Supply Chain Analytics 3 (2023) 100028

Contents lists available at ScienceDirect

Supply Chain Analytics

journal homepage: www.sciencedirect.com/journal/supply-chain-analytics

A multi-agent-based real-time truck scheduling model for cross-docking problems with single inbound and outbound doors

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ARTICLE INFO

Keywords:
Logistics
Cross-docking
Real-time scheduling
Multi-agent simulation
Multi-method modelling
Discrete-event simulation

ABSTRACT

Cross-docking is a logistics methodology employed in warehouses to gain a competitive advantage by consolidating and transferring freights directly from an inbound supplier to an outbound client with no or restricted storage. Real-time data processing is required for fast synchronisation of inflows and outflows. This study develops 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 flexible responses 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-to-door assignment 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 analysis demonstrates that the stock policy (SP) outperforms all the others by sustaining low stock levels and high on-time deliveries and truck fill rates across all traffic levels, while the time-related strategies are adequate for cases where outbound traffic is more elevated than inbound traffic.

1. Introduction

Cross-docking is a logistics method operated in a freight terminal to achieve efficiency by consolidating and transferring freights directly from an inbound dock to an outbound dock in less than 24 h with no or limited storage. To this end, cross-docking needs perfect coordination of incoming and outgoing flows in logistics platforms under uncertain conditions [1]. Therefore, recent studies on cross-docking began to concentrate on uncertainty. In a recent literature review, various uncertainties inherent in cross-docking operations are examined by taking a point of view on the methods, notably from robust and real-time perspectives [2]. In order to achieve efficiency against uncertainty in cross-docking processes, 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 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, since DES is process-oriented and thus the decision-making is not modelled through the entities (passive entities), the interactions between the entities and their actions towards dynamic events are disregarded [3]. In this context, DES can be deficient in considering each cross-docking entity and its 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 modelling approach.

The multi-agent-based simulation uses the notion of multi-agent systems within the bare design of simulation models [4]. The term agent-directed simulation may even be used as a more widespread concept [5]. Multi-agent-based systems are built upon the elementary

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https://doi.org/10.1016/j.sca.2023.100028
Received 20 February 2023; Received in revised form 15 June 2023; Accepted 7 July 2023

units called agents. 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 [6], an agent is a computational method communicating with an environment. This characteristic can be provided with the following points [6]:

- 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. [7], 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 [8]. 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 [3]. 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.

By the motivation of process-oriented DES and the individual-based MAS that accesses and employs real-time data, this article proposes a hybrid dynamic model for cross-docking combining both DES and MAS. We propose to use the MAS for truck scheduling decisions and DES for the execution of internal operations inside the cross-dock, in order to benefit from the strengths of both techniques. The multi-agent approach practices the autonomous, reactive and thus distributed responsibility characteristics and can respond flexibly to dynamic events such as truck arrivals. However, when the number of agents increases the communication burden gets very high, especially for real-time applications. Therefore some of the elements of the model need not be represented as agents. DES is an alternative for modeling a part of the system to reduce the computational burden.

The objective of this study is to explore the potentials of this type of hybrid models for real-time decision-making regarding truck scheduling at the cross-docks.

In this study, the proposed hybrid model is developed for a single-inbound and single-outbound door cross-docking platform. To the best of our knowledge, the multi-agent-based real-time scheduling of both inbound and outbound trucks has not been studied in the cross-docking literature. Our decision to focus on the single inbound and outbound cross-dock setting is motivated by the need to provide a comprehensive analysis and evaluation of our proposed multi-agent-based hybrid model. This approach enables us to dissect the complex dynamics and intricacies of the system, achieving a profound understanding of the underlying principles and mechanisms involved in multi-agent-based real-time truck scheduling for cross-docking. Focusing on the single inbound and outbound cross-dock also lays a solid groundwork for scaling up to more complex cross-docking systems, notably to multi-dock environments.

The paper is organised as follows. Section 2 discusses different simulation modelling methods commonly used in the cross-docking literature. In Section 3, the proposed multi-agent-based truck scheduling model is described. Section 4 presents simulation results based on the key performance indicators. Finally, Section 5 concludes the paper with discussions on the outcomes of the proposed model together with the future directions.

2. Literature review

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 [9], 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.

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 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 1. In this table, studies are grouped according to their problem types. Note that a descriptive study of Rohrer [10] 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 subsections study the usage of predominantly employed simulation tools in cross-docking.

2.1. 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. [32] and Manupati et al. [34] 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, Alpan and Greenwood [37] 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, Yalcin and Yankov [26] 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 [25] 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, Enea and Muriana [24] 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,

Table 1
Simulation methods and their usage types in the cross-docking literature.

