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Real-time Truck Scheduling in Cross-Docking: A Hybrid Multi-Agent Simulation Framework

Ayse Bilge Torbali

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THÈSE

Pour obtenir le grade de

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Planification temps réel de camions en cross-docking : un cadre de simulation hybride multi-agents

Real-time Truck Scheduling in Cross-Docking: A Hybrid Multi-Agent Simulation Framework

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“This thesis is dedicated to Mustafa Kemal Atatürk, the founder of modern Turkey, an exceptional individual who strived for international understanding, cooperation and peace. For all that I possess, I extend my profound gratitude to ‘the man beyond the centuries’ who has enriched my existence immeasurably with the legacy of enlightenment.”

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1

Introduction

This chapter introduces the thesis research by presenting the general context and explanations of the concepts together with their interrelations. In addition, this chapter articulates the research objectives, formulates the problem statement, highlights the contributions, and provides a detailed outline of the dissertation's structure.

1.1 Context of the study

In conventional warehouses, the goods from the suppliers are moved to the storage, held until needed, and then taken from the storage to meet customer demand. However, holding stock is costly; thus, organisations constantly seek methods of lessening the stock level in the supply chain.

In contrast to the traditional warehouse, Cross-docking, a just-in-time (JIT) logistics technique, responds to this quest by synchronising the material inflow and outflow with no or limited storage in between (less than 24 hours): once materials enter the receiving (inbound) dock, they are then conveyed directly to a shipping (outbound) dock to be loaded onto transportation means (e.g. truck, ship, and train) (Figure 1.1). As a result, it significantly reduces stock levels and ensures on-time deliveries. Therefore, it meets the expectations of both organisations and customers. The council of supply chain management professionals ([Council of Supply Chain Management Professionals \(CSCMP\), 2013](#)), defines cross-docking as:

"a distribution system in which merchandise received at the warehouse or distribution centre is not put away, but instead is readied for shipment to retail stores. Cross-docking requires close synchronisation of all inbound and outbound shipment movements. By eliminating the put-away, storage and selection operations, it can significantly reduce distribution costs."

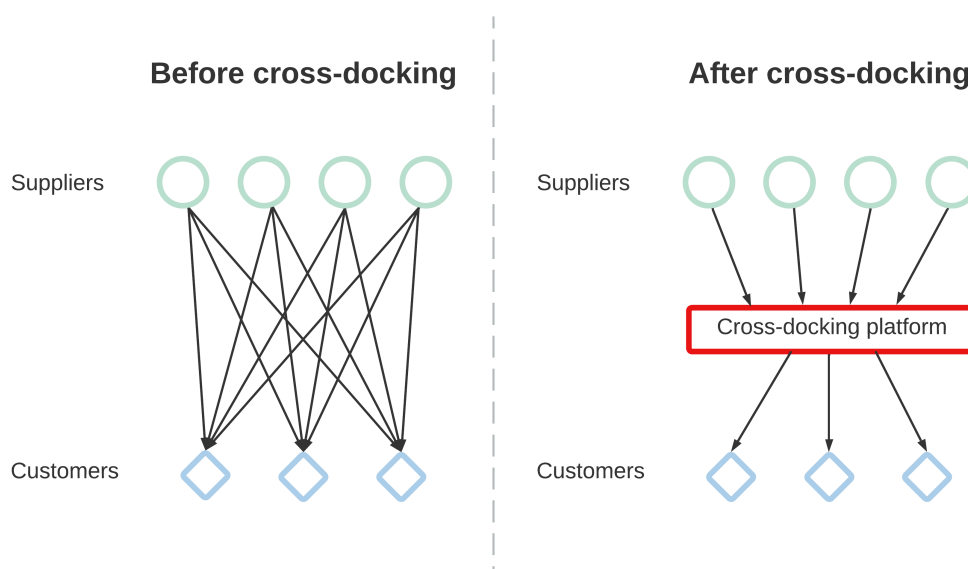


Figure 1.1: The transportation of goods in supply chain before and after practicing the cross-docking technique

Cross-docking is quite applicable for products that are always highly demanded and dispatched in substantial volumes. In addition, fast-moving products particularly benefit from cross-docking, demanding significantly less storage time. The survey which is conducted in 2011 among logistics professionals ([Saddle Creek Corporation, 2011](#)), clarifies the motivations that drive practitioners to do the cross-docking practice (see Table 1.1).

Although cross-docking provides numerous advantages, according to [Ladier and Alpan \(2016a\)](#), it needs perfect coordination of incoming and outgoing flows in logistics platforms under uncertain conditions. Indeed, practitioners and researchers face changing conditions and challenges, such as traffic delays causing truck arrival time uncertainties and dock door or equipment failure, while fulfilling the requirement of seamless material flow within the intricate context of cross-docking.

In the context of cross-docking, the intricacy arises from the many aspects that require consideration, such as truck scheduling, inventory management, workforce coordination, and resource

Greatest benefits of cross-docking	% of respondents
Improved service level	19.5%
Reduced transportation cost	14.3%
Consolidated shipments to destination	13.1%
Get products to market more quickly	10.2%
Reduced need for warehouse space	8.5%
Improved inventory management	8%
Saving from reduced inventory carrying costs	5.7%
Increased demand for JIT service	4.5%
Shipments / consignee customisation	4%
Reduced labor costs	4%
Other	8.3%

Table 1.1: The motivations that drive practitioners to use the cross-docking practice

Source: *Saddle Creek Corporation (2011)*

utilisation, all working together to ensure the efficient flow of goods. Each of these factors is interconnected, and any change in one aspect can have ripple impacts throughout the whole operation, making cross-docking complex and intricate.

To address this critical issue and enable effective decision-making under dynamic and uncertain conditions of cross-docking, we conduct a comprehensive, state-of-the-art literature review (Torballi and Alpan, 2023a). Our findings illuminate the important role of robust models in proactively managing uncertainty and establishing a solid basis. However, the real-time models appear as the dynamic caretakers of cross-docking operations when uncertainties exceed manageable levels. They ensure flexibility, stability, and efficient resource utilisation to sustain the seamless flow of cross-docking activities. Their presence is imperative for orchestrating agile answers to the ever-evolving challenges faced within the detailed nature of cross-docking.

However, given that real-time models acquire complete visibility on the system, they necessitate an increased amount of real-time data. Industry 4.0 technologies can bring a solution to this challenge since they support real-time planning.

While real-time models have a critical role in facilitating rapid decision-making in response to dynamic and uncertain conditions, our literature review highlights their limited application in the cross-dock domain. Despite the limited adoption of dynamic models, such as simulation and multi-agent-based models, they hold a strong promise in leveraging real-time data for responding to cross-docking scheduling challenges.

1.2 Problem and Motivations

In this thesis, we explore the dynamic environment of cross-docking to enhance operations to respond to various challenges, including delayed trucks, varied process times and, despite these challenges, the requirement of achieving fast synchronisation of the cross-dock.

Our research is supported by a comprehensive analysis of existing literature, detailed in the following chapter, highlighting the critical role of robust models as proactive solutions in

addressing uncertainty. These models are complemented by the reactivity of real-time models when uncertainties surge beyond manageable thresholds.

However, the applications of real-time models are limited despite their efficacy in tackling this intricate cross-dock environment and the potential offered by Industry 4.0 technologies. These gaps serve as the cornerstone for defining the objectives and motivations of this dissertation.

To this end, we put a strong emphasis on the development and application of real-time models. In the context of cross-docking, "real-time" signifies the capacity for rapid, adaptive decision-making, enhancing operational flexibility, efficiency, and responsiveness. Our research dedication to real-time models aligns with our understanding of the intricate aspects of dynamic cross-dock operations, necessitating the rapid coordination of its interconnected elements. These models provide the agility and adaptability required to manage truck scheduling, improve resource allocation and mitigate delays, ultimately elevating cross-docking efficiency against uncertainty.

1.2.1 Dissertation objectives

The main goal of this thesis is to develop a real-time model for cross-docking to be operated efficiently and effectively in an uncertain environment.

To better understand the essence of "real-time" in this context, it is necessary to clarify this temporal notion, given that it plays a key role in shaping our approach to cross-docking operations.

The definition of "real-time" may vary according to the application for which the real-time method is designed. "Time" may be in the range of ultra-fast, measured in nano-seconds, but may also extend up to several minutes based on the requirements of the application. In cross-docking, "real-time" scheduling requires prompt and efficient responses but can admit a decision time frame of a couple of minutes. This time-frame is to be decided by the decision-makers depending on the precise needs of the cross-docking operations. This ensures that scheduling stays highly responsive to varying conditions and facilitates efficient resource utilisation, mitigations of delays, and fast flow of goods within the cross-dock platform. In the context of this thesis, and without loss of generality, we adopt the assumption that a "real-time" schedule for cross-docking should not exceed the threshold of five minutes based on our earlier experience on truck scheduling problems ([Ladier and Alpan, 2016a](#); [Larbi et al., 2011](#)).

In this thesis, the term "real-time modelling" implies the method of monitoring, analysing, and optimising operations in real-time using data analytics and simulation. This means using real-time data to make cross-docking operations more efficient and effective.

1.2.2 Problem statement

To achieve the main objective, this thesis aims to answer the following:

- How to schedule incoming and outgoing trucks and thus pallet flow in a cross-docking terminal on a real-time basis?
- How to configure the internal operations of a cross-docking terminal to be responsive to real-time incoming and outgoing flows?
- How can real-time scheduling fit into the industrial context?
- How can real-time scheduling methods demonstrate their advantages and adaptability to the diverse problem configurations in the cross-docking literature specially tailored for deterministic scheduling methods?

To achieve the core objective of this thesis, we conduct a comprehensive literature review focused on simulation methodologies in cross-docking, empowering us with the tools to develop real-time models (*Chapter 3*). Building upon this analysis, we develop a real-time truck scheduling

model to address the first two research questions by providing a solid basis for us to achieve a rigorous evaluation of its effectiveness within a controlled, single inbound and outbound doors cross-docking platform (*Chapter 4*). Then, we extend this model to handle more complex scenarios involving multiple doors and real-world decision-making (*Chapter 5*). Hence, *Chapter 5* addresses the third research question. Finally, to address the fourth research question, we apply our real-time model to an existing cross-docking truck scheduling study, demonstrating its versatility and applicability to various problem configurations designed for deterministic scheduling methods (*Chapter 6*).

1.3 Research outline and main contributions

This dissertation is structured as follows (Figure 1.2):

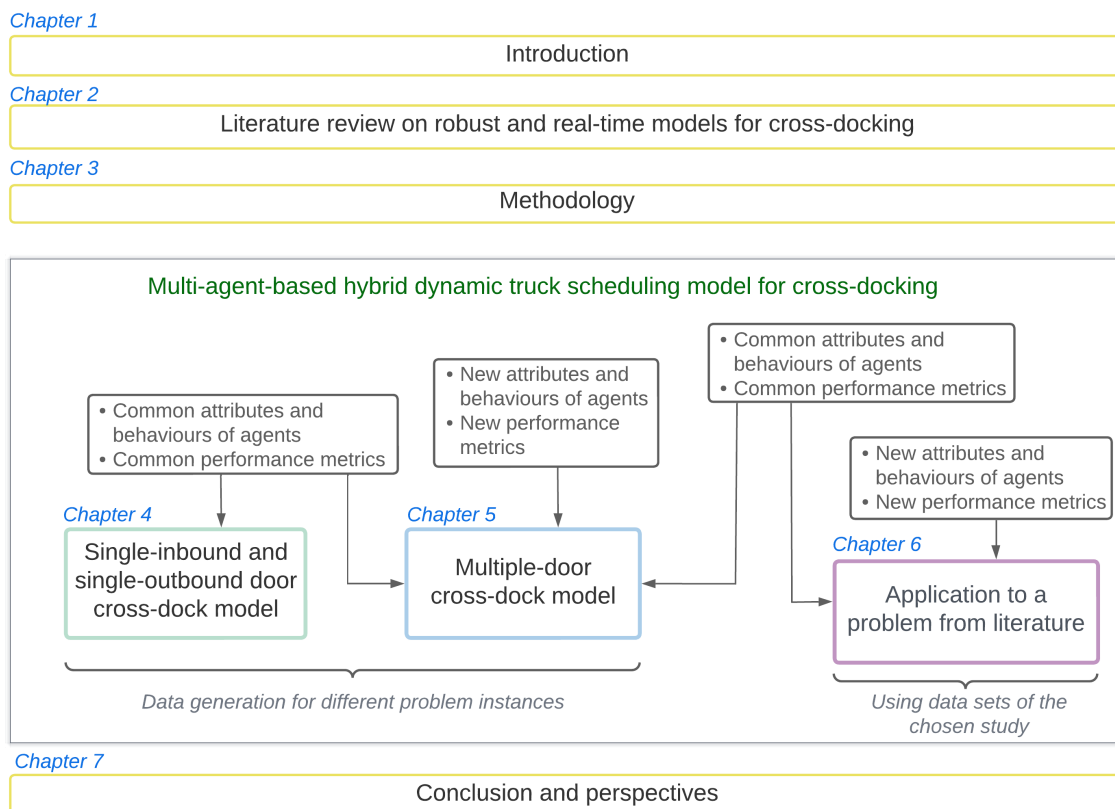


Figure 1.2: Dissertation structure

Chapter 1 introduces the thesis research by presenting the general context and explanations of the concepts together with their interrelations. In addition, this chapter articulates the research objectives, formulates the problem statement, highlights contributions, and provides a detailed outline of the dissertation's structure.

Chapter 2 presents the state-of-the-art review of robust and real-time models for cross-docking, with a particular focus on scheduling problems, especially within the road-to-road cross-dock environment. The conducted systematic literature review addresses the collection, identification, screening, eligibility, and inclusion steps to extract the most relevant literature. This review highlights the most relevant studies and pinpoints critical gaps in the existing literature. These identified gaps serve as the foundation for formulating the research questions addressed in this

dissertation.

Chapter 3 delves into the methodology underpinning this research, driven by the insights gained from the literature review presented in Chapter 2. Our primary objective is to provide a thorough account of the research methodology centred around real-time scheduling approaches. Furthermore, we present a general survey of prominent simulation modelling methods within the cross-docking literature. Subsequently, we explain these modelling techniques, focusing on their usefulness and considering their application limitations under different operational conditions.

Chapter 4 presents a novel model rooted in the multi-agent-based dynamic method, building upon the foundational insights in Chapter 3, which emphasises the significance of problem-driven methodology selection. This dynamic model is implemented as multi-method modelling, consisting of multi-agent-based and discrete-event simulations. It aims to rapidly synchronise cross-docking operations by exploiting the multi-agent systems' autonomous, reactive and distributed responsibility characteristics to realise shared computation and respond flexibly to dynamic events. To this end, the model is operated in a single inbound and outbound doors cross-dock setting, allowing for a comprehensive analysis of system dynamics and a profound understanding of multi-agent-based real-time truck scheduling within cross-docking operations. Moreover, it establishes a solid groundwork for scaling up to more complex cross-docking systems, notably multi-dock environments.

Chapter 5 expands upon the core concepts introduced in Chapter 4, undertaking a more comprehensive analysis by designing an advanced model aiming to be fit for real-world cross-docking scenarios. The developed model adapts the complexities of multiple doors and decision-making strategies to mimic the dynamics of cross-docking operations better. To this end, a detailed analysis of model adaptability and effectiveness across diverse scenarios is carried out. In alignment with our findings, we conduct a rigorous assessment of the model's scalability, monitoring its performance across a spectrum of door set configurations. In addition to these analyses, we analyse the model's computational efficiency in accordance with the practical temporal constraints that characterise real-world cross-docking operations. This assessment helps determine the model's suitability for real-time scheduling applications.

Chapter 6 introduces an adaptable version of our previously proposed multi-agent-based hybrid model, as presented in Chapters 4 and 5. This adaptation aims to demonstrate the model's versatility in a diverse range of truck scheduling problem configurations, specifically focusing on scenarios involving mathematical optimisation methods. To this end, an existing truck scheduling problem (Van Belle et al., 2013) in the cross-docking literature is selected. Furthermore, the decision-making configurations built in the previous two models are adapted towards the focus of the chosen truck scheduling study. We evaluate the proposed model using problem instances from the selected study, representing larger problem sizes and complex scenarios. The results are analysed from a comparative perspective, taking into account the advantages and limitations of both models.

Chapter 7 presents the findings of the thesis work, highlighting its primary contributions and outlining potential avenues for future research.

2

Literature review on robust and real-time models for cross-docking

Chapter 1 raised several key research questions to guide our investigation into real-time scheduling and operations in cross-docking terminals. We aimed to understand how to schedule incoming and outgoing trucks, configure internal operations to respond in real-time, seamlessly integrate real-time scheduling with the industrial context, and assess the advantages of real-time scheduling methods compared to deterministic approaches. To this end, in this chapter, we propose an overview of robust and real-time models for cross-dock problems focusing on scheduling problems. As we delve into the literature review presented in this chapter, we gain valuable insights that shed light on real-time scheduling models, showcasing their potential to address the intricate uncertainties that pervade cross-docking operations. This chapter bridges the foundational concepts established in Chapter 1 and the valuable insights drawn from existing research, offering a roadmap for our inquiries and significant contributions to this dynamic field of study. Furthermore, our findings from the gaps in the literature highlight the promise of real-time methods in effectively managing uncertainty within the cross-docking environment.

The research showcased within this chapter is also presented in the following article:

[Torballi and Alpan \(2023a\)](#). A literature review on robust and real-time models for cross-docking. *International Journal of Production Research*, 61(7):2372-2401, DOI: 10.1080/00207543.2022.2062580.

2.1 Introduction

Cross-docking is a logistics technique employed in a freight terminal, usually consisting of dock doors on two sides (inbound and outbound) with minimal storage space inside.

According to the definition of cross-docking given by [Kinnear \(1997\)](#), the focus is on the consolidation of freight to obtain cost-effective shipment. The name "cross-docking" describes the transportation of incoming goods from the inbound dock directly to the outbound shipment dock. In that manner, the transshipment process gets more focus than storage in a cross-docking facility. [Figure 2.1](#) depicts a classical cross-docking facility.

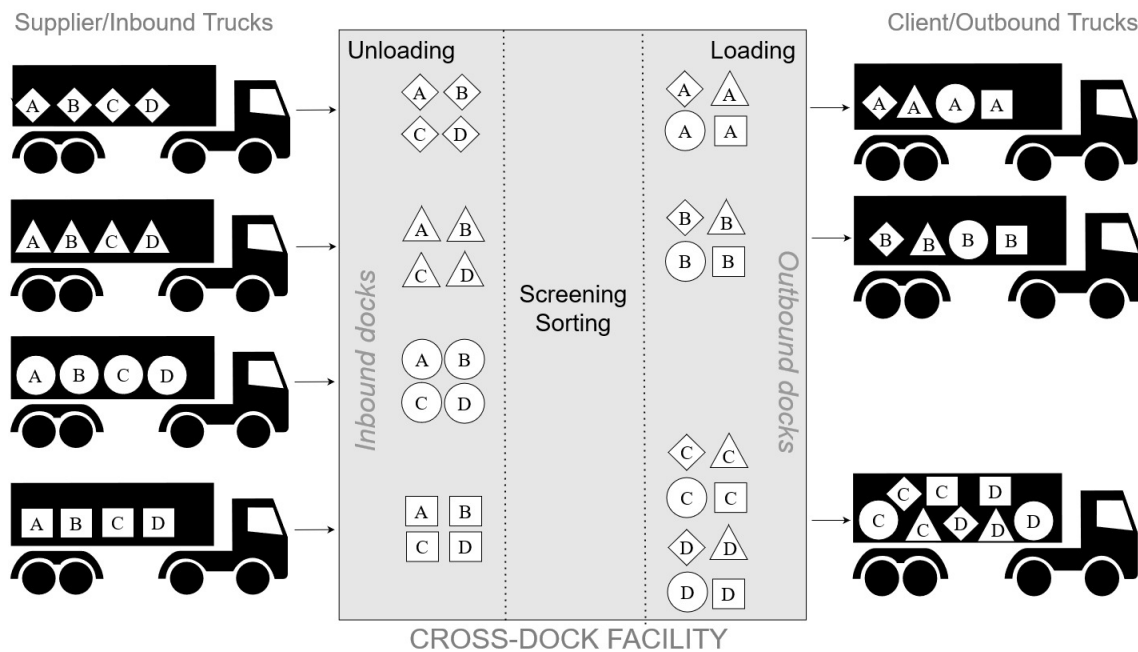


Figure 2.1: A classical cross-docking facility

In this figure, while letters indicate the destinations of each product, shapes state that these products are received from different suppliers.

As cross-docking reduces inefficiencies in supply chain operations, many companies are practising this strategy. Wal-Mart is a well-known initial user ([Stalk et al., 1992](#)). Other successful applications are also reported by Goodyear GB Ltd. ([Kinnear, 1997](#)) and Toyota ([Stephan and Boysen, 2011](#)).

Cross-docking brings numerous optimisation questions, either on strategic, tactical, or operational level and on different problem types. Several state-of-the-art review articles are proposed in the literature. Among them, [Van Belle et al. \(2012\)](#) propose a comprehensive analysis of the cross-docking literature and classify studies regarding decision levels (strategic, tactical, or operational). [Buijs et al. \(2014\)](#) distinguish decision levels of problems either locally at the cross-dock or elsewhere in the cross-docking network and cluster them into six cross-docking problem classes. [Ladier and Alpan \(2016a\)](#) consider operational optimisation problems in the cross-docking and suggest a framework highlighting the gaps between the literature and some cross-docking applications in France. Recently [Theophilus et al. \(2019\)](#) give a state-of-the-art review with a focus only on the truck scheduling problems at cross-docking facilities. Our article analyses papers according to the classification presented by [Van Belle et al. \(2012\)](#), [Buijs et al. \(2014\)](#) and [Ladier and Alpan \(2016a\)](#).

Cross-docking requires perfect coordination of incoming and outgoing flows in logistics platforms in an often uncertain context (Ladier and Alpan, 2016a). Naturally, recent publications on cross-docking started paying attention to uncertainty. In a recent literature review, Ardakani and Fei (2020) present various uncertainties inherent in cross-docking operations. They analyse articles on tactical and operational cross-docking problems based on the uncertainty types addressed. A limited number of research directions are then highlighted, related to truck arrivals and departures uncertainties, and resource capacities.

This chapter is intended to complement the previous literature surveys on cross-docking by focusing on robust and real-time models against uncertainties and point out future research opportunities in this field. Indeed, most of the articles related to robust and real-time scheduling are reported after the publication of Van Belle et al. (2012), Buijs et al. (2014) and Ladier and Alpan (2016a). Our article also complements Ardakani and Fei (2020), with an extended list of articles compared to this study, and by taking a point of view on the methodologies, notably on robust and real-time approaches. We also provide additional research directions that are not limited to uncertainty types as in Ardakani and Fei (2020). We believe that presenting a comprehensive study from a robust and real-time point of view is relevant for both practitioners and researchers. The current industrial context is challenging due to complex inter-dependencies of supply chains, but also conducive to solutions thanks to numerous new technologies. As highlighted by Ladier and Alpan (2016a), there is a clear need expressed by the cross-dock practitioners for methods that can provide robust solutions against uncertainties. There is not a unique definition of robustness in the literature since this concept might be understood differently depending on the scientific domain. In this article, when we make reference to robust models, we consider models that give robust solutions (i.e. robust plans or schedules). We refer to the definition given in Billaut et al. (2008), where "a schedule is defined as robust if its performance is rather insensitive to the data uncertainties". Therefore, the generated plan or schedule is expected to provide a similar result with respect to a given performance measure even when the model inputs are disturbed (provided that the disturbance is within a certain limit). While robust schedules are proactive solutions to deal with uncertainties, real-time models complement them perfectly as reactive counterparts. Indeed, if the disturbances in the input data are very high, even a robust solution may not cope with such high uncertainty. In this case, a real-time solution is necessary. This latter acquires a full visibility on the system and hence an increased amount of real-time data. Industry 4.0 technologies can bring a solution to this challenge since they support real-time planning.

The chapter is organised as follows. Section 2.2 addresses the research methodology. Section 2.3 presents six cross-docking problem classes and lists the related decision levels used as a framework to present the reviewed articles in Section 2.4, analysed papers are classified according to their decision levels, problem classes and methodology. Section 2.5 concludes the paper with discussions on the outcomes of analysed papers together with identified gaps in the literature.

2.2 Methodology

The process of collecting and selecting the papers is inspired by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) methodology (Moher et al., 2009). The key steps are listed below:

1. Collection: Various keyword combinations from different databases are queried to filter out studies related to this topic. Table 2.1 gives these keyword combinations and databases. Papers reported until the beginning of February 2022 are considered. A total of 95 publications are found. This number includes some duplicates, which will be eliminated. Since

the total number of papers found in the initial search is not extremely high, we do not use any restrictions on publication year and document type, except for an English language restriction. Table 2.2 shows the publication types and numbers related to the keywords. Note that only articles and proceedings papers exist in this survey. Publication types such as editorial material and book chapters are not found. The same paper can also be found using more than one different keyword combination. Thus, some papers are counted several times in the table. The duplicates are eliminated at the identification step.

2. Identification

- A total of 83 studies are identified by database searching.
- Twelve of the further studies are identified by other resources (from the references of the collected papers) and are included in the study.
- Sixteen duplicates are eliminated, resulting in 79 articles to screen.

3. Screening

- A total of 79 studies are screened based on title analysis.
- Four studies are eliminated since they were related to domains other than logistics; two articles were on biology and two on chemistry.

4. Eligibility

- A total of the 75 studies are analysed by scanning their abstracts for eligibility.
- Since the scope of this study is to propose an overview of robust and real-time models for cross-dock problems with a focus on the scheduling problems; we discard articles related to topics such as general supply chain management models and production planning where cross-docks are mentioned but are not the main focus area. Consequently, 22 studies are excluded.

5. Included

- A total of 53 studies are included in the analysis. The analysis is consisted of extracting the following information for each article:
 - (a) Problem class
 - (b) Aim
 - (c) Modelling and solution methods: if optimisation methods are used, categorise the solution methods as exact methods, heuristics, meta-heuristics, and state their objective functions
 - (d) Assumptions
 - (e) Results (contributions)
 - (f) Main takeaway
 - (g) Future research

With the steps mentioned above, we identify the primary outcomes of the selected literature distinguish their contributions and limitations and deduce research gaps (Figure 2.2). To this end, we propose several classifications of the studies depending on the decision levels (strategic, tactical, or operational), depending on the problems studied, and the type of techniques used for modelling.

Table 2.1: Databases and keywords employed for papers research

Databases	
Web of Science (webofknowledge.com)	
IEEE Xplore (ieeexplore.ieee.org)	
Inspec (ovidsp.dc2.ovid.com)	
ACM Digital Library (dl.acm.org)	
Keyword combinations	Number of combinations
(cross-dock/cross dock/cross-docking/cross docking/cross-dock hub/cross dock hub/cross-docking hub/cross docking hub)	8
(cross-dock/cross dock/cross-docking/cross docking/cross-dock hub/cross dock hub/cross-docking hub/cross docking hub)	8
(cross-dock/cross dock/cross-docking/cross docking/cross-dock hub/cross dock hub/cross-docking hub/cross docking hub)	16
(cross-dock/cross dock/cross-docking/cross docking/cross-dock hub/cross dock hub/cross-docking hub/cross docking hub)	16
(cross-dock/cross dock/cross-docking/cross docking/cross-dock hub/cross dock hub/cross-docking hub/cross docking hub)	16

Table 2.2: Publication types and numbers related to keywords - total of 95 publications

Keywords	Articles	Proceedings	Total
(cross-docking) AND (robust)	43	6	49
(cross-docking) AND (uncertainty)	41	6	47
(cross-docking) AND (real-time scheduling)	3	4	7
(cross-docking) AND (just-in-time scheduling)	4	-	4
(cross-docking) AND (online scheduling)	-	-	-

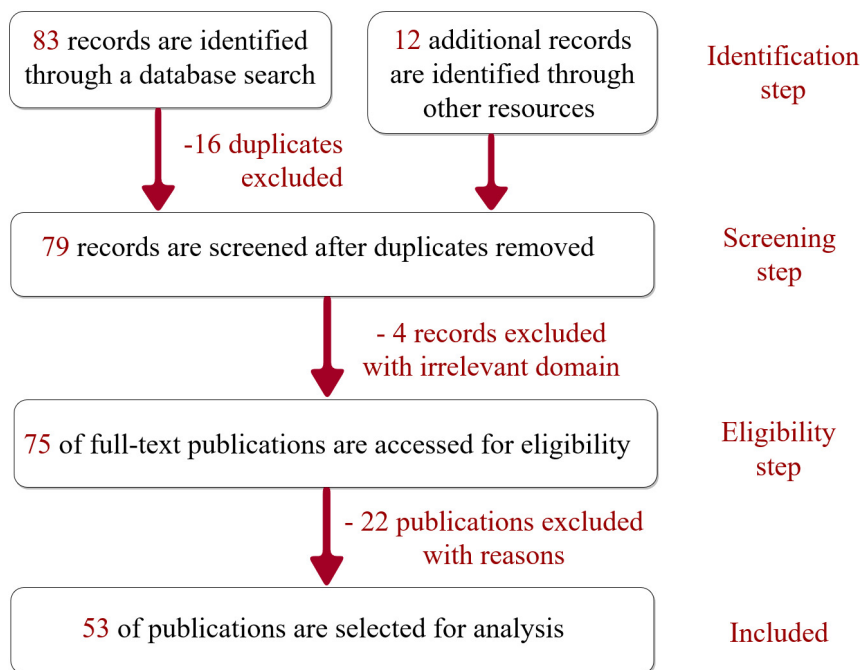


Figure 2.2: The entire range of stages regarding the methodical review

2.3 Corresponding framework

This section describes cross-dock characteristics based on decision levels and problem classifications. They are referred to in the subsequent sections to analyse papers reviewed in the literature.

The critical decisions and problem classes (used by the frameworks of [Van Belle et al., 2012](#); [Buijs et al., 2014](#)) are given in this section and also analysed in detail in Section 2.4, where a literature review is treated.

2.3.1 Cross-docking problem classification

Cross-docking users must consider numerous decisions based on the design and operational aspects of the cross-docks. These decisions can significantly impact the efficiency of the cross-dock, so they have to be carefully taken. Besides, some of these decisions have consequences in the long term (strategic or tactical level) while others include the short-term issues (operational level).

Defining the physical characteristics of cross-dock is considered as long-term or strategic level decisions. [Van Belle et al. \(2012\)](#) detail the physical characteristics of cross-dock into three groups: shape, number of dock doors and internal transportation method. Cross-dock terminals can have different shapes which are also represented with a letter (e.g. I, L, U, T, H, E). Each shape has a different impact on the performance of cross-docks. Another physical characteristic is the number of dock doors in the cross-dock centre. The total number of inbound (strip) and outbound (stack) dock doors is determined according to the service level of the cross-dock. Another strategic decision regarding a cross-dock terminal is internal transportation. For example, the material handling in cross-dock can be operated by man (e.g. pallet trucks or forklifts) or automated (e.g. conveyor belts).

Tactical level decisions are medium-term decisions. In a cross-docking terminal, several tactical decisions are stated by [Boysen and Fliedner \(2010\)](#). For instance, the service mode of the terminal doors (i.e. if a door serves uniquely as inbound, outbound, or both), decisions on the temporary storage capacities, the number of human resources, and the number of material handling resources are typical examples of tactical decisions inside a cross-docking terminal.

Operational level decisions impact daily activities in cross-dock. Cross-dock practitioners and researchers use the following parameters to make operational level decisions for the cross-dock. For example, the arrival and departure times of trucks and product interchangeability can be considered managerial-level constraints. In the case of consecutive truck arrivals, operations can be carried out for any truck at any time; then there is no time restriction on truck arrivals to the cross-dock facility. However, if the arrival of the truck depends on external conditions, then the arrival times are specified per truck. Furthermore, the departure time for trucks can be limited according to the presence of the next assignments of trucks. Otherwise, there is no restriction on the departure time for trucks. Departure time is determined both for inbound and outbound trucks. Additionally, if two products are similar and can replace one another, they are called interchangeable.

Buijs et al. (2014) propose six problem classes according to decision levels and whether a single or a network of cross-docks are considered. In this paper, we will use this classification in our analysis. Indeed, the problem types and the decisions made are quite different from one problem class to another. Therefore, most of the researchers that are working in the area of cross-docking concentrate on one or two problem types. Similarly, the practitioners who make decisions on strategic, tactical or operational levels are not the same. Therefore, a classification based on problem classes is handy for both researchers and practitioners. We first explain what these problem classes are.

Cross-dock design

Cross-dock design decisions define the shape of the cross-dock and determine its layout to ensure active transshipment and enough capacity to satisfy load throughput conditions. In this manner, the shape of cross-dock, number of dock doors, and automation of material handling equipment are considered as strategic level local cross-dock management decisions.

Cross-dock planning

Cross-dock planning aims to minimise the material handling work needed for transferring incoming load from inbound to outbound doors. Dock door specification, inbound / outbound door assignment, equipment, and workforce capacity plan are regarded as tactical level local cross-dock management decisions.

Cross-dock scheduling

Cross-dock scheduling decisions define the allocation of resources at the terminal promptly. Scheduling decisions for assisting individual trailers at the cross-dock enable a connected flow of shipping from inbound to outbound doors. These operational level decisions contain offline/online scheduling of inbound / outbound trailers and workforce, shipment allocation, temporary storage utilisation, and shipment to outbound trailer assignment.

Network design

Network design decisions define the physical infrastructure of the cross-docking network to fulfil transport requirements cost-effectively. These strategic level cross-docking network management decisions include defining the network structure and facility types, number and location of cross-docks.

Network planning

Network planning decisions focus on allocating and using network-wide logistics resources to achieve customer service level goals cost-effectively. The tactical level cross-docking management

decisions such as the capacity plan for network routes, shipping flow allocation, and shipment to destination assignment are considered network planning decisions.

Network scheduling

The network scheduling decisions hold temporary routing restrictions in a cross-docking network. This characteristic can be counted as a difference between network scheduling and network planning decisions. These operational level decisions consider shipment dispatching, collection, and delivery truck routing.

2.4 Literature review

In this section, we present the 53 references identified using the method described in Section 2.2. The papers are regrouped based on the framework described in Section 2.3. Consequently, the following sections explain the reviewed papers in detail according to their decision levels. The real-time models are indeed relevant only for operational problems (see Tables 2.3 and 2.4). However, robust models could concern tactical and strategic levels as well since some robust solutions may, for instance, require buffer resources to be put in place. Allocating extra resources concerns tactical or even strategic decisions. Therefore, even though the majority of the problems studied are expected to be on the operational level, we believe that it is also important to review tactical and strategic levels. Problem specifications of the reviewed publications are summarised in Table 2.5.

2.4.1 Strategic and tactical level

While cross-dock design problems consider cross-dock facility installation, network design problems analyse the physical infrastructure of the cross-docking network. They are both strategic-level decisions. Shi et al. (2013) suggest a physical structure for the cross-dock facility to tolerate supply uncertainty. Babazadeh et al. (2014) deal with operational and disturbance risks in the supply chain network design problem. Since the location selection of cross-docking facilities is a technical and managerial decision-making subject, most network design problems use a multi-criteria group decision-making (MCGDM) model. Therefore, Mousavi et al. (2019) proposed an MCGDM model, including interval-valued intuitionistic fuzzy sets for the location selection problem of cross-docking facilities in the supply chain network to handle the demand, supply and process time uncertainties. Similarly, Deng and Qu (2020) present MCGDM based upon an interval multi-granularity language model to cope with the ambiguous nature of linguistic location selection criteria for cross-docking centres. Barsing et al. (2018) introduce a social network analysis (SNA) to choose proper cross-docking centre locations for the food-chain industry. Their study overcomes the uncertainty related to food freshness by reducing transshipment time, and thus operations cost in the supply chain network. Mousavi et al. (2013) combine strategic and operational aspects for cross-dock centres, namely the location selection and the truck routing problems. The authors propose fuzzy possibilistic programming to address uncertainties regarding demand, supply and resource availability. The proposed approach reduces the operation cost for the cross-docking facility and transportation cost of trucks in the supply chain.

Tactical level decisions examine both cross-dock and network planning problems. Darvishi et al. (2020) study a logistics system composed of several suppliers, manufacturing facilities, and warehouses under uncertainty. They analyse buying alternatives, supplier selection, multi-site aggregate manufacturing, and inbound transportation as a whole. Their analysis shows that cross-docking reduces lead times by decreasing the product dwell time in the storage and transportation

costs compared to standard warehouse shipping. The authors introduce a novel two-phase hybrid algorithm for the model solution. The algorithm employs the defuzzification of fuzzy parameters according to the interval expected value and a possibilistic programming approach. Concerning the two-stage stochastic programming model, a robust optimisation formulation is used. Finally, the introduced model is tested for the industrial case.

Walha et al. (2014) study a dock door assignment problem for cross-docking in physical internet from tactical and operational points of view. The authors also classify the dock door assignment problems in the cross-docking literature based on their uncertainty types (internal or external uncertainties). The studied cross-docking pi-hub problem analyses the real-time control opportunities against the uncertainties, including truck arrival and departure time, process time and resource availability.

Wang and Alidaee (2019) analyse a multi-floor, cross-dock door assignment problem (MCDAP) to minimise the total handling expenses of large unit loads inside the cross-dock facility. The multi-floor, cross-dock system increases transportation speed for large-sized products by decreasing gate congestion and supplying a flexible handling way for various products. For instance, since the material handling for different products is performed on different floors, only the required type of handling equipment will be provided to each floor. Thus, the handling equipment cost will be optimised. The authors introduce a new mixed-integer nonlinear programming model and a traditional linearisation model for the given problem. Furthermore, the proposed algorithms are tested on large-sized examples.

These strategic and tactical level problems only deal with robust scheduling in cross-docking. As expected, no study investigates real-time scheduling in cross-docking at a strategic and tactical level.

2.4.2 Operational level

As shown in Table 2.4, cross-dock scheduling problems are the most popular studies, network scheduling problems are the second most popular (they are both operational level decisions). Most cross-dock scheduling problems examine truck scheduling and take time dimension into account. Network scheduling problems study to determine cross-docking centres (CDCs) and schedule truck routing problems with multiple CDCs to minimise the makespan, number of truck trips, and so transportation cost. The reviewed operational level problems are classified into five primary sections, as follows: (1) truck scheduling; (2) truck sequencing and truck-to-door assignment; (3) truck routing; (4) trailer-to-door assignment; (5) scheduling, planning, and coordination activities in cross-dock. A comprehensive analysis of the operational level studies is given in the following subsections of the paper.

Truck scheduling

Most of the cross-dock scheduling studies (30 of the total 43 cross-dock scheduling studies) analyse truck scheduling problems. Amini and Tavakkoli-Moghaddam (2016) study an outbound truck scheduling problem at a single-door cross-docking facility. The objective of the study is to minimise total completion time and truck tardiness against resource uncertainty. The study considers truck breakdowns that follow a Poisson distribution. A bi-objective optimisation model and three meta-heuristics are presented for small and large problem sizes, respectively.

Heidari et al. (2018) consider a truck scheduling problem at a multi-door cross-docking terminal under truck arrival time uncertainty. The authors define time windows for unknown truck arrivals. A mathematical model that minimises the total operation cost of the terminal is presented. Two meta-heuristics are employed for solving the problem.

Konur and Golias (2013a) study an inbound truck scheduling problem at a multi-door cross-docking terminal. The authors define time windows based on a triangular distribution for uncertain truck arrival times. The problem is solved by employing a genetic algorithm for a deterministic

case. A bi-level optimisation model is developed to solve cases where the total waiting times for trucks are expected to be maximum (pessimistic case) and minimum (optimistic case). According to the results, a hybrid case outperforms others in terms of minimum unloading and process times. In another study, [Konur and Golias \(2013b\)](#) introduce a cost aspect to the same problem settings. They minimise the impact of truck arrival time uncertainty on the scheduling cost.

[Ladier and Alpan \(2016b\)](#) examine truck scheduling problems with time slots. Their study analyses the truck arrival, loading, and unloading times under uncertainty. The study aims to minimise the total amount of pallets that go through the stock and the dissatisfaction of the transportation providers. Therefore, nine different methods, including the minimax method, the minimisation of expected regret, three models concerning the supply redundancy, and four models to the time redundancy, are compared for being robust against the changes in transfer, unloading, and arrival times. The carried mathematical analysis proves that the redundancy models provide the most favourable schedules in the sense of robustness, yet they are high priced to implement.

[Movassaghi and Avakh Darestani \(2020\)](#) combine various cross-docking subjects: truck-to-door assignment, truck routing, truck sequencing, and truck scheduling in their study. They propose a mixed-integer, non-linear programming model intending to minimise the transportation cost of trucks in the supply chain. Furthermore, fuzzy objective function coefficients are used in the proposed model to address uncertainties such as demand, process time, and resource availability.

[Nasiri et al. \(2019\)](#) study a truck scheduling problem for post-distribution cross-dock with no storage. A mathematical programming model including a whale meta-heuristics algorithm is employed to minimise the makespan under demand uncertainty. The performance of the model is tested under different uncertainty levels. According to the results, the model tolerates up to 20 % of demand uncertainty.

[Seyedi et al. \(2019\)](#) study the truck scheduling problem to minimise the makespan of a single door (one inbound-one outbound door) cross-docking terminal. For this purpose, the mixed-integer mathematical model developed by [Yu and Egbelu \(2015\)](#) is employed, and five new heuristics are proposed. The proposed heuristics are tested in small, medium and large problem sizes. According to the results, the proposed heuristics outperforms the previous algorithms in the literature by providing the minimum makespan.

[Shahmardan and Sajadieh \(2019\)](#) analyse a cross-dock truck scheduling problem. The inbound trucks are also utilised as outbound trucks, and they are allowed to be partly unloaded at the cross-dock facility. The mixed-integer model is introduced to minimise makespan by achieving optimum truck-to-door and truck-to-destination assignments. Because of the complex nature of the model, a hybrid heuristic-simulated annealing is implemented. Several generic and dedicated neighbourhood search methods are developed to explore the solution space. The study confirms that partial unloading of compound trucks has a significant impact on the makespan.

[Shakeri et al. \(2012\)](#) develop an algorithm to find a feasible solution for truck scheduling problems for different instances and difficulty levels. Therefore, a two-phase heuristic method is proposed to build a proper truck sequence for truck-to-door assignment, and the limited number of forklifts controls this process. The results confirm that the suggested method provides a robust solution and is applicable to industrial cases.

[Soltani and Sadjadi \(2010\)](#) analyse the truck scheduling problem for a cross-dock terminal where there is no temporary storage. Therefore, the authors seek to find the optimum matching pairs of inbound and outbound trucks to minimise the total flow time of merchandise in the terminal. For this aim, two-hybrid meta-heuristics are proposed. According to the outcomes, the suggested techniques provide an effective solution, especially for large-sized problems.

[Tavana et al. \(2017\)](#) study truck allocation and scheduling problems for cross-docks. Their study also considers drones for direct transportation between suppliers and customers. A bi-objective model is proposed to minimise scheduling cost and time. The solution performance of the proposed model is analysed with different problem instances. A sensitivity analysis is implemented to examine the impacts of parameter variations on the objective functions. According to the results,

the total number of dock doors in the cross-dock facility increases the completion time. Additionally, cost-related variations have more effect on drone shipment cost when compared to the truck delivery cost.

Vahdani and Zandieh (2010) study the truck scheduling problem for a cross-docking terminal where freights are directly transferred from inbound trucks to outbound trucks. Five different meta-heuristics are employed to achieve the optimum sequence of inbound and outbound trucks at the dock doors to minimise the makespan of the system. According to the results, the variable neighbourhood search (VNS) outperforms the other four algorithms for the given problem; however, it does not provide an optimum solution for real-size problems.

Vahdani et al. (2009) analyse a cross-dock facility where there is no temporary storage, and the complete unloading and loading are not allowed for the trucks. The best sequence of inbound and outbound truck pairs is determined to minimise the total processing time of the products inside the facility. Two meta-heuristics are employed for the solution. Moreover, the Taguchi approach is used to verify the robustness of the proposed model. The results verify the adequacy of the model for large-sized problems compared to former approaches.

Xi et al. (2020) examine a truck scheduling problem for a multi-door cross-docking centre where dock doors are reserved for serving as exclusive and mixed service modes. The authors present a notion called conflict, which occurs when the realised processing time of one truck coincides with the processing time of another truck's baseline schedule. A two-stage conflict robust optimisation model is then proposed to minimise the total cost resulting from truck waiting time and truck tardiness under truck arrival and operation time uncertainties.

Zarandi et al. (2014) study the cross-dock truck scheduling problem to minimise the total lateness and the number of pre-emption concerning the outbound trucks. The studied problem identified as NP-hard fits in the notions of just-in-time (JIT) production and supply chain management. Therefore, a JIT cross-dock model with the constraint satisfaction problem (CSP) and integer programming (IP) is proposed. Moreover, the performance of the suggested methods is evaluated by their solution quality on small problem instances.

Zouhaier and Ben Said (2017a) study real-time inbound truck scheduling for a cross-dock facility. They propose a multi-agent model to achieve a robust and optimal solution. The multi-agent systems (MAS) have autonomous, decentralised, and dynamic characteristics, and they give flexible responses to dynamic events. The proposed model comprises truck and resource agents with an ant colony intelligence (ACI). The ant colony optimisation provides global optimisation and decreases processing time by assisting the agents in completing tasks according to their priority.

Zouhaier and Ben Said (2017b) study a cross-dock truck scheduling problem with full and partial information regarding the truck arrivals for a resource-constrained cross-dock. According to the authors, the Appointment System (AS) application is one way to manage truck arrivals. The AS provides synchronisation between the cross-dock operators and trucks for unloading or loading processes. The uncertainty related to the presence of the truck and the workforce at a given time slot causes congestion. The main concern on the congestion is the long truck lines at the platform. The authors get inspired by the Queueing Theory (QT) to overcome this problem. A combined mathematical formulation and simulation model is introduced to optimise truck arrivals and resource scheduling. Besides, the introduced methodology minimises the total cost of the cross-docking terminal. The results confirm the robustness of the suggested model.

While three of the truck scheduling problems examine the optimal inbound and outbound trucks sequence (Wang et al., 2018a; Fathollahi-Fard et al., 2019; Movassaghi and Avakh Darestani, 2020), three of them examine truck-to-door assignment (Rijal et al., 2019; Vahdani and Shahramfard, 2019; Movassaghi and Avakh Darestani, 2020). Hence, these problems are given in the *truck sequencing* and *truck-to-door assignment* subsection. In addition, one of the truck scheduling problems (Li et al., 2012) also considers cross-docking planning, scheduling and operations coordination. Therefore, this study is explained in the *scheduling, planning and coordination activities in cross-dock* subsection.

The rest of the remaining network scheduling problems (six of them) consider both truck scheduling and truck routing (Vahdani et al., 2012; Mousavi et al., 2014; Yin et al., 2015; Mousavi and Vahdani, 2017; Rahbari et al., 2019; Movassaghi and Avakh Darestani, 2020). Thus, they are explained in the *truck routing* subsection - note that the study of Movassaghi and Avakh Darestani (2020) is given only in the *truck scheduling* subsection since it combines truck-to-door assignment, truck routing, truck sequencing and truck scheduling problems in their paper. Similarly, the study of Tavallali et al. (2020) is explained in *scheduling, planning and coordination activities in cross-dock* since it covers scheduling, planning and coordination activities in cross-dock and truck routing and scheduling problems.

Truck sequencing and truck-to-door assignment

While some of the operational level problems deal with the truck sequencing problems (Larbi et al., 2011; Wang et al., 2018a; Fathollahi-Fard et al., 2019) and truck-to-door assignment problems (Rijal et al., 2019; Vahdani and Shahramfard, 2019; Essghaier et al., 2021) one of them studies both truck-to-door assignment and truck sequencing problems (Kuo, 2013).

Fathollahi-Fard et al. (2019) analyse a cross-dock truck sequencing problem using modified versions of the Social Engineering Optimiser (SEO), which is motivated by social engineering phenomena. The proposed optimisers are verified by employing a collection of test functions. The Taguchi method calibrates all the algorithms. The real case research is directed to confirm the high efficiency of the improved optimisers.

Larbi et al. (2011) study a truck sequencing problem at a cross-dock centre with a single inbound and outbound dock door. The dock doors serve in exclusive mode, preemption is allowed, and temporary storage capacity is assumed to be infinite. The authors propose different scheduling methods against truck arrival time and supply uncertainties and evaluate the value of information. To this end, three problem settings are investigated: first, a deterministic case where truck arrivals and contents of each truck are known. The second and third cases are explored with partial or no information on arrival times and contents of trucks. An optimal graph-based algorithm is presented, and a polynomial-time algorithm is given for the deterministic case. Heuristics are presented for the stochastic cases. The results of three cases reveal that full or partial information is especially useful for near-future events and taking into consideration the uncertainties for distant events does not improve solutions.

Essghaier et al. (2021) study a truck-to-door assignment problem at a shared cross-docking terminal that allows horizontal collaboration between suppliers. At horizontal collaboration, common objectives such as cost reduction and service level enhancement are desired to be reached by managing operational risks and uncertainties. The authors propose a mathematical model to integrate horizontal collaboration into the truck-to-door assignment problem to reduce the total cost. The total cost includes pallet handling cost between inbound and outbound doors, penalty cost of late deliveries and rental cost of dock doors to suppliers. In addition, fuzzy triangular numbers are employed to model the uncertain transfer time of pallets inside the facility. Then, Fuzzy Chance Constrained Programming is suggested for defuzzification of the model to solve it by an exact solution algorithm.

Kuo (2013) studies both truck sequencing and truck-to-door assignment problems to minimise the makespan of a multi-door cross-docking system. The proposed model assigns trucks to dock doors based on a first-come, first-served rule. Moreover, to achieve optimum truck sequence, the variable neighbourhood search (VNS) method is employed. Four simulated annealing (SA) techniques are applied to compare the results. According to test outcomes, the suggested method provides higher performance on the solution quality than traditional solutions. Additionally, in contrast to SA algorithms, the VNS method does not provide better solutions; however, it performs robust outcomes. Therefore, the suggested approach is practical and useful for operational level cross-dock problems.

[Rijal et al. \(2019\)](#) consider both truck scheduling and truck-to-door assignment problems. The dock doors serve in a mixed service mode for the studied U-shaped cross-docking system (i.e. doors can be both inbound and outbound). An adaptive large neighbourhood search algorithm is introduced to achieve satisfactory solutions with minimum computational effort. The proposed approach determines the total number and location of mixed service mode doors. According to the results, the suggested algorithm decreases the operating costs of the cross-docking system in comparison to a sequential method.

[Vahdani and Shahrampard \(2019\)](#) study real-time truck scheduling and truck-to-door assignment problems for a cross-dock terminal where dock doors can serve in mixed service mode. The mathematical programming model is proposed to minimise total costs induced by storage, order delay, and truck waiting time. Moreover, two meta-heuristic algorithms are employed for the model solution. The proposed approach provides enhanced precision in the planning; however, it raises the total cost of the system. Additionally, the Queuing Theory is employed for truck arrivals and resource assignment to the operations for the cross-docking terminal.

[Wang et al. \(2018a\)](#) consider both truck sequence and truck-to-dock assignment problems of a multi-door cross-docking system. A mixed-integer linear programming (MILP) model and three meta-heuristics are applied to minimise the total operation time of the given system. Moreover, Taguchi experiments are used for optimising the solution parameters. Additionally, various numerical examples are performed to assess the achievements of the suggested model.

Truck routing

Ten of the total operational level problems focus on truck routing problem type. [Ahkamiraad and Wang \(2018\)](#) study the capacitated truck routing problem for a network, including multiple cross-docking terminals. The authors analyse pickup and delivery processes with time slots. Moreover, several truck routes are examined to minimise the total transportation and fixed costs of the given network. A mixed-integer linear programming (MILP) and hybrid meta-heuristic model is introduced for the problem solution. The numerical results validate the suggested approach for different problem sizes.

[Mousavi and Vahdani \(2017\)](#) consider both truck scheduling and truck routing problems for a network of cross-docks. The given problem includes the location selection of the cross-dock terminals in the given network. A novel two-phase deterministic mixed-integer linear programming (MILP) model is proposed to minimise the operating cost of cross-docks and the total cost related to truck routing. A robust optimisation model is employed against demand and supply uncertainties in the given network. A robust equivalent of the suggested deterministic model is proposed to manage the uncertainties of model parameters. The results confirm the adequacy of the suggested model.

[Mousavi et al. \(2014\)](#) study both truck routing and scheduling problems for a multi cross-dock network. The study considers the location selection of cross-dock facilities in the given network. Two new deterministic mixed-integer linear programming (MILP) models are introduced for this aim. Besides, a hybrid fuzzy possibilistic-stochastic programming method is applied to consider both quantity-related and time-related uncertainties. The performance of the suggested model is evaluated and confirmed for different problem sizes.

[Rahbari et al. \(2019\)](#) analyse both truck routing and scheduling problems regarding perishable products. According to the analysis, the uncertainty of truck departure time has a significant effect on product freshness. Therefore, two robust algorithms are generated for outbound truck departure time and product freshness time uncertainties. The results confirm that the introduced model provides a cost-effective solution for on-time deliveries while preventing wastes of products.

[Vahdani et al. \(2012\)](#) propose a novel hybrid meta-heuristic algorithm concerning the truck routing and scheduling problem. The suggested algorithm includes three meta-heuristics to improve solution performance. The Taguchi method is employed to test robustness regarding truck arrival and departure time uncertainties. The proposed model is compared to the Tabu search, and it

provides higher achievement in the results.

[Yin and Chuang \(2016\)](#) consider a truck routing problem from an environmental point of view. An adaptive memory artificial bee colony (AMABC) algorithm is generated to achieve optimum loading nodes for trucks in the supply chain network, decreasing transportation costs and CO₂ emissions. Besides, the results are compared with the Tabu search algorithm to show the performance of the proposed AMABC approach. According to the simulation results and geographic data, the proposed model is robust against supply and demand uncertainties.

[Yin et al. \(2015\)](#) combine two operational level decisions: network and cross-dock scheduling against the demand and truck arrival time uncertainties. The internal operations of the cross-docking facility are not taken into account, and the temporary storage is not included in their problem. A hyper-heuristic, including collaborative computing and collaborative service rules, is applied to minimise the makespan of a given cross-docking system.

Trailer-to-door assignment

[Acar et al. \(2012\)](#) study the trailer-to-door assignment problem for less-than-truckload terminals (LTL). A quadratic mixed-integer model is developed to uniformly distribute the idle times of each dock door in between the scheduled truck times to manage the truck arrival time uncertainty. Besides, a dedicated heuristic for trailer-to-door assignment is employed. The performance of the dedicated heuristic is analysed for different problem sizes by using Arena Simulation. According to the simulation outcomes, the suggested model is applicable for industrial cases, and it is robust against the changes in truck arrival and service times.

Scheduling, planning and coordination activities in cross-dock

Eight operational level problems deal with the scheduling activities in a cross-docking system ([Magableh et al., 2005](#); [Wang and Regan, 2008](#); [Boloori et al., 2010](#); [Li et al., 2012](#); [Zaerpour et al., 2014](#); [Castellucci et al., 2019](#); [Tadumadze et al., 2019](#); [Tavallali et al., 2020](#)) and three of them focus on local cross-dock management issues ([Rohrer, 1995](#); [Yan and Tang, 2009](#); [Tang and Yan, 2010](#)). [Boloori et al. \(2010\)](#) study the inbound and outbound trailer scheduling problem in a just-in-time (JIT) environment. The synchronisation between inbound and outbound trailers provides efficient distribution of goods to trailers and consequently improves the cross-docking performance. Multi-criteria scheduling is applied to minimise the earliness and tardiness of trailers to achieve this synchronisation. Moreover, three meta-heuristics are employed to improve the solution quality of the suggested model.

[Castellucci et al. \(2019\)](#) study the container loading problem to minimise the stay time of products inside the cross-docking facility, thus maximising the system's output. In addition, stochastic dynamic programming is employed to address the uncertainty in truck arrival time.

[Li et al. \(2012\)](#) study truck scheduling and handling equipment scheduling problems in the presence of real-time data. For this problem, the maximum throughput is achieved by minimising the product stay time in the cross-dock facility. Additionally, balancing the demand and resource availability, the system is robust against time-related and resource availability uncertainties.

[Magableh et al. \(2005\)](#) examine the internal operations of a cross-docking centre under several uncertainties, including demand, process time and resource availability. A simulation model is constructed to describe the studied cross-docking operations. The performance metrics such as lateness of product delivery and truck processing time deviation are analysed for the given problem.

[Tadumadze et al. \(2019\)](#) analyse the integrated truck and workforce scheduling (ITWS) problem. The analysis is carried out for two systems: a distribution centre where unloaded products wait in the terminal and a cross-dock facility where products are transferred immediately to outbound trucks. For both systems, the truck processing times are calculated according to the number of dedicated workforce to each truck. A mixed-integer model is employed. Both versions of ITWS are transformed into interval scheduling to solve the large-sized problems. Three heuristics are applied

to select the intervals. According to the results, the ITWS version of interval scheduling decreases product flow times and transshipment for both systems compared to a mixed-integer programming approach.

[Tavallali et al. \(2020\)](#) examine several decisions on the network and cross-dock scheduling to address uncertainty in the reverse logistics of perishable products. The problems of truck routing, truck scheduling and planning and coordination activities in cross-dock are studied to minimise transportation and inventory costs. A Mixed-Integer Linear Programming (MILP) and Non-Dominated Sorting Genetic Algorithm-II are proposed to solve the problem against the demand uncertainty.

[Wang and Regan \(2008\)](#) schedule the inbound trailers to decrease the dwell time of products in temporary storage. To this end, real-time information regarding material handling is exploited. Dynamic simulation models are applied to analyse the impact of the following policies: first-come-first-served, look-ahead, minimum processing time, and minimum total time. These policies are tested for different trailer routes, cross-dock facility layouts, and destination distributions. The results show that the time-related policies are more efficient on service levels than the first-come-first-served and look-ahead strategies for the given cross-dock system.

[Zaerpour et al. \(2014\)](#) suggest a perishable product storage policy for the cross-dock facility. A compact storage setup is chosen to provide cost-effective cooling for perishable products. However, it requires an additional product retrieval time from storage. Therefore a mathematical model and a dedicated heuristic are employed. The results verify that the suggested procedure is adequate for real-size applications and robust against time-related uncertainties.

[Rohrer \(1995\)](#) discusses local cross-dock management. In this descriptive study, the author offers an insight into the modelling of cross-docking operations. However, while the study recommends simulation systems as handy tools to avoid the problems before they are confronted, it does not provide any real-life or case study.

[Tang and Yan \(2010\)](#) focus on local cross-dock management. Pre-distribution and post-distribution strategies for cross-docking terminals are discussed regarding the performance measures such as inventory level and truck processing time deviation. According to analysis, the post-distribution strategy should be preferred when demand is uncertain, keeping in mind that it increases the operation cost. Similarly, [Yan and Tang \(2009\)](#) also examine these two cross-dock distribution strategies and include a traditional warehouse in this comparison as a benchmark. The same performance metrics with [Tang and Yan \(2010\)](#) are used. As a result, the pre-distribution strategy outperforms the traditional warehouse, and the post-distribution strategy gives the best performance among them under demand uncertainty.

Modelling approaches and solution methods employed by the reviewed studies are listed in [Table 2.6](#). As shown in this table, most papers take advantage of mathematical modelling approaches, notably meta-heuristics and heuristics, to handle uncertainties in their studies. The rest of the papers employ simulation, statistical, stochastic and fuzzy logic approaches for their problem solutions against uncertainty - as a side note, one study may use multiple solution approaches. Therefore, some papers are mentioned more than once in this table. In addition, the classification of the model settings for the total cross-dock and network scheduling problems are also given in [Table 2.7](#).

