a framework that reproduces key process dynamics. Then, the model is validated using operational data to create realistic behavior. This development phase contributes to answering sub-question 3.

Now that the model has been developed and validated, the next phase focuses on evaluating the performance of the proposed interventions. Different scenarios are simulated to assess how each design alternative affects KPIs. The experiments include both a baseline scenario that reflects current operations and several intervention scenarios that incorporate the improvements proposed during the suggestion phase. By comparing these scenarios, the effectiveness and potential trade-offs of each intervention can be quantified. This evaluation phase contributes to answering sub-question 4.

Based on the outcomes of the simulation experiments, conclusions are drawn regarding the effectiveness of the proposed improvements. The findings reveal which interventions contribute most to increasing dock & yard performance. These insights provide input for practical recommendations and highlight theoretical contributions to the understanding of landside air cargo logistics. This conclusion phase provides the results to answer the main research question.

In Table 1.2, an overview is given of how each phase of the DSR process aligns with the corresponding research questions and methodologies applied throughout this study.

DSR phase	Research question supported	Methodology
Awareness	Sub-question 1	Literature review & Expert interviews
Suggestion	Sub-question 2	Literature review & Expert interviews
Development	Sub-question 3	Discrete-event simulation
Evaluation	Sub-question 4	Discrete-event simulation
Conclusion	Main research question	Discrete-event simulation

Table 1.2: Alignment of DSR phases with research questions and methodology

Part I

Awareness

2

Understanding Landside Air Cargo Operations

This chapter introduces the Awareness phase by analyzing landside air cargo operations. The goal is to identify the principal drivers of dock and yard congestion. It consists of two parts: a System Analysis of general air cargo terminals, and a Theoretical Framework which covers literature on air cargo terminals. Additionally, expert input is covered to gain more operational knowledge. The chapter addresses Sub-question 1 and establishes the basis for the following Suggestion phase.

2.1. System Analysis

A system analysis based on the Delft Systems Approach by Veeke, Ottjes, and Lodewijks [60] is performed to gain an understanding of the operational dynamics of an air cargo terminal. The understanding of a system is a crucial part of the Awareness phase of the DSR process. Veeke, Ottjes, and Lodewijks [60] have identified three essential goals in their approach:

- Define system boundaries and environment
- Model structure, behavior and control within those boundaries
- Derive performance indicators and improvement levers

Following this approach, the analysis first defines the boundaries of the system, its main objectives, and how it interacts with its environment. Next, the system structure is described by identifying the key subsystems, resources, and flows that together form the operational setup of the terminal. After that, the system behavior is analyzed by studying how these elements influence each other over time, focusing on the movement of materials, information, and control signals. Performance indicators are then used to assess how well the system operates and to identify feedback loops or constraints that reduce efficiency. By following these steps, the Delft Systems Approach links the system's structure and its behavior.

2.1.1. System Context and Definition

An air cargo terminal is a specialized facility at an airport designed for handling, processing, and storing cargo that is transported by aircraft [10]. Its main responsibility is to ensure that cargo moves efficiently between aircraft and trucks. In general, a terminal is divided into three key operational areas: the Landside, the Cargo Service Area, and the Airside.

The Landside can be defined as the area where trucks arrive to pick up or deliver cargo before or after it enters the Cargo Service Area. It is responsible for truck management, cargo acceptance, and the docking process. The main components of the Landside include:

- Gate and Documentation: The entry point where trucks and drivers are registered and documentation is verified before entering the facility.
- Yard: The area where arriving trucks queue, park, and wait for dock assignment before loading or unloading their cargo.
- Docks: The designated points where trucks are positioned to transfer cargo between the vehicle and the Cargo Service Area.

The Cargo Service Area is where cargo is processed. For export cargo, this includes acceptance, storage, and preparation for air transport. For import cargo, it involves receiving and processing goods before they are released to the Landside. The Cargo Service Area generally consists of:

- Buffer zone: Temporary storage for export cargo after unloading, awaiting further processing.
- Storage racks: Areas for holding cargo until its next destination is known.
- Cooling cells: Facilities for temperature-sensitive cargo.
- Build-up: Stations where individual shipments are assembled into outbound ULDs.
- Break-down: Stations where inbound ULDs are disassembled and transferred to storage or awaiting trucks.

The Airside is responsible for transferring ULDs between aircraft and the Cargo Service Area. Its main component is:

- Airplane stands: Locations where aircraft are parked for loading and unloading, refueling, and other ground-handling operations.

This research focuses on the Landside cargo handling process of an air cargo terminal, specifically the coordination of truck arrivals, cargo acceptance, and truck departures. The main objective of this system is to ensure efficient and timely processing of incoming cargo flows. The system boundary extends from the arrival of a truck at the access gate to its departure after unloading. The internal warehouse processes that occur beyond the dock doors are outside the model scope but are treated as part of the system's environment, as they influence dock availability and unloading speeds. The external environment further includes freight forwarders, transport companies, airport authorities, and airlines whose schedules determine handling priorities.

The components of the system are shown in Figure 2.1, where the key areas are color-coded. The most important processes of these components are:

- Documentation - Red: At documentation, trucks enter the system. Documents and drivers are verified before access to the yard is given. This step functions as a control layer and determines whether the truck proceeds directly to the yard or is not given access to the yard.
- Entry and Exit Gates - Purple: The entry and exit gates form the physical access to the system, as the rest of the terminal is bordered by fences. After having permission to enter or exit, trucks drive through here, ensuring security regulations are followed.
- Yard - Green: After passing documentation and driving through the entry gate, trucks enter the yard, which serves as a staging and waiting area before docking. Here, trucks queue, park, and await dock assignment. The yard management process aims to balance incoming demand with available dock and floor capacity, preventing congestion near the unloading area.
- Export Docking Area - Blue: At the docks, the unloading process converts incoming truckloads into individual cargo flows entering the warehouse. This involves positioning the truck, performing safety checks, and transferring the cargo into the warehouse interface.

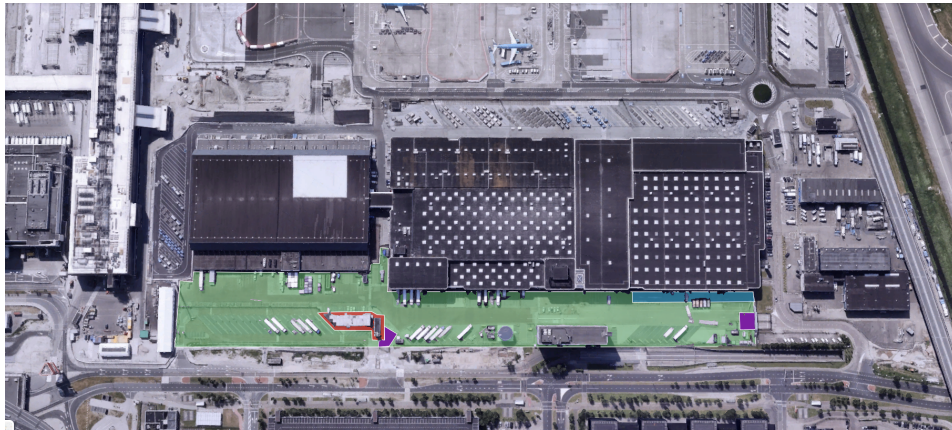


Figure 2.1: System components of the landside cargo handling process

According to the principles of the TU Delft course: Systems Analysis and Simulation [58], a system can be defined as:

“A system is a set of elements that can be distinguished from the entire reality, dependent on the objective of the researcher. These elements are mutually related and (eventually) related with other elements in the entire reality.”

In this study, the system can be described as an air cargo terminal with a yard and multiple docks for export trucks. Trucks arrive mainly during peak times, causing long queues and delays. Unloading time depends on truck load factor and staff or driver efficiency. The goal of this research is to reduce yard congestion and increase dock throughput.

To describe the system, a black-box model is used, consisting of inputs, outputs, requirements, and KPIs as shown in Figure 2.2. Loaded trucks enter the system, are unloaded, and then exit the system. Therefore, inbound loaded trucks are classified as inputs and outbound unloaded trucks are treated as outputs.

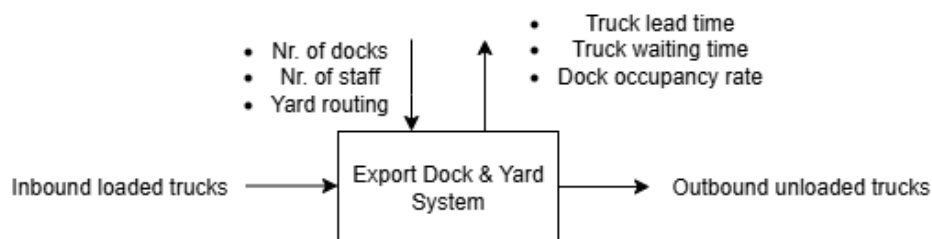


Figure 2.2: Black-box model of the landside cargo handling process

The system must always have a number of active docks and sufficient staff to operate them. Furthermore, yard routing is required to ensure safe movement across the facility. KPIs are used to measure the performance of the system and to compare design alternatives [44]. After literature review and expert inputs, the following KPIs were identified for this study:

- **Truck Lead Time (minutes):** Total time a truck spends in the system, from arrival to departure.
- **Truck Waiting Time (minutes):** Amount of time a truck spends waiting before being assigned to a dock.
- **Dock Occupancy Rate (%):** The percentage of time docks are actively in use.

Further, a CATWOE analysis (Table 2.1) is conducted to understand complex issues by examining different perspectives of the system. A CATWOE analysis provides a structured view of stakeholder roles and environmental factors [6].

Table 2.1: CATWOE analysis

Element	Description
Customer	Freight forwarders
Actors	Ground staff
Transformation	From loaded trucks to unloaded trucks
World view	It is essential to maintain reliable global air cargo flows, minimizing delays
Owners	Management
Environment	Airport traffic conditions, weather, external infrastructure limitations

2.1.2. System Structure

Following the black-box model from Figure 2.2, which defines the system in terms of inputs, outputs, and performance indicators, the next step is to understand how the system operates internally. This is done using the PROPER model, developed within the Delft Systems Approach by Veeke, Ottjes, and Lodewijks [60]. The PROPER model (Figure 2.3) provides a structured representation of the internal organization of a system. It captures the interaction between the Operational System, which performs the physical handling of trucks and cargo and the Control System, which handles decision-making processes. Both systems operate within boundaries and are influenced by the surrounding environment.

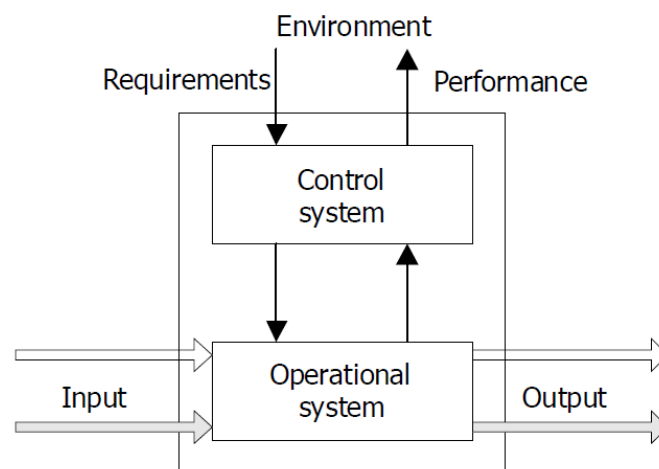


Figure 2.3: PROPER model by Veeke, Ottjes, and Lodewijks [60]

All PROPER elements for the air cargo terminal are displayed in Table 2.2.

Table 2.2: Specification of PROPER elements

PROPER Element	Definition	Description
Products	The goods or entities that are transformed by the system.	Loaded export trucks entering the system and unloaded trucks leaving it. The transformation converts truckloads into accepted cargo units delivered to the warehouse.
Resources	The means required to perform the transformation.	Physical and human elements enabling the transformation. Primary resources are the entry and exit gates, documentation building, yard, and export docking area. Supporting resources include ground staff, forklifts, pallet jacks, and MTDs, as well as the information systems used for registration and documentation.
Orders	The set of requests or tasks that define what has to be handled.	Freight instructions and booking requests specifying which shipments must be processed.
Processes	The activities that realize the transformation from input to output.	Each resource executes a distinct process within the operational flow: • Security verification: validating documentation and driver credentials • Gate admission: accepting arriving vehicles • Yard: transporting, parking and queuing trucks prior to dock allocation • Dock unloading: transferring cargo from trucks into the warehouse interface • Handover to warehouse: releasing unloaded cargo for further processing
Environment	The external context that provides requirements and receives performance feedback.	The wider air-cargo ecosystem consists of freight forwarders, transport companies, airport authorities, and internal warehouse operations that influence demand patterns, safety regulations, and available capacity.
Rules / Control	The mechanisms that regulate and coordinate system operations.	Decision logic and coordination mechanisms guiding operations, gate admission policies, and manual feedback control by operational staff.

The terminal itself consists of several subsystems that together form the operational structure. At the entry point, the documentation subsystem performs administrative and compliance checks before trucks are accepted in the system. The gate and yard subsystem manages vehicle arrival, parking, waiting and potential congestion. The dock subsystem provides the physical docks for unloading cargo from trucks, consisting of both conventional docks and specialized units for handling ULDs. Behind the docks, the front warehouse area functions as temporary storage before cargo is moved further into the terminal. Although this area lies outside the model scope, it is treated as part of the system's environment, as it can influence dock availability and unloading speeds.

Together, these subsystems form the Operational System, while the slot allocation, dock planning, and yard routing rules represent the Control System. Both layers interact to achieve efficient truck handling and ensure a smooth flow of cargo through the terminal.

2.1.3. System Behaviour

Based on the PROPER model, the system's behavior shows how the operational process and the control activities interact over time. In the landside handling process, this behavior is mainly influenced by the timing of truck arrivals and the coordination between the administrative and operational parts of the terminal. Truck arrivals often happen in short periods of high activity, which causes congestion in the yard and long waiting times before unloading. When several docks are working at the same time,

the limited floor space behind the doors fills up quickly. In a way, the unloading speed is therefore dependent of the available space in the warehouse buffer zone. Although the warehouse is outside the study's scope, its limited capacity acts as an external factor that influences how many docks can be used at once.

Control actions such as sequencing trucks, assigning docks, or temporarily holding trucks at the gate are used to keep operations running as smoothly as possible. According to the framework of Veeke, Ottjes, and Lodewijks [60], these measures form a feedback control loop: staff respond to the current situation in the yard by not allowing new trucks to enter. However, there is no forward control, meaning that the system does not plan or adjust in advance based on expected truck arrivals. Which results in the peaks.

In summary, the system shows strongly altering periods of high peaks and lower arrival rates and are the result of the current physical layout and operations. Understanding these patterns helps to identify where improvements in planning and coordination could reduce waiting times and improve overall performance.

2.1.4. System Control

In the Delft Systems Approach, control describes how a system is monitored and guided so that it works as intended [60]. Control makes sure the system can keep working even when conditions change. In the landside cargo process, control mainly happens through direct feedback between staff and the current situation in the yard.

The Control System uses encompasses what is happening in the yard to support decisions. When the yard becomes too full, as stated earlier staff can delay new trucks at the gate. Then, when space becomes available, trucks are called in again. These feedback actions help to keep operations stable during busy times.

Most of the control still depends on simple rules and staff experience rather than automatic systems. Trucks are lined up and docks are assigned based on urgency, available space, and staff input. There is currently no control that plans or adjusts operations in advance based on expected demand. This means control is reactive, it responds to problems as they happen instead of preventing them. Future improvements such as slot management or dynamic scheduling could make the control more proactive, as described by Veeke, Ottjes, and Lodewijks [60].

2.1.5. System Performance

System Performance is measured by comparing results of the improvements with the initial results, and according to the Delft Systems Approach, performance shows how well a system reaches its goals [60]. Performance indicators enable you to assess how efficiently the system operates and where improvements are needed. For this study, they have already been identified in 2.1.1. For the reason of clarity, the KPIs are repeated below:

- Truck Lead Time (minutes): Total time a truck spends in the system, from arrival at the gate to departure after unloading.
- Truck Waiting Time (minutes): Time a truck waits before being assigned to a dock.
- Dock Occupancy Rate (%): Percentage of time docks are in active use.

Each KPI looks at a different part of system performance. Truck lead time shows how efficient the total process is. Waiting time shows how much delay trucks face, and dock occupancy rate shows how well the available unloading capacity is used. Together, these indicators give feedback on how well the system is performing and help to compare future design changes during simulation.

2.2. Theoretical Framework

This section reviews the existing body of literature about the landside operations in air cargo logistics. The purpose is to establish a foundation for analyzing and improving dock and yard performance at air cargo terminals.

2.2.1. Air Cargo logistics

Air cargo terminals connect ground freight and air transport, serving numerous FWs. At cargo handling facilities, there is a strong supply/demand imbalance between the volume of trucks arriving to a GH and its actual processing capabilities [8]. One of the reasons for this imbalance is the limited number of loading docks [49]. Another common reason is the fact that the number of GHs at airports is limited. The imbalance ultimately leads to congestion and high waiting times, in particular at peak moments like Friday afternoons [61].

These peaks typically occur around flight cut-off (latest allowable time for delivering cargo) and arrival times, leading to long queues and delays. For example, a recent study showed that at one major European hub the average truck wait times reached 50 minutes, especially during late evenings [8]. Such delays risk missing flights and lower service quality.

Consequently, in line with developments observed in other sectors [21], an increasing number of airports are promoting enhanced coordination between FWs and GHs to improve operational efficiency. For instance, Brussels Airport has implemented an online slot booking system enabling FWs to schedule pick-up and delivery appointments with GHs in advance [37]. Similarly, one of the largest trucking companies in Europe, has advocated for deeper collaboration among airport stakeholders to mitigate congestion [55]. At Schiphol, collaborative initiatives such as the “Milkrun” [36] and “Drop & Collect” [52] are currently undergoing conceptual testing and pilot implementations. Several of these initiatives have been examined in the literature through analytical approaches, including discrete event simulation [3], system dynamics [11], and multi-criteria decision analysis [46]. However, the existing literature exposes a scarcity of detailed, operationally grounded studies in dock and yard management within air cargo.

Operational and environmental consequences are also substantial. At JFK Airport, chronic congestion and rising drayage costs reduced employment and even pushed business away [59]. Idle trucks also elevate emissions, harming local air quality as they generate avoidable emissions. This poses a serious concern for local air quality and public health [59]. Industry analyses indicate that outdated and undersized infrastructure is a key contributor to this issue. Many cargo facilities are not built for today’s freight volumes or modern 18-meter trailers. Poor truck aprons, limited queuing capacity, constrained maneuvering space, and a shortage of dock bays all lead to landside congestion. Without sufficient yards, inbound trucks are often forced to wait in lines along airport access roads or nearby streets, increasing congestion, operational costs, and carbon emissions [66].

In summary, the capacity of docks and yards at many air cargo terminals is frequently below the demand during peak periods. This mismatch creates delays and costs that motivate the search for innovative solutions.

2.2.2. Regulatory preconditions and constraints

Aviation is one of the highest regulated industries worldwide [40]. Aircraft carry large numbers of passengers, and safety risks are high since any incident would have global consequences. Furthermore, aircraft emissions, noise and fuel use have a large environmental impact as aviation is the fastest growing source of greenhouse gas emissions [14]. To address these key areas, preconditions and requirements are set which act as both constraints and enablers. Safeguarding safety and sustainability while requiring innovation and coordination. The following sections outline the key parts of these preconditions and requirements.

Safety Regulations

As stated, aviation is an industry in which small errors can have large consequences. Therefore many safety regulations have been put in place to minimize the risk of accidents. The International Civil Aviation Organization (ICAO) is a United Nations agency which is responsible for the air side cohesion between 193 countries. It serves as the global forum of States for international civil aviation and does so by developing policies and standards, undertaking compliance audits and more [23]. A regulation that stands out is that the ICAO requires all air operators (including cargo carriers) to implement Safety Management Systems (SMS). SMS frameworks create a structured approach to identifying and mitigating operational risks.

Furthermore, the European Union Aviation Safety Agency (EASA) is a European agency responsible for civil aviation safety in the European Union. It enforces uniform rules across all its member states. These rules cover fatigue management, airworthiness, and crew duty limits [18].

Environmental Standards

Besides safety regulations, the aviation industry also has a heavy impact on the global environment. Therefore global agencies also enforce environmental preconditions and requirements. An example of this is the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). CORSIA is the first global market-based scheme that applies to a sector. It caps CO₂ emissions from international flights to the level it was in 2019. This means that airlines must monitor and offset any emissions above this baseline by purchasing carbon credits or using approved sustainable aviation fuels (SAF) [24].

Apart from the ICAO, the European Union (EU) has also focused aviation policy around the environmental issues it presents. It has set targets to become the first climate neutral continent by 2050. To achieve this objective, the European Union has introduced the Climate Package. For aviation, this includes the ReFuelEU regulation which mandates the percentage of SAF in total fuel use: 2% in 2025, 6% in 2030 and about 70% in 2050 [19]. This applies to all flights departing EU airports. However, to this day the SAF market remains constrained by high costs and limited supply resulting in the reality that SAF use represents only a fraction of global fuel consumption [31]. As a result, airlines are confronted with elevated costs unless production expands significantly, posing substantial economic and infrastructure challenges for carriers such as KLM Cargo.

Customs and Security Compliance

Cargo is shipped worldwide, and is therefore also vulnerable to security risks. To counter such risks there are strong customs regulations and security compliances. Besides regular passenger customs, the EU has several cargo specific requirements. Two examples are the Union Customs Code and the Import Control System 2, which require airlines and FW's to file advance electronic cargo data before goods arrive. This allows risk assessment ahead of time and reduces custom clearance delays [17]. Further, Since 2014, all carriers flying cargo from non-EU airports into the EU must obtain ACC3 validation. A process which requires third-party audits to prove that security measures at the origin airports meet EU standards [15].