Publications	Simulation method (s)	Is simulation used to: validate and evaluate other modelling tool?	Is simulation used to: evaluate the system performance?	Performance measures	Cross-dock problem types
Shi et al. [11]	DES		✓	Stock level Lateness of product delivery Operation capacity of CDC*	Cross-dock design Scheduling, planning and coordination activities in CDC*
He and Prabhu [12]	DES		✓	AGV** utilisation	Cross-dock design Planning and coordination activities in CDC*
Piao and Yao [13]	DES		✓	Operation cost for CDC* Handling equipment utilisation	Scheduling, planning and coordination activities in CDC*
Buijs, Danhof and Wortmann [14]	DES		✓	Internal congestion of the CDC* Travel distance of load-carriers inside CDC* Lateness of product delivery Tardiness of outbound trucks	Scheduling, planning and coordination activities in CDC*
Yang, Balakrishnan and Cheng [15]	DES		✓	Operation capacity of CDC*	Scheduling, planning and coordination activities in CDC*
Magableh, Rossetti, and Mason [16]	DES		✓	Lateness of product delivery Truck processing time deviation	Scheduling, planning and coordination activities in CDC*
Chargui et al. [17]	DES		✓	Congestion Stock level Handling equipment utilisation Total unloading and loading time	Scheduling, planning and coordination activities in PI-hub
Pawlewski [18]	DES		✓	Travel distance inside PI-hub	Scheduling, planning and coordination activities in PI-hub
Liu and Takakuwa [19]	DES		✓	Inbound door utilisation Workforce utilisation	Scheduling, planning and coordination activities in CDC*
Liu [20]	DES		✓	Inbound door utilisation Workforce utilisation	Scheduling, planning and coordination activities in CDC*
Navin, Nithin and Ajimshad [21]	DES		✓	Average lead time of product delivery Service level Truck utilisation	Planning and coordination activities in CDC* Truck routing
Suh [22]	Hybrid		✓	Outbound truck utilisation Outbound truck fill rate Operation capacity of CDC*	Planning and coordination activities in CDC*
Chaiyarot and Pitiruek [23]	DES		✓	Operation capacity of CDC* Stock level Net profit	Planning and coordination activities in CDC*
Aiello, Enea and Muriana [24]	DES	✓		Transportation cost of trucks at supply chain	Truck routing
Lian [25]	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, Yalcin, and Yankov [26]	DES	✓		Door utilisation	Truck-to-door assignment
Walha et al. [27]	MAS		✓	Outbound truck utilisation Travel distance inside PI-hub	PI-containers-to-docks/trucks assignment (Rail-road PI-hub)
Chargui et al. [28]	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. [29]	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)
Sallez et al. [30]	MAS	✓		Evacuation time (i.e. makespan)	PI-containers grouping (Rail-road PI-hub)
Pach et al. [31]	MAS		✓	Evacuation time (i.e. makespan)	PI-containers grouping (Rail-road PI-hub)
Chargui et al. [32]	DES	✓		Tardiness of inbound and outbound trucks	Truck scheduling
Kusuma [33]	MAS		✓	Makespan Stock level	Truck scheduling
Manupati et al. [34]	DES	✓		Truck processing time deviation	Truck scheduling
Zouhaier and Ben Said [35]	MAS		✓	Truck processing time deviation	Truck scheduling
Zouhaier and Ben Said [36]	MAS		✓	Congestion Operation capacity of CDC* Operation cost for CDC* Truck processing time deviation	Truck scheduling

(continued on next page)

Table 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?		
Ladier, Alpan, and Greenwood [37]	DES	✓		Number of pallets put into storage Inbound and outbound truck docking times Inbound and outbound truck sojourn times	Truck scheduling
Wang and Regan [38]	DES		✓	Door utilisation Total unloading time Travel distance inside CDC*	Truck scheduling
This study	**Hybrid**		✓	**Average stock level** **Number of late pallets** **Pallet delay** **Outbound truck fill rate**	**Truck scheduling**

**CDC: cross-docking centre, **AGV: automated guided machine*

and the results are analysed. Similarly, Chaiyarot and Pitiruek [23] 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 repalletising (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. [11] 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 [38] 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 [39]. This method is referred as the simulation-optimisation method. Several scheduling studies in the cross-docking literature employ this method. Chargui et al. [29] 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 Yao [13] 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 [12,14–21]. Magableh, Rossetti, and Mason [16] 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, Balakrishnan and Cheng [15] 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 [12] 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. Lui [20] 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 [19] 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, Danhof and Wortmann [14], 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 [18] 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. [17] 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, Nithin and Ajimshad [21] 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.

2.2. 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 [27,28,30,31,33,35,36]. 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 [33] 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 the Kusuma [33], Zouhaier and Ben Said [35,36] 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 [36], 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 [35] 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 [28,30,31].

To this respect, Chargui et al. [28] 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. [31] 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 the Pach et al. [31], Sallez et al. [30] 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.

2.3. Cross-dock and hybrid simulation methods

When employing simulation methods to assess the feasibility and the consequences of implementing the cross-docking configuration, the particular requirements of the case should be investigated carefully. To that end, practitioners have initiated using hybrid simulation methods without being biased by the one method itself. To this respect, Suh [22] 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.

2.4. 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 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 [22]) 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 study is 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 study is oriented towards the truck scheduling problem with storage and time-related performance evaluation metrics.

The classification of the model settings for the cross-dock problems that employ different simulation techniques is given in Table 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 study, 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.

Finally, the model configuration of the agent-based approach of scheduling studies in the cross-docking domain is presented in Table 3. This summary table, together with Table 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 re-scheduling 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.

By the motivation of these concerns, in this article, we propose a novel hybrid simulation model composed of MAS and DES for real-time truck scheduling for cross-docking. Our study differs from the unique hybrid simulation model by Suh [22] because we model both the operational decisions to achieve effective coordination of 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 gives a detailed description of the proposed model.

3. Model description

This section describes the proposed multi-agent-based hybrid model. 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.

Figure 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 Fig. 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.

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-to-door assignment strategies are employed and compared, and the respective results are analysed.

3.1. Model specifications

The specifications of the presented model are given below.

The structure of the cross-dock (see Fig.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.

3.2. 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).

Table 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	Multi-product			
Shi et al. [11]		✓	✓				✓		✓			✓
He and Prabhu [12]		✓	✓					✓			✓	
Piao and Yao [13]		✓	✓						✓			✓
Buijs, Danhof and Wortmann [14]		✓		✓	✓							✓
Yang, Balakrishnan and Cheng [15]		✓	✓				✓			✓	✓	
Magableh, Rossetti, and Mason [16]		✓		✓	✓					✓		✓
Chargui et al. [17]		✓	✓				✓		✓			
Pawlewski [18]		✓	✓		✓							✓
Liu and Takakuwa [19]		✓	✓						✓			✓
Liu [20]		✓	✓						✓			✓
Navin, Nithin and Ajimshad [21]			✓				✓		✓		✓	
Suh [22]			✓						✓			✓
Chaiyarot and Pitiruek [23]		✓	✓				✓		✓			✓
Aiello, Enea and Muriana [24]							✓		✓	✓	✓	
Lian [25]								✓			✓	
Acar, Yalcin, and Yankov [26]		✓	✓		✓						✓	
Walha et al. [27]		✓	✓		✓				✓		✓	
Chargui et al. [28]		✓	✓		✓				✓		✓	
Chargui et al. [29]		✓	✓						✓		✓	✓
Sallez et al. [30]		✓	✓		✓						✓	
Pach et al. [31]		✓	✓		✓						✓	
Chargui et al. [32]		✓	✓				✓		✓			✓
Kusuma [33]	✓		✓			✓			✓	✓	✓	
Manupati et al. [34]		✓	✓		✓				✓		✓	
Zouhaier and Ben Said [35]			✓		✓						✓	
Zouhaier and Ben Said [36]		✓	✓		✓						✓	
Ladier, Alpan, and Greenwood [37]		✓	✓				✓	✓			✓	
Wang and Regan [38]		✓	✓		✓			✓			✓	
This study	✓		✓				✓		✓		✓	