Table 2.3: Planning and scheduling types in the total reviewed publications

Author(s)	Robust	Real-time	Just-in-time	Other
Acar et al. (2012)	✓			
Ahkamiraad and Wang (2018)	✓			
Amini and Tavakkoli-Moghaddam (2016)				✓
Babazadeh et al. (2014)	✓			
Barsing et al. (2018)				✓
Boloori et al. (2010)			✓	
Castellucci et al. (2019)				✓
Darvishi et al. (2020)	✓			
Deng and Qu (2020)				✓
Essghaier et al. (2021)				✓
Fathollahi-Fard et al. (2019)	✓			
Heidari et al. (2018)				✓
Konur and Goliias (2013a)				✓
Konur and Goliias (2013b)				✓
Kuo (2013)	✓			
Ladier and Alpan (2016b)	✓			
Larbi et al. (2011)				✓
Li et al. (2012)		✓		
Magableh et al. (2005)				✓
Mousavi et al. (2019)				✓
Mousavi and Vahdani (2017)	✓			
Mousavi et al. (2014)				✓
Mousavi et al. (2013)				✓
Movassaghi and Avakh Darestani (2020)				✓
Nasiri et al. (2019)	✓			
Rahbari et al. (2019)	✓			
Rijal et al. (2019)	✓			
Rohrer (1995)	✓			
Seyedi et al. (2019)	✓			
Shahmardan and Sajadieh (2019)	✓			
Shakeri et al. (2012)	✓			
Shi et al. (2013)	✓			
Soltani and Sadjadi (2010)	✓			
Tadumadze et al. (2019)	✓			
Tang and Yan (2010)	✓			
Tavallali et al. (2020)	✓			
Tavana et al. (2017)	✓			
Vahdani and Shahramfard (2019)		✓		
Vahdani and Zandieh (2010)	✓			
Vahdani et al. (2009)	✓			
Vahdani et al. (2012)	✓			
Walha et al. (2014)	✓	✓		
Wang and Alidaee (2019)	✓			
Wang and Regan (2008)		✓		
Wang et al. (2018b)	✓			
Xi et al. (2020)	✓			
Yan and Tang (2009)	✓			
Yin and Chuang (2016)	✓			
Yin et al. (2015)	✓			
Zaerpour et al. (2014)	✓			
Zarandi et al. (2014)			✓	
Zouhaier and Ben Said (2017a)	✓	✓		
Zouhaier and Ben Said (2017b)	✓			
Total	34	5	2	14

Table 2.4: Publications according to their decision level and problem class

Publications	Strategic level		Tactical level		Operational level	
	Cross-dock design	Network design	Cross-dock planning	Network planning	Cross-dock scheduling	Network scheduling
Acar et al. (2012)			✓		✓	
Ahkamiraad and Wang (2018)						✓
Amini and Tavakkoli-Moghaddam (2016)			✓		✓	
Babazadeh et al. (2014)		✓				
Barsing et al. (2018)		✓				
Boloori et al. (2010)					✓	
Castellucci et al. (2019)					✓	
Darvishi et al. (2020)						
Deng and Qu (2020)		✓		✓		
Essghaier et al. (2021)					✓	
Fathollahi-Fard et al. (2019)					✓	
Heidari et al. (2018)					✓	
Konur and Goliias (2013a)					✓	
Konur and Goliias (2013b)					✓	
Kuo (2013)					✓	
Ladier and Alpan (2016b)					✓	
Larbi et al. (2011)					✓	
Li et al. (2012)					✓	
Magableh et al. (2005)					✓	
Mousavi and Vahdani (2017)					✓	✓
Mousavi et al. (2019)		✓				
Mousavi et al. (2014)					✓	✓
Mousavi et al. (2013)		✓				✓
Movassaghi and Avakh Darestani (2020)					✓	✓
Nasiri et al. (2019)					✓	
Rahbari et al. (2019)					✓	
Rijal et al. (2019)					✓	✓

(continued)

Publications	Strategic level		Tactical level		Operational level	
	Cross-dock design	Network design	Cross-dock planning	Network planning	Cross-dock scheduling	Network scheduling
Rohrer (1995)	✓		✓		✓	
Seyedi et al. (2019)					✓	
Shahmardan and Sajadieh (2019)					✓	
Shakeri et al. (2012)					✓	
Shi et al. (2013)		✓				
Soltani and Sadjadi (2010)					✓	
Tadumadze et al. (2019)					✓	
Tang and Yan (2010)					✓	
Tavallali et al. (2020)					✓	✓
Tavana et al. (2017)					✓	
Vahdani and Shahrifard (2019)					✓	
Vahdani and Zandieh (2010)					✓	
Vahdani et al. (2009)					✓	
Vahdani et al. (2012)					✓	✓
Walha et al. (2014)				✓	✓	
Wang and Alidaee (2019)				✓		
Wang and Regan (2008)					✓	
Wang et al. (2018b)					✓	
Yan and Tang (2009)					✓	
Yin and Chuang (2016)						✓
Yin et al. (2015)					✓	✓
Xi et al. (2020)					✓	
Zaerpour et al. (2014)					✓	
Zarandi et al. (2014)					✓	
Zouhaier and Ben Said (2017a)					✓	
Zouhaier and Ben Said (2017b)					✓	
Total	2	5	3	1	43	9

Table 2.5: Problem specifications of the reviewed publications

Problem specifications based on decision levels	Publications on the specified problems
Strategic level problems	
Cross-dock design	Shi et al. (2013)
Local cross-dock management	Rohrer (1995)
Location selection of cross-docking center	Barsing et al. (2018); Deng and Qu (2020); Mousavi et al. (2019, 2013)
Risk management in supply chain	Babazadeh et al. (2014)
Tactical level problems	
Dock door assignment in cross-dock	Walha et al. (2014); Wang and Alidaee (2019)
Integrated inbound logistics choices and multi-site aggregate production planning	Darvishi et al. (2020)
Local cross-dock management	Rohrer (1995)
Operational level problems	
Local cross-dock management	Rohrer (1995); Tang and Yan (2010); Yan and Tang (2009)
Scheduling, planning and coordination activities in cross-dock	Boloori et al. (2010); Castellucci et al. (2019); Li et al. (2012); Magableh et al. (2005); Tadumadze et al. (2019); Tavallali et al. (2020); Wang and Regan (2008); Zaerpour et al. (2014)
Trailer-to-door assignment	Acar et al. (2012)
Truck-to-door assignment	Essghaier et al. (2021); Kuo (2013); Movassaghi and Avakh Darestani (2020); Rijal et al. (2019); Vahdani and Shahramfard (2019); Walha et al. (2014)
Truck routing	Ahkamiraad and Wang (2018); Mousavi and Vahdani (2017); Mousavi et al. (2014, 2013); Movassaghi and Avakh Darestani (2020); Rahbari et al. (2019); Tavallali et al. (2020); Vahdani et al. (2012); Yin and Chuang (2016); Yin et al. (2015)
Truck sequencing	Fathollahi-Fard et al. (2019); Kuo (2013); Larbi et al. (2011); Movassaghi and Avakh Darestani (2020)
Truck scheduling	Amini and Tavakkoli-Moghaddam (2016); Fathollahi-Fard et al. (2019); Heidari et al. (2018); Konur and Golias (2013a,b); Ladjer and Alpan (2016b); Li et al. (2012); Mousavi and Vahdani (2017); Mousavi et al. (2014); Movassaghi and Avakh Darestani (2020); Nasiri et al. (2019); Rahbari et al. (2019); Rijal et al. (2019); Shahmardan and Sajadieh (2019); Shakeri et al. (2012); Seyedi et al. (2019); Soltani and Sadjadi (2010); Tadumadze et al. (2019); Tavallali et al. (2020); Tavana et al. (2017); Vahdani and Shahramfard (2019); Vahdani and Zandieh (2010); Vahdani et al. (2009, 2012); Wang et al. (2018b); Xi et al. (2020); Yin et al. (2015); Zarandi et al. (2014); Zouhaier and Ben Said (2017a,b)

2.5 Main observations and research perspectives

In this section, we present several tables that provide a synthetic view of the articles described in Section 2.4. We draw main observations from these tables and provide potential research directions.

2.5.1 Analysis of problem types and decision levels

We provide three summary tables: Table 2.3 displays the scheduling types of reviewed publications as robust, real-time, just-in-time and other. This classification reflects the researched keywords. We note that no articles are found with the keywords "on-line/online scheduling". The category "other" corresponds to articles that employ fuzzy and stochastic planning/scheduling approaches to handle uncertainty in their studies. The analysed studies are categorised according to their decision level and problem class in Table 2.4 - note that a descriptive study of Rohrer (1995) and a cross-docking dock door assignment review of Walha et al. (2014) are counted more than once in this table since they cover the multiple cross-dock activities. The specific problem types per decision level are finally displayed in Table 2.5.

We draw several conclusions from these tables. We first observe that operational issues are more studied than strategic or tactical problems. This is quite understandable in the case of real-time models since such models are mainly addressing short-term problems. A limited number of articles propose robust models at the strategic and tactical levels. Robust solutions could be beneficial for tactical and strategic levels since they would add agility to the cross-dock. The Covid-19 pandemic has shown how vulnerable the logistics networks are. Indeed, the structural robustness of a cross-dock (or a network of cross-docks) has a high impact on the operational robustness of the system. Hence, we believe that future research could focus on robust tactical and strategical cross-dock management issues. A very related topic is risk management in cross-docks since the risk-averse cross-docks will be robust against uncertainties. Risk management issues in cross-docking are not included in our literature review. Babazadeh et al. (2014) has appeared through the keyword "robust". Some recent studies are reported in this domain (see, for instance, Hasani Goodarzi et al. (2021)). Cross-docks and cross-dock networks are lean logistics systems by definition and could be very sensitive to disruptions. Hence, a comprehensive study on risk management in cross-docks and future work in this domain would be valuable research directions.

The second and striking observation is the relative lack of real-time (on-line or just-in-time) models to handle operational problems in cross-docks. Only seven papers out of fifty-three apply real-time models for this context (Wang and Regan, 2008; Boloori et al., 2010; Li et al., 2012; Walha et al., 2014; Zarandi et al., 2014; Zouhaier and Ben Said, 2017a; Vahdani and Shahramfard, 2019). In the era of industry 4.0 (or similarly logistics 4.0), the available technologies (e.g. IoT, global positioning systems) and techniques (e.g. cloud computing, data analytic, artificial intelligence) have the potential to access and process real-time data for cross-docking and provide the background for real-time planning and scheduling models. Therefore, we believe that some research could be oriented towards real-time models. Such models can cope with various uncertainties such as traffic delays, inaccurate data regarding material flows, process time uncertainties, among others, by providing rapid response and enabling quick and timely updates in the system.

The third observation appears when we focus on the operational level in Table 2.4. In this class, we observe very few articles on network scheduling problems: Three articles out of nine are solely dedicated to these questions and the remaining six are studying both network and cross-dock scheduling together. We recall that the network scheduling level concerns problems such as shipment dispatching, collection, and delivery truck routing, etc. In a sense, the objective is to orchestrate the flows among the nodes of the network, in which the cross-docks are connected to each other or to other supply chain actors. Hence, alignment of local decisions with the global ones is at stake. Some scheduling decisions taken at the cross-dock level may no longer be feasible if they are not aligned with the decisions at the network level. Further research, hence, could be

inspired by the modest number of studies in this area.

Finally, in Table 2.5, we observe that the scheduling problems mostly concern truck scheduling and hence road-to-road type facilities. In the literature, there are also cross-docks linking roads to rails or vice versa (also called road-rail/rail-road hubs). Only one (Walha et al., 2014) article is found in our literature search mentioning these types of cross-docks. This could be due to the keywords combinations, but may also highlight some research directions. These hubs are especially of interest in the Physical Internet context. We believe that the concepts related to Physical Internet will gain importance, especially in the context of industry 4.0. As also highlighted by Walha et al. (2014), real-time models are especially relevant in this context and constitute promising research directions.

2.5.2 Analysis of modelling and solution approaches

In Table 2.6, we summarise the modelling and solution approaches used in each article. The modelling approaches are highlighted with bold characters and the solution approaches are indented. Walha et al. (2014) is a discussion article and does not present modelling or solution approaches.

This table shows that there is not a single way of dealing with uncertainty. Herroelen and Leus (2005) define five approaches to handle uncertainty: proactive (robust) scheduling, reactive (real-time) scheduling, fuzzy scheduling, stochastic scheduling, and sensitivity analysis.

In this table, the main modelling methods appear to be the mathematical modelling and (meta-)heuristic-based optimisation approaches. When we make a cross-analysis of Tables 2.3 and 2.6, we see that all articles tagged as robust scheduling in Table 2.3 enter in this class. Furthermore, they are counted both in the mathematical modelling line and the meta-heuristics or heuristics lines in Table 2.6. Indeed, cross-docking problems are mostly NP-hard problems. Therefore, in most cases, the authors present mathematical models first, which are solved optimally for very small instances. To solve larger instances meta-heuristic or heuristic approaches are then employed.

The real-time scheduling studies employ a dynamic simulation model (Wang and Regan, 2008) and mathematical modelling approaches, namely graph theory (Li et al., 2012) and meta-heuristic methods (Zouhaier and Ben Said, 2017a; Vahdani and Shahramfard, 2019) - note that the discussion paper of Walha et al. (2014) is regarded as a real-time scheduling study since it provides real-time opportunities. However, it does not propose any modelling approaches. We observe that the just-in-time scheduling studies (Boloori et al., 2010; Zarandi et al., 2014) take advantage of mathematical programming approach and meta-heuristic methods to satisfy model constraints simultaneously in the just-in-time (JIT) environment.

In Table 2.6, we also observe two other techniques to handle uncertainty cited by Herroelen and Leus (2005), namely stochastic and fuzzy approaches. The articles employing these techniques appear in their respective categories. These techniques are directly interested in the representation of the uncertain input data. Stochastic programming is a mathematical programming approach where some of the data incorporated into the objective function and/or the set of constraints is uncertain. This data is usually modelled as a probability distribution on the model parameters. Unlike the stochastic programming approach where uncertainty is represented through a statistical data modelling process, the fuzzy approaches deal with imprecise and non-numerical information. The fuzzy models provide mathematical means to represent vagueness and imprecise information. Proactive (robust) and reactive (real-time) approaches are different in the essence compared to fuzzy and stochastic models; they are mostly focused on the solution than the data itself. Therefore, it is not surprising to see different modelling and solution techniques for each one of these approaches used against uncertainty. Since each approach has a different philosophy against uncertainty, they are not comparable. Nevertheless, proactive and reactive approaches seem quite attractive for application purposes since they are solution-oriented and complementary approaches.

Finally, very few use dynamic models such as simulation, specially adapted to model uncertainties (Rohrer, 1995; Magableh et al., 2005; Wang and Regan, 2008; Zouhaier and Ben Said, 2017b).

Digital Twin (a concept very much related to simulation modelling) is gaining importance in industrial applications. Therefore, we believe that simulation, enhanced with digital twin concepts, will gain importance in the upcoming years in the logistics and cross-docking systems. Similarly, multi-agent-based dynamic models also have the potential to employ real-time data concerning cross-docking scheduling problems and provide an interesting perspective for future studies.

Table 2.6: *Modelling approaches and solution methods of the reviewed publications*

Modelling approaches and related solution methods	Publications using the methods
Fuzzy logic	Darvishi et al. (2020); Deng and Qu (2020); Mousavi et al. (2019, 2014); Movassaghi and Avakh Darestani (2020)
Multi-criteria group decision-making	Deng and Qu (2020); Mousavi et al. (2019); Movassaghi and Avakh Darestani (2020)
Fuzzy chance-constrained programming	Essghaier et al. (2021)
Fuzzy possibilistic programming	Darvishi et al. (2020); Mousavi et al. (2014, 2013)
Mathematical model	
Exact methods	
Column-and-constraint generation algorithm	Xi et al. (2020)
Constraint satisfaction programming	Zarandi et al. (2014)
Dynamic programming	Shi et al. (2013)
Graph theory	Larbi et al. (2011); Li et al. (2012)
Mathematical programming	Acar et al. (2012); Ahkamiraad and Wang (2018); Amini and Tavakkoli-Moghaddam (2016); Babazadeh et al. (2014); Boloori et al. (2010); Darvishi et al. (2020); Fathollahi-Fard et al. (2019); Heidari et al. (2018); Konur and Golias (2013a,b); Kuo (2013); Ladijer and Alpan (2016b); Mousavi and Vahdani (2017); Mousavi et al. (2013, 2014); Movassaghi and Avakh Darestani (2020); Nasiri et al. (2019); Rahbari et al. (2019); Rijal et al. (2019); Seyedi et al. (2019); Shahmardan and Sajadieh (2019); Shakeri et al. (2012); Soltani and Sadjadi (2010); Tadumadze et al. (2019); Tang and Yan (2010); Tavallali et al. (2020); Tavana et al. (2017); Vahdani and Shahramfard (2019); Vahdani and Zandieh (2010); Vahdani et al. (2009, 2012); Wang and Alidaee (2019); Wang et al. (2018b); Yan and Tang (2009); Yin and Chuang (2016); Yin et al. (2015); Zaerpour et al. (2014); Zarandi et al. (2014); Zouhaier and Ben Said (2017b)
Polynomial algorithm	Larbi et al. (2011)
Meta-heuristics	
Ant colony optimisation	Zouhaier and Ben Said (2017a)
Artificial bee colony algorithm	Yin and Chuang (2016)
Differential evolution	Boloori et al. (2010)
Electromagnetism-like algorithm	Vahdani and Zandieh (2010); Vahdani et al. (2009)
Genetic algorithm	Ahkamiraad and Wang (2018); Amini and Tavakkoli-Moghaddam (2016); Babazadeh et al. (2014); Boloori et al. (2010); Heidari et al. (2018); Konur and Golias (2013a,b); Vahdani and Shahramfard (2019); Vahdani et al. (2009); Wang et al. (2018b); Zarandi et al. (2014)
Genetic random-key algorithm	Wang and Alidaee (2019)
Harmony search	Wang et al. (2018b)

(continued)

Modelling approaches and related solution methods	Publications using the methods
Imperialist competitive algorithm	Mousavi and Vahdani (2017); Vahdani and Shahramfard (2019)
Non-Dominated Sorting Genetic Algorithm-II	Tavallali et al. (2020)
Particle swarm optimisation	Ahkamiraad and Wang (2018); Boloori et al. (2010); Vahdani et al. (2012)
Simulated annealing	Amini and Tavakkoli-Moghaddam (2016); Babazadeh et al. (2014); Shahmardan and Sajadieh (2019); Soltani and Sajjadi (2010); Vahdani and Zandieh (2010); Vahdani et al. (2012)
Social engineering optimiser	Fathollahi-Fard et al. (2019)
Tabu search	Ladrier and Alpan (2016a); Vahdani and Zandieh (2010); Vahdani et al. (2012); Wang and Alidaee (2019); Yin and Chuang (2016)
Variable neighborhood search	Kuo (2013); Shahmardan and Sajadieh (2019); Soltani and Sajjadi (2010); Vahdani and Zandieh (2010); Vahdani et al. (2012)
Heuristics	
Door assignment heuristic	Acar et al. (2012)
IP-based heuristics	Ladrier and Alpan (2016a); Kuo (2013); Vahdani et al. (2009, 2012)
Other dedicated heuristics	Konur and Gollas (2013b); Larbi et al. (2011); Rijal et al. (2019); Seyedi et al. (2019); Shakeri et al. (2012); Wang and Alidaee (2019); Yin et al. (2015); Zaerpour et al. (2014)
Simulation	Rohrer (1995); Zouhaier and Ben Said (2017b)
Dynamic simulation model	Magableh et al. (2005); Wang and Regan (2008)
Statistical method	
Latin hypercube sampling	Shi et al. (2013)
Response surface methodology	Amini and Tavakkoli-Moghaddam (2016); Shi et al. (2013); Vahdani and Zandieh (2010)
Social network analysis	Barsing et al. (2018)
Taguchi method	Babazadeh et al. (2014); Fathollahi-Fard et al. (2019); Soltani and Sajjadi (2010); Vahdani et al. (2009, 2012); Wang et al. (2018b)
Stochastic programming	Castellucci et al. (2019); Darvishi et al. (2020); Mousavi et al. (2014)
N/A	Walha et al. (2014)

2.5.3 Analysis of model assumptions

Problem settings and main model assumptions are summarised in Table 2.7. A significant number of the operational level studies consider an infinite capacity of the temporary storage and handling devices in their mathematical models. We observe the assumption of unlimited temporary storage mostly in truck scheduling studies (Vahdani and Zandieh, 2010; Zarandi et al., 2014; Amini and Tavakkoli-Moghaddam, 2016; Ladier and Alpan, 2016b; Tavana et al., 2017; Seyedi et al., 2019). Some papers that integrated truck routing and truck scheduling (Mousavi and Vahdani, 2017; Rahbari et al., 2019) and truck-to-door assignment and truck scheduling (Rijal et al., 2019; Vahdani and Shahramfard, 2019) and one truck sequencing study (Larbi et al., 2011) also assume unlimited temporary storage in their models. Even though such assumptions diminish the complex nature of the mathematical models, temporary storage and handling device capacities are limited in real life. Consequently, future studies should consider this fact when modelling cross-dock terminals. We note that the availability of resources favourably impacts the robustness of a solution. An infinite capacity can admit many solutions which are not feasible in reality. Hence a model under the assumption of an infinite resource capacity might appear robust, even though some of the solutions which appear admissible will not be applicable under real conditions.

We observe that only seven cross-docking studies practice the mixed service mode of dock doors (Magableh et al., 2005; Shakeri et al., 2012; Li et al., 2012; Rijal et al., 2019; Shahmardan and Sajadieh, 2019; Vahdani and Shahramfard, 2019; Xi et al., 2020), while the rest of the articles assume dedicated dock doors either as inbound only or outbound only doors. Having all or some dock doors serving as mixed-mode provides flexibility in docking operations when needed and reduces the distance of the door-to-door transfer, so that operation time and cost. Similarly, according to Bodnar et al. (2015), using a mixed service mode increases the practical usage of the terminal area and decreases the total costs. However, the authors also remark that as the number of mixed-mode doors increases, this improvement decreases. Therefore, the practice of mixed-mode dock doors deserves more attention from the cross-docking researchers. From a practical point of view, in a real cross-dock environment, the organisation of docks is easier for the operators when the dock doors are dedicated as inbound or outbound because the role of the dock is fixed, and there is no need for constant change management. Multiple service mode of dock doors requires additional operational care for employee adherence. Technological advances could help implementing such mixed service modes. These technologies can provide real-time information on dock conditions and operational needs. The studies on mixed-mode service docks can include a cost-benefit analysis.

Another gap appears regarding the applications. Even though almost all articles provide case studies to illustrate their results, only four articles record real-life applications. Despite the fact that the cross-dock planning and scheduling problems lead to very interesting and difficult theoretical problems, cross-docking is also a practical technique commonly used in logistics. Therefore, demonstration of developed methods on real-life applications is really expected by the practitioners. To this end, real cross-docking constraints shall be considered in the modelling process. We believe that more researchers will contribute in this respect. An encouraging observation can already be made through Table 2.7. Single door cross-docks with single product types was a common assumption in earlier studies, which is quite unrealistic. Recent articles consider multiple doors and multiple product types, which are realistic assumptions.

Finally, we would like to highlight the following research direction, which would be interesting to study. This issue is not necessarily related to robustness or real-time modelling issues, but impacts the cross-dock environment and, in consequence, the modelling assumption. Furthermore, it is quite relevant today and is not addressed in the articles we have analysed. Automation is gaining importance in logistics, and many cross-dock, primarily operated for standard pallets, and package types are totally or partially automated. We have observed that the truck scheduling problems in cross-docking often use hand-operated transportation modes such as forklift services to transfer goods inside the cross-docking terminals. This inference is also made by Theophilus

[et al. \(2019\)](#). Future studies could also concentrate on automatic transportation modes inside the cross-docking terminals. We believe that this topic concerns all decision levels. For instance, on a strategic level, research can focus on finding the most appropriate level of automation which operations shall be automated which others can be left to human operators. On an operational level, task assignment to automated equipment can be studied.

Table 2.7: Classification of the model settings for the total cross-dock and network scheduling problems

Publications	Number of doors		Door service mode	Temporary storage			Product type		All trucks are available at time zero	Case study	Real-life	Problem type
	Single door	Multi-door		Inbound only	Outbound only	Mixed mode	Not used	Limited				
Acar et al. (2012)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Trailer-to-door assignment
Ahkamirad and Wang (2018)			✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck routing
Amini and Tavakkoli-Moghaddam (2016)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Boloori et al. (2010)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock
Castellucci et al. (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock
Essghaier et al. (2021)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck-to-door assignment
Fathollahi-Fard et al. (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck sequencing, Truck scheduling
Heidari et al. (2018)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Konur and Goliias (2013a)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Konur and Goliias (2013a)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Kuo (2013)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck sequencing, Truck-to-door assignment
Ladler and Alpan (2016b)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Larbi et al. (2011)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck sequencing
Li et al. (2012)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling, Scheduling, planning and coordination activities in cross-dock
Magableh et al. (2005)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock
Mousavi and Vahdani (2017)									✓	✓	✓	Truck routing, Truck scheduling
Mousavi et al. (2014)									✓	✓	✓	Truck routing, Truck scheduling
Mousavi et al. (2013)									✓	✓	✓	Location selection of cross-docking center, Truck routing
Movassaghi and Avakh Darestani (2020)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck-to-door assignment, Truck routing, Truck sequencing, Truck scheduling
Nasiri et al. (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Rahbari et al. (2019)									✓	✓	✓	Truck routing, Truck scheduling
Rijal et al. (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck-to-door assignment, Truck scheduling
Seyedi et al. (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Shahmardan and Sajadieh (2019)	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling

(continued)

Publications	Number of doors		Door service mode		Temporary storage			Product type		All trucks are available at time zero	Case study	Real-life	Problem type
	Single door	Multi-door	Inbound only	Outbound only	Mixed mode	Not used	Limited	Unlimited	Single product				
Shakeri et al. (2012)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Soltani and Sadjadi (2010)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Tadumadze et al. (2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock, Truck scheduling
Tang and Yan (2010)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Local cross-dock management
Tavallali et al. (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock, Truck routing, Truck scheduling
Tavana et al. (2017)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Vahdani and Shahramfard (2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck-to-door assignment, Truck scheduling
Vahdani and Zandieh (2010)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Vahdani et al. (2009)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Vahdani et al. (2012)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck routing, Truck scheduling
Wang and Regan (2008)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock
Wang et al. (2018b)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Xi et al. (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Yan and Tang (2009)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Local cross-dock management
Yin and Chuang (2016)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck routing
Yin et al. (2015)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck routing, Truck scheduling
Zaerpour et al. (2014)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Scheduling, planning and coordination activities in cross-dock
Zarandi et al. (2014)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Zouhaier and Ben Said (2017a)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling
Zouhaier and Ben Said (2017b)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Truck scheduling

2.5.4 Analysis of the type of uncertainties considered and the way they are modelled

Type of uncertainties considered

A synthesis of uncertainty sources addressed in each article is provided in Table 2.8. The term "unspecified" is used for the papers that do not state precisely the type of uncertainty addressed in their studies. Moreover, while some papers used the term "tardiness" for time-related uncertainties, the others used the term "lateness". These two terms are labelled as "lateness" in the table.

We observe that existing studies propose robust solutions to overcome uncertainties mainly related to time, and more precisely on process times and truck arrival or departure times. This observation is also made by [Ardakani and Fei \(2020\)](#).

Another most observed uncertainty source addressed by publications is demand. Demand uncertainty is quite relevant at all decision levels. For instance, at the strategic level, the demand uncertainties impact the size (i.e. operation capacity) and location (i.e. proximity to suppliers and customers) of a cross-dock ([Mousavi et al., 2013](#); [Babazadeh et al., 2014](#); [Mousavi et al., 2019](#)). At the tactical level, demand uncertainty reveals the need for involving modern distribution facilities (i.e. cross-docks) against high inventory and transportation costs on logistics systems ([Darvishi et al., 2020](#)). On the operational level, the demand uncertainty has attracted more attention from researchers. Most of them are oriented on network-level issues such as distribution strategies, truck routing and scheduling problems ([Mousavi et al., 2014](#); [Yin et al., 2015](#); [Yin and Chuang, 2016](#); [Mousavi and Vahdani, 2017](#); [Nasiri et al., 2019](#); [Tavallali et al., 2020](#)). Very few concern operational issues in the cross-dock ([Movassaghi and Avakh Darestani, 2020](#); [Nasiri et al., 2019](#); [Tang and Yan, 2010](#); [Yan and Tang, 2009](#); [Magableh et al., 2005](#)). This observation is also in accordance with the inferences made by [Ardakani and Fei \(2020\)](#).

Cross-docking is known to be more appropriate for products with stable (or "highly predictable") demand ([Napolitano, 2000](#)). Considering demand uncertainty might hence seem surprising. However, demand is an exogenous variable which is, usually, not controllable, so it always has some variations. Therefore, demand uncertainty is still an issue to consider in cross-docks, especially at the tactical level, for which studies are still rare. Most of the articles address this issue at the network level (either strategic or operational).

Finally, only ten articles address uncertainties in resource availability. We believe that this is a valuable research direction, because resource availability and how resources are managed impact totally the internal operations, the processing times and consequently the overall performance of the cross-dock. In a cross-docking facility, there are human resources and material handling equipment. Despite the fact that human resources are very important, especially when the majority of the tasks are manual, very few articles study this aspect in cross-docks. In our article panel, only five ([Magableh et al., 2005](#); [Shakeri et al., 2012](#); [Shi et al., 2013](#); [Zouhaier and Ben Said, 2017a,b](#)) are identified. Unless automated, the handling equipment is used by human operators. We have discussed the interest in studying automated systems in an earlier section. When not automated, availability of the handling equipment can be considered together with human resources planning. In this case, competencies and competency levels to operate equipment must also be considered.

Table 2.8: The uncertainty sources based on each cross-docking problem for the total reviewed papers

Publications	Uncertainty sources							Type of cross-docking problem
	Quantity-related		Time-related		Unspecified			
	Demand	Supply	Freshness of products	Process time	Truck arrival & departure time	Resource availability	Linguistic input data	
Acar et al. (2012)					✓			Trailer-to-door assignment
Ahkamiraad and Wang (2018)							✓	Truck routing
Amini and Tavakkoli-Moghaddam (2016)						✓		Truck scheduling
Babazadeh et al. (2014)	✓							Risk management in supply chain
Barsing et al. (2018)			✓					Location selection of cross-dock
Boloori et al. (2010)							✓	Scheduling, planning and coordination activities in cross-dock
Castellucci et al. (2019)					✓			Scheduling, planning and coordination activities in cross-dock
Darvishi et al. (2020)	✓							Integrated inbound logistics choices and multi-site aggregate production planning
Deng and Qu (2020)								Location selection of cross-dock
Essghaier et al. (2021)				✓			✓	Truck-to-door assignment
Fathollahi-Fard et al. (2019)								Truck sequencing, Truck scheduling
Heidari et al. (2018)					✓			Truck scheduling
Konur and Goliias (2013a)					✓			Truck scheduling
Konur and Goliias (2013b)					✓			Truck scheduling
Kuo (2013)							✓	Truck-to-door assignment, Truck sequencing
Ladier and Alpan (2016b)								Truck scheduling
Larbi et al. (2011)		✓						Truck sequencing
Li et al. (2012)				✓			✓	Scheduling, planning and coordination activities in cross-dock
Magableh et al. (2005)	✓			✓			✓	Scheduling, planning and coordination activities in cross-dock
Mousavi et al. (2019)	✓							Location selection of cross-dock
Mousavi and Vahdani (2017)	✓	✓						Truck routing, Truck scheduling

(continued)

Publications	Uncertainty sources							Type of cross-docking problem
	Quantity-related		Time-related		Resource availability	Linguistic input data	Unspecified	
	Demand	Supply	Freshness of products	Process time				
Mousavi et al. (2014)	✓	✓			✓			Truck routing, Truck scheduling
Mousavi et al. (2013)	✓	✓				✓		Location selection of cross-dock, Truck routing
Movassaghi and Avakh Darestani (2020)	✓			✓		✓		Truck-to-door assignment, Truck routing, Truck sequencing, Truck scheduling
Nasiri et al. (2019)	✓							Truck scheduling
Rahbari et al. (2019)			✓		✓			Truck routing, Truck scheduling
Rijal et al. (2019)					✓			Truck-to-door assignment, Truck scheduling
Rohrer (1995)							✓	Local cross-dock management
Seyedi et al. (2019)							✓	Truck scheduling
Shahmardan and Sajadieh (2019)							✓	Truck scheduling
Shakeri et al. (2012)							✓	Truck scheduling
Shi et al. (2013)		✓			✓			Cross-dock design
Soltani and Sadjadi (2010)							✓	Truck scheduling
Tadumadze et al. (2019)							✓	Scheduling, planning and coordination activities in cross-dock,
Tang and Yan (2010)	✓							Truck scheduling
Tavallali et al. (2020)	✓							Local cross-dock management
Tavana et al. (2017)								Scheduling, planning and coordination activities in cross-dock,
Vahdani and Shahrampard (2019)					✓			Truck routing, Truck scheduling
Vahdani and Zandieh (2010)							✓	Truck scheduling
Vahdani et al. (2009)					✓			Truck-to-door assignment, Truck scheduling
Vahdani et al. (2012)					✓			Truck scheduling
								Truck routing, Truck scheduling

(continued)

Publications	Uncertainty sources							Type of cross-docking problem	
	Quantity-related		Time-related			Resource availability	Linguistic input data		Unspecified
	Demand	Supply	Freshness of products	Process time	Truck arrival & departure time				
Walha et al. (2014)				✓	✓	✓		Dock door assignment in cross-dock, Truck-to-door assignment	
Wang and Alidaee (2019)							✓	Dock door assignment in cross-dock	
Wang and Regan (2008)				✓				Scheduling, planning and coordination activities in cross-dock	
Wang et al. (2018b)							✓	Truck scheduling	
Xi et al. (2020)								Truck scheduling	
Yan and Tang (2009)	✓							Local cross-dock management	
Yin and Chuang (2016)	✓	✓						Truck routing	
Yin et al. (2015)	✓				✓			Truck routing, Truck scheduling	
Zaerpour et al. (2014)					✓			Scheduling, planning and coordination activities in cross-dock	
Zarandi et al. (2014)							✓	Truck scheduling	
Zouhaier and Ben Said (2017a)					✓		✓	Truck scheduling	
Zouhaier and Ben Said (2017b)					✓		✓	Truck scheduling	

Modelling ways of uncertainty sources

In Table 2.8, we have identified three main uncertainty types: quantity, time and resource related. Table 2.9 provides an analysis of modelling approaches for these uncertainty types. The papers that do not state precisely the type of uncertainty addressed in their studies are not included in this table.

The first observation we make in Table 2.9 is that the probabilistic and scenario-based approaches are the most dominant ways of modelling uncertainties. A second group of approaches employing fuzzy or uncertainty sets, and time windows are used with medium frequency. Only two studies are recorded for time and/or resource redundancy (Acar et al., 2012; Ladier and Alpan, 2016b). It is to be noted that time and resource redundancy do not model uncertainty implicitly, but are used to overcome its effects. In these studies, the objective is to find robust solutions (by adding redundancies) such that the proposed truck schedule is still valid despite uncertainties (within a predefined uncertainty limit). Similarly, the articles that use real-time scheduling, do not seek to model uncertainties implicitly. Instead, they use the available real-time data (e.g. Li et al. (2012) and Zouhaier and Ben Said (2017a) employ real-time truck arrival and departure times, Wang and Regan (2008) and Li et al. (2012) use real-time data on process times) to reduce uncertainty or to reschedule if the previously planned schedule is no longer valid due to unexpected events.

When we make a cross-analysis of Tables 2.8 and 2.9, we notice that time-related uncertainty sources, specifically truck arrival and departure time uncertainties, are modelled mainly with probability distributions. Very few papers use uncertainty sets (e.g. box/interval uncertainty set, polyhedral uncertainty set) (Rahbari et al., 2019; Xi et al., 2020), a given set of scenarios (Vahdani et al., 2012; Ladier and Alpan, 2016b; Xi et al., 2020), and fuzzy numbers (Mousavi et al., 2014). The other most common time-related uncertainty source is process time. A remarkable number of studies modelled the process time uncertainty with fuzzy sets. However, very few studies use a probability distribution (notably, triangular and normal distributions) (Magableh et al., 2005; Shi et al., 2013) and uncertainty sets (Vahdani et al., 2009; Tavana et al., 2017) for process time variations.

The quantity-related uncertainty sources addressed by reviewed papers are demand and supply. Demand uncertainty is mostly modelled with fuzzy sets, a given set of scenarios, probability distributions and uncertainty sets (i.e. box/interval and interval+polyhedral sets). As a side note, very few articles combined different modelling ways: fuzzy sets - given set of scenarios (Mousavi et al., 2019; Darvishi et al., 2020) and fuzzy sets - probability distributions (Mousavi et al., 2014) to model demand uncertainty. For supply uncertainty modelling, mainly probability distributions and fuzzy sets are used. Only the studies of Mousavi and Vahdani (2017) and Mousavi et al. (2019) use a set of scenarios and box-uncertainty set, respectively.

Finally, we do not observe a dominant approach for modelling the uncertainty related to resource availability. Fuzzy sets (Mousavi et al., 2013; Movassaghi and Avakh Darestani, 2020), scenario-based modelling (Shakeri et al., 2012; Zouhaier and Ben Said, 2017b), and probability distributions (Magableh et al., 2005; Shi et al., 2013; Amini and Tavakkoli-Moghaddam, 2016) are equally used.

Table 2.9: The modelling way classes of uncertainty sources in the reviewed studies

Publications	Uncertainty sources				Modelling way classes						
	Quantity-related	Time-related	Resource availability	Time redundancy	Resource redundancy	Probability distribution	Uncertainty set (e.g. box/interval, polyhedral sets)	Fuzzy set	Define intervals (e.g. time windows)	Scenario-based	Rescheduling /real-time scheduling
Acar et al. (2012)	✓		✓	✓							
Amini and Tavakkoli-Moghaddam (2016)			✓			✓					
Babazadeh et al. (2014)	✓						✓			✓	
Barsing et al. (2018)		✓				✓					
Castellucci et al. (2019)	✓							✓		✓	
Darvishi et al. (2020)		✓						✓			
Essghaier et al. (2021)		✓							✓		
Heidari et al. (2018)		✓				✓					
Konur and Gollias (2013a)		✓				✓			✓		
Konur and Gollias (2013b)		✓				✓			✓		
Ladier and Alpan (2016b)		✓		✓	✓	✓				✓	
Larbi et al. (2011)	✓					✓					
Li et al. (2012)		✓									✓
Magableh et al. (2005)	✓		✓			✓					
Mousavi et al. (2019)	✓		✓					✓			
Mousavi and Vahdani (2017)	✓						✓				
Mousavi et al. (2014)	✓					✓		✓			
Mousavi et al. (2013)	✓		✓					✓			
Movassaghi and Avakh Darestani (2020)	✓		✓					✓			
Nasiri et al. (2019)									✓		
Rahbari et al. (2019)		✓						✓			
Rijal et al. (2019)		✓							✓		
Shakeri et al. (2012)			✓			✓				✓	
Shi et al. (2013)	✓		✓			✓					
Tang and Yan (2010)	✓		✓							✓	
Tavallali et al. (2020)	✓									✓	

(continued)

Publications	Uncertainty sources			Modelling way classes							
	Quantity-related	Time-related	Resource availability	Time redundancy	Resource redundancy	Probability distribution	Uncertainty set (e.g. box/interval, polyhedral sets)	Fuzzy set	Define intervals (e.g. time windows)	Scenario-based	Rescheduling /real-time scheduling
Tavana et al. (2017)	✓									✓	
Vahdani and Zandieh (2010)	✓							✓			
Vahdani et al. (2009)	✓									✓	
Vahdani et al. (2012)	✓									✓	
Wang and Regan (2008)	✓										✓
Xi et al. (2020)	✓						✓				
Yan and Tang (2009)	✓					✓					
Yin and Chuang (2016)	✓					✓					
Yin et al. (2015)	✓					✓					
Zaerpour et al. (2014)	✓					✓			✓		
Zouhaier and Ben Said (2017a)	✓										✓
Zouhaier and Ben Said (2017b)	✓					✓			✓		

2.5.5 Analysis of the goal of the studies

Performance measures of the reviewed articles are summarised in Table 2.10. We regroup the performance measure under four categories: Time, Cost, Resource and Others.

Time-related performance measures

As can be noticed in this table, most of the cross-dock scheduling problems focus on minimising time-related measures. This focus creates an opportunity for developing real-time models to handle dynamic and uncertain data on the scheduling process.

Among time-related performance measures, makespan is one of the most popular one; a very common minimisation criterion in scheduling literature. It might be appropriate in a certain context (e.g. project management), however does not seem the most suitable in the context of cross-docking. Indeed makespan seeks to minimise the length of time that elapses from the start of unloading a group of inbound trucks to the end of loading the final outbound truck. A short makespan does not guarantee customer-oriented indicators such as minimising delays in truck departures, for instance.

The other most common performance measure is the truck processing performance at the dock doors. This performance is essential to assure fast turnover and on-time shipments since it directly affects truck departure time. Therefore, a significant number of scheduling studies examine truck processing time deviation as a performance measure of their analyses. Dwell times of products and idle times of trailers in the terminal are other time-related performance measures. Among the analysed articles, only three of them (Magableh et al., 2005; Amini and Tavakkoli-Moghaddam, 2016; Essghaier et al., 2021) seek to minimise tardiness in product delivery. While the indicators like makespan, loading/unloading and processing times, dwell time of products directly reflect the performance of the cross-dock operations, minimising tardiness directly targets customer satisfaction. A future research direction is to focus on customer-oriented performance measures.

Cost-oriented performance measures

Under this category, we observe three major cost components: The first one is related to transportation cost, in particular for studies that are at the network level and that study problems such as truck routing. This is very understandable for truck routing studies to obtain the minimum total system cost such as transportation, fuel consumption, and a penalty for delayed shipments. In our article panel, the unique study that connects fuel consumption cost with green gas emissions related to air quality, climate change, and energy issues is Yin and Chuang (2016). In this review, we did not have specific keywords to look for environmental aspects in cross-docking. Therefore, there might be other studies in this domain which do not naturally appear in our article panel. Nevertheless, green logistics is a topic gaining importance. The environmental impact of cross-docks and cross-docking networks would contribute to green logistics and cross-docking literature. Therefore, future studies should consider the environmental footprint as a performance criterion.

The other three performance criteria are the operation cost of the cross-dock terminal, the rental cost of dock doors and the inventory cost. The latter could also be considered as a component of the operation cost. In Table 2.10, we present it separately since usually this component is also expressed as an inventory level (from which one can deduce an inventory cost). From a cross-docking point of view, the inventory cost is a vital performance measure even if the storage time is limited to 24 hours. The inventory level is highly correlated to demand or supply uncertainty (and implicitly to truck arrivals and departures). When demand (and supply) is uncertain, which is a real-life situation, the cross-dock practitioners may experience uncontrolled inventory levels and consequently inventory costs (e.g. high inventory if trucks cannot depart or customer demand collapses, similarly low inventory if trucks do not arrive or in case of supply uncertainties). Therefore, the inventory level is analysed as a performance measure in several robust models against demand (Yan and Tang, 2009; Tang and Yan, 2010; Mousavi et al., 2014; Mousavi and Vahdani, 2017; Tavallali et al.,

2020), supply uncertainty (Larbi et al., 2011; Mousavi et al., 2014; Mousavi and Vahdani, 2017) or uncertainties against truck arrival and departure times (Mousavi et al., 2014; Ladier and Alpan, 2016b; Rijal et al., 2019).

Resource-related performance measures

Very few studies consider resource-related performance measures. To this end, two indicators are considered: the door utilisation rate and the operation capacity of the cross-dock facility. The door utilisation rate supports the determination of the required number of docking doors for unloading and loading activities. The operation capacity of cross-docks includes both physical layout factors of the terminal building and workforce capacity allocation. Both indicators significantly impact fast synchronisation at cross-dock operations by enabling the fast flow of goods.

We can conclude that even though resource availability is clearly identified as a source of uncertainty, resource-oriented performance measures are lacking in the current literature. One line of future research could explore this area.

Others

Other performance indicators that do not fall in time, cost and resource classes are used in a small group of articles. These indicators are usually context dependent, as the "total weighted freshness of delivered products" used in Rahbari et al. (2019).

Table 2.10: The performance measures of the total reviewed studies

Performance measures	Studies
Time/Delay	
Lateness of product delivery	Amini and Tavakkoli-Moghaddam (2016); Essghaier et al. (2021); Magableh et al. (2005)
Makespan	Fathollahi-Fard et al. (2019); Kuo (2013); Nasiri et al. (2019); Seyedi et al. (2019); Shahmardan and Sajadieh (2019); Shakeri et al. (2012); Softani and Sadjadi (2010); Tadumadze et al. (2019); Vahdani and Zandieh (2010); Vahdani et al. (2009); Yin et al. (2015)
Total loading time	Wang et al. (2018b)
Total product stay time	Castellucci et al. (2019); Li et al. (2012); Rohrer (1995); Tang and Yan (2010); Tavallali et al. (2020); Yan and Tang (2009)
Total unloading time	Konur and Golias (2013a,b); Wang and Regan (2008); Wang et al. (2018b)
Transhipment time of products in supply chain	Barsing et al. (2018)
Travel distance/time inside CD facility	Rohrer (1995); Wang and Regan (2008)
Truck processing time deviation	Amini and Tavakkoli-Moghaddam (2016); Castellucci et al. (2019); Konur and Golias (2013a,b); Rohrer (1995); Boloori et al. (2010); Ladier and Alpan (2016b); Magableh et al. (2005); Rahbari et al. (2019); Rijal et al. (2019); Tang and Yan (2010); Vahdani and Shahramfard (2019); Xi et al. (2020); Yan and Tang (2009); Zarandi et al. (2014); Zouhaier and Ben Said (2017a,b)
Cost	
Inventory level/cost	Babazadeh et al. (2014); Ladier and Alpan (2016b); Larbi et al. (2011); Mousavi and Vahdani (2017); Mousavi et al. (2014); Rahbari et al. (2019); Rijal et al. (2019); Tang and Yan (2010); Tavallali et al. (2020); Vahdani and Shahramfard (2019); Yan and Tang (2009); Zaerpour et al. (2014)
Operation cost for CD facility	Babazadeh et al. (2014); Barsing et al. (2018); Deng and Qu (2020); Essghaier et al. (2021); Heidari et al. (2018); Konur and Golias (2013b); Mousavi et al. (2019, 2014, 2013); Rijal et al. (2019); Shi et al. (2013); Tadumadze et al. (2019); Vahdani et al. (2012); Zaerpour et al. (2014); Wang and Alidaee (2019)
Preemption cost	Larbi et al. (2011); Zarandi et al. (2014)
Rental cost of dock docks	Essghaier et al. (2021)
Transportation cost of trucks at supply chain	Ahkamirad and Wang (2018); Babazadeh et al. (2014); Darvishi et al. (2020); Mousavi et al. (2019); Mousavi and Vahdani (2017); Mousavi et al. (2014, 2013); Movassaghi and Avakh Darestani (2020); Rahbari et al. (2019); Tadumadze et al. (2019); Tavallali et al. (2020); Vahdani et al. (2012); Yin and Chuang (2016)
Resource	
Door utilisation	Rohrer (1995); Acar et al. (2012); Wang and Regan (2008)
Operation capacity of CD facility	Mousavi et al. (2019)
Others	
Congestion	Rohrer (1995); Vahdani and Shahramfard (2019)
Expansion possibility of CD facility	Mousavi et al. (2019)
Proximity of CD facility to its suppliers and customers	Mousavi et al. (2019)
Suitability to the social environment	Deng and Qu (2020)
Total weighted freshness of delivered products	Rahbari et al. (2019)

2.6 Conclusion

This chapter presents a comprehensive literature review focusing on robust and real-time models for cross-dock problems, particularly emphasising scheduling problems.

Our exploration is guided by the research questions in Chapter 1, which directs our investigation into real-time scheduling and operational complexities within cross-dock platforms. We uncover valuable insights that underline the significance of real-time scheduling models in tackling the intricate uncertainties inherent to cross-docking operations. Our findings illuminate the critical role of robust models as proactive solutions in addressing uncertainty, complemented by the reactivity of real-time models when uncertainties surge beyond manageable thresholds.

Moreover, this literature review forms a crucial foundation for our study. It reveals a significant research direction: the relative absence of real-time models in cross-docking operations despite the potential offered by Industry 4.0 technologies.

A limited number of studies use dynamic models, such as simulation; we believe that simulation, enhanced with digital twin concepts, will gain importance in logistics and cross-docking systems in the upcoming years. Similarly, multi-agent-based dynamic models also have the potential to employ real-time data concerning cross-docking scheduling problems and provide an interesting perspective for future studies.

This chapter is integral to addressing our research questions given in Chapter 1 by uncovering the practical implementations of multi-agent-based systems in achieving real-time truck scheduling for cross-docking. Moreover, it strengthens the promises of the agent-based models for real-time scheduling within large-scale industrial cross-dock environments, as well as its flexibility to be applied to diverse problem configurations in the face of deterministic methods. However, it also highlights the limited utilisation of agent-based models in the existing literature. These findings are pivotal in forming the methodological basis of this thesis study. To this end, we decided to concentrate on multi-agent-based models for efficient and effective synchronisation of cross-dock operations, explicitly focusing on real-time truck scheduling. Chapter 3 elaborates on the methodology of this thesis work.

3

Methodology

This chapter delves into the methodology that forms the foundation of this thesis study, driven by the insights gained from the comprehensive literature review presented in Chapter 2. The pivotal role of Chapter 2 in shaping our research direction becomes evident in the primary aim of this chapter: to provide a thorough account of our research methodology, which is centred around real-time scheduling approaches. Furthermore, we present a general survey of prominent simulation modelling methods within the cross-docking literature. Subsequently, we explain these modelling techniques, focusing on their usefulness and considering their application limitations under different operational conditions in the cross-docking literature.

3.1 Introduction

The main objective of this thesis is to assist cross-docking practitioners and researchers in achieving fast synchronisation of inbound and outbound trucks together with the internal operations of cross-dock facilities against uncertainty. Thanks to the literature review findings presented in Chapter 2, we pinpointed that methods with a real-time perspective, notably dynamic simulation methods such as agent-based simulation, have the potential to handle uncertainty in cross-docking operations. However, the application of these techniques in the cross-dock domain is rare at the moment, and they need to be well-investigated to exploit their potential. This inference is one of the primary drivers of the methodology selection of this thesis study. Therefore, this chapter presents the motivations behind the hybrid use of multi-agent-based and discrete-event simulations as the methodology. To this end, it explains the functioning of the selected hybrid simulation modelling. Furthermore, it discusses the usage and application limitations of the mainly employed simulation tools in cross-dock literature.

3.2 Simulation

Simulation is a well-established tool with a wide range of use in research, education, science, and industry to design, run and analyse a system by reproducing (imitating) it. According to [Robinson \(2004\)](#), simulation is

"experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system".

Simulation can be used either as a validation and evaluation method or the primary method itself (e.g. scheduling tool), depending on the modellers' preference and the type of a particular problem at hand. Modellers commonly encounter issues when using simulation either as validation and evaluation or as a primary method. These problems need to be well defined and carefully managed. [Ladier et al. \(2015\)](#) address issues that a modeller has to handle when validating simulation models to evaluate the performance of optimisation models in a stochastic environment. Their study concerns cross-docking operations, but many different domains confront these concerns. Simulation can be linked to optimisation in different ways in the cross-docking literature. In their cross-dock truck scheduling study that combine simulation and optimisation models to assess robustness under stochastic conditions, [Ladier et al. \(2015\)](#) specify different ways of linking optimisation models and simulation:

- A simulation model utilises the output of the optimisation as an input.
- An optimisation model uses the output of the simulation as an input.
- An optimisation model is built-in into the simulation model.
- A simulation model is operated as an integrated tool within the optimisation model. It is also named as "simulation-optimisation" by [Olafsson and Kim \(2002\)](#).

In cross-docking processes, in order to achieve efficiency against uncertainty, practitioners and researchers use simulation as a handy tool to test the performance of their built systems under different operating conditions, so as to prevent issues before they are encountered. To this end, three main simulation modelling techniques are used in the cross-docking domain: discrete-event

simulation (DES), multi-agent-based simulation (MAS) and hybrid models (i.e. integration of DES and MAS).

Discrete-event simulation (DES) is employed to model queuing systems. The system is composed of entities flowing from one process (with a duration) to another. Queues divide processes (Robinson, 2004). The DES is the predominant simulation tool in the supply chain (e.g. distribution networks, shipping, route optimisation), logistics (e.g. airports, distribution centres, warehouses), and manufacturing. However, according to Siebers et al. (2010), since DES is process-oriented (top-down modelling approach), while the focus is to model the system in detail, the entities are ignored, and intelligence (e.g. decision-making) is modelled as a system component, not through the entities (passive entities). Therefore, the interactions between the entities and their actions towards dynamic events are disregarded in DES. In this context, to achieve fast synchronisation of cross-docking, DES can be deficient in considering each cross-docking entity and their interactions and defining specific goals related to their tasks. This issue directed cross-docking researchers to explore the potential of MAS, which practices an individual-based (bottom-up) modelling approach.

MAS includes active entities (i.e. agents) that initiate taking the actions emerging from their individual-based intelligence (Siebers et al., 2010). This decentralised characteristic of MAS creates shared responsibility to react to dynamic events and thus provides complete system visibility. Therefore, MAS can be an ideal strategy to access and employ real-time data concerning the operations within the system, given that the fast synchronisation of inflows and outflows is an absolute must for cross-docking efficiency.

The following section introduces the multi-agent-based modelling concept and its components.

3.2.1 Multi-agent-based modelling and simulation: concept and components

The multi-agent-based simulation uses the notion of multi-agent systems within the bare design of simulation models (Klügl and Bazzan, 2012). The term agent-directed simulation may even be used as a more widespread concept (Ören et al., 2000).

Multi-based models have been developed for different domains, such as biological sciences, economics, political sciences, social sciences, mathematics and logic. Within agent-based models, it is attainable to discover an environment among its features, predict and explore its future states, test potential alternative decisions, set different values for the decision variables and analyse the outcomes of these changes (Axelrod, 1997).

So what is an agent? One can define an agent as an active entity, or decision-maker developed and executed by implementing agent-related notions and technologies. According to Wooldridge and Jennings (1995), an agent is a computational method communicating with an environment. This characteristic can be provided with the following points (Wooldridge and Jennings, 1995):

- Independence: Each agent runs without the direct authority of human beings or other means.
- Social ability: Intercommunications happen among entities by a communication language to meet the objectives.
- Reactiveness: Agents respond precisely to signals originating from the environment.
- Proactiveness: Agents are provided with goal-directed behaviours. They take the initiative to accomplish their objectives.

According to the survey of Barbati et al. (2012), agents express physical entities (operators, devices, sources, vehicles) included in the particular problem to be answered. Moreover, an agent is empowered to generate optimising behaviours for some purposes (scheduling, sequencing, material handling) related to rules. The agents can function independently in their environment and interact with each other, at least over a limited range of conditions that interest a defined model.

The agents have methods (behaviours) that link information sensed by the agents to their decisions and actions (Axelrod, 1997). The methods of these agents differ according to being autonomous or not. In our study, agents model trucks, pallets and dock doors. They make real-time decisions on scheduling incoming and outgoing trucks and pallet flow inside the cross-dock facility. While trucks and doors are autonomous agents making these decisions, pallet agents are embedded agents within truck agents, enabling the pallet flow from the multi-agent system (inbound truck agents) to the discrete-event model (cross-dock operations). Pallet agents do not have any decision-making mechanism defined in them.

MAS includes active entities (i.e. agents) that initiate taking the actions emerging from their individual-based intelligence (Siebers et al., 2010). This decentralised characteristic of MAS creates shared responsibility to react to dynamic events and thus provides complete system visibility. Therefore, MAS can be an ideal strategy to access and employ real-time data concerning the operations within the system, given that the fast synchronisation of inflows and outflows is an absolute must for cross-docking efficiency.

3.2.2 Literature on simulation in cross-docking

In the cross-docking domain, practitioners operate and test the performance of their constructed systems at the strategical level (e.g. design configuration of a cross-dock terminal), tactical level (e.g. the service mode of the dock doors, resource capacity plannings of the facility) and operational level (e.g. scheduling of terminal resources, truck-to-door assignments, truck scheduling, truck routing). Nevertheless, most of the works in the literature concern the operational level problems (see Table 3.1).

Three main simulation modelling techniques are used in the cross-docking problems: discrete-event simulation (DES), multi-agent-based simulation (MAS) and hybrid models (i.e. integration of DES and MAS). These mainly employed simulation methods; their usage for cross-docking problems with the performance metrics is given in Table 3.1. In this table, studies are grouped according to their problem types. Note that a descriptive study of Rohrer (1995) gives insights on simulation configuration with related cross-docking issues but does not employ any simulation models; therefore, this study is not included in this table. The following sections study the usage of predominantly employed simulation tools in cross-docking.

Table 3.1: Simulation methods and their usage types in the cross-docking literature

Publications	Simulation method(s)	Is simulation used to		Performance measures	Cross-dock problem types
		validate and evaluate other modelling tool?	evaluate the system performance?		
Shi et al. (2013)	DES	✓	✓	Stock level; Lateness of product delivery; Operation capacity of CDC ¹	Cross-dock design; Scheduling, planning and coordination activities in CDC ¹
He and Prabhu (2022)	DES	✓	✓	AGV ² utilisation	Cross-dock design; Planning and coordination activities in CDC ¹
Piao and Xiang (2017)	DES	✓	✓	Operation cost for CDC ¹ ; Handling equipment utilisation	Scheduling, planning and coordination activities in CDC ¹
Buijs et al. (2016)	DES	✓	✓	Internal congestion of the CDC ¹ ; Travel distance of load-carriers inside CDC ¹ ; Lateness of product delivery; Tardiness of outbound trucks	Scheduling, planning and coordination activities in CDC ¹
Yang et al. (2010)	DES	✓	✓	Operation capacity of CDC ¹	Scheduling, planning and coordination activities in CDC ¹
Magableh et al. (2005)	DES	✓	✓	Lateness of product delivery; Truck processing time deviation	Scheduling, planning and coordination activities in CDC ¹
Chargui et al. (2018)	DES	✓	✓	Congestion; Stock level; Handling equipment utilisation; Total unloading and loading time	Scheduling, planning and coordination activities in PI-hub
Pawlewski (2015)	DES	✓	✓	Travel distance inside PI-hub	Scheduling, planning and coordination activities in PI-hub
Liu and Takakuwa (2010)	DES	✓	✓	Inbound door utilisation; Workforce utilisation	Scheduling, planning and coordination activities in CDC ¹
Liu (2010)	DES	✓	✓	Inbound door utilisation; Workforce utilisation	Scheduling, planning and coordination activities in CDC ¹

(continued)

Publications	Simulation method(s)	Is simulation used to		Performance measures	Cross-dock problem types
		validate and evaluate other modelling tool?	evaluate the system performance?		
Navin et al. (2016)	DES	✓	✓	Average lead time of product delivery; Service level; Truck utilisation	Planning and coordination activities in CDC ¹ ; Truck routing
Suh (2015)	Hybrid	✓	✓	Outbound truck utilisation; Outbound truck fill rate; Operation capacity of CDC ¹	Planning and coordination activities in CDC ¹
Chaiyarot and Pitiruek (2021)	DES	✓	✓	Operation capacity of CDC ¹ ; Stock level; Net profit	Planning and coordination activities in CDC ¹
Aiello et al. (2012)	DES	✓	✓	Transportation cost of trucks at supply chain	Truck routing
Lian (2021)	DES	✓	✓	Carbon emission; Damage cost of deteriorated products; Transhipment time of products in supply chain; Number of products delivered on time; Transportation cost of trucks at supply chain	Truck routing
Acar et al. (2012)	DES	✓	✓	Door utilisation	Truck-to-door assignment
Walha et al. (2016)	MAS	✓	✓	Outbound truck utilisation; Travel distance inside PI-hub	PI-containers-to-docks/trucks assignment (Rail-road PI-hub)
Chargui et al. (2020)	MAS	✓	✓	Number of used wagons; Travel distance inside PI-hub; Tardiness of inbound trucks	Truck scheduling; PI-containers grouping (Road-Rail PI-hub)
Chargui et al. (2019)	DES	✓	✓	Number of used wagons; Outbound truck utilisation; Travel distance inside PI-hub; Tardiness of inbound trucks; Total loading time	Truck scheduling; PI-containers grouping (Road-Rail & Rail-road PI-hub)

(continued)

Publications	Simulation method(s)	Is simulation used to		Performance measures	Cross-dock problem types
		validate and evaluate other modelling tool?	evaluate the system performance?		
Sallez et al. (2015)	MAS	✓		Evacuation time (i.e. makespan)	PI-containers grouping (Rail-road PI-hub)
Pach et al. (2014)	MAS		✓	Evacuation time (i.e. makespan)	PI-containers grouping (Rail-road PI-hub)
Chargui et al. (2022)	DES	✓		Tardiness of inbound and outbound trucks	Truck scheduling
Kusuma (2021)	MAS		✓	Makespan; Stock level	Truck scheduling
Manupati et al. (2018)	DES	✓		Truck processing time deviation	Truck scheduling
Zouhaier and Ben Said (2017a)	MAS		✓	Truck processing time deviation	Truck scheduling
Zouhaier and Ben Said (2016)	MAS		✓	Congestion; Operation capacity of CDC ¹ ; Operation cost for CDC ¹ ; Truck processing time deviation	Truck scheduling
Ladier et al. (2014)	DES	✓		Number of pallets put into storage; Inbound and outbound truck docking times; Inbound and outbound truck sojourn times	Truck scheduling
Wang and Regan (2008)	DES		✓	Door utilisation; Total unloading time; Travel distance inside CDC ¹	Truck scheduling

¹CDC: cross-docking centre²AGV: automated guided machine

3.2.3 Cross-dock and discrete-event simulation

Many operational-level cross-dock problems that develop optimisation models employ DES to validate and evaluate their model performances. Among them, cross-dock truck scheduling studies of [Chargui et al. \(2022\)](#) and [Manupati et al. \(2018\)](#) take advantage of DES to test the time-related performance metrics (i.e. tardiness of inbound and outbound trucks and truck processing time deviation, respectively). [Ladier et al. \(2014\)](#) develop an integer programming model for scheduling trucks and pallet flows inside the cross-dock terminal. DES serve to evaluate the robustness of the integer programming model in terms of time-related and inventory level-based metrics under stochastic environment. [Acar et al. \(2012\)](#) proposed an optimisation approach for a truck-to-door assignment problem to evaluate resource-related performance measures. Similarly, a truck routing optimisation problem of [Lian \(2021\)](#) assesses cost and time-related performance metrics and environmental footprint criterion (i.e. CO2 emission of trucks at the supply chain network) using DES. [Aiello et al. \(2012\)](#) present an integer nonlinear programming approach to analyse the effects of cross-docking practice on the cost-related performance metric (i.e. transportation cost of trucks at the supply chain) in a deterministic environment. The optimum solutions are then fed into the simulation by introducing demand uncertainty to the model, and the results are analysed. Similarly, [Chaiyarot and Pitiruek \(2021\)](#) focus on the internal operations of cross-docking production zones, particularly on rail freight cross-docking centres (RFCDC). First, a DES model is developed to analyse bottleneck points in the studied platform. According to simulation results, the authors detect bottlenecks in re-palletising (i.e. placing products on pallets for shipment) and final recording (i.e. documentation of product details and directing them to retailers for shipping) processes. Next, an optimisation model is implemented to improve the system under resource allocation limitations. The best scenarios are then fed into the simulation to analyse the system's throughput, stock level, net profit and cycle time.