A final example of customs regulations also comes from the EU. 100% of cargo carried on passenger flights has to be screened. Typically this is done through X-ray, CT scanners, explosive trace detection or detection dogs. These technologies are now embedded into standard airport infrastructure [16].

2.2.3. Stakeholder Analysis

A stakeholder analysis done to identify people, groups and organizations that influence daily air cargo terminal operations. By doing so, a greater understanding of the whole system is obtained. Also, it can reveal conflicting interest and later on help assess feasibility of proposed design alternatives. The first step is to make a preliminary list of stakeholders and answer the following question per stakeholder[57]:

- What are their resources?
- What are their major concerns?

- How do they see the project or issue?

An overview of the stakeholders is provided in Table 2.3:

Table 2.3: Stakeholder overview

Stakeholder	Resources	Major concerns	View on the project
Truck Drivers	Time, vehicle capacity, driving hours, on-site presence.	Long waiting times, unclear queue order, poor communication about delays.	Supportive if it improves predictability and reduces idle time.
Freight Forwarders	Shipment planning tools, control over dispatch timing, logistics knowledge.	Delivery time compliance, cost efficiency, lack of slot guarantees, few incentives to avoid peaks.	Neutral to positive if it brings visibility, flexibility, or cost benefits.
Document Handling Team	Access systems, document validation tools, staff capacity, freight document knowledge.	System delays, high workload, bottlenecks, incomplete information.	Supportive if digital processing improves; cautious of added complexity.
Operations (Dock & Yard Staff)	Forklifts, dock planning tools, manpower, warehouse layout control.	Truck clustering, overloaded docks, unclear truck priority, limited flow control.	Supportive due to direct operational benefit from smoother flows.
Management	Strategic authority, budget, operational data, planning tools.	Scalability, peak-time instability, cost of interventions, stakeholder alignment.	Strongly supportive; aligns with long-term capacity and efficiency goals.
Airport	Land ownership, infrastructure control, road access management.	Traffic flow across the airport site, space constraints, integration with other operations.	Cautiously positive if airport-wide impact is managed.
Customs	Legal authority, risk systems, clearance protocols.	Secure and compliant flows, timely and complete data, avoiding delays.	Neutral to positive; supportive of automation and pre-arrival compliance.
Municipality of airport	Zoning authority, environmental and traffic policy.	Road congestion, noise, air pollution, safety.	Supportive if it reduces truck traffic and supports sustainable logistics.
Cargo IT System Providers	Software infrastructure, data exchange platforms, integration capability.	Data latency, compatibility issues, regulatory integration, user feedback.	Supportive if it improves real-time data and automation across systems.
Other Ground Handlers at airport	Own terminals, personnel, handling equipment, shared infrastructure.	Infrastructure competition, congestion imbalance, coordination gaps.	Mixed—supportive if improvements are fairly distributed across handlers.

2.3. Expert Interviews

Interviews are often used as a qualitative data collection method. The aim of such interviews are to gain a deeper understanding of human experiences on systems. For complex logistical systems, it

allows people to explain their thoughts in their own words, which gives insights that is harder to get from literature or data. Moreover, system issues can be discovered which are not mentioned anywhere else, but preferences for the future system can also be identified[1].

A variety of interviewing techniques exist, including structured, semi-structured, unstructured, and focus group formats. Structured interviews are predefined, with a fixed set of questions. Unstructured interviews are highly flexible and allows participants to elaborate freely. Semi-structured interviews combine structure with flexibility, uses a prepared document but allows for follow-ups. Focus group interviews are conducted with a group of selected participants focused on one topic where the goal is to develop ideas collectively [1].

This research uses the semi-structured interviewing technique. A list of open questions were prepared containing the questions. After, follow-up questions were asked dependent on the participants response. This way, the crucial answers were answered but new information was gathered by answering follow-up questions based on the answers. This technique was used because it allows for both structure and freedom during the interview. Further, in operational environments like logistics, it helped to understand processes and challenges from the perspective of people working every day.

Appendix C contains the specific content per interview. This content is used for answering sub-question 1 and sub-question 2.

2.3.1. Interviews - Sub Question 1

From the interviews with operational managers and coordinators, several consistent causes of congestion in dock and yard operations were identified. The first and most frequently mentioned cause is the peaked arrival pattern of trucks. FWs consolidate their shipments throughout the day and deliver them in bulk during the evening or night, often just before flight cut-off times or weekend closing hours. This results in strong peaks for the available dock and yard capacity within a short time window.

Secondly, physical and infrastructural constraints within the terminal limit operational flexibility. While multiple docks are available, only a few can be used simultaneously because the buffer area is quickly congested. Once this space is full, internal movement for forklifts and staff becomes nearly impossible, forcing operations to slow down. The yard space is also too limited to buffer incoming trucks effectively, meaning that vehicles are blocked at the entrance.

A third cause lies in process and system inefficiencies. Data exchange between connected systems is slow and occasionally inconsistent. These delays cause “compliance blocks”, where shipments cannot be processed until all electronic messages are received, leading to additional waiting times for truck drivers.

Moreover, a lack of transparency and communication contributes to driver frustration and operational inefficiency. The current system does not provide drivers with real-time updates on their position in the queue or estimated waiting time. Priority rules based on the urgency are also not visible to drivers, making the process appear unorganized and unfair.

Finally, coordination challenges within the wider air cargo chain play a major role. Freight forwarders and transport companies largely operate independently and optimize for truck utilization and cost efficiency rather than for synchronized delivery patterns. As a result, there is little incentive to deliver outside of peak hours. Efforts such as slot management systems and collaborative initiatives are under development, but behavioral and organizational barriers still limit their effectiveness.

2.4. Conclusion

To answer sub-question 1 : *What are the main causes of dock & yard congestion in air cargo logistics?*, this chapter combined system analysis, literature review, and expert interviews to identify the underlying mechanisms of congestion within landside operations.

Dock and yard congestion arises from an imbalance between operational capacity and demand. The limited number of usable docks, restricted yard space, and the small buffer area behind the doors con-

strain how efficiently trucks can be processed. Truck arrivals are strongly concentrated around flight cut-off times and weekends, creating short but intense peaks that exceed available capacity and lead to long queues and waiting times. Control of the process is mostly reactive. Staff respond to congestion once it occurs, adjusting truck admission and unloading only after queues have already formed. Manual documentation, limited automation, and slow information exchange further delay operations. In addition, the warehouse area behind the docks often becomes a bottleneck, as its limited floor space restricts unloading speed and reduces dock availability.

In combination, these factors extend total truck time on site, increase waiting before unloading, and lower the overall use of resources. The analysis shows that congestion mainly results from infrastructural constraints, unbalanced truck arrivals, reactive operational control, and slow data exchange. This understanding provides the starting point for the next chapter, which will explore and test improvement strategies aimed at reducing waiting times and achieving a smoother and more predictable truck flow through the terminal.

Part II

Suggestion

3

Design Alternatives

This chapter follows up the Awareness phase by introducing the Suggestion phase according to DSR. The first step is to identify what interventions exist that improve overall landside air cargo logistics. These findings are extracted from researching literature and expert input. The next step is to find the correct method in order to analyze the effectiveness of the proposed interventions, which is also done using existing literature. Subsequently, this chapter addresses sub-question 2.

3.1. Design Alternatives

This part discusses the interventions found in the literature review and expert interviews around landside air cargo terminal operations.

3.1.1. Dock and yard capacity management

To manage congestion, some stakeholders are exploring truck scheduling or appointment systems, which spread arrivals more evenly than the first-come, first-served (FCFS) method. Currently, many GHs rely on the FCFS method. However, according to Bombelli and Fazi [8] this method is suboptimal during peak hours. A 2022 European case study showed that sequencing truck arrivals significantly reduced peak hour delays compared to FCFS [34]. This idea draws from successful port strategies like truck arrival slot bookings, which have smoothed truck flows at container terminals [63].

Despite the promise, truck arrival systems are rarely used in air cargo. Most academic work focuses on seaports, leaving a gap in the air cargo industry. Even when it faces stricter timing constraints tied to flight schedules [63]. One queuing model illustrated how time-dependent truck arrivals impact wait times, but more empirical work is needed [34]. At Schiphol, a 2022 simulation study highlighted that even with collaboration among FWs, dock capacity remained a hard constraint [49]. And efforts at JFK and London Heathrow to introduce centralized truck scheduling are still in early stages [41].

Overall, academic research on dock scheduling in air cargo is limited, and there is a clear need for optimization tools that are context specific. The studied research mark that the industry is innovating but there is work ahead in order to develop the air cargo environment.

3.1.2. Automation for terminal operations

The logistics sector is facing increasing demand for speed, flexibility and reliability, largely driven by the growing global service expectations [13]. This pressure, means that warehouses need to adapt and adjust which is why warehouses are transforming into smart warehouses by using automation solutions. Implementing automation in air cargo logistics can increase throughput, reliability and reduce dependency on manual labour. Within air cargo terminals, they are commonly used for repetitive transport

tasks and pallet handling. Different types of automated vehicles can be deployed, such Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs).

AGVs are self-driving vehicles that move unit loads without human operators [13]. They have been in use for more than 50 years, originally for heavy goods, but now also for smaller goods [25]. Since no human handling is required, they lower labor costs and human error. Earlier AGVs use various methods to navigate their way around. Some AGVs use wire guidance to navigate their way around, following cables or magnetic tape on the floor. In addition, some AGVs rely on colored reflective tape, rather than magnetics to indicate routes [20]. Other AGVs use inertial guidance, navigating by magnets positioned at regular intervals on the floor to detect their position [13]. A last method is to use laser guidance, which triangulates its position using a rotating laser and reflective landmarks [45].

While these traditional methods provide reliability, they are outdated. Facility layouts need to undergo reconstruction and they are inflexible and costly if facility layouts are changed after implementation. New developments of advanced navigation technologies have emerged such as vision based systems and Simultaneous Localization and Mapping (SLAM). These technologies allow vehicles to create virtual maps of the environment and reroute themselves when obstacles appear [43]. In dynamic air cargo terminals, where vehicles are constantly crossing paths and disruptions occur, these systems are particularly relevant as they require no dedicated infrastructure.

Besides navigation, operational challenges arise. These include choosing the optimal fleet size, unloading policies, and routing strategies. The number of AGVs must be carefully considered. If too few AGVs are used, bottlenecks arise, but if too many are used, congestion and idle times increase. Furthermore, research has shown that efficiency gains are maximized when the number of vehicles is balanced with the facilities workload. Parallel to this, routing algorithms must be designed to minimize empty runs and travel distances [13].

Different AGV types provide various functions within air cargo handling. Automated forklifts can combine horizontal and vertical movements, enabling the transfer of ULDs to build-up workstations. Pallet movers can handle repetitive transport tasks. Tugger AGVs can tow cargo between yards and warehouses. However, automated coupling is still difficult to achieve. Unit load AGVs are suited for heavy goods and can integrate directly with conveyor systems.

More recently, AMRs have emerged as a flexible alternative because they do not rely on fixed paths and can dynamically navigate using onboard sensors, LiDAR, and AI algorithms. This makes them adaptable to the unpredictable environment of air cargo terminals [20].

In addition to AGVs and AMRs, Rail Guided Vehicles (RGVs) represent another option. RGVs operate on closed-loop rail tracks and can connect different areas of the facility, such as storage zones and docks further in the facility. They can achieve higher speeds than AGVs, up to 4.4 m/s compared to 2.0 m/s. However the disadvantage is physical rail and the throughput depends on the number of vehicles on the rail, which can create congestion when traffic density is high [20].

Despite these advances, adoption inside air cargo warehouses remains limited. Current trials focus mainly on outdoor dolly towing, while indoor deployment faces issues given the diverse nature of air cargo. The next goal is to autonomously transfer ULDs, from acceptance to intake point [9].

AGVs and AMRs are evolving into connected fleets that are able to communicate with each other. This communication can allow vehicles to take on prioritized cargo, balance workloads, and prevent bottlenecks. And once this level of integration is achieved, it can mean a large step for air cargo terminals [43].

3.1.3. Interviews - Sub Question 2

To complement the literature review, experts were interviewed. They provide a practical perspective on potential interventions to improve dock and yard performance. Several improvement measures were mentioned that align closely with findings from the literature but reflect the realities of daily operations at an air cargo terminal.

Slot management and arrival scheduling

All interviewees emphasized that a structured slot management system is one of the most promising measures to alleviate congestion. By assigning time windows for truck arrivals, peaks could be spread more evenly throughout the day and night. The experts described ongoing efforts at Schiphol to develop such a system, noting that import processes already use limited forms of slot allocation, while export flows still rely heavily on uncoordinated arrivals. Extending slot management to export operations would create predictability for both ground handlers and forwarders, enabling better planning of staff and resources. The experts also suggested linking slot allocation to flight departure schedules and cargo urgency. This would align arrival patterns with handling priorities and prevent unnecessary waiting times. However, they stressed that cooperation from forwarders and transport companies is essential, as their consolidation practices strongly influence peak formation.

Pre-gate control and yard access management

A second intervention discussed across interviews was the introduction of controlled access to the terminal area. The idea is to regulate the number of trucks entering the yard so that vehicles are only admitted when docks and floor space are available. This could be achieved through pre-gate buffering areas, where trucks wait until they are allowed in the system. Such a system would reduce congestion and allow smoother coordination between administrative checks and physical unloading. However, this can be already partly solved by implementing a slot management system as this would control the incoming trucks.

Digitization and faster information exchange

The interviews highlighted the need for improved digitization of documentation and communication processes. They noted that many current administrative steps are still handled manually, leading to unnecessary delays between truck registration, document checks, and dock assignment. Accelerating data exchange between connected systems and enabling real-time message transfer would allow shipments to be processed more efficiently.

Automation of documentation, would shorten the total lead time per truck and prevent idle time at docks. The experts also supported the idea of integrating risk assessment systems (risky cargo) more directly into the cargo management platform, so that approvals can be processed instantly and without manual intervention.

Transparency and communication with drivers

Improving communication and transparency toward drivers was another commonly mentioned intervention. The experts observed that the current prioritization logic for truck unloading is not well understood by drivers, which often leads to frustration and confusion. They suggested displaying expected waiting times and providing a clear explanation for the unloading sequence, for example through the token or pager system already in use.

Making the prioritization criteria transparent such as linking them to shipment deadlines or pre booked slots would increase trust and reduce tension at the gates. Further, giving drivers better visibility into their position in the queue and the progress of documentation checks could enhance yard operations.

Use of overflow capacity and flexible operations

To relieve pressure during peak hours, the experts proposed making temporary use of additional warehouse space, specifically by activating secondary facilities as overflow capacity. This measure would prevent the main terminal floor from becoming saturated during heavy inflow periods. Coordinating such flexible use of space requires clear operational guidelines on which cargo types can be diverted and how transfers are handled between facilities. In addition, more dynamic use of existing docks by activating or deactivating them, was mentioned as a means to optimize throughput without overloading the handling area.

Cooperation

Finally, the interviews highlighted the need to influence arrival behavior through incentives. The experts suggested exploring measures such as differentiated service fees or rewards for off-peak deliveries to encourage FWs to distribute shipments more evenly over time. Coordinated planning among FWs was also seen as a longer-term approach, potentially supported by shared data platforms that allow mutual visibility of capacity and expected arrivals.

3.2. Design Methods

This part discusses methods found in order to analyze the effectiveness of new design interventions in land side air cargo operations.

3.2.1. Operations Research

The application of operations research (OR) to air cargo logistics has grown substantially over the past three decades. As stated before, the air cargo supply chain involves a multiple stakeholders including airlines, FWs, GHs and airport authorities. This multi-actor environment creates operational challenges. OR methods have been applied to address problems ranging from strategic decision-making to daily operational scheduling. Existing literature can be categorized into three perspectives: airline centric models, service supply chain coordination, and freight FWs-focused studies.

OR research has focused significantly on the airline side of air cargo logistics. Especially in the domains of revenue management, aircraft routing and terminal operations. In revenue management, dynamic programming and stochastic optimization techniques have been developed to guide overbooking decisions under demand uncertainty [2]. Terminal operations have been modeled to improve truck unloading and cargo routing processes at airport cargo terminals [42, 65]. This often comes with the objective of minimizing handling and storage costs.

Moreover, research on fleet routing and flight scheduling includes the integration of air cargo flows into passenger flight schedules, aircraft loading problems, and crew assignment models [51, 32]. Studies on ULD loading have used integer programming and heuristic methods to improve payload efficiency. Subsequently they ensure compliance with aircraft balance and safety constraints [48].

FWs represent a critical yet less researched component of the air cargo supply chain. Prior OR research has addressed capacity booking and container consolidation problems. Often through bin-packing and mixed-integer linear programming approaches [64, 22]. These studies generally aim to minimize costs related to overbooking and the under estimating of ULD capacity.

In recent years, routing and scheduling problems specific to FWs have gotten attention. Leung and Hui [30] introduced a two-stage stochastic model for resource allocation and assignment under demand uncertainty. Archetti and Peirano [4] formulated the Air Transportation Freight Forwarders Service Problem, an exact model aimed at optimizing door-to-door shipment routing.

Bombelli and Fazi [8] investigated the coordination of landside air cargo logistics by introducing the Ground Handler Dock-Capacitated Pickup and Delivery Problem with Time Windows. Their research focuses on optimizing the routing and scheduling of trucks transporting ULD's from FWs to GHs. All the while accounting for constraints such as limited dock capacity, time windows, and Last-In-First-Out (LIFO) unloading rules. They propose a centralized, cooperative planning framework to reduce waiting times in congested yards.

Research has also started to explore cooperative mechanisms among FWs. This includes auction-based platforms for capacity sharing and cooperative routing. Concluding, Lai, Xue, and Hu [27] study the possibility of capacity sharing for such market requests with an efficient auction strategy.

3.2.2. Modeling and Simulation Techniques

To experiment with changes to systems there are two possibilities. One can either adapt the real system and observe what effect changes have on the environment. Or one can create a virtual environment

of the system and observe what effect changes have on the environment.

The first possibility would seem the easiest, however this is often not possible as adaptations in the real system would cause disruptions which can become very costly. The second possibility is known as simulation, which is a widely used approach to analyze real world systems. It enables researchers to translate complex systems to adjustable models in order to better understand specific behavior of the system [62]. In general, models are made when experiments in the real system are impractical or impossible but changes to the system need to be researched. The air cargo industry is a high risk, costly and dynamic industry in which real life trial and error is very impractical. Hence, modeling provides a good solution to understand, summarize or generalize new model behavior [56].

There are two main types of models [39]: analytical models and simulation models. Analytical models use mathematical relationships to describe how a system works. If the model is validated, its behavior should be similar to the real system. When a system is simple, an analytical solution can be found, which is quick and inexpensive to use [29].

For complex systems however, analytical models often become too difficult to solve. In these cases, simulation models are more practical. Instead of solving equations directly, a simulation model imitates the operation of the system over time, allowing performance to be estimated through experiments. Simulation can also capture detailed, variable, and random behavior that is hard to represent in an analytical model [39]. Because of this, simulation is often the preferred choice for complex logistics systems.

Simulation

Simulation is a method for studying how a system behaves by creating a model that copies its structure and operation. Based on this model, experiments are conducted to observe outcomes [29]. Systems can be categorized in several ways. A system may be static, representing a situation at a single point in time, or dynamic, where its state evolves over time. It can be deterministic, producing the same results whenever the inputs are the same, or stochastic, where randomness and uncertainty influence outcomes. Finally, systems can be continuous, with variables that change smoothly over time, or discrete, where changes occur only at specific points. In practice, logistics environments such as air cargo terminals are usually dynamic, stochastic, and discrete. A range of simulation approaches can be used to model such environments. System Dynamics is a continuous method that represents systems using stocks, flows, and feedback loops [53]. It is particularly effective for exploring strategic or long-term scenarios. For example, SD could be used to analyze how a city's population changes over several decades by modeling births, deaths, and migration flows to identify trends. Agent-Based Simulation models a system as a collection of autonomous agents. Each with its own rules and behaviors that interact with their environment [33]. A simple example is simulating shoppers in a store, each with different habits and decisions, to observe how their choices influence queue formation at the checkout. Monte Carlo Simulation relies on repeated random sampling to estimate the probability distribution of outcomes [35]. For instance, it could be used to estimate the chance of rain on a particular date by generating thousands of random weather scenarios based on historical data. DES models a system as a sequence of discrete events such as arrivals, service starts, or completions that occur at specific times and cause the system state to change [56]. DES is especially useful when events are dynamic, random, and occur in discrete (non-continuous) steps. For air cargo terminal operations, DES is the preferred approach because its operations are event-driven and change rapidly. Trucks arrive at varying times, move through the yard, and unload at docks. All these events can be irregular and/or unpredictable. DES can represent these events in detail, showing how queues develop, how docks are used, and how delays happen through the system. This ability to test operational and infrastructural changes makes DES the most appropriate method for this case.

Discrete Event Simulation

DES is a method for studying how a system operates by breaking it down into a chain of distinct events. These events occur at certain points in time and each one changes the state of the system in some way. An event could be as simple as a vehicle arriving at a gate, a machine beginning its cycle, or a shipment being unloaded. Between these moments, the system does not change but time in the

simulation simply moves to the next event [5].

In DES, the clock jumps from one event to another, rather than moving in fixed intervals. This makes it different from continuous simulation methods, which model systems as if they are changing all the time. The approach is especially useful when you need to capture queues, resource limits, and randomness in processes. In doing so, bottlenecks can be easily identified and overall system performance can be measured [38].

DES has been applied in a wide range of settings, such as Banking & Finance services, Healthcare, Logistics & Transportation and the Public Sector [5]. It can be concluded that it has proved to be a valuable tool in many different industries. In the logistic sector it has been used for modeling system performance, inventory- and production planning [54]

One of the strengths of DES is its ability to test changes safely. This makes DES a valuable tool for improving efficiency and reducing risk in complex, fast-changing environments. DES also has some disadvantages, for example building a reliable model can take time and requires accurate data. If the data is incomplete or the assumptions are wrong, the results may lead to incorrect conclusions. Complex models can also become very large, and interpreting the results still requires experience and judgment, even though the software is user friendly. Concluding, DES can show what happens in the system, however it cannot reveal the underlying reasons. This however, will become clear after analyzing the results of the simulation run.

