Production & Manufacturing Research

An Open Access Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tpmr20

Integrating arrival time estimation in truck scheduling: an explorative study in grocery retailing

Tiziana Modica, Elena Tappia, Claudia Colicchia & Marco Melacini

To cite this article: Tiziana Modica, Elena Tappia, Claudia Colicchia & Marco Melacini (2024) Integrating arrival time estimation in truck scheduling: an explorative study in grocery retailing, Production & Manufacturing Research, 12:1, 2425678, DOI: 10.1080/21693277.2024.2425678

To link to this article: https://doi.org/10.1080/21693277.2024.2425678

PRODUCTION & MANUFACTURING RESEARCH
2024, VOL. 12, NO. 1, 2425678
https://doi.org/10.1080/21693277.2024.2425678

Integrating arrival time estimation in truck scheduling: an explorative study in grocery retailing

Tiziana Modica[a], Elena Tappia[b], Claudia Colicchia[b] and Marco Melacini[b]

[a]ECR Italia, GS1 Italy, Milano, Italy; [b]Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milano, Italy

ABSTRACT

This paper studies a new managerial approach that integrates predictive trucks' estimated time of arrival (ETA) into truck scheduling to deal with the truck arrival time uncertainty. The approach exploits ETA to reschedule trucks by the up-to-date information and aims to minimize the trucks' waiting time. The approach was applied in a real case. Results quantified the impact of adopting ETA for truck scheduling, also showing how the ETA accuracy and peak truck arrival rate affect the total trucks' waiting time. The paper enriches both truck scheduling literature, investigating a new managerial approach to deal with truck arrival time uncertainty, which greatly threatens the synchronization of logistics flows, and Industry 4.0 literature, showing how real-time data availability can change traditional decision-making processes. Insights for the approach application are discussed, together with the economic, environmental, and social benefits by supply chain actors (i.e. carriers, warehouse managers, and drivers).

ARTICLE HISTORY
Received 11 February 2024
Accepted 30 October 2024

KEYWORDS
Industry 4.0; logistics; truck scheduling; estimated time of arrival; real-time data

1. Introduction

In a context where customer service level is gaining more and more importance over time, supply chains are involved in a crucial challenge towards the achievement of efficient and fast logistics distribution systems (Ladier & Alpan, 2018). The synchronization of logistics flows can bring rapidity and reactivity at each stage of the supply chain, e.g. parts feeding and production (Napoleone et al., 2023), transportation and warehousing process (Buijs et al., 2014), production scheduling and outbound transportation (Zhang et al., 2024), and replenishment and picking (Leung et al., 2022). With a focus on the synchronization between transportation and warehousing processes, the variability of truck travel times generated by unexpected events, such as traffic and congestion, represents a threat (van der Spoel et al., 2017). Late and early truck arrivals pose several managerial challenges for both the carrier and the receiving facility: managers report that, as the peak time approaches, it gets more and more difficult to compensate for delays, and 'even 5 min of [truck] delay make the entire facility go wrong' (Ladier & Alpan,

CONTACT Elena Tappia elena.tappia@polimi.it Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via Raffaele Lambruschini 4/B, Milano 20156, Italy

2016b). In this context, having managerial approaches for truck scheduling able to deal with the uncertainty of truck arrivals becomes extremely relevant to meet customers' requirements and to improve the competitiveness of logistics distribution systems (Amini et al., 2014; Xu et al., 2022). A strategy to synchronize the transportation and warehousing processes is truck scheduling optimization (Amini et al., 2014). The truck scheduling problem aims at determining the processing order and docking time of trucks at a logistics facility. The truck scheduling optimization could refer, for instance, to the minimization of trucks earliness and tardiness or the minimization of trucks waiting times (Ladier & Alpan, 2016a), allowing the reduction of the goods throughput time along the supply chain.