In case where simulation is employed to emulate the cross-docking system and does not provide optimum solutions itself, an optimisation model serves to obtain the best results on defined performance metrics. [Shi et al. \(2013\)](#) use simulation to imitate the inside operations of the real cross-docking facility. The obtained results from simulation on resource/time-related and inventory-based performances metrics are fed into the robust optimisation model to protect the system against supply uncertainty.

The built-in optimisation algorithms within a simulation model render optimum results in a dynamic environment. [Wang and Regan \(2008\)](#) use real-time information on process times to reschedule operations of a cross-docking facility if the initial schedule is no longer valid due to perturbations. They embed optimisation algorithms within the simulation model to attain robustness on resource and time-related performance criteria.

Simulation can also be built into an optimisation model and assess the objective function derived from the solution of the optimisation model ([Ladier et al., 2015](#)). This method is referred as the simulation-optimisation method. Several scheduling studies in the cross-docking literature employ this method. [Chargui et al. \(2019\)](#) examine truck scheduling and PI-containers grouping problem in road-rail and rail-road PI-hub. A simulation-optimisation approach is used to assess time-related and sustainability-based (i.e. the energy consumption of PI-containers) performance measures under perturbations.

Simulation and optimisation can be carried out not only using operations research theories. For instance, [Piao and Xiang \(2017\)](#) emulate scheduling, planning and coordination activities of a real cross-docking centre by using simulation. The outcomes of simulation model analysed based on several principals related to cost and time efficiency. The acquired optimum configurations serve as a decision-making instrument for cross-docking practitioners.

Cross-dock studies concerning scheduling, planning and coordination activities within the facility take advantage of simulation to address the operational issues ([Magableh et al., 2005](#); [Yang et al., 2010](#); [Buijs et al., 2016](#); [Chargui et al., 2018](#); [He and Prabhu, 2022](#); [Pawlewski, 2015](#); [Liu](#)

and Takakuwa, 2010; Liu, 2010; Navin et al., 2016). Magableh et al. (2005) model a large-scale cross-docking facility in a dynamic environment where demand is not stable. Simulation is used as an evaluation tool on time-related performance measures (i.e. the lateness of product delivery and truck processing time deviation). Yang et al. (2010) analyse the effects of resource utilisation level (e.g. the number of dock doors and their allocated workforce) and material flow (e.g. door-to-door transfer of pallets) on the operation capacity of a cross-dock terminal with the a simulation model. He and Prabhu (2022) analyse the impact of practising cross-docking with warehouses to manage the supply and demand imbalance. The authors also present automated guided vehicles (AGVs) for material handling to improve cross-docking operations. Liu (2010) employs a simulation model for a cross-docking centre to schedule internal operations to achieve the best performances on the resource-related criterion. Similarly, in another study, Liu and Takakuwa (2010) propose a simulation model for a real cross-docking platform that performs just-in-time shipments. The simulation serves as a decision-making tool for logistics managers on resource-related performance metrics (i.e. inbound door utilisation and workforce utilisation). According to Buijs et al. (2016), a holistic approach that integrates the management decisions of a cross-dock and its network brings the whole system to better performance. To that end, they use simulation to model and evaluate the performance metrics of the proposed theory. Pawlewski (2015) focuses on asynchronous (i.e. the task is performed on demand when required) multimodal transportation for cross-docking and discusses the Physical Internet application for a classical cross-dock. The author presents a simulation model to test the total distance travelled by material handling equipment inside the platform. Chargui et al. (2018) employ a simulation model to build a Physical Internet in a cross-docking and evaluate its impacts. Performance measures on inventory level, time and resource utilisation of new configuration and traditional cross-dock are compared.

In addition to cross-dock scheduling, Navin et al. (2016) study network scheduling problem. They employ DES to analyse the effects of practicing multiple cross-docks under supply uncertainty for the studied network. Performance metrics on service level of the cross-dock, order lead time and truck utilisation are analysed.

3.2.4 Cross-dock and agent-based simulation

In the cross-docking literature, a few studies take advantage of the reactive and autonomous nature of agent-based systems to imitate and improve their studied system (Kusuma, 2021; Chargui et al., 2020; Zouhaier and Ben Said, 2017a, 2016; Walha et al., 2016; Pach et al., 2014; Sallez et al., 2015). One of the essential elements in the rapid synchronization of the cross-dock is the scheduling of the inbound and outbound trucks since truck scheduling accelerates the product flow between the inbound and outbound doors and thus prevents the stack of goods in the temporary storage. To that end, with agents' reactive and autonomous nature and distributed responsibility, information flow between the inbound and outbound sides of the facility is ensured, and actions that need to be urgently taken can be handled without delay.

To this respect, Kusuma (2021) employs MAS in a just-in-time cross-docking system. The proposed MAS is composed of inbound trucks scheduler agent, outbound trucks scheduler agent, and material handler agent. The inbound trucks scheduler makes the truck-to-door assignment based on the capacity limit of storage and the outbound truck's presence. Then, the material handler agent controls the product flow between dock doors and storage. The outbound trucks scheduler agent selects a truck that can receive many types of products from storage. It is noted in the study that door-to-door transfer is prioritised to minimise the wait times of inbound trucks. However, in this study, the outbound trucks scheduler agent does not communicate with the inbound trucks scheduler agent. The outbound truck selection can be made by considering the contents of the currently docked inbound truck to promote door-to-door transfer. In addition, the trucks are not configured to directly negotiate their processing order and time preferences with the truck scheduler agents. In fact, the improved inter-communication between agents and system entities could serve

more of the objective of minimising the total time of trucks.

Contrary to [Kusuma \(2021\)](#), [Zouhaier and Ben Said \(2017a, 2016\)](#) analyse the inbound side of the cross-docking terminal without considering temporary storage and focus on the truck congestion at the gate, the parking yard and the dock doors of the facility.

In the study of [Zouhaier and Ben Said \(2016\)](#), a truck appointment system is used to control truck arrivals by allocating a time window to each truck under truck arrival time uncertainty. An optimisation model is presented for the truck appointment system to minimise the truck deviation time under the resource restrictions (i.e. availability of dock doors, gate lines, parking yard and workforce). Furthermore, a multi-agent-based model is employed to enable a real-time negotiation between truck agents and a resource agent on the adequate service of resources from the perspective of both agents. Similarly, in another study, [Zouhaier and Ben Said \(2017a\)](#) combined ant colony intelligence (ACI) with the multi-agent-based model for real-time scheduling of trucks at the parking area and inbound doors. Integrating ACI in the multi-agent system, composed of resource and truck agents, aims to process jobs based on their priorities. The ACI helps each agent express their set of constraints (e.g. upcoming due dates of trucks) and make a real-time decision based on it. These two studies are limited to the inbound side of the cross-dock facility. However, the proposed MAS can be developed for inbound and outbound truck scheduling together with the material flow control inside the terminal to achieve complete system efficiency.

In addition to classical cross-docking configuration, some studies propose multi-agent-based systems for Physical Internet (PI) cross-docks ([Chargui et al., 2020](#); [Sallez et al., 2015](#); [Pach et al., 2014](#)).

To this respect, [Chargui et al. \(2020\)](#) propose a multi-agent-based system to a road-rail PI-hub. The presented MAS schedules trucks and assigns and groups PI-containers in the PI-hub. The study's objective is threefold: minimisation of inbound truck tardiness, the total distance travelled by PI-containers (energy consumption) and the number of utilised wagons (CO2 emission of the train). The model includes truck agents, a train agent, three parallel scheduling agents and a synchronisation agent. The schedule is employed at the beginning of the day, and when a perturbation occurs (i.e. dock breakdown), the rescheduling is executed based on the current state. In addition, the authors build an optimisation model to evaluate the performance of the presented MAS in a deterministic context (i.e. without perturbation). In this study, the information flow among agents and the resulting decisions are directed via the synchronisation agent. The proposed MAS can be configured to enable the direct intercommunication and negotiation of the agents.

[Pach et al. \(2014\)](#) study PI-containers grouping problem for a rail-road PI-hub. The study employs MAS to group PI-containers for loading onto their destined trucks to speed up the overall shipment. To this end, PI-containers are defined as active agents exchanging information on their arrival times and grouping size limits based on the capacity of their predefined truck. Suppose the train arrives at the PI-hub later than expected (i.e. external perturbation), and another train arrives while trucks are already positioned for the delayed train. In that case, each PI-container regroups itself and others to be loaded onto the already positioned trucks.

Similarly to [Pach et al. \(2014\)](#), [Sallez et al. \(2015\)](#) study the PI-containers grouping problem for rail-road PI-hubs. The authors employ MAS to manage internal (i.e. breakdown of conveying units while routing PI-containers) and external perturbations (i.e. delay in the train arrival time) reactively. The study aims to reduce the makespan (i.e. evacuation time), that is, the duration between unloading the first PI-container from the train and loading the last PI-container onto its destination truck. The proposed MAS is composed of PI-container agents with initially predictive behaviours and switching to the active state when they encounter internal and external perturbations. In this case, the rescheduling is performed based on the present condition.

3.2.5 Cross-dock and hybrid simulation methods

A hybrid approach combining (DES) and (MAS), plays distinct but complementary roles in evaluating cross-docking configurations. DES effectively represents modelling logistical flow, resource allocation, and temporal aspects, representing the movement of goods, optimising resource utilisation, and ensuring timely distribution. On the other hand, MAS specialises in modelling dynamic interactions, behavioural modelling, and adaptability among individual agents, simulating real-time decisions and adaptive responses. Together, this hybrid model brings a holistic simulation environment, allowing scenario exploration, adaptation to changing conditions, sensitivity analysis, and a thorough assessment of cross-docking feasibility and consequences. To that end, practitioners have initiated using hybrid simulation methods without being biased by the one method itself, ultimately assisting decision-makers in optimising the process to fulfil specific needs.

To this respect, [Suh \(2015\)](#) studies the optimisation of a cross-dock system by employing a hybrid model composed of DES and MAS. The problem includes incoming supplies by manufacturers, cross-docking facility operations and shipments of customer orders. In addition, a traditional warehouse configuration is also integrated into the system for the long-run storage of customer orders concerning demand uncertainty. The study aims to minimise order throughput time and the number of used trucks while maximising the truck fill rate. The simulation model is divided into three main modules. The first module is modelling incoming supplies with different types and due dates using MAS. The second module, the cross-docking, is modelled by DES. This module is divided into two parts: the inbound and outbound sides. The inbound side unloads the arrivals of supplies and handles order matching. In case the order is unpaired by the outbound trucks, they are then sent to the warehouse to stay until the next shipment. The shipment of orders follows FCFS (first-come-first-served) rule. The second part of the cross-docking module, the outbound side, operates the loading process based on order match and load capacity of trucks. The last module, the distributor module, is modelled by MAS. It places various customer demands and manages the loading of the matched orders into its trucks. The performance of the proposed model is assessed by sensitivity analysis and Monte Carlo simulation.

3.2.6 Main take-away from the literature review

In this section, we summarise the main findings from our literature search that motivate our study.

As can be noticed in [Table 3.1](#), the majority of the studies (69%) use discrete-event simulation as a modelling tool. Some studies are emerging on multi-agent simulation and only one work (by [Suh \(2015\)](#)) is reported on hybrid simulation, which mixes both techniques. There is obviously room for further research on MAS and hybrid simulation techniques in cross-docking.

The performance evaluation of systems being the major utilisation of simulation, it is not surprising to see that most of the earlier studies use the simulation for this purpose. Some have employed it to validate the solution obtained by other tools (e.g. optimisation). These essentially concern works that evaluate the robustness of such solutions via simulation. Our studies presented in [Chapters 4 and 5](#) are oriented toward the first type of use.

Performance measures and problem types are quite diverse in the earlier literature. Nevertheless, we can observe that MAS is predominantly preferred in truck scheduling and PI-containers grouping studies. Moreover, both problems mainly seek to minimise time-related performance metrics and stock level. These performance measures are quite relevant for cross-docks since the main objective is to speed up the process in the logistics platform with zero or very little temporary storage. Our studies in [Chapters 4 and 5](#) are oriented towards the truck scheduling problem with storage and truck fill rate along with the time-related performance metrics, including the number of late pallets and pallet lateness. Specifically, [Chapter 5](#) expands our analysis of time-related performance metrics, integrating further measures (i.e. pallet travel time within the platform and model computation time) in addition to the initial metrics introduced in [Chapter 4](#). Moreover, [Chapter 5](#) raises another performance indicator, which is related to resource utilisation (i.e. door occupancy). These

enhancements are a direct result of our research into multiple-door cross-dock settings along with the aim of meeting the real-time scheduling requirements of the industrial context described in Chapter 5.

The classification of the model settings for the cross-dock problems that employ different simulation techniques are given in Table 3.2. As can be noticed from this Table, a significant number of studies consider multiple-door cross-dock and multiple product settings. While we keep the multiple product setting in our studies, in Chapter 4, we propose to consider a single inbound and outbound dock case as a fundamental building block for a hybrid simulation model for multiple dock setting. By the foundational visions gained from Chapter 4, in Chapter 5, we propose a multiple-door setting tailored towards real-world cross-docking scenarios.

Finally, the model configuration of the agent-based approach of scheduling studies in the cross-docking domain is presented in Table 3.3. This summary table, together with Table 3.1, reveal that the potential of agent-based approaches to real-time scheduling still needs to be explored, even if few papers already exist on this topic.

The main advantage of MAS is clearly the capacity of agents to communicate among themselves for quick and distributed decision-making. Therefore, real-time (or just-in-time) scheduling and rescheduling are the main applications. We notice that all studies do not make use of the decentralised decision-making capability. We also observe that the studies mostly focus either on the inbound or the outbound side of the cross-dock. It is essential to considering both inbound and outbound sides along with the internal operations needs more attention since it is inevitable for fast synchronisation of cross-docks.

The performed literature review shows that multi-agent-based approaches are effective techniques for solving real-time truck scheduling problems for cross-docking. However, it also revealed that the application of the MAS to real-time truck scheduling still needs to be explored. This thesis study addresses this issue by proposing a hybrid model composed of MAS and DES for real-time truck scheduling for cross-docking. It is essential to mention that our study differs from the unique hybrid simulation model by [Suh \(2015\)](#) because we model both the operational decisions to effectively coordinate inbound and outbound trucks and the operations inside the cross-dock facility. Unlike some earlier studies, we make use of direct negotiation among agents for decentralised decision-making.

The following section explains our motivation for adopting the hybrid simulation approach in our study, delving into the respective merits and constraints of both DES and MAS.

Table 3.2: Classification of the model settings of the cross-docking problems that employ simulation

Publications	Number of doors		Door service mode		Temporary storage		Product type		All trucks are available at time zero	Case study	Real-life
	Single door	Multi-door	Exclusive mode	Mixed mode	Not used	Limited	Unlimited	Single product			
Shi et al. (2013)	✓		✓				✓	✓			✓
He and Prabhu (2022)	✓		✓					✓		✓	
Piao and Xiang (2017)	✓		✓								✓
Buijs et al. (2016)	✓		✓	✓	✓						✓
Yang et al. (2010)	✓		✓				✓		✓	✓	
Magableh et al. (2005)	✓		✓	✓	✓				✓		✓
Chargui et al. (2018)	✓		✓				✓				✓
Pawlewski (2015)	✓		✓		✓						✓
Liu and Takakuwa (2010)	✓		✓					✓			✓
Liu (2010)	✓		✓					✓			✓
Navin et al. (2016)			✓					✓			✓
Suh (2015)			✓					✓		✓	✓
Chaiyarat and Pitiruek (2021)			✓					✓			✓
Aiello et al. (2012)			✓					✓		✓	✓
Lian (2021)										✓	✓
Acar et al. (2012)	✓		✓								✓
Walha et al. (2016)	✓		✓								✓
Chargui et al. (2020)	✓		✓								✓
Chargui et al. (2019)	✓		✓								✓
Sallez et al. (2015)	✓		✓								✓
Pach et al. (2014)	✓		✓								✓
Chargui et al. (2022)	✓		✓								✓
Kusuma (2021)		✓	✓				✓				✓
Manupati et al. (2018)		✓	✓								✓
Zouhaier and Ben Said (2017a)		✓	✓								✓
Zouhaier and Ben Said (2016)		✓	✓								✓
Ladrier et al. (2014)		✓	✓							✓	✓
Wang and Regan (2008)		✓	✓							✓	✓

Table 3.3: The MAS configuration of the studies in the cross-docking literature

Publications	Simulation method(s)	Scheduling type	Direct negotiation between agents	Which part of the cross-dock is considered?
Chargui et al. (2020)	MAS	Rescheduling		Inbound (road-rail PI-hub)
Walha et al. (2016)	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Sallez et al. (2015)	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Pach et al. (2014)	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Kusuma (2021)	MAS	Just-in-time		Inbound, outbound
Zouhaier and Ben Said (2017a)	MAS	Real-time	✓	Inbound
Zouhaier and Ben Said (2016)	MAS	Real-time	✓	Inbound
Suh (2015)	Hybrid	Robust		Internal operations

3.2.7 Assessing DES and MAS: Advantages and Limitations

In cross-docking operations, selecting an appropriate modelling technique is crucial as it directly affects the system's functionality and performance. The methodology selection involves investigating different simulation methods and considering the trade-offs between their strengths and weaknesses. This approach helps discover the best-suited modelling method to address the specific problem at hand.

DES offers notable advantages owing to its process-oriented characteristics. It provides a structured representation of system operations and enables the modelling of a precise sequence of processes. It organises and presents the different tasks or actions within a system systematically and visually comprehensibly, allowing for a clear understanding of how the system operates. This can be especially valuable for researchers, analysts, or decision-makers to gain insights into system behaviour and performance. Moreover, it prioritises the overall system goal by focusing on the processes rather than the system entities when individual preferences are not the focus.

However, when representing the dynamic interactions and decision-making behaviours of system entities also of interest, DES may fall short in that respect. DES lacks the capability to model the real-time, adaptive decision-making processes of individual entities to respond to changing conditions within the system environment.

In that case, individual-based MAS offers distinct advantages by modelling both entities individually and their interactions. This way, MAS represents each entity's intelligence, adaptability, and initiative. Moreover, MAS's decentralised control structure (each agent has its own control thread) allows for real-time decision-making and adaptability. It is well-suited for scenarios where individual decisions are of interest.

However, handling many active agents, each with its own decision-making capabilities can introduce computational complexity in MAS. As agent populations extend, computational demands may rise, potentially leading to slowdowns in the system.

Furthermore, while realistic, the emergent behaviour in MAS can introduce unpredictability, which may pose challenges. For instance, imagine a cross-docking facility that relies on MAS for internal operations. The agents are programmed to prioritise larger shipments over smaller ones, assuming it expedites the process. While this adaptability can be valuable, it may lead to unin-

tended results. Smaller shipments, though numerous, could end up waiting longer for processing, generating bottlenecks and delivery delays. This real-time decision-making behaviour introduces unpredictability, challenging the cross-docking operation's efficiency and timely distribution. This emergent behaviour may become more serious in highly controlled or safety-critical environments (such as nuclear power plants or pharmaceutical manufacturing facilities).

In conclusion, the preference between DES and MAS for cross-docking operations hinges on the specific system conditions and purposes. As [Siebers et al. \(2010\)](#) emphasise, even though an agent-based system is more flexible to answer a wide range of questions better than other simulation tools, it should still not be considered as a replacement. Instead, different simulation methods can be combined based on system characteristics to serve as an efficient problem-solving tool. To this end, we summarise the advantages and limitations of both DES and MAS in [Table 3.4](#) intending to assist modellers in the methodology selection.

Table 3.4: Advantages and limitations of DES and MAS

	DES	MAS
Advantages	Provides a structured representation of system (enhances the modeller's understanding of system behaviour)	Models both entities individually (their intelligence, objectives) and their interactions
	Facilitates precise process sequencing	Allows for real-time decision-making and adaptability
	Prioritises the overall system goal	
Disadvantages	Unable to model the behaviours of the individual entities	System slowdowns occur as computational complexity increases with more agents
		The emergent behaviour can introduce unpredictability (may pose challenges in highly controlled or safety-critical environments)

Drawing from insights gained through our literature review and assessment of the strengths and limitations of DES and MAS, we introduce a novel hybrid simulation model for real-time truck scheduling in cross-docking operations in the following chapter. This model is specifically tailored for a single inbound and outbound doors cross-docking setting, allowing us to dissect intricate system dynamics and mechanisms. This setting empowers us to gain a deep understanding of multi-agent-based real-time truck scheduling in cross-docking operations. Our main objective is to establish a strong foundation for scaling up to more intricate cross-docking systems, notably multi-dock environments.

Our study in the following chapter focuses on the operations inside the cross-dock facility and the essential decision-making processes involved in effectively coordinating inbound and outbound trucks. We address numerous operational issues that need to be addressed in the development of daily operations:

- Which inbound (outbound) truck should be assigned to the inbound (outbound) door and when?
- Which pallet is needed to be loaded to which outbound truck and when?
- How many/Which pallets need to be taken to temporary storage?
- What tasks should be prioritised in the cross-dock platform, and how are the resources chosen to perform these tasks?

In the proposed model, the multi-agent approach practices the autonomous, reactive and thus distributed responsibility characteristics of agents to realise shared computation and respond flexibly to dynamic events. Moreover, the process-oriented feature of DES is employed to model the internal operations of the terminal in detail. The DES is adopted instead of MAS for inside operations for several reasons:

1. DES is a top-down modelling approach; it is an ideal tool to model the macro behaviour of internal operations (i.e. adequate flow of pallets through the facility) without focusing on its elements.
2. DES is smoothly configured to permit the real-time control of reactive MAS over its processes.
3. Since MAS is composed of inter-communicating agents, the increase in the number of agents in the simulation model provokes communication overload and, thus, low system performance in terms of computation time.
4. The multi-agent-based modelling increases the model-building complexity.

In addition, for model implementation, we select AnyLogic Simulation Software due to its efficient support for our hybrid model. AnyLogic offers extensive flexibility and numerous opportunities for modellers to implement their ideas, with valuable support from an active and resourceful community.

Finally, to assess the performance of the proposed model, we develop key performance measures. The following chapter (Chapter 4) gives a detailed description and the implementation of the proposed model.

4

Real-time truck scheduling model for single inbound and outbound doors cross-dock

This chapter proposes a real-time multi-agent truck scheduling model for single inbound-single outbound cross-docking for fast synchronisation of inflows and outflows. The proposed model exploits the autonomous, reactive, and distributed responsibility characteristics of the multi-agent systems to realise shared computation and respond flexibly to dynamic events. This type of model is novel in the cross-docking literature for scheduling of both inbound and outbound trucks. The responsiveness of the proposed model is evaluated by employing a combination of different traffic levels based on truck arrival times. Furthermore, various truck selection strategies are implemented to achieve the best performance based on key performance indicators such as the average stock level, the number of late pallets, the pallet delay and the outbound truck fill rate. To validate the experimental results, ANOVA (analysis of variance) is performed.

The research showcased within this chapter is also presented in the following article:

[Torballi and Alpan \(2023b\)](#). A multi-agent-based real-time truck scheduling model for cross-docking problems with single inbound and outbound doors. *Supply Chain Analytics*, 3:100028, DOI: 10.1016/j.sca.2023.100028.

Building upon the foundational insights from Chapter 3, which emphasises the significance of problem-driven methodology selection, this chapter proposes a multi-agent-based hybrid model for real-time truck scheduling. This model is specifically tailored for a single inbound and outbound door cross-docking design, allowing us to dissect complex system dynamics and mechanisms. This chapter, therefore, aims to achieve a profound understanding of multi-agent-based real-time truck scheduling within cross-docking operations. Moreover, it establishes a solid groundwork for scaling up to more complex cross-docking systems, notably multi-dock environments.

After presenting the model specifications in Section 4.1.1, the implementation details are explained in Section 4.1.2. Section 4.1.3 delves into the behavioural dynamics of the agents operating within the model. In Section 4.1.4, we define key performance metrics for comprehensive model assessment. Section 4.2 details input generation and output analysis procedures and subsequently conducts a performance analysis based on the defined metrics.

4.1 Model description

In this section, the proposed multi-agent-based hybrid model is described. Figure 4.1 depicts the physical components of the studied single inbound and outbound doors cross-dock. The unified modelling language (UML) diagram that describes the structure of the model is given in Figure 4.2.

As represented in this diagram, different agents in the cross-dock facility are identified to allow each agent to utilise a subset of control elements. The control elements help decision-making at the agent level by using various policies for dock doors and inbound and outbound trucks to manage material handling equipment and merchandise (i.e. pallets) within the cross-dock terminal. Note that this UML diagram is a generic case of real-time truck scheduling for cross-docking. However, the studied problem, which is a case of a single inbound and outbound door, is adapted from this diagram.

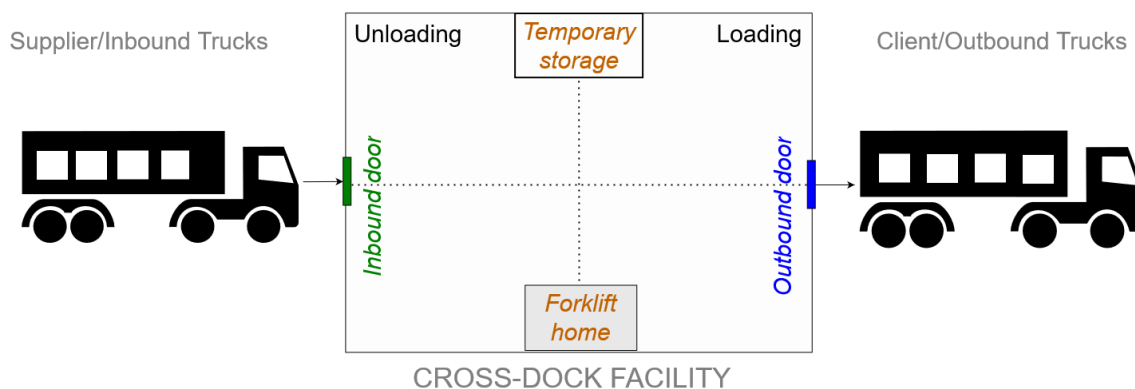


Figure 4.1: The physical structure of the studied single inbound and outbound doors cross-dock

To assess the performance of the proposed model, we use stock and time related performance measures. Therefore, the objective of the proposed model is quadruple: minimisation of average stock level, minimisation of the pallet delay, minimisation of the number of late pallets and maximisation of the outbound truck fill rate. To that end, several truck selection strategies are employed and compared, and the respective results are analysed.

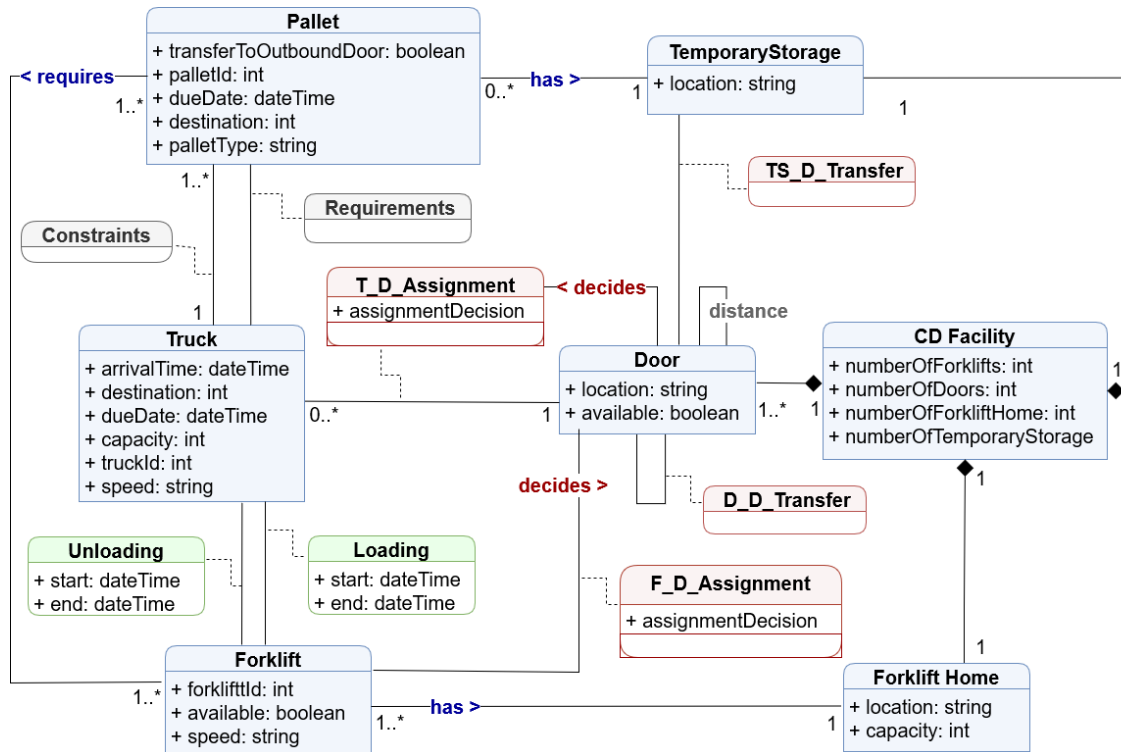


Figure 4.2: The UML diagram of the proposed multi-agent-based dynamic model

4.1.1 Model specifications

The specifications of the presented model are given below.

The structure of the cross-dock (see Figure 4.1)

- A single door (one inbound-one outbound door) cross-dock facility is considered, and dock doors are dedicated only for unloading or loading (exclusive service mode).
- The capacity of temporary storage is assumed to be unlimited.
- The facility's workforce is defined over forklifts to perform unloading, carrying and loading processes.
- The capacity of each inbound and outbound truck is fixed and equal to 26 pallets per truck.
- All the actions in the simulation model (e.g. travels of trucks from the parking area to dock doors, forklift movements, pallet handling) are based on spatial and temporal dimensions.

The functioning of the cross-dock:

- The inbound trucks arrive at the facility fully loaded and are fully unloaded on the dock.
- The unloading process cannot be interrupted until it is completed (preemption is not allowed).
- The due date of the outbound truck is defined as a hard constraint; if an outbound truck's due date is expired, the truck leaves the system without waiting for the loading operation to end (in case the loading is currently ongoing) or begin (if the outbound truck is waiting in the queue to be processed).

- The direct transfer from the inbound to the outbound truck (door-to-door transfer) has priority over the pallet transfer from storage to the outbound truck. Therefore, the pallet is touched only once instead of twice, and thus the stock level increment is avoided.
- Temporary storage provides a buffer between inbound and outbound processes by keeping the unloaded pallets in a single area until the destined outbound truck is available. Therefore it avoids congestion at the unloading and loading dock doors and facilitates a smoother flow of pallets inside the platform.

4.1.2 Model implementation

The model is implemented as multi-method modelling, consisting of multi-agent-based and discrete-event simulations. The modelling process is realised using Java Programming Language on the AnyLogic Simulation Software (University edition 8.7.10).

The model inputs:

- The arrival time and the contents (the type, destination and due date of pallets) of each inbound truck are obtained from the external data source (Excel file) that is imported into the built-in simulation database. Then, this data is used as input in the model by querying the simulation database tables.
- The arrival time, destination and due date of each outbound truck are also obtained from the external data source (Excel file) and queried the same way.

The details regarding the input data generation (the contents of the Excel file) is explained at Section 4.2 (Experimentation).

The multi-agent component

- The cross-docking elements of inbound/outbound trucks, pallets and inbound/outbound dock doors are defined as agents for the multi-agent-based model to bring dynamic and autonomous characteristics to the system. It should be noted that the pallet agent is defined as an embedded agent within the inbound trucks to enable the pallet flow from the multi-agent system (inbound truck agents) to the discrete-event model (cross-dock operations). Pallet agents do not have any decision-making mechanism defined in them.
- Unlike the outbound trucks, the due date of inbound trucks is defined based on the due dates of the pallets they carry. Accordingly, when an inbound truck agent arrives in the system, it selects the minimum due date value among all its pallets' due dates and sets this value as its own due date.
- When a truck arrives at the parking area, it asks permission from the door for docking and exposes its arrival time, due date and destination information (only valid for outbound trucks) to the door. Two cases happen:
 1. If the dock door is available, it accepts the docking request. Then the truck starts moving from the parking area to the respective door of the facility for docking.
 2. If the dock door is busy, it refuses the docking request. Then, the truck waits for the respective door to become available and calls the truck for docking.
- The behaviours of the inbound/outbound trucks and inbound/outbound dock doors are defined by their corresponding state charts and functions. For the details of the respective state charts for these agents, please consult Figures A.1 to A.4 in Appendix A.

The discrete-event component

- The utilisation of the workforce and temporary storage, in other words, the inside operations of the cross-dock facility, are defined by discrete-event modelling.
- The workforce of the facility is defined by the forklifts (i.e. one forklift = one logistics operator).
- Forklifts are assigned to the nearest tasks (i.e. selecting a forklift closest to that task) to avoid delays in internal operations.
- The forklifts create the link between the multi-agent component and the discrete-event component. For example, if an inbound truck docks at the inbound door, forklifts arrive at the inbound door and start unloading pallets from that inbound truck one by one.
- Once a forklift attaches to a pallet of the inbound truck at the inbound door, all the processes (unloading, transfer to temporary storage, transfer to the outbound door and loading) are performed by the forklifts and, thus, by discrete-event simulation until the completion of its loading process onto the outbound truck.

4.1.3 Decision-making mechanism

Inbound and outbound door agents employ truck selection strategies by communicating with inbound and outbound trucks. All the strategies define how the following actions are implemented:

1. How the inbound door agent selects the next inbound truck for docking when the inbound door becomes available.
2. How the outbound door agent selects the next outbound truck for docking when the outbound door becomes available.

The truck selection strategies employed in the model are namely; first-come-first-served (FCFS), earliest due date (EDD) and stock policy (SP).

- The FCFS rule is employed as a primitive strategy rather than a random selection of trucks for the dock assignments. This strategy may be reasonable concerning truck waiting times; however, it may not be a proper fit for on-time deliveries because of the different due dates of pallets in each truck.
- The EDD strategy selects both inbound and outbound trucks based on their due dates. The door agent selects the truck with the minimum due date for docking. The objective of this strategy is to minimise the pallet delay and the number of late pallets exiting the facility.
- The SP strategy only considers the selection of outbound trucks and aims to reduce the stock level of the cross-dock. In this respect, the outbound door agent determines the destination with the highest count of pallets in temporary storage. Then, it selects an outbound truck with the matching destination. If it cannot find a truck with the matching destination, it tries to find a matching destination with the second highest count of pallets. This process is repeated until the door agent finds a matching truck. While the outbound door agent practices this rule for the outbound truck selection, the inbound door agent uses the earliest due date rule for selecting the inbound trucks.

The architecture of the proposed hybrid model is presented in Figure 4.3. In this figure, the *release pallets* procedure indicated at both pallet selection decision and temporary storage-to-door transfer is developed as a function in the model. This function is responsible for the pallet transfer in the facility (Figure 4.4). The pallet transfer is done in three ways:

1. From the inbound door to the temporary storage for short-term storing
2. From the inbound door to the outbound door (i.e. the door-to-door transfer) for loading
3. From the temporary storage to the outbound door for loading

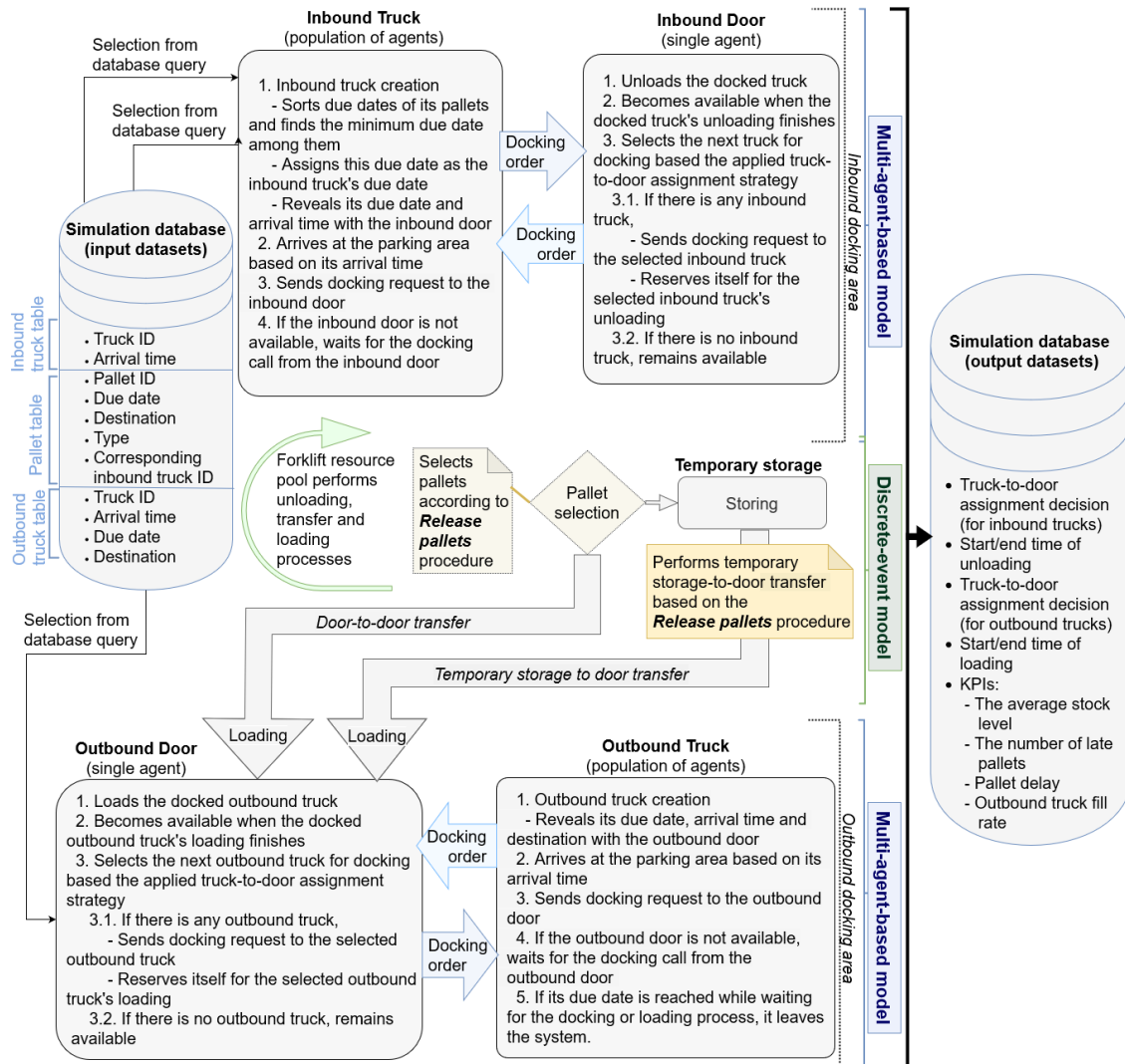


Figure 4.3: The configuration of the proposed hybrid simulation model

As indicated in Figure 4.4, for the pallet transfers (2) and (3), the *release pallet* function checks whether there is "enough time" to carry a pallet to the outbound door to avoid operational inefficiencies in the cross-dock platform. Recall that the outbound trucks have fixed due dates. They leave the cross-dock when their due date is reached without waiting for any transferring pallets. Therefore, before selecting a pallet for a given outbound truck, a simple time check is performed to guarantee that the pallet can reach that truck before its departure. This verification helps avoid unnecessary handling operations by the forklifts and congestion in the dock area (i.e. moving a pallet which cannot be loaded on a truck on time has to be returned to the temporary storage; otherwise, it blocks the dock area until an appropriate truck arrives).

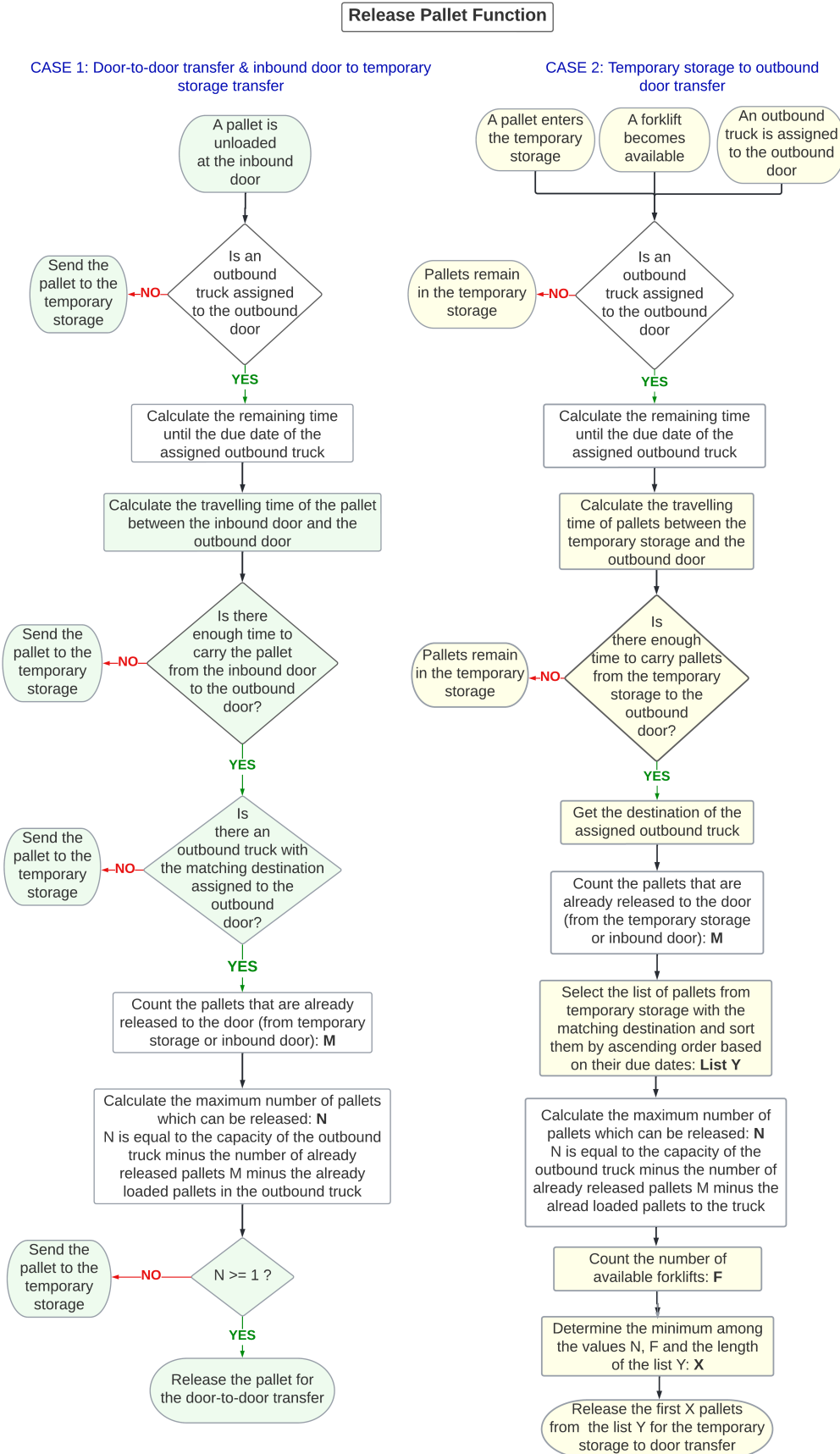


Figure 4.4: The process flow chart of the release pallet function

4.1.4 Performance evaluation

The key performance indicators (KPIs) of the proposed model are defined as follows:

- **Average stock level:** The stock level indicates the number of unloaded pallets, pallets that are currently being moved by the forklifts and the number of pallets in temporary storage. The stock level is the number of pallets inside the cross-dock facility. It is tracked throughout the simulation every hour, and the average level is calculated.
- **The pallet delay (in minutes) and number of late pallets:** The destination of each pallet and each outbound truck are defined by input datasets. The model transfers pallets to the dock door by checking the presence of an outbound truck with the matching destination. If there is no matching outbound truck at the system to load the pallet, the pallet waits in the temporary storage without considering its due date. In this case, the pallet delay and the number of late pallets should be considered as performance indicators of the model. The number of late pallets is the sum of the number of late exited pallets throughout the simulation and the number of late pallets in the last truck at the end of the simulation. The pallet delay is the sum of the delay of exited pallets during the simulation run and the pallet delay in the last truck at the end of the simulation divided by the total number of late pallets.
- **Outbound truck fill rate:** It is assumed that the outbound trucks leave the system according to their due dates without satisfying the condition of being full-loaded. Tracing the load rate of outbound trucks is an important KPI to assess the model's performance. To that end, the fill rate of the outbound trucks is monitored for the trucks that dock to the outbound door and complete the loading process or leave without being fully loaded due to their expired due dates. It should be remarked that trucks that leave the system after their due dates expire while waiting at the facility's parking area to be docked are not considered in this KPI. The outbound truck fill rate is the sum of the fill rates of docked outbound trucks divided by the total number of docked outbound trucks.

To ensure the reliability of the proposed model, we conduct a thorough model validation process. Utilising a fixed simulation seed for reproducible model runs, we track the simulation step by step with deterministic inputs. This involves a focus on the behaviours of the trucks, dock doors, and forklifts, as well as the logic of pallet selection and release. The validation process instils confidence in subsequent model experimentation (Section 4.2).

4.2 Experimentation

This section provides the experimentation performed on the proposed model. The model experimentation is carried out on the AnyLogic Simulation Software (University edition 8.7.10), using a PC with an Intel(R) Core(TM) i5-8250U CPU at 1.60 GHz, and 16.0 GB of RAM.

In this section, we first explain how the input data are generated and the results are evaluated, before giving the experimental results.

Input generation

The input datasets are randomly generated with a program written in the C# language. Six traffic level combinations are specified for the experiments with 10 instances generated for each (see Table 4.1). Three different truck selection strategies are used in the model to test 60 instances, resulting in a total of 180 experiments. The input generation scheme is explained below and the simulation parameters are delivered in detail in Table 4.2.

- **Truck capacity:** According to some European shipping companies, a Full Truck Load (FTL) shipment can range between 24 to 33 pallets, but this number can vary depending on the size of the vehicle and type of pallets (e.g. Euro pallets have different dimensions compared to standard pallets used in US) (de Barbara Claire, 2022). On the other hand, according to some Mexican-American-Canadian shipping companies, a full truck contains 26 pallets (Terán, 2019). Therefore, we assume that inbound and outbound trucks have the same fixed truck capacity, 26 pallets.
- **Inter-arrival times of trucks** are generated randomly with triangular distributions. The triangular distribution can be used if restricted data regarding the process is known (Jannat and Greenwood, 2012). It also has the advantage of providing a more controlled data set (e.g. negative inter-arrival times cannot be generated with a triangular distribution having positive parameters).
- **Process times (unloading/loading)** are modelled with triangular distributions.
- **Forklift speed:** According to the recommendation of The Material Handling Equipment Distributors Association (MHEDA) (Reddon, 2020), the forklift speed is set at 3.6 meters per second.
- **Pallet due date:** Since storage limitation at cross-docks is 24 hours, pallet due dates are defined as their arrival times to the system (by inbound trucks) plus 24 hours.
- **Outbound truck due date:** It is assumed that the outbound truck due date is their arrival time to the system plus three hours.
- **Number of replications:** Following the above-mentioned input data generation scheme, we created an input database composed of 10 instances per traffic level combination (i.e. a total of 60 instances for six traffic levels). For a fair comparison between strategies, each strategy is tested using the same set of 10 instances at each traffic level. Then, we compare the strategies based on the average of 10 instances. This is equivalent to making 10 replications per strategy and per traffic level combination.

Table 4.1: Different traffic levels for truck inter arrival times

Combination	Inbound traffic level	Outbound traffic level
1	High (H)	High (H)
2	Medium (M)	High (H)
3	Medium (M)	Medium (M)
4	Low (L)	High (H)
5	Low (L)	Medium (M)
6	Low (L)	Low (L)

To access the input datasets associated with the model presented in this chapter, please refer to Appendix D, where the relevant link is provided.

Output Analysis

The analysis is made on the average simulation outcomes of 10 instances for each traffic level combination by applying each truck selection strategy individually (FCFS, EDD, and SP). The warm-up period of the simulation varies for each strategy and traffic level. In this respect, the hourly stock level throughout the simulation run for each traffic level of the average of the 10 instances

Table 4.2: Input parameters of the proposed hybrid simulation model

Parameters	Values
Number of dock doors	
Number of inbound doors	1
Number of outbound doors	1
Number of forklifts	15
Forklift speed (meter per second)	3.6
Cross-dock facility area (in m2)	10875
Number of freight (defined as a pallet) types	3 (type A, B, C)
Truck speed (meter per second)	8.3
Truck capacity	
Inbound truck capacity (in pallets)	26
Outbound truck capacity (in pallets)	26
Truck inter arrival time	
High traffic (in minutes)	Triangular(7, 10, 13)
Medium traffic (in minutes)	Triangular(17, 20, 23)
Low traffic (in minutes)	Triangular(37, 40, 43)
Due dates	
Pallet due date (in minutes)	Inbound truck arrival time + Uniform(60, 1440)
Outbound truck due date (in minutes)	Outbound truck arrival time + Uniform(60, 180)
Process times	
Unloading time (per pallet in seconds)	Triangular(35, 62, 69)
Loading time (per pallet in seconds)	Triangular(35, 69, 79)
Number of destinations	
Destinations of pallets	3 (destination 1, 2, 3)
Destinations of outbound trucks	3 (destination 1, 2, 3)
Temporary storage capacity	Unlimited
Simulation length excluding warm-up (in hours)	48

is monitored. The warm-up periods are defined based on the hour until the stock level reaches a steady state. It should be noted that the stock level cannot reach a steady state for M-H traffic when FCFS is applied. Therefore, only for this situation the warm-up time is assumed to be equal to the warm-up time of the same traffic level where EDD is employed.

The output analysis is carried out based on the KPI results of 48 hours of simulation outcomes beyond the warm-up period. The box plots for each strategy's effects on the performance indicators for each instance and traffic level are presented in Figures 4.5 to 4.8. In addition, an analysis of variance (ANOVA) is included in the output analysis to validate the results. To this end, a one-way ANOVA is conducted to compare the impacts of the three strategies on each of the total six traffic levels. The experiment of ANOVA is composed of the following:

- Independent variables (factors): truck selection strategies (i.e. FCFS, EDD and SP)
- Dependent variables (groups): the KPI results of each strategy on the average of ten instances per traffic level combination

- The level of significance: $\alpha = 0.05$
- The null hypothesis (H_0): There is no statistically significant difference among the KPI results of strategies.
- The alternative hypothesis (H_a): At least one strategy has a statistically significant different impact on the KPI results.

The prerequisite tests of the parametric ANOVA analysis are performed for all test groups (normality test and correlation analysis to check dependence of test groups). For sample groups that fail the normality test (Shapiro-Wilk test), which is one of the prerequisite tests of parametric ANOVA analysis,

1. A normalisation technique is applied by using the following formula:

$$Z_i = (x_i - \bar{x})/\sigma$$

where,

x_i is the value of instance i

\bar{x} is the mean

σ is the standard deviation of the test group.

2. The outliers (if they exist) are omitted from each group.

Based on the results of the normality test and correlation analysis, the following analyses are conducted:

- For normally distributed samples:
 - ANOVA (independent samples)
 - Repetitive ANOVA (dependent samples)
- For not normally distributed samples:
 - Kruskal-Wallis test (independent samples)
 - Friedman test (dependent samples)

In addition, a follow-up test which includes the pairwise comparisons of the strategies is used to determine which strategy contributes to the overall significant difference found in the one-way ANOVA results. To this end, the following post hoc tests are performed:

- For the parametric one-way ANOVA: For the independent samples, the Tukey HSD (honestly significant difference) is applied when the assumption of homogeneity of variances is validated; otherwise, the Games-Howell test is used. For the dependent samples, pairwise comparisons of the repetitive ANOVA are used.
- For the nonparametric one-way ANOVA: The Dunn test for the independent groups and Wilcoxon-signed ranks test for the dependent groups are employed.

The results of the one-way ANOVA are given in Tables 4.3 to 4.6. Note that the mean differences of strategy pairs found statistically significant by the post hoc tests are presented in bold in these tables.

The analyses based on each key performance indicator are given in the following sections.

4.2.1 Analysis of the average stock level

Figure 4.5 delivers the average stock dispersion of the strategies at each traffic level combination. To validate the observations extracted from this figure, one-way ANOVA results are also provided (see Table 4.3).

When we conduct a cross-analysis of Figure 4.5 and Table 4.3, we conclude that SP outperforms FCFS and EDD by achieving the minimum average stock level for H-H and M-M traffic levels, and the results are statistically significant (p -values $< [0.05]$). This situation is quite expected because SP aims to minimise stock level by selecting outbound trucks based on the destination of the highest number of pallets in the facility.

Even though we observe slight differences between EDD and SP for M-H and L-H traffic levels in Figure 4.5, the performed post hoc test reveals that the mean value of the average stock level is not significantly different between these strategies (see Table 4.3, $p = [0.066]$ for M-H and $p = [1.000]$ for L-H). In addition, as can be seen in Figure 4.5 that at the L-M traffic level, EDD and SP have the same impacts on the average stock level and its variations between the instances. This result is also validated by the pairwise comparison of EDD and SP in Table 4.3 ($p = [1.000]$). These similar impacts of EDD and SP are understandable because when the inbound traffic is lower than the system's capacity and the outbound traffic is higher, the outbound truck selection policies have lower effects on the stock level. On average, two and four times more trucks arrive in the system in high traffic than in medium and low traffic, respectively (see Table 4.3). In addition, EDD and SP have the same inbound truck selection policy but different outbound truck selection policies. These reasons explain why they have similar stock levels for these scenarios (M-H, L-H and L-M traffic levels).

As can be noticed from Figure 4.5, FCFS has the lowest performance on the mean stock level and high variability through the instances for all traffic levels. An exception is the H-H traffic case, where EDD falls behind it. However, the performed pairwise test in Table 4.3 indicates that the mean value of the average stock level is not significantly different between FCFS and EDD ($p = [0.495]$) at the H-H traffic level. Similarly, there is no statistically significant difference between these strategies at the M-M traffic level (see Table 4.3, $p = [1.000]$), and this result can also be observed in Figure 4.5.

Although we observe in Figure 4.5 that SP brings minimum mean stock value with the lowest variation at L-L traffic while the other strategies have similar results, the overall test does not show significant differences (in Table 4.3, the p -value of ANOVA = $[0.366]$). Therefore, pairwise comparisons of strategies cannot be performed, meaning that when the system is operated four times lower than its capacity, it can effectively evacuate pallets from the facility regardless of the truck selection policy.

Table 4.3: The one-way ANOVA results of multiple comparisons of strategies based on the average stock level

$\alpha = 0.05$	Parametric		Nonparametric		Pairwise comparisons of the strategies		
	one-way ANOVA		one-way ANOVA		FCFS-EDD	EDD-SP	FCFS-SP
Traffic levels	F statistic	p-value	H statistic	p-value			
H-H	8.647	0.001			0.495	0.001	0.020
M-H			24.657	0.000	0.023	0.066	0.000
M-M	85.268	0.000			1.000	0.002	0.002
L-H			20.318	0.000	0.000	1.000	0.002
L-M			17.702	0.000	0.000	1.000	0.001
L-L	1.044	0.366			-	-	-

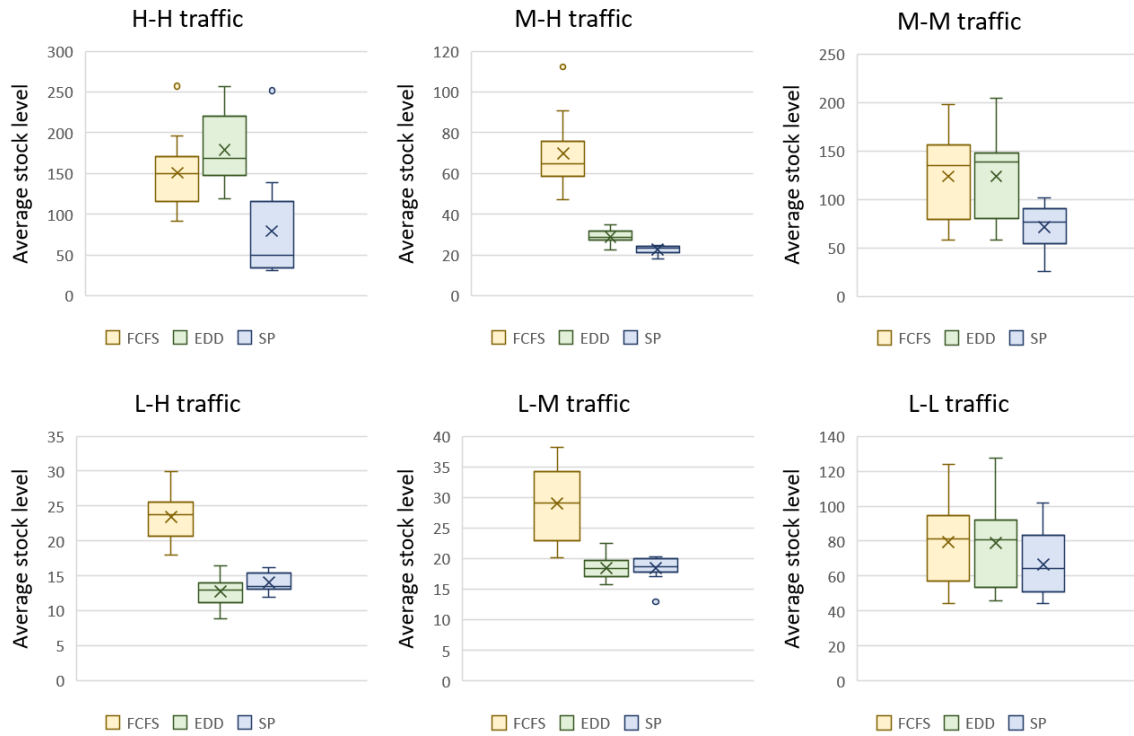


Figure 4.5: Stock levels dispersion based on each strategy

4.2.2 Analysis of the number of late pallets and the pallet delay

The number of late pallets for each traffic level and the pallet delay (in minutes) are given in Figure 4.6 and 4.7, respectively. Their respective ANOVA results are also delivered in Tables 4.4 and 4.5. Although we expect EDD to minimise pallet delay and the number of late pallets by selecting trucks based on their earliest due dates, we clearly see that FCFS and SP have prominent effects on the outcomes with the lowest variability in pallet delays and the number of late pallets when the traffic levels are medium and high on both ends. The pairwise comparisons of the strategies also validate these results. There is no statistically significant difference between FCFS and SP at both H-H and M-M traffic levels (the respective p-values are greater than [0.05] in Tables 4.4 and 4.5). As we observe in Figure 4.7 that SP brings lower mean and variations in pallet delay than EDD at M-M traffic, ANOVA pairwise comparison test also validates this result (see Table 4.5, $p = [0.015]$). However, SP is indifferent to FCFS ($p = [0.400]$) in pallet delay (see Table 4.5). Note that at low traffic levels (i.e. L-H and L-M traffic), EDD still achieves the highest mean performance among all strategies for the number of late pallets and has the same impact as the SP for the pallet delay.

Reasons for the poor performance of EDD with high variations at H-H and M-M traffic levels compared to FCFS and SP are explained as follows:

- SP practices the earliest due date strategy like EDD for inbound truck selection and thus prioritises the pallets whose due dates are approaching since the pallet due date determines the inbound truck's due date. However, for the outbound side, SP selects the matching outbound trucks with the destination of the majority of the pallets in stock, in contrast to EDD. Therefore, SP guarantees to take as many pallets as possible from the stock and thus delivers them with no or less delay even in the high and medium traffic of inbound trucks.
- FCFS chooses trucks based on their arrival time, thus reducing the waiting time of trucks. Note that outbound trucks leave as soon as their due dates expire. FCFS allows outbound trucks more time to load before leaving the system than EDD. Therefore, outbound trucks

chosen by FCFS take more pallets from the system and thus avoid pallet delay compared to EDD, with lower variations in the results.