3.3. Selected Designs

Based on the findings from literature and expert interviews, a set of design configurations will be formulated for testing in the simulation. These configurations directly target the system performance identified during the awareness phase: long waiting times, limited dock capacity, and congestion during peak hours. They include both infrastructural and procedural interventions that can be implemented within the context of the case company. Each configuration is modeled as a separate experiment to evaluate its influence on the key performance indicators of the current system: Lead time, waiting time and dock utilization. Table 3.1 provides an overview of all selected configurations and explanation.

3.3.1. Design Alternatives

The configurations range from physical capacity measures to behavioral and organizational interventions. The first 5 experiments (configuration 1-5) focus on infrastructure utilization and dock configuration, while the last configuration address process control. Together, these alternatives provide a comprehensive view of both operational and systemic improvements that can be achieved within the terminal.

Table 3.1: Overview of selected configurations for simulation experiments

Configuration	Description
1	A second MTD dock is activated to increase unloading capacity for ULD trucks, reducing bottlenecks in MTD handling and congestion at conventional docks.
2	The second MTD dock is deactivated and replaced by an additional normal dock to examine the effect of redistributing capacity from MTD to conventional docks when the ULD share is low.
3-5	The total number of active docks is increased to 4, 5 and 6 to analyse how additional dock capacity affects overall performance.
6	A digital slot-booking mechanism is introduced to regulate truck inflow based on pre-assigned time windows, smoothing arrival patterns and improving dock predictability.

3.3.2. Design Method

The selected design alternatives will be analyzed using DES. This method is chosen because air cargo terminal operations are inherently event-driven, stochastic, and capacity-constrained. DES enables modeling detailed process flows in which entities interact dynamically through discrete events, such as arrivals, registrations, and unloading activities. By replicating the real system in a virtual environment, DES allows controlled experimentation without disrupting daily operations. Each experiment is replicated multiple times to capture stochastic variation, and performance is assessed using predefined key indicators: lead time, waiting time, and dock utilization. The application of DES in this research follows three main steps. First, the base case model representing current operations is developed and validated using empirical data. Second, each design alternative is implemented as a scenario modification that alters specific control logic or capacity settings. Finally, an analysis of the simulation results provides evidence of how each design alternative affects system performance. This approach ensures that both infrastructural and procedural interventions can be objectively assessed within a consistent analytical framework.

3.4. Conclusion

To answer sub-question 2: *which methods can be applied to improve dock and yard performance in air cargo operations*, this chapter explored suitable analytical methods and practical interventions for improving landside performance.

Two approaches were identified. Operations research provides optimization for structured problems such as scheduling or routing, but it is less effective for systems with high uncertainty. Simulation offers greater flexibility to study complex operations safely. Among the simulation types, discrete event simulation is most appropriate, as it captures time based processes such as arrivals, queuing, and unloading, allowing realistic performance evaluation.

Several interventions were found to improve performance: slot management and arrival scheduling to spread peaks, use of overflow capacity to manage busy periods, dock capacity alternations, better communication with drivers, and improved coordination with FWs. It was decided to further explore the effects of the following identified configurations:

- Activate 2nd MTD Dock next to regular docks
- Deactivate one MTD dock and replace for regular dock
- Activate one extra regular dock
- Activate two regular docks
- Activate three regular docks
- Implement a digital slot-booking mechanism

The next chapter introduces the Development phase, in which a simulation model is developed, verified and validated. Concluding, first results are compared to historical data.

Part III

Development

4

Simulation Model Design

Building on the Awareness and Suggestion phases, this chapter covers the Development phase. First, the system is translated into a conceptual model that captures the key entities, flows, and decision rules of landside operations at FB3. Next, this conceptual model is implemented as a DES model. Finally, the model is verified and validated to confirm that it behaves credibly and represents the real system closely enough for its intended use. Together, these steps address Sub-question 3 by delivering a simulation model that is suitable for evaluating improvement options for dock and yard operations.

4.1. Modeling Approach

This section explains how the real operation is translated into a model that can be used for analysis. The approach connects the findings from the system analysis to a simulation model that tests potential improvements and measures their effects. Only the essential elements identified in Section 2.1 are included, while unnecessary detail is avoided.

The first step is the requirements analysis, which ensures that the model reflects the needs and objectives of all stakeholders. This is followed by the development of a conceptual model of the landside process and a description of the operational control logic required for the model to behave as the real system. Together, these steps form the basis for translating system knowledge into a simulation-ready representation.

The model examines how three main factors: truck arrivals, yard capacity, and dock operations—affect the KPIs. By focusing on these aspects, the model achieves an appropriate balance between detail and simplicity. It captures the dominant causes of congestion and delay while remaining efficient for scenario testing and performance evaluation.

4.1.1. Requirements Analysis

Improving an existing operational system effectively creates a new one, and its success depends on how well it satisfies stakeholder needs. A requirements analysis (RA) is therefore conducted to ensure that the developed simulation model and its design alternatives align with the system's actual operational and managerial objectives. RA is the process of identifying, interpreting, and refining stakeholders' needs and expectations. It distinguishes between functional requirements, what the system must do, and non-functional requirements, how the system must perform in terms of accuracy, usability, and reliability [28].

In this research, the requirements were derived from expert interviews and insights from the literature review. The interviews captured multiple perspectives from stakeholders involved in landside air cargo operations, providing valuable input on existing bottlenecks and desired performance improvements. Based on this input, several core requirements were formulated to guide the design of the simulation

model:

- The model must accurately represent current truck arrival, yard parking, and dock allocation processes.
- Performance evaluation must focus on lead time, waiting time, and dock utilization as key indicators of landside efficiency.
- The model must allow for testing both infrastructural and operational interventions.
- The design should remain flexible to accommodate alternative dock configurations and scheduling strategies.

4.1.2. Conceptual Model

A conceptual model is developed to provide a structured understanding of the landside terminal system. It offers a simplified representation of reality that captures the main components and flows in the system. In this study, the conceptual model is in the form of a flow diagram, which represents the start to finish process that occur as trucks move through the terminal (Figure 4.1). This flow-oriented representation visualizes how trucks progress through the different stages and pass corresponding system components as earlier described in Figure 2.1. By mapping how these elements interact from start to finish, the conceptual model ensures that the system is correctly understood before it is translated into a simulation model.

The process starts when the driver reports at the documentation desk, where freight papers and booking details are checked. This step ensures that the shipment meets all acceptance requirements. Delays can occur here when information from the transporter is incomplete or when data systems are having issues.

After documentation is approved, the driver enters the terminal through the entry gate and drives towards the export area via the yard. The truck is then parked in the designated export parking area, where vehicles wait until dock capacity becomes available. Yard space is limited, and during busy periods congestion can occur near the entrance. Road marshals are present to manage traffic and maintain safe vehicle movement.

At the export area, the driver collects a bleeper device, which indicates when the truck is called forward for unloading. While waiting, the driver remains in the truck until the bleeper signals that a dock has been assigned. The driver then moves the vehicle from the yard to the allocated dock.

At the dock, cargo and safety checks are performed before unloading starts. Dock staff prepare equipment, verify safety conditions, and unload the cargo using forklifts or pallet jacks. Once unloading is complete and the cargo has been accepted into the warehouse, the driver leaves the terminal through the exit gate.

Overall, the conceptual model captures the processes that determine how trucks progress through the terminal. It is not intended to reproduce every operational detail, but rather to represent the mechanisms that ensure truck movements and dock utilization. This allows the following simulation model to explore how variations in designs will affect the KPIs.

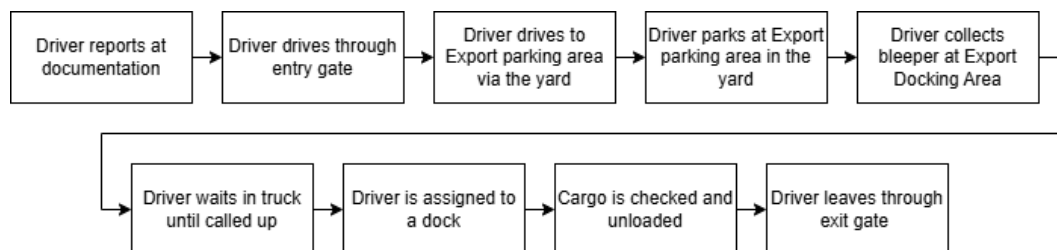


Figure 4.1: Conceptual model driver journey

4.1.3. Control Logic

Dock assignment is managed by ground staff. In principle, trucks are allocated by FCFS. However, exceptions are made for time critical shipments, particularly those approaching the LAT linked to out-bound flights. This prioritization can create irritation among drivers, as they are not always aware of this rule. At maximum, 5 doors are be used simultaneously: Doors 3032, 3034, 3035, 3037 and 3038.

Once the bleeper goes off, the truck drives to the correct dock. Parking and preparation for unloading takes several minutes, during which dock staff prepare equipment and verify safety protocols. The unloading process is done manually: skids or pallets are manually transferred from the truck into the warehouse, using forklifts or pallet jacks. The unloading time of the truck depends on the load factor of the truck and the experience of the staff. If a truck carries one skid, unloading is done quickly, but larger trucks with mixed shipments can require longer unloading.

FWs can deliver cargo 2 different ways: Skids or ULDs (Figures 4.2a & 4.2b). Skids are pallets used to transport cargo. They can be handled using forklifts or pallet jacks, which is done manually. Skids are not airworthy and therefore the cargo must be built on a ULD after acceptance, therefore all air cargo is transported on ULDs. Doors 3035, 3037 and 3038 are used only for skids.

ULDs are large units on which multiple pieces of cargo are placed and can be held together. These are used so the cargo does not shift while flying, preventing aircraft imbalance which could potentially cause accidents. FWs that are specialized in air cargo, deliver cargo prebuilt onto ULDs. When accepting these ULDs, they are transported directly to storage using an MTD (Figure 4.3) until processed to fly. Doors 3032 and 3034 are used only for ULDs, as they are directly connected to an MTD.



(a) Skid



(b) ULD

Figure 4.2: Skid and ULD

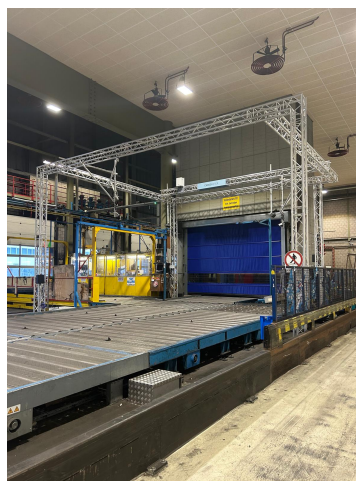


Figure 4.3: MTD

4.2. Data and Model Parameters

To build a realistic and reliable simulation model, accurate input data and parameter values are essential. This section describes the datasets, operational parameters, and assumptions that form the foundation of the model. The data originates from KLM Cargo's internal export handling records and captures the real operational performance of the system. After data collection, preparation steps are applied to clean and structure the data for use in the simulation environment. In addition to the dataset, several operational parameters and assumptions are introduced to represent process times, handling logic, and system constraints that cannot be directly derived from available data.

4.2.1. Data Collection

As stated, the system performance will be measured by using KPIs. In order to measure these KPIs, data is needed, which is available in the air cargo terminal. For this research, the focus lies on export, and for this the dataset of 2024 will be used. However, this file contains data about every piece of cargo that has entered the system and it exceeds 161,357 packages (export only). Logically, this dataset is too large to use for the simulation and it is necessary to reduce this number. After internal communication, it was decided to trim the dataset down to include only the months June, July, August. The decision for these months was made because these are the busiest, and the system is put under a lot of stress.

The dataset contains the following crucial data to measure KPIs:

- Air Waybill (AWB) Number: A unique identifier assigned to each air waybill.
- Number of Pieces on AWB: The total count of packages registered under a specific AWB.
- Export Start Process Time: The timestamp marking when the export handling process for a shipment begins.
- Export End Process Time: The timestamp marking the completion of the export handling process. Together with the start process time, this provides the total process duration.
- Export Start Unload Time: The moment when unloading operations for a specific truck or trailer carrying export cargo begin at the assigned dock.
- Export End Unload Time: The moment when the unloading of export cargo from the vehicle is completed. The difference between start and end unload time reflects the unloading time.
- Documentation Actual Arrival Time: The moment a driver arrives at documentation to hand over documents.
- Export Documentation Total Delivery Start Time: The timestamp when documentation starts checking driver and cargo documents.
- Export Documentation Total Delivery End Time: The timestamp when documentation finishes checking driver and cargo documents.
- LAT: The deadline by which cargo and its documentation must be accepted into the terminal to ensure that it can be loaded onto the scheduled flight.
- Number of Pieces: The physical number of pieces handled during unloading. This may differ from the declared number of pieces on the AWB in case of irregularities.
- Export Unloading Door: The specific dock door assigned to a vehicle to unload its cargo.

4.2.2. Data Preparation

After the initial data collection, several processing steps were required to ensure the dataset was suitable for simulation and analysis. The raw dataset contained records of all export truck arrivals at KLM Cargo during 2024. Since individual shipments could belong to the same truck arrival, the data first had to be aggregated to truck only level. Duplicate entries, representing multiple shipments for a single vehicle, were removed, resulting in a cleaned dataset of 9,162 unique truck arrivals.

To capture peak-period dynamics, the sample was restricted to the summer period from June to August, the busiest months of the year. Furthermore, only export operations at FB3 were included by filtering for

unloading doors 3032, 3034, 3035, 3037, and 3038. Arrivals that are handled at other docks contained express or valuable goods which is out of scope as they are handled in FB1.

For each truck, the earliest recorded ExportStartUnloadDateTime and the latest ExportEndUnloadDateTime were combined to calculate the total unloading duration. Additional derived variables were generated to represent critical time components of the truck handling process:

- ArrivalTime: the time of entry into the system, derived from
- DocumentationActualArrivalDateTime;
- UnloadSec: the unloading duration per truck (in seconds), computed from the time difference between unloading start and end;
- ArrivalToUnload: the waiting time between system entry and the start of unloading, representing queuing delay prior to dock assignment.

Extreme outliers are excluded to prevent distortion of simulation inputs. Specifically, truck arrivals exceeding ten hours between registration and unloading, or unloading durations longer than four hours, are removed. This filtering reduces noise while keeping the variability of operational data.

The resulting dataset forms a representation of real-world export truck operations, providing the inputs for the discrete-event simulation model. Each truck record was assigned a corresponding dock number (ExportUnloadingDoor) and time attributes, enabling the creation of an Arrival List within the simulation environment. The Arrival List is made of cumulative arrival times in seconds. Through this preparation process, the dataset was transformed from raw operational logs into a structured, simulation-ready input foundation.

4.2.3. Operational Input Parameters

Besides data derived from the dataset, there is more information needed in order to create the model and analyze KPIs. These are operational input parameters, primarily focused on process & handling times and vehicle/cargo measurements. The parameters are derived internally after consulting prior research.

- Security Lodge (registration + documentation): 180 sec
- Parking + dock positioning: 150 sec
- Bleeper collection: 90 sec
- Walking speed (driver/unloader): 1.0 m/s
- Unloading: 18 sec per skid
- MTD Doors open: 150 sec
- Check ULD documents: 30 sec
- ULD maneuvering: 20 sec
- Unloading to MTD: 50 sec
- Unloading to conveyor: 5 sec

4.2.4. Assumptions

In order to represent the current situation within the simulation, a number of assumptions are introduced. These are required as not all operational details, and human behavior can realistically be incorporated into the model.

1. Trucks arrive according to historical data, following a fixed arrival sequence without randomness.
2. At the entrance, drivers always stop at documentation for registration and document check. This takes a fixed time of 90 seconds.
3. Trucks enter and exit the terminal through entry and exit gates. These have a fixed cycle time of 10 seconds.

4. After documentation, all trucks must first park in the yard before being assigned to a dock, even if a dock is available.
5. Walking speeds are fixed: 1 m/s for drivers.
6. Driving speeds are fixed: 1,4 m/s for trucks.
7. Trucks cannot overtake each other when driving and always drive in a single line.
8. Only one truck can be inside one parking spot at the same time.
9. Drivers always collect a bleeper at the same place before unloading starts, regardless of dock availability.
10. The number of active unloading docks is fixed per scenario, with 5 docks at FB3 used as default.
11. Dock priority is set: doors 3032, 3034, 3035, 3037 and 3038 are chosen first, other doors are not considered unless specified.
12. Dock assignment is based on one of the following priority rules: FCFS, LAT
13. Parking and door positioning time is fixed at 150 seconds per truck.
14. Unloading speed is based on historical data per dock.
15. For ULD trucks, all plates always pass through the MTD process and the lift, regardless of possible shortcuts.
16. Unloading times in the MTD process are fixed: open doors 150 sec, check papers 30 sec, maneuvering 20 sec, unloading to MTD 50 sec per plate, unloading to conveyor 5 sec.
17. Defects or breakdowns of MTDs, lifts, or other equipment are not considered.
18. Trucks with empty plates are not considered in the model.

4.3. Model Implementation

The DES model was developed in Enterprise Dynamics to represent the landside export process at the air cargo terminal. The model captures the full flow of arriving export trucks, from documentation registration to unloading and departure, based on real data. Each component and process has been modeled to replicate the physical layout, timing, and logic of the current operation, allowing for analysis of yard congestion and dock utilization under different scenarios. The model layout in Enterprise Dynamics is seen in Figure 4.4

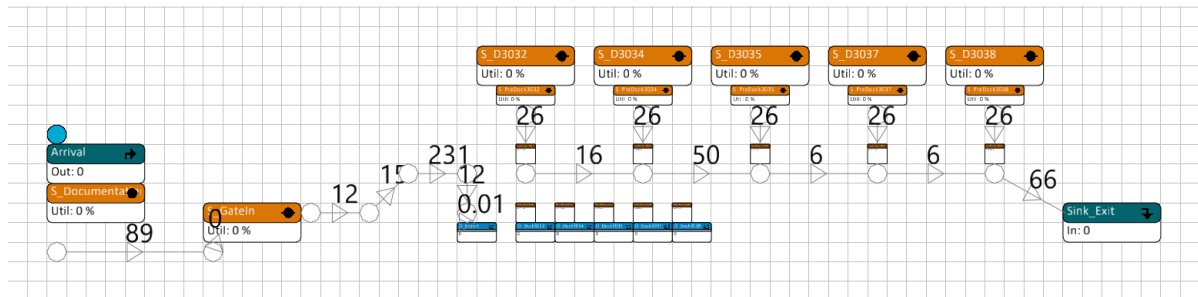


Figure 4.4: Enterprise Dynamics model layout

All nodes and links in the model are defined using user-based distances, which represent real distances even though the layout is not to scale. Vehicles drive at a constant speed of 1.4 m/s, providing realistic travel times between locations.

Trucks are generated in the model through an *Arrival List* atom, using cumulative inter-arrival times derived from historical data. Each truck receives a set of labels that define its routing, identification, and data collection properties. Upon creation, two labels are assigned to each truck:

1. routeRnd: A random number drawn from a uniform distribution between 0 and 100.
2. DockRoute: A label determining which dock route the truck will follow, based on the probability distribution observed in the historical data.

Formally, the assignment can be expressed as:

$$\text{routeRnd}_i \sim \text{Uniform}(0, 100)$$

$$\text{DockRoute}_i = \begin{cases} 1, & \text{if } \text{routeRnd}_i < 0.07, \\ 2, & \text{if } 0.07 \leq \text{routeRnd}_i < 13.8, \\ 3, & \text{if } 13.8 \leq \text{routeRnd}_i < 49.6, \\ 4, & \text{if } 49.6 \leq \text{routeRnd}_i < 79.3, \\ 5, & \text{otherwise.} \end{cases}$$

Subsequently, the truck receives a label indicating the dock door code:

$$\text{DoorCode}_i = \begin{cases} 3032, & \text{if } \text{DockRoute}_i = 1, \\ 3034, & \text{if } \text{DockRoute}_i = 2, \\ 3035, & \text{if } \text{DockRoute}_i = 3, \\ 3037, & \text{if } \text{DockRoute}_i = 4, \\ 3038, & \text{if } \text{DockRoute}_i = 5. \end{cases}$$

This probability distribution reflects the empirical dock usage share from the historical dataset, ensuring that the simulated routing of trucks mirrors real-world unloading patterns. The labels serve two primary purposes:

- DockRoute determines to which queue and pre-dock atom the truck is later routed.
- DoorCode allows performance indicators such as lead time, waiting time, and dock utilization to be recorded per physical door.