The truck scheduling problem has been widely discussed in literature, especially in its deterministic form. Extant academic literature that considers the uncertainty in truck arrival times within the problem highlights two main types of managerial approaches to deal with it (Ladier & Alpan, 2016a). The first, *proactive approaches*, account for uncertainty in the off-line stage, by defining in advance a robust truck schedule, which is not updated, aimed at reducing the impact of arrival times variability by, for instance, introducing resources (i.e. doors or operators) redundancy (e.g. Heidari et al., 2018; Konur & Golias, 2013a; Ladier & Alpan, 2016a). The second, *reactive approaches*, dynamically revise the current truck schedule according to actual truck arrivals through pre-defined rules such as the well-known scheduling strategies First-Come-First-Served (FCFS) and Shortest Processing Time rules (SPT) (e.g. Cekała et al., 2015; Yu et al., 2008). Both the proposed approaches present some drawbacks. Existing proactive approaches might be complex to understand and implement in companies, and they might ensure robustness at the cost of resources redundancy, while reactive approaches generate suboptimal solutions as the scheduling relies on only the trucks that have already arrived (Cekała et al., 2015). To overcome these drawbacks, some authors combined both approaches by defining an initial schedule first and then proposing a rescheduling system that adjust the initial proposal (Nasiri et al., 2022, Xu et al., 2022). These are the so-called *predictive-reactive approaches*. These approaches require understanding the system status to trigger the rescheduling activity. Nasiri et al. (2022) performed a periodical rescheduling according to the actual truck arrival time. No predictive information about the truck arrival times is used. Xu et al. (2022) proposed a dynamic truck-appointment rescheduling model that reschedule late trucks before their arrival. Information about delays is collected by asking the driver 30 minutes before the agreed-upon appointment time.

The rise of Industry 4.0 and the related solutions to collect and analyze data in an automatic way, such as IoT in combination with GPS sensors and artificial intelligence, fosters the implementation of data-driven managerial approaches for decision-making, also opening room for studies discussing how to deal with uncertainty, thanks to data availability (Modica et al., 2021). In the field of transportation, for example, studies have focused on improving the efficiency of the delivery using real-time product data (Viet et al., 2020) or proposing alternative routes to the decision makers through real-time monitoring (Zafarzadeh et al., 2023). Regarding truck scheduling, the reliable real-time prediction of the incoming trucks' estimated time of arrival (ETA) represents an interesting application area for data-driven decision making (Barbour et al., 2018; Flores da Silva et al., 2023). By elaborating real-time data including for instance the truck position, road traffic, and weather conditions, predictive algorithms offer the possibility to know in advance the truck ETA (Zhao et al., 2020). Predicting trucks ETA with sufficient accuracy could help deal with the issues connected with arrival time uncertainty in a more efficient and effective way compared to extant approaches. Indeed, as opposed to proactive approaches, ETA information allows considering truck delays when they occur, avoiding the costs required by the adoption of strategies that mitigate the impact of arrival times variability in advance. Moreover, ETA information could be used to reschedule both late and early trucks before they arrive at the facility, thus improving the optimization of time and/or costs compared to reactive and predictive-reactive approaches. Last, being ETA automatically shared between the truck telematics and the warehouse systems, it avoid asking information to truck drivers. Moreover, it could support the sustainable development of companies by potentially improving resource productivity (i.e. trucks, drivers, warehousing operators) and shortening lead times along the supply chain (considering the economic and environmental perspectives), and by increasing drivers' safety and improving drivers work-life balance (considering the social perspective). In this context where literature about Industry 4.0 and its applications is growing pushed by an increasing interest in theory and practice, studies that redesign traditional decision-making instruments and approaches to take advantage of the use of real-time data represents an open debate in logistics (Aron et al., 2023; Dhiaf et al., 2021; Wang et al., 2023).

Given these premises, the present work aims to study the impacts stemming from the use of ETA information for truck scheduling under uncertainty in truck arrival times. Two research questions drove the study:

RQ1: How can ETA information on truck arrival times be exploited to improve truck scheduling?

RQ2: What is the impact of exploiting ETA information on truck arrival times for truck scheduling in terms of the total truck waiting time reduction?

section 2 reports the methodology followed in the study. To answer the research questions, we first conducted a literature review on truck scheduling models, which is presented in section 3. The ETA-based reactive truck scheduling approach, which introduces real-time ETA information in a reactive truck scheduling approach, is described in section 4. To explore the application and impacts of the approach, this was applied to a real case conducted with one of the largest Italian grocery retailers (section 5). section 6 discusses the results and presents implementation insights. Finally, in section 7, conclusions are drawn identifying the study's theoretical and managerial implications, the limitations, and suggesting directions for future research.