Although we notice minor differences between the strategies at the L-L traffic level for both KPIs, the ANOVA results do not bring significant differences. Thus multiple comparisons of the strategies cannot be executed (see Tables 4.4 and 4.5). The same case is observed in the average stock level, and the given explanation is also valid for this case.

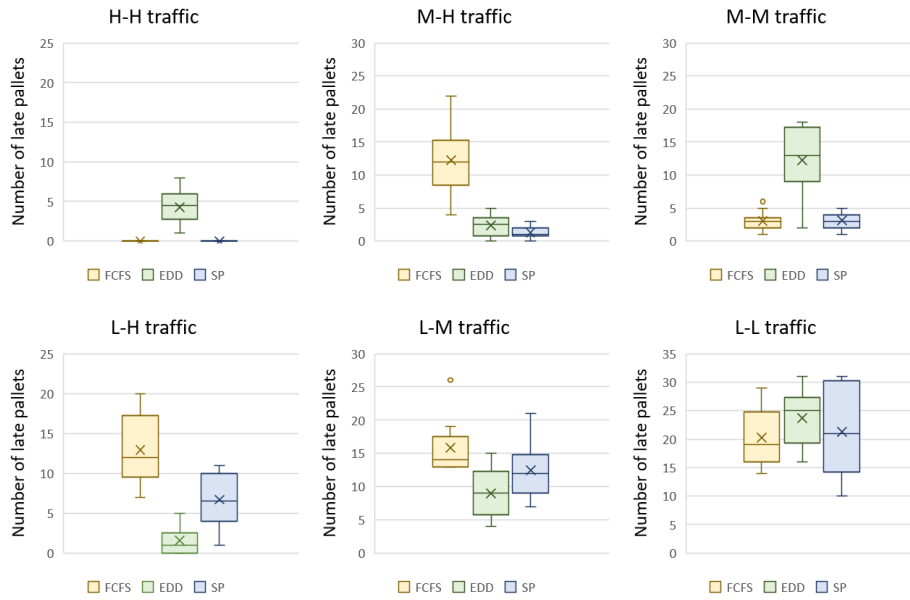


Figure 4.6: The number of late pallets based on each strategy

Table 4.4: The one-way ANOVA results of multiple comparisons of strategies based on the number of late pallets

$\alpha = 0.05$	Parametric		Nonparametric		Pairwise comparisons of the strategies		
	one-way ANOVA		one-way ANOVA				
Traffic levels	F statistic	p-value	H statistic	p-value	FCFS-EDD	EDD-SP	FCFS-SP
H-H			27.514	0.000	0.000	0.000	1.000
M-H			19.962	0.000	0.004	0.883	0.000
M-M			14.063	0.001	0.002	0.006	1.000
L-H	75.241	0.000			0.000	0.001	0.004
L-M	7.467	0.003			0.002	0.134	0.165
L-L	0.841	0.442			-	-	-

4.2.3 Analysis of the outbound truck fill rate

The impact of each strategy on the outbound truck fill rate for each traffic level and the ANOVA results are given in Figure 4.8 and Table 4.6, respectively. As can be noticed, when inbound and outbound traffic levels are equal, all strategies have similar impacts by ensuring that outbound trucks are fully loaded. The ANOVA results also validates this inference since the overall test does not show significant differences (in Table 4.6, the p-values of ANOVA are greater than the significance level, [0.05]). Therefore, pairwise comparisons of strategies cannot be performed.

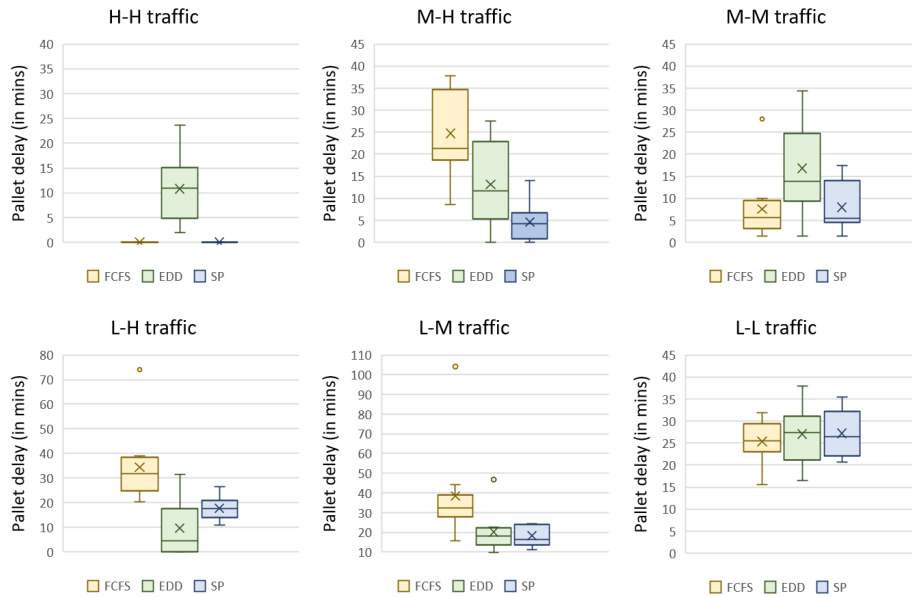


Figure 4.7: The pallet delay (per pallet in minutes) based on each strategy

Table 4.5: The one-way ANOVA results of multiple comparisons of strategies based on the pallet delay

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA			Pairwise comparisons of the strategies			
	Traffic levels	F statistic	p-value	H statistic	χ^2 statistic	p-value	FCFS-EDD	EDD-SP	FCFS-SP
	H-H			27.506		0.000	0.000	0.000	1.000
	M-H	15.158	0.000				0.037	0.061	0.000
	M-M				12.400	0.002	0.008	0.015	0.400
	L-H	13.790	0.000				0.001	0.157	0.001
	L-M			11.090		0.004	0.012	1.000	0.012
	L-L	0.333	0.720				-	-	-

However, when the outbound traffic is higher than the inbound traffic, SP achieves the best results with the lowest variations regarding the fill rates of outbound trucks. Note that at M-H traffic, there is no statistically significant difference is found between FCFS and SP (see Table 4.6, $p = [0.075]$). The superior performance of SP is expected since it aims to reduce the stock level by selecting the outbound trucks based on the destination of the temporary storage pallets. Thus, it fills the outbound trucks with the maximum number of pallets possible. However, when FCFS and EDD are compared based on their performance on outbound truck fill rate, it is noticed that EDD falls behind FCFS. The basis for why the fill rates of outbound trucks are low for EDD is identical to the reasons explained for other KPIs: it is known that EDD selects outbound trucks with the earliest due dates meaning that these trucks have limited time for loading. Therefore, the trucks leave the system without having time to load more pallets due to their upcoming departure time.

4.2.4 Summary on the strategies' performances

The numerical results of the average of all instances per strategy are given in Table 4.7. The strategies that give the best KPI results for each traffic level are summarised in Table 4.8. The strategy that outperforms the others for each KPI based on the traffic levels is presented in bold in

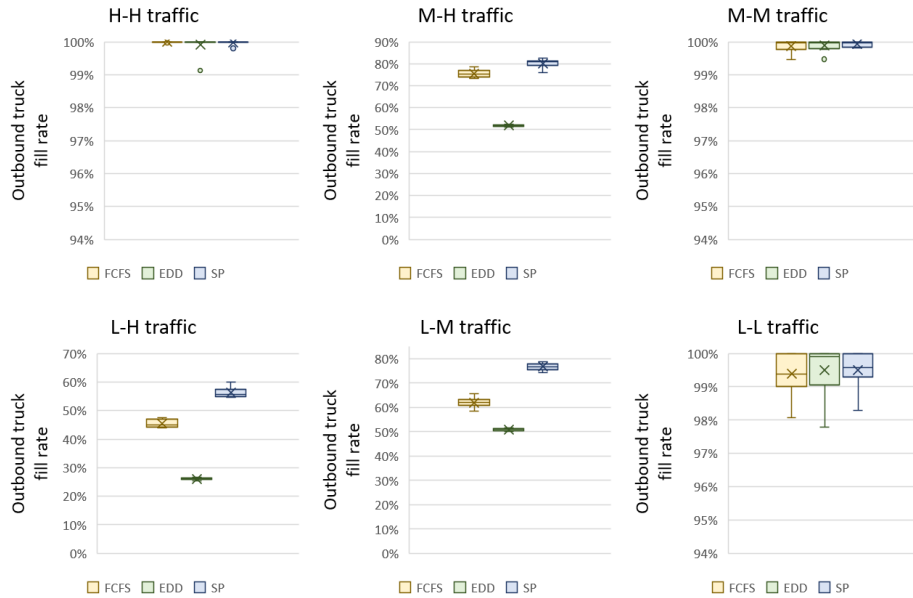


Figure 4.8: The outbound truck fill rates based on each strategy

Table 4.6: The one-way ANOVA results of multiple comparisons of strategies based on the outbound truck fill rate

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA			Pairwise comparisons of the strategies		
	F statistic	p-value	H statistic	χ^2 statistic	p-value	FCFS-EDD	EDD-SP	FCFS-SP
Traffic levels								
H-H			2.000		0.368	-	-	-
M-H			24.954		0.000	0.018	0.000	0.075
M-M				2.000	0.368	-	-	-
L-H			26.454		0.000	0.030	0.000	0.030
L-M			26.250		0.000	0.031	0.000	0.031
L-L				0.875	0.646	-	-	-

Table 4.8.

As can be noticed in Tables 4.7 and 4.8,

- SP is an ideal strategy for achieving the best results with the lowest variation regarding the minimum average stock level across all traffic levels (see Tables 4.7 and 4.8). When the traffic level is high and medium for both ends meaning the system is pushed to operate at full or a moderate capacity, SP outperforms all other strategies by efficiently evacuating a significant number of pallets from the facility. However, as can be noticed in Table 4.7, the performance gap between SP and EDD tends to diminish as traffic levels decrease on the inbound side relative to the outbound side (M-H, L-H, L-M). This similarity can be attributed to the fact that, in such scenarios, the system effectively evacuates pallets regardless of the outbound truck selection policy. In addition, both EDD and SP employ the same inbound truck selection policy (i.e. EDD), further explaining their similar stock levels in these specific traffic scenarios. In contrast, the FCFS strategy consistently exhibits poor performance with the lowest mean stock levels and high variability. Therefore, the study advises managers to adopt the SP strategy for efficient stock management.
- Even though SP has comparable results with the other strategies on the number of late pallets

and the pallet delay in specific traffic conditions, it consistently emerges as the frontrunner by maintaining the best results with the lowest deviations across all traffic levels. This persistent performance is emphasised by an in-depth review of Tables 4.7 and 4.8, which reveal SP's superiority in all scenarios except for the L-H traffic level, where the EDD strategy outperforms it. The rigorous statistical analyses in Tables 4.4 and 4.5 further strengthen the findings. These statistical studies provide substantial evidence supporting SP's effectiveness in controlling on-time pallet delivery. The strategic utilisation of the earliest due date approach for inbound truck selection, coupled with the wise choice of outbound trucks based on the majority destination of pallets in stock, accounts for the superior performance of the SP strategy. Given the significance of these findings, it is strongly recommended to prioritise SP across diverse scenarios to mitigate delays, ultimately achieving timely deliveries.

- All the strategies have comparable results by attaining the maximum fill rates with low variations when inbound and outbound traffic levels are equal. However, when the outbound traffic exceeds the inbound traffic, the SP strategy emerges as the most effective, exhibiting the lowest variations in fill rates for outbound trucks (in Table 4.7, fill rates range between 56% and 80%). FCFS also performs better in this aspect than EDD, primarily due to the latter's limited loading time for outbound trucks. Nevertheless, SP maximises the number of pallets loaded onto outbound trucks regardless of traffic level. The outstanding performance of SP can be attributed to its purpose of minimising the stock level by strategically selecting outbound trucks based on the destinations of temporary storage pallets.
- Finally, it is crucial to note that all the strategies yield comparable KPI results in the L-L traffic scenario. This inference is further supported by the ANOVA analysis, which fails to reveal any significant differences among the strategies. This can be attributed to low resource requirements at this traffic level.

Table 4.7: The numerical results of the average of all instances per strategy

Traffic levels	Strategies	KPIs			
		Average stock level	Number of late pallets	Pallet delay	Outbound truck fill rate
H-H	FCFS	151	0	0	100%
	EDD	179	4	11	100%
	SP	79	0	0	100%
M-H	FCFS	70	12	25	76%
	EDD	29	2	13	52%
	SP	23	1	5	80%
M-M	FCFS	124	3	8	100%
	EDD	124	12	17	100%
	SP	71	3	8	100%
L-H	FCFS	23	13	34	45%
	EDD	13	2	10	26%
	SP	14	7	18	56%
L-M	FCFS	29	16	39	62%
	EDD	18	9	20	51%
	SP	18	13	18	77%
L-L	FCFS	80	20	25	99%
	EDD	79	24	27	99%
	SP	67	21	27	100%

Table 4.8: The strategies that give the best average results for each traffic level per KPI

KPIs	H-H	M-H	M-M	L-H	L-M	L-L
Average stock level	SP	EDD, SP	SP	EDD, SP	EDD, SP	FCFS, EDD, SP
Number of late pallets	FCFS, SP	EDD, SP	FCFS, SP	EDD	EDD, SP	FCFS, EDD, SP
Pallet delay	FCFS, SP	EDD, SP	FCFS, SP	EDD, SP	EDD, SP	FCFS, EDD, SP
Outbound truck fill rate	FCFS, EDD, SP	FCFS, SP	FCFS, EDD, SP	SP	SP	FCFS, EDD, SP

This analysis is performed for the system described in Table 4.2. In order to verify the robustness of the SP strategy, a sensitivity analysis must be performed by varying different parameters of the system.

4.3 Conclusion

This study shows that multi-agent-based approaches are effective techniques for solving real-time truck scheduling problems for cross-docking. However, the conducted literature review in the previous chapter revealed that the application of the MAS to real-time truck scheduling still needs to be explored. This study addresses this issue by proposing a multi-agent-based hybrid model for real-time scheduling of both inbound and outbound trucks and internal cross-docking operations. Main findings of this study are as follows:

First of all, our study provides a proof of concept on the use of a hybrid model (of MAS and DES) for real-time truck scheduling in cross-docks. To this end, the inbound and outbound trucks, and inbound and outbound doors are defined as agents for decision-making, while the inside operations of the cross-docking facility are built employing DES for its simplicity and to reduce communication burdens inherent MAS models with many agents.

By focusing on the single inbound and outbound cross-dock, we created a controlled and manageable environment that allows us to form and evaluate our proposed model's effectiveness rigorously. We believe that the single inbound and outbound dock model proposed in this chapter provides a solid backbone towards multi-dock context.

A second outcome of the study is the in-depth analyses of different truck scheduling strategies that are easy to apply in a real-time manner (SP, EDD and FCFS), subject to different traffic levels. The significance of the results is attested using rigorous techniques such as ANOVA. Stock-oriented policy (SP strategy) is observed to surpass other strategies, particularly at high and medium traffic levels, by efficiently evacuating pallets from the facility. All strategies render comparable KPI results in the low inbound and outbound traffic scenarios. It has to be noted that the preconised strategies for truck scheduling apply under the assumptions of the system and the parameters of the numerical tests and must be redone in case of any changes to system parameters or experimental settings. Nevertheless, the method for analyses can be kept the same as a guideline.

This study confirms the performance of the proposed multi-agent-based hybrid model for the studied single-inbound and single-outbound door cross-dock. Can the model presented in this chapter scale up to the multiple inbound and outbound case to fit the industrial context? Are there

any challenges moving from a single to multiple inbound and outbound docks? Chapter 5 aims to answer these questions.

5

Real-time truck scheduling model for multiple-door cross-dock

This chapter proposes a more advanced version of the model described in Chapter 4, which is extended to a multiple-door cross-dock with further and more developed decision-making configurations. The performance evolution of the model is analysed by scaling up the model in terms of the size of the cross-dock platform (i.e. the number of dock doors). This analysis is carried out with the generated instances. To validate the experimental results, ANOVA is performed. Furthermore, since the proposed model provides real-time scheduling, the computation time is a vitally important measure, especially in an industrial context, whether the model is fit for the purpose of logistics practitioners. To this end, the computation time of the model is monitored periodically as the model scales up and the results are analysed.

This chapter expands upon the foundational concepts introduced in Chapter 4, undertaking a more comprehensive analysis by designing an advanced model aiming to be fit for real-world cross-docking scenarios. The model presented in this chapter adapts the complexities of multiple doors and intricate decision-making strategies to better mimic the subtle dynamics of cross-docking operations. After introducing the model specifications in Section 5.1.1, the implementation details are explained in Section 5.1.2. Section 5.1.3 goes into the evolved behavioural dynamics of the agents functioning within the model. To comprehensively measure the model's performance, we define and elaborate on key performance metrics in Section 5.1.4. Section 5.2 further explains the input generation and subsequent output analysis procedures.

In the subsequent section, the performance analysis of the model is carried out based on two perspectives. Section 5.3 presents a detailed analysis of model adaptability and effectiveness across diverse scenarios based on varying traffic levels along with two door set configurations. In alignment with our findings (from Section 5.3), in Section 5.4, we conduct a rigorous assessment of the model's scalability, monitoring its performance across a spectrum of door set configurations and the selected strategies and traffic level. In addition to these analyses, the model's computational time is examined in line with practical temporal constraints imposed by real-world cross-docking operations to evaluate the model's applicability to real-time scheduling.

5.1 Model description

The developed multi-door model is built upon the model presented in Chapter 4, but the cross-dock facility is expanded to multiple inbound and outbound doors, and the agents are equipped with additional and more advanced attributes and decision-making capabilities.

5.1.1 Model specifications

The UML diagram that describes the design of the proposed model is given in Figure 5.1.

Note that this UML diagram is adapted from the single-inbound and single-outbound door model investigated in Chapter 4. However, the studied problem in this chapter, which involves a multiple inbound and outbound door model, is derived from this diagram with increments in the agent populations and their enhanced intercommunications within the system. Now,

- The inbound and outbound dock doors (i.e. agents) belong to a door agent population (the model is scaled-up). Note that for the door class represented in the UML diagram in Chapter 4, the labelling of individual doors was not required since the model contains single inbound and outbound doors. However, as the model evolved to a more intricate multiple inbound and outbound door cross-docking system in this chapter, it became necessary to bring a unique identification mechanism for each door. To this end, the door class in Figure 5.1 now contains a *doorId* attribute of type integer. This attribute serves as a crucial identifier, allowing us to distinguish and track each inbound (outbound) door within the inbound (outbound) door population.
- Truck agents are improved to have the ability to decide on the dock door selection (different behaviours are added). Therefore, the door selection decision of truck agents is defined as *D_assignment* on the UML diagram (see Figure 5.1).
- The temporary storage located at one area of the cross-dock in the simplified model is now distributed to the inbound doors. That means pallets will remain at the inbound doors where they were initially unloaded until they are sent to an outbound door where a docked outbound

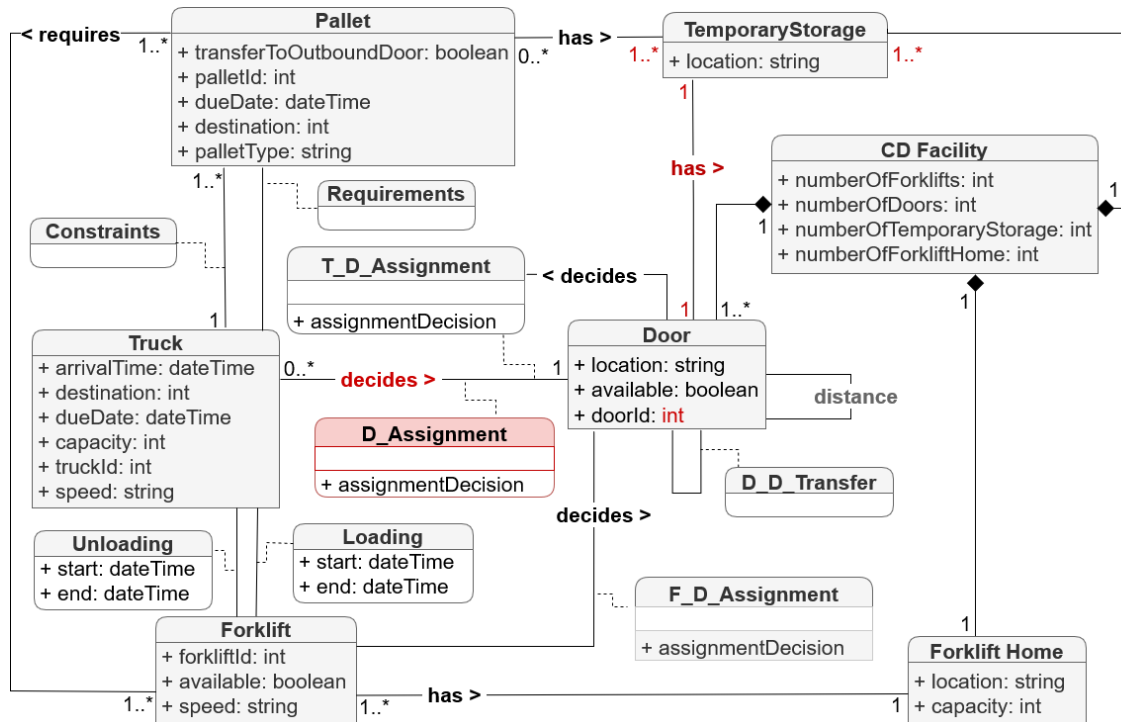


Figure 5.1: The UML diagram of the proposed multi-agent-based dynamic model

truck is present. Consequently, the storage is considered distributed rather than central to help integrate decision rules such as minimising distance travelled. This distributed temporary storage practice is represented by a one-to-one association (i.e. each inbound door can have only one temporary storage and vice-versa) between the temporary storage class and door agent class on the UML diagram (see Figure 5.1).

- Since the temporary storage is distributed to the inbound doors, the total number of storage areas equals the total number of inbound doors. Therefore, the temporary storage class now has a zero-to-many and a many-to-one association between the pallet and the CD Facility classes, respectively (see Figure 5.1).

For the sake of clarity, these structural and functional differences are highlighted in red in this UML (see Figure 5.1).

The proposed model in this chapter pursues the common objectives with the simplified case model studied in Chapter 4:

- The minimisation of the average stock level and pallet delay
- The maximisation of the outbound truck fill rate

With the introduction of multiple dock doors, the scale of the cross-dock facility has considerably expanded, having the system handle a higher volume of inbound and outbound operations. However, this increase in structural size brings forth a new challenge in the form of door selection for the system. As the number of dock doors grows, choosing the most proper door becomes a strategic decision to be made by the truck agents since it directly affects the pallet travel distance in the cross-dock. The shorter the travelling distance within the facility, the faster the pallets can be transferred from inbound trucks to outbound trucks. This streamlined approach avoids potential congestion in the platform, fastens turnaround times and ensures on-time deliveries. Thus, the travelling time per pallet becomes a critical metric to be regarded. Therefore, the proposed model in this chapter seeks to

- minimise the average travelling time of pallets inside the facility

In addition to these key performance indicators, the model is monitored under different metrics such as door occupancy and computation time. As in Chapter 4, different door and truck selection strategies are employed, and the results are compared.

5.1.2 Model implementation

As stated in Chapter 4, the model is implemented as multi-method modelling, consisting of multi-agent-based and discrete-event simulations. The modelling process is carried out using Java Programming Language on the AnyLogic Simulation Software (University edition 8.7.10).

The visual representation of the proposed hybrid model on the AnyLogic Simulation Software is provided in Figure 5.2. It illustrates a case of five inbound and five outbound door platform. This figure encapsulates our hybrid simulation environment, seamlessly incorporating multi-agent-based and discrete-event simulation components. Within this model, various entities, their attributes and behaviours (i.e. functions), along with their environment, play a significant role in mimicking the cross-docking system under analysis in this chapter. The subsequent sections provide detailed descriptions of the dynamic relationships and dependencies among these entities.

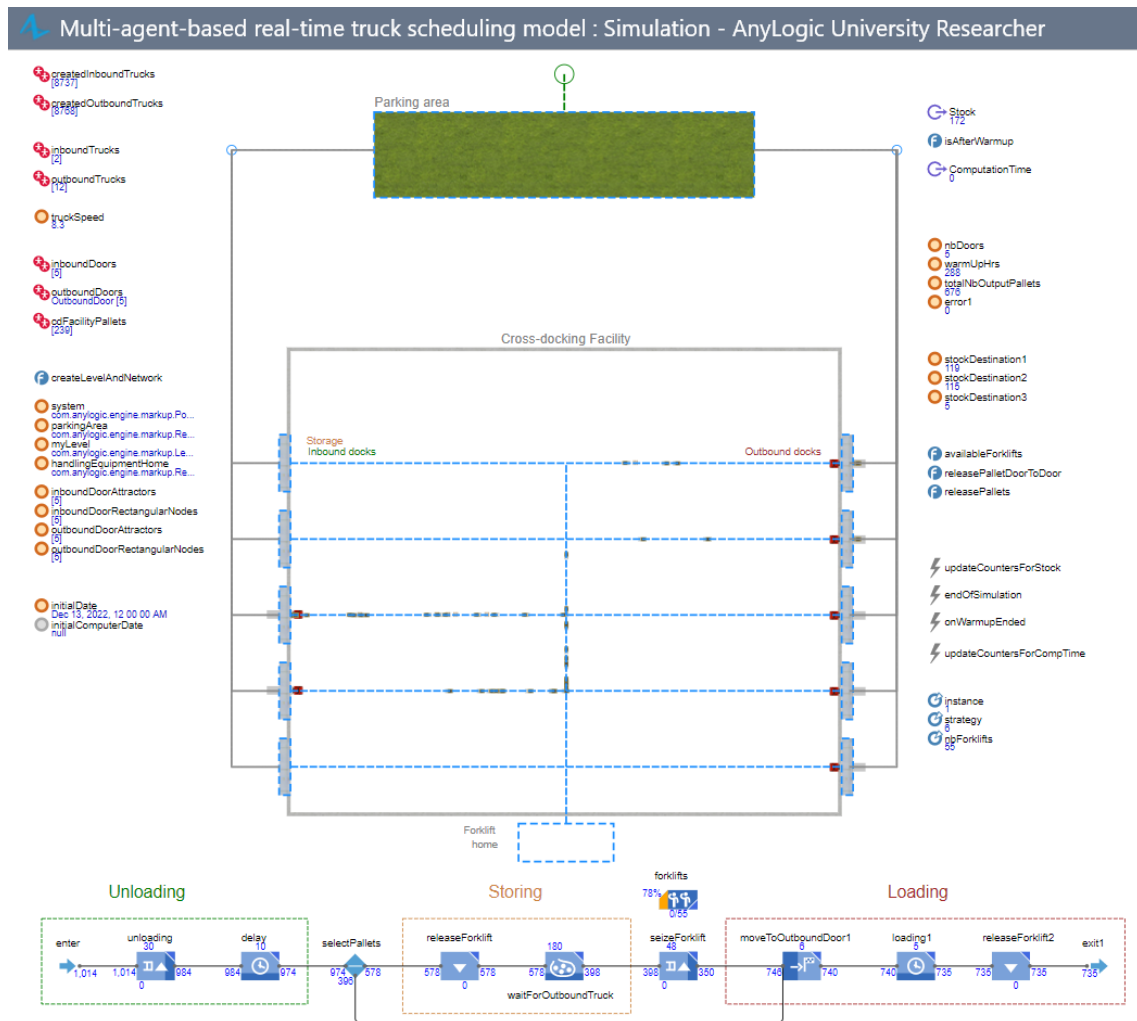


Figure 5.2: The screenshot of the proposed hybrid simulation model on the AnyLogic Software

The model implementation details (i.e. model inputs, multi-agent and discrete-event components) of multiple inbound and outbound doors problem and the simplified model studied in

Chapter 4 are the same. Therefore, all the details given in the model specifications in Section 4.1.1 are still valid for the studied problem in this chapter.

5.1.3 Decision-making mechanism

With the expansion of the model to multiple-door case, door agents now became a choice for truck agents. That means when a truck agent is present in the system, it can select a door for docking based on its preferences (i.e. door selection policies) among other door agents. Consequently, the agent-level communication and decision-making between truck and door agents are advanced, as they each apply different selection policies to achieve their respective goals.

Truck selection

Recall from the single-inbound and single-outbound door model presented in Chapter 4, inbound and outbound door agents employ truck selection strategies by communicating with inbound and outbound trucks.

The same truck selection strategies with the simplified model (Chapter 4) are employed in this multiple-door model: first-come-first-served (FCFS), earliest due date (EDD) and stock policy (SP). Their logic is explained in Section 4.1.3 in the previous chapter.

Door selection

As stated earlier, truck agents can now decide on the door selection with the transition to the multiple inbound and outbound door model. To this end, inbound and outbound trucks use door selection strategies by communicating with the inbound and outbound doors.

The door selection strategies operated in the model are, the first available door (FAD) and the minimum total travelling time of pallets (MTTP).

- The FAD rule is operated as a primitive strategy rather than a random selection of doors. It selects the first available door in the door list (i.e. door agent population) for docking. This strategy may be practical by making a quick decision for door selection; however, it may cause unequal door utilisation among doors.
- The MTTP selects the dock door that provides the minimum total travelling time of pallets. The total travelling time of pallets is calculated for a pair of a truck and a door. It expresses what would be the total travelling time of the truck's pallets if the truck decided to select that door for docking.
 - When an inbound truck wants to select its inbound door, it considers all available inbound doors and calculates the total travelling time for each pallet it carries. When determining the travelling time for each pallet, we consider two scenarios: if the pallet's destination truck is already docked at an outbound door, we calculate the actual travelling time between the dock doors. However, if the destination truck has not yet docked, we consider the maximum possible travelling time, corresponding to the distance to the furthest outbound door from the inbound door. Finally, the inbound truck selects the inbound door, providing the minimum total travelling times for its pallets.
 - When an outbound truck wants to select its outbound door, it considers all available outbound doors and calculates the total travelling time for each pallet that it will receive. Similar to the inbound scenario, we evaluate two conditions for each pallet. If it has already been unloaded at an inbound door or is currently being unloaded from a docked inbound truck, we consider the actual travelling time between doors. If neither condition is met, we calculate the maximum possible travelling time, representing the distance to

the furthest inbound door from the outbound door. Finally, the outbound truck selects the outbound door, providing the minimum total travelling times for pallets that it will receive.

The architecture of the proposed hybrid model is presented in Figure 5.3. This figure is derived from Figure 4.3 in Chapter 4 to adopt the multiple-door model configurations studied in this chapter. As highlighted in Figure 5.3, now;

- The model is expanded to a multiple-door cross-dock system (i.e. both inbound and outbound docks belong to the door agent population)
- Both inbound and outbound trucks are configured to choose their respective dock doors based on the applied door selection policy.
- The temporary storage is distributed to the inbound doors. Therefore, pallets stored at the inbound doors are directly transferred to outbound doors for loading onto the respective outbound trucks.
- The door selection decisions of trucks, the computation time (at every hour and at the end of the simulation) and the additional performance metrics are logged onto the simulation database (i.e. output datasets).

In this figure, the *release pallet* procedure shown at the pallet selection decision is developed as a function in the model. This function is responsible for the seamless transfer of pallets in the facility (Figure 5.4). With the application of the distributed temporary storage to the inbound doors, the pallet transfer inside the cross-dock is done only between the inbound and outbound doors for loading.

5.1.4 Performance evaluation

The model shares the common key performance indicators (KPIs) with the single-inbound and single-outbound door model. To recall their names:

- The average stock level
- Pallet delay (in minutes)
- Outbound truck fill rate

Moreover, as Rohrer (1995) remarks, monitoring useful metrics strengthens the assessment of cross-docking performance. In line with this, this model defines the following performance metrics alongside the KPIs mentioned above:

- **The average travelling time of pallets (in seconds):** With the presence of multiple dock doors, the size of the cross-dock is expanded, and door selection is required to be a decision to be made by the truck agents. Thus, the average travelling time of pallets becomes a critical metric. The average travelling time of pallets is calculated by following these steps:
 1. When a forklift is attached to a pallet, the system starts counting the time (based on simulation time).
 2. This counter stops when the forklift releases this pallet.
 3. The loading and unloading durations of this pallet are subtracted from the obtained time. Given that the forklift is also responsible for unloading and loading of this pallet, we exclude the time spent on these processes from the duration obtained in step (2). Therefore we ensure that the calculated travel time solely includes the pallet's travel time between its inbound and outbound doors.

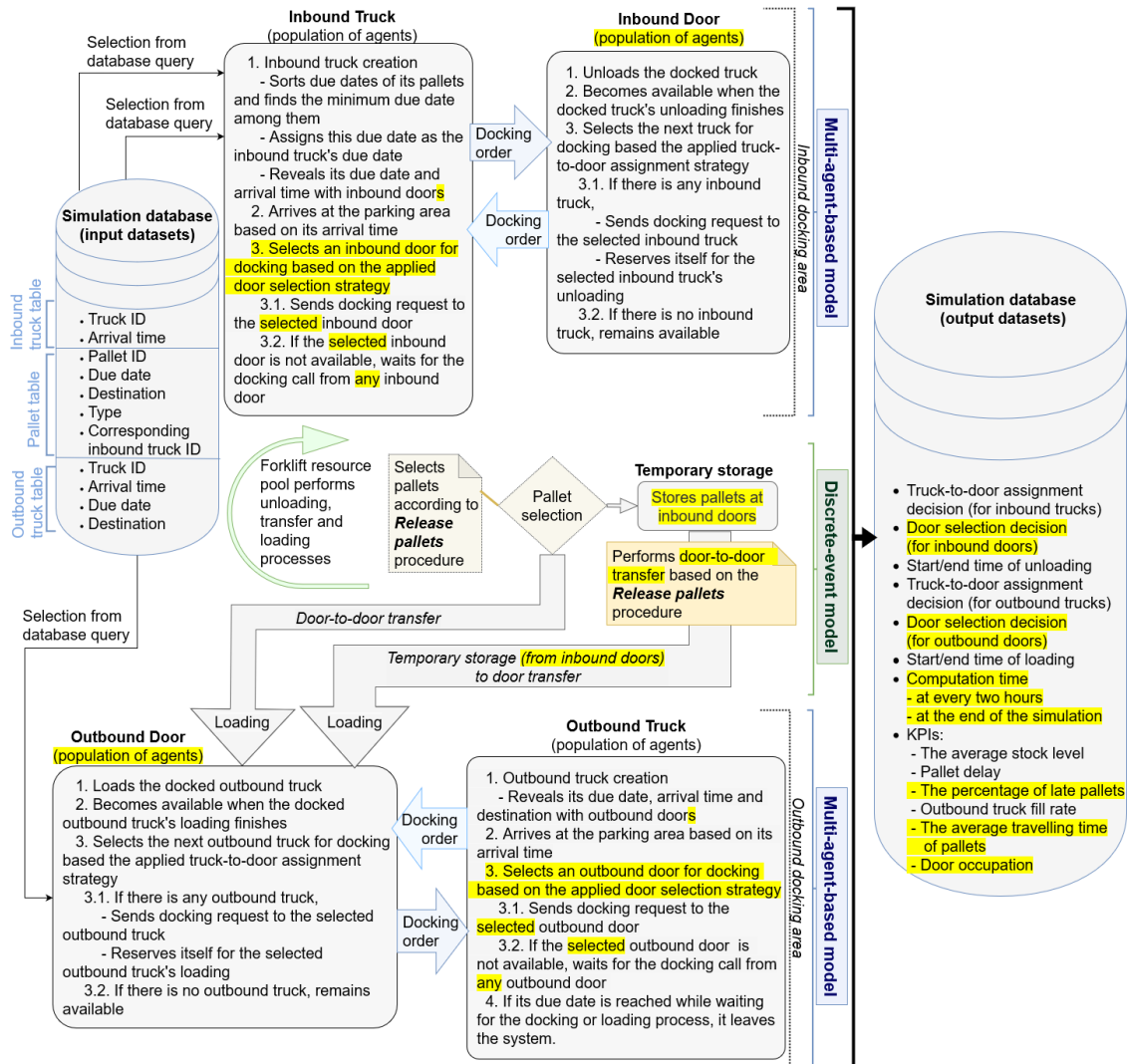


Figure 5.3: The configuration of the proposed hybrid simulation model

- The resulting time duration is logged into the system as the travelling time of that specific pallet. This process is done for each pallet that is moving with the forklift.
 - At the end of the simulation, the algorithm sums up all travelling times and divides this sum by the total count of pallets that have exited the facility. The result is then logged into the system as the average travelling time of pallets.
- Door occupancy:** The dock door occupancy of the platform is tracked in terms of the percentage of time the door is busy serving trucks and the total number of trucks served by each door. This metric also assists in determining the total number of doors the platform requires to synchronise inflows and outflows efficiently.
 - The percentage of late pallets:** Since the multiple-door model proposed in this chapter analyse the system behaviour as the model scales up, the number of pallets handled varies from one cross-dock setting to another. The late pallets ratio is considered as a performance metric to facilitate a more accurate and significant comparison of the diverse cross-dock settings. The percentage of late pallets is calculated by dividing the total number of late pallets by the total number of exited pallets.
 - Computation time:** Since we are exploring the real-time utilisation of the model, the

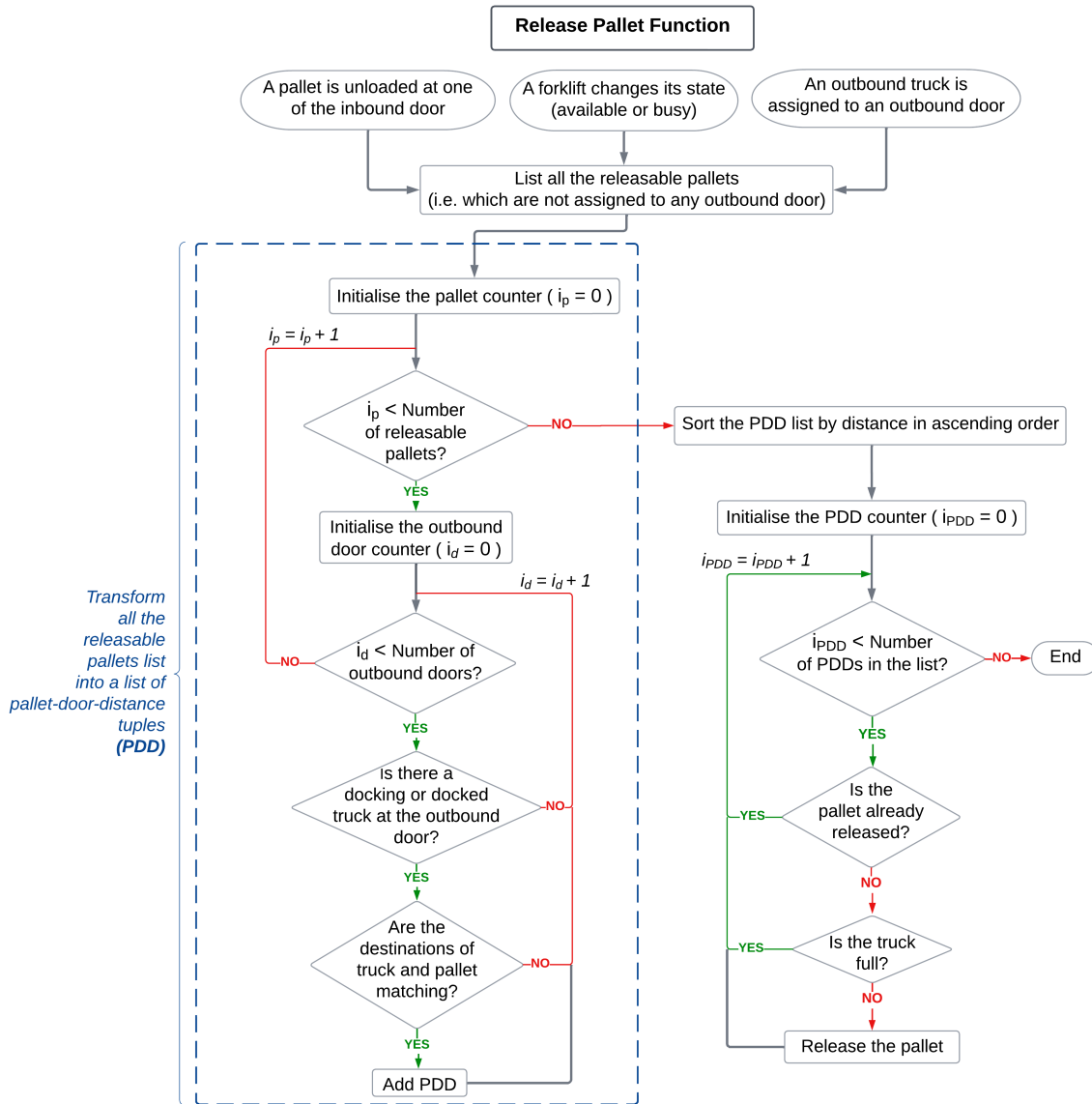


Figure 5.4: The process flow chart of the release pallet function

computation time is a crucial metric, particularly in an extended model, to determine whether the model provides quick scheduling within a reasonable time limit. To this end, the computation time of the model is regarded in two ways:

1. The total computation time of each scenario is logged into the system output at the end of the simulation.
2. The computation time of the model is logged into the system every two hours (in simulation time) to analyse its evolution with the length of the simulation. This strategic approach allows us to gauge precisely how computation time grows as the simulation progresses.

5.2 Experimentation Settings

Before presenting the experimental results in the next section, we provide an initial explanation of how the input data are generated and the results are evaluated within this section. The simulation model is built using the AnyLogic Simulation Software (University edition 8.7.10). The experiments are carried out on a PC with an Intel(R) Core(TM) i5-8250U CPU at 1.60 GHz and 16.0 GB of RAM.

Input generation

As stated in Section 4.2, the input datasets are randomly generated with a program written in the C# language. The multiple-doors model's responsiveness is tested over the combination of various traffic levels. To that end, six traffic level combinations are specified: H-H, M-H, M-M, L-H, L-M and L-L (see Table 4.1 in Section 4.2).

Next, ten input datasets are generated for each traffic level combination. Combinations of three different truck selection and two different door selection strategies resulting in a total of six strategy combinations are operated in the model to test the generated instances (see Table 5.1).

Table 5.1: Combination of truck and door selection strategies

Combinations	Truck selection		Door selection	
	Inbound truck	Outbound truck	Inbound door	Outbound door
S1	FCFS	FCFS	FAD	FAD
S2	FCFS	FCFS	MTTP	MTTP
S3	EDD	EDD	FAD	FAD
S4	EDD	EDD	MTTP	MTTP
S5	EDD	SP	FAD	FAD
S6	EDD	SP	MTTP	MTTP

To observe the performance evolution of the multiple-door model, different cross-docking configurations based on several door sets (i.e. the number of inbound and outbound doors) are used for the experimentation.

- Door set 1: 2-inbound and 2-outbound doors
- Door set 2: 5-inbound and 5-outbound doors
- Door set 3: 10-inbound and 10-outbound doors
- Door set 4: 15-inbound and 15-outbound doors
- Door set 5: 20-inbound and 20-outbound doors

For door sets 1 and 2: A total of six traffic level combinations are used for each of ten instances. For the resulting 60 instances, combinations of six strategies are applied, which completes 360 instances.

For door sets 3, 4 and 5: Only H-H traffic level is used to observe the impact of door number expansion on the model's performance. The reason for choosing this traffic level is that even minor differences in the system's behaviour can be detected easily when the system is pushed to operate at its highest capability. For the strategy choice, as seen in Table 5.1, the most primitive (S1) and the most advanced (S6) strategies are determined. The aim of selecting only these two distinct strategies is to observe the system behaviour clearly as the model scales up. Therefore, for each of

these sets, only one traffic level combination (H-H traffic) and two strategy combinations (S1 and S6) are applied, resulting in a total of 20 instances per door set.

The input generation framework for the multiple-door model presented in this chapter is the same as that of Chapter 4. Moreover, the simulation parameters initially created for the single-inbound and single-outbound door case are adapted for the multiple-door configuration. These simulation parameters are presented in Tables 5.2 and 5.3. Table 5.2 outlines the constant simulation parameters shared across all door sets. Note that these constant parameters are inherited from the single-inbound and single-outbound door case and remain the same for the multiple-door model. The only distinction is that the model's temporary storage is now distributed rather than central. However, its capacity is still unlimited, as in Chapter 4. Meanwhile, Table 5.3 details the varying simulation parameters tailored for each diverse door set configuration of the multiple-door model presented in this chapter.

Table 5.2: Constant input parameters of the proposed hybrid simulation model

Parameters	Values
Forklift speed (meter per second)	3.6
Number of freight (defined as a pallet) types	3 (type A, B, C)
Truck speed (meter per second)	8.3
Truck capacity	
Inbound truck capacity (in pallets)	26
Outbound truck capacity (in pallets)	26
Due dates	
Pallet due date (in minutes)	Inbound truck arrival time + Uniform(60, 1440)
Outbound truck due date (in minutes)	Outbound truck arrival time + Uniform(60, 180)
Process times	
Unloading time (per pallet in seconds)	Triangular(35, 62, 69)
Loading time (per pallet in seconds)	Triangular(35, 69, 79)
Number of destinations	
Destinations of pallets	3 (destination 1, 2, 3)
Destinations of outbound trucks	3 (destination 1, 2, 3)
Distributed temporary storage capacity	Unlimited
Simulation length excluding warm-up (in hours)	48

Table 5.3: Varied input parameters for each doors set of the proposed hybrid simulation model

	Door set 1	Door set 2	Door set 3	Door set 4	Door set 5
Number of dock doors					
Inbound doors	2	5	10	15	20
Outbound doors	2	5	10	15	20
Number of forklifts	20	55	115	175	230
Cross-dock facility area (in m2)	28275	63075	121075	179075	237075
Distance between dock doors (in meters)					
Minimum	145	145	145	145	145
Maximum	165	225	325	425	525
Truck inter arrival time (in minutes)					
High traffic	Tri(2.6, 5.6, 8.6)	Tri(-0.7, 2.3, 5.3)	Tri(-1.8, 1.2, 4.2)	Tri(-2.2, 0.8, 3.8)	Tri(-2.4, 0.6, 3.6)
Medium traffic	Tri(8.1, 11.1, 14.1)	Tri(1.6, 4.6, 7.6)	-	-	-
Low traffic	Tri(19.3, 22.3, 25.3)	Tri(6.2, 9.2, 12.6)	-	-	-
Average pallet flow per hour					
High traffic	280	680	1300	1900	2500
Medium traffic	140	340	-	-	-
Low traffic	70	170	-	-	-

To access the input datasets associated with the model presented in this chapter, please refer to Appendix D, where the relevant link is provided.

Output analysis

The analysis is made on the average simulation outcomes of ten instances for each traffic level combination by applying the combination of each truck selection policy (FCFS, EDD, and SP) and each door selection rule (FAD and MTTP) (see Table 5.1). The warm-up period of the simulation varies for each strategy and traffic level. In this respect, the hourly stock level throughout the simulation run for each traffic level of the average of the ten instances is monitored. The warm-up periods are defined based on the hour until the stock level reaches a steady state.

The output analysis is based on the KPI results of 48 hours of simulation outcomes beyond the warm-up period. The box plots for each strategy's effects on the performance metrics for each instance and traffic level are presented in Figures 5.5 to 5.23. In addition, as in Chapter 4, ANOVA is included in the output analysis to validate the results of the multiple-door model presented in this chapter. To this end,

1. For the analysis of door sets 1 and 2: A one-way ANOVA is conducted to compare the impacts of the six strategies on each KPI based on the total six traffic levels. The experiment of the one-way ANOVA is composed of the following elements:
 - Independent variables (factors): Strategies (i.e. S1, S2, S3, S4, S5, S6)
 - Dependent variables (groups): The KPI results of each strategy on the average of ten instances per traffic level combination (i.e. H-H, M-H, M-M, L-H, L-M, L-L traffic levels)
 - The level of significance: $\alpha = 0.05$
 - The null hypothesis (H_0): There is no statistically significant difference among the KPI results of strategies
 - The alternative hypothesis (H_a): At least one strategy has a statistically significant different impact on the KPI results
2. For the analysis of the model scalability, one-way ANOVA is performed to test the individual impacts of the two key factors (i.e. strategies and door sets) on each KPI based on one traffic level (i.e. the H-H traffic). Note that since the ANOVA can only be used to test more than two populations, the suited statistical tests are also employed to analyse two sample groups. The detailed explanations of these statistical tests and ANOVA are given as follows:
 - For case 1:
 - Independent variables (factors): Strategies (i.e. S1 and S6)
 - For case 2:
 - Independent variables (factors): Door sets (i.e. door sets 1, 2, 3, 4 and 5)
 - Dependent variables (groups): The KPI results of each strategy and door set on the average of ten instances of the H-H traffic level
 - The level of significance: $\alpha = 0.05$
 - The hypothesis testing:
 - For case 1:
 - * The null hypothesis (H_{01}): There is no statistically significant difference among the KPI results of strategies
 - * The alternative hypothesis (H_{a1}): Strategies have a statistically significant different impact on the KPI results

- For case 2:
 - * The null hypothesis (H_{02}): There is no statistically significant difference among the KPI results of door sets
 - * The alternative hypothesis (H_{a2}): At least one door set has a statistically significant different impact on the KPI results

As in Chapter 4, the prerequisite tests of the parametric ANOVA are performed for all test groups (normality test and correlation analysis to check the dependence of test groups). A normalisation technique is applied for sample groups that fail the normality test (Shapiro-Wilk test), which is one of the prerequisite tests of parametric ANOVA analysis, and the outliers (if they exist) are omitted from each group.

Based on the results of the normality test and correlation analysis, the following analyses are conducted:

- For case 1:
 - Paired t-test (normally distributed and dependent samples)
 - Wilcoxon-signed ranks test (not normally distributed and dependent samples)
- For the analysis of door sets 1 and 2 and the case 2 of the scalability analysis:
 - Repetitive ANOVA (normally distributed and dependent samples)
 - Kruskal-Wallis test (not normally distributed and independent samples)
 - Friedman test (not normally distributed and dependent samples)

In addition, for the case 2, a follow-up test, which includes the pairwise comparisons of the door sets, is used to determine which door set contributes to the overall significant difference found in the one-way ANOVA results. To this end, the following post hoc tests are performed:

- For the parametric one-way ANOVA, pairwise comparisons of the repetitive ANOVA are used.
- For the nonparametric one-way ANOVA, the Dunn test for independent groups and the Wilcoxon-signed ranks test for dependent groups are employed.

Note that the scalability analysis in Section 5.4 investigates how the model's performance evolves across different door set configurations and strategies. While a two-way ANOVA would typically be appropriate for assessing the main and interactive effects of door sets and strategies, it is necessary to note that the normality assumption is violated for most test samples, even after applying the normalisation technique. Consequently, we cannot reliably test the interaction effect between strategies and door sets with nonparametric data. Thus, including a two-way ANOVA for this purpose is not feasible. For this reason, we used alternative statistical tests along with the one-way ANOVA in our analysis.

The analyses based on each key performance metric are given in the following sections. Note that for the sake of brevity, we present the statistical test results of the performance analysis in Appendix B. For readers interested in the detailed outcomes of the statistical tests, please refer to Tables B.1 to B.22 in Appendix B.

5.3 Performance analysis on door sets 1 and 2

This section analyses the model's performance based on the defined KPIs for door sets 1 and 2. The analysis uses a comprehensive approach, including all combinations of truck and door selection

strategies and all varying traffic levels. The main purposes of the analysis in this section are as follows:

1. To understand the adaptability and effectiveness of the proposed multi-agent-based hybrid model across all scenarios based on diverse traffic levels (six traffic levels) on varying door settings.
2. To compare and distinguish the performance of six combinations of truck and door selection strategies across diverse configurations of the cross-dock platform. This analysis gives insights into the versatility and limitations of the strategies across changing operational contexts. Therefore, through these tests, we can pinpoint more effective and reliable strategies regardless of cross-dock size in terms of door sets, creating a backbone for model scalability to assess its real-world implementation.
3. To investigate how the performance of distinct strategies alters with varying truck arrivals (i.e. traffic levels). This analysis helps understand strategies' sensitivity to changes in traffic intensity.
4. Finally, to determine the best strategies given a traffic level.

5.3.1 Analysis of the average stock level

The average stock levels for door sets 1 and 2 based on each strategy are presented in Figure 5.5. One-way ANOVA results are also provided to validate the observations extracted from this figure (see Table B.1). Note that the results found to be statistically significant based on the p-values of the analysis that are below a prespecified threshold (i.e. significance level: $\alpha = 0.05$) are highlighted in bold within this table.

When we conduct a cross-analysis of Figure 5.5 and Table B.1, we conclude that S5 and S6 outperform other strategies (S1, S2, S3 and S4) by achieving the minimum average stock level with the lowest variability for all traffic levels except L-L traffic. Note that at M-M traffic, even though the stock level dispersions of S5 and S6 are quite similar to the other strategies, they consistently secure the minimum average stock levels for both door sets. This result aligns logically with the strategies' adoption of the SP policy for truck selection. As employed by S5 and S6, this policy aims to minimise stock level by selecting outbound trucks based on the destination of the highest count of pallets in the facility.

Although mean stock levels at L-L traffic slightly vary among the strategies for door set 1, these distinctions diminish as the facility extends in size at door set 2 (see Figure 5.5). This outcome is understandable because when the system is operated four times lower than its capacity, it can effectively evacuate pallets from the facility regardless of the truck selection policy. On average, the pallet flow per hour at high traffic is four times that of low traffic (see Table 5.3). These findings are further verified by ANOVA, which reveals no statistically significant differences among strategies at the L-L traffic for door set 2 (see Table B.1).

As can be noticed from Figure 5.5, S1 and S2, both practising the FCFS rule for truck selection, have the poorest performance on the mean stock level across all traffic levels and door sets. An exception occurs in the case of door set 2, where S3 and S4 bring comparable outcomes to S1 and S2 at M-H traffic while falling behind at L-H traffic. These findings are further confirmed by pairwise tests detailed in Table B.1. This observation reveals that as the facility extends in size from door set 1 to door set 2, strategies implementing the EDD policy (i.e. S3 and S4) fail to evacuate pallets from the system, particularly at high outbound traffic. This problem occurs due to EDD's nature, which provides limited loading time for outbound trucks by selecting them based on their earliest due dates. Consequently, outbound trucks leave the system due to their expired due dates before entirely using their loading capacities. This situation renders a bottleneck in the

pallet evacuation from the system, ultimately driving elevated stock levels associated with the EDD policy.

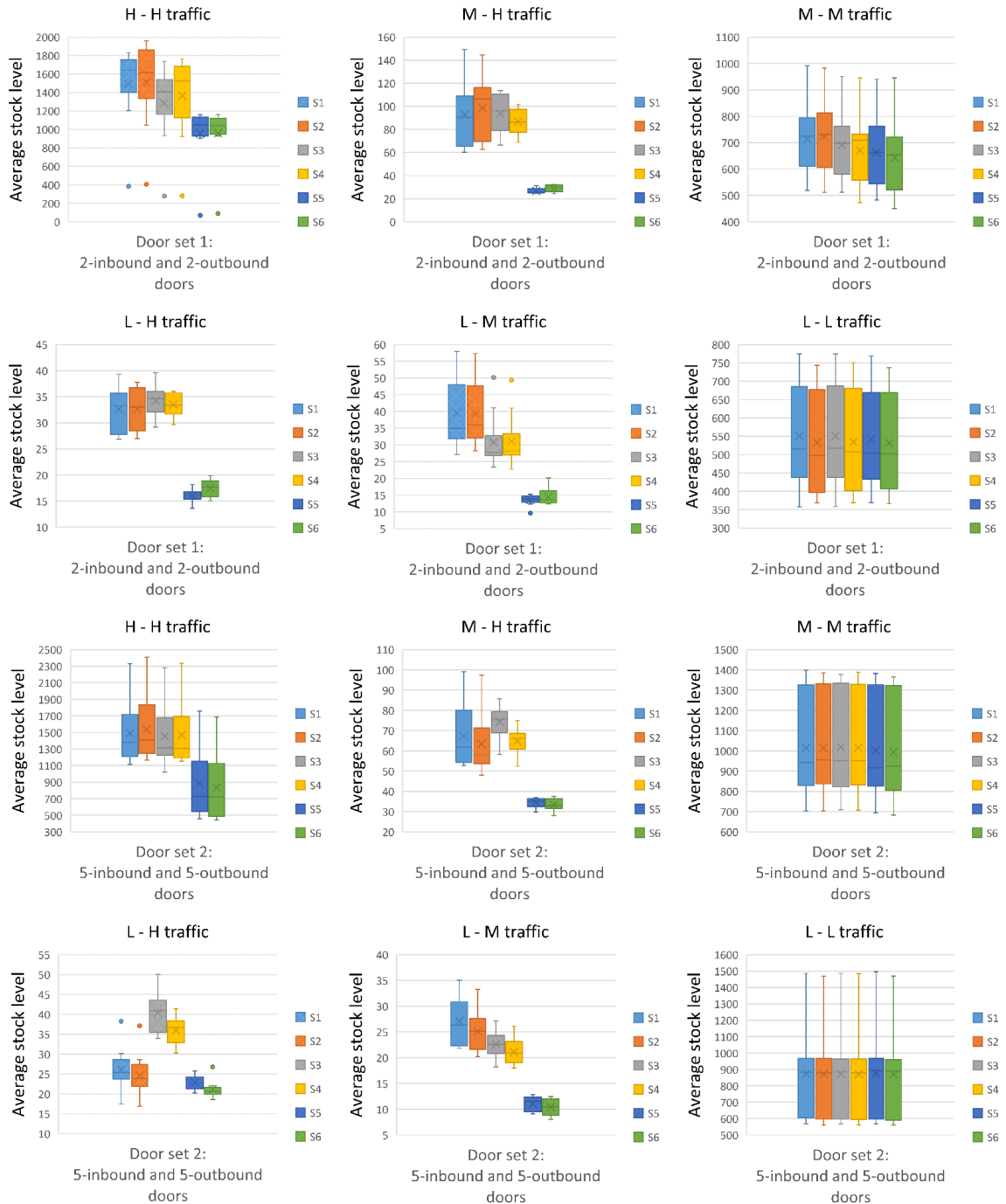


Figure 5.5: The average stock levels for door sets 1 and 2 based on each strategy

5.3.2 Analysis of the percentage of late pallets and the pallet delay

The percentage of late pallets for each traffic level and the pallet delay (in minutes) for door sets 1 and 2 are presented in Figures 5.6 and 5.7, respectively, while Tables B.2 and B.3 detail the corresponding ANOVA results.

Although we expect S3 and S4 to obtain superior performance on these KPIs by practising EDD, meaning choosing both inbound and outbound trucks based on their earliest due dates, we

clearly see that S5 and S6 have a prominent effect by achieving the best results at most traffic levels.

Reasons for the poor performance of S3 and S4 with high variations at most traffic levels compared to S5 and S6 are explained as follows: S5 and S6 practice the earliest due date strategy like S3 and S4 for inbound truck selection and thus prioritise the pallets whose due dates are approaching since the pallet due date determines the inbound truck's due date. However, for the outbound side, S5 and S6 select the matching outbound trucks with the destination of the majority of the pallets in stock, in contrast to S3 and S4. Therefore, S5 and S6 guarantee to take as many pallets as possible from the stock and thus deliver them with no or less delay even in the high and medium traffic of outbound trucks regardless of inbound truck traffic level.

Note that although S1 and S2 constantly yield the poorest performance on these KPIs, the impacts of all strategies tend to converge as the traffic levels decrease at both ends (i.e. M-M and L-L traffic levels for both door sets). This observation also aligns with the ANOVA results, especially for the case of door set 2 (see Tables B.2 and B.3).

5.3.3 Analysis of the outbound truck fill rate

The impact of each strategy on the outbound truck fill rate and the respective ANOVA results for each traffic level for doors set 1 and 2 are given in Figure 5.8 and Table B.4, respectively.

As evident from Figure 5.8, when inbound and outbound traffic levels are equal, all strategies have the same impacts by assuring the outbound trucks be almost fully loaded for both door sets. The ANOVA results also validate this inference (see Table B.4).

As the outbound traffic level becomes more elevated than the inbound traffic, S1 and S2 outperform S5 and S6 by a small margin at M-H and L-H traffic levels. Note that, at L-H traffic for door set 1, even if we observe differences in the performances of these strategies, the margin is negligible (1%). ANOVA results also confirm the insignificance of the performance disparities between these strategies at the L-H traffic level.

However, as can be seen in both Figure 5.8 and Table B.4, S5 and S6 surpass S1 and S2 at L-M traffic, exclusively for door set 1. Nevertheless, a complete analysis involving diverse door set configurations is needed to decide whether these distinctions in strategy performance are due to different door sets.