Table 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. [28]	MAS	Rescheduling		Inbound (road-rail PI-hub)
Walha et al. [27]	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Sallez et al. [30]	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Pach et al. [31]	MAS	Rescheduling	✓	Outbound (rail-road PI-hub)
Kusuma [33]	MAS	Just-in-time		Inbound, outbound
Zouhaier and Ben Said [35]	MAS	Real-time	✓	Inbound
Zouhaier and Ben Said [36]	MAS	Real-time	✓	Inbound
Suh [22]	Hybrid	Robust		Internal operations
This study	**Hybrid**	**Real-time**	✓	**Inbound, outbound**

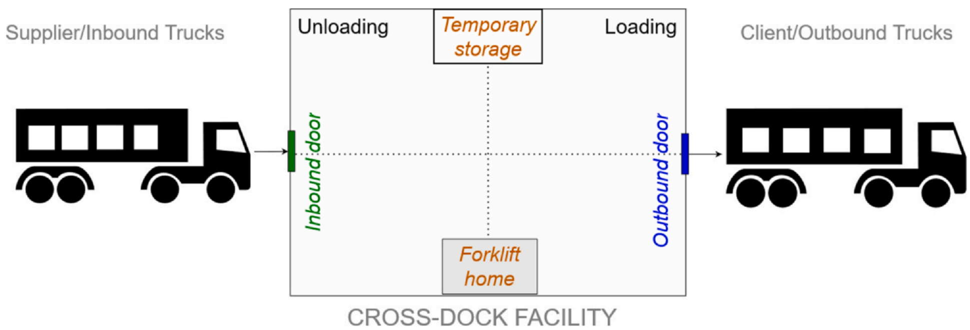

Fig. 1. The physical structure of the studied single inbound and outbound doors cross-dock.

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.

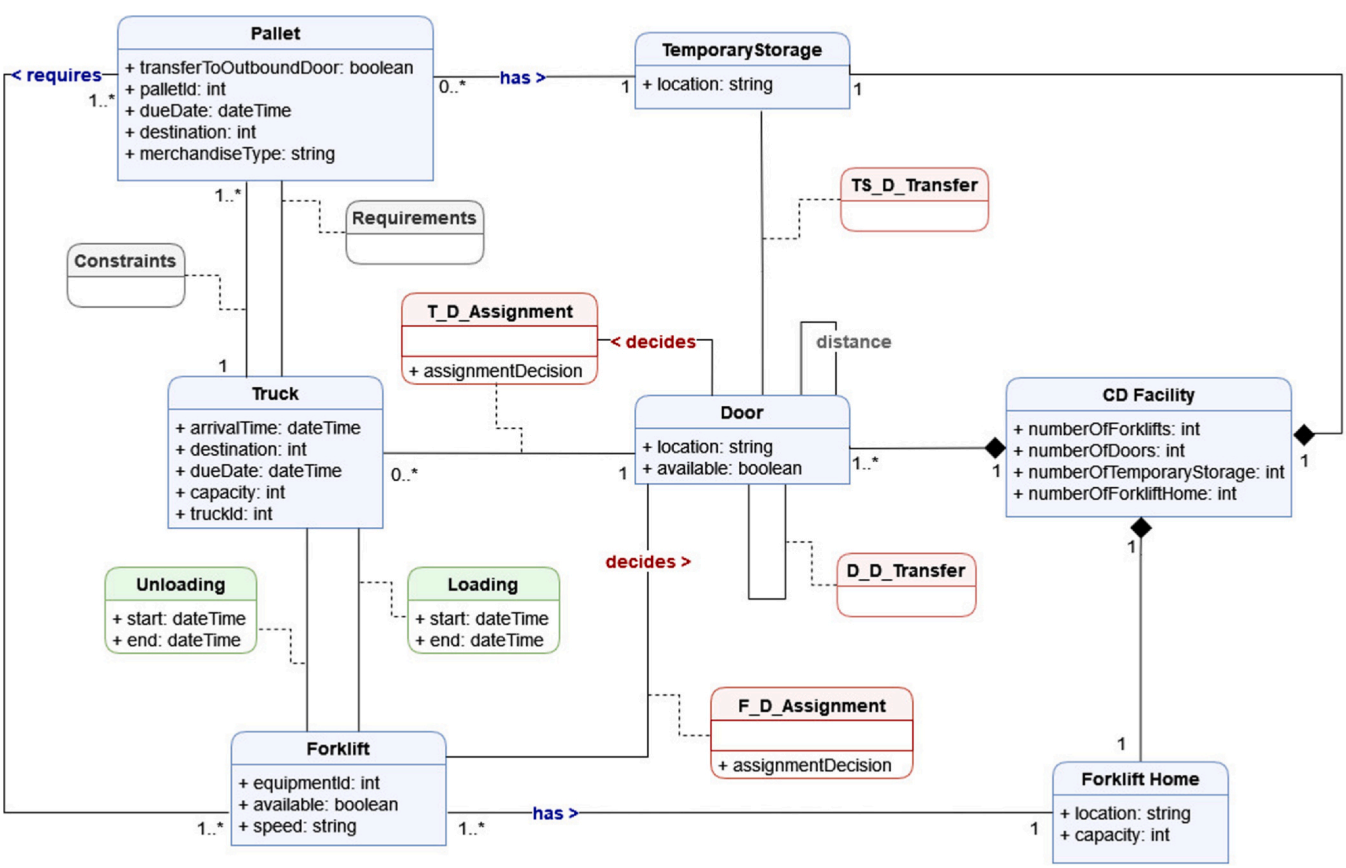

Fig. 2. The UML diagram of the proposed multi-agent-based dynamic model.

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

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 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.