After creation, each truck first travels to *S_Documentation*, representing the documentation office. Here, a fixed cycle time of 90 seconds models the document verification process. Once the documentation step is completed, trucks proceed to *S_GateIn*, the gate entry atom, where a fixed cycle time of 10 seconds models security clearance and gate passage. Both locations are connected via node links using real travel distances, and trucks move at the constant speed of 1.4 m/s. After entering the yard, trucks travel to the export parking area, modeled by the atom *Q_Export*. The parking area has a combined capacity of 10 trucks. To improve realism and avoid blocking behavior, five individual parking queues are used. One for each dock:

- Q_Dock3032
- Q_Dock3034
- Q_Dock3035
- Q_Dock3037
- Q_Dock3038

The *Send To* function of *Q_Export* directs trucks to the correct dock-specific parking queue according to their assigned *DockRoute*. This design prevents unrealistic queuing situations that occurred with a single FCFS queue, where trucks destined for busy docks delayed those assigned to free docks. By separating the parking areas per dock, the model ensures independent queueing while keeping a shared yard capacity limit of 10 trucks. To enforce this total capacity limit, each queue's *Trigger on entry* and *Trigger on exit* contains the following logic:

```
Do(
  if(
    Content(AtomByName([Q_Dock3032], Model)) +
    Content(AtomByName([Q_Dock3034], Model)) +
```

```

    Content(AtomByName([Q_Dock3035], Model)) +
    Content(AtomByName([Q_Dock3037], Model)) +
    Content(AtomByName([Q_Dock3038], Model)) < 10,
    OpenOutput(AtomByName([Q_Export], Model)),
    CloseOutput(AtomByName([Q_Export], Model))
  )
)

```

This code continuously checks the total number of parked trucks and dynamically opens or closes the *Q_Export* output depending on whether capacity is available. When a dock becomes available, the first truck in line for that specific dock is sent from its parking queue to the corresponding pre-dock atom:

- S_PreDock3032
- S_PreDock3034
- S_PreDock3035
- S_PreDock3037
- S_PreDock3038

Each pre-dock atom has the following *On Entry* trigger:

```
CloseInput(c)
```

This ensures that only one truck can enter a pre-dock at a time. The cycle time at each pre-dock is defined as the sum of a fixed maneuvering time and a stochastic human handling delay. Docks 3032 and 3034 have, as defined in the assumptions, an extra cycle time of 255 seconds for MTD handling:

- Docks 3032 and 3034: $150 \text{ s} + 255 \text{ s} + \mathcal{N}(\mu, \sigma)$
- Docks 3035, 3037, 3038: $150 \text{ s} + \mathcal{N}(\mu, \sigma)$

This models both the physical maneuvering and the variability in human coordination time observed in the empirical data. After completing the pre-docking phase, the truck proceeds to its assigned dock atom:

- S_D3032
- S_D3034
- S_D3035
- S_D3037
- S_D3038

Each dock operates as a single-server process, where the cycle time follows a statistical distribution derived from the measured unloading times of that specific dock. To prevent overlapping truck entries, each dock contains the following *Trigger on exit* command:

```
OpenInput(in(1,c))
```

This reopens the input channel after the current truck has finished unloading, allowing the next waiting truck to enter. After the unloading process is complete, trucks follow their assigned exit path and leave the system through the exit gate, marking the end of the export flow. Data Recorders were placed behind the docks to automatically record the departure times of trucks. These Data Recorders were used to export simulation results, including lead times, waiting times, and dock occupancy rates directly to Excel for further analysis.

4.4. Verification and Validation

Verification and validation ensure that the simulation is both correctly implemented and a sufficiently accurate representation of the real system for its intended purpose. Rather than proving the model is “true,” the aim is to establish credible behavior within the scope of the study, using a structured process that combines conceptual checks, data checks and operational comparison [47, 50].

4.4.1. Model Verification

Model verification ensures that the computerized model correctly implements the conceptual logic and behaves as intended prior to empirical comparison. During simulation runs, animation and live monitoring were used to observe truck movements, queue formation, and dock utilization. Entities followed the expected path without loss or duplication. Tracing of trucks verified correct flow by recording timestamps at key steps such as arrival times at different elements and completion times. Lead times constructed from these stamps matched expected durations, confirming the correct separation of pre-dock, dock, and post-dock activities. Further, cycle-time parameters also resulted in realistic durations.

Extreme condition tests further confirmed logical stability:

- Unlimited dock capacity: queues disappeared; lead times reduced to manoeuvring and unloading only.
- No parking capacity: trucks were directed to the overflow queue.
- Low/high arrival rates: docks became idle or massive queues built.

4.4.2. Model Validation

Various validation methods were used throughout the validation process. Conceptual model validation assesses whether the assumptions, structure, and level of detail are appropriate for the study objectives. The conceptual design of the simulation was reviewed with operational experts and stakeholders. These reviews confirmed that the flow from documentation arrival to truck departure reflects current procedures, while excluding out-of-scope subsystems (warehouse interior and air-side logistics). The model captures the critical relationships between congestion, queuing, and dock utilization, providing a foundation for computer implementation.

Data validation ensured that empirical inputs used for model development and testing were accurate, consistent, and representative of normal export operations. The dataset contained documentation arrival times, earliest unloading times, and door allocations for 9,162 truck movements. All timestamp fields were verified to maintain chronological order ($\text{arrival} \leq \text{unload start} \leq \text{unload end}$) and physical feasibility (no negative or implausibly long durations). Records with incomplete or extreme values were removed, as these represented atypical operational disruptions outside the model's scope. This cleaning produced a consistent dataset representing regular export operations and a sound basis for calibration.

To verify realistic temporal behavior, two graphical analyses were performed. Figure 4.5 shows the hourly distribution of truck arrivals with strong afternoon and night activity, matching operational experience. Figure 4.6 presents the distribution of inter-arrival times; the right-skewed shape confirms a stochastic arrival process with many short intervals and occasional long gaps.

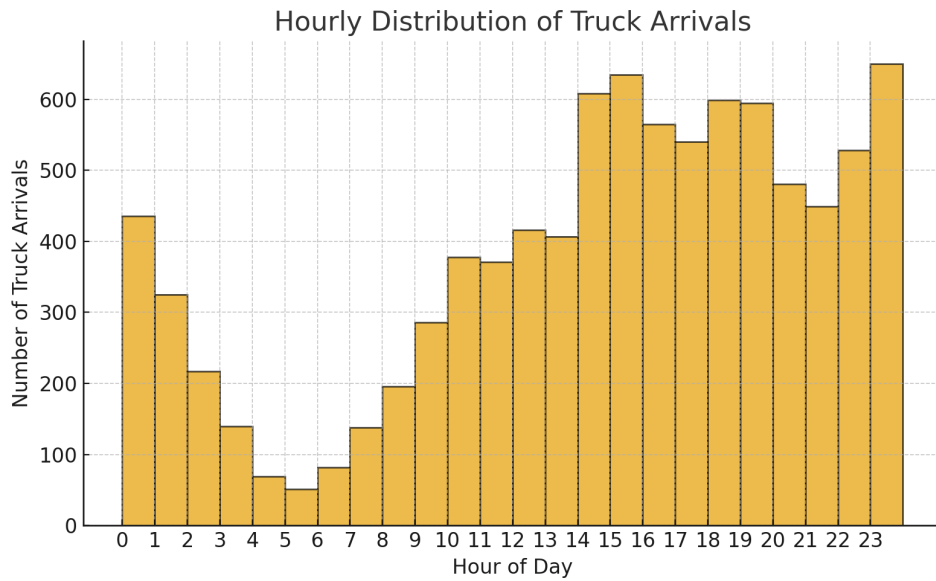


Figure 4.5: Hourly distribution of truck arrivals

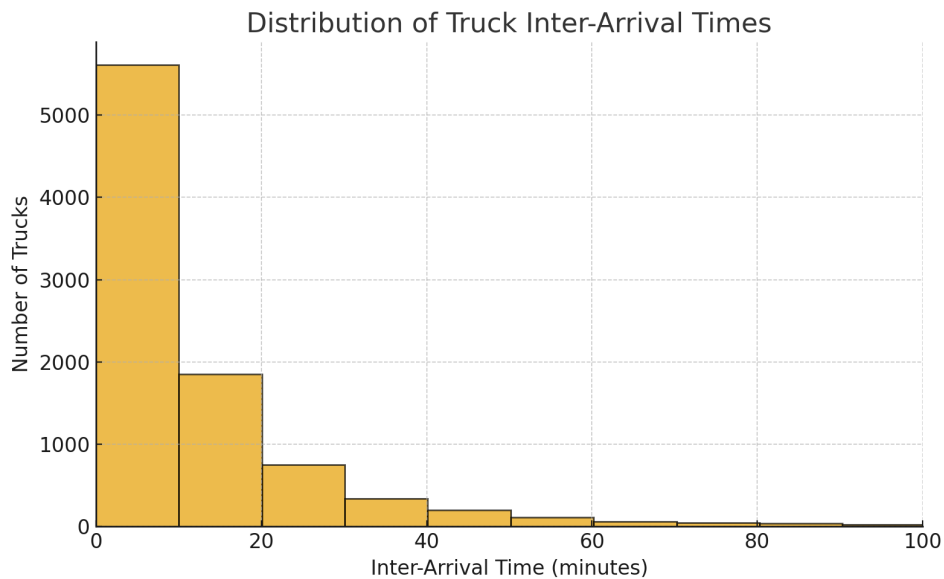


Figure 4.6: Distribution of truck inter-arrival times

Process times were validated separately for pre-dock waiting and unloading operations. Figures 4.7–4.16 display empirical waiting- and unloading-time distributions per dock. Figures 4.7 and 4.8 differ from the others because the number of trucks at Dock 3032 in 2024 was very low. Nevertheless, these observations were kept for completeness. Other waiting-time distributions are right-skewed, while unloading times cluster around short durations.

The model uses the historical data per dock to implement a form of human delay. This means that each dock gets its own delay factor based on real cycle times, so the simulation can reflect the typical human and operational delays that occur at that specific dock.

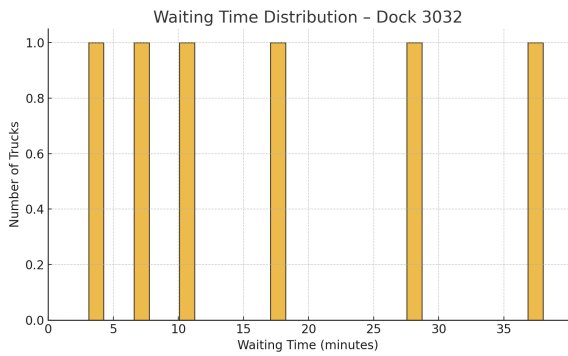


Figure 4.7: Waiting time distribution for Dock 3032

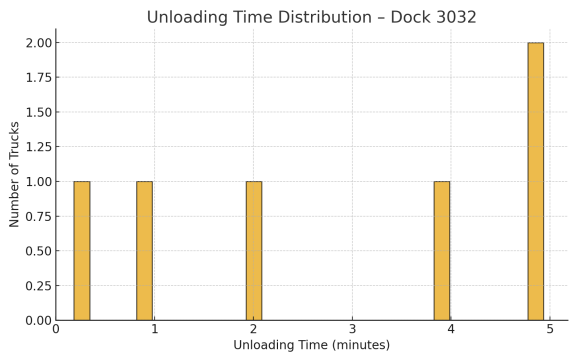


Figure 4.8: Unloading time distribution for Dock 3032

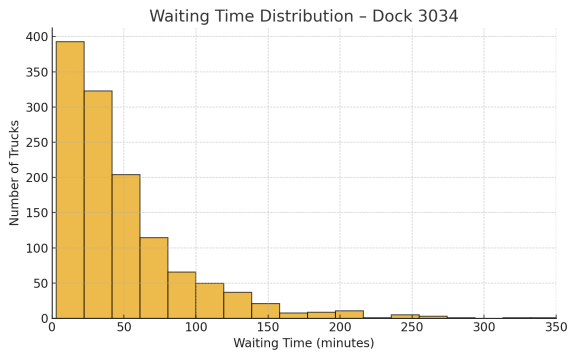


Figure 4.9: Waiting time distribution for Dock 3034

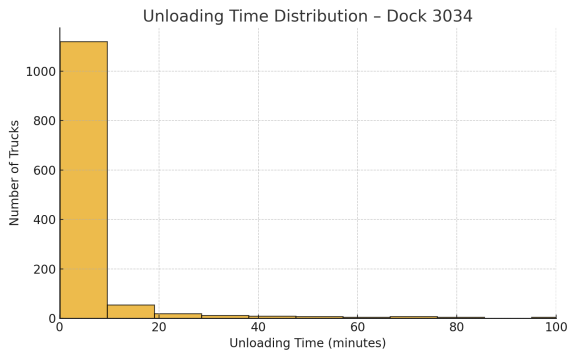


Figure 4.10: Unloading time distribution for Dock 3034

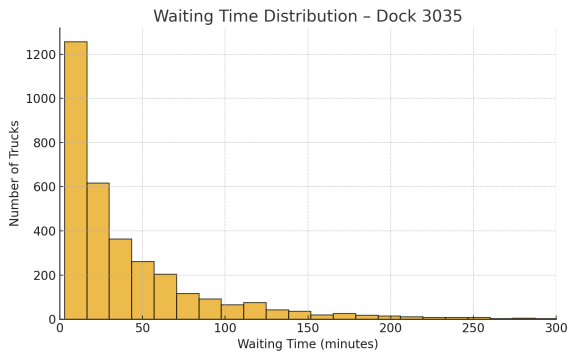


Figure 4.11: Waiting time distribution for Dock 3035

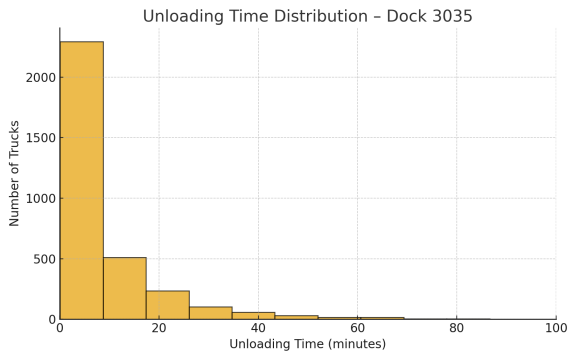


Figure 4.12: Unloading time distribution for Dock 3035

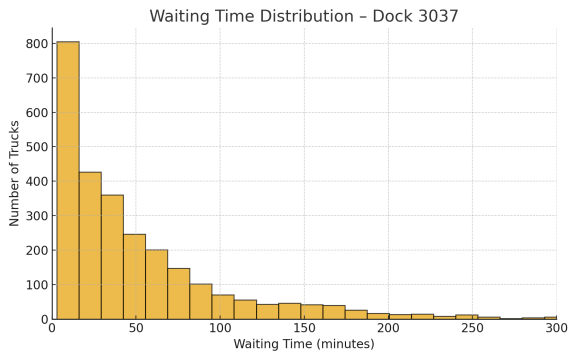


Figure 4.13: Waiting time distribution for Dock 3037

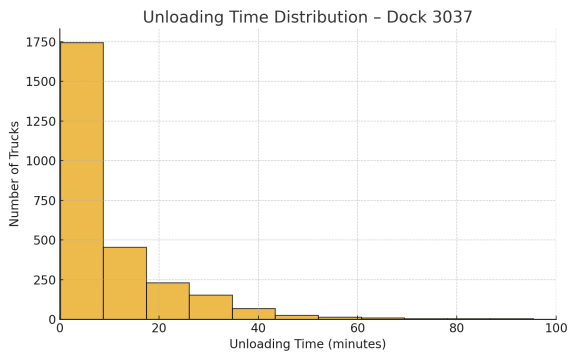


Figure 4.14: Unloading time distribution for Dock 3037

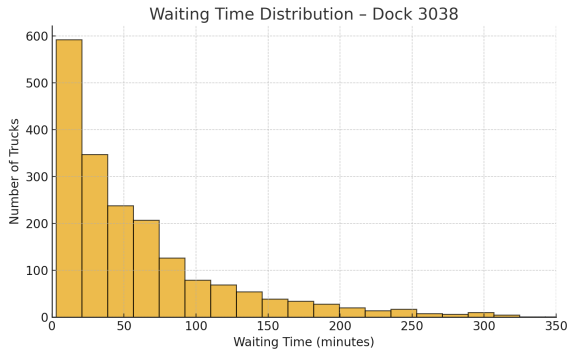


Figure 4.15: Waiting time distribution for Dock 3038

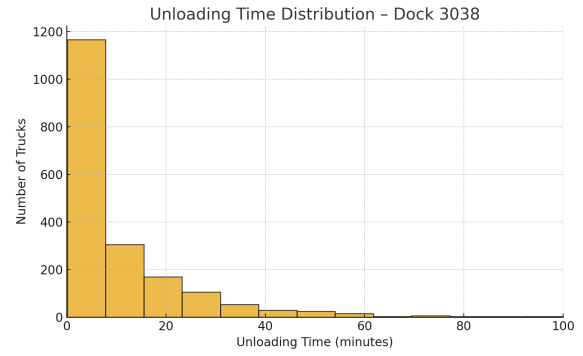


Figure 4.16: Unloading time distribution for Dock 3038

Overall, the empirical inputs satisfy both logical and behavioral consistency and provide a solid basis for model experimentation.

Operational validation assesses whether the simulation model reproduces the behavior of the real system with sufficient accuracy for the intended analysis. In this study, this was done through a black-box validation approach, where the simulated outputs were compared directly with historical performance. The key question was whether the simulated KPIs align with the observed values at the five docks. Because the model includes stochastic arrival and service processes, ten independent simulation runs were conducted to obtain statistically reliable KPI estimates. Ten replications provide a good balance between statistical accuracy and computational effort. With this number of runs, the variability across replications can be evaluated through standard deviations and confidence intervals, enabling a meaningful comparison with historical data. Table 4.1 presents the weighted mean, standard deviation, and 95% confidence intervals for each KPI, while Figure 4.17 visualizes the comparison between historical and simulated data.

Table 4.1: Historical Data vs. Simulation Data Averages & Statistics

Dock	KPI	Historical Data	Simulation Data	SD	95% CI ($\pm$)
3032	Lead Time [min]	33.05	40.75	6.16	4.33
	Waiting Time [min]	17.3	13.97	6.2	4.36
	Dock Occupancy [%]	0.0	0.00	0.0	0.0
3034	Lead Time [min]	65.23	57.14	5.26	3.26
	Waiting Time [min]	32.05	25.72	4.29	2.66
	Dock Occupancy [%]	6.2	6.30	0.7	0.33
3035	Lead Time [min]	61.8	61.53	2.6	1.61
	Waiting Time [min]	42.3	41.40	2.57	1.61
	Dock Occupancy [%]	21.7	21.97	0.6	0.27
3037	Lead Time [min]	71.26	63.68	6.55	4.06
	Waiting Time [min]	49.43	40.39	6.46	4.00
	Dock Occupancy [%]	20.6	20.74	0.7	0.32
3038	Lead Time [min]	77.70	71.35	3.74	2.32
	Waiting Time [min]	47.15	40.37	3.57	2.21
	Dock Occupancy [%]	15.3	15.21	0.5	0.22

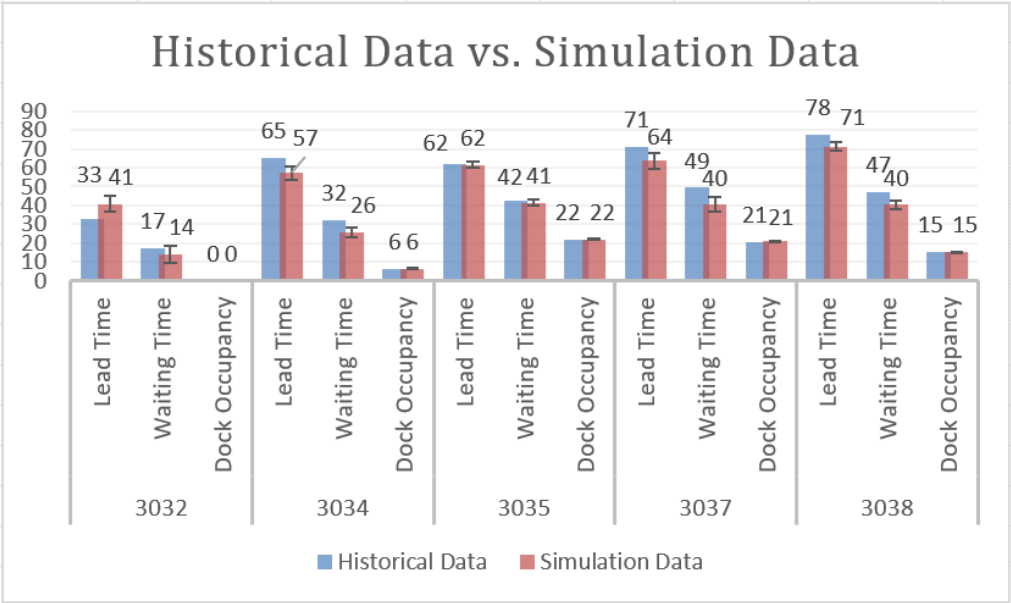


Figure 4.17: Comparison of historical and simulated KPI values

Overall, the confidence intervals indicate that most simulated averages fall close to the empirical values. Lead times and dock occupancies generally lie within or near the corresponding confidence bounds, suggesting that the model captures the essential queuing and resource utilization patterns of the real world. Waiting times, however, show a more consistent difference. The simulation underestimates observed waiting times across all docks but dock 3035. This can be explained by the fact that the number of trucks unloaded at dock 3035 is the highest meaning. The model was built in such a way that every dock had its own fictive queue. As dock 3035 had the highest number of trucks to handle, queues formed more frequently than other docks, increasing waiting times. Further, simplified decision rules are another reason why the model behaves this way and it indicates a small but systematic structural bias, where queues form less frequently or disappear faster in the model than in reality. Despite the minor bias, the effect is moderate, and the relative differences between docks are reproduced correctly, ensuring the model’s capability for comparative scenario analysis.

The averages reported in Table 4.1 are weighted means across all simulation runs. Although all runs follow the same arrival distribution, the exact number of processed trucks per dock varies due to the models stochastic nature. Weighting the runs by their number of observed events ensures that runs with more information contribute proportionally to the final KPI estimate, thereby improving statistical accuracy. This method avoids distortions that could arise from simple unweighted averaging and is consistent with best practices for simulation output analysis. Taken together, the results demonstrate that the model is sufficiently accurate for the study’s purpose. While minor structural biases exist, primarily the underestimation of waiting times, the simulation reliably represents key operational relationships and provides a valid foundation to explore alternative configurations.

4.5. Conclusion

To address sub-question 3: *How can a model be designed and developed to evaluate the identified improvement methods for dock and yard operations?*, this chapter showed how the landside export process was translated into a discrete-event simulation model. The model was built from the main flows, decision rules, and historical data so it reflects how trucks actually move through FB3.

Verification and validation were done together. During verification runs, the routing and queue behaviour looked logical and the model reacted correctly under extreme conditions. For the validation, the simulated KPIs were compared with the historical results. Lead times and dock occupancies were close to the real values, and most outcomes stayed within or near the expected confidence ranges.