Furthermore, it is noteworthy that S3 and S4, the strategies applying the EDD rule for the truck selection, bring the lowest performance on truck fill rates. This poor performance can be attributed to the characteristics of the EDD policy that selects outbound trucks based on their earliest due dates. Therefore, the loading times of the trucks are limited by their approaching departure times. As a result, trucks arriving at the dock doors under the EDD rule often face due date constraints that force them to leave the dock before reaching full load capacity.

5.3.4 Analysis of the average travelling time of pallets

The average travelling time of pallets at each traffic level for door sets 1 and 2, corresponding to each strategy, are presented in Figure 5.9. The corresponding one-way ANOVA outcomes are also detailed in Table B.5.

It is essential to mention that since the pallet flow varies by different door sets, a fair and meaningful comparison can be reached by considering the average pallet travelling times rather than the total values. While Figure 5.9 presents the travelling times per pallet to be smaller, they become high values (presented in hours) when we sum them up (as shown in Table 5.4).

As Figure 5.9 depicts, strategies that employ the MTTP policy for door selection, namely S2, S4 and S6, obtain lower travelling times of pallets for both door sets 1 and 2.

When we compare the strategies that apply the MTTP rule (i.e. S2, S4 and S6), we note performance disparities, such as during the M-H traffic for door set 1 and H-H traffic for door set 2. It is necessary to emphasise, however, that these variations are minor; for instance, the difference in the average pallet travel time between S2 and S6 remains limited to less than 0.5 seconds at

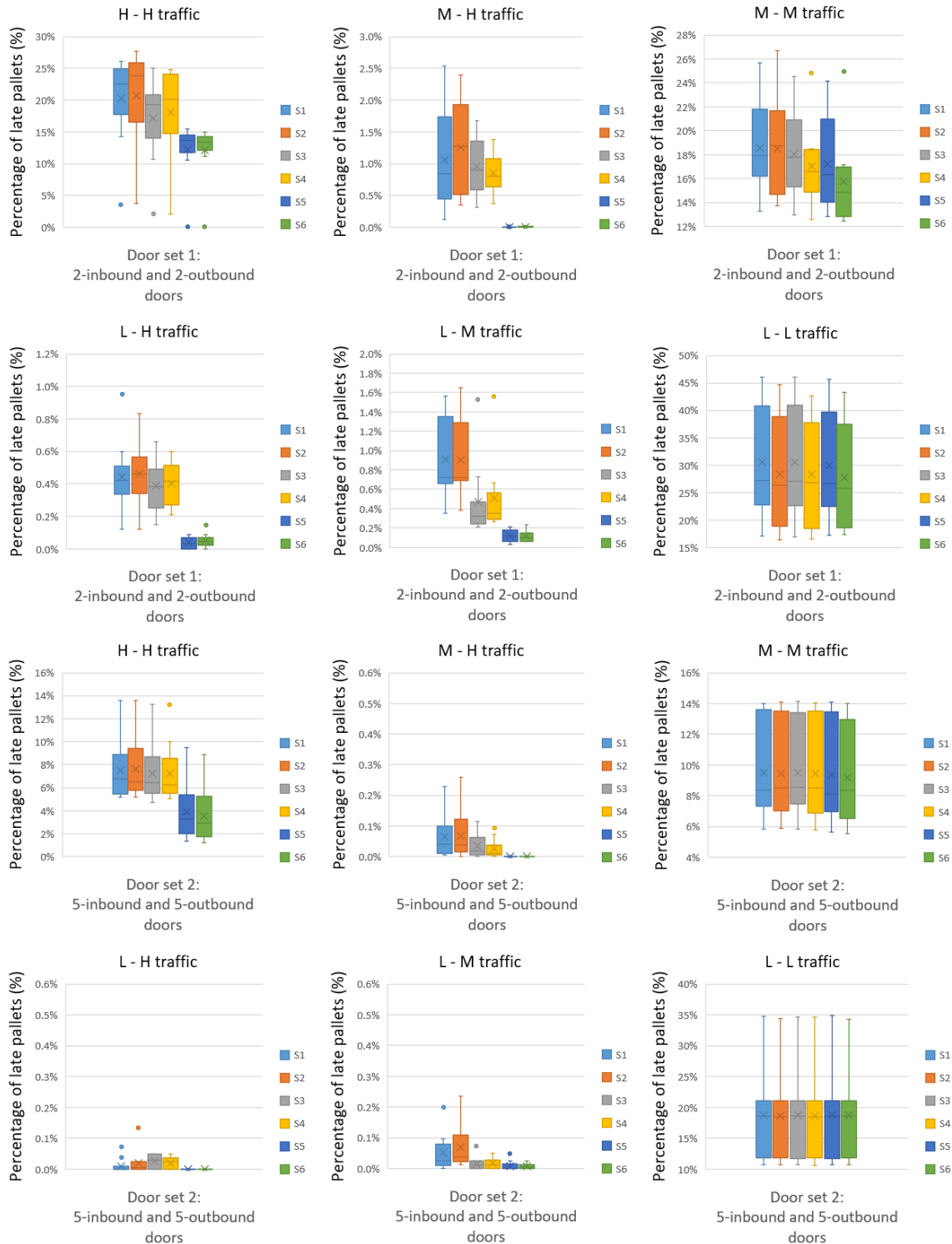


Figure 5.6: The percentage of late pallets for door sets 1 and 2 based on each strategy

these specific traffic conditions (i.e. M-H traffic for door set 1 and H-H traffic for door set 2). Nevertheless, an in-depth analysis, including diverse door sets, is required to determine whether these observed differences can indeed be attributed to the door set configurations.

It is noteworthy that the door selection policy becomes very effective on the pallet travelling time when the dock doors of the facility increase. As evident in Figure 5.9 and further supported by the ANOVA results given in Table B.5, the disparities in the impacts of the strategies for door

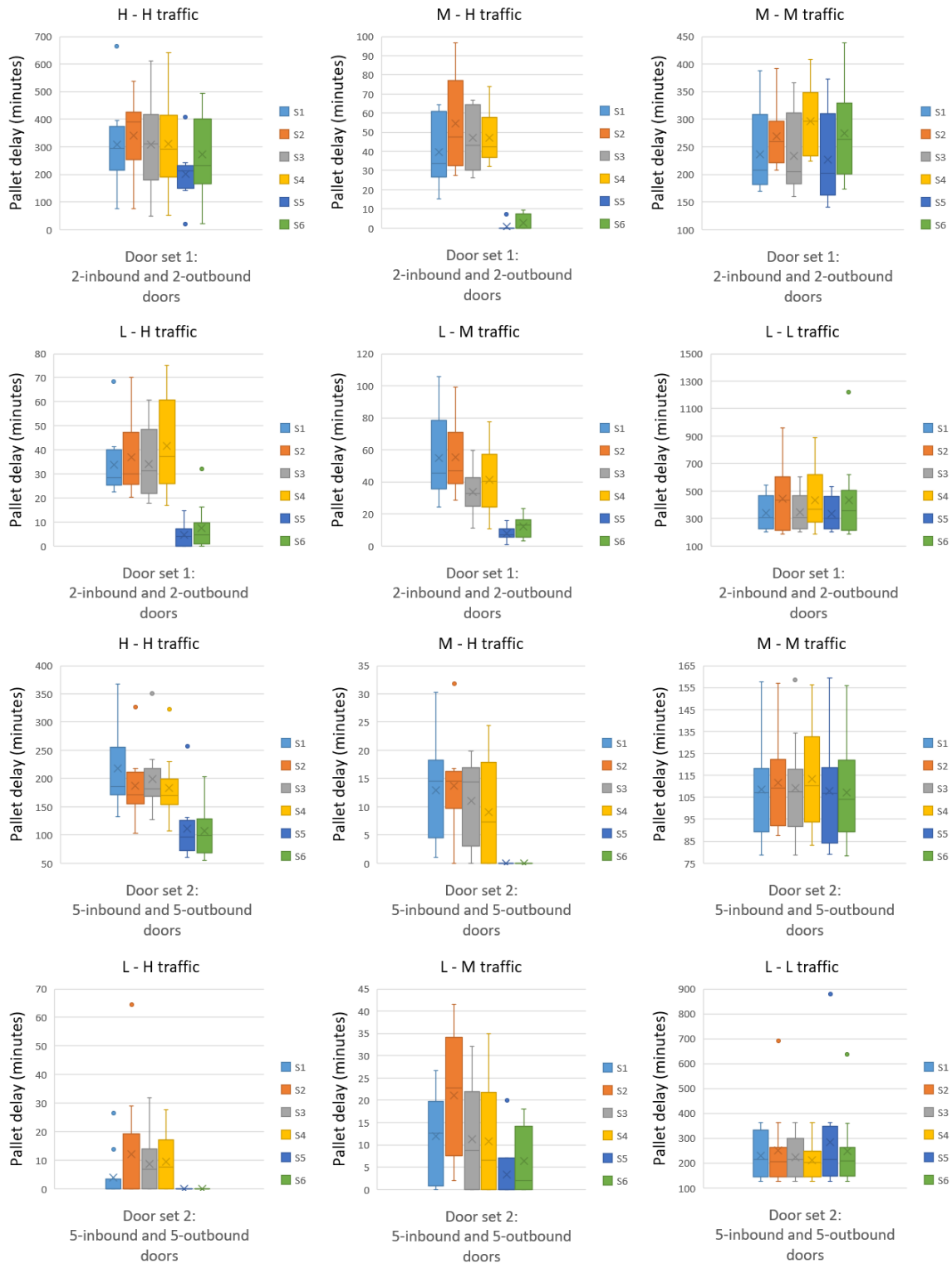


Figure 5.7: The pallet delay (per pallet in minutes) for door sets 1 and 2 based on each strategy

set 1 tend to diminish, particularly pronounced in scenarios with medium and low traffic levels. However, a distinct effect appears for door set 2, where the strategies that employ the MTP policy provide the best results across all traffic levels. Note that both FAD-based and MTP-oriented strategies yield comparable results in the L-L traffic level for both door sets. These consequences stem from the fact that the pallet flow in the system is four times lower than its handling capacity. ANOVA results also confirm the statistical insignificance of the performance disparities between

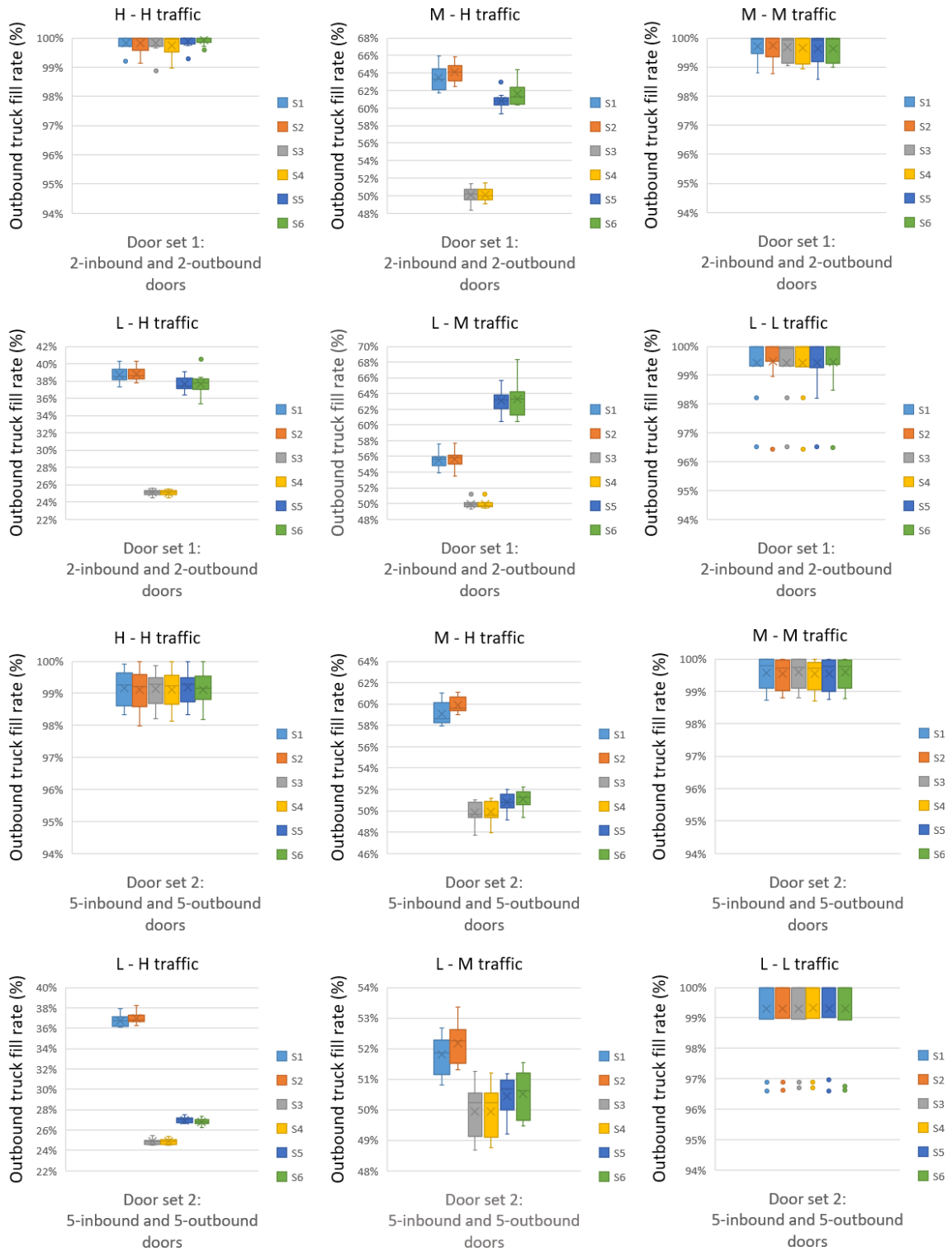


Figure 5.8: The outbound truck fill rates for door sets 1 and 2 based on each strategy

these strategies at the L-L traffic level for both door sets (see Table B.5).

5.3.5 Analysis of the door occupancy

As noted in Section 5.1.4, door occupancy of the platform is monitored based on the number of trucks served per door and the percentage of time the door is busy serving trucks. The impact of

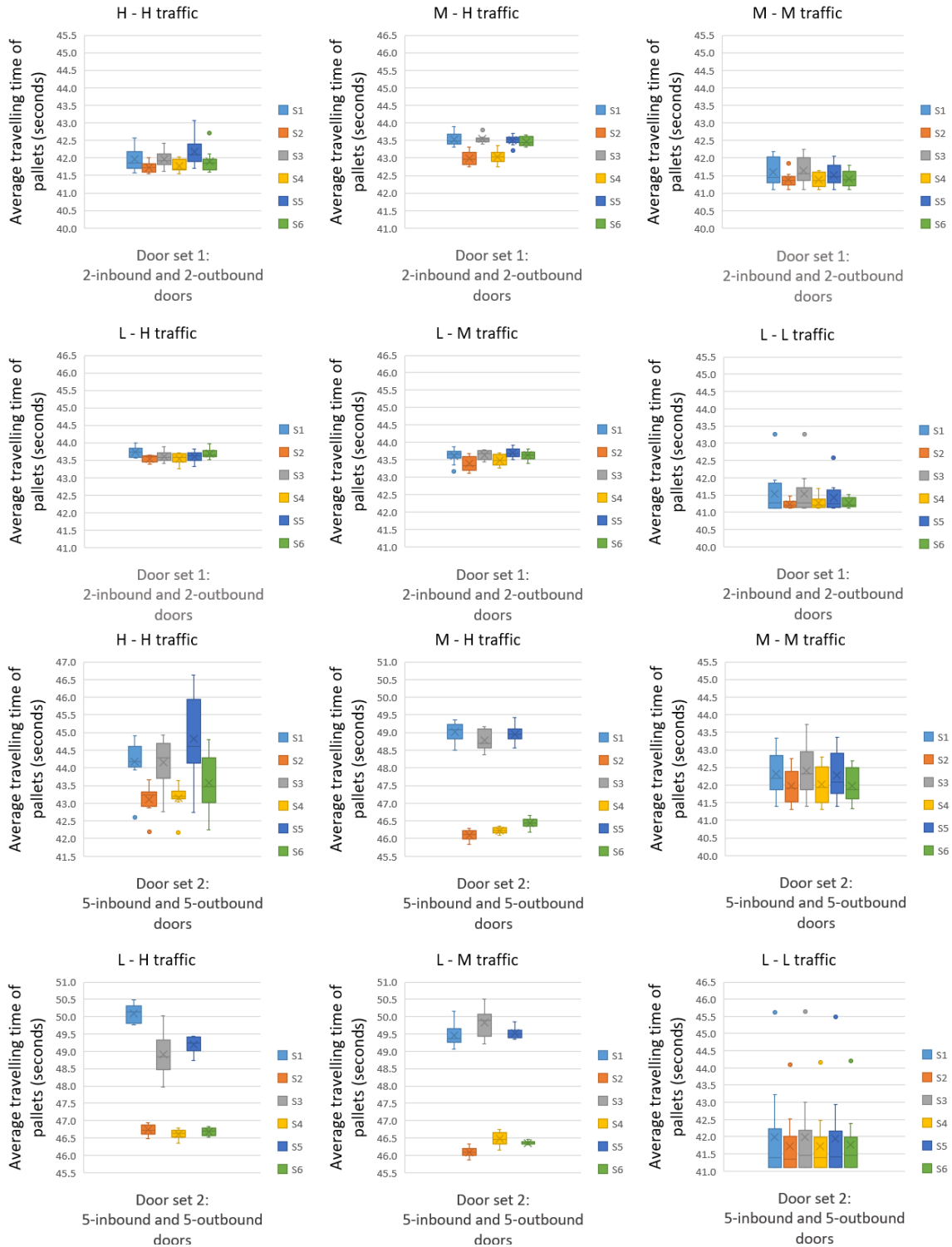


Figure 5.9: The average travelling time of pallets (in seconds) for door sets 1 and 2 based on each strategy

each strategy on the door occupancy for both door sets is given in Figures 5.10 to 5.12. In these figures, the results regarding the inbound doors are given on the left-hand side of the figure, while the outbound doors are presented on the right-hand side. The corresponding ANOVA results are also given in Tables B.6 and Table B.8 to validate the findings.

Note that the door occupancy results reveal similarities between M-M and L-L traffic levels,

Table 5.4: The total travelling time of pallets (in hours) for door sets 1 and 2 based on each strategy

	Door set 1						Door set 2					
	H - H	M - H	M - M	L - H	L - M	L - L	H - H	M - H	M - M	L - H	L - M	L - L
S1	156	81	78	41	41	38	400	223	192	114	112	95
S2	155	80	78	41	41	38	390	210	190	106	105	94
S3	156	81	78	41	41	38	400	221	192	111	113	95
S4	156	80	78	41	41	38	390	210	190	106	105	94
S5	156	81	77	41	41	38	406	222	192	111	112	95
S6	155	81	77	41	41	38	395	211	190	106	105	94

as well as between M-H and L-H and L-M traffic levels. Therefore, for the sake of brevity, we comment here only the H-H, M-H and M-M traffic levels. For readers interested in the detailed outcomes of the L-H, L-M and L-L traffic levels, please refer to Figures C.1 to C.3 in Appendix C.

When we look at Figures 5.10 and 5.11, for both door sets, the MTTP-oriented strategies (i.e. S2, S4, S6) for door selection tend to distribute trucks between doors more even than other strategies that use the FAD rule (i.e. S1, S3, S5) under specific traffic conditions (i.e. H-H and M-H traffic). However, this observation still needs to be validated by a comprehensive analysis, including a spectrum of diverse door sets.

As can be observed from Figure 5.12, as the traffic level reduces (i.e. M-M traffic for door set 2), the middle door of the platform (i.e. inbound door 3) remains notably occupied with serving the trucks. In contrast, the others either have minimal activity or are entirely idle. This situation occurs even under S2, S4 and S6 strategies. Consequently, all the strategies, including the ones that employ the FAD rule, yield comparable results on the inbound door occupancy at this traffic level (see ANOVA results in Table B.8).

It is essential to mention that the MTTP-based strategies mainly opt for the platform's middle doors. This tendency is quite reasonable since the shortest distance at the platform is between the middle doors facing each other (i.e., middle inbound and middle outbound dock door pairs)

On the other hand, as evident in Figures 5.10 to 5.12, the strategies that employ the FAD rule mainly select the platform's first couple of door sets (e.g. first inbound door and the first outbound door). The basis for this is, as stated in Section 5.1.3, the FAD rule chooses the first available door in the door list. Therefore, the inbound and outbound door pairs located at the first part of the platform are preferred under the application of these strategies. However, for door set 2, as the traffic level reduces (i.e. M-M traffic), while the middle door of the platform (i.e. inbound door 3) remains notably occupied with serving the trucks, the others either have minimal activity or are entirely idle. This situation occurs even under S2, S4 and S6 strategies (see Figure 5.12). Consequently, all the strategies, including the ones that employ the FAD rule, yield comparable results on the inbound door occupancy at this traffic level (see Table B.8).

In addition, in cases where inbound traffic is lower than outbound traffic (i.e. M-H, L-H and L-M), a distinct trend appears for both door sets: the outbound doors are busy 100% of the time. This outcome contrasts to the cases in scenarios where the traffic levels are the same at both ends (i.e. H-H, M-M and L-L). This result is expected since outbound trucks stay docked at the doors for the duration to be fully loaded before their due dates expire. When the pallet flow to the system is low (i.e. the traffic at the inbound is lower than the outbound), trucks have to wait longer before being able to be fully loaded. Consequently, even though the number of trucks served per outbound door is low at these traffic levels (M-H, L-H and L-M), the outbound doors consistently remain occupied at 100% capacity of the time. As a result, as can be seen from the corresponding ANOVA

results, all the strategies yield comparable results at these traffic levels (see Tables B.6 and B.8).

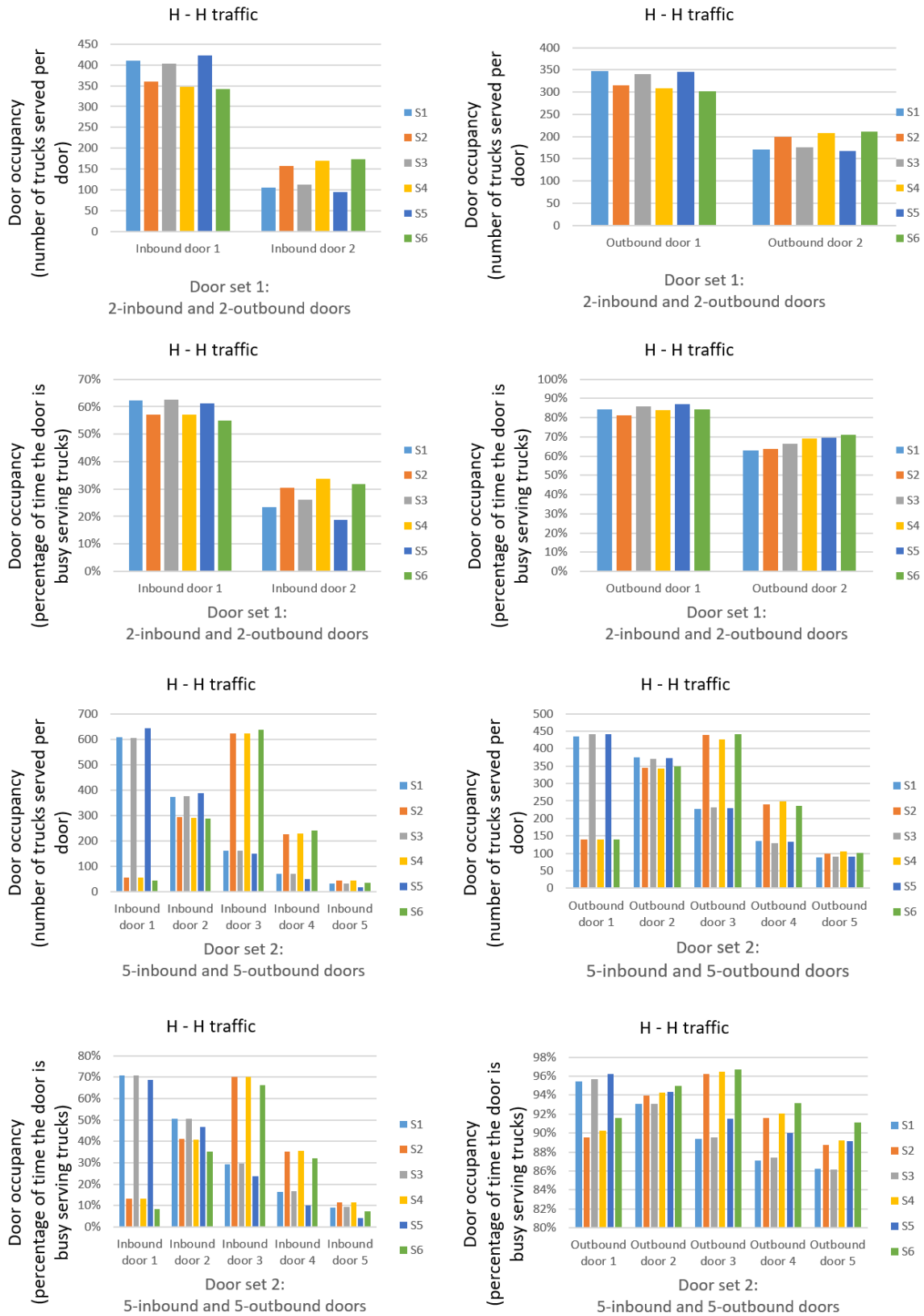


Figure 5.10: The door occupancy at H-H traffic for door sets 1 and 2 based on each strategy

5.3. Performance analysis on door sets 1 and 2

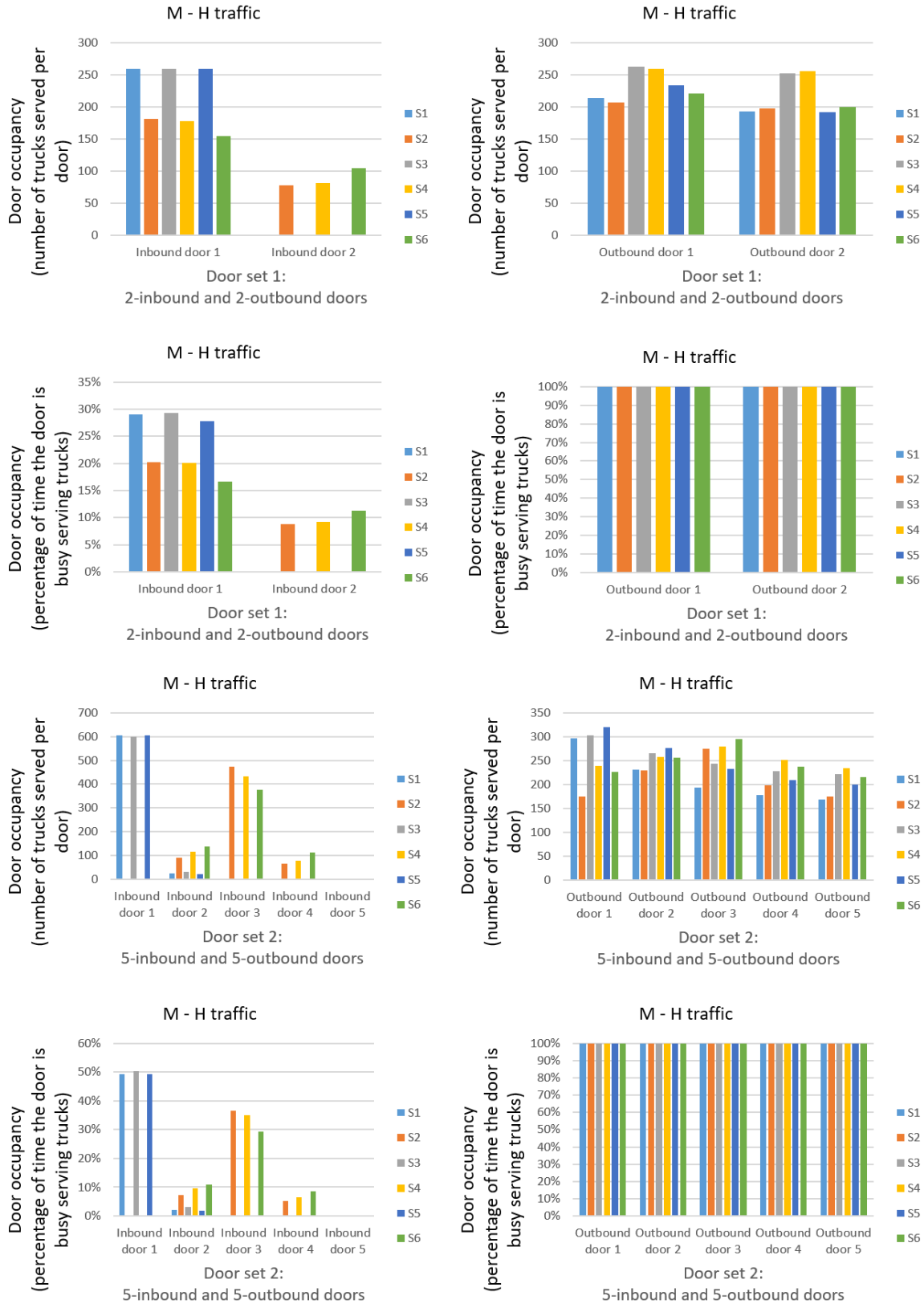


Figure 5.11: The door occupancy at M-H traffic for door sets 1 and 2 based on each strategy

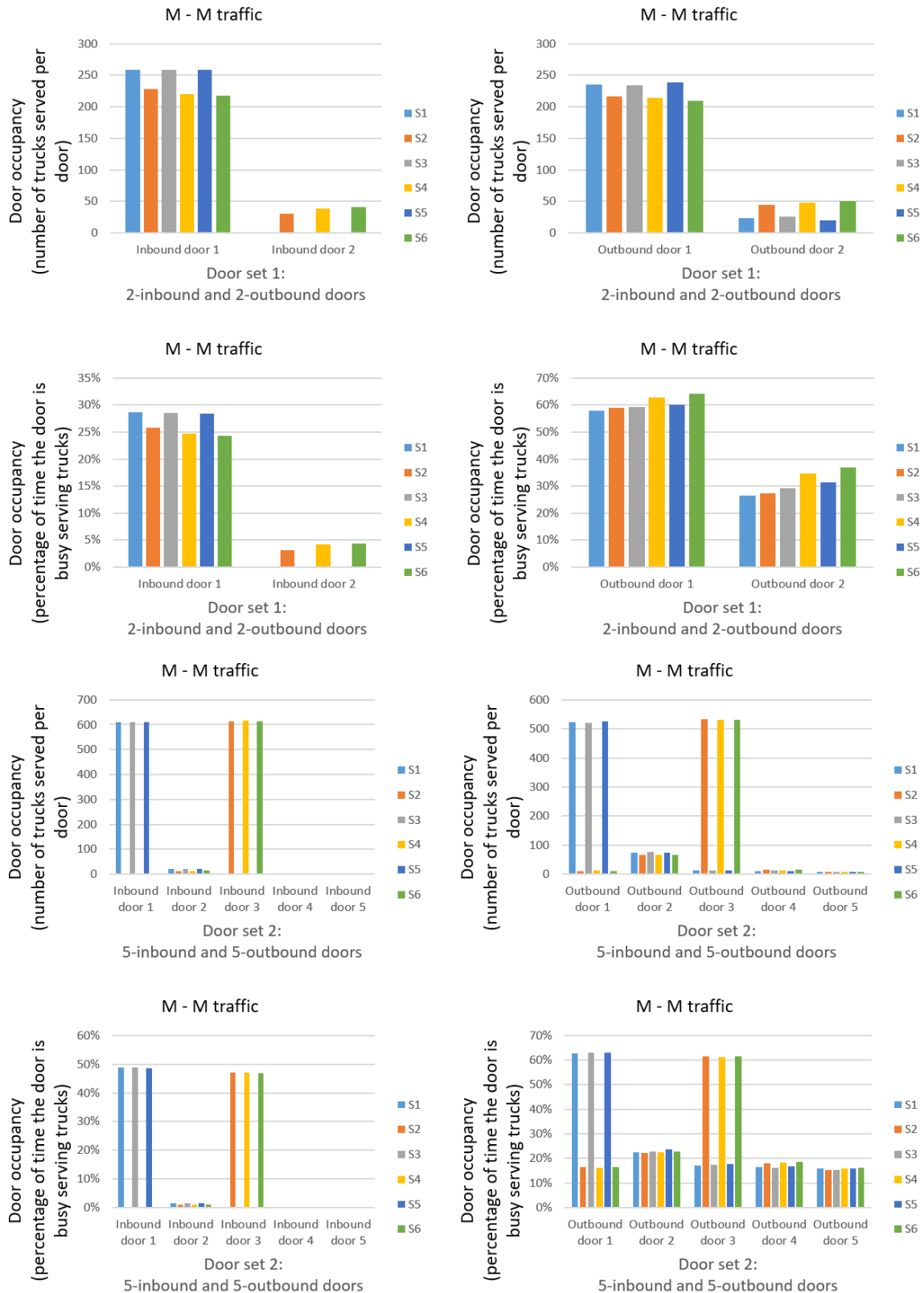


Figure 5.12: The door occupancy at M-M traffic for door sets 1 and 2 based on each strategy

5.3.6 Summary on the average performance of strategies for door sets 1 and 2

The key findings and tendencies observed in the system regarding the performances of the strategies under all traffic levels for door sets 1 and 2 are highlighted in the following points:

The strategies that adopt SP policy (i.e. S5 and S6) stand out by achieving the most satisfactory results on the minimum average stock levels with the lowest variations across all traffic levels and door sets. However, when the traffic gradually declines to low levels (i.e. L-M and L-L), the strategies that employ the EDD rule (i.e. S3 and S4) catch up with the performances of the S5 and S6. The observed similarity can be explained by the situations in which the system efficiently clears out pallets in these scenarios, regardless of the outbound truck selection policy. In addition, both these strategy sets (S3-S4 and S5-S6) operate the same inbound truck selection procedure (i.e. EDD), further explaining their comparable stock levels in these particular traffic scenarios. In contrast, the strategies that adopt the FCFS rule constantly exhibit the most deficient performances. Note that as the facility is transitioning from door sets 1 to 2, meaning expanding in size, the performance gap between the strategies that employ EDD and FCFS for truck selection tends to decline, and at the L-L traffic level, it becomes the same (see Table B.1). It is essential to mention that while minor differences are observed among strategies adopting different door selection rules, the salient observation is truck selection policies' consistent and prominent effect on stock levels. Notably, the SP policy emerges as the best choice among them. Based on the solid performance of the SP reaching minimum stock levels at all traffic levels and door sets, it is recommended to adopt S5 and S6.

For both door sets, S5 and S6 outperform other strategies on the percentage of late pallets and the pallet delay across all traffic levels, except for the L-L scenario. Even though some minor performance discrepancies appear between S5 and S6 on the pallet delay (specifically at the H-H and M-M traffic levels for the door set 1), their solid achievements are emphasised by an in-depth review of Tables B.2 and B.3 for both door configurations. These statistical findings support the fact that the employment of the SP policy guarantees control of on-time pallet delivery. Both strategies, S5 and S6, incorporate the earliest due date procedure for inbound truck selection, integrated with the smart choice of outbound trucks based on the dominant destination of pallets within the stock. This clever incorporation of the EDD and SP drives S5 and S6 as preferred strategies to achieve timely deliveries across diverse operational scenarios.

All the strategies have comparable results by achieving the maximum fill rates for both door sets when traffic levels are equal at both ends (i.e. H-H, M-M and L-L traffic) (see Table B.4). For the other scenarios where outbound traffic is high while inbound traffic is medium and low, it is likely to expect prominent performances from S5 and S6. This expectation stems from their employment of SP to evacuate pallets from stock efficiently by selecting trucks based on the dominant pallet destinations. However, S1 and S2 significantly outperform S5 and S6 by providing high truck fill rates in scenarios where outbound traffic exceeds inbound traffic for door set 2 (i.e. M-H, L-H, L-M traffic) (see Table B.4). Note that even though S1 and S2 reach higher truck fill rates than S5 and S6 for door set 2, the performance of S5 and S6 is still competitive and even superior for door set 1 during L-H and L-M traffic levels, respectively. Nevertheless, a complete analysis involving diverse door set configurations is needed to verify whether these discrepancies in strategy performances are attributed to the door set variations. This approach will identify the prominent strategy for truck fill rates.

Strategies that apply the MTTP rule (S2, S4 and S6) surpass others on the average travelling time of pallets across all traffic levels and door sets (see Table B.5). This result is even more significant for door set 2, where the facility expanded in size. The skills of these strategies in minimising pallet travel time emphasise their effectiveness in managing the increased operational intricacies. On the other hand, when we make a comparison between MTTP-based strategies (i.e. S2, S4 and S6), we observe minor performance disparities for both door sets under certain traffic conditions. Nevertheless, a complete analysis involving diverse door set configurations is needed to determine whether these discrepancies in strategy performances are indeed a result of distinct door set configurations.

For both door sets, the MTTP-driven strategies mostly prefer the platform's central doors, as they provide the shortest distance in the facility. In contrast, FAD-based strategies (i.e. S1, S3,

S5) prioritise initial door pairs of the platform (first inbound and first outbound docks), leading to particular doors being constantly busy; others have the lowest activity or idleness. Even though these results are seen for both FAD and MTTP strategies, a potential observation is that the MTTP strategies do not result in drastically uneven door utilisation compared to FAD-based strategies. Moreover, they appear to distribute trucks to dock doors more even compared to FAD-based strategies. However, it is necessary to emphasise that this observation requires validation through a further analysis covering a spectrum of diverse door sets, possibly through a scalability assessment.

As the results of the multiple-door model presented in this chapter are compared with the single inbound and outbound doors model from the previous chapter, noticeable tendencies appear: the stock-oriented policy, SP is efficient for stock control and on-time deliveries. Despite the added intricacy of door selection policies in the multiple-door model, the significant effect of truck selection policies, as emphasised in the previous chapter, remains valid. Therefore, the effectiveness of the SP rule still stands out under the title of S5 and S6 by incorporating the door selection policies (i.e. FAD and MTTP), making it a superior option for handling stock and assuring punctual deliveries constantly across all scenarios (see Tables B.1 to B.3). Moreover, as concluded in the previous chapter, the truck selection procedure of EDD remains a drawback, as it gives tight time windows for outbound trucks to load, resulting in diminished performance for the strategies that incorporate EDD (i.e. S3 and S4). Similarly, FCFS, as implemented in S1 and S2, remains an inferior policy, even if combined with door selection rules (i.e. FAD and MTTP).

These findings drive us to investigate the impacts of combining distinct door selection practices with the same truck selection rules. To this end, we compare strategies that share the same truck selection policy but differ in the door selection rules. Through these analyses, coupled with further supporting statistical tests (i.e. pairwise comparison of the strategies), it is apparent that minor fluctuations occur between the performances of these strategy pairs (i.e. S1-S2, S3-S4, S5-S6) on the KPIs (such as stock level and pallet lateness). However, these variations do not consistently manifest across all traffic levels and door sets (see Tables B.1 to B.4).

The lack of persistent differences in the performance of these strategy pairs prevents us from drawing a definitive conclusion: the combination of the distinct door selection practices with the same truck selection rules significantly influences all KPIs. However, as discussed earlier, it is crucial to highlight that door selection rules are effective on the pallet travel time and door occupancy metrics (see Tables B.5 to B.9). In contrast, the impacts of truck selection policies on the other KPIs, such as stock levels, pallet delays, percentage of late pallets and truck fill rates, remain significant (see Tables B.1 to B.4).

Finally, as observed in Chapter 4, all the strategies yield relative KPI results in the L-L traffic scenario. The ANOVA analysis further validates this inference, failing to uncover significant disparities among the strategies (see Tables B.1 to B.5, B.7 and B.9). As stated in the previous chapter, this phenomenon can be attributed to low resource requirements at this particular traffic level.

5.4 Scalability analysis

This section analyses the effects of scaling up the model by increasing the number of doors of the platform on the model performance evolution. Unlike the analysis performed in the previous section, the purposes of the tests executed in this section go beyond being only a performance measurement across different strategies. The model scalability analysis contains a holistic assessment of the behaviour, adaptability, tendencies and limits of the model with the ultimate purpose of enabling informed decision-making and enhancing the accuracy of future scalability planning in the face of growing operational intricacy.

With this purpose in mind and the experiment's results discussed in the previous section, two distinctive strategies and a particular traffic level serve in the scalability analysis for the following reasons:

- **Strategy selection:** For the analysis in this section, we will use only S1 and S6 among the six previous strategies. The main reason is that the algorithms executed by S1 for truck and door selections are built upon relatively simple rules (i.e. FCFS and FAD) making it a good candidate for a base-line strategy. Compared to S1, S6 has more refined approaches decision making mechanisms (i.e. EDD-SP and MTTP). This dissimilarity is noteworthy because, within the model scalability analysis, the execution complexity increases as the facility expands across various door sets. Therefore, operating both complex and simple execution algorithms as alternatives can provide us valuable insights on the potential scalability of the model. Additionally, we have observed that S6 positions itself as a strong challenger by often arising as the dominant strategy by reaching superior or at least comparable results compared to other strategies. Therefore, it is understandable to test the best performing strategy in a more complex environment.
- **Traffic level selection:** As stated in Section 5.2, the H-H traffic level is chosen because we want to observe the impact of scaling up. The H-H traffic pushes the system to its highest capacity.

The analyses of the model performance evolution based on each key performance indicator are given in the following sections.

5.4.1 Analysis of the average stock level

The average stock levels across all door sets on S1 and S6 are displayed in Figure 5.13. The statistical test results are also presented to validate the observations extracted from this figure (see Tables B.10 and B.11). To this end, Table B.10 gives a pairwise comparison of S1 and S6 per door set, while Table B.11 delivers the one-way ANOVA results of multiple comparisons of door sets for S1 and S6.

When we conduct a cross-analysis of Figure 5.13 and Table B.10, we conclude that S6 outperforms S1 by achieving the minimum average stock level for all door sets. As discussed in the analysis of door sets 1 and 2 in the previous section, this result is expected since S6 employs the SP policy to minimise stock level by choosing outbound trucks according to the destination of the highest number of pallets in the platform.

However, as can be noticed in Figure 5.13, as the number of doors increases, even though S6 delivers a lower stock level than S1, the stock level variations between the instances of both strategies increase.

The ANOVA results highlight how the average stock levels remain consistent or show variations across diverse operational scenarios represented by different door set comparisons (see Table B.11) under the application of both strategies. The existence or lack of statistically significant differences reveals the performance behaviour of the system across door sets. For instance, under S1, we observe stable stock levels from door sets 1 to 3. Note that although we notice a slight stock level increase at door set 3 compared to door sets 1 and 2 in Figure 5.13, this disparity lacks statistical significance (see Table B.11). However, as validated by ANOVA results, stock level contrasts become more pronounced beginning from door set 4, holding consistency from door sets 4 to 5. These results highlight the system's strength, adjusting operational complexity to the threshold of door set 3. While undergoing a performance decline beyond this threshold, it eventually stabilises despite the elevated complexity of door set 5.

A parallel behaviour pattern appears in S6, where door set 2 serves as a stability threshold before stock levels climb at the door set 3 to stabilise again in subsequent door sets.

These tendencies emphasise a notable understanding: despite facing performance challenges at certain thresholds that differ between strategies, the model establishes adaptability, eventually regaining stability to the increasing operational intricacies.

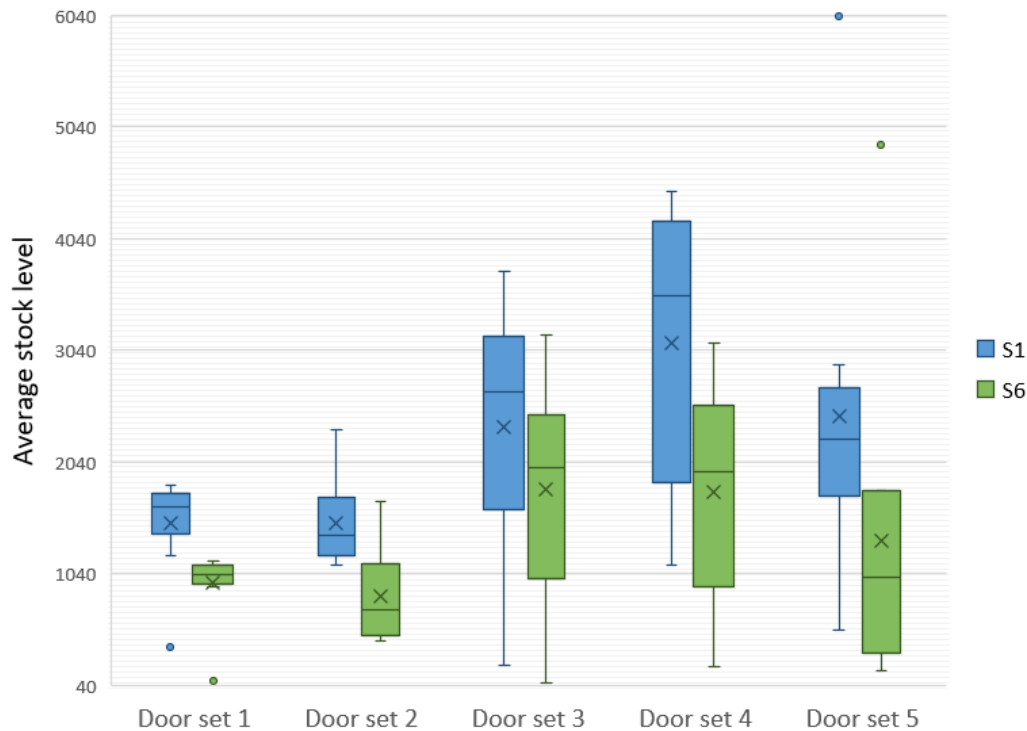


Figure 5.13: Average stock level for all door sets based on S1 and S6

5.4.2 Analysis of the percentage of late pallets and the pallet delay

The percentage of late pallets for each traffic level and the pallet delay (in minutes) for all door sets are presented in Figures 5.14 and 5.15, respectively, while Tables B.12 and B.13 deliver the corresponding statistical test results.

As can be observed in Figures 5.14 and 5.15, S6 outperforms S1 by consistently providing the best results on the percentage of late pallets and pallet lateness across all door sets, except for the pallet delay metric of door set 1, where both strategies yield comparable results (see Table B.12).

Although the unique distinctions between S6 and S1 primarily emerge in the percentage of late pallets, a significant similarity in the behaviours of both strategies becomes noticeable. Both S1 and S6 reveal a common tendency: beginning with a high ratio of the late pallets at the door set 1 and gradually declining as the size of the cross-dock expands. Eventually, this movement diminishes after door set 4, persisting into door set 5 (see Figure 5.14 and Table B.13). This result highlights a noteworthy observation. The model adapts to the increasing operational intricacies, regardless of the effectiveness of the applied strategies.

Similarly, although the system results in high pallet delay for door set 1, it demonstrates its ability to mitigate pallet delays as the facility expands. However, this outcome is observed under the application of S6. Despite the responsive behaviour of S6, the pallet delay stays constant across all door sets under the employment of S1.

5.4.3 Analysis of the outbound truck fill rate

displayed in Figure 5.16. Table B.14 provides the pairwise comparison of S1 and S6 across all door sets to validate the insight drawn from this figure. To support the findings further, Table B.15

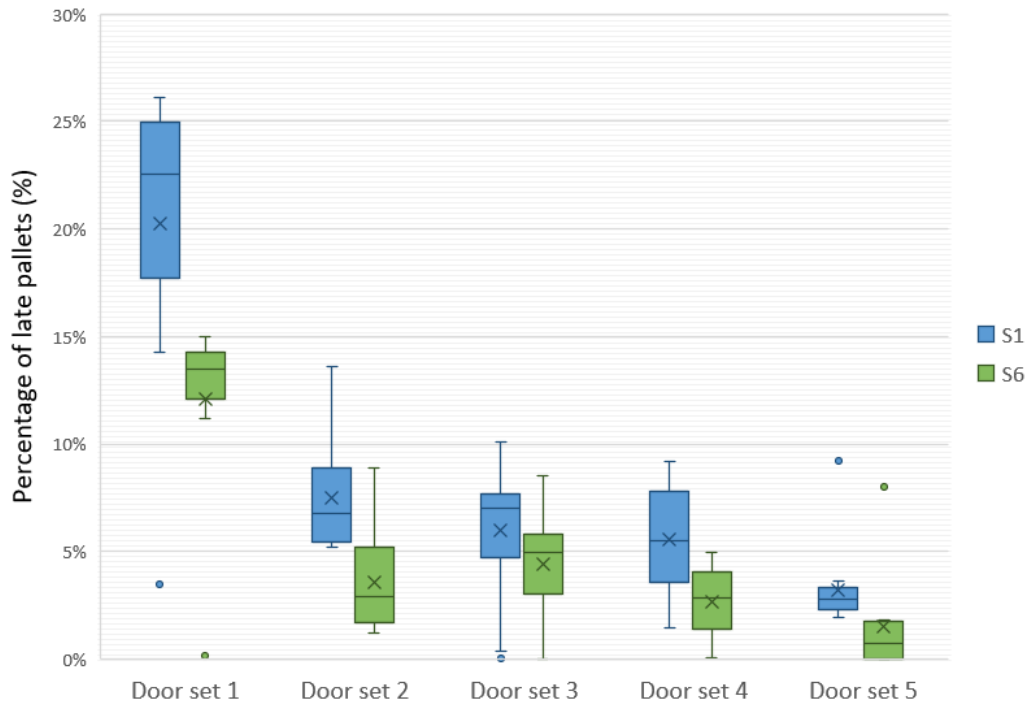


Figure 5.14: The percentage of late pallets for all door sets based on S1 and S6

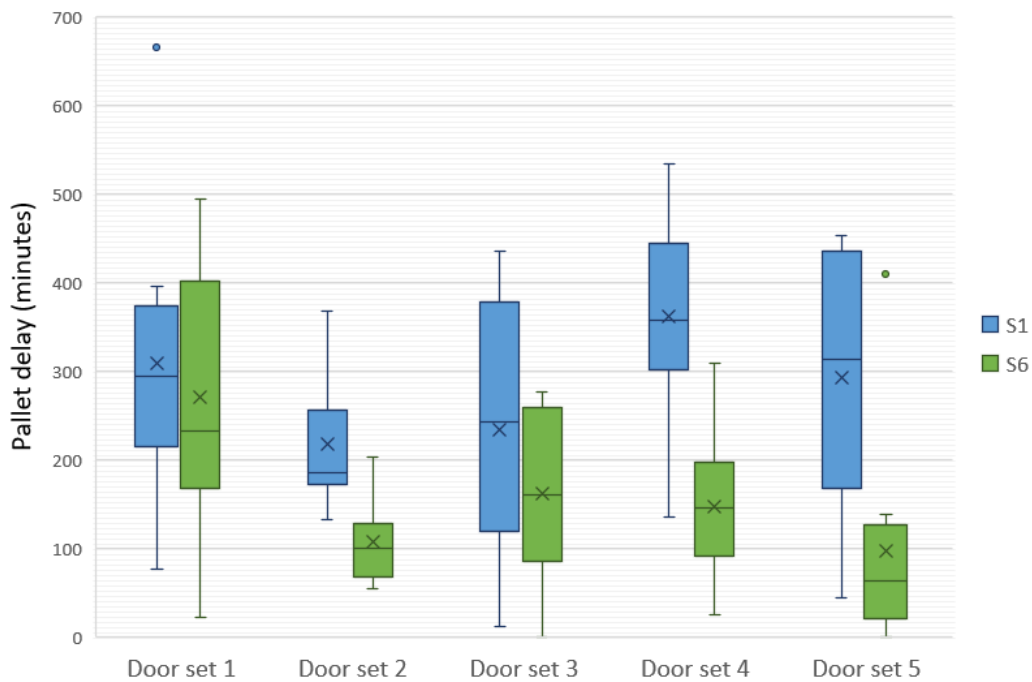


Figure 5.15: The pallet delay (per pallet in minutes) for all door sets based on S1 and S6

delivers the ANOVA results based on multiple comparisons of door sets for each strategy.

As evident in Figure 5.16, both S1 and S6 have the same effect on outbound truck fill rates across all door sets. The pairwise comparison of the strategies in Table B.14 further supports this inference.

In addition to the comparable results of the strategies, it is also noteworthy for highlighting the model behaviour on truck fill rates within the broader context of model scalability. As shown in Figure 5.15, while the system has high truck fill rates at the door set 1, there is a declined

performance as the facility scales to the door set 2. However, a notable behaviour emerges beyond the threshold of door set 2: the model maintains persistent performance across the remaining door sets. Even though the performance differences occur between door sets 2 and 4 under the application of S6, this persistent behaviour of the model remains valid for both S1 and S6.

This result guides us to grasp the sense of the model behaviour. Even though the model encounters difficulties during the transition from door set 1 to door set 2, it shows adaptability to the increasing complexities faced at door set 5. Significantly, this behaviour is observed under both strategies, mirroring the resilience of the model and the capacity to steer escalating complexities regardless of the applied strategy.

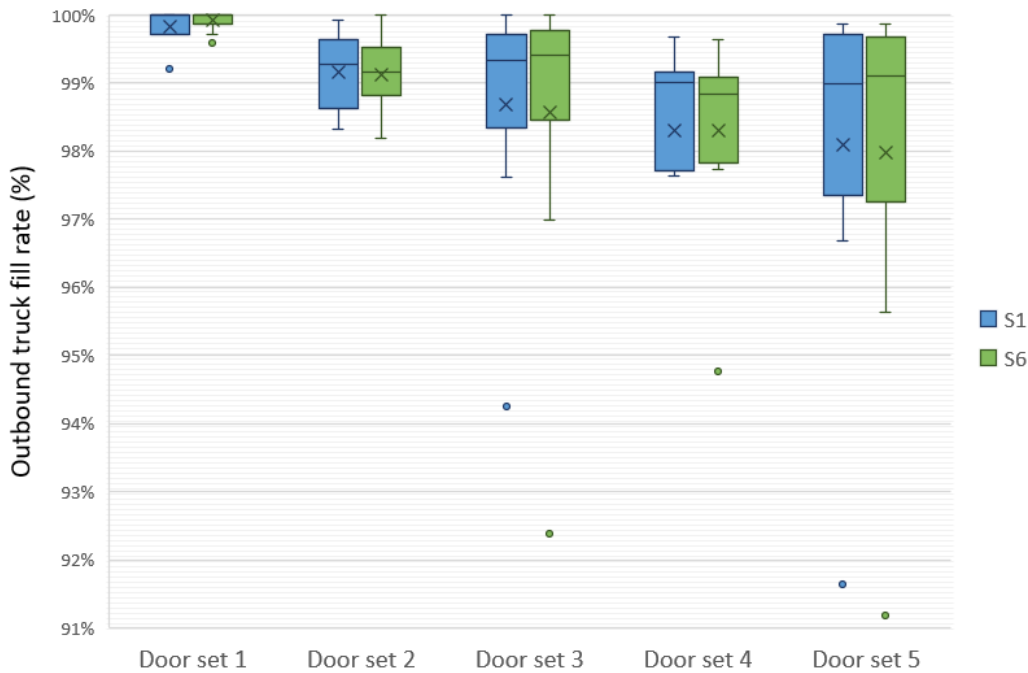


Figure 5.16: The outbound truck fill rates for all door sets based on S1 and S6

5.4.4 Analysis of the average travelling time of pallets

Figure 5.17 presents the average travelling time of pallets under the application of S1 and S6 across all door sets. The pairwise comparison of strategies for all door sets is also delivered in Table B.16. To provide further validation of the findings, Table B.17 provides the ANOVA results based on the pairwise comparisons of door sets for each strategy.

As shown in Figure 5.17, the strategies reveal comparable impacts on the average travelling time of pallets. Even though S6 appears to yield lower travel times per pallet for door set 2, the shared behaviour between S1 and S6 is persistent across the remaining door sets. This observation is further confirmed by the pairwise comparison of the strategies for each door set (see Table B.16).

In addition, as evident in Figure 5.17, the average travelling time of pallets exhibits an increasing trend as the model scales from door set 1 to door set 5. Notably, despite the fact that the differences between door sets 4 and 5 for S1 (similarly, door sets 3 and 4 for S6) on the pallet travel times are not statistically significant (see Table B.17), the upward trend remains persistent throughout the door sets. This result aligns with expectations, given that the distance pallets need to take proportionally increases with the expansion of the platform across different door set configurations.

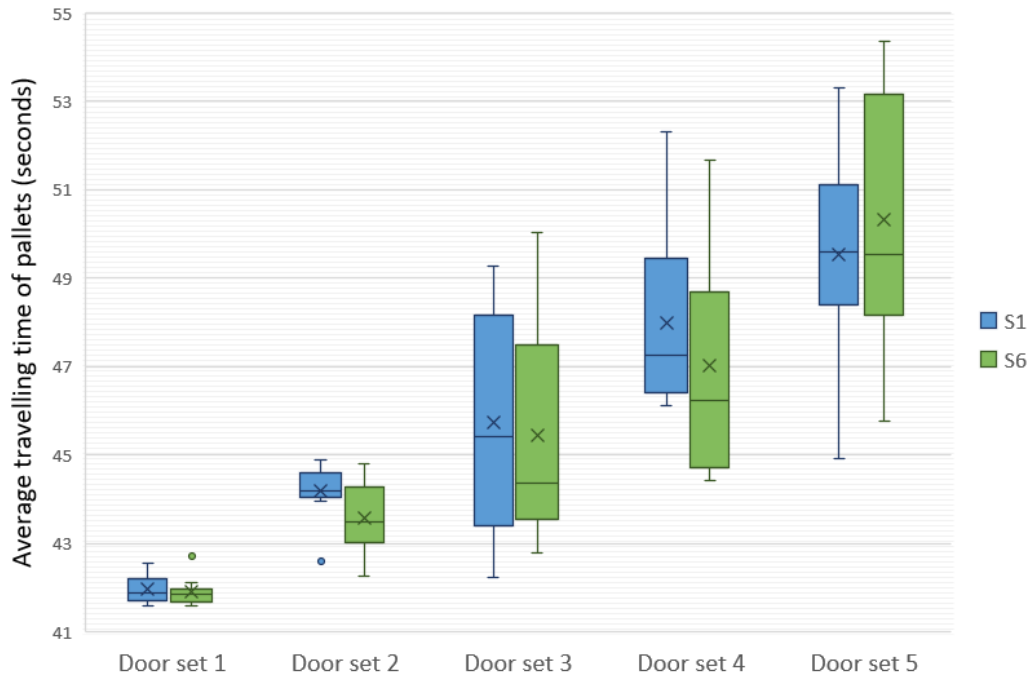


Figure 5.17: The average travelling time of pallets (in seconds) for all door sets based on S1 and S6

5.4.5 Analysis of the door occupancy

The system's door occupancy (i.e., the number of trucks served per door and the percentage of time the door is busy serving trucks) under the application of S1 and S6 across all door sets is presented in Figures 5.18 to 5.21. The pairwise comparison of strategies across all door sets is also provided in Tables B.18 to B.22 to validate the findings extracted from these figures.

Note that the door occupancy metric is individually regarded for each inbound and outbound door. Therefore, the ANOVA analysis of these doors by spanning all door set configurations is infeasible. For instance, while door set 2 contains inbound doors ranging from 1 to 5, door set 1 only has two inbound doors. Consequently, performing ANOVA based on the comparison of corresponding doors among distinct door sets is impossible.

When we compare the mean occupancy across all door sets, we observe that as the facility size increases, the average number of trucks served per door decreases significantly, with a 12% decrease for inbound doors and a 15% decrease for outbound doors when moving from door set 1 to 5.

However, the percentage of time doors are busy serving trucks increases notably, especially for outbound doors, with a 25% increment on average when the facility expands to door set 5.

These trends are explained by longer pallet travel times within the facility as it expands, resulting in extended truck dock times since trucks wait longer to receive their pallets. Consequently, it reduces the availability of dock doors for the subsequent trucks. These factors together explain the high door occupancies and reduced truck service capacity as the facility scales up.

In addition, recall the conclusions drawn from the door occupancy analysis based on door sets 1 and 2 (in Section 5.3.5). It was remarked that the MTTP-oriented strategies tend to distribute trucks across doors more evenly than FAD-based strategies. However, the analysis strongly emphasises that this potential observation requires validation through further analysis, including a spectrum of diverse door sets. As in this section, owing to the scalability analysis, we can now distinctly see that S6 indeed distributes trucks to dock doors more evenly compared to S1 (see Figures 5.18 and 5.20). This result supports the earlier observation with enhanced confidence.

Another observation that aligns with the insights from the previous section is related to the distinct door preferences between S6 and S1. Even though S6 allocate trucks to the door more

evenly than S1, as evident in Figures 5.18 and 5.20, S6 opts for the platform’s central doors, as they provide the minimum distance in the facility. In contrast, S1 prioritise the initial door pairs (i.e. first inbound and first outbound docks). These characteristic impacts of the strategies on door occupancy are further verified through the pairwise tests performed between S1 and S6, evaluated across each individual dock door within all door sets (see Tables B.18 to B.22).