3.3. Decision-making mechanism

Inbound and outbound door agents employ truck-to-door assignment 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-to-door assignment 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 truck-to-door assignment 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 Fig. 3. In this figure, the *release pallet 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 (Fig. 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

As indicated in Fig. 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 any transiting pallets. Therefore, before selecting a pallet for a given outbound truck a simple time check is performed to guarantee that the pallet can reach the truck before its departure. This verification helps avoiding unnecessary handling operations by the forklifts and/or congestion in dock area (i.e. moving a pallet which cannot be loaded on a truck on time either has to be returned on the temporary storage or blocks the dock area until an appropriate truck is docked).

3.4. 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. Similarly, the pallet delay is the sum of the delay of exited pallets

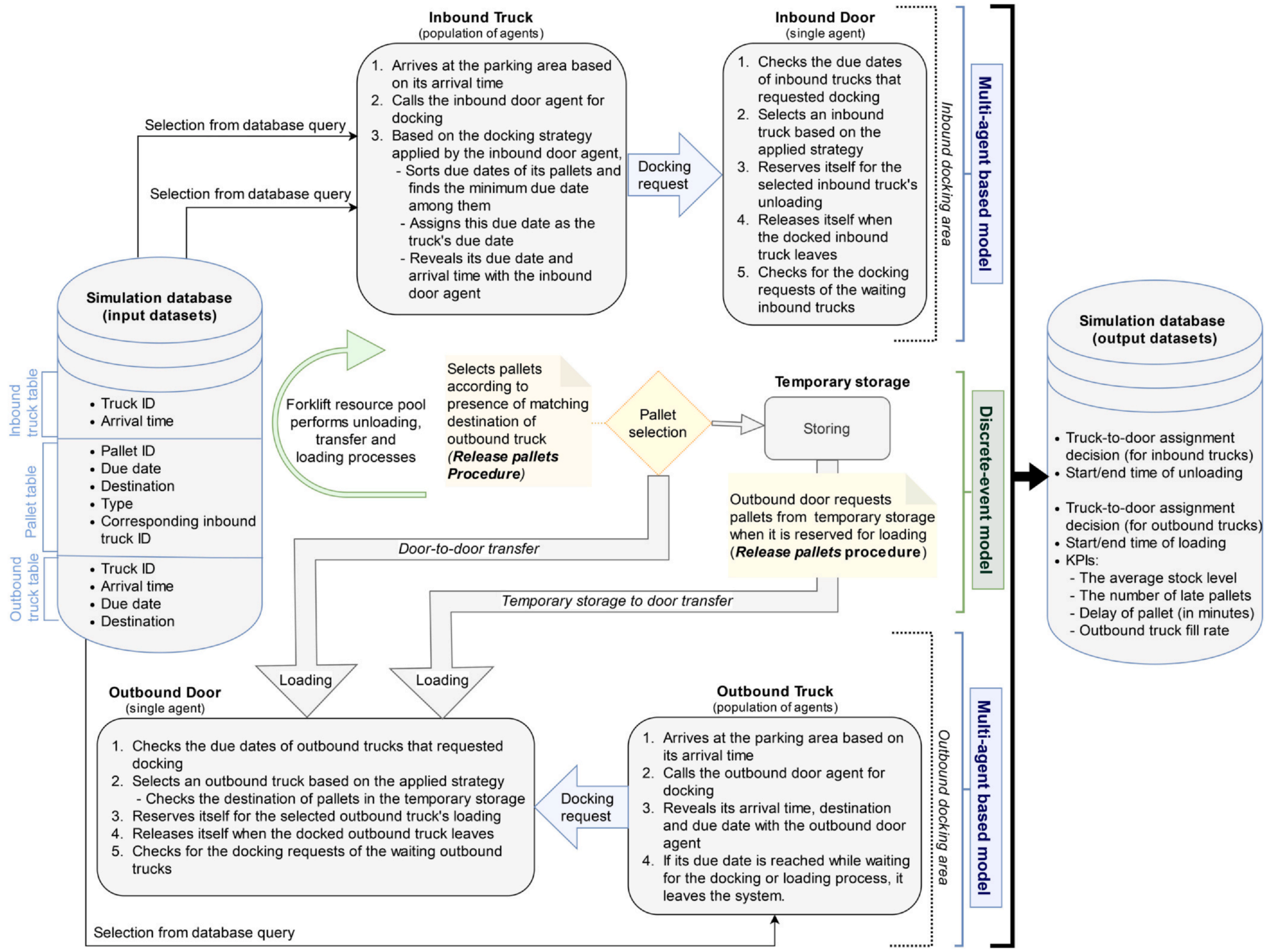

Fig. 3. The configuration of the proposed hybrid simulation model.

during the simulation run and the pallet delay in the last truck at the end of the simulation.

- **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.

4. 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) i5–8250 U 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.

4.1. 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). Three different truck-to-door assignment 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 5.

- Truck capacity: According to some European shipping companies, a Full Truck Load (FTL) shipment can range between 24 and 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) [40]. On the other hand, according to some Mexican-American-Canadian shipping companies, a full truck contains 26 pallets [41]. 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 [42]. 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) [43], the forklift speed is set at 3.6 m per second.
- Pallet due date: Since storage limitation at cross-docks is 24 h, pallet due dates are defined as their arrival times to the system (by inbound trucks) plus 24 h.