Waiting times were slightly underestimated for most docks, except for Dock 3035. This dock handled by far the highest number of trucks in the dataset, which means queues formed more frequently and the model had more data points to match the real pattern. Because of this larger sample size, Dock 3035 showed a much closer fit between simulated and historical waiting times.

Overall, the model captures the main behavior of the real system, especially the long waiting before docking and the higher workload at the normal docks, while staying simple enough for scenario testing. It provides a reliable foundation for evaluating the improvement configurations in the next chapter.

Part IV

Evaluation

5

Scenario Analysis

Now that the model has been developed and validated, this chapter introduces the Evaluation phase. The simulation model is used to test several new configurations and measure their impact on the defined KPIs. By comparing these results to the current situation, Sub-question 4 is addressed.

5.1. Experimental Designs

To evaluate the potential dock and yard improvements, six new configurations are tested within the simulation environment. These configurations are derived from the design alternatives presented in Section 3.3, which were formulated based on literature findings and insights obtained through expert interviews. Each configuration represents an infrastructural or organizational adaptation, allowing the model to measure their effects on overall system performance. To assess the personnel limitations, each configuration is also tested to see how much personnel is needed in total. Per dock, 2 employees are needed which will be addressed in the result section of each configuration.

In case of an infrastructural configuration, like adding a dock. The average cycle time performance of the real world docks is taken for this new dock since the performance can not be guaranteed. The cycle times of all existing docks stays even throughout all configurations.

All configurations are evaluated under the same arrival scenario, which is based directly on historical truck arrival patterns and dock-specific cycle times. This scenario reflects the real arrival rates, peak periods, and workload distribution observed in practice, and therefore serves as the baseline loading of the system. Because it captures realistic operational pressure on the docks, this historical arrival pattern was chosen as the primary scenario for all configurations.

Only for the final configuration, slot-booking implementation, an additional arrival scenario was created. This second scenario represents a controlled and more evenly distributed arrival pattern, reflecting how scheduled time slots would structure the flow of trucks.

Although more alternative arrival scenarios could have been explored, the focus of this study is on evaluating improvements under realistic operational conditions. Therefore, the historical arrival scenario serves as the main reference throughout the analysis, with the slot-booking scenario added as the only configuration under a different arrival scenario.

The results of all simulation runs per configuration are listed in Appendix B. Table 5.1 shows the results of the base case simulation runs, which correspond with Table 4.1. To ensure that the performance indicators for each configuration are statistically reliable, all reported averages are calculated as weighted means. Each simulation run processes a different number of trucks due to stochastic variation in arrivals and cycle times. Weighting each run by the number of observed events prevents runs with fewer processed trucks from disproportionately influencing the final KPI values. This method aligns with best practices in simulation analysis and provides more accurate estimates than simple

unweighted averaging.

An important observation is the low dock occupancy rates. This is due to the fact that docks are not continuously constrained by arriving trucks. Although peak periods create moments of congestion, the overall arrival pattern is highly uneven, with long periods of less arrivals between peaks. As a result, docks remain idle for a significant part of the day. In addition, the unloading process itself is relatively fast compared during lower arrival periods compared to peaks. This is because the buffer zone is not congested when less trucks arrive. Meaning that trucks are processed quicker than they arrive during non-peak hours. Together, these factors lead to a structurally low dock occupancy.

Table 5.1: KPI Results and Weighted Averages for Base Case

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	6	40.75	13.97	0.00
3034	1263	57.14	25.72	6.30
3035	3296	61.53	41.40	21.97
3037	2698	63.68	40.39	20.74
3038	1899	71.35	40.37	15.21
Weighted Average Performance				
MTD Docks (3032, 3034)	–	57.06	25.66	6.27
Normal Docks (3035–3038)	–	64.63	40.81	19.92
System Overall	–	63.58	38.71	18.03

5.1.1. Configuration 1: Activation of Second MTD Dock

In the current situation, only one MTD dock is active due to personnel limitations. In this experiment, a second MTD dock is activated. This configuration increases the unloading capacity for ULD trucks and tests whether higher MTD throughput can decrease a potential bottleneck observed in the ULD handling process and reduce congestion at the conventional docks. Each dock needs two people to operate it. This configuration needs 10 personnel to

To implement this scenario, the model was adjusted to activate Dock 3032, which is rarely used under normal operations. The distribution logic for incoming MTD trucks was modified so that Docks 3032 and 3034 each received approximately half of all MTD arrivals. All other model parameters were kept identical to the base case.

Results

Table 5.2 shows the KPI results for Configuration 1. Activating Dock 3032 and splitting the MTD flow between two doors leads to a more balanced use of the MTD docks. Dock 3034 shows lower lead and waiting times compared to the base case, while Dock 3032 takes over part of the workload and reaches a modest occupancy level. On the MTD side, the average lead time decreases from about 57 minutes to 45.7 minutes, and waiting time drops from 25.7 minutes to 14.8 minutes.

The effect on the normal docks (3035–3038) is limited. Their average waiting time decreases only slightly, and dock occupancy remains close to the base case. At system level, the overall lead time reduces from 63.6 minutes to 61.4 minutes and waiting time from 38.7 minutes to 36.7 minutes, while overall dock occupancy remains around 18%. Since each dock requires two workers, this configuration needs 10 full-time employees to keep all doors operational. In summary, activating the second MTD dock improves the performance of the MTD flow but has a very low impact on the normal docks and the system as a whole.

Table 5.2: KPI Results and Weighted Averages for Configuration 1

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	644	45.06	15.22	3.00
3034	634	46.38	14.33	3.10
3035	3198	58.44	37.84	21.48
3037	2765	63.08	40.39	21.38
3038	1921	74.24	44.03	15.16
Weighted Average Performance				
MTD Docks (3032, 3034)	–	45.71	14.78	3.05
Normal Docks (3035–3038)	–	63.92	40.24	19.91
System Overall	–	61.38	36.69	17.55

5.1.2. Configuration 2: Replacement of Second MTD Dock by One Extra Normal Dock

This alternative scenario investigates the effect of redistributing capacity from MTD to normal docks. Instead of operating two MTD docks, the second one is deactivated and replaced with one additional normal dock. The objective is to examine whether this adjustment improves overall system throughput, particularly when the share of ULD cargo remains low.

In this experiment, one MTD dock (Dock 3032) was deactivated and replaced by an additional conventional dock (Dock 3039). This adjustment redistributes unloading capacity while keeping the total MTD share (13.8%) constant. The remaining 86.2% of trucks correspond to the normal ULD flow, which is now spread over four docks instead of three. Dividing this share evenly results in approximately:

$$\frac{86.2\%}{4} = 21.6\%$$

per dock. To maintain realistic variation in dock usage, the allocation was slightly weighted, assigning about 24% to Dock 3035, 22% to Dock 3037, and 20% to both Docks 3038 and 3039. This balanced distribution enables a controlled assessment of how adding one conventional dock affects system throughput and waiting times.

Results

Table 5.3 presents the KPI results for Configuration 2, in which the second MTD dock is converted into an extra normal dock (3039). The MTD flow remains concentrated at Dock 3034, with performance similar to the base case, while the conventional trucks are now distributed over four normal docks instead of three. This redistribution clearly reduces the pressure on the busiest doors.

The average lead time at the normal docks falls to 46.6 minutes and the average waiting time to 22.8 minutes. Compared to the base case, this corresponds to roughly a 20–25% reduction in lead time and about a 40% reduction in waiting time for the conventional flow. Dock 3039 operates with a relatively low waiting time and moderate occupancy, which helps to stabilise the overall process.

On a system level, the overall lead time decreases from 63.6 minutes in the base case to 47.4 minutes, and the average waiting time drops from 38.7 minutes to 22.7 minutes. Dock occupancy at system level decreases to about 13%, which means that there is more capacity in the system. Since each dock is staffed by two workers, this configuration still requires 10 full-time employees. Overall, Configuration 2 shows a clear improvement in performance, mainly driven by the additional normal dock and the more even distribution of the ULD workload.

Table 5.3: KPI Results and Weighted Averages for Configuration 2

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3034	1269	52.23	21.41	5.96
3035	2207	41.43	20.52	14.72
3037	2004	46.24	22.83	15.18
3038	1840	68.25	36.33	14.49
3039	1842	32.09	11.34	12.36
Weighted Average Performance				
MTD Dock (3034)	–	52.23	21.41	5.96
Normal Docks (3035–3039)	–	46.55	22.77	14.25
System Overall	–	47.41	22.67	13.10

5.1.3. Configuration 3: Increasing Number of Normal Docks to 4

In this configuration, the number of simultaneously active docks at FB3 is increased to four doors. This experiment evaluates to what extent an additional door decreases truck waiting times and increase overall throughput, while also monitoring potential yard congestion effects. The share of arriving trucks assigned to the normal docks is kept identical to the distribution used in Configuration 2. The MTD share remains fixed at 13.8%, meaning that 86.2% of all trucks are allocated to the conventional flow. This flow is divided across the four active normal docks using the same proportions as before.

Results

Table 5.4 shows the KPI outcomes for Configuration 3, where both MTD docks are active and four normal docks are used for the conventional flow. The MTD performance is similar to Configuration 2 in terms of averages, while the ULD workload is now spread over Docks 3035, 3037, 3038, and 3039.

Compared to Configuration 2, the conventional docks experience a slight further reduction in average lead time and a small increase in waiting time, resulting in a average lead time of 47.7 minutes and waiting time of 23.9 minutes. Dock 3038 continues to show higher lead and waiting times and a somewhat higher occupancy, which can be explained by its original stochastic cycle time. The other normal docks operate with shorter queues and moderate occupancy levels.

At system level, the overall lead time is 48.3 minutes and the waiting time 23.5 minutes, both clearly better than the base case and close to Configuration 2. Overall dock occupancy remains around 13%. Because this configuration uses six active docks, 12 full-time employees are needed. The results indicate that adding a fourth normal dock and keeping the second MTD dock active stabilizes the system further, but the additional improvement compared to Configuration 2 is limited relative to the extra labor required.

Table 5.4: KPI Results and Weighted Averages for Configuration 3

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	6	37.43	10.71	0.00
3034	1275	52.24	21.37	6.20
3035	1983	37.27	16.83	13.30
3037	1986	45.16	21.65	15.30
3038	1963	71.59	40.51	15.90
3039	1948	36.70	16.51	12.90
Weighted Average Performance				
MTD Docks (3032, 3034)	–	52.17	21.32	6.17
Normal Docks (3035–3039)	–	47.67	23.86	14.35
System Overall	–	48.30	23.51	13.21

5.1.4. Configuration 4: Increasing Number of Normal Docks to 5

In this strategy, the number of simultaneously active docks at FB3 is increased to five docks. This experiment evaluates to what extent an additional door decreases truck waiting times and increase overall throughput, while also monitoring the utilization of buffer capacity and potential yard congestion effects. As in the previous configuration, the total share of MTD and conventional trucks remains unchanged: 13.8% of arrivals are routed to the MTD dock, while 86.2% belong to the conventional ULD flow. In this experiment, the 86.2% conventional share is redistributed across five normal docks. Dividing this evenly results in:

$$\frac{86.2\%}{5} = 17.24\%$$

per dock. This allocation ensures that each normal dock receives an equal portion of the ULD flow, allowing the experiment to isolate the operational effect of increasing the number of active doors from four to five under the same overall arrival pattern.

Results

Table 5.5 presents the KPI outcomes for Configuration 4, in which five normal docks are used alongside the two MTD docks. The MTD performance remains comparable to earlier configurations, while the conventional flow is now distributed evenly across Docks 3035, 3037, 3038, 3039, and 3040.

This leads to a clear improvement in the normal dock KPIs. The average lead time at the normal docks decreases to 40.3 minutes and the average waiting time to 17.1 minutes. Compared to the base case, this represents a reduction of more than one third in lead time and more than half in waiting time for the conventional flow. Dock occupancy at the normal docks stabilises around 11–13%, indicating that the workload is well spread but that there is also more spare capacity.

At system level, the overall lead time falls to 42.0 minutes and the waiting time to 17.7 minutes, both a strong improvement compared to the base case. System-wide dock occupancy drops to around 10.6%, reflecting the larger number of doors in use. With seven active docks, 14 full-time employees are required. Configuration 4 therefore offers a substantial reduction in waiting times and more robust operations, but at the cost of higher labour input and lower average occupancy per dock.

Table 5.5: KPI Results and Weighted Averages for Configuration 4

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	7	32.46	6.04	0.00
3034	1249	52.50	21.71	6.10
3035	1554	33.71	13.42	10.31
3037	1593	38.72	15.49	11.91
3038	1586	59.90	28.68	13.11
3039	1580	33.33	13.28	10.31
3040	1434	35.03	14.10	10.67
Weighted Average Performance				
MTD Docks (3032, 3034)	–	52.39	21.62	6.07
Normal Docks (3035–3040)	–	40.27	17.07	11.28
System Overall	–	41.96	17.70	10.55

5.1.5. Configuration 5: Increasing Number of Normal Docks to 6

In this strategy, the number of simultaneously active docks at FB3 is increased to six docks. This experiment evaluates to what extent an additional door decreases truck waiting times and increase overall throughput, while also monitoring the utilization of buffer capacity and potential yard congestion effects.

As in the previous configurations, the total share of MTD and conventional trucks remains unchanged: 13.8% of arrivals are routed to the MTD dock, while 86.2% belong to the conventional ULD flow. In this experiment, the 86.2% conventional share is redistributed across six normal docks. Dividing this evenly results in:

$$\frac{86.2\%}{6} = 14.37\%$$

per dock. This even allocation ensures that each dock receives a similar workload, allowing the experiment to isolate the effect of increasing the number of active doors from five to six under the same overall arrival pattern.

Results

Table 5.6 shows the KPI outcomes for Configuration 5, where six normal docks are used in addition to the two MTD docks. The MTD performance remains largely unchanged, while the conventional workload is now spread over Docks 3035, 3037, 3038, 3039, 3040, and 3041.

The effect on the normal docks is a further reduction in lead and waiting times. The average lead time decreases to 35.6 minutes and the average waiting time to 13.0 minutes. Relative to the base case, this corresponds to roughly a 40% reduction in lead time and more than 60% reduction in waiting time for the conventional flow. However, normal dock occupancy drops to around 9%, which indicates that the system now has considerable spare capacity.

On a system level, the overall lead time is 38.1 minutes and the average waiting time 14.2 minutes. Compared to the base case, this means that lead time is reduced by about 40% and waiting time by more than 60%. At the same time, system-wide dock occupancy falls below 9%. With eight active docks, this configuration requires 16 full-time employees. Configuration 5 therefore delivers strong performance improvements, but at the cost of low dock utilization and a relatively high labor requirement per unit of throughput.

Table 5.6: KPI Results and Weighted Averages for Configuration 5

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	5	32.24	6.08	0.00
3034	1263	53.54	22.16	6.51
3035	1335	32.53	12.02	9.12
3037	1307	35.89	12.77	9.81
3038	1302	50.32	19.18	10.40
3039	1305	30.90	10.76	8.70
3040	1318	32.87	11.90	8.81
3041	1328	31.25	11.21	8.81
Weighted Average Performance				
MTD Docks (3032, 3034)	–	53.46	22.10	6.48
Normal Docks (3035–3041)	–	35.59	12.96	9.27
System Overall	–	38.06	14.22	8.89

5.1.6. Configuration 6: Slot Booking Implementation

This scenario introduces a digital slot-booking system that regulates the inflow of trucks based on pre assigned arrival windows. To implement this, a regulated arrival pattern in which trucks are distributed across the day based on fixed arrival windows is necessary. The slot mechanism was calibrated directly to the empirical arrival data. The dataset contains 9,162 arrivals over 93 days, corresponding to an average of approximately 99 trucks per day. The required mean inter-arrival time to reproduce this

daily volume and keep up with demand is therefore

$$\text{Mean Interarrival} = \frac{86,400 \text{ s}}{99} \approx 880 \text{ s (14.7 min)},$$

which represents the average slot interval needed to match the real system's demand.

Because trucks do not always arrive exactly at their assigned time, the slot system takes into account early and late arrivals. This is implemented in Enterprise Dynamics using a triangular distribution around the calculated slot interval:

$$\text{Interarrival} \sim \text{Triangular}(880, 704, 1056)$$

introducing a controlled spread of approximately $\pm 20\%$ around the mean. This creates a smooth non-deterministic arrival flow that eliminates peak-hour congestion while keeping operational variability intact. All other model logic remains unchanged, ensuring that differences in waiting time, lead time, and door utilization can be attributed directly to the introduction of the slot-booking system.

Results

Table 5.7 presents the KPI outcomes for Configuration 6, in which the number and type of docks remain the same as in the base case, but arrivals are regulated through a slot-booking mechanism. The controlled arrival pattern reduces peak congestion and spreads the workload more evenly across the day.

For the MTD docks, the average lead time decreases to 40.4 minutes and the average waiting time to 10.1 minutes. For the normal docks, the average lead time drops to 36.6 minutes and the waiting time to 12.0 minutes. Compared to the base case, this means that lead time at the conventional docks is reduced by more than 40% and waiting time by roughly 70%. Dock 3035 and Dock 3037 show relatively high occupancy levels (around 20–22%), which in this context reflects an efficient and continuous use of these docks rather than congestion.

At system level, Configuration 6 achieves an overall lead time of 37.1 minutes and an average waiting time of 11.7 minutes. This is the best performance of all configurations, while the overall dock occupancy remains around 17%, close to the base case but with much lower delay. Since the number of docks is unchanged, 10 full-time employees are sufficient, the same order of magnitude as in the current situation. In summary, the slot-booking system increases the efficiency of existing docks by smoothing arrivals, achieving short lead and waiting times without adding physical capacity.

Table 5.7: KPI Results and Weighted Averages for Configuration 6

	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Per-Dock KPI Results				
3032	6	32.55	5.99	0.00
3034	1256	40.40	10.16	6.00
3035	3300	33.31	12.30	21.70
3037	2722	35.14	10.57	19.20
3038	1879	44.32	13.39	14.60
Weighted Average Performance				
MTD Docks (3032, 3034)	–	40.36	10.14	5.97
Normal Docks (3035–3038)	–	36.56	11.96	19.15
System Overall	–	37.08	11.71	17.34

5.2. Summary of Results

The simulation results provide a clear overview of how each configuration affects dock performance and yard congestion at FB3. In the base case, the normal docks (3035–3038) carry almost all of the workload, while the MTD docks are only lightly used. Dock 3032 is practically inactive. Most of the total

lead time is caused by trucks waiting before they can dock, especially during the peak moments in the afternoon and evening. At the same time, the average dock occupancy remains relatively low because arrivals are uneven across the day and unloading is comparatively fast during quieter periods.

Configuration 1, where the second MTD dock is activated, mainly improves the performance of the MTD flow. The MTD workload is spread more evenly and waiting times at Dock 3034 decrease. However, the impact on the normal docks and on the overall system stays small. Lead times and waiting times improve only slightly compared to the base case, while the number of active docks and required staff remain the same. This confirms that increasing MTD capacity is not a key lever, given the relatively small MTD share.

A more visible improvement appears in Configuration 2, where the second MTD dock is replaced by an additional normal dock. This redistributes the conventional ULD flow across four normal docks instead of three. Average lead time and waiting time at the normal docks decrease clearly, and overall system waiting time is reduced by around 40% compared to the base case. The new dock takes pressure away from the busiest doors and helps stabilise operations. However, system-wide dock occupancy falls, indicating that some extra capacity remains unused.

Configurations 3, 4, and 5 gradually increase the number of normal docks up to six in total. Each additional dock further reduces average lead and waiting times, but the size of the improvement becomes smaller with every step. Configuration 4 already brings a substantial reduction in waiting time, while Configuration 5 delivers the lowest waiting times of all capacity-based scenarios. At the same time, dock occupancy decreases as more doors are added, which means that the system becomes less efficient in terms of capacity use. More docks also require more staff, since each dock is operated by two workers. This raises the operational cost per unit of throughput. In addition, it is uncertain how realistic the highest-capacity configurations are when considering the capacity of the pre-dock area. Even if more docks are available, the buffer zone still limits how quickly freight can be moved into the warehouse. During strong arrival peaks this space is quickly congested, so simply adding doors does not automatically solve the underlying structural constraint.

Configuration 6, the slot-booking scenario, shows the strongest structural improvement. By smoothing the arrival pattern, peak congestion is reduced at its source. This leads to much lower waiting times and shorter lead times, while dock utilization at the normal docks remains relatively high. The key advantage is that this is achieved without constructing new docks. The required investment is mainly related to planning, digital support tools, and cooperation with forwarders. Reducing waiting times also benefits the forwarders directly, since drivers spend less time idle and labour costs on their side decrease. This creates a mutual gain: KLM achieves a more stable and predictable landside flow, while forwarders face lower operational costs.

Overall, the results show that adding normal docks improves performance, but with decreasing marginal benefits and increasing labor and infrastructure costs. Dock occupancy drops as more doors are added, which indicates that the system gradually becomes over-dimensioned. In contrast, slot-booking makes better use of existing capacity and achieves the best combination of low lead time, low waiting time, and dock occupancy. Regulating arrivals therefore appears more cost-effective than expanding the number of docks under the current hall layout.

5.3. Conclusion

To address sub-question 4: *To what extent do the proposed improvements increase dock & yard performance?*, this chapter compared six new configurations to the current situation.

Figure 5.1 summarizes the main KPI outcomes for all configurations. These values are the final weighted averages of the system overall performance per configuration. Weighted values are used because of the different number of trucks arriving at each dock due to the stochastic nature of the model. All scenarios perform better than the base case to some extent. The configurations that add normal docks (Configurations 2 to 5) show a clear pattern: as the number of doors increases, both lead time and waiting time decrease. Compared to the base case, the best capacity scenario (Configuration 5) reduces average lead time by roughly 40% and average waiting time by more than 60%. However, this

comes at the cost of lower dock occupancy and higher staffing needs. With many docks operating in parallel, the system has considerable spare capacity and requires up to 16 full-time employees to keep all doors staffed.