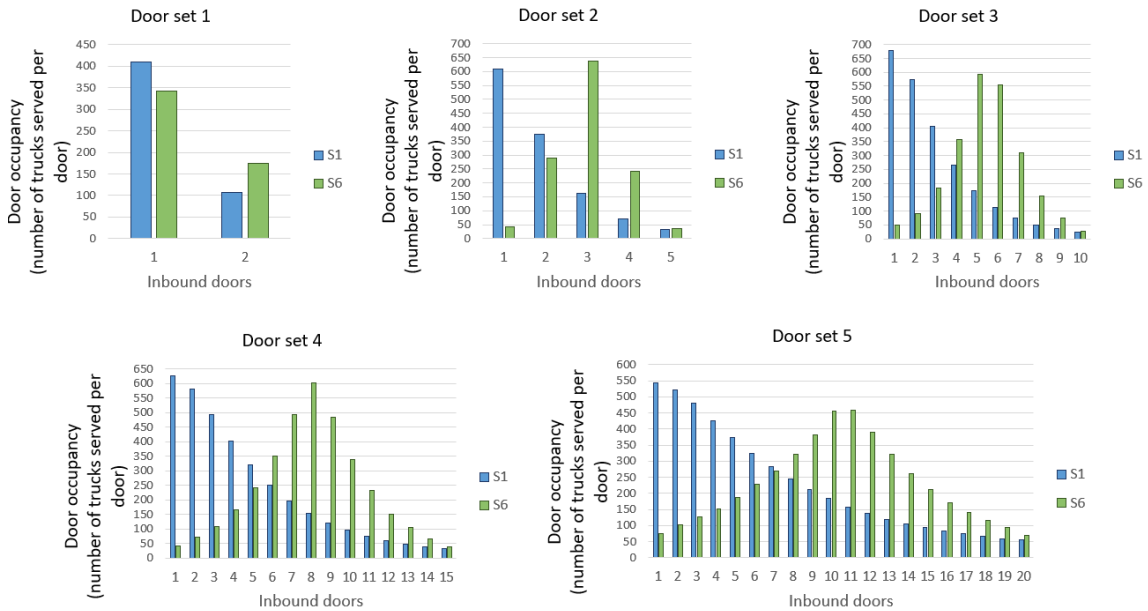


Figure 5.18: The inbound door occupancy (number of trucks served per door) for all door sets based on S1 and S6

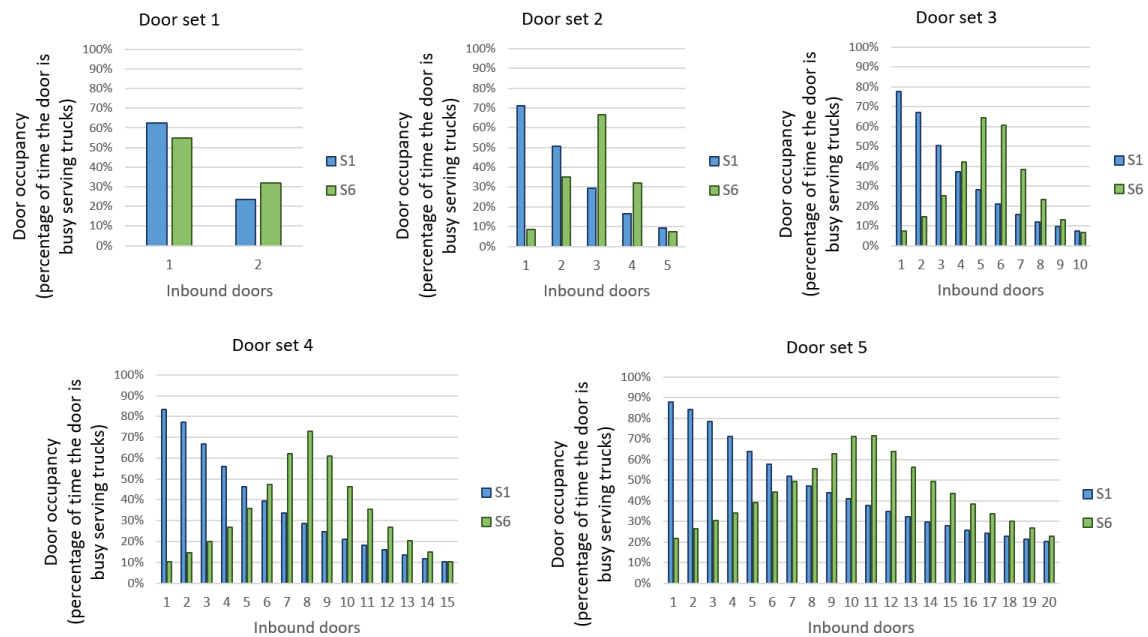


Figure 5.19: The inbound door occupancy (percentage of time the door is busy serving trucks) for all door sets based on S1 and S6

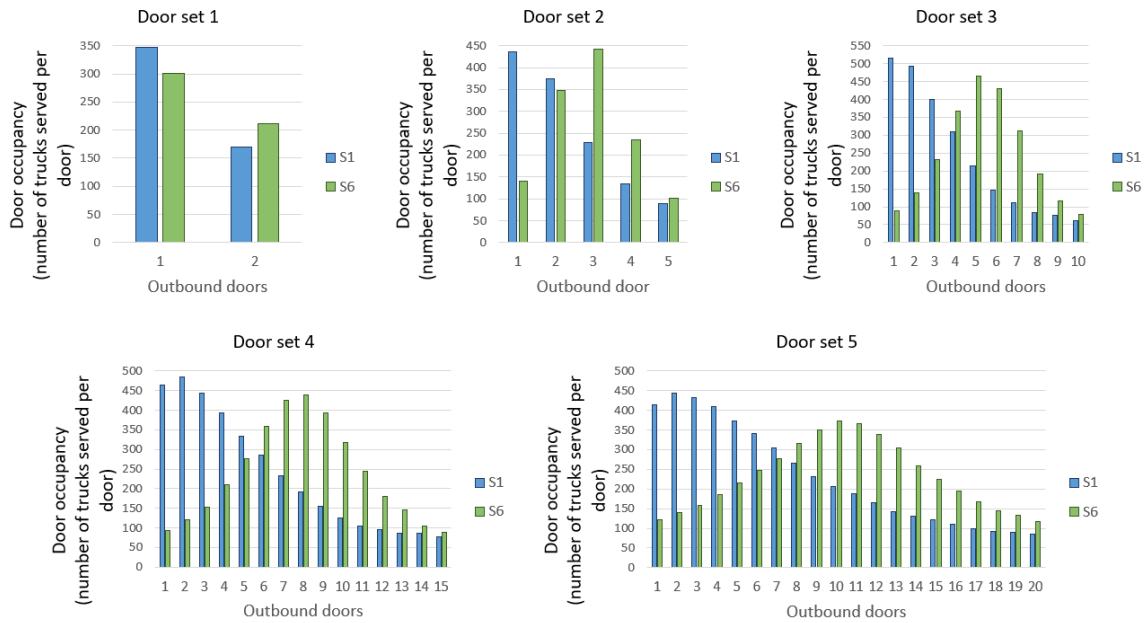


Figure 5.20: The outbound door occupancy (number of trucks served per door) for all door sets based on S1 and S6

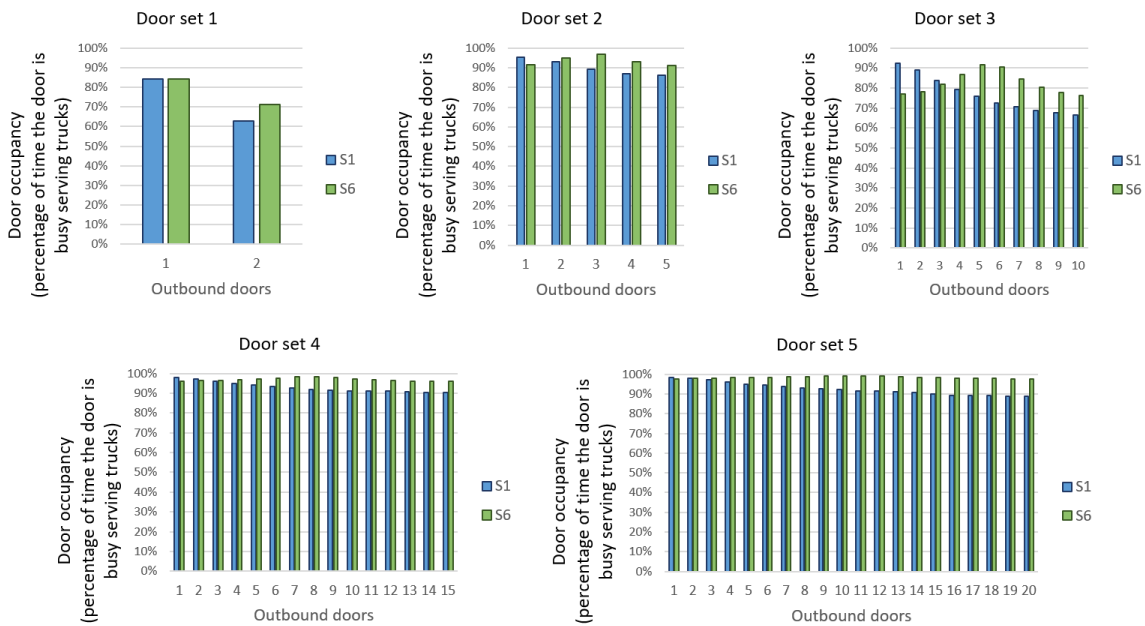


Figure 5.21: The outbound door occupancy (percentage of time the door is busy serving trucks) for all door sets based on S1 and S6

5.4.6 Summary on the scalability performance of the model

The pivotal takeaways on the model's behaviour, adaptability and limits as the model scales up are emphasised in the following points:

As the previous analysis in Section 5.3.6 concludes, S6 achieves the best results on the average stock level metric. We observe the exact behaviour of S6 against S1 in the model scalability analysis, further strengthening the significance of the stock-oriented policy (i.e. SP) under the title of S6. Despite the performance disparities between strategies, a salient behaviour of the model emerges during its transition from door set 1 to door set 5. While encountering performance challenges at specific thresholds (which may vary between strategies), the model consistently demonstrates its

capability by eventually regaining stability to the introduced intricacies. This behaviour serves as solid evidence of the model's scalability, showcasing its adaptability in response to escalating operational complexities.

The model displays its solidity in the percentage of late pallets and pallet delay performance by displaying a persistent trend of adjusting to rising operational intricacies as the facility expands. This adaptability is evident during the transitioning between door sets by the gradual decline of late pallet rates and the mitigation of pallet delays. Although differences exist between the strategies, with S6 generally outperforming S1, both strategies showcase the model's ability to sustain performance stability after specific thresholds, generally starting at door set 4 and persisting into door set 5. These findings emphasise the model's strength and ability to be easily scaled up to accommodate the intricacies of larger operational configurations.

The similar behaviours of the strategies on the truck fill rates across all door sets further underscore the consistency of the model performance. Despite the high records of the system at door set 1, followed by a performance degradation at door set 2, beyond this threshold, noteworthy stability emerges as the model consistently keeps stable performance levels across successive door sets. While performance disparities arise between certain door sets under S6, this constant behaviour sustains for both S1 and S6. These findings shed light on fundamental characteristics of the model's behaviour and demonstrate its adaptability during the transition from door set 1 to door set 2 and its resilience in controlling increasing complexities up to door set 5. This strong, strategy-independent behaviour emphasises the model's ability to steer escalating intricacies effectively.

As it aligns with the expectations, the distance covered by pallets increases with the platform's expansion due to varying door set configurations. While S6 achieves lower travel times for door set 2, both strategies yield notably comparable results across other door sets. This intriguing convergence in performance between the MTP-oriented S6 and the FAD-based S1 reveals a pivotal observation. It points out the crucial need to design more robust door selection approaches to steer the escalating intricacies of the system more competently. While statistical significance may elude the differences in pallet travel times between specific door sets, the regular upward trend remains consistent across door set configurations. This persistent behaviour of the system stems from the proportional increase in travel distances as the platform expands.

As the facility scales up from door set 1 to door set 5, the mean occupancy per door, represented by the number of trucks served, lowers for both inbound and outbound doors. In contrast, door occupancy, reflecting the time doors are busy serving trucks, notably increases for outbound doors and experiences a more modest rise for inbound doors. As discussed earlier, these tendencies align with the corresponding increase in pallet travel times, which extends truck turnover times and lessens door availability for successive trucks. As another significant finding, our scalability analysis confirms that S6 effectively distributes trucks more evenly across dock doors than S1 and displays characteristic door preferences, with S6 favouring central doors due to their shorter distances. At the same time, S1 prioritises the initial door pairs of the platform.

Since model scalability analysis contains a holistic assessment of its behaviour, adaptability and limits to enhance the accuracy of scalability planning, it is essential to assess its compatibility with real-time scheduling principles. To this end, in the following section, we analyse the computation time of the model based on its execution performance as it scales up. This analysis considers the model in the face of the increased intercommunication of its agents and the coordination of the related activities of the platform.

5.4.7 Analysis of the computation time

Computation times of all door sets are given in Figure 5.22 for a simulation length of 48 hours. As can be observed from this figure, the computation time increases exponentially as the number of doors extends linearly. This result is reasonable since the model tries to respond and handle the increased intercommunication of its agents, the coordination of the related activities of the platform,

the door increment and the traffic level that adapted to this door number growth.

It has to be noted that there is a significant difference in average pallet flow, varying from 280 pallets per hour at the door set 1 to an escalated 2,500 pallets per hour as the facility expands to the door set 5. This significant difference serves as a concrete exemplification of the profound consequence that door set increase yields over the system's performance.

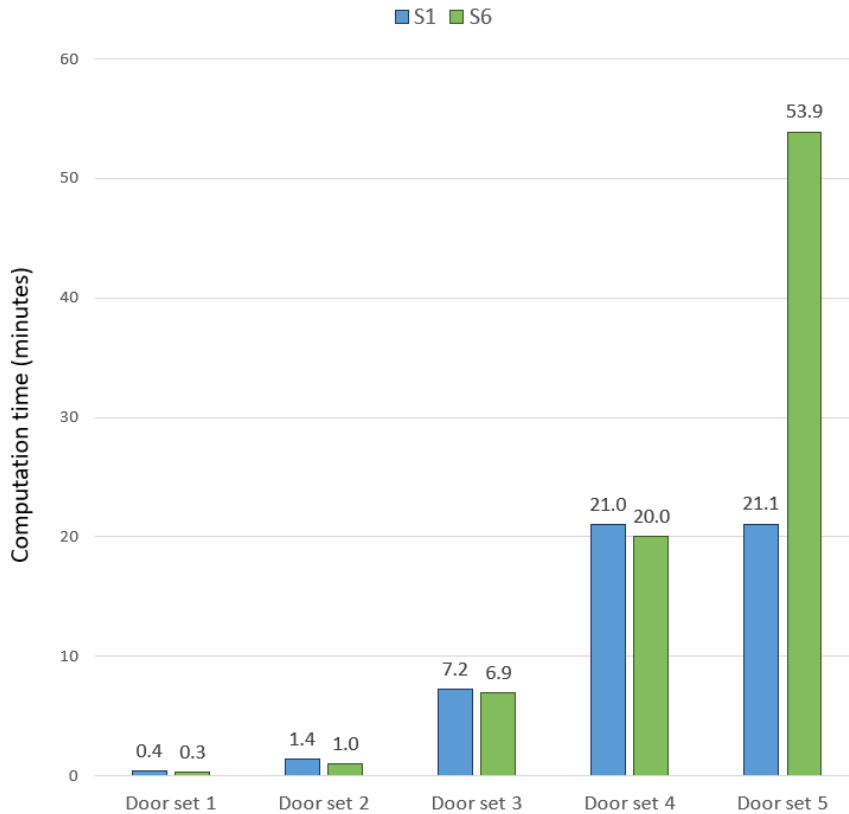


Figure 5.22: Computation time for all door sets based on S1 and S6

We also observe that the computation times for both S1 and S6 are comparable upto a certain size of the platform but starts diverging highly for the case of 20-inbound and 20-outbound doors cross-dock platform. This result is explained by the high number of implementation steps of S6. It is known that when S6 is employed, the following actions are pursued:

1. Recall from the MTTP rule for door selection: Each inbound and outbound truck scans each dock door and each pallet of the platform to select the best door to obtain the minimum travelling time of pallets.
2. Recall from SP policy for outbound truck selection: Each outbound door determines the destination with the highest count of pallets in the facility. Then, it selects an outbound truck with the matching destination. If it cannot find a truck with the matching destination, it tries to find a matching destination with the second-highest count of pallets. This process is repeated until the door agent finds a matching truck. Note that while the outbound door agent practices this rule for the outbound truck selection, the inbound door uses the earliest due date rule for selecting the inbound trucks. It is essential to mention that, since the EDD rule has a lower number of implementation steps than SP and execution stages similar to FCFS, the high computation time of S6 cannot be attributed to the EDD policy.

While S6 has extensive implementation stages, S1 employs the FAD policy for door selection and the FCFS rule for truck selection. Both rules are rather simple to conduct compared to the ones S6 performs.

Regarding the computation time, one question remains to be answered: How does the model fit for real-time scheduling? In the context of real-time scheduling, the definition of "real-time" is crucial and can significantly vary depending on the applications. It may range from ultra-fast, such as in nano-seconds, to a few minutes in various systems. In our application of cross-dock truck scheduling, we make the assumption that a "real-time" schedule should not exceed five minutes. Under this assumption, the results in Figure 5.22 might seem crippling. However, it has to be recalled that the computation times in Figure 5.22 correspond to a simulation length of 48 hours, which is way too long for real-time scheduling purposes, as the need to predict events (such as truck arrivals) ten hours beforehand may not align with making rapid decisions that concern the next few minutes. For a "real-time" schedule, it would be sufficient to fix a schedule for a short period of time. Therefore, we propose to monitor the evolution of the computation time as the simulation length varies.

For this analysis, we selected door set 5 (i.e. 20-inbound and 20-outbound doors) and used five generated instances. The computation time of each instance is recorded over two-hour intervals, employing both S1 and S6. Figure 5.23 exhibits the average computation time of five instances at two-hour intervals.

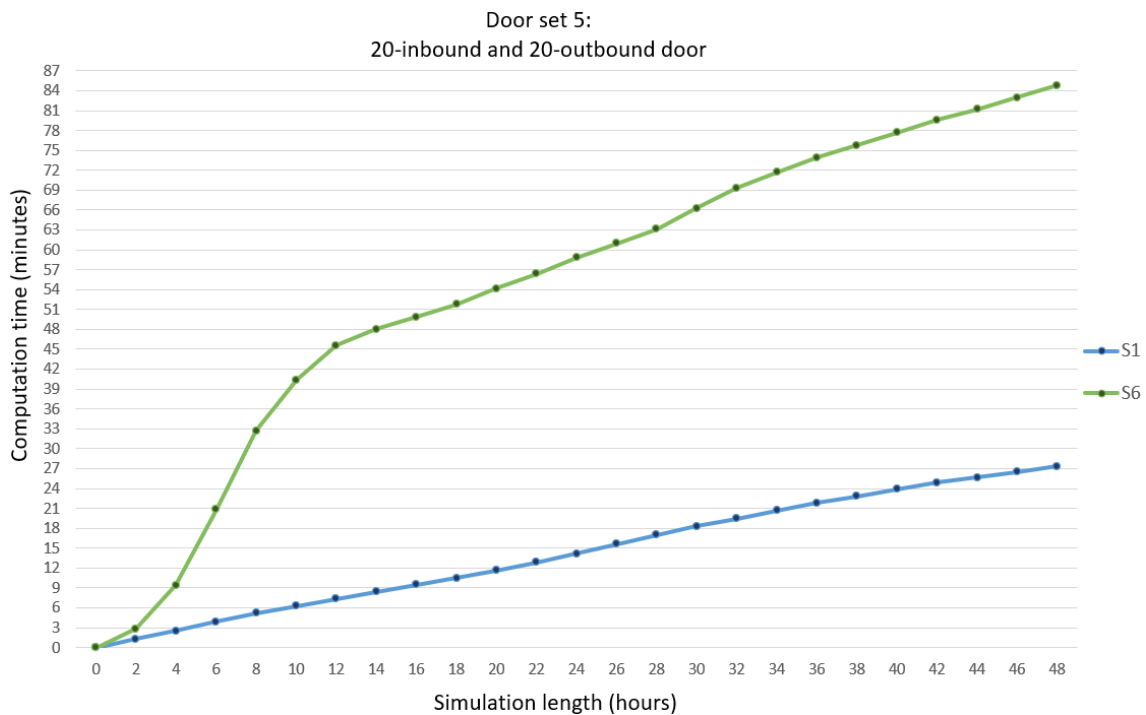


Figure 5.23: Computation time at every two hours based on S1 and S6 for door set 5

Two major observations can be made through Figure 5.23:

First of all, for a simulation length of two hours, the computation time is below 3 minutes, both for S1 and S6. A schedule for a time window of up to two hours can be considered relevant for real-time scheduling. This way, unexpected events that occur in a relatively near future can be considered while not bothering for long-term events that are not relevant for real-time decisions. We can hence conclude that the approach proposed in this thesis can be applicable for real-time truck scheduling with short planning horizons.

Secondly, we observe that the computation time is sensitive to the mechanisms used for decision-making, even for shorter simulation lengths. Consequently, there is a trade-off to be made between the complexity of the decision-making mechanisms (and, thus, potentially, the quality of the schedule) and the simulation length. This decision is left to the appreciation of the users.

5.5 Conclusion

This chapter expands upon the foundational concepts introduced in Chapter 4, with in-depth analysis by developing a refined model aiming to be fit for real-world cross-docking scenarios. To this end, the model is extended to the multiple-door configuration. This expansion necessitates configuring inbound and outbound truck agents to make door selection decisions based on defined objectives, thereby enhancing the decision-making capabilities of the model. Integrating door selection policies allows for applying combined strategies, encompassing both door and truck selection policies. Additionally, the distribution of central temporary storage to inbound doors aims to gain efficiency in internal operations.

The evaluation of the proposed multiple-door model hinges on a set of specifically designed performance metrics in cooperation with those inherited from Chapter 4. To comprehensively measure the model's performance, we conduct our analysis based on two perspectives. The model's adaptability and effectiveness are analysed across various scenarios. In alignment with the findings, we conduct a rigorous assessment of the model's scalability. Our findings confirm that the model establishes scalability by revealing performance resilience after certain thresholds.

However, it is crucial to address the computational challenges that emerge in larger configurations, particularly when the total number of dock doors exceeds 30. This issue becomes even more pronounced with the application of more elaborate door selection strategies at the 20-inbound and 20-outbound door configuration. Nevertheless, based on the findings of the computation time monitoring at two-hour intervals within a 48-hour simulation length, the model confirms that it can perform real-time scheduling if the simulation length is kept between 2-3 hours.

This finding paves the way for future improvements within the scope of this research. The model may undergo shorter simulations (e.g., 2 hours, 3 hours, and 4 hours) with the benchmark 48-hour simulation to explore differences in resource (such as computational resources and processing time) utilisation. Furthermore, this comparative approach will enable an examination of any divergences in scheduling decisions due to varying simulation durations. This way, the model's proficiency in achieving real-time scheduling objectives can be methodically confirmed.

In addition, the algorithms used for the model's door and truck selection strategies could be optimised so that they consume less memory, and thus execute more rapidly.

This study confirms both the real-time applicability within short planning horizons and the scalability of the proposed multi-agent-based hybrid model. To extend our inquiry, we aim to assess its reactivity and performance across diverse problem configurations through a comparative analysis. In pursuit of this objective, the proposed model in Chapter 4 and the extended model in this chapter will be adapted towards the focus of a chosen truck scheduling problem in the cross-docking literature in Chapter 6, enabling a comparative assessment of the outcomes.

6

Real-time application to the truck scheduling problem in the literature

This chapter introduces a comparison model to illustrate that the suggested multi-agent-based approach can successfully apply to different truck scheduling problem configurations. To this end, an existing truck scheduling problem ([Van Belle et al., 2013](#)) in the cross-docking literature, which employs a mathematical optimisation, is selected. Furthermore, the decision-making mechanisms created in the models described in Chapters 4 and 5 are adapted towards the focus of the chosen truck scheduling study. The performance of the proposed model is analysed through the same problem instances of the chosen study for comparison purposes. Finally, the analysis of the results on the performance metrics is presented from a comparative point of view.

The models introduced in Chapters 4 and 5 prove that the proposed multi-agent-based hybrid models effectively handle real-time truck scheduling problems for cross-docks ranging from single-inbound and single-outbound doors to more extended sizes.

This chapter seeks to validate the practical applicability of our proposed multi-agent-based hybrid model in solving various configurations of truck scheduling problems encountered in the cross-docking literature. To achieve this objective, we have chosen to conduct a truck scheduling case study motivated by the work of Van Belle et al. (2013). This selection is based on the alignment of their research with essential characteristics of the advanced model presented in Chapter 5, which include:

- Utilisation of a cross-dock facility featuring multiple inbound and outbound doors.
- Implementation of distributed temporary storage at the inbound dock doors.
- Consideration of pallet travel times within the cross-dock facility.

Furthermore, the authors have shared their input dataset, allowing us to use the same dataset in our model to conduct unbiased and meaningful comparisons of the results.

Note that for the sake of simplicity, we will refer to this problem as "VB" in this chapter.

After presenting the VB (Section 6.1), we deliver the details of the multi-agent-based hybrid model implementation of the problem (Section 6.1.2) and the developed decision-making mechanisms of the agents (Section 6.1.3). Then, to evaluate the model's performance, we define key performance indicators based on the objective function of the selected truck scheduling problem (Section 6.1.4). Finally, in Section 6.2, the model experimentation is carried out, and the discussions on the reactivity and performance of the proposed model compared to the mathematical optimisation method are given.

6.1 Problem description

The VB concentrates on scheduling both inbound and outbound trucks at a multiple-door cross-docking platform in a static environment. In this context, uncertainty and variability in factors such as process times and truck arrivals are not considered. The authors propose a mixed integer programming (MIP) model to solve the problem. The problem being NP-hard, a tabu search approach is used to provide high-quality solutions within a reasonable time for large instances.

6.1.1 Assumptions

In VB, the considered cross-docking platform has three inbound and three outbound dock doors operating as an exclusive serving mode (i.e. inbound and outbound doors are dedicated only for unloading and loading, respectively.) Preemption is not allowed (i.e. unloading and loading of trucks cannot be interrupted).

Temporary storage inside the platform is allowed and distributed to the inbound doors, meaning that the products can be unloaded from trucks at the inbound doors before the destined outbound truck is available for loading. The capacity of the temporary storage is assumed to be unlimited.

The unloaded products at the inbound doors are transferred to the outbound door to be loaded onto the destined outbound truck. Internal operations such as labelling and sorting are not considered. The workforce capacity dedicated to unloading, loading and product transfer is assumed to be unlimited.

The products are unloaded and loaded successively (i.e. only one product unit can be unloaded or loaded at a time). Each product enters the platform as standardised cargo (e.g. pallets). Consequently, unloading and loading times are fixed and proportional to the number of products.

The sequence of the product unloading from inbound trucks is not known. Therefore, the product transfer from inbound doors to outbound doors is performed only after the complete unloading of the products from their inbound truck.

The product transfer time is proportional to the rectilinear distance between inbound and outbound doors.

The product interchangeability is forbidden: each product is devoted to a specific outbound truck.

The arrival time of each inbound and outbound truck is known. Both inbound and outbound trucks have predefined departure times (i.e. due dates). However, the due dates of trucks are not defined as hard constraints, meaning that trucks only leave the system after completing the unloading or loading processes, even if their due dates expire.

The changeover times of trucks are fixed.

The objective is the minimisation of the weighted sum of the total travel time of goods inside the platform and the weighted sum of the total tardiness of inbound and outbound trucks.

The following subsection presents the implementation of the proposed multi-agent-based real-time model to *VB*.

6.1.2 Multi-agent-based hybrid model implementation

The implementation of the multi-agent-based hybrid model to *VB* is carried out using Java Programming Language on the AnyLogic Simulation Software (University edition 8.7.10), as in Chapters 4 and 5.

The implementation details of the model, including model inputs, multi-agent and discrete event components, are similar to those studied in Chapters 4 and 5. However, while the multi-agent component remains the same as in the previous models, the differences in model inputs and the discrete-event component are explained below.

The model inputs:

Recall from Chapters 4 and 5 that the simulation in those models dynamically determines the pallet flow between inbound and outbound trucks on a real-time basis. In contrast, the *VB* model relies on a predetermined schedule for pallet flow, represented as a matrix specifying the number of products (pallets) to be transported from a given inbound truck to a pre-determined outbound truck. Therefore, for the model presented in this chapter, this matrix is imported from an external data file (Excel file) into the simulation's built-in database, in addition to other model inputs such as truck arrival times.

The discrete-event component:

Recall from Section 4.1.1 that the platform's workforce is defined over forklifts for both models presented in Chapters 4 and 5. However, in the model presented in this chapter, the unloading, loading, and transfer of products are defined solely through discrete-event blocks, without the use of material handling equipment, in contrast to the previous two models. This approach aligns with *VB*, as its system has no precise workforce that is defined for these processes. To closely mimic *VB*, we also refrain from defining any specific workforce for the model presented in this chapter. The rest of the discrete-event component specifications explained in Section 4.1.1 are still valid for this model.

6.1.3 Decision-making mechanism

In pursuit of aligning with the objectives of *VB*, our model incorporates certain truck and door selection policies. Note that since *VB* employs an optimisation method, it simultaneously determines both truck and door selections (i.e. truck-to-door assignments), aiming to minimise truck tardiness and pallet travel time together. In contrast, our simulation model has a different approach, making these decisions separately: we determine which truck to assign and then decide where to dock this truck, specifically selecting the door for its arrival. To align with *VB*'s truck-to-door assignments, which are made simultaneously, our separate truck and door selection rules are as follows.

The truck selection rules are, namely, first-come-first-served (FCFS), earliest due date (EDD), and minimum average travelling times of pallets (MATP). Note that FCFS is already applied by the constraints of *VB*'s mathematical model, and therefore, we adapt this constraint as a truck selection rule in our model. Furthermore, we add the EDD rule from the previous models (in Chapters 4 and 5) to align with the *VB*'s objective, which is the minimisation of truck tardiness. Both the FCFS and EDD policies operate based on the principles outlined in Section 4.1.3. In addition, we introduce a novel policy, MATP, as a further truck-to-door assignment rule designed explicitly for this model. This rule is added to consider the *VB*'s objective function related to the minimisation of the average travelling time of pallets. The MATP policy operates based on a distinct logic we precisely developed for this model, which prioritises the selection of trucks according to the following principles:

- The MATP selects the truck that provides the minimum average travelling time of pallets. The average travelling time of pallets is calculated for a truck and a door. It expresses what would be the average travelling time of the pallets if the door decided to select the truck.
 - When an inbound door wants to select its inbound truck, it considers all the available inbound trucks and calculates the total travelling time of each pallet that is carried by each truck. For each pallet, if the destination truck of the pallet is already docked at an outbound door, then we count the actual travelling time it would take for the pallet to travel between inbound and outbound doors. If the destination truck of the pallet is not docked, then we count the maximum possible travelling time (the furthest outbound door to that inbound door). The sum is then divided by the number of pallets in the inbound truck to obtain the average. Note that the reason for obtaining the average value is to avoid the situation where the truck which brings (for inbound trucks) or takes (for outbound trucks) a higher number of pallets will never be selected if only the sum of the travelling time of pallets is considered. Finally, the inbound door selects the inbound truck that provides the minimum average travelling time of pallets.
 - When an outbound door wants to select its outbound truck, it considers all the available outbound trucks and calculates the total travelling time of each pallet that will be loaded onto each truck. For each pallet, if it is already unloaded at an inbound door or currently being unloaded from a docked inbound truck, then we count the actual travelling time between the inbound and outbound doors. Otherwise, we count the maximum possible travelling time (the furthest inbound door to that outbound door). The sum is then divided by the number of pallets to be loaded onto the outbound truck to obtain the average. Finally, the outbound door selects the outbound truck that provides the minimum average travelling time of pallets.

The same door selection strategies as the multiple-door model (Chapter 5) are employed in this model: first available door (FAD) and minimum total travelling time of pallets (MTTP). They operate based on the logic explained in the previous chapter (Section 5.1.3). To recall their logic:

- The FAD rule functions as a straightforward policy that makes trucks prioritise the selection of the first available door from the door list (i.e. the door agent population) for docking.

- The MTTP rule selects the dock door that minimises the total travelling time of pallets. This calculation is performed for each pair, including a truck and a door, assessing the hypothetical total travelling time if the truck decided to select that door for docking.
 - When an inbound truck wants to select its inbound door, it considers all available inbound doors and calculates the total travelling time for each pallet it carries. When determining the travelling time for each pallet, we consider two scenarios: if the pallet's destination truck is already docked at an outbound door, we calculate the actual travelling time between the dock doors. However, if the destination truck has not yet docked, we consider the maximum possible travelling time, corresponding to the distance to the furthest outbound door from the inbound door. Finally, the inbound truck selects the inbound door, providing the minimum total travelling times for its pallets.
 - When an outbound truck wants to select its outbound door, it considers all available outbound doors and calculates the total travelling time for each pallet that it will receive. Similar to the inbound scenario, we evaluate two conditions for each pallet. If it has already been unloaded at an inbound door or is currently being unloaded from a docked inbound truck, we consider the actual travelling time between doors. If neither condition is met, we calculate the maximum possible travelling time, representing the distance to the furthest inbound door from the outbound door. Finally, the outbound truck selects the outbound door, providing the minimum total travelling times for pallets that it will receive.

6.1.4 Performance evaluation

The proposed model's key performance indicators (KPIs) are specified according to the objective function of VB : the weighted sum of the total travelling time of pallets and the total tardiness of inbound and outbound trucks. Therefore, the model KPIs are defined as follows:

- **Total travelling time of pallets (in minutes):** This metric closely parallels the one defined for the model studied in Chapter 5. The only difference lies in the method of calculating pallet travelling time. Unlike the model in Chapter 5, which uses a pallet travel time counter, the model in this chapter relies on the rectilinear distances between dock doors, which VB already predetermined. Note that VB does not specify a time unit for these distances. Therefore, in this model, we assume that travel times between dock doors are measured in minutes. These rectilinear distances between dock doors within the platform are presented in Table 6.2 in Section 6.2.1.
- **Inbound and outbound truck tardiness (in minutes):** When a truck leaves the system, the model calculates the difference between the due date and the leaving time of that specific truck. If the resulting calculation is greater than zero, that truck is marked as late, and its tardiness is logged into the simulation's output.
- **Computation time:** As stated in Chapter 5, the computation time is an important metric since the proposed model is intended to be used for real-time scheduling. We recall that VB employs the MIP method. Since MIP requires high computation time (more than 7200 seconds) to solve large problem instances, the authors use a tabu search approach to solve the problem within a reasonable time. Therefore, we defined the computation time as a performance metric to determine whether the proposed model provides quick scheduling within a reasonable time limit compared to the MIP model. To this end, the total computation time of each problem type is logged into the system output at the end of the simulation.

6.2 Experimentation

In this section, we first describe the data set used for the experimentation. Then, we provide the experimental settings used in this chapter, followed by the analyses on the main KPI presented in Section 6.1.4.

6.2.1 Description of the input data

We use the same data set as *VB*. In this section, we give a brief description of this data set for the sake of completeness. In *VB*, the input is generated by varying the following three parameters as follows:

1. **The number of trucks:** This parameter is defined by both the problem size based on the number of trucks and dock doors and the proportion between the number of trucks and dock doors. It can take one of the following values:
 - Low: 4 or 5 trucks for each inbound and outbound truck set.
 - Medium: 6 or 7 trucks for each inbound and outbound truck set.
 - High: 8 or 9 trucks for each inbound and outbound truck set.
 - Extra-high: 25 or 30 trucks for each inbound and outbound truck set.
2. **Flow mix:** It determines the distribution amount of product flow to outbound trucks:
 - Low: 25-50% of the outbound trucks receive their contents from each inbound truck.
 - Medium: 50-75% of the outbound trucks receive their contents from each inbound truck.
 - High: 75-100% of the outbound trucks receive their contents from each inbound truck.
3. **Time window:** This parameter specifies the arrival and departure times of both inbound and outbound trucks. For each arrival and departure time of trucks, a particular time interval is specified, and it is defined as low, medium and high.

The problem instances are grouped into two sets based on specific combinations of parameter values presented above. These two sets are given as follows:

- **Set 1:** In this set, the parameters take low, medium, and high values, resulting in 27 unique problem types. For each problem type, ten instances are generated, resulting in 270 instances. Two weighting factors are used to address the relevant importance of the two objectives: w_1 represents the weighting factor for the total travel time of the pallets, while w_2 represents the weighting factor for the total tardiness of trucks. The following three combinations of these factors are used to solve the total of 270 instances: $(w_1 = 1; w_2 = 2)$, $(w_1 = 1; w_2 = 5)$, and $(w_1 = 1; w_2 = 10)$.
- **Set 2:** In contrast, Set 2 focuses on a different scenario. Here, parameter 1, which corresponds to the number of trucks, takes an extra-high value. Parameters 2 and 3 contain all available values. Consequently, this set has nine unique problem types, each represented by five instances, resulting in 45 instances. To solve these instances within Set 2, the following values of the weighting factors are used: $(w_1 = 1; w_2 = 2)$.

The constant simulation parameters and the travel times between inbound and outbound dock doors inside the cross-dock are delivered in detail in Tables 6.1 and 6.2, respectively. Note that since the time unit is not provided by *VB*, we assumed the time unit in minutes in our proposed model.

Table 6.1: Constant input parameters of the proposed hybrid simulation model

Parameters	Values
Number of dock doors	
Inbound doors	3
Outbound doors	3
Truck capacity (in pallets)	33
Process times	
Unloading time (per pallet in minutes)	2
Loading time (per pallet in minutes)	2
Truck changeover time (in minutes)	3
Distributed temporary storage capacity	Unlimited

Table 6.2: Travel times (in minutes) between inbound and outbound dock doors

Inbound doors	Outbound doors		
	1	2	3
1	2.0	3.0	4.0
2	3.0	2.0	3.0
3	4.0	3.0	2.0

Recall from Chapters 4 and 5 that the proposed multi-agent-based approach is proven efficient for solving very large problem instances compared to the instances of VB (e.g. for single-inbound and single-outbound door model: 288 inbound and 288 outbound trucks and 7488 pallets; for 20 inbound and 20-outbound door model: 4615 inbound and 4615 outbound trucks and 120000 pallets in a single simulation run). Therefore, for the solution of the proposed model in this chapter, we select the problem types from the benchmark instances of VB with the following parameter values below:

- **Number of trucks:** high (H), medium (M), low (L) (for instance set 1) and extra-high (E) (for instance set 2).
- **Flow mix:** high (H) (for both instance sets 1 and 2).
- **Time window:** high (H) (for both instance sets 1 and 2).

The model's responsiveness is tested over the average simulation outcomes of the instances based on the specified parameters given above. To this end,

- Ten instances of each of the total three problem types (from the instance set 1) are selected. For the solution, the three combinations of weighting factors w_1 and w_2 are used, resulting in a total of ninety instances.
- Five instances of one problem type (from the instance set 2) are used, and for the solution, one combination of weighting factors w_1 and w_2 are employed, which resulted in five instances.

The selected benchmark instances and the combinations of the weighting factors w_1 and w_2 for the solution of the proposed model are presented in Table 6.3.

Table 6.3: The selected benchmark instances for the proposed multi-agent hybrid model

	Problem type combinations	Weighting factor combinations
Instance set 1	(L, H, H); (M, H, H); (H, H, H)	$(w_1=1, w_2=2)$; $(w_1=1, w_2=5)$; $(w_1=1, w_2=10)$
Instance set 2	(E, H, H)	$(w_1=1, w_2=2)$

6.2.2 Experimental settings

The model experimentation is carried out on the AnyLogic Simulation Software (University edition 8.7.10), using a PC with an Intel(R) Core(TM) i5-8250U CPU at 1.60 GHz, and 16.0 GB of RAM.

The analysis is made on the average simulation outcomes by applying the combination of each truck selection policy (i.e. FCFS, EDD, and MATP) and each door selection rule (i.e. FAD and MTTP) (see Table 6.4). Each strategy combination is employed for each of the total ninety-five instances, resulting in 570 instances.

Table 6.4: Combination of truck and door selection strategies

Combinations	Truck-to-door assignment		Door selection	
	Inbound truck	Outbound truck	Inbound door	Outbound door
S1	FCFS	FCFS	FAD	FAD
S2	FCFS	FCFS	MTTP	MTTP
S3	EDD	EDD	FAD	FAD
S4	EDD	EDD	MTTP	MTTP
S5	MATP	MATP	FAD	FAD
S6	MATP	MATP	MTTP	MTTP

6.2.3 Analysis on the KPI results

The average results of the first instance set are presented in Tables 6.5 to 6.7. The first column of these three tables displays the problem types, denoted by the value (L = low, M = medium, H = high) for its three parameters, taking the values of L, M and H for the number of trucks and H for flow mix and time window. The tabu search heuristics are shown with the simplified representation (TS1) and (TS2). Note that to avoid the long computation times, the authors use a simplified constraint for MIP to determine outbound truck end times, and TS1 is also provided with this simplified equation for an impartial comparison of the results. However, another constraint that obtains the exact end times of outbound trucks is employed by the TS2 approach only for the first instance set. The relative deviation (%) of the TS1 to MIP is delivered in the fifth column. The results of the proposed multi-agent-based hybrid method based on the six strategies (i.e. S1 to S6) are shown in the subsequent columns. The following columns deliver each strategy's relative deviations (%) to TS1.

Note that due to the close alignment between the results of TS1 and MIP, we have chosen to exclusively display the relative deviations of the strategies to TS1 for the sake of brevity. For a complete presentation of the relative deviations of the strategies to both TS1 and MIP, as well as the results for instances of each problem type, please refer to Tables E.1 to E.3 in Appendix E.

The results of the second instance set are summarised in Table 6.8. The structure of this table is the same as the tables of the first instance set results. However, contrary to them, one problem type is displayed by one combination of its three parameters. These parameters take the values of E

(extra-high) for the number of trucks and H (high) for the flow mix and time window. As for the first instance set, in Table 6.8, only the relative deviations of the strategies to TS1 are displayed for simplicity. The complete results are available in Table E.4 in Appendix E.

As shown in Tables 6.5 to 6.7, our proposed multi-agent-based real-time model exhibits varying levels of average relative deviation from the optimal solution of *VB* across different problem types within the first instance set. Specifically, the relative deviations range from 17% to 30% for problem types presented in Tables 6.5 to 6.7.

Regarding the second instance set, characterised by a higher average number of trucks (ranging from 50 to 60 trucks on average), our proposed multi-agent-based hybrid model maintains a consistent performance profile. The results indicate relative deviations ranging from 20% to 25% above *VB*, as shown in Table 6.8.

These results emphasise the consistent performance of our proposed multi-agent-based real-time model across various problem types and instance sets. However, we also observe that the yielding results are away from the optimal solutions provided by *VB* by a margin varying between 17% and 30% margin from the optimal solution of *VB*. This result is quite expected, given that the optimal solutions in *VB* are calculated in a deterministic environment, meaning that the complete information on the system, such as truck arrivals and departure times and their contents (i.e., pallet types and their inbound and outbound truck pairs), are known in advance. In our case, the proposed model employs real-time data from the system and makes the related best decisions on a real-time basis. In other words, the information related to pallets and trucks is revealed only when the truck arrives at the cross-dock. Therefore, there is no visibility on the upcoming events and, of course, no visibility on the overall data.

The central objective of this chapter is not to compare the individual performance of the various strategies tested here. Our focus lies in analysing the responsiveness and effectiveness of our proposed multi-agent-based real-time approach across diverse problem settings. Nevertheless, we can say a few words about the performance of the strategies tested on the setting of *VB*: Even though the results are within relatively close ranges for all strategies, we observe that S6 gives the best results in most cases, followed by S5 for some configurations. This is a relevant result because S6 incorporates policies with the aim of minimising pallet travel times, both for truck and door selection (MATP and MTTP for truck and door selections, respectively). Similarly, S5, which gives the best performance for two instance settings, uses MATP for truck selection, influencing hence the travelling time of pallets.

Table 6.5: Results (average values) of the multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=2$

Problem instance	Objective value			Relative deviation (%)						KPI value						Relative deviation to TSI (%)						
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	
(L, H, H)	957.740	974.641	957.740	0.000	1141.206	1131.326	1142.706	1133.426	1141.506	1126.226	20.412	19.310	20.604	19.525	20.305	18.539	18.539	18.539	18.539	18.539	18.539	18.539
(M, H, H)	1704.644	1723.057	1703.419	0.065	2062.061	2040.469	2054.043	2024.244	2018.411	1997.043	20.949	19.752	20.768	19.029	18.550	17.217	17.217	17.217	17.217	17.217	17.217	17.217
(H, H, H)	2437.626	2466.332	2436.826	0.035	3056.216	3063.336	3054.471	3072.651	2974.959	3008.247	25.502	25.793	25.403	26.167	22.102	23.368	23.368	23.368	23.368	23.368	23.368	23.368

Table 6.6: Results (average values) of the multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=5$

Problem instance	Objective value			Relative deviation (%)						KPI value						Relative deviation to TS1 (%)						
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	
(L, H, H)	2076.650	2123.041	2076.650	0.000	2520.165	2501.616	2523.165	2505.816	2520.765	2490.816	22.744	21.807	22.923	22.003	22.643	21.062	21.062	21.062	21.062	21.062	21.062	21.062
(M, H, H)	3748.651	3794.954	3743.348	0.142	4608.402	4566.872	4583.407	4526.910	4511.878	4466.709	22.892	21.872	22.547	21.056	20.516	19.230	19.230	19.230	19.230	19.230	19.230	19.230
(H, H, H)	5428.291	5496.029	5420.664	0.144	6942.739	6965.789	6943.479	6987.876	6753.546	6844.717	28.074	28.492	28.067	28.903	24.526	26.081	26.081	26.081	26.081	26.081	26.081	26.081

Table 6.7: Results (average values) of the multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=10$

Problem instance	Objective value		Relative deviation (%)						KPI value						Relative deviation to TS1 (%)							
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	
(L, H, H)	3939.701	4037.049	3938.501	0.022	4818.430	4785.431	4823.930	4793.131	4819.530	4765.131	23.783	22.908	23.956	23.098	23.684	22.175						
(M, H, H)	7151.902	7246.665	7142.277	0.134	8852.303	8777.543	8799.013	8698.020	8667.655	8582.817	23.733	22.784	23.323	21.933	21.366	20.100						
(H, H, H)	10406.981	10540.869	10390.860	0.157	13420.278	13469.879	13425.157	13513.253	13051.193	13238.835	29.147	29.616	29.177	30.042	25.540	27.209						

Table 6.8: Results (average values) of the multi-agent-based hybrid model on benchmark instance set 2 with $w_1=1$ and $w_2=2$

Problem instance	Objective value		Relative deviation (%)						KPI value						Relative deviation to TS1 (%)						
	TS1	MIP	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	
(E, H, H)	30387.582	30213.511	0.494	37922.195	37845.211	37498.342	37525.444	36984.698	36639.331	24.820	24.516	23.504	23.581	21.875	20.833						

6.2.4 Analysis on the computation times

As [Van Belle et al. \(2013\)](#) stated, *VB* is difficult to solve since the computation times of CPLEX growth as the parameter values within the problem types are increased. However, the tabu search employed in *VB* provides results in less than 1.2 seconds, and the average calculation time per problem type is less than 1 second for the first instance set. The proposed multi-agent-based hybrid model provides results in less than 0.2 seconds, ranging between 0.05 seconds and 0.6 seconds per instance within the same problem type (see [Tables 6.9 to 6.11](#)).

For the second instance set, the proposed model delivers results in 1.5 seconds on average (see [Table 6.12](#)). Although the calculation times of TS1 are short, the proposed model solves the problem on an average of six times quicker than TS1 (e.g. for (H, H, H) problem type in [Table 6.9](#), the average calculation times of TS1 and S6 are 1.025 and 0.157 seconds, respectively).

These results provide a potential finding: while the computation time difference between the proposed model and TS1 may seem comparable in the current problem configuration, where there are 50 to 60 trucks and an average of 750 pallets in a single simulation run for a 3-inbound and 3-outbound door cross-dock, it is essential to recall the capabilities of our multi-agent-based model in [Chapters 4 and 5](#). The models in these chapters showcased their efficiency by successfully handling significantly higher traffic levels of trucks and pallet flows, specifically handling a total of 4615 inbound and 4615 outbound trucks and 120,000 pallets in a single simulation run for a 20-inbound and 20-outbound door cross-dock. It is also important to note that the original models of *VB* (as tested by [Van Belle et al. \(2013\)](#)) and our proposed model are run on the computers with different processing power and RAM capacities. These hardware differences may have also contributed to variations in computation times and should be taken into consideration when interpreting the results.

Table 6.9: Computation time of the proposed multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=2$

Problem instance	Computation time (in seconds)								
	Mathematical optimisation model			Multi-agent-based hybrid model					
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6
(L, H, H)_1	0.156	0.686	0.560	0.070	0.088	0.049	0.057	0.049	0.096
(L, H, H)_2	0.160	0.640	0.280	0.065	0.073	0.082	0.078	0.053	0.078
(L, H, H)_3	0.154	0.671	0.520	0.080	0.070	0.079	0.072	0.083	0.092
(L, H, H)_4	0.158	0.735	1.670	0.112	0.089	0.093	0.118	0.099	0.101
(L, H, H)_5	0.118	0.406	0.280	0.093	0.076	0.071	0.076	0.103	0.136
(L, H, H)_6	0.116	0.390	0.230	0.102	0.106	0.096	0.084	0.075	0.115
(L, H, H)_7	0.119	0.469	0.360	0.083	0.079	0.102	0.070	0.077	0.098
(L, H, H)_8	0.159	0.717	0.640	0.101	0.101	0.085	0.094	0.076	0.087
(L, H, H)_9	0.158	0.718	0.250	0.129	0.101	0.077	0.119	0.072	0.109
(L, H, H)_10	0.217	1.155	1.720	0.087	0.092	0.118	0.096	0.092	0.104
Average	0.152	0.659	0.651	0.092	0.088	0.085	0.086	0.078	0.102
(M, H, H)_1	0.438	3.417	46.350	0.144	0.136	0.160	0.163	0.126	0.130
(M, H, H)_2	0.421	3.511	100.320	0.172	0.130	0.127	0.129	0.137	0.126
(M, H, H)_3	0.359	2.388	11.970	0.134	0.106	0.112	0.137	0.115	0.120
(M, H, H)_4	0.703	4.853	1012.900	0.146	0.165	0.171	0.148	0.136	0.176
(M, H, H)_5	0.562	5.009	2021.740	0.131	0.121	0.137	0.136	0.127	0.139
(M, H, H)_6	0.422	3.386	6.500	0.125	0.107	0.117	0.117	0.142	0.113
(M, H, H)_7	0.608	4.556	209.600	0.154	0.120	0.114	0.143	0.107	0.116
(M, H, H)_8	0.484	3.839	86.220	0.134	0.152	0.161	0.116	0.130	0.147
(M, H, H)_9	0.577	4.614	1483.430	0.128	0.134	0.134	0.133	0.125	0.124
(M, H, H)_10	0.484	3.318	35.160	0.131	0.163	0.109	0.119	0.114	0.105
Average	0.506	3.889	501.419	0.140	0.133	0.134	0.134	0.126	0.130
(H, H, H)_1	0.988	5.009	7201.100	0.119	0.153	0.174	0.163	0.159	0.158
(H, H, H)_2	1.177	5.008	7200.910	0.173	0.174	0.201	0.169	0.142	0.183
(H, H, H)_3	0.985	5.008	7200.630	0.610	0.190	0.211	0.171	0.151	0.150
(H, H, H)_4	0.816	5.008	7200.760	0.120	0.121	0.161	0.111	0.123	0.123
(H, H, H)_5	1.224	5.008	7201.240	0.166	0.174	0.201	0.177	0.175	0.168
(H, H, H)_6	1.024	5.009	7200.730	0.167	0.192	0.162	0.194	0.163	0.126
(H, H, H)_7	0.807	5.009	7200.880	0.139	0.135	0.520	0.132	0.152	0.146
(H, H, H)_8	1.156	5.009	7200.990	0.193	0.165	0.170	0.185	0.192	0.160
(H, H, H)_9	1.001	5.009	7201.070	0.174	0.179	0.181	0.187	0.168	0.168
(H, H, H)_10	1.071	5.009	7201.220	0.196	0.138	0.176	0.171	0.223	0.185
Average	1.025	5.009	7200.953	0.206	0.162	0.216	0.166	0.165	0.157

Table 6.10: Computation time of the proposed multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=5$

Problem instance	Computation time (in seconds)								
	Mathematical optimisation model			Multi-agent-based hybrid model					
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6
(L, H, H)_1	0.162	0.718	0.580	0.070	0.098	0.059	0.067	0.059	0.106
(L, H, H)_2	0.161	0.672	0.280	0.085	0.073	0.082	0.078	0.073	0.098
(L, H, H)_3	0.160	0.702	0.270	0.080	0.070	0.079	0.072	0.083	0.092
(L, H, H)_4	0.161	0.765	0.690	0.112	0.089	0.093	0.118	0.099	0.101
(L, H, H)_5	0.122	0.437	0.390	0.093	0.076	0.071	0.076	0.103	0.136
(L, H, H)_6	0.120	0.421	0.170	0.102	0.106	0.096	0.084	0.095	0.115
(L, H, H)_7	0.120	0.500	0.360	0.083	0.079	0.102	0.070	0.077	0.098
(L, H, H)_8	0.161	0.749	0.500	0.101	0.101	0.085	0.094	0.076	0.087
(L, H, H)_9	0.158	0.749	0.410	0.149	0.101	0.097	0.139	0.092	0.129
(L, H, H)_10	0.217	1.156	1.560	0.087	0.092	0.118	0.096	0.092	0.104
Average	0.154	0.687	0.521	0.096	0.089	0.088	0.089	0.085	0.107
(M, H, H)_1	0.455	3.551	64.430	0.164	0.136	0.160	0.163	0.126	0.130
(M, H, H)_2	0.437	3.991	162.540	0.172	0.130	0.127	0.129	0.137	0.126
(M, H, H)_3	0.370	2.421	9.480	0.134	0.106	0.112	0.137	0.115	0.120
(M, H, H)_4	0.637	5.002	1205.250	0.146	0.165	0.171	0.148	0.136	0.176
(M, H, H)_5	0.550	5.002	2341.260	0.131	0.121	0.137	0.136	0.127	0.139
(M, H, H)_6	0.434	3.431	8.030	0.125	0.107	0.117	0.117	0.142	0.113
(M, H, H)_7	0.544	4.901	404.540	0.154	0.120	0.114	0.143	0.107	0.116
(M, H, H)_8	0.512	4.502	78.110	0.134	0.152	0.161	0.116	0.130	0.147
(M, H, H)_9	0.520	4.711	7200.680	0.128	0.134	0.134	0.133	0.125	0.124
(M, H, H)_10	0.446	3.401	31.950	0.131	0.163	0.109	0.119	0.114	0.105
Average	0.491	4.091	1150.627	0.142	0.133	0.134	0.134	0.126	0.130
(H, H, H)_1	0.968	5.001	7201.180	0.139	0.173	0.194	0.183	0.179	0.198
(H, H, H)_2	1.186	5.001	7200.570	0.173	0.174	0.221	0.169	0.142	0.183
(H, H, H)_3	1.000	5.001	7200.870	0.618	0.195	0.218	0.175	0.152	0.152
(H, H, H)_4	0.796	5.001	7200.730	0.148	0.141	0.181	0.131	0.143	0.143
(H, H, H)_5	1.141	5.001	7201.160	0.166	0.174	0.206	0.177	0.175	0.168
(H, H, H)_6	1.015	5.002	7201.460	0.167	0.192	0.162	0.194	0.163	0.196
(H, H, H)_7	0.874	5.001	7200.680	0.139	0.135	0.540	0.152	0.152	0.166
(H, H, H)_8	1.156	5.001	7201.240	0.193	0.165	0.170	0.185	0.192	0.160
(H, H, H)_9	0.984	5.003	7200.690	0.194	0.199	0.181	0.187	0.168	0.168
(H, H, H)_10	1.078	5.001	7201.080	0.196	0.138	0.176	0.171	0.223	0.185
Average	1.020	5.001	7200.966	0.213	0.169	0.225	0.172	0.169	0.172

Table 6.11: Computation time of the proposed multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=10$

Problem instance	Computation time (in seconds)								
	Mathematical optimisation model			Multi-agent-based hybrid model					
	TS1	TS2	MIP	S1	S2	S3	S4	S5	S6
(L, H, H)_1	0.281	0.718	0.440	0.090	0.098	0.059	0.067	0.059	0.106
(L, H, H)_2	0.172	0.677	0.520	0.085	0.078	0.082	0.081	0.083	0.101
(L, H, H)_3	0.156	0.685	0.160	0.080	0.070	0.079	0.072	0.083	0.092
(L, H, H)_4	0.234	1.141	1.440	0.112	0.089	0.093	0.118	0.099	0.101
(L, H, H)_5	0.110	0.398	0.270	0.093	0.076	0.071	0.076	0.103	0.136
(L, H, H)_6	0.109	0.425	0.440	0.102	0.106	0.096	0.084	0.095	0.115
(L, H, H)_7	0.124	0.487	0.310	0.083	0.079	0.102	0.070	0.077	0.098
(L, H, H)_8	0.156	0.733	0.500	0.101	0.106	0.085	0.094	0.076	0.087
(L, H, H)_9	0.157	0.766	0.470	0.149	0.101	0.097	0.139	0.092	0.129
(L, H, H)_10	0.234	1.131	1.670	0.087	0.092	0.118	0.096	0.092	0.104
Average	0.173	0.716	0.622	0.098	0.090	0.088	0.090	0.086	0.107
(M, H, H)_1	0.468	3.440	155.850	0.164	0.136	0.160	0.163	0.126	0.130
(M, H, H)_2	0.421	3.607	106.630	0.172	0.134	0.127	0.129	0.137	0.126
(M, H, H)_3	0.344	2.369	10.280	0.134	0.106	0.112	0.137	0.115	0.120
(M, H, H)_4	0.624	5.001	964.490	0.149	0.165	0.173	0.148	0.138	0.177
(M, H, H)_5	0.577	5.001	1774.450	0.131	0.121	0.137	0.136	0.127	0.139
(M, H, H)_6	0.437	3.411	3.990	0.125	0.107	0.117	0.117	0.142	0.113
(M, H, H)_7	0.546	4.371	231.490	0.156	0.122	0.116	0.143	0.109	0.129
(M, H, H)_8	0.640	3.663	102.900	0.134	0.152	0.162	0.116	0.130	0.147
(M, H, H)_9	0.515	4.548	7200.630	0.128	0.134	0.134	0.133	0.125	0.124
(M, H, H)_10	0.437	3.367	35.320	0.131	0.163	0.109	0.119	0.114	0.105
Average	0.501	3.878	1058.603	0.142	0.134	0.135	0.134	0.126	0.131
(H, H, H)_1	0.968	5.003	7200.800	0.139	0.173	0.194	0.183	0.179	0.198
(H, H, H)_2	1.171	5.002	7200.900	0.173	0.174	0.221	0.169	0.142	0.183
(H, H, H)_3	0.999	5.002	7201.050	0.618	0.195	0.218	0.175	0.152	0.152
(H, H, H)_4	0.811	5.002	7200.880	0.148	0.141	0.181	0.131	0.143	0.143
(H, H, H)_5	1.125	5.002	7200.820	0.166	0.174	0.206	0.177	0.175	0.168
(H, H, H)_6	0.999	5.002	7200.960	0.167	0.192	0.162	0.194	0.163	0.196
(H, H, H)_7	0.827	5.002	7200.690	0.139	0.135	0.540	0.152	0.152	0.166
(H, H, H)_8	1.141	5.003	7200.910	0.193	0.165	0.171	0.185	0.192	0.160
(H, H, H)_9	0.952	5.001	7200.770	0.194	0.205	0.183	0.187	0.168	0.168
(H, H, H)_10	0.999	5.002	7200.730	0.196	0.138	0.176	0.171	0.223	0.185
Average	0.999	5.002	7200.851	0.213	0.169	0.225	0.172	0.169	0.172

Table 6.12: Computation time of the proposed multi-agent-based hybrid model on benchmark instance set 2 with $w_1=1$ and $w_2=2$

Computation time (in seconds)								
Problem	Mathematical optimisation model		Multi-agent-based hybrid model					
instance	TS1	MIP	S1	S2	S3	S4	S5	S6
(E, H, H)_1	5.025	7200.180	1.727	1.785	1.696	1.697	1.652	1.683
(E, H, H)_2	5.008	7200.240	1.053	1.037	1.077	1.016	1.063	1.007
(E, H, H)_3	5.008	7200.210	1.795	1.830	1.766	1.784	1.779	1.755
(E, H, H)_4	5.010	7200.240	1.155	1.186	1.150	1.104	1.117	1.146
(E, H, H)_5	5.024	7200.190	1.901	1.829	1.845	1.873	1.866	1.964
Average	5.015	7200.212	1.526	1.533	1.507	1.495	1.495	1.511

6.3 Conclusion

This chapter presents an adaptable version of our multi-agent-based hybrid model, as presented in Chapters 4 and 5. This adaptation addresses a wide range of truck scheduling problem configurations, particularly those involving mathematical optimisation. To illustrate its adaptability to other settings, we selected a truck scheduling study by [Van Belle et al. \(2013\)](#), referred to as *VB*, in this chapter.