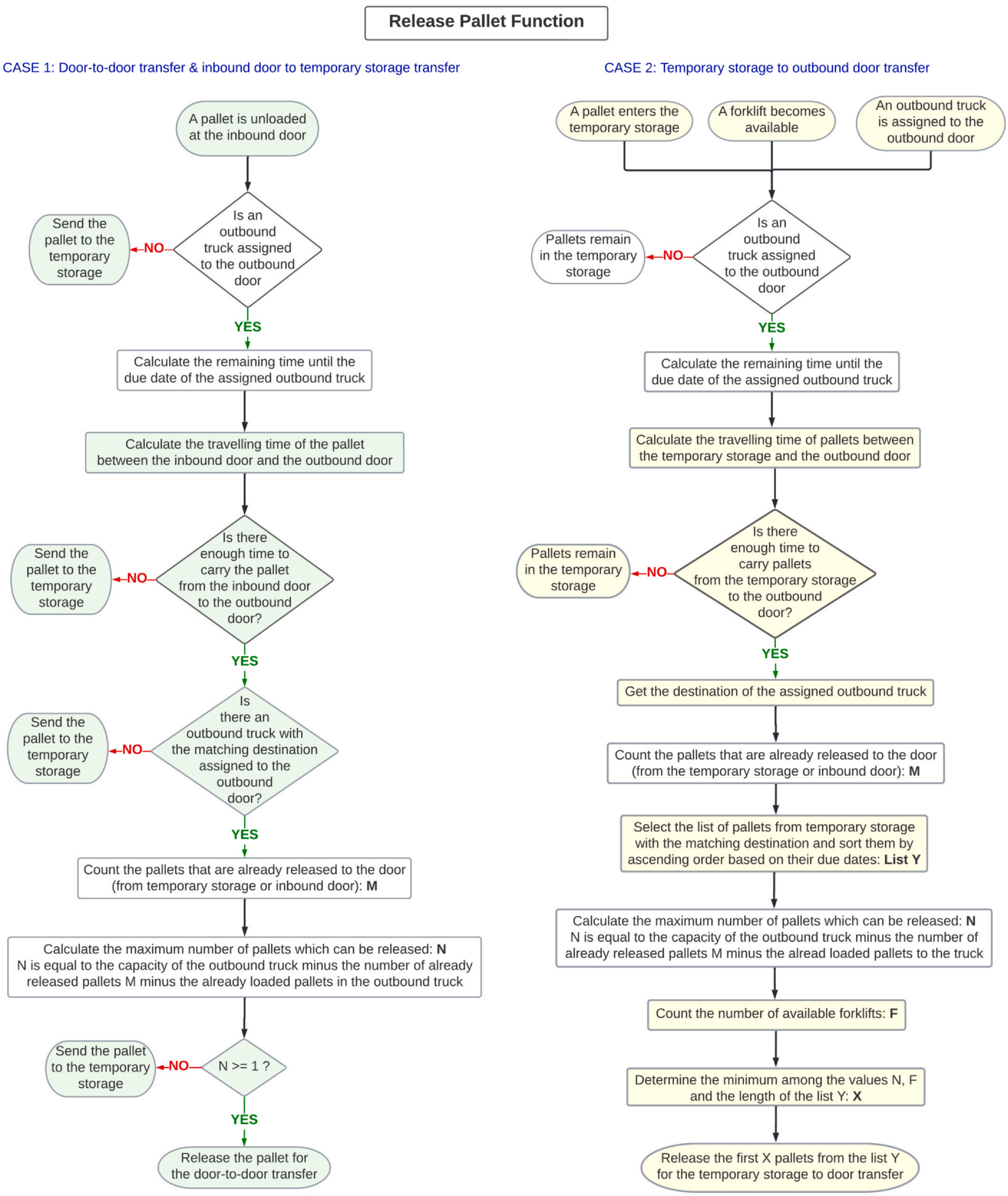

Fig. 4. The process flow chart of the *release pallet function*.

- 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
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)

Table 5
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/second)	3.6
Cross-dock facility area (in m2)	10,875
Number of freight (defined as a pallet) types	3 (type A, B, C)
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 date	
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 second)	Triangular(35, 62, 69)
Loading time (per pallet in second)	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

4.2. Output analysis

The analysis is made on the average simulation outcomes of 10 instances for each traffic level combination by applying each truck-to-door assignment 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 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 h 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 Figs. 5 to 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-to-door 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 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,

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

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

   where,
   1. x_i is the value of instance i
   2. $\bar{x}$ is the mean
   3. 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 independent groups and Wilcoxon-signed ranks test for dependent groups are employed.

The results of the one-way ANOVA are given in Tables 6 to 9. 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.

4.3. Analysis of the average stock level

Figure 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 6).

When we conduct a cross-analysis of Fig. 5 and Table 6, 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 Fig. 5, the performed post hoc test reveals