Configuration 6, with the slot-booking system, outperforms all other scenarios in terms of the balance between performance and resource use. It achieves the lowest overall lead time (around 37 minutes) and the lowest waiting time (around 12 minutes), while using the same number of docks as the base case and a similar level of dock occupancy. The docks, especially the busiest normal doors, are used more intensively but in a controlled way, without creating long queues. This means that throughput is increased not by adding capacity, but by using the existing capacity more efficiently through a smoother arrival pattern.

Overall, the experiments show that both capacity expansion and arrival regulation can reduce yard congestion and improve dock throughput. Increasing the number of normal docks is effective, but the marginal benefit of each additional dock becomes smaller, and the required labor and infrastructure investment become higher. Under the current hall layout and buffer capacity, a higher number of docks is also difficult to obtain in practice. In contrast, the slot-booking configuration delivers the strongest improvement in lead time and waiting time with relatively low structural cost and without changing the physical layout of FB3.

	Lead Time [min]	Waiting Time [min]	Dock Occupancy [%]
Base Case	63,58	38,71	18,03
Configuration 1	61,38	36,69	17,55
Configuration 2	47,41	22,67	13,10
Configuration 3	48,30	23,51	13,21
Configuration 4	41,96	17,70	10,55
Configuration 5	38,06	14,22	8,89
Configuration 6	37,08	11,71	17,34

Figure 5.1: Overview of KPI Results

Part V

Conclusion

6

Conclusions & Discussion

Now that all configurations have been evaluated, this chapter introduces the Conclusion phase. The results from the scenario analysis are used to answer the main research question and reflect on the performance of the proposed improvements. By interpreting these findings in relation to the research objectives, the Main Research Question is answered.

6.1. Conclusions per Research Question

The answer to the main research question is derived from all sub-questions. Therefore, the conclusions to the sub-questions are first repeated before formulating the main research question conclusion.

Sub-Question 1

What are the main causes of dock and yard congestion in air cargo logistics?

The analysis in Chapter 2 showed that congestion mainly results from sharp arrival peaks combined with limited infrastructure. Most forwarders deliver their shipments shortly before flight cut-off times, which concentrates demand in a few intense periods that exceed available dock and yard capacity.

Infrastructure constraints amplify the problem. The buffer zone fills up quickly, slowing unloading, and the yard cannot accommodate all incoming trucks, leading to queues and blockages.

Several operational factors contribute as well. Slow or inconsistent data exchange and manual checks delay processing, and limited communication with drivers leaves them uncertain about waiting times.

There is also little coordination between forwarders and the terminal, making it difficult to evenly spread arrivals.

Sub-Question 2

Which methods can be applied to improve dock & yard performance in air cargo operations?

The conclusion of Chapter 3 shows that there are several practical methods to improve dock and yard performance. The best approach for this system is to use discrete-event simulation to test different operational and infrastructural changes, given the terminal's high level of uncertainty and time-dependent processes.

From the literature and interviews, a few types of interventions stood out. First, managing truck arrivals, for example, with slot booking or better coordination with forwarders, helps spread the workload and reduce the big peaks. Second, using extra capacity, such as activating more normal docks or replacing

an MTD dock with a standard dock, can increase unloading performance. Third, overflow and buffer strategies can help during very busy periods, so operations do not stall when the yard is full.

Also, improvements in communication and information flow, like giving drivers clearer updates or improving data exchange between systems, can reduce delays caused by confusion or missing information.

In short, Chapter 3 shows that improvements can come from spreading arrivals, increasing or reallocating dock capacity, improving communication, and using DES to compare these options in a structured way.

Sub-Question 3

How can a model be designed and developed to evaluate the identified improvement methods for dock and yard operations?

Chapter 4 showed how the landside export process can be modeled as a discrete-event simulation by focusing on three core drivers of congestion: truck arrivals, yard capacity, and dock operations. The model was based on a clear conceptual structure and supported by operational data, ensuring that the main flows and delays at FB3 are represented accurately enough for analysis.

Verification and validation indicated that the model reasonably reflects the real system. Lead times and dock occupancies aligned with historical values, and differences between docks were reproduced effectively. Waiting times were slightly lower across most docks, except at Dock 3035, where the larger dataset enabled the model to better match the observed queuing behaviour.

Overall, Chapter 4 demonstrated that the DES model captures the key bottlenecks in the operation and can be used confidently to compare improvement scenarios.

Sub-Question 4

To what extent do the proposed configurations increase dock & yard performance?

The results in Chapter 5 show that the proposed configurations mainly affect performance by reducing the time trucks spend waiting before unloading, which is the largest contributor to total delay in the base case.

Configuration 1, where the second MTD dock is activated, adds little value. This is expected, since the MTD flow is small and does not limit the system.

A clearer effect appears in Configuration 2, where the unused MTD dock is replaced by a normal dock. Average waiting time drops by roughly one third, and overall lead time decreases in a similar proportion. The workload across the normal docks becomes more balanced, although occupancy naturally falls due to the added capacity.

Configurations 3, 4, and 5 extend this pattern: additional normal docks continue to lower waiting time, but the benefit diminishes with each step. At the highest capacity level, yard congestion is very low, yet dock occupancy becomes low because the number of docks might be too large.

Configuration 6, the slot-booking scenario, reaches the highest performance without adding infrastructure. A smoother arrival pattern reduces peak pressure, driving waiting times to very low levels while keeping dock occupancy close to the base case.

Overall, the results show that adding normal docks increases throughput but with diminishing returns, while slot booking delivers a major improvement at much lower cost. Adjusting MTD capacity has minimal influence due to its small share of the flow.

Main Research Question

How can landside air cargo terminal operations be optimized to increase dock & yard performance?

The results of this research show that dock and yard performance at FB3 can be improved mainly by reducing the long waiting times before trucks can start unloading and by creating a smoother and more balanced use of the available docks. In the base case, the average lead time is about 64 minutes and trucks wait on average almost 39 minutes before they can dock, while overall dock occupancy is only around 18%. This means that trucks experience substantial delays even though the docks are far from fully utilized on average.

The scenarios with additional normal docks show clear improvements in these KPIs. Replacing the unused MTD dock with a normal dock (Configuration 2) reduces the overall lead time to about 47 minutes and the average waiting time to around 23 minutes, a reduction of roughly 40% in waiting time compared to the base case. Adding more normal docks up to a total of six (Configuration 5) brings the overall lead time down further to about 38 minutes and the average waiting time to roughly 14 minutes. However, these gains come with a drop in average dock occupancy to below 9% and a higher labour requirement, which shows that the system benefits most from the first few layout changes, while later expansions mainly add spare capacity.

At the same time, the slot-appointment configuration (Configuration 6) shows that performance can also be improved by changing the arrival pattern instead of adding doors. With the slot-booking mechanism, the overall lead time decreases to about 37 minutes and the average waiting time to around 12 minutes, which is even slightly better than the highest-capacity configuration. In this scenario, overall dock occupancy remains close to 17%, similar to the base case, but with much shorter time on site. This indicates that a smoother and more even arrival pattern can unlock the existing dock capacity and reduce peak congestion without building extra docks.

Across all scenarios, increasing MTD capacity has almost no effect on system performance. The MTD share is only 13.8% of all arrivals, and activating a second MTD dock mainly improves MTD waiting times from about 26 minutes to roughly 15 minutes, without a noticeable change in overall lead time or waiting time. This confirms that the main bottlenecks are located at the normal docks rather than in the MTD process.

Overall, the study shows that improvements at FB3 can come from two directions: a better balance in normal dock capacity and a smoother arrival flow. Quantitatively, the best-performing scenarios reduce average waiting times around 65-70 % compared to the base case, while either maintaining dock occupancy at a similar level (slot booking) or accepting lower occupancy in exchange for additional physical capacity (extra docks). The simulation results form the basis for the practical recommendations in the next section.

6.2. Practical Recommendations for KLM Cargo

The simulation results show that there are two main directions to improve dock and yard performance at FB3: adjusting the physical dock capacity or managing the arrival pattern of trucks. Based on the findings, the following recommendations can be made.

Increasing normal dock capacity

Replacing the unused MTD dock with a normal dock already gives a clear improvement in waiting times. Adding more normal docks (up to five or six) continues to reduce congestion, although the gains become smaller each time. More normal docks make the system more flexible during busy periods and reduce the pressure on the busiest doors.

However, additional docks require investment in construction, equipment, and possibly extra staff to operate them. Because of these higher costs and the decreasing returns, it is important to evaluate if the improvement is worth the investment. One feasible option is to explore the possibility of using FB2 as extra unloading capacity after 22:00, when that building becomes available. This would allow extra capacity during peak hours without building completely new docks at FB3.

Introducing a slot-booking system

The slot-booking scenario performs even better than the high-dock-capacity scenarios, even though no extra docks are added. By spreading arrivals more evenly across the day, peak congestion becomes much lighter and waiting times drop significantly. This makes the process more predictable and reduces the pressure on the yard during busy hours.

The main advantage is that slot-booking requires much lower investment compared to building new docks. It mainly involves planning adjustments, digital support tools, and cooperation with forwarders. If compliance can be ensured, slot-booking offers a strong improvement with relatively little cost and fast implementation.

As lead time and waiting time in the slot-booking system are the lowest, another benefit rises. Since drivers are often paid by the hour, long waiting times directly increase labour costs on the forwarder side. By reducing queueing at the docks, KLM effectively lowers the time trucks spend idle on the premises. This creates a mutual benefit: KLM achieves a smoother and more predictable landside flow, while forwarders experience reduced labour expenses, strengthening the incentive to participate in a slot-booking system.

Improving information sharing and communication

Some congestion can already be reduced by giving forwarders better information about expected peak periods and by providing drivers with clearer updates about expected waiting times. This helps prevent unnecessary clustering of arrivals around certain hours.

Monitoring the balance between capacity and arrivals

Even after improvements, the effectiveness of the system depends on how truck demand develops. If arrival peaks increase in the future or if more cargo flows through FB3, additional dock capacity might still be needed. Regularly repeating scenario testing can help determine whether the chosen strategy still fits the operational situation.

6.3. Scientific Contribution

The goal of this study was to understand the causes of congestion at the FB3 docks and yard, to build a model that represents the real landside process, and to test how different interventions influence performance. These goals guide the scientific contribution of the research.

The literature shows that most academic work on air cargo focuses on warehouse operations, ULD handling, or flight-side planning. The landside process, where trucks enter, wait, and unload, receives far less attention. This left an important research gap: the combined effect of infrastructural and operational changes on landside congestion is largely unknown, and no integrated modeling approach exists to test these changes together.

This study fills that gap by developing a discrete-event simulation model that covers the full driver journey from documentation to unloading. The model links truck arrivals, yard capacity, and dock operations in one framework, which is not commonly found in the air cargo literature. By using detailed empirical data, the model provides an grounded representation of how queues form and how bottlenecks develop during peak periods.

Scientifically, the research shows how arrival patterns and dock configuration shape congestion. The model also provides structured insight into why measures such as extra MTD capacity have almost no effect, while changes in normal dock capacity or arrival spreading can strongly influence the system, albeit decreasing gains per extra dock. This contributes to both DES modelling practice and the academic understanding of landside terminal behavior.

Overall, the study provides a validated and data-driven modeling approach for landside air cargo operations and offers new insight into how infrastructural and operational interventions affect performance, a topic that has received limited attention in prior research.

6.4. Limitations

The model can reproduce the real-world situation. However, it also has its limitations. The first limitation is that it tends to underestimate specific performance measures. Despite the usefulness of the simulation model, several limitations should be acknowledged. The most important one is that the model tends to underestimate specific performance measures, especially lead time and truck waiting time. When comparing simulated outputs with historical data, the simulations often produce lower values, even when confidence intervals are taken into account.

This gap between the model and reality likely stems from simplifications necessary during modeling. Real operations contain many small sources of delay that are hard to capture. For example, human behavior, communication issues, disruptions, or small administrative tasks can all slow down the process. These elements do not always appear in the data and are therefore not represented in the model. As a result, the simulated system runs more smoothly than it does in practice.

Another factor is the way processing times and arrival patterns were modelled. They rely on statistical distributions and averages, which reduce the variability relative to the real system. Less variability often means shorter queues and lower waiting times in simulation. This is a common outcome in discrete-event models and not necessarily a sign of incorrect modelling, but it does limit how precisely the results reflect the actual operation. Some model assumptions also contribute to this trend. The availability of resources is assumed to be stable, queues follow rules, and exceptional situations are not included. These choices make the model easier to handle and analyse, yet they also remove inefficiency that do exist in real life.

Overall, the model performs well for studying patterns, relative differences between scenarios, and general system behaviour. However, the absolute values should be interpreted with care. The real system is more complex and more variable than the simulated one, and future work could focus on incorporating more detailed operational behaviour or additional forms of uncertainty to reduce this gap.

6.5. Future Research

This study used one arrival pattern based on the historical data from the busiest months. Future research could explore additional arrival patterns or implement stochastic arrivals instead of a fixed sequence. This would provide insight into how robust the proposed improvements are under varying demand conditions.

The simulation model in this thesis was intentionally simplified to focus on the key elements of the yard and dock process. While this level of abstraction supported a clear comparative analysis, it also contributed to a systematic underestimation of certain KPIs, especially waiting time. Future modelling work could incorporate more detailed control rules, more detailed human behaviour, or additional sources of human delay to narrow this gap and better reflect operational reality.

Several technological options that were outside the scope of this study also merit further investigation. Examples include partial automation, real-time dock-assignment tools, advanced scheduling algorithms, and digital yard-management platforms. Evaluating these technologies in a simulation environment could help quantify their potential contribution to reducing congestion and increasing reliability.

The current model focuses primarily on the yard and dock areas. However, the interaction between the yard, the buffer zones, and internal warehouse processes can also influence congestion patterns. Extending the model to include these components would allow researchers to examine how delays inside the warehouse propagate toward the yard and whether shifting workload between areas could stabilize operations.

A cost-benefit analysis could further support decision-making by comparing the financial impact of each configuration with its operational benefits. This would help determine which improvements offer the highest value relative to required investment.

Finally, repeating the scenario analysis with forecasted cargo volumes or alternative demand scenarios would support long-term planning. As volumes grow or truck behaviour changes, the effectiveness of the selected configuration may evolve. Periodic reassessment will therefore be essential for ensuring

that KLM remains prepared for future operational conditions.

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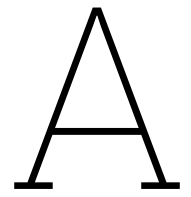
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Scientific Paper

A Simulation-Based Approach to Reducing Congestion at an Air Cargo Terminal

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Abstract

Landside air cargo terminals face increasing pressure from growing truck volumes, unpredictable arrival patterns, and limited dock capacity. At KLM Cargo, this results in longer truck waiting- and lead times and congested operations, especially during peak hours. This study aims to evaluate different operational and infrastructural strategies by developing a simulation model of the landside air cargo operations. The model represents the Dock & Yard area, excluding the interior terminal and airside. Data is obtained through internal datasets from KLM Cargo, and model validation is conducted by comparing historical data KPIs to model output KPIs. Several configurations are analyzed, including changes in dock capacity, dock expansion, and a slot booking system. The results show that slot booking and adding new docks provide measurable impact on lead- and waiting times, thereby reducing congestion. These findings provide insights into the effect of dock configuration and improved coordination can improve Dock & Yard performance.

Keywords: Air Cargo Operations, Landside Logistics, Cargo Handling, Discrete Event Simulation, Transport, Dock & Yard Performance, KLM Cargo.

1. Introduction

Global air cargo demand has increased significantly over the past decade. After the COVID-19-related decline, the market recovered quickly, with a post-pandemic growth of 21% and a long-term forecast of 4.1% annual growth [1]. This upward trend is placing increasing pressure on the capacity of air cargo terminals, where trucks deliver and collect shipments. Several studies show that landside areas and in particular dock & yard areas often form bottlenecks that lead to long waiting times, congestion, and reduced service reliability [2]. Major cargo hubs have faced multi-day delays during periods of high workload, as observed at Chicago O'Hare in 2021 [3]. Because air cargo volumes are growing, improving landside performance will become essential for maintaining efficient and predictable cargo handling operations [4].

At air cargo terminals, trucks enter the site via a security checkpoint before proceeding through a yard area to one or more freight buildings. These facilities commonly experience strong arrival peaks, especially towards the end of the week. This is a common pattern

as forwarders prefer emptying their docks before the weekend. During such "peaks", available dock and yard capacity can be exceeded, resulting in queues forming at the yard and limited ability to process trucks in a stable manner. Although multiple short term measures are often used to manage peaks, they do not always resolve the structural congestion and stress on the terminals operational procedures.

A review of existing literature shows that landside bottlenecks in air cargo are well recognized, but detailed, data-driven evaluations of dock and yard operations are less researched. Much of the existing work focuses on appointment systems, theoretical scheduling models, or general logistics process improvements. Few studies investigate the combined effects of infrastructure, arrival patterns, and yard behavior in an operational air cargo setting. Industry insights also highlight that congestion is caused by something else. For example: Layout constraints and administrative procedures. These interactions are difficult to analyze without a quantitative model that captures the dynamics of the system.

To address this gap, this study investigates how landside operations at an air cargo terminal can be improved through a combination of infrastructural and operational interventions. A discrete-event simulation (DES) model is developed to represent the truck handling process

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from arrival to departure, including queue formation, dock assignment, service times, and yard movements. The model is based on operational data and validated using observed performance indicators. Several improvement strategies are then tested to evaluate their impact on congestion levels and overall identified KPIs.

This paper is guided by the following main research question:

How can landside air cargo terminal operations be optimised to increase dock and yard performance?

The following sub-questions to support the main research question are:

1. What are the main causes of dock and yard congestion in air cargo logistics?
2. Which methods can be applied to improve dock and yard performance?
3. How can a simulation model be designed and developed to evaluate these methods?
4. To what extent do the proposed configurations increase dock throughput and reduce yard congestion?

By answering these questions, the paper contributes to the limited qualitative and quantitative research on landside air cargo operations and provides insights in how different infrastructural and operational measures can improve performance during peak periods.

2. System Description and Problem Analysis

2.1. System description

An air cargo terminal is a specialized facility at an airport where freight is transferred between trucks and aircraft [5]. In general, the terminal can be divided into three main operational areas: landside, cargo service area, airside and this study focuses on the landside export process.

On the landside, three subsystems are defined:

- Gate and documentation: the point where trucks and drivers are registered and documentation is checked before access is granted.
- Yard: the area where trucks queue, park, and wait for a dock assignment.
- Docks: the interface where cargo is transferred from the truck into the cargo service area.

The system boundary in this study runs from the moment a loaded export truck arrives at the gate until it departs the terminal after unloading. Processes inside the warehouse behind the docks are treated as part of the environment. This means that they are not modeled but are treated as an influencer in the dock availability and unloading speed. The external environment further includes freight forwarders, transport companies, airport authorities, and airlines, whose planning decisions and schedules determine the timing and priority of shipments.

Figure 1 gives an overview of the main components of the landside cargo handling process. Trucks enter at documentation (red), pass the entry gate (purple), move through the yard where they also park (green), and are eventually processed at one of the export docks (blue).

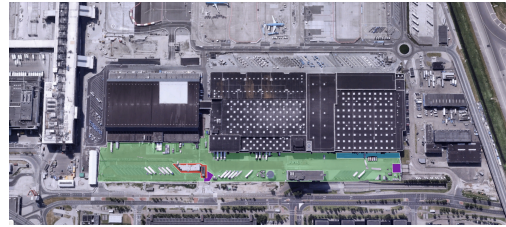


Figure 1: System components of the landside cargo handling process

Following a systems approach [6], the landside process can be viewed as a transformation from loaded to unloaded trucks. From a black-box perspective (Figure 2, loaded trucks are the inputs, unloaded trucks are the outputs, and the transformation is constrained by infrastructure, staff capacity, safety rules, and available warehouse space.

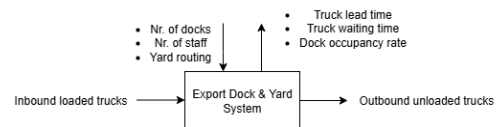


Figure 2: Black-box model

2.2. Key performance indicators

To evaluate the performance of the landside system and compare different design alternatives, three KPIs are used, based on literature and expert input [7]:

- Truck lead time (minutes): total time a truck spends in the system, from arrival at the gate to departure after unloading.
- Truck waiting time (minutes): time a truck spends waiting before being assigned to a dock.

- Dock occupancy rate (%): percentage of time that docks are actively used for unloading.

2.3. Problem analysis

Using the system description, literature, and expert interviews, several structural causes of dock and yard congestion at air cargo terminals are identified. First, trucks arrive around high peaks. Forwarders also show behavior of delivering shipments very close to the Latest Acceptance Time (LAT), resulting in short but intense demand peaks [8, 9]. During these peaks, the number of arriving trucks exceeds dock and yard capacity, which leads to long queues and stressed processing times.

Second, physical and infrastructural constraints limit operational flexibility. The yard is often too small to buffer all arriving trucks, and parking and moving areas are quickly filled. Behind the docks, the buffer and front-warehouse area can also fill quickly. This results in docks closing and only reopening once cargo is in the front-warehouse is carried away. Industry reports confirm that many cargo facilities are not designed for today's volumes or modern truck sizes, and that under-sized yards and docks contribute directly to congestion and emissions from halted trucks [10, 11].

Third, process and information delays add to waiting times. Slow or inconsistent data exchange between systems can create procedural blocks, where cargo cannot be accepted or released until all required messages are processed. Expert interviews also pointed to limited transparency for drivers: they do not always know their position in the queue or the expected waiting time, which creates frustration and makes the process appear unfair.

Finally, coordination with external stakeholders like forwarders is limited. Forwarders and transport companies mainly optimize their own operations, for example by maximizing truck fill rates, and have few incentives to spread deliveries outside peak periods [12]. Collaborative initiatives exist at some airports [13, 14, 15, 16], but their effectiveness strongly depends on behavioral and organizational changes, which are not always in place.