The main contributions of the paper consist in (i) showing how ETA information could be integrated into truck scheduling, providing an original example of decision making redesign that integrates Industry 4.0, (ii) quantifying the impact that can be expected from integrating ETA in truck scheduling. The research does not focus on proposing new scheduling optimization model and algorithms. Integrating ETA into truck scheduling could help companies cope with late and early trucks more effectively and efficiently, thanks to the predictive visibility offered by ETA, thus reducing waiting time on-site and synchronizing the logistics flows. This could improve both trucks utilization and the drivers' work life balance, offering a way to mitigate the persistent 'driver shortage' faced by the logistics industry. Finally, by discussing how Industry 4.0 could improve decision making, this paper could support the digital transformation of companies.

2. Methodology

To answer the research questions, a two-phase methodology was adopted, as described in Figure 1.

Phase 1 started with a literature review on truck scheduling models aimed to identify the main approaches and solutions adopted in truck scheduling and the relevant variables involved in the truck scheduling problem. Then, the new approach which introduces real-time ETA information into truck scheduling was developed. The approach was intended to offer a new method for truck scheduling by combined real-time ETA information and optimization. Since the main focus of the research was to propose a new approach to combine ETA information in truck scheduling, extant optimization models were selected from literature and adapted to our problem.

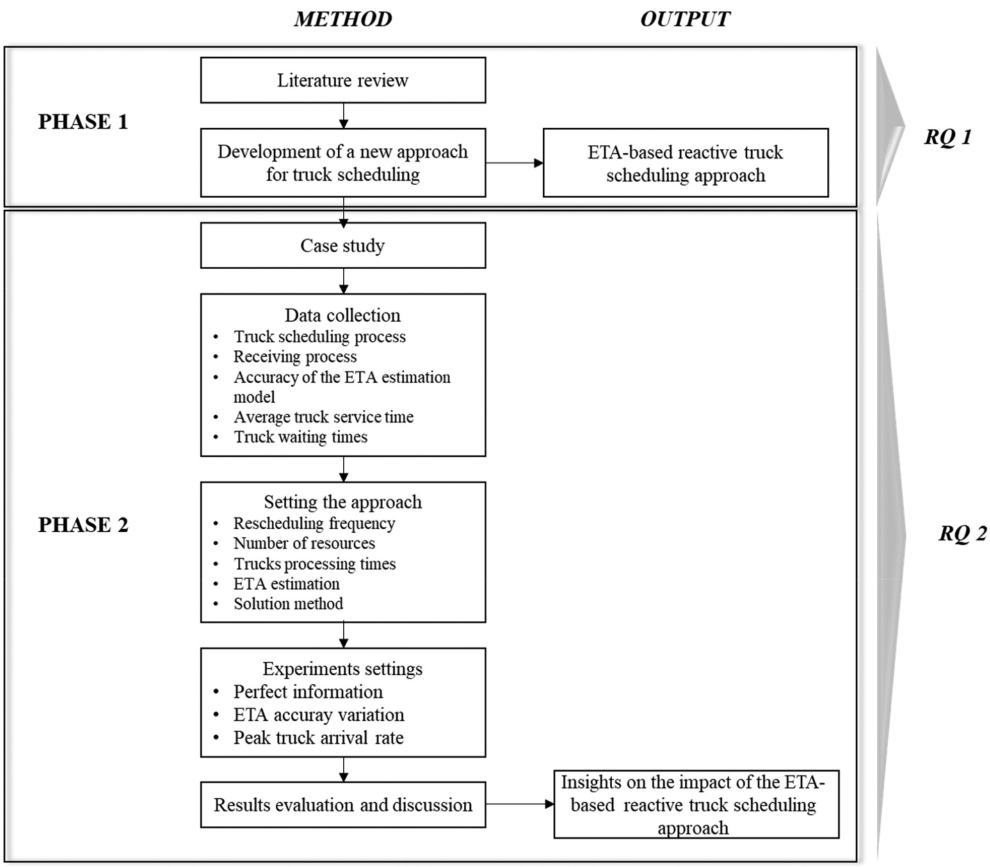

Figure 1. Research methodology.