Our model incorporates door and truck agents making crucial truck and door selection decisions, respectively. This combined decision-making mechanism improves the model's capacity to align with the objectives of *VB*. We also integrate various truck and door selection policies from our prior models, resulting in six specific combinations of truck selection (i.e. FCFS, EDD, MATP) and door selection (i.e. FAD, MTTP) rules. These combinations allow us to assess the model's performance comprehensively. To evaluate the model, we define key performance indicators based on the objective function of *VB*. We test our model using benchmark instances from *VB* with various scenarios.

From the numerical experiments we can draw several conclusions:

Firstly, we have shown that the proposed multi-agent-based hybrid model can be adapted to other problem settings. This adaptation requires modification of the model's physical setting and decision-making mechanisms. These modifications can be done with more or less effort, depending on the model's assumptions. For the case of *VB*, we can say that the modifications have been rather easy since *VB* has many simplifying assumptions, especially for the execution of internal operations.

Secondly, we have observed that the execution times are extremely fast for all instances, including the biggest ones. They are comparable to TS1 proposed in [Van Belle et al. \(2013\)](#). In the previous chapter, we have tested our model on much bigger instances and more complex environments. It might be interesting to test the performance of TS1 on such bigger instances as well.

Thirdly, we have observed that, regarding the key performance indicators, our hybrid model gives results within 17% to 30% of the results provided by the best algorithm presented in [Van Belle et al. \(2013\)](#) for the *VB*. This is a considerable gap but, as mentioned before this was also expected since the optimisation models developed in [Van Belle et al. \(2013\)](#) have the complete information while generating the solution. In contrast, in our hybrid model, the decisions are made in real-time without knowledge of future events.

A possible future direction of this study can be operating the proposed multi-agent-based model with the moving time window of the known future. For instance, if we have a sliding time window of fifteen minutes, the model would be informed about events, such as truck arrivals, departures, and their contents, expected to occur within the next fifteen minutes. With this additional knowledge, the model can make more informed decisions. In the given example, the inbound door agent could select the inbound truck that minimises the total travelling time of pallets by considering not only the current situation but also the expected future arrivals and their impact. By experimenting with different time window lengths, we can assess how much the model's performance improves when it has access to varying degrees of future information. We believe that this will approach the performance of our model to the optimisation model, but this still remains to be proven.

To wrap up, it is essential to acknowledge the assumptions and limitations of both modelling approaches. Given that realistic scenarios of truck scheduling involve complexities and uncertainties, the mathematical optimisation models may not fully capture them. For instance, mathematical optimisation models often rely on idealised assumptions, assuming perfect information availability and deterministic inputs. These assumptions can limit their applicability in scenarios with uncertain data and variations, such as unpredictable truck arrivals or equipment failures. On the other hand, agent-based hybrid models can handle more realistic settings by considering the challenges faced in real-world cross-docking practices. For instance, it can incorporate more easily uncertainty into

the scheduling process or model complex internal operations inside the platform for cross-docking applications.

7

Conclusion and perspectives

In this concluding chapter, we summarise the key research findings aligning with the research aims and questions, highlighting their significance and contributions. Then, we discuss the study's limitations while addressing the potential directions for future research which could enhance and expand upon the proposed models.

7.1 Summary of the contributions

Cross-docking is a just-in-time (JIT) logistics practice implemented in a warehouse to achieve a competitive advantage by consolidating and transferring goods directly from an inbound supplier to an outbound customer on short notice and with no or limited storage. Despite its significant advantages of optimising distribution, reducing handling and inventory costs and facilitating faster delivery times, cross-docking requires prompt synchronisation of its inbound and outbound processes under fast-changing and uncertain conditions.

Robust models play a crucial part in addressing this challenge. However, when these challenges surpass manageable thresholds, there is a need for new planning methods to react promptly to fast-changing and uncertain conditions as they arise. To this end, real-time models empowered by Industry 4.0 technologies take centre stage, offering complete and synchronised visibility of the processes.

This thesis study aimed to develop a real-time model to schedule incoming and outgoing trucks and, thus, pallet flow in a cross-docking platform in an uncertain environment.

As an initial contribution, Chapter 2 presents the state-of-the-art review of robust and real-time models in the context of cross-docking, with a specific emphasis on scheduling problems, particularly within the road-to-road cross-dock environment. The systematic literature review encompasses various steps, including collecting, identifying, screening, eligibility, and inclusion to extract the most relevant research, but also highlights critical gaps within the existing literature. First of all, there is a limited implementation of real-time models in the cross-docking literature despite their potential for adaptive decision-making, enhancing operational flexibility, efficiency, and responsiveness. Secondly, dynamic models, such as simulation and multi-agent-based models, are firmly committed to achieving this pursuit.

Based on the findings of the previous chapter, Chapter 3 performs an in-depth analysis of the literature focusing on the predominantly employed simulation methods in cross-dock problems, namely, multi-agent-based and discrete-event simulations and their hybrid applications (i.e. the combination of MAS and DES). Within this chapter, we explain these modelling techniques by discussing their practical usefulness and limitations under different operational conditions. This chapter highlights the importance of problem-driven methodology selection. Consequently, it aims to equip us with the essential tools for designing a novel model capable of real-time scheduling incoming and outgoing trucks and, thus, pallet flow in a cross-docking terminal. Moreover, it provides valuable insights into configuring the terminal's internal operations to be responsive to real-time incoming and outgoing flows.

In Chapter 4, we develop a novel model for real-time truck scheduling for cross-docking. By the motivation of the insights in Chapter 3, which highlights the significance of problem-driven methodology selection, this dynamic model is implemented as multi-method modelling, consisting of multi-agent-based and discrete-event simulations. We aim to rapidly synchronise cross-docking operations using the multi-agent systems' autonomous, reactive and distributed responsibility attributes to enable shared computation and react flexibly to dynamic events. Our study provides a proof of concept on the use of a hybrid model for real-time truck scheduling in cross-docks. To this aim, both trucks and dock doors are defined as agents for decision-making. For the configurations of the internal operations of the facility, we used DES for its simplicity and to reduce communication

burdens rooted in MAS models with numerous agents. The model is implemented for a single inbound and outbound doors cross-dock environment, allowing for an in-depth analysis of the interconnected components of the system. This way, we capture a deep sense of multi-agent-based real-time truck scheduling within cross-docking operations. The model analysis is carried out under the various truck scheduling strategies and across different traffic levels. The significance of the results is assessed by performing ANOVA. This model builds a concrete groundwork for scaling up to more complex cross-docking systems, notably multi-dock environments.

In Chapter 5, we develop an extended model upon the primary notions presented in Chapter 4 and launch a more thorough analysis to align with an industrial context. This model incorporates the nuances of managing multiple dock doors and decision-making strategies, providing a more accurate representation of the dynamic nature of cross-docking operations. Our study in this chapter contains a wide array of scenarios, including varying traffic levels and door configurations, with diverse truck and door selection rules. Through these investigations, supported by the statistical tests, we measure the adaptability and effectiveness of our model, confirming its applicability in diverse operational contexts. Following our findings, we assess the model's scalability by subjecting it to a broad spectrum of door set configurations. In parallel, we monitor its computational efficiency under the applicable temporal conditions representing real-world cross-docks. It becomes evident that computational challenges arise, especially when the total number of dock doors exceeds 30. This challenge becomes even more noticeable under intricate door selection strategies at the 20-inbound and 20-outbound door configurations. To address these computational challenges, we examine computational performance, monitoring computation times at two-hour intervals during a 48-hour simulation period. Our findings indicate that the model can effectively achieve real-time scheduling if the simulation duration remains within the 2-3 hour range. This insight enables us to measure the model's practical utility for real-time scheduling applications, affirming its potential as a valuable tool in the cross-docking domain.

In Chapter 6, we develop a model in pursuit of validating the practical applicability of our proposed multi-agent-based hybrid model in solving various configurations of truck scheduling problems encountered in the cross-docking literature. To this end, we chose a truck scheduling study, referred to as "VB" within this thesis, specially tailored for deterministic scheduling methods. We adapted the decision-making mechanisms built in the models studied in Chapters 4 and 5 towards the focus of VB, along with the further mechanisms explicitly designed for that purpose. For the performance assessment, we use the same input datasets of VB for a fair comparison. Our analysis of the results balances the assumptions and limitations inherent in both modelling approaches. Our hybrid model's results fall behind (within 17% to 30%) those provided by the best algorithm presented in [Van Belle et al. \(2013\)](#) for the VB. This outcome is expected due to a fundamental difference in approach: the optimisation models developed by [Van Belle et al. \(2013\)](#) operate with complete information when generating solutions, while our hybrid model operates in real-time without knowledge of future events. In addition, mathematical optimisation models are limited in capturing the complexities and uncertainties inherent in real-world truck scheduling scenarios. In contrast, the strengths of our multi-agent-based hybrid model are in managing the practical challenges faced in actual cross-docking operations.

7.2 Perspectives

The research performed in this thesis paves the way for several short-, mid-, and long-term perspectives. To present a structured outline, we will first focus on the short-term research directions, followed by a discussion on the mid- and long-term prospects.

Short-term perspectives

In Chapters 4 and 5, we develop our models assuming unlimited temporary storage capacity in the studied cross-dock. However, the temporary storage could be subjected to the capacity limitation for a more realistic representation. Given that the unlimited storage presumption does not necessitate space allocation concern, when faced with capacity constraints, as in real-world scenarios, the efficient allocation of space becomes a critical factor. This adjustment towards real-life conditions will influence the performance of our existing storage-oriented strategies. In our models (in Chapters 4 and 5), pallets have specific destinations and can only be loaded onto trucks with matching destinations. When temporary storage operates within capacity limitations, our algorithms could strategically group pallets with the same destination inside the temporary storage area. This strategic allocation would optimise space utilisation, minimise retrieval times, mitigate congestion, and ultimately speed up the pallet flow throughout the platform.

In Chapter 5, we assess the performance and reliability of our real-time truck scheduling model in a multi-dock environment across diverse door sets and traffic levels while we assume unlimited temporary storage and workforce. To this end, a complete sensitivity analysis would be a valuable direction. It could be performed based on further input parameters, such as having a temporary storage capacity and its varying degrees and workforce availability (both operator and handling equipment). By varying input parameters and conditions, we could observe how changes in these parameters affect scheduling decisions and overall performance. This analysis could help identify which parameters have the most significant impact on the model's responsiveness. This identification will empower decision-makers to make informed choices to ensure that efforts are concentrated on the areas that have the most significant impact on performance, eventually leading to more efficient and responsive planning.

In addition, in Chapter 5, the algorithms operated for the model's door and truck selection rules, specifically more elaborated strategies (i.e. S6), appear to be computationally expensive. These algorithms could be optimised so that they consume less memory and thus execute more quickly. To this end, precise areas within these algorithms where memory-intensive processes or data structures originate would be identified. This identification could be achieved by code profiling techniques. For instance, the AnyLogic Software, where we built our hybrid model, is operated by using Java Programming Language. There are several tools to perform code profiling for Java (e.g. VisualVM, YourKit Java Profiler, JProfiler). By using these tools, we could run our hybrid model. The selected profiling tool will collect data on different metrics, such as function execution times and memory allocation. Then, we could inspect the yielded profiling outcomes, including CPU time used by each function, memory usage ways (including allocation and deallocation), function call hierarchy and call counts and finally, execution time and resource consumption. Based on the outcomes of these metrics, we could search for functions or code parts with high execution times or memory usage that are potential candidates for optimisation. Code optimisation includes operations such as decreasing unnecessary function calls, enhancing algorithm efficiency, adjusting data structures to minimise memory overhead and parallelising or optimising critical branches of the code. This code profiling could be performed iteratively until the expected improvements are reached.

Mid- and long-term perspectives

One notable advantage of our multi-agent-based hybrid model is its capability to simulate various scenarios. Although Chapters 4 and 5 primarily explored directly real-time scheduling, the robust-

ness of the truck schedules obtained by proactive methods (e.g. optimisation) could be evaluated by simulating these solutions. We could subject the truck schedules obtained from proactive methods to simulated perturbations within our model. These perturbations could include both internal factors, such as the unavailability of dock doors or equipment failures, and external factors, like unexpected truck delays, which commonly occur in real-world cross-dock environments. We could assess its real-time problem-solving abilities under adverse conditions by introducing these perturbations and observing how our model reacts. The model's reactivity to these disruptions and capacity to propose real-time solutions could be precisely tested. This assessment could add a layer of robustness evaluation to our research and further confirm the real-world relevance of our multi-agent-based hybrid model.

In Chapters 4 to 6, we operate our hybrid models in real-time, presenting an instantaneous perspective on cross-docking operations. However, as we encounter computational challenges, specifically when dealing with scenarios concerning more than 30 total dock doors, in Chapter 5, it would be interesting to implement a moving time window. This approach will supply the model with foresight into upcoming events, such as truck arrivals, departures, and their shipment contents, expected to occur within a specified timeframe, such as one hour. This approach could become especially relevant considering that our hybrid model in Chapter 6 falls short of reaching the performance of the optimisation model of Van Belle et al. (2013) for VB. Introducing a moving time window allows for creating a look-ahead environment where our simulation can approach the optimisation level. This further temporal dimension could equip our models with the ability to make more informed decisions, surpassing the limits of the present state. For instance, if we consider the decision-making process of the inbound door agent in these models, it could select the inbound truck that minimises the total travelling time of pallets. This decision would no longer be based only on current events but also consider the expected future arrivals and their potential impact on the operations. By experimenting with different time window lengths, we could assess the extent of performance enhancement attainable through varying degrees of future information access. Fine-tuning our models using this dynamic time window could significantly enhance real-time decision-making capabilities and overall operational efficiency.

While in many cross-docking facilities, internal operations are often focused on optimising the flow of goods, reducing handling time, and ensuring timely deliveries, sustainability considerations within internal operations may be minimal. As we face the severe impacts posed by climate change, it is crucial to integrate sustainability into cross-docking operations, ensuring that logistics practices not only optimise efficiency but also contribute to environmental responsibility. To this end, as a long-term perspective, a sustainability-driven approach could be incorporated into the internal operations of the facility, along with real-time truck scheduling. For instance, the model could incorporate algorithms that assess different route alternatives based on factors such as distance, traffic conditions, and fuel efficiency. Truck agents could be designed to prioritise routes that minimise fuel consumption and emissions. They may select routes with less congestion or pick highways with lower carbon emissions. Another approach to sustainability would be load consolidation: our hybrid model could optimise the allocation of pallets to trucks regarding factors such as weight distribution and capacity use. The model could prioritise consolidating shipments to minimise the number of trucks needed for transportation, reducing emissions per unit of pallet. By combining sustainability-driven internal operations with real-time truck scheduling, the facility could reach a more holistic practice of sustainability, benefiting both the environment and its bottom line.

In Chapters 4 to 6, our current work primarily counts on fundamental decision controls to drive our model's functionality. However, as we look towards the future, an exciting avenue that could be worth exploring is infusing our system with advanced intelligence. This could be through Reinforcement Learning (RL) application via autonomous agents. This forward-looking standpoint aims to strengthen our model with the capacity for learning and adaptation. For instance, RL agents would base their decisions on a cumulative learning ground created from earlier experiences and

interactions within the cross-docking environment. This learning-driven approach could improve the model's decision-making abilities, allowing it to evolve and optimise its strategies over time. This way, a more involved and intelligent design would be created, where decisions emerge from the collaborative knowledge of the agents. This long-term perspective of the transition towards learning will represent an exciting development in our study, promising more significant adaptability and efficiency in real-time truck scheduling for cross-docking processes.

Finally, as we stated, the model presented in Chapter 4 provides a proof of concept on the use of a hybrid model (of MAS and DES) for real-time truck scheduling in cross-docks. Furthermore, the extended model developed in Chapter 5, confirms its applicability to the real-world cross-dock environments. Therefore, as a long-term perspective, our proposed dynamic hybrid model could be applied more broader concept by the considering collaborative scheduling across multiple supply chain nodes. Given that our research focuses on the cross-dock scheduling, we ignore the network scheduling operations. However, our proposed hybrid model could be designed to reach into the broader supply chain. It could provide reactive solutions by communicating with suppliers and retailers to collect real-time data on order changes, delivery windows, and inventory levels. For instance, if a retailer would encounter sudden high demand on a specific product, the model could adjust the distribution plan to prioritise those items and assign more resources to ensure that retailers could meet customer demand on-time. The potential of such integration could provide holistic solutions for supply chain optimisation.

Appendix



The respective state charts of the truck and door agents

The corresponding state charts that define the behaviours of the inbound/outbound truck and inbound/outbound door agents in Chapter 4 are presented in Figures A.1 to A.4.

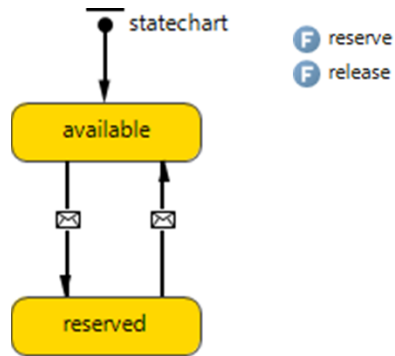


Figure A.1: The state chart of the inbound door agent

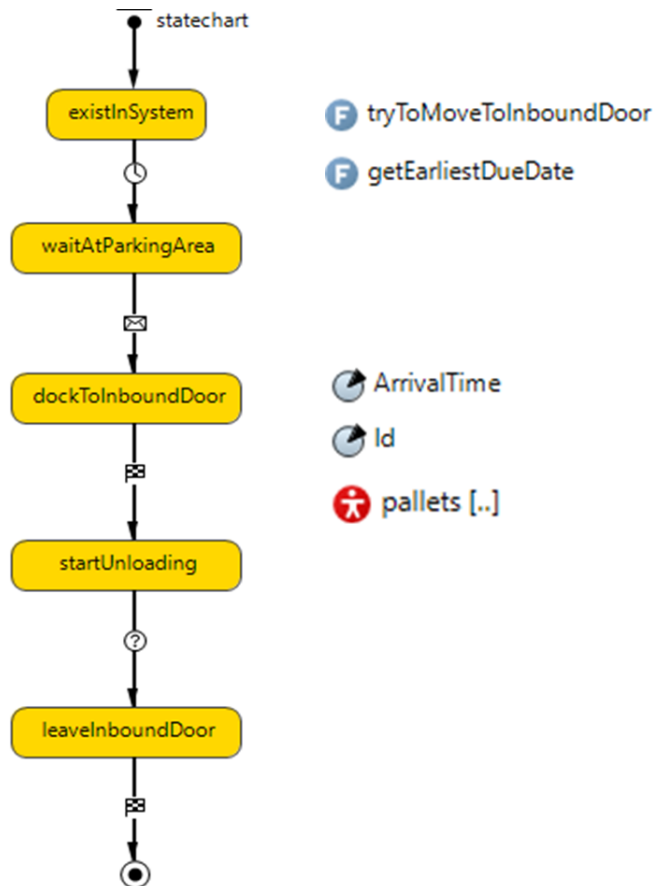


Figure A.2: The state chart of the inbound truck agent

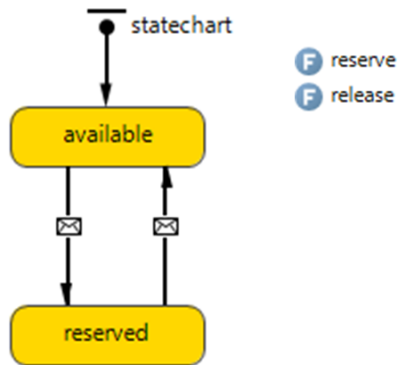


Figure A.3: The state chart of the outbound door agent

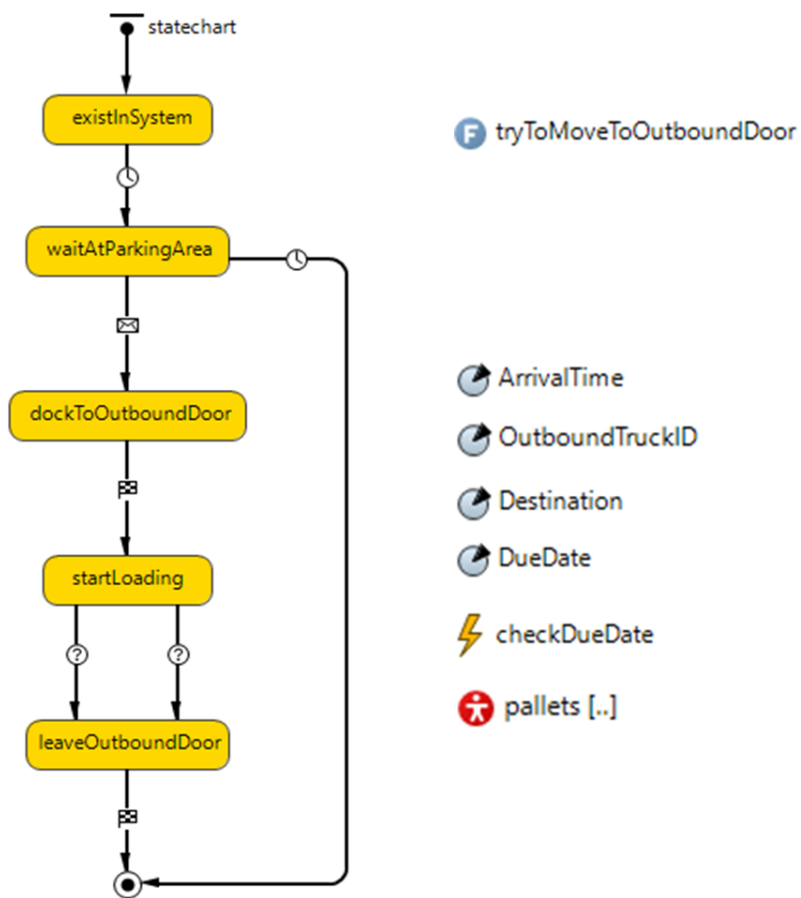


Figure A.4: The state chart of the outbound truck agent

B

Statistical test results for the model studied in
Chapter 5

The statistical test results of the multiple-door model studied in Chapter 5 are delivered in Tables B.1 to B.22.

Below, we present one-way ANOVA results alongside pairwise comparisons (see Tables B.1 to B.9 and B.11, B.13, B.15, and B.17). The tables organise dependent variables by traffic levels on the leftmost column, displaying parametric and nonparametric one-way ANOVA outcomes and corresponding pairwise comparisons in subsequent columns.

Parametric one-way ANOVA reveals results of the repetitive ANOVA for normally distributed, dependent samples denoted by F statistics and p-values. Nonparametric one-way ANOVA includes Kruskal-Wallis (H statistic, p-value) for independent samples and Friedman (χ^2 statistic, p-value) for dependent, not normally distributed samples. Note that for sample groups with not normally distributed data, only the nonparametric ANOVA results are presented in the corresponding tables (see Tables B.4, B.7, B.11, B.13, B.15, and B.17).

The significance (p-value) for both parametric and nonparametric ANOVA is assessed at a predetermined significance level ($\alpha = 0.05$). When p-value < 0.05 , ANOVA indicates significance, necessitating follow-up tests (i.e. pairwise comparisons) to determine contributing factors. Statistically significant results (p-value < 0.05) in the follow-up tests are shown in bold in the pairwise comparisons column.

When the overall p-value for both parametric and nonparametric one-way ANOVA exceeds the predetermined significance level (p > 0.05), dashes are employed in the corresponding tables' pairwise comparisons columns, indicating the nonsignificant results to signify the infeasibility of factor comparisons.

For the analysis of two sample groups, the paired t-tests (T statistic for normally distributed, dependent samples) and Wilcoxon-signed ranks tests (Z statistic for non-normally distributed, dependent samples) are applied (see Tables B.10, B.12, B.14, B.16, B.18 to B.22). The rightmost column in each table contains the corresponding p-values with the statistically significant results (p-value < 0.05) highlighted in bold. Note that in Tables B.14 and B.16, only the Wilcoxon-signed ranks test results are delivered since the corresponding samples are not normally distributed.

Table B.1: The ANOVA results of multiple comparisons of strategies based on the average stock level for door sets 1 and 2

$\alpha = 0.05$	Parametric		Nonparametric		Pairwise comparisons of the strategies														
	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Door set 1																			
Traffic levels																			
H - H	40.399	0.000			1.000	0.022	0.625	0.000	0.000	0.035	0.073	0.001	0.002	0.804	0.005	0.009	0.005	0.009	1.000
M - H			35.771	0.000	0.169	0.959	0.386	0.005	0.005	0.386	0.169	0.005	0.005	0.114	0.005	0.005	0.005	0.005	0.093
M - M	19.595	0.000			1.000	0.080	0.008	0.003	0.000	0.633	0.038	0.012	0.000	0.080	0.633	0.259	0.330	0.010	0.380
L - H			38.571	0.000	0.919	0.203	0.241	0.005	0.005	0.169	0.333	0.005	0.005	0.139	0.005	0.005	0.005	0.005	0.013
L - M			44.743	0.000	0.799	0.007	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.475	0.005	0.005	0.005	0.005	0.445
L - L			18.919	0.002	0.028	0.889	0.037	0.028	0.013	0.037	0.314	0.139	0.959	0.022	0.093	0.013	0.241	0.508	0.047
Door set 2																			
H - H	57.666	0.000			1.000	1.000	1.000	0.000	0.000	0.538	0.187	0.001	0.000	1.000	0.001	0.000	0.001	0.000	0.351
M - H			41.791	0.000	0.066	0.059	0.721	0.005	0.005	0.047	0.285	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.285
M - M			15.458	0.009	0.959	0.508	0.646	0.047	0.012	0.721	0.878	0.059	0.009	0.646	0.074	0.005	0.110	0.007	0.139
L - H			40.914	0.000	0.007	0.005	0.005	0.047	0.022	0.005	0.005	0.445	0.093	0.005	0.005	0.005	0.005	0.005	0.059
L - M			47.543	0.000	0.013	0.005	0.005	0.005	0.005	0.009	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.047
L - L			8.524	0.130	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table B.2: The ANOVA results of multiple comparisons of strategies based on the percentage of late pallets for door sets 1 and 2

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies														
	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Door set 1																			
Traffic levels																			
H - H	31.632	0.000		1.000	0.030	0.423	0.000	0.001	0.020	0.009	0.002	0.002	1.000	0.014	0.013	0.009	0.011	1.000	
M - H			37.626	0.000	0.056	0.515	0.005	0.005	0.262	0.101	0.005	0.005	0.234	0.005	0.005	0.005	0.005	1.000	
M - M		0.010		1.000	0.199	0.671	0.007	0.020	1.000	1.000	1.000	0.060	1.000	0.456	0.049	1.000	0.573	0.767	
L - H			34.124	0.000	0.705	0.481	0.006	0.006	0.268	0.481	0.007	0.007	0.557	0.005	0.007	0.005	0.005	0.564	
L - M			47.280	0.000	0.414	0.007	0.005	0.005	0.005	0.007	0.005	0.005	0.020	0.011	0.005	0.005	0.004	0.655	
L - L			25.101	0.000	0.007	0.394	0.009	0.011	0.011	0.444	0.097	0.646	0.005	0.074	0.012	0.017	0.646	0.014	
Door set 2																			
H - H	34.223	0.000		1.000	1.000	1.000	0.006	0.002	1.000	0.156	0.008	0.003	1.000	0.008	0.002	0.012	0.003	0.200	
M - H			12.841	0.025	0.180	0.180	0.059	0.059	0.317	0.317	0.102	0.102	1.000	0.157	0.157	0.157	0.157	1.000	
M - M			17.264	0.004	0.308	0.336	0.039	0.012	0.443	0.855	0.178	0.021	0.558	0.088	0.005	0.196	0.012	0.121	
L - H			5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
L - M			18.056	0.003	1.000	0.046	0.059	0.059	0.046	0.059	0.059	0.059	0.317	0.317	0.317	1.000	1.000	1.000	
L - L			5.386	0.371	-	-	-	-	-	-	-	-	-	-	-	-	-	-	

Table B.3: The ANOVA results of multiple comparisons of strategies based on the pallet delay for door sets 1 and 2

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies																
	F statistic	p-value	H statistic	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6	
Door set 1																					
Traffic levels																					
H - H		0.004		17.371	0.004	0.333	0.445	0.333	0.009	0.386	0.333	0.508	0.013	0.169	0.386	0.009	0.241	0.007	0.203	0.013	
M - H		0.000		39.070	0.000	0.203	0.169	0.203	0.005	0.005	0.203	0.333	0.005	0.005	0.445	0.005	0.005	0.005	0.005	0.068	
M - M		0.002		19.086	0.002	0.093	0.575	0.022	0.114	0.074	0.093	0.059	0.114	0.646	0.022	0.241	0.059	0.022	0.445	0.037	
L - H	14.715	0.001				1.000	1.000	1.000	0.000	0.001	1.000	1.000	0.001	0.000	0.916	0.004	0.042	0.006	0.036	1.000	
L - M	19.078	0.000				1.000	0.446	1.000	0.008	0.016	0.130	0.607	0.002	0.004	0.716	0.006	0.049	0.019	0.052	1.000	
L - L		0.024		12.914	0.024	0.037	0.721	0.028	0.059	0.047	0.037	0.959	0.028	0.721	0.028	0.074	0.047	0.017	0.386	0.037	
Door set 2																					
H - H	19.915	0.000				0.874	1.000	0.992	0.021	0.022	0.411	1.000	0.007	0.006	0.278	0.002	0.003	0.005	0.003	1.000	
M - H		0.000		30.966	0.000	0.953	1.000	0.386	0.005	0.005	0.959	0.260	0.008	0.008	0.386	0.008	0.008	0.018	0.018	1.000	
M - M	1.096	0.339				-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
L - H			17.966		0.003	1.000	0.732	0.956	1.000	1.000	1.000	1.000	0.554	0.554	1.000	0.048	0.048	0.069	0.069	1.000	
L - M		0.033		12.129	0.033	0.114	0.889	0.515	0.058	0.293	0.093	0.241	0.009	0.013	0.832	0.075	0.310	0.063	0.327	0.310	
L - L		0.130		8.524	0.130	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	

Table B.4: The ANOVA results of multiple comparisons of strategies based on the outbound truck fill rate for door sets 1 and 2

$\alpha = 0.05$	Nonparametric		Pairwise comparisons of strategies															
	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6	
Traffic levels																		
H - H	7.143	0.210	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
M - H	43.940	0.000	0.098	0.005	0.005	0.007	0.031	0.005	0.004	0.005	0.011	0.564	0.004	0.005	0.004	0.005	0.107	
M - M	5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
L - H	42.199	0.000	0.564	0.005	0.005	0.027	0.079	0.004	0.004	0.023	0.062	1.000	0.005	0.004	0.005	0.004	0.763	
L - M	48.636	0.000	1.000	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.317	0.005	0.005	0.005	0.005	0.429	
L - L	2.857	0.722	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Door set 2																		
H - H	2.171	0.825	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
M - H	47.699	0.000	0.014	0.004	0.004	0.004	0.005	0.005	0.004	0.004	0.004	0.157	0.007	0.004	0.008	0.002	0.046	
M - M	5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
L - H	49.172	0.000	0.317	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.317	0.002	0.002	0.002	0.002	0.317	
L - M	43.682	0.000	0.564	0.005	0.005	0.004	0.010	0.004	0.005	0.004	0.006	1.000	0.025	0.008	0.025	0.020	0.157	
L - L	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table B.5: The ANOVA results of multiple comparisons of strategies based on the average travelling time of pallets for door sets 1 and 2

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies																
	F statistic	p-value	H statistic	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6	
Door set 1																					
Traffic levels																					
H - H		0.009		15.314	0.009	0.093	0.575	0.093	0.009	0.878	0.059	0.285	0.017	0.203	0.093	0.022	0.721	0.022	0.241	0.022	
M - H	38.353	0.000			0.002	1.000	0.004	1.000	1.000	1.000	0.000	1.000	0.001	0.009	0.001	1.000	1.000	0.003	0.019	1.000	
M - M		0.011		14.763	0.050	0.161	0.086	0.327	0.161	0.161	0.012	0.678	0.012	0.889	0.021	0.036	0.050	0.051	0.374	0.123	
L - H		0.089		9.543		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
L - M		0.036		11.886	0.013	0.721	0.139	0.386	0.959	0.959	0.047	0.241	0.009	0.013	0.059	0.508	0.799	0.013	0.037	0.333	
L - L		0.687		3.086		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
Door set 2																					
H - H		0.000		38.286	0.005	0.959	0.005	0.074	0.022	0.005	0.005	0.646	0.005	0.017	0.005	0.093	0.017	0.005	0.037	0.005	
M - H		0.000		43.486	0.005	0.074	0.005	0.575	0.005	0.005	0.005	0.022	0.005	0.005	0.005	0.169	0.005	0.005	0.013	0.005	
M - M		0.000		32.397	0.000	0.169	0.005	0.678	0.005	0.005	0.005	0.139	0.022	0.721	0.005	0.575	0.005	0.028	0.508	0.005	
L - H		0.000		44.286	0.000	0.005	0.005	0.005	0.005	0.005	0.005	0.169	0.005	0.333	0.005	0.139	0.005	0.005	0.285	0.005	
L - M		0.000		43.086	0.005	0.059	0.005	0.386	0.005	0.005	0.005	0.005	0.005	0.007	0.005	0.059	0.005	0.005	0.139	0.005	
L - L	2.466	0.147				-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	

Table B.6: The ANOVA results of multiple comparisons of strategies based on the door occupancy for door set 1 (H-H, M-H and M-M traffic levels)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies															
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Inbound door 1	H - H	16.245	0.000	48.766	0.000	0.054	1.000	0.011	1.000	0.009	0.087	0.262	0.103	1.000	0.008	0.933	0.022	0.031	1.000	0.006
	M - H					0.005	1.000	0.005	1.000	0.005	0.005	0.207	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	M - M					0.012	1.000	0.012	1.000	0.012	0.012	0.401	0.012	0.108	0.012	1.000	0.012	0.012	0.484	0.012
Inbound door 2	H - H			30.043	0.000	0.009	0.168	0.007	0.093	0.005	0.007	0.022	0.012	0.086	0.005	0.074	0.005	0.012	0.799	0.005
	M - H					0.005	1.000	0.005	1.000	0.005	0.005	0.207	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	M - M					0.012	1.000	0.012	1.000	0.012	0.012	0.401	0.012	0.108	0.012	1.000	0.012	0.012	0.484	0.012
Outbound door 1	H - H	18.886	0.000	43.314	0.000	0.000	0.404	0.000	1.000	0.006	0.006	1.000	0.108	1.000	0.000	1.000	0.022	0.017	1.000	0.000
	M - H					0.125	0.005	0.005	0.013	0.153	0.005	0.005	0.005	0.005	0.139	0.005	0.005	0.009	0.005	0.016
	M - M					0.017	0.441	0.012	0.484	0.008	0.017	0.779	0.021	1.000	0.012	0.093	0.008	0.012	0.476	0.008
Outbound door 2	H - H	14.878	0.001	35.589	0.000	0.000	1.000	0.000	1.000	0.014	0.009	1.000	0.075	1.000	0.000	1.000	0.103	0.030	1.000	0.000
	M - H					0.284	0.005	0.005	0.476	0.308	0.005	0.005	0.260	0.357	0.126	0.005	0.005	0.005	0.005	0.169
	M - M					0.012	0.173	0.012	0.397	0.008	0.017	0.726	0.012	0.906	0.011	0.042	0.008	0.012	0.594	0.008
Inbound door 1	H - H			42.744	0.000	0.008	1.000	0.008	0.040	0.005	0.005	0.680	0.011	0.010	0.005	0.035	0.005	0.008	0.005	0.005
	M - H					0.005	0.059	0.005	0.007	0.005	0.005	0.721	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	M - M					0.011	1.000	0.011	0.093	0.012	0.011	0.263	0.013	0.042	0.011	0.022	0.011	0.013	0.335	0.013
Inbound door 2	H - H	9.000	0.002	48.968	0.000	0.091	1.000	0.016	1.000	0.116	0.910	1.000	0.229	1.000	0.012	0.601	1.000	0.080	1.000	0.006
	M - H					0.005	1.000	0.005	1.000	0.005	0.005	0.139	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	M - M					0.011	1.000	0.011	1.000	0.012	0.011	0.340	0.011	0.109	0.011	1.000	0.012	0.011	0.516	0.012
Outbound door 1	H - H			24.310	0.000	0.011	0.040	0.798	0.072	0.170	0.007	0.027	0.008	0.107	0.057	0.778	0.160	0.352	0.483	0.007
	M - H					-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M					0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-
Outbound door 2	H - H			17.258	0.004	0.159	0.231	0.043	0.241	0.012	0.350	0.141	0.508	0.049	0.018	0.333	0.008	0.241	0.205	0.013
	M - H					0.033	0.481	0.020	0.205	0.044	0.137	0.012	0.235	0.015	0.027	0.678	0.678	0.441	0.919	0.497
	M - M					1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-
The percentage of time trucks spent at each door	H - H			18.230	0.003	0.161	0.128	0.025	0.123	0.013	0.327	0.116	0.674	0.091	0.012	0.123	0.013	0.161	0.309	0.021
	M - H					-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M					0.003	0.161	0.128	0.025	0.123	0.013	0.327	0.116	0.674	0.091	0.012	0.123	0.013	0.161	0.309

Table B.7: The one-way ANOVA results of multiple comparisons of strategies based on the door occupancy for door set 1 (L-H, L-M and L-L traffic levels)

$\alpha = 0.05$	Nonparametric one-way ANOVA										Post hoc test									
	Traffic levels	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6		
The number of trucks served per door	Inbound door 1	48.452	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.918	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005		
	Inbound door 2	48.645	0.000	0.005	1.000	0.005	1.000	0.005	0.307	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005	0.005		
	Outbound door 1	30.000	0.000	0.018	1.000	0.027	1.000	0.018	0.593	0.018	0.018	0.400	0.027	1.000	0.018	0.027	0.127	0.018		
	Outbound door 2	48.452	0.000	0.005	1.000	0.005	1.000	0.005	0.918	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005	0.005		
	Outbound door 1	48.645	0.000	0.005	1.000	0.005	1.000	0.005	0.307	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005	0.005		
	Outbound door 2	30.000	0.000	0.018	1.000	0.027	1.000	0.018	0.593	0.018	0.018	0.400	0.027	1.000	0.018	0.027	0.127	0.018		
	Inbound door 1	36.153	0.000	0.759	0.005	0.005	0.333	0.074	0.005	0.005	0.307	0.141	0.151	0.005	0.005	0.005	0.005	0.878		
	Inbound door 2	37.009	0.000	0.210	0.011	0.011	0.017	0.005	0.013	0.012	0.021	0.008	0.348	0.005	0.005	0.005	0.005	0.332		
	Outbound door 1	22.517	0.000	0.011	0.713	0.012	0.344	0.011	0.042	0.443	0.032	0.496	0.018	0.197	0.042	0.021	0.072	0.051		
Outbound door 2	34.828	0.000	0.574	0.005	0.005	0.262	0.594	0.005	0.005	0.241	0.646	0.151	0.005	0.005	0.005	0.005	0.878			
Inbound door 1	46.652	0.000	0.312	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.307	0.005	0.005	0.005	0.005	0.342			
Inbound door 2	18.287	0.003	0.016	1.000	0.018	0.141	0.042	0.065	0.527	0.032	0.496	0.028	0.144	0.084	0.021	0.072	0.051			
Inbound door 1	42.457	0.000	0.005	0.059	0.005	0.508	0.005	0.005	0.508	0.005	0.005	0.799	0.005	0.005	0.005	0.007	0.005			
Inbound door 2	43.829	0.000	0.005	0.241	0.005	0.139	0.005	0.005	0.445	0.005	0.005	0.575	0.005	0.005	0.005	0.005	0.005			
Outbound door 1	27.086	0.000	0.005	0.575	0.013	0.169	0.007	0.005	0.028	0.005	0.508	0.022	0.878	0.013	0.037	0.139	0.017			
Outbound door 2	48.387	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.959	0.005	0.005	1.000	0.005	0.005	0.005	0.005	0.005			
Inbound door 1	48.968	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.169	0.005	0.005	1.000	0.005	0.005	0.005	0.005	0.005			
Inbound door 2	25.159	0.000	0.068	1.000	0.028	1.000	0.018	0.068	0.600	0.068	0.310	0.028	1.000	0.018	0.028	0.176	0.018			
Outbound door 1	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
Outbound door 2	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
Inbound door 1	17.324	0.004	0.007	0.959	0.028	0.721	0.013	0.059	0.721	0.037	0.646	0.059	0.386	0.059	0.047	0.799	0.028			
Inbound door 2	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
Outbound door 1	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
Outbound door 2	7.849	0.165	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			

Table B.8: The ANOVA results of multiple comparisons of strategies based on the door occupancy for door set 2 (H-H, M-H and M-M traffic levels)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies															
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Inbound door 1	H - H		0.000	42.057	0.000	0.005	0.646	0.005	0.007	0.005	0.005	0.573	0.005	0.028	0.005	0.007	0.005	0.005	0.028	0.005
	M - H		0.000	46.494	0.000	0.005	0.005	0.005	0.411	0.005	0.005	0.023	0.005	0.564	0.005	0.007	0.005	0.005	0.059	0.005
	M - M		0.000	44.556	0.000	0.005	0.764	0.005	0.480	0.005	0.005	1.000	0.005	1.000	0.005	0.567	0.005	0.005	1.000	0.005
Inbound door 2	H - H		0.000	41.420	0.000	0.005	0.725	0.005	0.011	0.005	0.005	0.508	0.005	0.214	0.005	0.016	0.005	0.005	0.441	0.005
	M - H		0.000	47.779	0.000	0.005	0.005	0.005	0.411	0.005	0.005	0.005	0.005	0.005	0.005	0.008	0.005	0.005	0.007	0.005
	M - M	42.751	0.000			0.000	1.000	0.001	1.000	0.002	0.000	1.000	0.000	1.000	0.001	1.000	0.002	0.000	0.329	0.001
Inbound door 3	H - H		0.000	42.378	0.000	0.005	0.812	0.005	0.007	0.005	0.005	0.919	0.005	0.114	0.005	0.012	0.005	0.005	0.114	0.005
	M - H		0.000	49.241	0.000	0.005	0.157	0.005	1.000	0.005	0.005	0.005	0.005	0.005	0.005	0.157	0.005	0.005	0.005	0.005
	M - M		0.000	46.447	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.481	0.005	0.323	0.005	1.000	0.005	0.005	0.011	0.005
Inbound door 4	H - H		0.000	43.477	0.000	0.005	1.000	0.005	0.007	0.005	0.005	0.192	0.005	0.016	0.005	0.008	0.005	0.005	0.047	0.005
	M - H		0.000	48.968	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.014	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	M - M		0.000	31.900	0.000	0.016	1.000	0.018	1.000	0.011	0.016	0.798	0.016	0.680	0.018	1.000	0.011	0.018	1.000	0.011
Inbound door 5	H - H	12.225	0.000			0.007	1.000	0.041	0.463	1.000	0.028	1.000	0.009	0.766	0.014	0.153	1.000	0.012	0.944	0.003
	M - H		0.000	23.991	0.000	0.317	1.000	0.317	1.000	0.023	0.317	1.000	0.317	0.020	0.317	1.000	0.023	0.317	0.038	0.023
	M - M		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outbound door 1	H - H		0.000	39.470	0.000	0.005	0.385	0.005	0.594	0.005	0.005	0.683	0.005	0.959	0.005	0.959	0.005	0.005	0.959	0.005
	M - H		0.000	46.146	0.000	0.005	0.139	0.005	0.013	0.005	0.005	0.005	0.005	0.005	0.005	0.012	0.005	0.005	0.015	0.005
	M - M		0.000	39.751	0.000	0.005	0.185	0.005	0.720	0.005	0.005	0.528	0.005	0.397	0.005	0.858	0.005	0.005	0.287	0.005
Outbound door 2	H - H	10.364	0.001			0.000	1.000	0.003	1.000	0.202	0.031	1.000	0.039	1.000	0.021	1.000	0.721	0.002	1.000	0.000
	M - H		0.000	33.729	0.000	1.000	0.000	0.003	0.000	0.009	0.001	0.002	0.000	0.043	0.489	0.186	0.371	0.003	1.000	0.056
	M - M		0.000	11.465	0.000	0.025	1.000	0.038	1.000	0.014	0.018	1.000	0.018	1.000	0.017	1.000	0.055	0.197	1.000	0.110

The number of trucks served per door

(continued)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies															
	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6	
	Traffic levels																			
	H - H	40.229	0.000	0.005	0.507	0.005	0.005	0.575	0.005	0.005	0.013	0.005	0.721	0.005	0.837	0.005	0.005	0.169	0.005	
	M - H	46.971	0.000	0.005	0.005	0.005	0.005	0.005	0.005	0.221	0.005	0.005	0.005	0.005	0.028	0.005	0.005	0.007	0.005	
	M - M	40.000	0.000	0.005	0.799	0.005	0.723	0.005	0.005	0.171	0.005	0.878	0.005	0.005	0.944	0.005	0.005	0.906	0.005	
	H - H	40.648	0.000	0.005	0.207	0.005	0.953	0.005	0.005	0.139	0.005	0.168	0.005	0.005	0.878	0.005	0.005	0.074	0.005	
	M - H	47.572	0.000	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.059	0.005	0.005	0.008	0.044	0.005	0.005	0.005	
	M - M	3.989	0.551	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
	H - H	1.589	0.183	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
	M - H	89.548	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.011	0.002	1.000	0.000	0.057	0.035	
	M - M	2.132	0.831	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
	H - H	44.240	0.000	0.005	0.537	0.005	0.010	0.005	0.005	0.943	0.005	0.021	0.005	0.005	0.007	0.005	0.005	0.015	0.005	
	M - H	48.037	0.000	0.004	0.014	0.004	0.180	0.004	0.004	1.000	0.004	1.000	1.000	0.004	0.007	0.004	0.004	1.000	0.004	
	M - M	48.387	0.000	0.004	1.000	0.004	1.000	0.004	0.004	1.000	0.004	1.000	1.000	0.004	1.000	0.004	0.004	1.000	0.004	
	H - H	87.651	0.000	0.000	1.000	0.000	0.080	0.000	0.000	1.000	0.002	0.010	0.010	0.000	0.051	0.000	0.001	0.010	0.000	
	M - H	47.803	0.000	0.005	0.005	0.005	0.285	0.005	0.005	0.004	0.005	0.004	0.004	0.005	0.010	0.005	0.005	0.011	0.004	
	M - M	24.623	0.000	0.025	1.000	0.034	0.317	0.025	0.025	0.317	0.014	1.000	1.000	0.034	0.317	0.025	0.020	0.317	0.014	
	H - H	45.748	0.000	0.005	0.389	0.005	0.008	0.005	0.005	0.470	0.005	0.007	0.005	0.005	0.008	0.005	0.005	0.012	0.005	
	M - H	49.337	0.000	0.004	1.000	0.005	1.000	0.005	0.004	0.014	0.004	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005	
	M - M	49.505	0.000	0.004	1.000	0.004	1.000	0.004	0.004	0.317	0.004	1.000	1.000	0.004	1.000	0.004	0.004	0.317	0.004	
	H - H	44.373	0.000	0.005	0.721	0.005	0.009	0.005	0.005	0.669	0.005	0.017	0.005	0.005	0.007	0.005	0.005	0.015	0.005	
	M - H	49.419	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.007	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005	
	M - M	5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	

The number of trucks served per door

The number of trucks served per door

The number of trucks served per door

The percentage of time the door is busy serving trucks

The percentage of time the door is busy serving trucks

(continued)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Pairwise comparisons of strategies															
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Inbound door 5	H - H		0.000	25.390	0.000	0.013	0.799	0.028	0.013	0.878	0.034	0.861	0.008	0.021	0.010	0.008	0.856	0.008	0.013	0.005
	M - H		0.000	25.227	0.000	0.317	1.000	0.317	1.000	0.028	0.317	0.655	0.317	0.028	0.317	1.000	0.028	0.317	0.028	0.028
	M - M		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outbound door 1	H - H		1.000	0.107	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - H		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M		0.000	40.362	0.000	0.005	0.721	0.005	0.646	0.005	0.005	0.086	0.005	0.484	0.005	0.203	0.005	0.005	0.441	0.005
Outbound door 2	H - H		0.063	10.476	0.063	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - H		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M		0.009	15.371	0.009	0.114	0.508	0.285	0.878	0.508	0.074	0.646	0.074	0.333	0.093	0.721	0.169	0.074	0.878	0.074
Outbound door 3	H - H		0.000	26.190	0.000	0.028	0.917	0.028	0.046	0.028	0.028	0.028	0.028	0.116	0.028	0.046	0.028	0.028	0.753	0.028
	M - H		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M		0.000	39.133	0.000	0.005	0.594	0.005	0.953	0.005	0.005	0.575	0.005	0.959	0.005	0.859	0.005	0.005	0.799	0.005
Outbound door 4	H - H		0.004	17.455	0.004	0.028	0.917	0.028	0.046	0.028	0.028	0.173	0.345	0.499	0.028	0.116	0.028	0.173	0.345	0.028
	M - H		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M		0.004	17.508	0.004	0.066	0.515	0.021	0.678	0.038	0.086	0.953	0.139	0.260	0.051	0.678	0.038	0.066	0.214	0.021
Outbound door 5	H - H		0.000	22.621	0.000	0.028	0.600	0.028	0.028	0.028	0.028	0.225	0.917	0.080	0.028	0.046	0.028	0.463	0.225	0.028
	M - H		1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	M - M		0.734	2.778	0.734	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

The percentage of time the door is busy serving trucks

Table B.9: The one-way ANOVA results of multiple comparisons of strategies based on the door occupancy for door set 2 (L-H, L-M and L-L traffic levels)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA		Post hoc test															
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Inbound door 1	L-H			50.000	0.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005
	L-M			50.000	0.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005
	L-L			50.000	0.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005	1.000	0.005	1.000	0.005	0.005	1.000	0.005
Inbound door 2	L-H			44.903	0.000	0.005	1.000	0.005	1.000	0.005	0.032	0.005	0.017	0.005	0.005	1.000	0.005	0.005	0.202	0.005
	L-M			48.645	0.000	0.005	1.000	0.005	1.000	0.005	0.114	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	L-L			5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Inbound door 3	L-H			49.419	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.007	0.005
	L-M			49.030	0.000	0.005	0.005	0.005	0.005	1.000	0.041	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	L-L			49.343	0.000	0.005	1.000	0.005	1.000	0.005	0.005	0.317	0.005	0.317	0.005	1.000	0.005	0.005	0.317	0.005
Inbound door 4	L-H			48.258	0.000	0.005	1.000	0.005	1.000	0.005	0.025	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.008	0.005
	L-M			48.452	0.000	0.005	1.000	0.005	1.000	0.005	0.508	0.005	0.005	0.005	0.005	1.000	0.005	0.005	0.005	0.005
	L-L			5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Inbound door 5	L-H			0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	L-M			0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	L-L			0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outbound door 1	L-H			47.543	0.000	0.009	0.005	0.005	0.005	0.007	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.759	0.005	0.005
	L-M	85.918	0.000			0.000	0.001	0.000	1.000	0.000	0.056	0.000	0.000	1.000	0.002	0.001	0.000	0.000	0.064	0.000
	L-L			44.578	0.000	0.005	0.916	0.005	0.084	0.005	0.005	0.414	0.005	1.000	0.005	0.136	0.005	0.005	0.461	0.005
Outbound door 2	L-H			47.292	0.000	0.139	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.022
	L-M	5.412	0.001			1.000	1.000	0.003	0.517	1.000	1.000	0.047	1.000	1.000	1.000	0.088	1.000	0.007	1.000	1.000
	L-L			10.440	0.064	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

The number of trucks served per door

(continued)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA																	
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6
Outbound door 3	L - H			43.851	0.000	0.083	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.799	0.005	0.050	0.013
	L - M	31.263	0.000	0.001	0.305	0.000	1.000	0.000	1.000	0.000	0.001	0.083	0.014	1.000	0.000	1.000	0.000	0.100	0.003	0.001
	L - L			44.038	0.000	0.005	0.197	0.005	0.317	0.005	0.005	0.832	0.005	0.172	0.005	0.104	0.005	0.005	0.173	0.005
Outbound door 4	L - H			44.971	0.000	0.646	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.011	0.005	0.017	0.005	0.009	0.074
	L - M	9.185	0.000	1.000	0.435	0.179	1.000	0.363	0.009	0.005	1.000	0.118	1.000	0.004	1.000	0.000	1.000	0.000	1.000	0.093
	L - L			9.444	0.093	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outbound door 5	L - H	166.212	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.199	0.004	1.000	0.000	1.000	0.631
	L - M			26.710	0.000	0.138	0.008	0.005	0.179	0.838	0.016	0.012	0.168	0.475	0.474	0.005	0.007	0.005	0.005	0.575
	L - L			5.706	0.336	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Inbound door 1	L - H			48.871	0.000	0.002	0.083	0.002	1.000	0.002	0.004	1.000	0.002	1.000	0.004	0.083	0.004	0.002	1.000	0.002
	L - M			50.000	0.000	0.002	1.000	0.002	1.000	0.002	0.002	1.000	0.002	1.000	0.002	1.000	0.002	0.002	1.000	0.002
	L - L			50.000	0.000	1.000	0.002	1.000	0.002	1.000	0.002	1.000	0.002	1.000	0.002	1.000	0.002	0.002	1.000	0.002
Inbound door 2	L - H			45.609	0.000	0.004	1.000	0.005	1.000	0.005	0.004	0.194	0.004	0.031	0.005	1.000	0.005	0.005	0.201	0.005
	L - M			49.085	0.000	0.004	1.000	0.004	1.000	0.005	0.004	0.163	0.004	0.005	0.004	1.000	0.005	0.004	0.005	0.005
	L - L			5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Inbound door 3	L - H			49.512	0.000	0.004	1.000	0.004	1.000	0.004	0.004	0.024	0.004	0.004	0.004	1.000	1.000	0.004	0.004	1.000
	L - M			49.267	0.000	0.004	1.000	0.004	1.000	0.004	0.004	0.054	0.004	0.005	0.004	1.000	0.004	0.004	0.005	0.004
	L - L			49.343	0.000	0.002	1.000	0.002	1.000	0.002	0.002	0.317	0.002	0.137	0.002	1.000	0.002	0.002	0.137	0.002
Inbound door 4	L - H			47.673	0.000	0.004	1.000	0.004	1.000	0.004	0.004	0.157	0.004	0.010	0.004	1.000	0.004	0.004	0.014	0.004
	L - M			48.876	0.000	0.005	1.000	0.004	1.000	0.003	0.005	1.000	0.005	0.005	0.004	1.000	0.003	0.004	0.004	0.003
	L - L			5.000	0.416	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

(continued)

$\alpha = 0.05$	Parametric one-way ANOVA		Nonparametric one-way ANOVA												Post hoc test											
	Traffic levels	F statistic	p-value	χ^2 statistic	p-value	S1-S2	S1-S3	S1-S4	S1-S5	S1-S6	S2-S3	S2-S4	S2-S5	S2-S6	S3-S4	S3-S5	S3-S6	S4-S5	S4-S6	S5-S6						
Inbound door 5	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
Outbound door 1	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	40.729	0.000	40.729	0.000	0.005	0.646	0.005	0.959	0.005	0.005	0.753	0.005	0.310	0.005	0.799	0.005	0.005	0.753	0.005	0.005					
Outbound door 2	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	6.020	0.304	6.020	0.304	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
Outbound door 3	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	40.888	0.000	40.888	0.000	0.005	0.237	0.005	0.237	0.005	0.005	0.445	0.005	0.074	0.005	0.310	0.005	0.005	0.959	0.005	0.005					
Outbound door 4	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	25.372	0.000	25.372	0.000	0.018	1.000	0.018	0.686	0.028	0.018	0.463	0.018	0.091	0.028	0.612	0.018	0.018	0.176	0.018	0.018					
Outbound door 5	L - H	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - M	0.000	1.000	0.000	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
	L - L	6.143	0.293	6.143	0.293	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-					

The percentage of time trucks spent at each door

Table B.10: The pairwise comparison of S1 and S6 based on the average stock level per door set

$\alpha = 0.05$	Pairwise comparison (S1-S6)		
Door sets	T statistic	Z statistic	p-value
DS1	9.536		0.000
DS2	8.750		0.000
DS3		2.803	0.005
DS4		2.803	0.005
DS5		2.803	0.005

Table B.11: The ANOVA results of multiple comparisons of door sets based on the average stock level per strategy

$\alpha = 0.05$	Nonparametric one-way ANOVA		Pairwise comparisons of door sets									
	χ^2 statistic	p-value	DS1-DS2	DS1-DS3	DS1-DS4	DS1-DS5	DS2-DS3	DS2-DS4	DS2-DS5	DS3-DS4	DS3-DS5	DS4-DS5
S1	14.560	0.006	0.575	0.139	0.022	0.022	0.074	0.013	0.022	0.093	0.799	0.285
S6	10.400	0.034	0.386	0.059	0.059	0.028	0.022	0.386	0.508	0.508	0.508	0.169

Table B.12: The pairwise comparison of S1 and S6 based on the percentage of late pallet and pallet lateness per door set

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
	Door sets	T statistic	Z statistic	p-value
Percentage of late pallets (%)	DS1	7.571		0.000
	DS2	7.797		0.000
	DS3		2.803	0.005
	DS4		2.803	0.005
	DS5		2.803	0.005
Pallet delay (minutes)	DS1		0.866	0.386
	DS2	4.498		0.001
	DS3		2.599	0.009
	DS4		2.803	0.005
	DS5		2.599	0.009

Table B.13: The ANOVA results of multiple comparisons of door sets based on the percentage of late pallets and pallet lateness per strategy

		Nonparametric one-way ANOVA		Pairwise comparisons of door sets																			
		χ^2 statistic	p-value	DS1-DS2	DS1-DS3	DS1-DS4	DS1-DS5	DS2-DS3	DS2-DS4	DS2-DS5	DS3-DS4	DS3-DS5	DS4-DS5	DS1-DS2	DS1-DS3	DS1-DS4	DS1-DS5	DS2-DS3	DS2-DS4	DS2-DS5	DS3-DS4	DS3-DS5	DS4-DS5
Percentage of late pallets (%)	S1	17.840	0.001	0.007	0.007	0.007	0.007	0.646	0.074	0.007	0.333	0.037	0.074	-	-	-	-	0.203	0.203	0.241	0.445	0.169	0.241
	S6	17.040	0.002	0.009	0.009	0.007	0.007	0.445	0.241	0.022	0.114	0.028	0.139	-	-	-	-	0.203	0.203	0.241	0.445	0.169	0.241
Pallet delay (minutes)	S1	8.400	0.078	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.203	0.203	0.241	0.445	0.169	0.241
	S6	11.920	0.018	0.007	0.114	0.059	0.074	0.203	0.203	0.241	0.445	0.169	0.241	-	-	-	-	0.203	0.203	0.241	0.445	0.169	0.241

Table B.14: The pairwise comparison of S1 and S6 based on the outbound truck fill rate per door set

$\alpha = 0.05$ Pairwise comparison (S1-S6)		
Door sets	Z statistic	p-value
DS1	1.095	0.273
DS2	0.663	0.508
DS3	0.059	0.953
DS4	0.255	0.799
DS5	0.255	0.799

Table B.15: The ANOVA results of multiple comparisons of door sets based on the outbound truck fill rate per strategy

$\alpha = 0.05$	Nonparametric one-way ANOVA		Pairwise comparisons of door sets									
	χ^2 statistic	p-value	DS1-DS2	DS1-DS3	DS1-DS4	DS1-DS5	DS2-DS3	DS2-DS4	DS2-DS5	DS3-DS4	DS3-DS5	DS4-DS5
S1	13.760	0.008	0.013	0.017	0.005	0.037	0.445	0.074	0.203	0.386	0.575	0.721
S6	20.640	0.000	0.005	0.017	0.005	0.005	0.878	0.022	0.241	0.386	0.575	0.575

Table B.16: The pairwise comparison of S1 and S6 based on the average travelling time of pallets per door set

$\alpha = 0.05$ Pairwise comparison (S1-S6)		
Door sets	Z statistic	p-value
DS1	0.153	0.878
DS2	2.293	0.022
DS3	0.663	0.508
DS4	1.784	0.074
DS5	1.172	0.241

Table B.17: The ANOVA results of multiple comparisons of door sets based on the average travelling time of pallets per strategy

$\alpha = 0.05$	Nonparametric one-way ANOVA		Pairwise comparisons of door sets									
	χ^2 statistic	p-value	DS1-DS2	DS1-DS3	DS1-DS4	DS1-DS5	DS2-DS3	DS2-DS4	DS2-DS5	DS3-DS4	DS3-DS5	DS4-DS5
S1	32.560	0.000	0.005	0.005	0.005	0.005	0.047	0.005	0.005	0.037	0.013	0.203
S6	31.840	0.000	0.007	0.005	0.005	0.005	0.028	0.005	0.005	0.169	0.022	0.028