3. Methodology

This section describes the research approach used to analyze and improve landside operations at an air cargo terminal. The study combines input from literature, expert interviews, and quantitative data with a DES model that evaluates the performance of selected infrastructural and procedural interventions.

3.1. Research Approach

Experimentation with the real world system is difficult because of the complexity of operations and the fact that airplanes cannot afford delays due to an experiment. Instead, the research follows a methodological approach in which problem understanding, design, and evaluation are linked in the form of Design Science Research (DSR) [17]. Literature and expert interviews were used to identify new configurations, while empirical data provided the basis for model development and validation. The resulting simulation model should be able to provide a setting to test alternative configurations compared to the base case.

3.2. Discrete-Event Simulation

DES was chosen because of the event driven processes in the landside air cargo terminal [18, 19]. In contrast to analytical models, which are often restrictive for systems with high variability and resource interactions [20], DES can represent queues, stochastic behavior, and capacity limitations in detail. This makes it suitable for analyzing performance and testing how congestion develops under different dock and yard configurations.

3.2.1. Conceptual Model and Control Logic

A conceptual process flow (Figure 3) was created to translate the real operation into a structure ready for simulation. The model represents all steps from a truck's arrival at documentation to its departure after unloading. The flow diagram is used to create the simulation model but also to check with stakeholders if all aspects of the process are taken into account like: documentation checks, yard parking, dock allocation, unloading processes, and exit procedures.

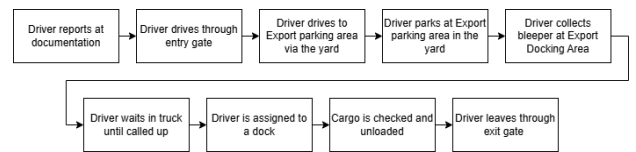


Figure 3: Conceptual model driver journey

3.2.2. Data, Parameters and Assumptions

Historical data was used to obtain arrival patterns, unloading durations, and dock usage shares. The dataset included 9,162 export truck movements over the summer peak months (June–August). From this data, inter-arrival times, unloading times, and door allocations were extracted and used as (in)direct model inputs.

Operational parameters such as walking times, gate cycle times, and maneuvering durations were based on internal guidelines and expert knowledge. Additional assumptions were introduced where exact data was unavailable, such as fixed parking times, single-vehicle parking per slot, and movement speeds. These assumptions were necessary in order to create the dynamics of the model to resemble real world practice as close as possible.

To ensure statistically reliable performance measures, all KPI values were calculated as weighted averages across the ten simulation replications. Because each run processes a slightly different number of trucks due to stochastic variation, weighting the results by the number of observed events prevents runs with fewer processed trucks from disproportionately influencing the final KPI values. This approach follows best practices in simulation output analysis and yields more accurate estimates than simple unweighted averaging.

3.2.3. Verification and Validation

Verification and validation ensure that the simulation model is both correctly implemented and sufficiently accurate for its intended use. Following established guidelines in simulation research, both processes were applied iteratively during model development [21, 22].

The model was verified by checking whether the implemented logic matched the conceptual design. Flow tracing was done to confirm that trucks followed correct routing behavior, docks operated correctly, and queues formed and dismantled. Extreme-condition tests were also carried out like setting unlimited dock capacity or zero parking space. This showed that the model responded in line with theoretical expectations. These tests ensured model consistency before comparing the model to empirical data [18].

Validation assessed how well the model reproduced the real system’s performance. Historical data for 9,162 export truck movements were used as a benchmark. Consistent with recommended practices for operational validation [21, 22], ten independent replications were conducted to obtain stable KPI estimates and to account for stochastic variation. Simulated lead times and dock occupancy rates closely matched historical averages, while waiting times were slightly underestimated for some docks due to simplified decision rules. Nevertheless, the relative differences between docks were preserved. This indicates that the model captures the essential dynamics of the real operation. Given these results, the model is considered sufficiently accurate for comparative scenario analysis.

3.3. Scenario Design

Based on literature and expert interviews, a set of design configurations was selected to address the causes of congestion: peaked arrivals, limited dock capacity, and restricted buffer space. The configurations represent practical interventions that can realistically be implemented at an air cargo terminal. Table 1 summarizes the configurations tested in the simulation.

Table 1: Overview of selected configurations for simulation experiments

Configuration	Description
1	A second MTD dock is activated to increase unloading capacity for ULD trucks and ease congestion at conventional docks.
2	The second MTD dock is replaced by an extra normal dock to redistribute capacity when the ULD share is low.
3	Total number of active docks increased to 4 to assess the effect of limited capacity expansion.
4	Total number of active docks increased to 5 to evaluate performance under moderate expansion.
5	Total number of active docks increased to 6 to test a more extensive capacity increase.
6	A digital slot-booking system is introduced to regulate truck inflow using pre-assigned arrival windows.

Each scenario modifies the base-case model in one of two ways: adapting dock capacity, or regulating truck arrivals. All scenarios were evaluated using the same dataset, and KPI definitions: truck lead time, truck waiting time, and dock occupancy.

The DES model allows each configuration to be assessed under identical conditions, which ensures a structured comparison can be made of how each intervention affects the KPIs across the terminal.

4. Results

4.1. Base Case Performance

The base case represents the current landside operation. Figure 4 compares simulated KPIs with the KPI values obtained from historical data. The validation shows that the model reproduces the overall performance pattern well: lead times and dock occupancy levels lie closely with historical values, while waiting times are slightly underestimated for most docks. This difference is expected due to simplified decision logic in the model. As human behavior has a high influence

in air cargo operations. However, the relative differences between docks remain consistent. This does mean that when consulting the results, the underestimations should be taken into account.

On average, trucks spend nearly 64 minutes on site (lead time), of which 39 minutes are waiting before being assigned to a dock. The average dock occupancy level is 18%, indicating that docks are consistently used. This does show that as there is congestion during peaks, the dock usage throughout the day is spread unevenly. These values serve as the performance benchmark for evaluating all improvement configurations.

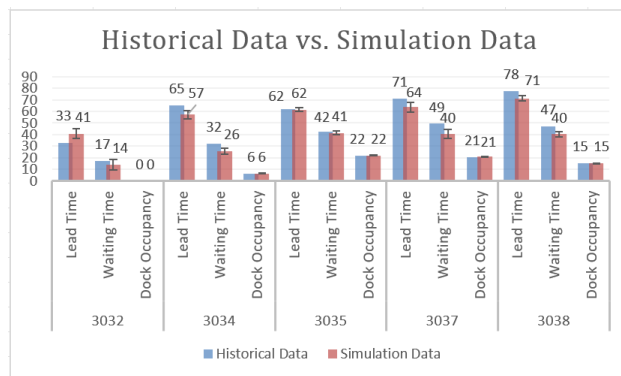


Figure 4: Historical vs. simulated KPI values for the base case

4.2. Configuration Performance

Figure 5 summarizes the KPI outcomes of all six tested configurations relative to the base case. Several clear trends emerge. First, all configurations lead to performance improvements, though the magnitude varies. Configuration 1 shows only limited progress, confirming that increasing MTD capacity alone does not resolve the congestion.

All KPI values shown in Figure 5 represent weighted averages across the ten simulation replications, ensuring that differences in the number of processed trucks per run do not bias the comparison between configurations.

Configurations that increase normal dock capacity (Configurations 2–5) show a corresponding improvement: more doors result in shorter waiting times and lower congestion. Lead time decreases from 63.58 minutes in the base case to around 37.08 minutes in the best-performing setups.

Finally, Configuration 6 offers performance levels comparable to those of the best infrastructure solution. Waiting time falls to 11.71 minutes and lead time to 37.08 minutes, the lowest across all configurations. Dock occupancy increases to 17.34%, indicating that

the docks are used more efficiently rather than being overloaded, as both lead and waiting times decline.

	Lead Time [min]	Waiting Time [min]	Dock Occupancy [%]
Base Case	63,58	38,71	18,03
Configuration 1	61,38	36,69	17,55
Configuration 2	47,41	22,67	13,10
Configuration 3	48,30	23,51	13,21
Configuration 4	41,96	17,70	10,55
Configuration 5	38,06	14,22	8,89
Configuration 6	37,08	11,71	17,34

Figure 5: Overview of KPI results for all configurations

5. Discussion

The results show that most delays at the landside originate from the waiting time before trucks can start unloading. In the base case, the normal docks carry almost all of the workload, so queues build up quickly during peak moments. Even though dock occupancy is not extremely high, the combination of clustered arrivals and limited yard space creates long waiting times, which then dominate the total lead time.

The configurations help clarify what actually makes a difference. Activating a second MTD dock brings almost no improvement because the volume of ULD trucks is minimal. This means the bottleneck is not in the MTD process but in the flow of regular trucks that arrive in large numbers during peak hours. So expanding MTD capacity is not an effective strategy.

Replacing the unused MTD dock with an extra standard dock does lead to a clear reduction in waiting and lead times. This shows that the system benefits most from extra capacity at the standard docks. When more normal docks are activated, the improvements continue, although the gains become smaller each time. This pattern suggests that physical expansion helps, but the effect gradually levels off once the queues are reduced. Also, the cost of operating multiple docks must be accounted for. Therefore, it could be worthwhile to investigate using FB2 to provide additional unloading capacity after closing hours to manage peaks. This would save money and make the system more efficient.

The slot-booking scenario stands out because it improves performance without adding new physical capacity. By spreading arrivals more evenly, the large peaks disappear and the waiting time drops to a level below configuration 5. Dock utilization also becomes more balanced. This shows that part of the congestion problem is not the number of docks but the timing of arrivals. A slot-booking system can therefore be a cost-effective measure, provided that forwarders comply and arrive close to their allocated times.

Overall, the results indicate that a mix of moderate capacity expansion and better arrival management can reduce congestion at the yard and docks. Adding more normal docks helps, but it comes with decreasing benefits and can be an expensive solution. Managing arrivals through slot-booking appears to be the most efficient option, offering strong improvements with much lower cost and implementation effort.

6. Conclusion

This study examined how landside operations at an air cargo terminal can be improved by identifying the primary sources of congestion and testing several interventions with a DES model. The results show that delays mainly occur before docking, with the base case reaching a lead time of 63.58 minutes and a waiting time of 38.71 minutes. These delays arise from strong peaks in truck arrivals rather than from continuous capacity shortages. MTD docks contribute little to overall performance, as the share of ULD trucks is low, and increasing MTD capacity (Configuration 1) only reduces lead time to 61.38 minutes and waiting time to 36.69 minutes.

Adding extra standard docks reduces waiting time and stabilizes operations more effectively. Configurations 2–5 reduce lead time to 47.41–38.06 minutes and waiting time to 22.67–14.22 minutes, although the marginal improvement decreases with each additional dock. Activating a second MTD dock has almost no effect. The slot-booking scenario (Configuration 6) delivers the greatest improvement without expanding infrastructure. By spreading arrivals more evenly, waiting time drops to 11.71 minutes and lead time to 37.08 minutes, while dock occupancy increases to 17.34 %, indicating more balanced utilization during peak periods.

Overall, the findings show that smoothing arrival patterns is more effective than adding substantial dock capacity. Since congestion primarily arises from arrival peaks rather than from a structural shortage of docks, operational measures that manage arrival behavior appear to be the most efficient improvement strategy.

6.1. Recommendations

The results show that performance can be improved through a mix of operational measures and moderate capacity adjustments. Converting the unused MTD dock into a normal dock is a practical first step that reduces waiting times without major investment. Adding one or two extra normal docks provides further benefits, although the improvement becomes smaller with each additional door, meaning the financial justification should

be evaluated carefully. Because expanding infrastructure is expensive, making temporary use of existing capacity at other facilities, such as FB2 during late-evening peaks, can offer a realistic alternative.

The slot-booking approach stands out as a highly effective option with relatively low cost. By smoothing arrivals, waiting times drop significantly and the docks are used more evenly throughout the day. Implementing such a system would require cooperation with forwarders and supporting digital tools, but the potential impact makes it a promising one for the terminal.

6.2. Future Work

Future research should examine how the system performs under different arrival patterns, including stochastic arrivals, since this study relied on historical peak-month data. More detailed behavioural and control mechanisms could be added to reduce simplifications in the current model and address the systematic underestimation of indicators such as waiting time.

A further step would be to test technologies that were outside the scope of this work, such as partial automation, digital yard-management tools, or real-time dock assignment. Expanding the model to include internal warehouse processes—such as buffer zones, forward staging areas, and more detailed MTD operations—could also clarify how delays inside the warehouse interact with yard performance.

A cost-benefit analysis could help quantify the financial implications of the proposed configurations and identify which improvements offer the best value. Finally, performing scenario analyses with forecasted volumes or alternative demand conditions would support long-term planning as cargo flows and truck behaviour evolve.

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B

Simulation Results

B1 - Results: Base Case

Table B.1: Base Case simulation Results

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	2	32.80	6.10	0.0
	3034	1268	61.70	30.40	6.4
	3035	3219	64.20	44.10	21.1
	3037	2765	77.90	54.40	22.2
	3038	1908	68.50	38.00	14.6
Run 2	3032	6	32.90	6.00	0.0
	3034	1249	52.10	21.60	5.6
	3035	3337	65.00	44.60	22.6
	3037	2724	57.90	35.00	20.1
	3038	1846	68.90	38.20	14.4
Run 3	3032	12	40.30	12.60	0.0
	3034	1308	58.00	26.00	7.0
	3035	3251	64.50	44.40	22.0
	3037	2725	63.90	40.80	21.0
	3038	1866	70.30	39.50	15.0
Run 4	3032	4	33.70	8.30	0.0
	3034	1261	61.80	29.00	6.0
	3035	3298	61.20	41.00	22.0
	3037	2725	63.20	39.90	20.0
	3038	1874	72.60	41.10	15.0
Run 5	3032	8	49.30	21.80	0.0
	3034	1260	55.70	24.90	6.0
	3035	3273	62.10	41.50	22.0
	3037	2671	66.20	42.70	21.0
	3038	1950	72.70	41.90	16.0
Run 6	3032	2	32.50	6.30	0.0
	3034	1259	68.80	34.80	8.0
	3035	3327	57.40	37.80	21.0
	3037	2676	59.20	35.50	21.0
	3038	1898	67.70	36.80	15.0
Run 7	3032	5	50.20	24.00	0.0
	3034	1211	52.80	21.20	6.0
	3035	3349	63.70	43.50	23.0
	3037	2702	58.50	35.10	21.0
	3038	1895	70.80	39.90	15.0
Run 8	3032	5	44.70	18.10	0.0
	3034	1301	55.60	25.10	6.0
	3035	3290	60.90	40.80	22.0
	3037	2713	72.40	49.00	21.0
	3038	1853	67.90	36.60	15.0
Run 9	3032	12	43.20	17.30	0.0
	3034	1259	53.60	23.30	6.0
	3035	3330	59.30	39.30	22.0
	3037	2637	56.70	33.60	20.0
	3038	1924	81.00	49.50	16.0
Run 10	3032	7	33.40	6.10	0.0
	3034	1254	51.00	20.60	6.0
	3035	3287	57.10	37.10	22.0
	3037	2640	60.30	37.30	20.0
	3038	1974	72.70	41.80	16.0

B2 - Results: Configuration 1

Table B.2: Activation of Second MTD Dock Results

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	632	47.96	16.34	4.0
	3034	649	44.78	13.61	3.0
	3035	3270	59.68	39.28	22.0
	3037	2678	64.56	41.10	21.0
	3038	1933	73.53	42.41	15.0
Run 2	3032	664	43.80	13.83	3.0
	3034	623	48.30	16.39	3.0
	3035	3222	55.20	35.59	20.0
	3037	2761	63.10	39.74	21.0
	3038	1892	76.40	45.29	15.0
Run 3	3032	655	45.38	15.51	3.0
	3034	675	45.39	14.61	3.0
	3035	3062	58.69	36.28	22.0
	3037	2857	62.71	42.83	22.0
	3038	1913	75.59	45.75	14.0
Run 4	3032	665	46.09	16.10	3.0
	3034	618	47.02	14.13	3.0
	3035	3207	59.36	37.95	22.0
	3037	2743	62.36	43.20	21.0
	3038	1929	77.90	44.89	16.0
Run 5	3032	678	48.44	15.94	3.0
	3034	687	48.10	15.05	3.0
	3035	3099	61.02	37.07	22.0
	3037	2737	60.31	39.27	21.0
	3038	1961	69.89	42.29	15.0
Run 6	3032	672	45.73	15.71	3.0
	3034	623	44.03	14.98	3.0
	3035	3215	58.44	38.32	23.0
	3037	2769	62.63	42.02	21.0
	3038	1883	76.13	44.72	15.0
Run 7	3032	619	43.70	15.15	3.0
	3034	585	47.62	14.77	4.0
	3035	3301	57.01	38.14	20.0
	3037	2761	62.90	39.71	21.0
	3038	1896	79.35	45.63	15.0
Run 8	3032	605	43.78	14.46	3.0
	3034	615	44.20	15.10	3.0
	3035	3132	61.71	38.92	22.0
	3037	2803	66.45	39.99	22.0
	3038	2007	71.73	41.89	15.0
Run 9	3032	608	45.37	14.41	3.0
	3034	609	44.81	15.26	3.0
	3035	3333	58.72	37.78	20.0
	3037	2735	64.18	40.40	21.0
	3038	1877	72.71	43.63	15.0
Run 10	3032	639	45.11	15.34	3.0
	3034	654	48.56	14.83	3.0
	3035	3142	58.38	38.04	20.1
	3037	2809	62.42	38.21	20.6
	3038	1918	77.93	42.74	15.3

B3 - Results: Configuration 2

Table B.3: Simulation results for scenario: replacing second MTD dock with one additional normal dock (total: 4 normal docks)

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3034	1269	54.48	23.91	6.20
	3035	2187	37.62	17.60	14.00
	3037	2015	45.09	21.56	15.50
	3038	1870	66.93	35.52	15.40
	3039	1821	32.56	11.60	12.20
Run 2	3034	1307	52.51	21.81	6.40
	3035	2152	37.49	17.70	13.50
	3037	1941	39.86	17.01	14.10
	3038	1901	73.19	41.59	15.50
	3039	1861	30.70	10.16	12.10
Run 3	3034	1265	55.67	23.76	6.30
	3035	2170	43.70	23.04	15.10
	3037	2055	42.74	19.38	15.60
	3038	1832	64.30	33.41	14.10
	3039	1840	29.87	9.35	12.00
Run 4	3034	1273	51.40	20.56	6.00
	3035	2203	42.24	21.86	14.40
	3037	1978	48.99	24.84	15.70
	3038	1821	65.88	35.61	14.00
	3039	1887	33.76	12.43	12.90
Run 5	3034	1283	56.75	26.59	5.70
	3035	2244	48.56	27.86	15.20
	3037	2021	52.58	28.92	15.50
	3038	1772	69.28	38.20	14.20
	3039	1842	36.86	15.86	12.40
Run 6	3034	1294	50.94	20.47	6.00
	3035	2257	40.82	19.96	15.40
	3037	1966	43.89	20.15	15.20
	3038	1836	68.84	37.32	15.30
	3039	1809	30.19	10.16	11.50
Run 7	3034	1252	53.46	22.83	5.60
	3035	2208	36.62	16.75	13.80
	3037	1956	39.16	16.53	14.10
	3038	1925	69.50	38.30	15.40
	3039	1821	30.86	9.83	12.50
Run 8	3034	1249	53.05	22.25	5.90
	3035	2200	46.73	26.26	15.00
	3037	2070	54.17	29.83	16.40
	3038	1843	65.01	33.92	14.40
	3039	1800	36.49	16.24	11.60
Run 9	3034	1249	51.07	20.76	5.80
	3035	2227	36.80	16.41	14.30
	3037	2065	45.03	21.80	15.50
	3038	1803	69.64	38.52	14.40
	3039	1818	31.90	10.43	12.80
Run 10	3034	1253	48.15	17.66	5.60
	3035	2223	37.77	17.40	14.70
	3037	1970	44.19	21.46	14.30
	3038	1795	71.43	39.37	15.20
	3039	1921	32.45	11.20	13.00

B4 - Results: Configuration 3

Table B.4: Simulation results for scenario with 4 normal docks

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	6	76.95	48.78	0.00
	3034	1228	49.44	18.53	6.00
	3035	2003	36.32	16.08	13.00
	3037	1972	52.53	28.60	15.00
	3038	1958	72.84	41.66	16.00
	3039	1995	38.59	18.93	13.00
Run 2	3032	6	34.00	6.16	0.00
	3034	1246	58.18	27.47	6.00
	3035	1965	46.97	25.24	14.00
	3037	2005	48.36	24.40	16.00
	3038	1902	71.34	39.71	16.00
	3039	2038	40.78	21.03	13.00
Run 3	3032	5	32.81	6.09	0.00
	3034	1212	52.27	20.84	6.00
	3035	1967	32.77	12.94	13.00
	3037	1978	40.55	18.10	14.00
	3038	2014	73.54	42.22	17.00
	3039	1986	35.97	15.78	13.00
Run 4	3032	8	31.62	6.06	0.00
	3034	1229	54.59	21.98	7.00
	3035	2034	37.77	17.03	14.00
	3037	2010	46.69	23.39	15.00
	3038	2008	70.01	39.66	15.00
	3039	1873	38.16	17.99	13.00
Run 5	3032	5	32.34	6.00	0.00
	3034	1299	51.30	19.91	7.00
	3035	1986	37.22	16.89	13.00
	3037	1944	42.86	18.37	16.00
	3038	1942	63.93	33.49	15.00
	3039	1986	35.17	15.04	13.00
Run 6	3032	8	32.73	6.25	0.00
	3034	1325	49.67	19.56	6.00
	3035	1982	36.15	15.93	13.00
	3037	1994	43.85	20.92	15.00
	3038	1972	68.51	37.67	16.00
	3039	1881	33.31	13.14	12.00
Run 7	3032	7	32.13	6.17	0.00
	3034	1292	57.93	26.71	7.00
	3035	1979	39.20	18.76	13.00
	3037	2008	48.91	25.02	16.00
	3038	1977	76.92	45.66	16.00
	3039	1899	40.14	19.24	13.00
Run 8	3032	5	33.36	5.99	0.00
	3034	1314	47.90	18.46	5.00
	3035	1926	34.02	13.69	13.00
	3037	2023	41.56	18.80	15.00
	3038	1942	72.43	40.87	16.00
	3039	1952	35.76	15.52	13.00
Run 9	3032	5	36.95	10.24	0.00
	3034	1263	49.04	18.54	6.00
	3035	2005	37.53	16.75	14.00
	3037	1965	45.06	21.39	15.00
	3038	1979	74.73	43.84	16.00
	3039	1945	35.04	14.53	13.00
Run 10	3032	5	32.60	5.99	0.00
	3034	1345	52.30	21.75	6.00
	3035	1986	34.72	15.00	13.00
	3037	1962	41.18	17.36	16.00
	3038	1936	71.55	40.19	16.00
	3039	1928	33.86	13.63	13.00