In Phase 2, the approach was applied to a real case to explore its application and impacts. One of the largest Italian grocery retailers was selected as case study, owing to a turnover of more than 2 billion, with reference to its largest distribution center located in the North of Italy. To improve the understanding about how to apply the new approach and to perform the impact assessment, this company was selected because it has recently applied ETA for its fleet. The retailer currently uses the FCFS policy for truck scheduling. During the research, information about the truck scheduling processes, the receiving process, the warehouse, and the ETA estimation model were studied to understand the feasibility of the application of the new approach, and data were collected to feed the parameters required by the approach. The data collected for the study and additional information about the company's truck scheduling processes were supported by semi-structured interviews with the Logistics Director of the company (Carson John, 2002). Once the approach was set, it was applied to the company to understand its impact. The approach was compared to the performance of the current way of working of the warehouse. Three different experiments were set to test the approach. First, the maximum benefits achievable were assessed, by considering a perfect information scenario where ETA always equals the actual time of arrival (ATA), and is assumed known at the facility at the beginning of the day. Then, the assumption of perfect information was relaxed, and the impact of ETA accuracy and truck arrival rate on the performance of the proposed approach was tested.

3. Literature review

Literature addressed the truck scheduling problem mainly concerning cross-docking facilities; here, both inbound and outbound doors need to be scheduled properly to achieve synchronization of inbound and outbound trucks with internal handling activities (Amini et al., 2014). Three main elements characterize truck scheduling problems: (1) doors environment, (2) operational characteristics, and (3) objective to be pursued (Boysen & Fliedner, 2010). Doors environment refers to the capacity of the receiving logistics facility, which is in most cases related to the dock doors but can also be connected to the resources dedicated to loading and unloading operations. Doors environment is characterized by the number of doors available at the facility, and the service mode of each door, which can be exclusively dedicated to inbound operations or outbound operations, or mixed, meaning that each door can serve an intermixed sequence of either inbound or outbound trucks (Van Belle et al., 2012). Operational characteristics represent the rules and logic underlying the operational management of the receiving facility, including for example pre-emption or constraints restricting the departure time of trucks (Boysen & Fliedner, 2010). Examples of objectives refer to the minimization of trucks earliness and tardiness, the minimization of trucks waiting times, or the minimization of the cross-docking process operational time (Khalili-Damghani et al., 2017).

Extant literature on truck scheduling mainly assumes concentrated arrivals, meaning that trucks are all present at the yard of the receiving facility at the beginning of the time horizon when the scheduling starts, or deterministic scattered arrivals, assuming that truck arrivals have no uncertainty and are distributed during the day (refer to Van Belle et al., 2012). Nonetheless, in reality, many unexpected events caused by exogenous factors, such as road congestion (van der Spoel et al., 2017), constantly change the trucks arrivals, affecting the performance of the logistics facility if no adjustment to the original schedule is performed (Ladier & Alpan, 2016b). When dealing with truck arrival time uncertainty, the literature highlights two main kinds of managerial approaches (Ladier & Alpan, 2016a). Table 1 provides an overview of the previous contributions about truck scheduling under uncertain arrival times classified into the two main approaches.