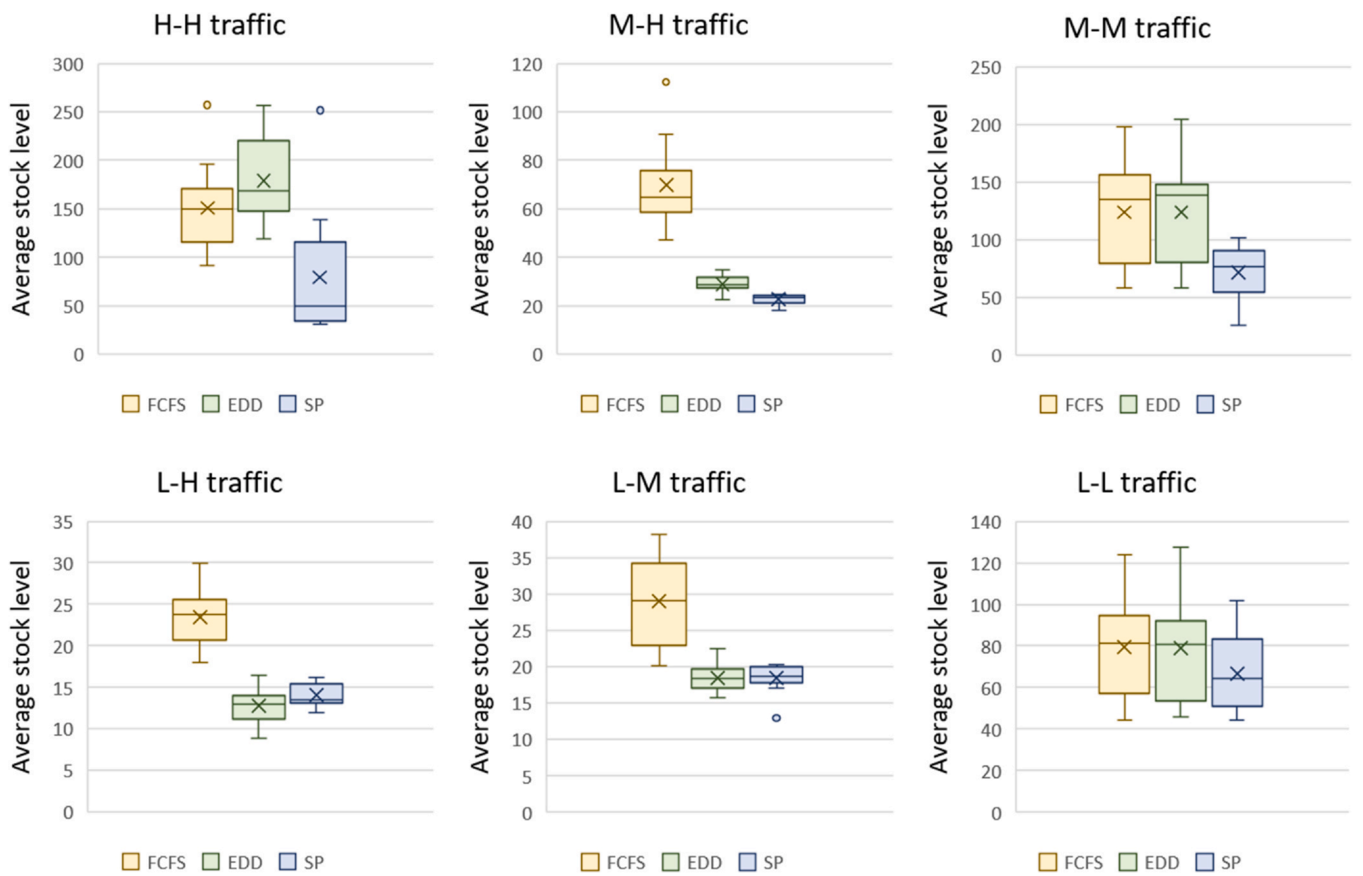

Fig. 5. Stock levels dispersion based on each strategy.

Table 6
The one-way ANOVA results of multiple comparisons of strategies based on the average stock level.

Significance level = 0.05		Parametric one-way ANOVA		Nonparametric one-way ANOVA		Post hoc test (Pairwise comparisons of the strategies)		
	Traffic levels	F statistic	p-value	H statistic	p-value	FCFS-EDD	EDD-SP	FCFS-SP
	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			0.999	0.449	0.420

that the mean value of the average stock level is not significantly different between these strategies (see Table 6, p = [0.066] for M-H and p = [1.000] for L-H). In addition, as can be seen in Fig. 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 6 (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 5). 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 Fig. 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 6 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 6, p = [1.000]), and this result can also be observed in Fig. 5.

Although we observe in Fig. 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 6, 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.

4.4. 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 Fig. 6 and Fig. 7, respectively. Their respective

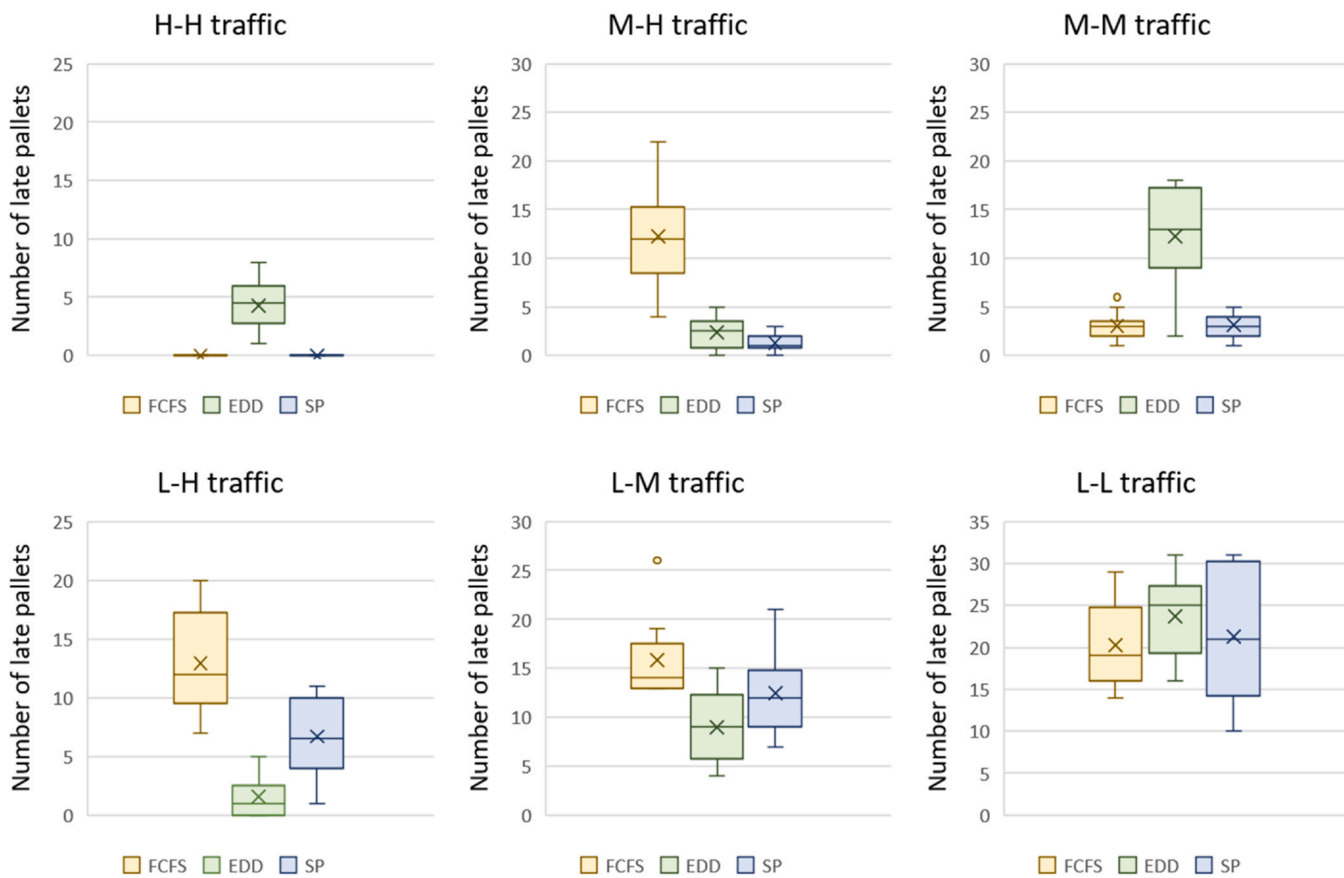

Fig. 6. The number of late pallets based on each strategy.