B5 - Results: Configuration 4

Table B.5: Simulation results for scenario with 5 normal docks

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	6	30.22	5.99	0.00
	3034	1254	53.81	22.89	6.00
	3035	1526	33.38	13.58	10.00
	3037	1554	34.48	12.00	11.00
	3038	1582	58.86	28.16	13.00
	3039	1630	32.42	12.50	11.00
	3040	1610	35.12	14.81	11.00
Run 2	3032	7	31.94	5.99	0.00
	3034	1247	51.08	19.79	6.00
	3035	1517	33.40	12.84	10.00
	3037	1638	38.60	14.70	13.00
	3038	1606	56.75	25.32	13.00
	3039	1526	35.53	14.74	10.00
	3040	1621	33.66	12.80	11.00
Run 3	3032	4	33.08	5.99	0.00
	3034	1223	50.35	19.07	6.00
	3035	1542	31.34	11.48	10.00
	3037	1555	37.50	13.68	12.00
	3038	1600	54.11	23.85	12.00
	3039	1584	30.99	11.58	10.00
	3040	54	32.47	12.28	11.00
Run 4	3032	9	32.51	6.04	0.00
	3034	1237	47.80	17.58	6.00
	3035	1573	33.84	12.90	11.00
	3037	1620	39.39	15.70	13.00
	3038	1583	64.07	32.56	13.00
	3039	1530	29.99	10.53	10.00
	3040	1610	33.37	12.54	11.00
Run 5	3032	6	33.15	5.99	0.00
	3034	1211	52.95	21.48	7.00
	3035	1567	30.54	11.31	10.00
	3037	1673	39.44	15.70	13.00
	3038	1602	56.10	24.58	13.00
	3039	1521	30.62	10.81	10.00
	3040	1582	32.99	12.29	11.00
Run 6	3032	7	32.30	6.14	0.00
	3034	1270	47.97	17.91	6.00
	3035	1548	32.09	12.26	10.00
	3037	1566	37.18	14.23	12.00
	3038	1523	60.47	29.11	13.00
	3039	1645	32.61	12.33	11.00
	3040	1603	33.94	12.78	11.00
Run 7	3032	7	32.77	5.99	0.00
	3034	1235	57.40	27.27	6.00
	3035	1582	35.74	14.92	11.00
	3037	1576	38.32	15.96	11.00
	3038	1540	56.82	25.71	12.00
	3039	1660	34.48	13.99	11.00
	3040	1562	40.93	19.74	11.00
Run 8	3032	8	31.59	6.03	0.00
	3034	1260	54.24	22.99	6.00
	3035	1543	34.08	13.91	10.00
	3037	1603	34.81	12.31	11.00
	3038	1601	58.45	26.59	14.00
	3039	1556	32.40	12.14	10.00
	3040	1591	35.91	13.76	10.00
Run 9	3032	4	34.47	6.28	0.00
	3034	1288	50.41	19.76	6.00
	3035	1542	33.31	12.08	10.00
	3037	1589	38.99	15.34	11.00
	3038	1609	59.93	29.44	14.00
	3039	1549	32.99	12.68	10.00
	3040	1581	32.23	11.64	10.00
Run 10	3032	9	33.36	6.03	0.00
	3034	1260	59.00	28.39	6.00
	3035	1597	39.14	18.72	11.00
	3037	1552	48.60	25.37	12.00
	3038	1614	73.28	41.33	14.00
	3039	1601	41.01	21.25	10.00
	3040	1529	37.40	16.78	10.00

B6 - Results: Configuration 5

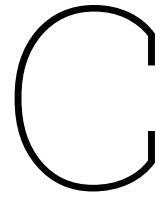
Table B.6: Simulation results for scenario with 6 normal docks

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	3	31.28	6.03	0.00
	3034	1255	49.66	18.98	6.00
	3035	1346	30.93	10.13	9.00
	3037	1326	35.02	11.52	10.00
	3038	1306	48.74	17.09	11.00
	3039	1304	31.38	11.18	9.00
	3040	1292	30.43	10.09	9.00
	3041	1330	32.69	11.47	10.00
Run 2	3032	6	31.74	6.03	0.00
	3034	1276	58.14	26.06	7.00
	3035	1335	31.85	10.92	9.00
	3037	1282	37.44	14.12	11.00
	3038	1270	47.92	17.52	9.00
	3039	1324	28.79	9.48	8.00
	3040	1298	32.39	11.23	9.00
	3041	1371	30.55	11.29	9.00
Run 3	3032	5	31.64	6.03	0.00
	3034	1189	48.98	18.41	6.00
	3035	1314	29.24	9.60	8.00
	3037	1348	36.04	12.73	10.00
	3038	1299	50.49	19.91	10.00
	3039	1327	29.94	9.56	9.00
	3040	1318	35.74	14.03	10.00
	3041	1362	32.62	11.48	10.00
Run 4	3032	6	30.78	6.03	0.00
	3034	1255	51.86	20.40	7.00
	3035	1375	32.55	11.76	10.00
	3037	1328	35.79	12.87	10.00
	3038	1268	51.65	19.69	11.00
	3039	1280	28.87	9.01	8.00
	3040	1264	30.12	9.59	8.00
	3041	1386	29.83	10.54	8.00
Run 5	3032	8	32.99	6.11	0.00
	3034	1251	51.98	20.21	6.00
	3035	1302	30.28	10.06	9.00
	3037	1328	34.77	11.83	10.00
	3038	1339	47.83	17.16	10.00
	3039	1325	31.36	10.32	9.00
	3040	1262	31.43	11.22	8.00
	3041	1347	29.72	10.28	8.00
Run 6	3032	6	33.39	6.03	0.00
	3034	1272	58.63	26.36	7.00
	3035	1331	31.03	10.44	9.00
	3037	1362	35.06	12.44	10.00
	3038	1275	49.23	18.28	10.00
	3039	1331	29.97	9.92	9.00
	3040	1325	29.80	9.54	8.00
	3041	1260	29.57	9.94	8.00
Run 7	3032	2	33.68	6.03	0.00
	3034	1303	52.37	20.61	7.00
	3035	1344	31.90	11.52	9.00
	3037	1262	34.88	11.77	9.00
	3038	1282	49.93	18.53	11.00
	3039	1316	36.51	15.77	9.00
	3040	1403	33.66	10.77	9.00
	3041	1250	31.08	11.31	8.00
Run 8	3032	3	32.55	6.03	0.00
	3034	1264	59.53	28.45	6.00
	3035	1393	43.51	21.59	11.00
	3037	1269	36.46	13.28	9.00
	3038	1298	52.90	21.65	10.00
	3039	1294	33.12	13.07	9.00
	3040	1326	41.82	20.33	9.00
	3041	1315	34.97	15.03	9.00
Run 9	3032	7	32.21	6.28	0.00
	3034	1310	53.67	22.35	7.00
	3035	1290	31.02	11.20	8.00
	3037	1259	36.41	13.71	9.00
	3038	1342	54.23	22.63	11.00
	3039	1292	27.99	8.57	8.00
	3040	1370	32.38	12.10	9.00
	3041	1292	30.86	10.01	9.00
Run 10	3032	4	32.49	6.03	0.00
	3034	1253	50.17	19.42	6.00
	3035	1322	32.40	12.44	9.00
	3037	1303	37.16	13.55	10.00
	3038	1339	50.20	19.26	11.00
	3039	1255	31.07	10.71	9.00
	3040	1324	30.59	10.01	9.00
	3041	1262	30.59	10.75	9.00

B7 - Results: Configuration 6

Table B.7: Simulation results for slot booking implementation

Run	Dock	Count	Lead Time [min]	Truck Waiting [min]	Dock Occupancy [%]
Run 1	3032	6	32.87	5.99	0.00
	3034	1199	44.21	11.45	7.00
	3035	3328	34.77	12.62	23.00
	3037	2729	35.03	10.55	20.00
	3038	1900	44.90	13.67	15.00
Run 2	3032	7	32.89	5.99	0.00
	3034	1213	40.64	9.83	6.00
	3035	3285	34.79	13.09	22.00
	3037	2782	34.26	9.80	21.00
	3038	1875	44.82	13.30	15.00
Run 3	3032	3	31.98	5.99	0.00
	3034	1294	42.68	11.38	6.00
	3035	3246	37.51	15.66	22.00
	3037	2717	36.69	11.44	21.00
	3038	1902	44.71	13.20	15.00
Run 4	3032	8	32.77	5.99	0.00
	3034	1271	40.30	9.68	6.00
	3035	3269	30.14	9.35	21.00
	3037	2716	34.54	10.32	20.00
	3038	1898	46.01	14.15	15.00
Run 5	3032	6	31.21	5.99	0.00
	3034	1271	41.13	10.09	6.00
	3035	3346	35.03	13.47	22.00
	3037	2708	34.75	10.83	19.00
	3038	1831	43.96	13.10	14.00
Run 6	3032	4	32.65	5.99	0.00
	3034	1271	39.86	9.95	5.00
	3035	3241	30.29	9.36	20.00
	3037	2728	36.03	10.89	21.00
	3038	1918	45.49	13.29	16.00
Run 7	3032	7	32.18	5.99	0.00
	3034	1247	41.58	10.23	6.00
	3035	3370	31.55	10.02	22.00
	3037	2712	33.97	9.67	20.00
	3038	1826	45.46	13.88	15.00
Run 8	3032	4	32.08	5.99	0.00
	3034	1262	39.00	8.95	5.00
	3035	3285	31.05	9.78	21.00
	3037	2726	35.43	10.95	20.00
	3038	1885	45.08	13.38	15.00
Run 9	3032	4	33.12	5.99	0.00
	3034	1274	41.95	9.82	7.00
	3035	3271	32.57	11.11	21.00
	3037	2739	34.93	10.81	20.00
	3038	1874	43.79	13.22	14.00
Run 10	3032	7	32.91	5.99	0.00
	3034	1254	39.17	8.86	6.00
	3035	3364	32.65	11.36	22.00
	3037	2659	35.44	11.06	19.00
	3038	1878	43.81	13.19	14.00



Interviews

C1: Unit Manager Import/Export

What do you consider to be the main causes of congestion during peak hours at KLM Cargo?

“What we see very clearly is that we are dealing with significant peak loads. Especially during the nights from Monday to Tuesday, Tuesday to Wednesday, and Friday to Saturday night, major bottlenecks occur. During the day it is fairly quiet, but in the evening everything arrives at once. This has to do with how the air cargo chain functions: agents consolidate their shipments during the day and then send them in one optimized truck movement toward the ground handler—so toward us. And yes, then everyone shows up at the same moment.

We operate with maximum staffing during those periods, but even then we hit the limit of what we can physically handle. Although we technically have more than three docks, operationally we can only use three at the same time. When more docks are opened, the front floor—the area where cargo is temporarily placed after unloading—fills up so quickly that it becomes unworkable. It turns into a bumper-car situation: colleagues with transport equipment can hardly move. That is a structural bottleneck.

And then there is the new system, iCargo. It was introduced at the beginning of June and currently causes processes to run somewhat slower. The system itself works, but it is new, people need time to get used to it, and it requires more steps. And if something goes wrong somewhere in the process—for instance with documentation—everything stops. For loose shipments we can set freight aside, but with an MTD (Moving Truck Dock) the entire process halts until the issue is solved.”

Where do you see the biggest operational and infrastructural constraints?

“The way the warehouse is designed makes it difficult to work more efficiently. The front floor in particular is a major constraint. Once too much freight is placed there, we can hardly move anymore. You could say: open more docks, but that only makes the problem worse, because the floor fills up faster than we can clear it.

For trucks arriving with aircraft pallets—via the MTD—the process generally runs well. Those trucks are unloaded quickly, on average within ten to fifteen minutes. However, at the moment one of the lifts is operating on only one of its three pumps. As a result, we can effectively unload with only one ‘train,’ whereas normally we could use two. Once that lift is fully operational again, we can scale the process back up.

Another issue is the lack of space to admit trucks only when a dock is actually available. Right now, they all enter the site at once and then the waiting begins. Ideally, you would organize this differently, but the physical layout simply does not allow it.”

What does the current process look like for a driver, and where do you see inefficiencies?

“A driver arrives, parks, and then reports to documentation. That is often where queues already begin, because everything is still checked manually. That is something I believe should really be digital by now. Afterward, the driver receives a token and may enter the site. Then they report to us, register, receive a pager, and wait in their cabin until called.

The pager system works reasonably well—it is similar to waiting for a table in a restaurant. What makes it difficult is that we use an algorithm to determine which truck is unloaded first, and that is based on cargo urgency. So if a truck carries important shipments that need to catch a flight soon, it gets priority. The problem is that we can hardly explain this to drivers. They see someone who arrived later being served earlier, which understandably leads to frustration. It is simply not transparent.”

What solutions or ideas do you see to improve the situation, and where are the challenges?

“There is definitely movement. At Schiphol we are working on developing a slot management system, where we make agreements with agents and transport companies about delivery times. Serious work is being done on this, and it is happening at an airport-wide level. For import processes, we already use limited slot times, but this still needs further development for export. The first steps have been taken.

At the same time, chain behaviour is difficult to change. Everyone knows that Friday afternoon is quiet, yet they still arrive around midnight. This is because agents often cannot depart earlier—they first need to collect cargo from their customers, who themselves run tight schedules. And to be fair: everyone wants a full truck, so you wait until everything has arrived and then drive at night.

We are in discussion with parties such as Bostransport and Middelkoop to deliver earlier, but often the conversation already stalls at the first question: what can you deliver outside the peak? Without clarity on that, we cannot determine how to unload other trucks faster. And then there is the tension between sustainability and spreading arrivals: if you spread deliveries, you may end up with less full trucks and thus more trips. That conflicts with the desire to operate more sustainably. Yet every truck that is removed from the peak period is one less source of congestion.”

C2: Team Coordinator Documentation

What do you consider to be the main causes of congestion during peak hours at KLM Cargo?

“The largest cause of congestion is that many agents deliver their freight just before the weekend, for example on Friday evening and Saturday night. This has several causes, but the most important is that many companies close during the weekend. They want to deliver their cargo before Saturday morning so they can close afterward. The LAT (Latest Acceptance Time) also plays a role. We notice that during peak moments, much freight is delivered well before the LAT, which creates congestion.

In addition, import trucks also contribute. From IMPAX we process import shipments: trucks with Amsterdam as final destination, but also shipments that continue elsewhere in Europe via road feeder services. All these flows come together and create pressure on the yard.”

Where do you see the largest operational and infrastructural constraints?

“At documentation we face staffing issues. During peak times we raise our staffing levels to manage deliveries properly, but that only works if we also have the right tools. After the introduction of iCargo, staff at documentation have more work. The system requires additional actions, which creates delays. These are bottlenecks we would like to solve.

There are also technical limitations. Communication between systems such as CGOACI and iCargo is slow. This results in compliance blocks, meaning that we cannot accept a shipment until all required messages are processed. This causes delays, which again lead to waiting and frustration in the process.”

What does the current process look like for a driver, and where are the inefficiencies?

“The driver registers at the kiosk. This is a type of pre-check connected to iCargo. It verifies, for example, whether the ACN pass is valid and who has registered. Previously this was done through another system, which actually worked faster. So the kiosk has both pros and cons.

After registration, the driver must show the freight documents at documentation. If everything is in order, they can enter the site. Then they receive location information through the token, which we forward to IMPEX. There the driver receives a pager. When called, they are assigned a dock and can unload.

The inefficiency lies mainly in the slow communication between systems. We can only perform checks once all messages are available. CGOACI performs a risk analysis and assigns a traffic-light status (red, orange, or green). If the system is green, the shipment should automatically move through iCargo, but currently there is a delay of about five minutes, sometimes longer. This causes unnecessary manual actions.”

What solutions do you see, and where are the challenges?

“The most important step is giving staff the right tools to do their job properly. To use a comparison: you also give a child floaties before letting them into the water. The same applies to our team. The tools must be in order.

In practice, this mainly means faster and more reliable communication between systems. The delays currently cause blocks that would otherwise clear automatically. This is being worked on, and solving it will already save a lot of time and workload.

Ideally, messages between systems should be processed in real time, so shipments can flow through immediately. There are still some ‘teething problems,’ but the goal is to resolve them as quickly as possible.”

C3: Operations Manager Benelux

What do you consider to be the main causes of congestion during peak hours at KLM Cargo?

“The biggest cause of congestion lies in the delivery behaviour of freight agents. What we often see is that agents collect freight from various shippers throughout the week, consolidate it, and then deliver everything at once—often on Friday evening or during the weekend. This is linked to popular flights: much freight needs to arrive at the destination by Monday so that recipients can use it immediately. This creates a major peak at the end of the week, while the beginning of the week is much quieter. It makes it difficult to distribute capacity evenly.

We also see that freight is often delivered far too early—sometimes 10 to 36 hours before the LAT. Those shipments occupy valuable space in the warehouse while they do not need to be processed yet. At the same time, customers try to avoid storage costs, so they deliver right before the moment at which it becomes free of charge, again creating congestion.

Another difficulty is that the information flow is not always accurate. Freight is sometimes already registered in the system while it has not yet arrived physically, or vice versa. This leads to planning based on incorrect assumptions. Agents and carriers themselves often do not know exactly when shipments will be ready, which creates uncertainty and eventually chaos in the yard and at the docks.”

Where do you see the largest operational and infrastructural constraints?

“Operationally, the problem is the lack of control over the delivery moment. There is almost no regulation of when freight may or must arrive. Agents prefer sending one full truck rather than three half-full ones, which makes sense from a sustainability and cost perspective, but it means that we suddenly receive a large amount of freight at once. Instead of a steady flow, we get a pulse that is difficult to handle.

In terms of IT and handling systems, there are clear limitations. The PCS system is not designed for real-time control, and processing speed is low. This means unloading takes longer than necessary because administrative steps have not yet been completed. Too many checks are still performed manually.

Infrastructure-wise, the building is simply outdated. The number of unloading doors is limited and the space behind them is tight. You cannot just open multiple docks simultaneously, because there is not enough room to handle the freight properly. The floor capacity is small; when three trucks unload at the same time, the area is already congested.

In addition, flights are clustered into blocks, meaning processing also occurs in batches. This makes

it difficult to react flexibly when a truck arrives late or when an urgent shipment must be handled. The system is not agile enough to deal with real-life variability.”

What does the current process look like for a driver, and where are the inefficiencies?

“A driver arrives, registers with a token, and is then sent to a waiting area. There they receive a pager, which signals when it is their turn. The system works reasonably well, but there is no predictability for the driver. They do not know how long the wait will be or why someone else is called earlier.

Prioritisation is still often based on a single express shipment in the load, without considering the rest. A truck with one urgent shipment and the rest long-LAT cargo may be helped earlier than a truck with several shipments close to deadline. This feels unfair and leads to frustration.

There is also no feedback or waiting-time indication. Drivers cannot see how busy it is or what their expected waiting time will be. A system providing that insight would help significantly. It would also be fairer if the algorithm prioritised based on the earliest LAT or an average LAT of the truck rather than a single shipment.

Drivers often lack insight into documentation status—they do not know whether everything is in order or why they are sometimes waiting. That lack of clarity leads to stress and misunderstanding at the gate.”

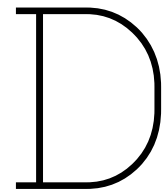
What solutions or ideas do you see to improve the situation, and where are the challenges?

“A first step would be implementing a slot management system. That way, delivery moments can be spread out more effectively and we avoid everyone arriving at the same time. Slot times could be linked to LATs, creating better balance between supply and handling capacity.

Additionally, I believe there is value in encouraging customers to deliver freight grouped by departure day. For example: everything departing on Monday in green, Tuesday in blue, and so on. This creates clarity and prevents freight from remaining in the warehouse longer than necessary. It is also beneficial for temperature-controlled shipments, which then do not stay in cooling unnecessarily long.

The challenge lies mainly in changing the behaviour of agents and carriers. They optimise for truck utilisation and cost savings, not necessarily for LAT. Without joint agreements or incentives, that behaviour will not change. You could consider rewards for off-peak delivery or adjusting storage fees based on behaviour.

Finally, cooperation between stakeholders is lacking. Everyone operates individually, and there is too little collective coordination. Yet many problems can only be solved through collaboration—even with competitors. That makes this also an organisational challenge.”



Use of AI Tools

During the writing of this thesis, ChatGPT was used to help structure sentences into more academic and grammatically consistent forms. The tool was also applied to summarize transcripts from expert interviews and to support the structuring of the LaTeX document in Overleaf. All generated outputs were reviewed afterwards to ensure that they remained consistent with the author's own writing and intentions.

An attempt was also made to use ChatGPT for coding in Enterprise Dynamics, but the tool did not appear to be sufficiently familiar with the software at the time.

The final interpretations, formulations, and conclusions presented in this thesis are entirely the responsibility of the author. AI served only as a supportive resource and did not replace independent academic reasoning.