Proactive approaches aim at tackling uncertainty during the off-line stage by defining robust truck scheduling models aimed at reducing the impact of arrival time variability. Extant robust truck scheduling leverages generic robust optimization techniques or resource (i.e. doors or operators) redundancy to generate schedules that show the smallest deterioration of the performance under unfavorable truck arrival patterns. Among authors discussing generic robust optimization techniques, Xi et al. (2020) include truck arrival time uncertainty by developing a Conflict Robust Optimization truck scheduling model based on the minimization of conflicts (i.e. situations where a truck realized schedule overlaps with those of other trucks assigned to the same dock when executing the planned schedule). A series of discrete scenarios obtained through historical data on truck arrival times were defined to characterize the uncertainty. The deviation from the optimal deterministic schedule considering no uncertainty in truck arrival time was evaluated. Ladier and Alpan (2016a) proposed two different robust truck scheduling models. The first, based on Minmax optimization, tackles uncertainty in truck arrival times by minimizing the objective of the deterministic truck scheduling model in the worst-case scenario. The second, the Minimization of the expected regrets, minimizes the expected deviation of the realized schedule performance from the deterministic model by considering one single scenario. Konur and Golias (2013a, 2013b) and Heidari et al. (2018) developed the Stable Scheduling Problem, a bi-level, bi-objective cost-stable scheduling strategy that minimized the truck service costs, including truck waiting time and processing time, and reduced their range to avoid high variations in truck arrivals. Their work assumed deterministic truck arrival time windows. Redundancy-based proactive approaches to truck scheduling solve trucks arrival time uncertainty by introducing idle resources or idle time. Resource redundancy approaches usually introduce buffer doors to ensure available resources to execute a job when disruptions occur. Door availability is obtained through (i) the minimization of the average number of trucks per door during the planning horizon T (i.e. door occupation rate), (ii) the minimization of the number of doors used in a certain time, or (iii) the minimization of critical trucks, defined as trucks 'that, when late, propagates its delay to the next arriving trucks' (Ladier & Alpan, 2016a, p. 22). Time redundancy approaches introduce time buffers between subsequent trucks to mitigate small variations in truck arrival time. Idle time is introduced by inserting buffers between successive trucks (Ladier & Alpan, 2016a; Rajabi & Shirazi, 2017) and mitigating their length through different techniques (e.g. the minimization of the standard deviation of the buffer lengths (Acar et al. (2012) or the maximization of the weighted sum of buffers (Ladier & Alpan, 2016a)). Both redundancy approaches estimate truck arrival time through statistic distribution or through scenarios based on historical data.

Reactive approaches are used in high uncertainty contexts since they revise the current truck schedule online according to actual truck arrivals. By scheduling online the trucks as they enter the receiving facility, they keep truck arrival time uncertainty out of the

Table 1. Summary of literature on truck scheduling with truck arrival times uncertainty.

Managerial approach for truck scheduling	Objective	Truck arrival time estimation	How to deal with arrival time uncertainty	References
Proactive approaches				
Conflict Robust Optimization	Minimum penalty cost for truck delays	Historical data	Minimize the expected deviation of the deterministic schedule performance	Xi et al. (2020)
Minmax	Minimum penalty costs for truck delays + minimum inventory level	20% of trucks arrive late and their delay follows an exponential distribution	Minimize the expected deviation of the deterministic schedule performance in the worst case scenario	Ladier and Alpan (2016a)
Minimization of expected regrets	Minimum penalty costs for truck delays + minimum inventory level	20% of trucks arrive late and their delay follows an exponential distribution	Minimize the expected deviation of the deterministic schedule performance	Ladier and Alpan (2016a)
Stable Scheduling Problem	Minimum of total service cost (=truck processing cost + truck waiting cost)	Deterministic (time window)	Minimize the expected deviation of the deterministic schedule performance considering the average total service costs and the range of the total service costs	Konur and Golias (2013a); Konur and Golias (2013b); Heidari et al. (2018);
Resource Redundancy	• Minimum door occupation ratio • Minimum number of doors used in T* • Minimum critical trucks	20% of trucks arrive late and their delay follows an exponential distribution	Idle doors	Ladier and Alpan (2016a)
Time Redundancy	• Minimum slack time variance • Maximum weighted sum of buffers • Minimum total truck waiting time	• Historical data • Statistics	Idle time	Acar et al. (2012); Ladier and Alpan (2016a); Rajabi and Shirazi (2017)
Reactive approaches				
First Come First Served (FCFS)	Minimum total truck waiting time	n.a.	Schedule trucks once they arrive	Yu et al. (2008); Konur and Golias (2013b); Larbi et al. (2011); Acar et al. (2012); Cekała et al. (2015); Mejía et al. (2023)
Shortest Processing Time	Minimum total number of man hours	n.a.	Schedule trucks once they arrive	Yu et al. (2008)
Earliest Point in Time	Minimum total truck waiting time	n.a	Rescheduling waiting trucks periodically	Cekała et al. (2015)

(*Continued*)

Table 1. (Continued).