Table B.18: The pairwise comparison of S1 and S6 based on the door occupancy for door set 1

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Inbound door 1	5.161		0.001
	Inbound door 2		2.803	0.005
	Outbound door 1	5.527		0.000
	Outbound door 2	-4.810		0.001
Percentage of time the door is busy serving trucks	Inbound door 1		2.810	0.005
	Inbound door 2	-3.409		0.008
	Outbound door 1		1.372	0.170
	Outbound door 2		2.016	0.044

Table B.19: The pairwise comparison of S1 and S6 based on the door occupancy for door set 2

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Inbound door 1		2.805	0.005
	Inbound door 2		2.803	0.005
	Inbound door 3		2.805	0.005
	Inbound door 4		2.805	0.005
	Inbound door 5	-0.652		0.531
	Outbound door 1		2.803	0.005
	Outbound door 2	3.065		0.013
	Outbound door 3		2.803	0.005
	Outbound door 4		2.803	0.005
	Outbound door 5	-1.332		0.216
Percentage of time the door is busy serving trucks	Inbound door 1		2.812	0.005
	Inbound door 2	10.938		0.000
	Inbound door 3		2.803	0.005
	Inbound door 4		2.803	0.005
	Inbound door 5		0.153	0.878
	Outbound door 1		0.507	0.612
	Outbound door 2		1.992	0.046
	Outbound door 3		2.201	0.028
	Outbound door 4		2.197	0.028
	Outbound door 5		2.201	0.028

Table B.20: The pairwise comparison of S1 and S6 based on the door occupancy for door set 3

	$\alpha = 0.05$	Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Inbound door 1		2.805	0.005
	Inbound door 2		2.803	0.005
	Inbound door 3	14.493		0.000
	Inbound door 4	-11.406		
	Inbound door 5		2.803	0.005
	Inbound door 6		2.803	0.005
	Inbound door 7		2.803	0.005
	Inbound door 8		2.805	0.005
	Inbound door 9		2.805	0.005
	Inbound door 10	-0.699		0.502
	Outbound door 1		2.803	0.005
	Outbound door 2	13.868		0.000
	Outbound door 3	18.247		0.000
	Outbound door 4	-4.218		0.002
	Outbound door 5	-7.807		0.000
	Outbound door 6		2.803	0.005
	Outbound door 7		2.803	0.005
	Outbound door 8	-15.737		0.000
	Outbound door 9	-3.226		0.010
	Outbound door 10	-1.879		0.093
Percentage of time the door is busy serving trucks	Inbound door 1	58.996		0.000
	Inbound door 2	24.273		0.000
	Inbound door 3	12.926		0.000
	Inbound door 4	-5.597		0.000
	Inbound door 5	-11.980		0.000
	Inbound door 6		2.803	0.005
	Inbound door 7	-22.906		0.000
	Inbound door 8	-6.609		0.000
	Inbound door 9	-1.998		0.077
	Inbound door 10	0.391		0.705
	Outbound door 1	2.069		0.069
	Outbound door 2	1.958		0.082

(continued)

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Percentage of time the door is busy serving trucks	Outbound door 3	0.590		0.569
	Outbound door 4	-2.696		0.025
	Outbound door 5	-3.081		0.013
	Outbound door 6	-3.118		0.012
	Outbound door 7	-2.975		0.016
	Outbound door 8	-2.715		0.024
	Outbound door 9	-2.371		0.042
	Outbound door 10	-1.984		0.079

Table B.21: The pairwise comparison of S1 and S6 based on the door occupancy for door set 4

	$\alpha = 0.05$	Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Inbound door 1	44.119		0.000
	Inbound door 2	42.147		0.000
	Inbound door 3	30.271		0.000
	Inbound door 4	23.102		0.000
	Inbound door 5	14.434		0.000
	Inbound door 6		2.803	0.005
	Inbound door 7	-11.543		0.000
	Inbound door 8		2.803	0.005
	Inbound door 9		2.805	0.005
	Inbound door 10	-41.408		0.000
	Inbound door 11	-15.579		0.000
	Inbound door 12	-6.044		0.000
	Inbound door 13	-3.590		0.006
	Inbound door 14	-2.321		0.045
	Inbound door 15	-1.110		0.296
	Outbound door 1		2.803	0.005
	Outbound door 2	18.893		0.000
	Outbound door 3	19.652		0.000
	Outbound door 4	19.100		0.000
	Outbound door 5	11.389		0.000
	Outbound door 6	-4.916		0.000
	Outbound door 7	-8.527		0.000
	Outbound door 8		2.803	0.005
	Outbound door 9	-10.089		0.000
	Outbound door 10	-20.604		0.000
	Outbound door 11	-22.923		0.000
	Outbound door 12	-8.526		0.000
	Outbound door 13	-4.526		0.001
	Outbound door 14	-2.021		0.074
	Outbound door 15	-1.666		0.130
Inbound door 1	99.503		0.000	
Inbound door 2	61.029		0.000	
Inbound door 3	30.309		0.000	

(continued)

	$\alpha = 0.05$	Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Percentage of time the door is busy serving trucks	Inbound door 4	20.495		0.000
	Inbound door 5	13.193		0.000
	Inbound door 6	-7.269		0.000
	Inbound door 7	-10.226		0.000
	Inbound door 8		2.803	0.005
	Inbound door 9	-14.744		0.000
	Inbound door 10	-26.492		0.000
	Inbound door 11	-16.990		0.000
	Inbound door 12	-5.777		0.000
	Inbound door 13	-3.523		0.006
	Inbound door 14	-1.806		0.104
	Inbound door 15	-0.083		0.936
	Outbound door 1		0.169	0.866
	Outbound door 2		0.338	0.735
	Outbound door 3		0.507	0.612
	Outbound door 4		1.014	0.310
	Outbound door 5		2.366	0.018
	Outbound door 6		2.366	0.018
	Outbound door 7		2.366	0.018
	Outbound door 8		2.366	0.018
	Outbound door 9		2.201	0.028
	Outbound door 10		2.366	0.018
	Outbound door 11		2.201	0.028
	Outbound door 12		2.201	0.028
	Outbound door 13		2.201	0.028
	Outbound door 14		2.201	0.028
	Outbound door 15		2.201	0.028

Table B.22: The pairwise comparison of S1 and S6 based on the door occupancy for door set 5

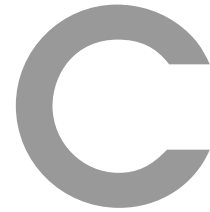
	$\alpha = 0.05$	Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Inbound door 1	43.127		0.000
	Inbound door 2	35.806		0.000
	Inbound door 3	29.084		0.000
	Inbound door 4		2.805	0.005
	Inbound door 5	18.321		0.000
	Inbound door 6	14.085		0.000
	Inbound door 7	5.666		0.000
	Inbound door 8	-8.056		0.000
	Inbound door 9	-9.979		0.000
	Inbound door 10	-11.197		0.000
	Inbound door 11	-12.376		0.000
	Inbound door 12	-15.384		0.000
	Inbound door 13	-22.580		0.000
	Inbound door 14	-35.385		0.000
	Inbound door 15	-13.523		0.000
	Inbound door 16	-8.423		0.000
	Inbound door 17	-5.757		0.000
	Inbound door 18		2.803	0.005
	Inbound door 19	-3.788		0.004
	Inbound door 20	-2.189		0.056
Outbound door 1		2.803	0.005	
Outbound door 2	21.177		0.000	
Outbound door 3	15.223		0.000	
Outbound door 4	16.405		0.000	
Outbound door 5	13.552		0.000	
Outbound door 6	9.803		0.000	
Outbound door 7	4.265		0.002	
Outbound door 8	-5.029		0.001	
Outbound door 9	-8.128		0.000	
Outbound door 10	-7.935		0.000	
Outbound door 11		2.803	0.005	
Outbound door 12	-10.005		0.000	
Outbound door 13	-12.468		0.000	

(continued)

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Number of trucks served per door	Outbound door 14	-18.350		0.000
	Outbound door 15	-11.354		0.000
	Outbound door 16	-16.260		0.000
	Outbound door 17	-7.921		0.000
	Outbound door 18	-6.286		0.000
	Outbound door 19	-6.773		0.000
	Outbound door 20	-4.077		0.003
Percentage of time the door is busy serving trucks	Inbound door 1	38.450		0.000
	Inbound door 2	25.615		0.000
	Inbound door 3	19.795		0.000
	Inbound door 4	14.730		0.000
	Inbound door 5	11.513		0.000
	Inbound door 6	6.788		0.000
	Inbound door 7	1.309		0.223
	Inbound door 8	-5.027		0.001
	Inbound door 9	-8.371		0.000
	Inbound door 10	-11.110		0.000
	Inbound door 11	-12.147		0.000
	Inbound door 12	-12.966		0.000
	Inbound door 13	-14.693		0.000
	Inbound door 14	-13.275		0.000
	Inbound door 15	-8.291		0.000
	Inbound door 16	-6.612		0.000
	Inbound door 17	-4.698		0.001
	Inbound door 18	-3.521		0.007
	Inbound door 19	-2.888		0.018
	Inbound door 20	-1.319		0.220
	Outbound door 1		0.105	0.917
	Outbound door 2		0.314	0.753
	Outbound door 3		0.943	0.345
	Outbound door 4		1.782	0.075
	Outbound door 5		2.201	0.028
	Outbound door 6		1.992	0.046

(continued)

$\alpha = 0.05$		Pairwise comparison (S1-S6)		
		T statistic	Z statistic	p-value
Percentage of time the door is busy serving trucks	Outbound door 7		1.992	0.046
	Outbound door 8		2.201	0.028
	Outbound door 9		2.201	0.028
	Outbound door 10		1.992	0.046
	Outbound door 11		2.201	0.028
	Outbound door 12		2.201	0.028
	Outbound door 13		2.201	0.028
	Outbound door 14		1.992	0.046
	Outbound door 15		1.992	0.046
	Outbound door 16		2.201	0.028
	Outbound door 17		2.201	0.028
	Outbound door 18		2.201	0.028
	Outbound door 19		1.992	0.046
	Outbound door 20		1.992	0.046



Door occupancy results in Chapter 5 for certain
traffic levels

Below, presented in Figures C.1 to C.3, are the door occupancy results of Section 5.3.5 in Chapter 5, containing the L-H, L-M, and L-L traffic levels. Note that these figures are not presented in the main body of Chapter 5 due to similarities with other traffic levels.

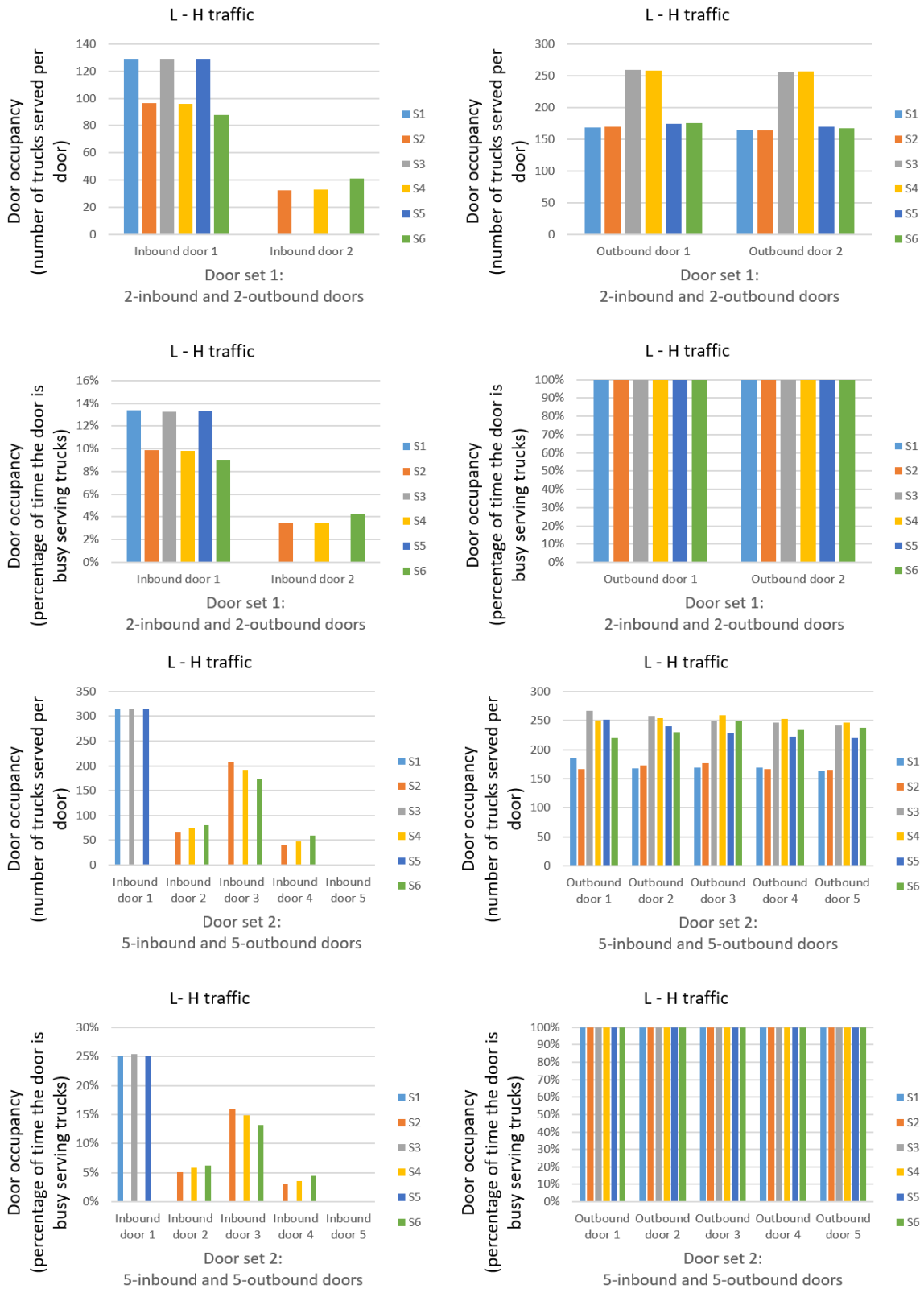


Figure C.1: The door occupancy at L-H traffic for door sets 1 and 2 based on each strategy

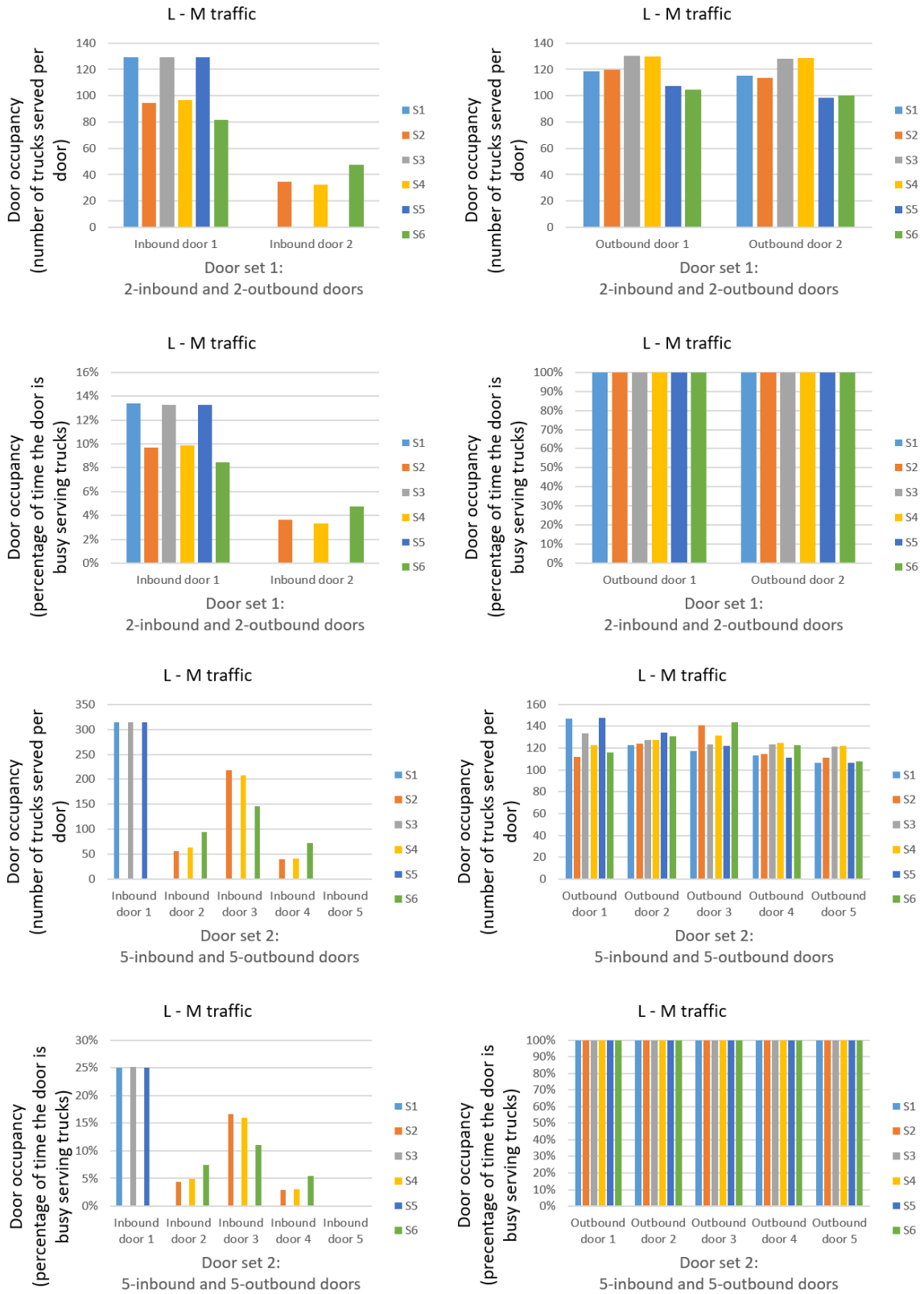


Figure C.2: The door occupancy at L-M traffic for door sets 1 and 2 based on each strategy

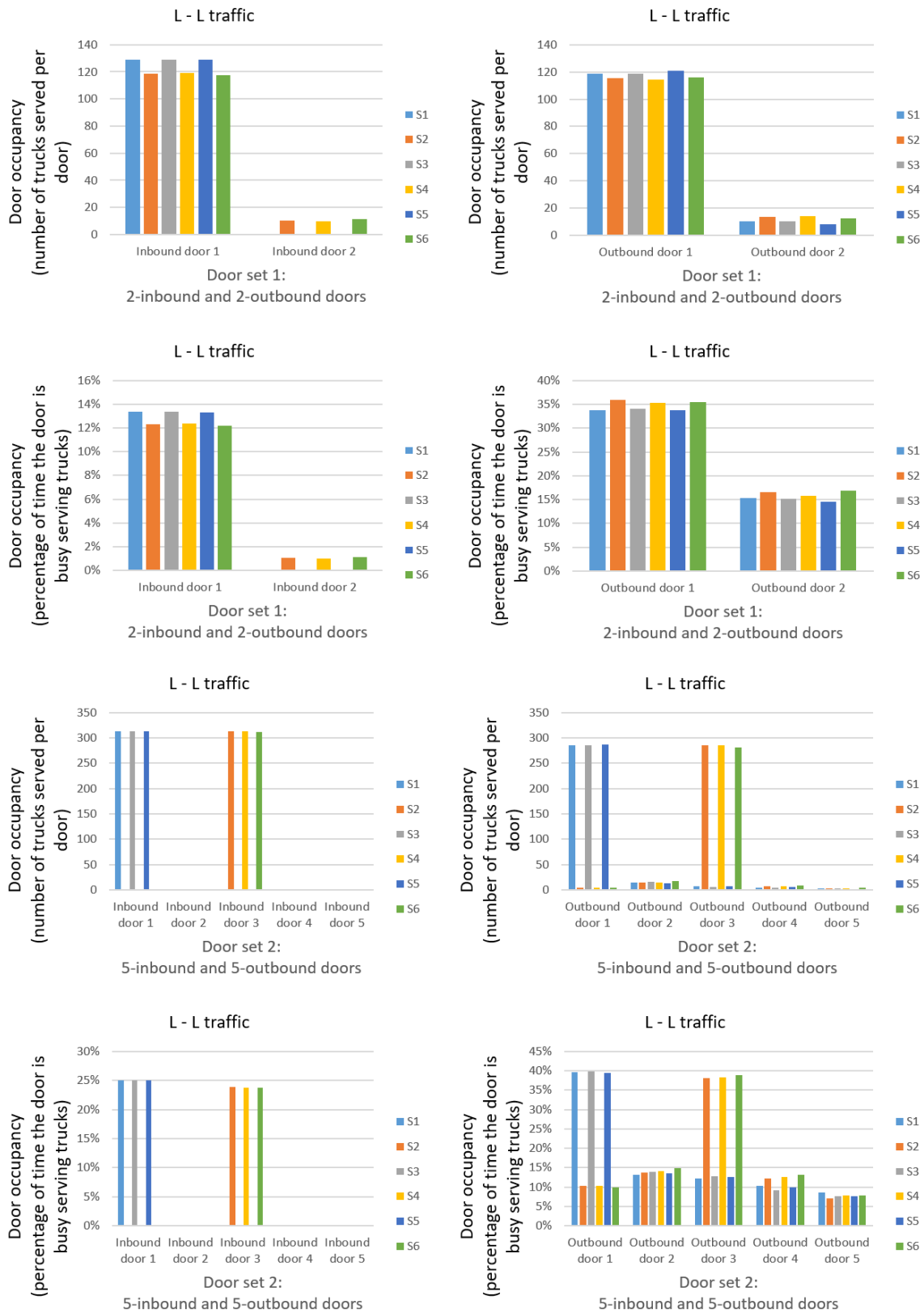


Figure C.3: The door occupancy at L-L traffic for door sets 1 and 2 based on each strategy



Access to input datasets

In this appendix, access to the input datasets used in the research presented in this thesis is provided. The datasets are organised by the respective chapters of the thesis to facilitate easy access and understanding.

Chapter 4

[Torbalı, Bilge; Alpan, Gülgün (2023), “Real-time truck scheduling model for single inbound and outbound doors cross-dock”, Mendeley Data, V1, doi: 10.17632/bgbspn8bxm.1]

Link: <https://data.mendeley.com/datasets/bgbspn8bxm/1>

Chapter 5

[Torbalı, Bilge; Alpan, Gülgün (2023), “Real-time truck scheduling model for multiple-door cross-dock”, Mendeley Data, V1, doi: 10.17632/9dnrc6s3ck.1]

Link: <https://data.mendeley.com/datasets/9dnrc6s3ck/1>

E

Results of the Model Presented in Chapter 6

The results of the model studied in Chapter 6 are presented in Tables E.1 to E.4.

Tables E.1 to E.3 display results for the first instance set, featuring ten instances for each of the three problem types alongside their respective average values. Each of these tables includes a different combination of weighting factors, w_1 and w_2 and their respective results.

Additionally, Table E.4 delivers the results for the second instance set, including one combination of weighting factors w_1 and w_2 . It displays the outcomes for five instances of one problem type and their corresponding average value.

Table E.1: Results of the multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=2$

Problem instance	Objective value		Relative deviation (%)										Relative deviation to TSI (%)										Relative deviation to MIP (%)																		
	MIP		TS1		TS2		TS3		TS4		TS5		TS6		TS1		TS2		TS3		TS4		TS5		TS6		TS1		TS2		TS3		TS4		TS5		TS6				
	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2	TS1	TS2					
(L, H, H)_1	581.807	584.789	581.807	584.789	758.998	781.805	758.998	781.805	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	743.998	
(L, H, H)_2	845.174	845.174	845.174	845.174	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	1030.236	1000.350	
(L, H, H)_3	878.768	901.296	878.768	901.296	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087	1001.201	1025.087
(L, H, H)_4	1310.156	1310.156	1310.156	1310.156	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458	1453.572	1466.458
(L, H, H)_5	748.481	796.837	748.481	796.837	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	966.781	911.897	
(L, H, H)_6	937.218	982.662	937.218	982.662	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	1274.717	1259.832	
(L, H, H)_7	973.594	973.594	973.594	973.594	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	1076.004	1071.889	
(L, H, H)_8	1115.014	1127.612	1115.014	1127.612	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	1279.967	1267.226	
(L, H, H)_9	1206.779	1219.081	1206.779	1219.081	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	1345.603	1368.717	
(L, H, H)_10	980.411	1005.211	980.411	1005.211	1188.208	1196.774	1188.208	1196.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	1179.208	1217.774	
Average	957.740	974.641	957.740	974.641	1141.206	1131.326	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	1142.706	1133.426	1141.206	1131.326	
(M, H, H)_1	2008.941	2009.185	2008.941	2009.185	2349.665	2299.737	2349.665	2299.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	2348.737	
(M, H, H)_2	1807.109	1827.394	1807.109	1827.394	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	2231.974	2206.088	
(M, H, H)_3	1340.923	1340.923	1340.923	1340.923	1619.938	1574.052	1619.938	1574.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	1636.567	1580.052	
(M, H, H)_4	1989.839	2026.750	1989.839	2026.750	2437.825	2377.338	2437.825	2377.338	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825	2431.766	2422.825
(M, H, H)_5	1962.640	1978.640	1962.640	1978.640	2471.391	2428.507	2471.391	2428.507	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278	2338.795	2307.278
(M, H, H)_6	1174.111	1224.936	1174.111	1224.936	1401.696	1417.580	1401.696	1417.580	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	1467.043	1435.042	
(M, H, H)_7	1372.577	1403.004	1372.577	1403.004	1700.032	1691.182	1700.032	1691.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032	1703.182	1694.032		
(M, H, H)_8	1961.861	1979.298	1961.861	1979.298	2277.944	2298.830	2277.944	2298.830	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	2250.291	2148.406	
(M, H, H)_9	1899.211	1911.211	1899.211	1911.211	2248.803	2244.919	2248.803	2244.919	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171	2220.172	2219.171		
(M, H, H)_10	1529.226	1529.226	1529.226	1529.226	1781.339	1766.453	1781.339	1766.453	1777.220	1759.453																															

Table E.3: Results of the multi-agent-based hybrid model on benchmark instance set 1 with $w_1=1$ and $w_2=10$

Problem instance	Objective value			Relative deviation (%)	KPI value										Relative deviation to TSI (%)										Relative deviation to MIP (%)									
	TS1	TS2	MIP		S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6						
(L, H, H)_1	2364.033	2377.033	2364.033	0.000	3186.988	3289.024	3186.988	3289.024	3131.988	3157.024	34.811	39.128	34.811	39.128	32.485	33.544	34.811	39.128	34.811	39.128	32.485	33.544	34.811	39.128	34.811	39.128	32.485	33.544	34.811	39.128	34.811	39.128	32.485	33.544
(L, H, H)_2	3458.869	3471.869	3458.869	0.000	4339.182	4213.752	4427.182	4213.752	4339.182	4213.752	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	21.825	25.451	
(L, H, H)_3	3551.840	3670.480	3551.840	0.000	4257.434	4146.003	4257.434	4146.003	4257.434	4146.003	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	16.728	19.866	
(L, H, H)_4	5558.782	5558.782	5546.782	0.216	6304.291	6267.861	6304.291	6267.861	6304.291	6267.861	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	12.756	13.411	
(L, H, H)_5	3068.404	3328.183	3068.404	0.000	4081.907	3899.483	4081.907	3899.483	4081.907	3899.483	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085	33.030	27.085		
(L, H, H)_6	3798.088	4071.987	3798.088	0.000	5393.587	5347.162	5393.587	5347.162	5393.587	5347.162	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786	42.008	40.786		
(L, H, H)_7	4033.972	4033.972	4033.972	0.000	4564.021	4543.447	4564.021	4543.447	4564.021	4543.447	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630	13.140	12.630		
(L, H, H)_8	4607.072	4682.060	4607.072	0.000	5391.836	5360.128	5391.836	5360.128	5391.836	5360.128	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346	17.034	16.346		
(L, H, H)_9	4897.893	4975.403	4897.893	0.000	5616.015	5687.587	5616.015	5687.587	5616.015	5687.587	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123	14.662	16.123		
(L, H, H)_10	4058.054	4200.722	4058.054	0.000	5049.041	5099.868	5016.041	5176.868	5016.041	5028.868	24.420	25.673	23.607	27.570	23.607	23.923	24.420	25.673	23.607	27.570	23.607	23.923	24.420	25.673	23.607	27.570	23.607	23.923	24.420	25.673	23.607	27.570		
Average	3939.701	4037.049	3938.501	0.022	4818.431	4823.930	4793.131	4819.530	4765.131	4819.530	23.783	22.908	23.956	23.098	23.684	23.098	23.783	22.908	23.956	23.098	23.684	23.098	23.783	22.908	23.956	23.098	23.684	23.098	23.783	22.908	23.956	23.098		
(M, H, H)_1	8468.705	8497.927	8468.705	0.000	10116.324	9922.686	10302.115	10139.686	10221.115	10171.686	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169	19.455	17.169		
(M, H, H)_2	7595.543	7703.543	7595.543	0.000	10083.869	10002.440	9951.869	9837.440	9377.869	9320.440	32.760	31.688	31.022	29.516	23.465	22.709	32.760	31.688	31.022	29.516	23.465	22.709	32.760	31.688	31.022	29.516	23.465	22.709	32.760	31.688	31.022	29.516		
(M, H, H)_3	5566.614	5566.614	5566.614	0.000	6867.690	6686.260	6933.690	6774.260	6962.837	6708.260	23.373	20.114	24.558	21.694	25.082	20.509	23.373	20.114	24.558	21.694	25.082	20.509	23.373	20.114	24.558	21.694	25.082	20.509	23.373	20.114	24.558	21.694		
(M, H, H)_4	8441.193	8638.996	8441.193	0.000	10573.123	10378.688	10494.123	10574.831	10329.394	10436.688	25.256	22.953	24.320	25.276	22.369	23.640	25.256	22.953	24.320	25.276	22.369	23.640	25.256	22.953	24.320	25.276	22.369	23.640	25.256	22.953	24.320	25.276		
(M, H, H)_5	8429.202	8525.202	8429.202	0.000	10972.957	10770.536	10353.396	10158.975	10144.391	10273.975	30.178	27.776	22.828	20.321	20.348	21.885	30.178	27.776	22.828	20.321	20.348	21.885	30.178	27.776	22.828	20.321	20.348	21.885	30.178	27.776	22.828	20.321		
(M, H, H)_6	4742.556	4988.680	4742.556	0.000	5828.480	5899.902	6071.213	5967.208	5851.213	5824.208	22.897	24.403	28.016	25.823	23.377	22.807	22.897	24.403	28.016	25.823	23.377	22.807	22.897	24.403	28.016	25.823	23.377	22.807	22.897	24.403	28.016			
(M, H, H)_7	5667.720	5787.018	5641.695	0.461	7176.159	7175.912	7154.159	7219.912	6978.159	6995.159	26.615	26.610	26.226	27.387	23.121	23.421	27.199	27.194	26.809	27.974	23.689	23.990	27.199	27.194	26.809	27.974	23.689	23.990	27.199	27.194	26.809	27.974		
(M, H, H)_8	8241.304	8332.490	8241.304	0.000	9725.722	9810.151	9567.454	9202.028	9848.614	9323.028	18.012	19.036	16.092	11.657	19.503	13.126	18.012	19.036	16.092	11.657	19.503	13.126	18.012	19.036	16.092	11.657	19.503	13.126	18.012	19.036	16.092			
(M, H, H)_9	8089.054	8149.054	8018.831	0.876	9776.015	9748.593	9776.015	9748.593	9675.857	9652.862	20.855	20.516	20.855	20.516	19.617	19.332	21.913	21.571	19.617	19.332	21.913	21.571	19.617	19.332	21.913	21.571	19.617	19.332	21.913	21.571	19.617			
(M, H, H)_10	6277.129	6277.129	6277.129	0.000	7402.697	7380.267	7386.101	7357.267	7287.101	7121.862	17.931	17.574	17.667	17.208	16.090	13.457	17.931	17.574	17.667	17.208	16.090	13.457	17.931	17.574	17.667	17.208	16.090	13.457	17.931	17.574	17.667			
Average	7151.902	7246.665	7142.277	0.134	8852.303	8777.543	8799.013	8698.020	8667.655	8582.817	23.733	22.784	23.323	21.933	21.366	20.100	23.898	22.948	23.487	22.097	21.528	20.261	23.487	22.097	21.528	20.261	23.487	22.097	21.528	20.261	23.487			
(H, H, H)_1	11186.945	11195.367	11112.656	0.669	14184.611	14283.188	14085.476	14441.052	12842.392	13594.825	26.796	27.677	25.910	29.088	14.798	21.524	27.644	28.531	26.752	29.951	15.565	22.336	27.644	28.531	26.752	29.951	15.565	22.336	27.644	28.531	26.752			
(H, H, H)_2	12165.717	12411.775	12165.717	0.000	15362.541	15319.817	15436.224	15259.589	15153.560	15797.169	26.277	25.926	26.883	25.431	24.560	29.850	26.277	25.926	26.883	25.431	24.560	29.850	26.277	25.926	26.883	25.431	24.560	29.850	26.277	25.926	26.883			
(H, H, H)_3	9441.868	9492.935	9424.868	0.180	11361.831	11579.407	11361.831	11579.407	11334.831	11325.407	20.335	22.639	20.335	22.639	20.049	19.949	20.335	22.639	20.049	19.949	20.335	22.639	20.049	19.949	20.335	22.639	20.049	19.949	20.335	22.639	20.049			
(H, H, H)_4	9265.295	9265.295	9265.295	0.000	11618.561	11683.991	11662.561	11661.991	10952.491	11086.921	25.399	26.105	25.874	25.867	18.210	19.661	25.399	26.105	25.867	18.210	19.661	25.399	26.105	25.867	18.210	19.661	25.399	26.105	25.867	18.210	19.661			
(H, H, H)_5	11728.096	11958.220	11728.096	0.000	15058.175	15293.813	15167.292	15385.289	15494.668	15438.927	28.394	30.403	29.324	31.183	32.116	31.641	28.394	30.403	29.324	31.183	32.116	31.641	28.394	30.403	29.324	31.183	32.116	31.641	28.394	30.403	29.324			
(H, H, H)_6	9905.192	10017.566	9905.192	0.000	13482.331	13473.337	12928.262	13095.269	12353.412	13321.911	36.114	36.023	30.520	32.206	24.717	34.494	36.114	36.023	30.520	32.206	24.717	34.494	36.114	36.023	30.520	32.206	24.717</							

Table E.4: Results of the multi-agent-based hybrid model on benchmark instance set 2 with $w_1=1$ and $w_2=2$

Problem instance	Objective value		Relative deviation (%)	KPI value						Relative deviation to TSI (%)						Relative deviation to MIP (%)											
	TSI	MIP		S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6						
(E, H, H)_1	34411.247	34411.247	0.000	44308.048	44385.808	43672.442	44029.442	43507.026	42056.269	28.760	28.986	26.913	27.951	26.433	22.217	28.760	28.986	26.913	27.951	26.433	22.217	28.760	28.986	26.913	27.951	26.433	22.217
(E, H, H)_2	24257.959	24257.959	0.000	30224.609	30138.839	29527.575	29467.309	29397.720	29093.408	24.597	24.243	21.723	21.475	21.188	19.933	24.597	24.243	21.723	21.475	21.188	19.933	24.597	24.243	21.723	21.475	21.188	19.933
(E, H, H)_3	34193.078	34193.078	0.000	41638.831	41637.830	41372.191	41292.421	40147.981	40416.140	21.776	21.773	20.996	20.763	17.416	18.200	21.776	21.773	20.996	20.763	17.416	18.200	21.776	21.773	20.996	20.763	17.416	18.200
(E, H, H)_4	22982.897	22982.897	0.000	28783.956	28565.931	29014.132	29047.129	28606.269	28695.224	25.241	24.292	26.242	26.386	24.468	24.855	25.241	24.292	26.242	26.386	24.468	24.855	25.241	24.292	26.242	26.386	24.468	24.855
(E, H, H)_5	36092.728	35222.376	2.471	44655.532	44497.647	43905.372	43790.918	43264.496	42935.615	23.724	23.287	21.646	21.329	19.870	18.959	26.782	26.333	24.652	24.327	22.832	21.899	26.782	26.333	24.652	24.327	22.832	21.899
Average	30387.582	30213.511	0.494	37922.195	37845.211	37498.342	37525.444	36984.698	36639.331	24.820	24.516	23.504	23.581	21.875	20.833	25.431	25.126	24.105	24.180	22.467	21.421	25.431	25.126	24.105	24.180	22.467	21.421

F

Résumé étendu

Dans les entrepôts conventionnels, les marchandises provenant des fournisseurs sont placées dans le stock, conservées, puis retirées du stock quand nécessaire pour répondre à la demande des clients. Cependant, détenir un stock coûte cher. Ainsi, les organisations recherchent constamment des méthodes pour réduire le niveau des stocks dans la chaîne d'approvisionnement.

Contrairement à l'entrepôt traditionnel, le cross-docking, technique logistique juste-à-temps, répond à cette quête en synchronisant les entrées et sorties de marchandises avec un stockage nul ou limité entre les deux (moins de 24 heures) : une fois les marchandises entrées sur le quai de réception (entrée), elles sont consolidées avec d'autres flux de marchandises ayant les mêmes caractéristiques, puis acheminées directement vers un quai d'expédition (sortie) pour être chargées sur des moyens de transport (par exemple camion, bateau et train). En conséquence, cela réduit considérablement les niveaux de stock et garantit des livraisons à temps, répondant ainsi aux attentes à la fois des organisations et des clients.

Bien que le cross-docking présente de nombreux avantages, selon [Ladier and Alpan \(2016a\)](#), il nécessite une parfaite coordination des flux entrants et sortants des plateformes logistiques dans des conditions incertaines. En effet, les praticiens et les chercheurs sont confrontés à des conditions changeantes et à des défis, tels que des retards de circulation entraînant des incertitudes sur l'heure d'arrivée des camions et des pannes de portes ou d'équipements, tout en répondant à l'exigence d'un flux de marchandises fluide dans le contexte complexe du cross-docking.

Dans le contexte du cross-docking, des difficultés peuvent surgir de nombreux aspects, tels que la planification des camions, la gestion des stocks, la coordination de la main-d'œuvre et l'utilisation des ressources, tous travaillant ensemble pour garantir un flux efficace des marchandises. Chacun de ces facteurs est interconnecté, et tout changement dans l'un peut avoir des répercussions sur l'ensemble des opérations, rendant le cross-docking complexe.

Pour faire face à ces difficultés et permettre une prise de décision efficace dans des conditions de cross-docking dynamiques et incertaines, nous avons mené une revue complète de la littérature ([Torbalı and Alpan, 2023a](#)). Nos résultats mettent en évidence le rôle important des modèles robustes en tant que solutions proactives pour faire face à l'incertitude, complété par la réactivité des modèles en temps réel lorsque les incertitudes dépassent certains seuils. Cependant, d'après notre étude bibliographique, l'application limitée des modèles en temps réel dans le domaine du cross-dock est apparue comme une lacune significative dans la littérature. Nous avons aussi constaté que malgré l'adoption limitée de modèles dynamiques dans la littérature, tels que les modèles de simulation et les modèles multi-agents, ils sont prometteurs en matière d'exploitation des données en temps réel pour répondre aux défis de planification du cross-docking.

Les modèles en temps réel sont essentiels pour garantir la flexibilité, la stabilité et l'utilisation efficace des ressources. Ils jouent un rôle important dans le maintien du flux des activités de cross-docking. Leur présence est impérative pour orchestrer des réponses agiles aux défis en constante évolution rencontrés dans le cadre du cross-docking.

Cependant, étant donné que les modèles temps réel acquièrent une visibilité complète sur le système, ils nécessitent une quantité accrue de données en temps réel. Les technologies de l'Industrie 4.0 peuvent apporter une solution puissante à ce défi puisqu'elles prennent en charge la planification en temps réel.

Dans cette thèse, nous explorons l'environnement dynamique du cross-docking pour améliorer les opérations afin de répondre à divers défis, notamment les retards de camions et les temps de traitement variés tout en respectant les exigences d'une synchronisation rapide du cross-dock. L'objectif principal de cette thèse est de développer un modèle en temps réel permettant une exploitation cross-docking efficace et efficiente dans un environnement incertain.

Le *temps réel* représente une capacité de prise de décision rapide et adaptative qui améliore la flexibilité, l'efficacité et la réactivité opérationnelles. Pour mieux comprendre l'essence du *temps réel* dans ce contexte, il est nécessaire de clarifier cette notion temporelle, étant donné qu'elle joue un rôle clé dans l'élaboration de notre approche des opérations de cross-docking. La définition du terme *temps réel* peut varier selon l'application pour laquelle la méthode temps réel est conçue.

Le *temps* peut être de l'ordre de l'ultra-rapide, mesuré en nanosecondes, mais peut également s'étendre jusqu'à plusieurs minutes en fonction des exigences de l'application. En cross-docking, la planification en *temps réel* nécessite des réponses rapides et efficaces, mais peut admettre un délai de décision de quelques minutes. Ce délai est à déterminer par les décideurs en fonction des besoins précis des opérations de cross-docking. Cela garantit que la planification reste très réactive aux conditions variables et facilite une utilisation efficace des ressources, une réduction des retards et un flux rapide des marchandises au sein de la plate-forme de cross-dock. Dans le cadre de cette thèse, et sans perte de généralité, nous adoptons l'hypothèse selon laquelle un planning de cross-docking en *temps réel* ne doit pas dépasser le seuil de cinq minutes en nous basant sur notre expérience antérieure sur les problèmes de planning de camions (Ladier and Alpan, 2016a; Larbi et al., 2011).

Dans cette thèse, le terme *modélisation en temps réel* implique une méthode de surveillance, d'analyse et d'optimisation des opérations en temps réel à l'aide d'analyse de données et de simulation. Cela signifie utiliser des données en temps réel pour rendre les opérations de cross-docking plus efficaces et efficientes.

Pour atteindre l'objectif principal de cette thèse, nous avons orienté notre attention vers quatre thèmes :

- la planification en temps réel des camions entrants et sortants, ce qui impacte directement le flux de palettes dans un terminal de cross-docking ;
- l'adaptation des opérations internes d'un terminal de cross-docking pour répondre dynamiquement aux flux entrants et sortants en temps réel ;
- l'ajustement de la planification en temps réel pour intégrer efficacement des scénarios de cross-dock réalistes ;
- et la démonstration des avantages et capacités d'adaptation des méthodes de planification en temps réel dans le contexte de diverses configurations de problèmes trouvés dans la littérature sur le cross-docking, particulièrement appropriés aux méthodes de planification déterministes.

La figure F.1 résume visuellement la portée de nos recherches dans cette thèse.

En première partie de cette thèse, nous avons réalisé un état de l'art des modèles robustes et temps réel dans le contexte du cross-docking, avec un accent particulier sur les problèmes de planification, notamment dans l'environnement du cross-dock route-à-route. L'examen systématique de la littérature comprend diverses étapes, notamment la collecte, l'identification, la sélection, l'éligibilité et l'inclusion afin d'en extraire les recherches les plus pertinentes et de mettre en évidence les lacunes critiques de la littérature existante. Tout d'abord, il existe une mise en œuvre limitée des modèles en temps réel dans la littérature sur le cross-docking malgré leur potentiel dans la prise de décision adaptative, l'amélioration de la flexibilité, de l'efficacité et de la réactivité opérationnelle. Ensuite, les modèles dynamiques, tels que les simulations et les modèles multi-agents, sont fermement engagés dans la réalisation de cet objectif.

En nous appuyant sur notre enquête approfondie sur le corpus de recherche existant et en identifiant les lacunes critiques dans la littérature, nous avons mené une analyse approfondie axée sur les principales méthodes de simulation dominantes dans les problèmes de cross-docking. Plus précisément, notre enquête s'est concentrée sur les simulations multi-agents et à événements discrets et leurs applications hybrides, qui fusionnent les atouts des deux (SMA et SED). Nous avons approfondi ces techniques de modélisation, discutant de leur applicabilité et de leurs limites dans divers scénarios opérationnels. Cette exploration a souligné l'importance de sélectionner une méthodologie adaptée au problème spécifique en question. Les enseignements de cette analyse ont servi de pierre angulaire au développement d'un modèle innovant capable de planifier en temps réel les camions entrants et sortants ainsi que les flux de palettes au sein d'un terminal de cross-docking.

Chapitre 1

Introduction

Chapitre 2

Revue de la littérature sur les modèles robustes et en temps réel pour le cross-docking

Chapitre 3

Methodologie

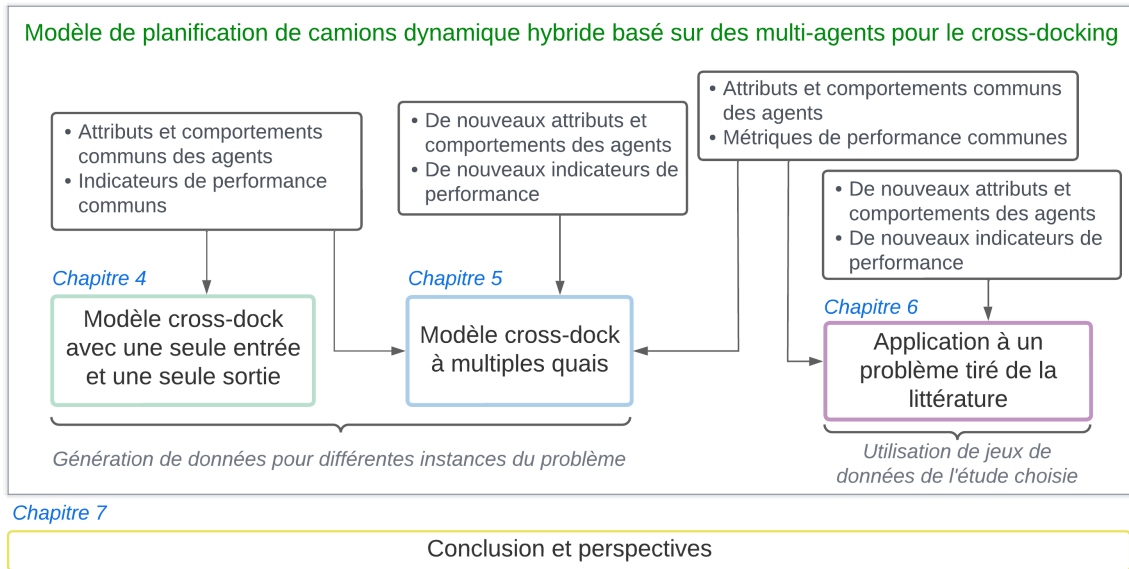


Figure F.1: Structure de la thèse

De plus, nous disposons des connaissances nécessaires pour configurer les opérations internes du terminal de manière très réactive aux fluctuations en temps réel des flux entrants et sortants.

Dans notre enquête visant à concrétiser nos objectifs, nous avons lancé la première étape du développement d'un modèle innovant de planification des camions en temps réel dans les opérations de cross-docking. Reconnaisant l'importance de la sélection de méthodologies axée sur les problèmes, nous avons mis en œuvre ce modèle dynamique comme une approche multi-méthodes, intégrant à la fois des simulations multi-agents et à événements discrets. Notre objectif était de synchroniser rapidement les opérations de cross-docking en utilisant les attributs d'autonomie, de réactivité et de responsabilité distribuée des systèmes multi-agents pour permettre un calcul partagé et pour réagir avec flexibilité aux événements dynamiques. Notre étude sert de preuve de concept sur l'utilisation d'un modèle hybride pour la planification des camions en temps réel dans les cross-docks. Pour atteindre cet objectif, nous avons défini les camions et les portes de quai comme des agents autonomes responsables de la prise de décision. Pour les opérations internes de l'entrepôt, nous avons utilisé SED pour sa simplicité et pour réduire les frais de communication souvent associés aux systèmes multi-agents impliquant de nombreux agents. Le modèle a été implémenté pour un environnement de cross-dock à une seule porte entrante et une porte sortante, permettant une analyse approfondie des composants interconnectés du système. Cette approche nous a donné une compréhension approfondie de la planification multi-agents des camions en temps réel dans le cadre des opérations de cross-docking. L'analyse du modèle a été réalisée selon différentes stratégies de planification des camions et avec différents niveaux de trafic. La signification des résultats a été évaluée en réalisant une analyse de variance (ANOVA). Les connaissances acquises grâce à ce modèle nous ont doté des outils et de la compréhension nécessaires pour étendre notre modèle à des systèmes de cross-docking plus complexes, notamment des environnements multi-dock.

Dans une deuxième étape, nous avons développé un modèle étendu en généralisant les principales conclusions du modèle à une seule porte entrante et une porte sortante. Nous avons lancé

une analyse plus approfondie pour nous aligner sur un contexte industriel. Dans ce modèle étendu, nous avons pris en compte les subtilités de la gestion de plusieurs portes de quai et incorporé un large éventail de stratégies de prise de décision. Ce développement a permis une représentation plus précise de la nature dynamique des opérations de cross-docking. Notre recherche était profondément ancrée dans l'aspect pratique alors que nous explorions divers scénarios, notamment des niveaux de trafic fluctuants et diverses configurations de portes, chaque scénario étant contrôlé par des règles distinctes de sélection de camions et de portes. Grâce à ces investigations, appuyées par des tests statistiques, nous avons mesuré l'adaptabilité et l'efficacité de notre modèle, confirmant son applicabilité dans divers contextes opérationnels. Suite à nos conclusions, nous avons évalué l'évolutivité du modèle en le soumettant à un large éventail de configurations de portes. En parallèle, nous avons surveillé son efficacité de calcul dans les conditions temporelles applicables représentant des cross-docks réels. Il est devenu évident que des défis sur la complexité des calculs se posent, en particulier lorsque le nombre total de portes de quai dépasse 30. Ce défi est devenu encore plus visible dans le cadre de stratégies complexes de sélection de portes dans les configurations de 20 portes entrantes et 20 portes sortantes. Pour relever ces défis informatiques, nous avons examiné les performances du modèle, en surveillant les temps de calcul à intervalles de deux heures pendant une période de simulation de 48 heures. Nos résultats ont mis en évidence un seuil critique : le modèle peut réaliser efficacement une planification en temps réel si la durée de la simulation reste comprise entre 2 et 3 heures. Ces informations nous permettent de mesurer l'utilité pratique du modèle pour les applications de planification en temps réel, affirmant ainsi son potentiel en tant qu'outil précieux dans le domaine du cross-docking dynamique.

Enfin, nous avons développé un modèle pour démontrer l'applicabilité de notre modèle hybride multi-agents pour résoudre diverses configurations de problèmes de planification de camions rencontrés dans la littérature sur le cross-docking. À cette fin, nous avons sélectionné une étude de planification des camions, appelée *VB* dans cette thèse, spécialement adaptée aux méthodes de planification déterministes. En adaptant nos mécanismes de prise de décision de nos deux modèles précédents pour les aligner sur l'orientation de *VB*, nous avons introduit des mécanismes supplémentaires conçus explicitement à cet effet. Nous avons utilisé les mêmes jeux de données d'entrée que ceux utilisés dans *VB* pour une comparaison équitable et une évaluation des performances. Notre analyse des résultats impliquait un examen attentif des hypothèses et des limites inhérentes aux deux approches de modélisation. Notamment, les résultats générés par notre modèle hybride ont pris du retard (entre 17% et 30%) par rapport à l'algorithme le plus performant présenté dans [Van Belle et al. \(2013\)](#) pour *VB*. Ce résultat était attendu en raison d'une différence fondamentale d'approche : les modèles d'optimisation développés par [Van Belle et al. \(2013\)](#) fonctionnent avec des informations complètes lors de la génération de solutions, tandis que notre modèle hybride fonctionne en temps réel sans connaissance des événements futurs. De plus, les modèles d'optimisation mathématique présentent des limites inhérentes à la capture des complexités et des incertitudes dominantes dans les scénarios réels de planification des camions. En revanche, les points forts de notre modèle hybride multi-agents résident dans sa capacité à relever les défis pratiques rencontrés dans les opérations de cross-docking réelles, où l'adaptation en temps réel et la réactivité aux événements dynamiques sont essentielles.

La principale contribution de cette thèse réside dans le développement et la validation d'une nouvelle approche hybride multi-agents permettant une synchronisation rapide des opérations de cross-docking face à des conditions en constante évolution. En intégrant de manière transparente des systèmes multi-agents et des simulations à événements discrets, le modèle hybride proposé fournit un cadre dynamique et adaptatif pour la prise de décision en temps réel en matière de cross-docking, améliorant ainsi la flexibilité, l'efficacité et la réactivité opérationnelle. L'approche proposée comble une lacune critique dans la littérature existante, où l'adoption de modèles en temps réel pour le cross-docking est limitée. De plus, nos travaux posent les bases de futures applications de modélisation en temps réel dans ce domaine pour la gestion et l'amélioration des opérations de cross-docking.

Cette thèse ouvre également de nombreuses perspectives de recherche à court et long terme. La première perspective implique une analyse de sensibilité approfondie sur des paramètres clés tels que la disponibilité de la main d'œuvre (opérateurs et matériels de manutention), la capacité de stockage et leurs contraintes. Cette analyse révélera comment ces paramètres impactent les décisions de planification et les performances globales du modèle. Ces informations permettront aux décideurs de planifier plus efficacement et de manière plus réactive en scénarios réels.

Une autre orientation future concerne l'optimisation des stratégies les plus élaborées au sein de notre modèle à portes multiples, qui apparaissent coûteuses en temps de calcul. Cette optimisation consistera à utiliser des techniques de profilage de code pour identifier les processus et les structures de données gourmands en mémoire et en temps d'exécution, dans le but de réduire l'utilisation de la mémoire et d'accélérer l'exécution des calculs.

D'autres recherches incluent la simulation de nos modèles hybrides dans divers scénarios, notamment l'évaluation des horaires des camions à partir de méthodes proactives. En soumettant ces horaires à des perturbations courantes dans les opérations réelles de cross-dock, telles que des facteurs internes (par exemple l'indisponibilité des portes de quai) et externes (par exemple les retards des camions), nous améliorerons l'évaluation de la robustesse de nos modèles, confirmant leur applicabilité dans le monde réel.

Une autre perspective consiste à mettre en œuvre une fenêtre temporelle glissante pour relever les problèmes de temps de calcul, en particulier pour les scénarios dépassant 30 portes de quai. L'implémentation d'une fenêtre temporelle glissante est particulièrement pertinente en raison de l'écart de performances de notre modèle hybride par rapport au modèle d'optimisation de [Van Belle et al. \(2013\)](#) pour VB. Cette approche devrait permettre de réduire les temps de calcul de notre simulation. Grâce à des expériences avec différentes durées de fenêtre temporelle, nous pouvons affiner nos modèles pour améliorer l'efficacité opérationnelle et de la prise de décision en temps réel.

Une perspective écologiquement responsable de cette recherche implique l'utilisation d'une approche axée sur la durabilité dans l'exploitation des installations et la planification des camions en temps réel. Le modèle pourrait inclure des algorithmes permettant de prioriser les itinéraires écologiques pour les agents routiers. Une autre approche de durabilité consisterait en la consolidation des charges, où le modèle optimiserait l'allocation des palettes pour réduire le nombre de camions utilisés afin de réduire les émissions par unité de palette. Cette approche holistique profiterait à la fois à l'environnement et aux résultats financiers de l'installation.

Une orientation future passionnante consistera à insuffler à notre système une intelligence avancée, en particulier avec l'apprentissage par renforcement via des agents autonomes. Cette approche confèrera au modèle des capacités d'apprentissage et d'adaptation, améliorant ainsi la prise de décision basée sur l'apprentissage cumulatif. Elle promet une plus grande adaptabilité et efficacité dans la planification des camions en temps réel pour les processus de cross-docking, ce qui représente un développement des plus exaltant dans notre étude.

Enfin, notre approche hybride de planification des camions en temps réel dans les cross-docks sera étendue à la planification collaborative entre les nœuds de la chaîne d'approvisionnement, offrant ainsi une optimisation globale de la chaîne d'approvisionnement grâce à la communication de données en temps réel avec les fournisseurs et les détaillants.

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Résumé

Dans cette thèse nous proposons une nouvelle approche de planification en temps réel en entrepôts cross-dock. Le cross-docking est une technique de logistique permettant l'accélération du flux de marchandises dans un entrepôt avec zéro ou minimum stockage (moins de 24 heures), en orchestrant efficacement les activités entrantes et sortantes ainsi que les opérations internes de l'entrepôt. À travers une revue littéraire complète, nous soulignons d'abord le besoin d'explorer les approches temps réel pour le cross-docking.

Le cadre de planification de camions en temps réel proposé est basé sur un modèle hybride combinant simulation multi-agent (SMA) et simulation à événements discrets (SED). Nous proposons d'utiliser la SMA pour les décisions de planification de camions et la SED pour l'exécution des opérations internes au cross-dock afin de bénéficier des forces des deux techniques : l'approche multi-agent a les propriétés d'autonomie, de réactivité et un caractère distribué, lui permettant de répondre de manière flexible aux événements dynamiques tels que l'arrivée de camions. La SED, orientée sur les procédés, permet le contrôle centralisé des opérations internes. Le cadre proposé est implémenté en trois configurations différentes.

Nous nous intéressons tout d'abord à la configuration de cross-dock avec une seule entrée et une seule sortie afin de bien comprendre les dynamiques complexes du système et les mécanismes à l'œuvre dans la planification multi-agent de camions en temps réel. Ce modèle initial est ensuite porté à l'échelle dans une configuration de cross-dock avec multiples quais d'entrée et multiples quais de sortie en augmentant graduellement le nombre de quais. Les mécanismes de décision de sélection de camion sont alors portés à l'échelle et de nouveaux mécanismes de décision (ex. sélection de quai) sont ajoutés au modèle. De manière similaire, le fonctionnement interne de l'entrepôt est adapté aux besoins de la configuration multi-quai (ex. espace de stockage temporaire distribué). Pour chacune de ces configurations, la performance du modèle est évaluée pour une combinaison de différents niveaux de trafic et des stratégies variées de sélection de camion-à-quai. L'impact des résultats est attesté par des tests d'analyse de variance (ANOVA). De plus, des analyses de comportement et de temps de calcul du modèle multi-quais sont effectuées. Enfin, un troisième modèle est développé dans le but d'illustrer le fait que l'approche proposée peut être appliquée avec succès à d'autres configurations de problèmes de planification de camion. Ainsi, un problème de planification de camion existant dans la littérature, qui fait appel à une optimisation mathématique, est sélectionné. Les instances du problème de l'étude choisie sont exploitées dans le but d'effectuer un comparatif. L'analyse des résultats des métriques de performances est présentée d'un point de vue comparatif.

L'approche hybride multi-agent proposée révèle son efficacité en permettant une rapide synchronisation des cross-docks face à l'incertitude. Elle ouvre la voie à de futures applications temps réel dans le domaine.

Mots-clés

Cross-docking, Planification temps réel, Simulation multi-agents, Modélisation multi-méthodes, Simulation à événements discrets

Abstract

In this thesis we propose a novel framework for real-time truck scheduling in cross-dock warehouses. Cross-docking is a logistics technique that enables fast material flows with minimal (less than 24 hours) or no intermediate storage by efficiently orchestrating the inbound and outbound activities together with the internal operations. Through a comprehensive literature review, we first highlight the need to explore real-time approaches for cross-docking.

The proposed framework for real-time truck scheduling problem is based on a hybrid model combining multi-agent-based simulation (MAS) and discrete-event simulation (DES). We propose to use the MAS for truck scheduling decisions and DES for the execution of internal operations inside the cross-dock to benefit from the strengths of both techniques: The multi-agent approach practices the autonomous, reactive and thus distributed responsibility characteristics of the agents to realise shared computation and respond flexibly to dynamic events such as truck arrivals. The process-oriented DES enables central control of internal operations. The framework is implemented on three different settings.

We first focus on the single inbound and outbound cross-dock setting, for a better understanding of the complex dynamics of the system and the mechanisms involved in multi-agent-based real-time truck scheduling. This initial model is then scaled up to multiple inbound and outbound door cross-dock settings by gradually increasing the number of doors. To this end, the decision mechanisms on truck selection are scaled up, and new decision mechanisms (i.e. door selection) are added to the model. Similarly, the internal configuration of the platform is adapted towards the requirements of the multiple-door settings (e.g. distributed temporary storage). For both model settings, the performance of the proposed models is evaluated by employing a combination of different traffic levels and various truck-to-door assignment strategies. The significance of the results is attested using ANOVA (analysis of variance) tests. In addition, model behaviour and computational complexity analyses are performed as the model scales up. Finally, a third model is developed to illustrate that the proposed approach can successfully apply to other truck scheduling problem configurations. To this end, an existing truck scheduling problem in the cross-docking literature, which employs a mathematical optimisation, is selected. The problem instances of the chosen study are used for comparison purposes. The analysis of the results on the performance metrics is presented from a comparative point of view.

The proposed multi-agent-based hybrid approach reveals its efficacy in enabling fast synchronisation of cross-docks against uncertainty. It paves the way for future real-time applications in this field.

Keywords

Cross-docking, Real-time planning, Multi-agent simulation, Multi-method modelling, Discrete-event simulation