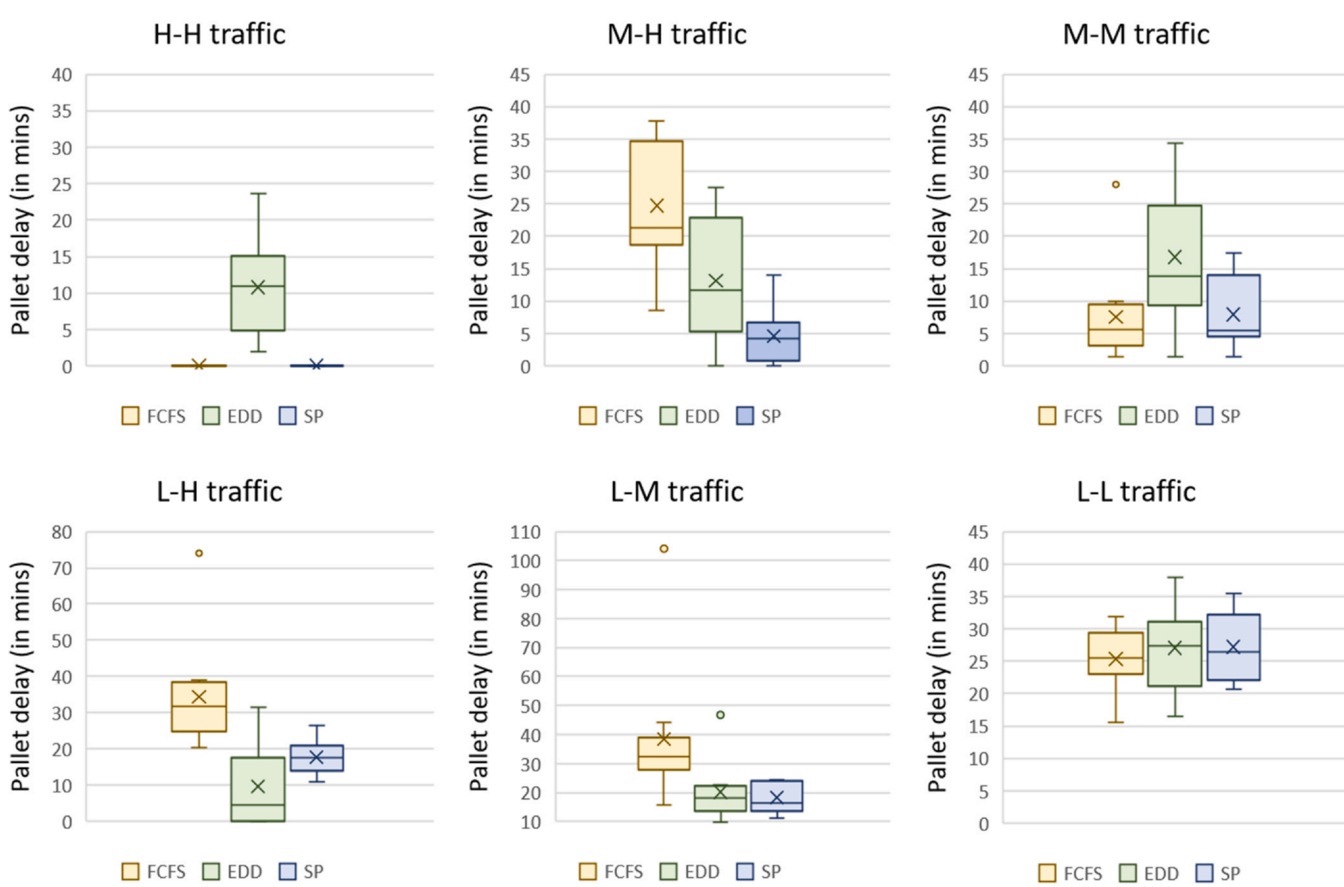

Fig. 7. The pallet delay (per pallet in minutes) based on each strategy.

Table 7
The one-way ANOVA results of multiple comparisons of strategies based on the number of late pallets.

Significance level = 0.05		Parametric one-way ANOVA		Nonparametric one-way ANOVA		Post hoc tests (Pairwise comparisons of the strategies)		
	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			0.428	0.651	0.927

ANOVA results are also delivered in Tables 7 and Table 8. 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 7 and 8). As we observe in Fig. 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 8, p = [0.015]). However, SP is indifferent to FCFS (p = [0.400]) in pallet delay (see Table 8). 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 7 and 8). The same case is observed in the average stock level, and the given explanation is also valid for this case.

4.5. 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 Fig. 8 and Table 9, 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 9, the p-values of ANOVA are greater than the significance level, [0.05]). Therefore, pairwise comparisons of strategies cannot be performed.

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 9, 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.

4.6. Summary on the strategies' performances

The numerical results of the average of all instances per strategy are given in Table 10. The strategies that give the best KPI results for each

Table 8
The one-way ANOVA results of multiple comparisons of strategies based on the pallet delay.

Significance level = 0.05		Parametric one-way ANOVA		Nonparametric one-way ANOVA			Post hoc test (Pairwise comparisons of the strategies)		
	Traffic levels	F statistic	p-value	H statistic	$\chi2$ 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				0.774	0.999	0.751