Managerial approach for truck scheduling	Objective	Truck arrival time estimation	How to deal with arrival time uncertainty	References
ETA-based reactive approach	Minimum total truck waiting time	Real time forecasted	Rescheduling all trucks expected during the day periodically	This paper
Predictive-Reactive approaches				
Based on the system status (assumed known)	Minimum total tardiness cost of the outbound truck	Known once the truck arrived	Rescheduling all trucks periodically	Nasiri et al. 2022
Dynamic Appointment Rescheduling	• Minimum total operating cost • Limited number of trucks in queue	• Predicted by the driver • Real time forecasted	• Reschedule only late trucks before their arrival • Reschedule early and late trucks before their arrival	Xu et al. (2022); Flores da Silva et al. (2023)

*T = planning horizon.

schedule. Usually, reactive approaches take advantage of heuristics and rules to schedule trucks. The most common reactive approach cited in the literature and adopted by companies is the FCFS rule (Amini et al., 2014; Konur & Golias, 2013b; Mejía et al., 2023). This simple heuristic assigns every incoming truck to the first resource available in the same order of arrival. Yu et al. (2008) proposed a reactive heuristic to deal with online truck-to-door allocation, the SPT, which allocates inbound trucks to doors as they arrive so that the man-hours needed to consolidate the freight is minimized. In doing this, they assign higher priority to trucks that have short processing time. The last reactive approach found in literature, the Earliest Point in Time, was developed by Cekała et al. (2015). The authors proposed an approach that periodically (i.e. every 30 minutes) revises an initial loading appointment schedule to reschedule delayed trucks to minimize the total truck waiting times by minimizing deviation from an initial truck appointment schedule.

While proactive approaches ensure a small deviation from the initial deterministic optimal schedule, they present some drawbacks. First of all, proactive approaches based on generic robust optimization techniques might be difficult to test, implement, and communicate in industrial contexts (Ladier & Alpan, 2018), thus some authors claim the superiority of redundancy-based scheduling (Ladier & Alpan, 2016b). Nevertheless, managerial approaches based on redundancy might introduce a cost for additional resources (i.e. time or door buffers) needed to face trucks arrival time uncertainty. Also, robust optimization techniques could introduce additional scheduling costs: Xi et al. (2020) proved that the robustness of the truck schedule can be improved by increasing the total system cost. Finally, the probability distribution of truck arrival might be difficult to predict in advance, and the proactive schedule might become infeasible or inefficient during the day. Against this backdrop, in a high uncertainty context, reactive approaches might perform better than proactive ones, since they can dynamically adjust the extant truck schedule (Yu et al., 2008). In this way, they could quickly react to disruptions, improving the performance of the scheduling. Moreover, reactive approaches do not require redundant resources to face trucks arrival time uncertainty; thus, they enable cost savings against extant redundancy-based proactive approaches. Nevertheless, also reactive approaches have drawbacks. By scheduling trucks at their arrival, or rescheduling trucks when a disruption occurs, these approaches are myopic and might result in suboptimal solutions (Konur & Golias, 2013b).