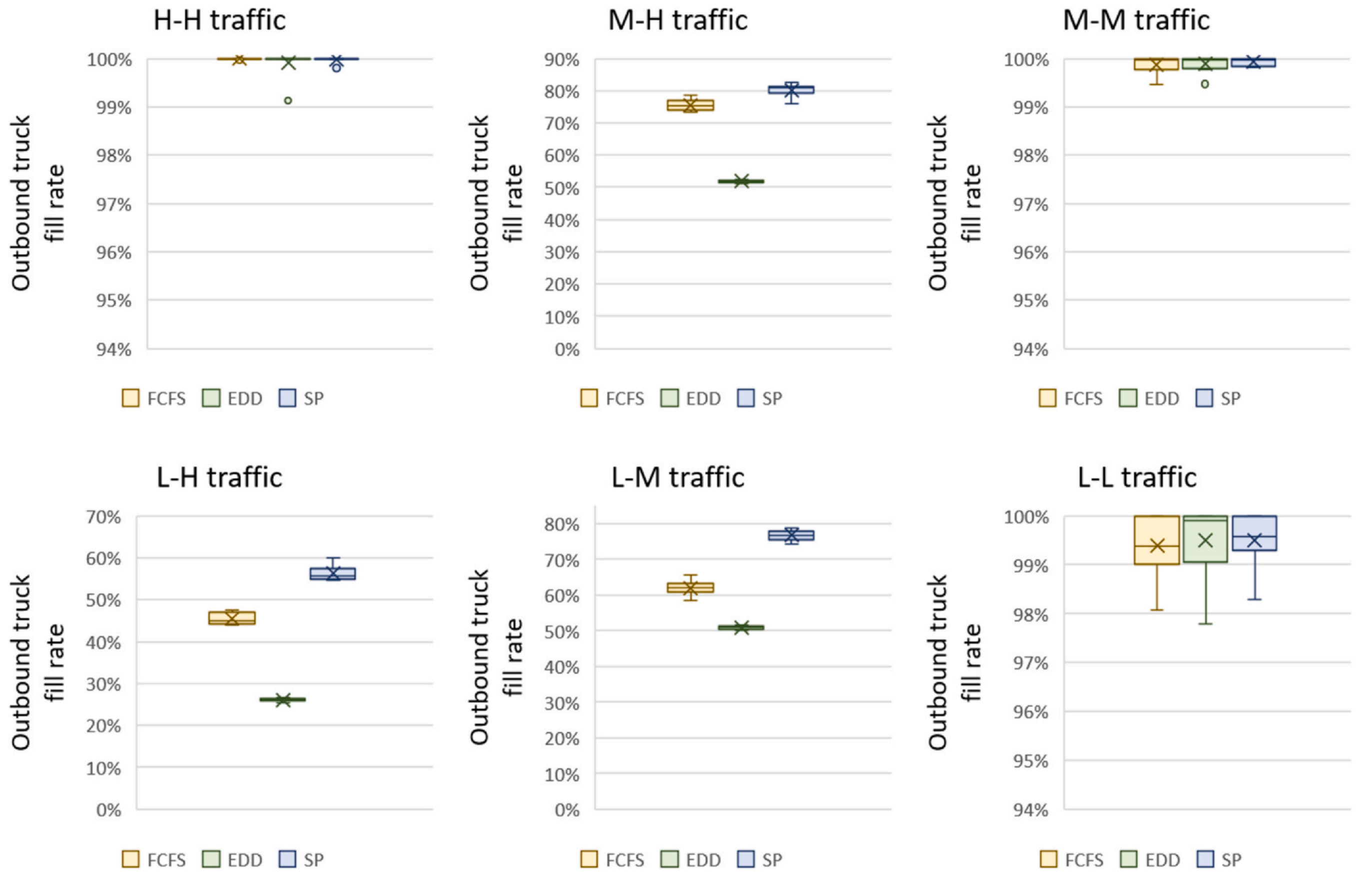

Fig. 8. The outbound truck fill rates based on each strategy.

Table 9
The one-way ANOVA results of multiple comparisons of strategies based on the outbound truck fill rate.

Significance level = 0.05		Parametric one-way ANOVA		Nonparametric one-way ANOVA			Post hoc tests (Pairwise comparisons of the strategies)		
	Traffic levels	F statistic	p-value	H statistic	χ2 statistic	p-value	FCFS-EDD	EDD-SP	FCFS-SP
	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	–	–	–

traffic level are summarised in Table 11. The strategy that outperforms the others for each KPI based on the traffic levels is presented in bold in Table 11.

As can be noticed in Tables 10 and 11,

- 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 10 and 11). 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 10, 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 10 and 11, 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 7 and 8 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

Table 10
The numerical results of the average of all instances per strategy.

		KPIs			
Traffic levels	Strategies	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 11
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

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 10, 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, which fails to reveal any significant differences among the strategies. This can be attributed to low resource requirements at this traffic level.

This analysis is performed for the system described in Table 5. In order to verify the robustness of the SP strategy, a sensitivity analysis must be performed by varying different parameters of the system.

5. 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 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 article provides a solid backbone towards multi-dock context.

A second outcome of the study is the in-debth 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. However, it also has some limitations that help us to draw several perspectives for future studies.

The most valuable extension to this work will be scaling up the model to the multiple inbound and outbound case. Obviously, both inbound and outbound doors need to be defined as agent populations instead of a single agent. This is quite straightforward, thanks to the single dock model. Basic decision mechanisms on strategies regarding truck selection also scale up easily based on the single dock model. Nevertheless, moving from a single to multiple inbound and outbound docks has several challenges: First of all, new decision mechanisms have to be added to the model. For instance, in the single dock case, the arriving trucks have no choice in docks. In the multiple dock case, however, a decision mechanism for the choice of the best door to dock is needed. Another challenge is the computational complexity as we scale up the model. Analyses of the model behaviour and computational complexity need to be performed as the model scales up.

Other structural changes might be interesting to consider. For instance, the temporary storage of the studied cross-dock is assumed to be unlimited. For a more realistic configuration, a capacity constraint can be added to the temporary storage. This will certainly influence the performance of storage-oriented strategies.

One advantage of this multi-agent-based hybrid model is its capacity to simulate scenarios. In this article, we did not focus on robust solutions. However, the robustness of the truck schedules obtained by proactive methods (e.g. optimisation) can be evaluated by simulating these solutions using the model while introducing several perturbations to the system. In a real cross-dock environment, these perturbations can be internal such as the unavailability of dock doors or failure of handling equipment and external such as truck delays. In case of perturbations, the proposed model can propose real-time solutions, and the reactivity of the MAS to these perturbations can be tested.

Finally, in this article, we only tested basic decision rules. Another interesting perspective is to bring intelligence to the system by employing Reinforcement Learning (RL) via agents, where the decisions emerge from earlier experiences of the agents.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bilge Torbali reports financial support was provided by Grenoble Alpes Multidisciplinary Institute in Artificial Intelligence.

Acknowledgements

This work has been partially supported by MIAI@Grenoble Alpes, (ANR-19-P3IA-0003).

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