To combine the benefits of both approaches, *predictive-reactive rescheduling* systems have also been developed. These adjust an initial schedule considering the up-to date information on truck arrival times. The approach developed by Nasiri et al. (2022) consists in revising an initial schedule with a rescheduling system including two components: a rescheduling optimization model and a short interval repair policy. The rescheduling optimization model updates the schedule at discrete review times, while the short interval repair policy defines how to handle trucks considering their actual arrival time. In this study, it is assumed to know the system status at each review time, and no predictive information about the truck arrival times are used. They also performed computational experiments under different uncertainty level and rescheduling frequency, discussing that increasing the rescheduling frequency yields in better results but also implies more and more frequent changes to the initial plan. Predictive-reactive approaches have been also discussed in port terminal operations literature. Here, truck scheduling is supported by Truck Appointment System (TAS), a service approach that allows drivers to book an appointment at the port terminal in advance. Despite this allows for more efficient planning by port authorities, thus reducing congestion in the port hinterland, the performance of the system can be reduced by uncertain truck arrival (Flores da Silva et al., 2023). To solve this issue, authors introduced some predictive-reactive approaches that starting from the initial appointment list reschedule trucks according to a certain rescheduling policy. Xu et al. (2022) proposed a dynamic truck-appointment rescheduling model for port operations that reschedule late trucks before their arrival. Information about truck delays is collected by asking the driver 30 minutes before its agreed upon appointment time. If the truck is late, rescheduling is performed through mixed integer nonlinear programming solved with double-chain real quantum genetic algorithm, and the driver is required to confirm the new appointment. Flores da Silva et al. (2023) introduced a machine learning prediction of truck status that periodically compute the estimated travel time (ETT) of incoming trucks and identify early and late ones. These are then assigned to a new appointment considering the actual number of trucks queuing outside the port through simulation with the objective of reducing the congestion inside the port. The focus is on the management of the queue outside the port, and the supported decision relates to the identification of the trucks which should be allowed entering the facility. Extant predictive reactive scheduling approaches also show some issues. Some reschedule truck only when they are already at the facility or limit the use of predictive information about truck arrival to the management of the queue outside the facility. Others requires an active role of drivers in communicating information, potentially annoying or endangering them while driving.

Different from the extant managerial approaches for truck scheduling, this paper proposes to take advantage of ETA information and from the expected processing time of each truck to periodically reschedule all the incoming trucks, selecting for each the optimal place in the unloading schedule so that total truck waiting times are minimized. Since ETA is continuously updated with real-time data, we argue that this online information could be better exploited by adopting a reactive approach. The logic is to dynamically change the initial schedule to take into account the predictive information on truck delays.

The problem investigated is strictly related to the literature of stochastic job scheduling on parallel machines. Most studies consider processing times to be the source of uncertainty, and only a few consider the variability of release dates which correspond to the truck processing time in our model (Liu et al., 2021). Ronconi and Powell (2010) considered random arrival time but in the context of single machine. Zhang et al. (2012) investigate an unrelated parallel machine scheduling problem to minimize the mean weighted tardiness with stochastic arrival times and due dates. In the manufacturing literature, many contributions considered rescheduling environments (Vieira et al., 2003), but only Nasiri et al. (2022) investigated rescheduling in a crossdocking system.

4. The ETA-based reactive truck scheduling approach

4.1. Integrating ETA in truck scheduling: the managerial approach

This section presents how ETA information could be integrated into the truck scheduling decision process offering a managerial approach to deal with truck arrival time uncertainty, which has been called 'ETA-based reactive truck scheduling approach'. Inbound truck scheduling process was selected as the focus of the analysis, being inbound transportation subject to a higher level of uncertainty (Konur & Golias, 2013b). Essentially, the ETA-based reactive truck scheduling approach adjusts the current truck schedule taking into account the up-to-date information about all the incoming trucks arrival time, thus providing more informed scheduling with respect to the previous one.

As shown in Figure 2, developing a decision support system for inbound truck scheduling according to the proposed approach means working on different layers, i.e. from the physical to the analytical one. The analytical layer represents the core module and refers to the development of a model to optimize inbound truck scheduling decisions. The optimization model considers the dynamically updated list of incoming trucks (those that have not yet been served or are waiting, and assigns each truck to a door based on the following input parameters: i) the up-to-date ETA for each incoming truck (i.e. all the trucks that have not yet been served), ii) the estimated processing time for each truck, and iii) the currently available warehouse resources. In order to feed the model, a company needs to collect data from the physical layer and integrate information from multiple sources. Specifically, information on inbound trucks can be acquired using location-based technologies such as GPS and geofencing, while IoT sensing devices can be installed to obtain the real-time status of material handling equipment and warehouse doors. The processing time for each truck is subject to variability and can be estimated based on the current status of the physical layer in terms of workload and available unloading operators, as well as other factors such as facility-related characteristics (e.g. the distance between the door and the storage area) and the specific content of the truck (in terms of quantity and features such as the type of handling units).

The optimization model can then be used to update truck scheduling decisions based on a rescheduling frequency. Starting from the facility opening time, the

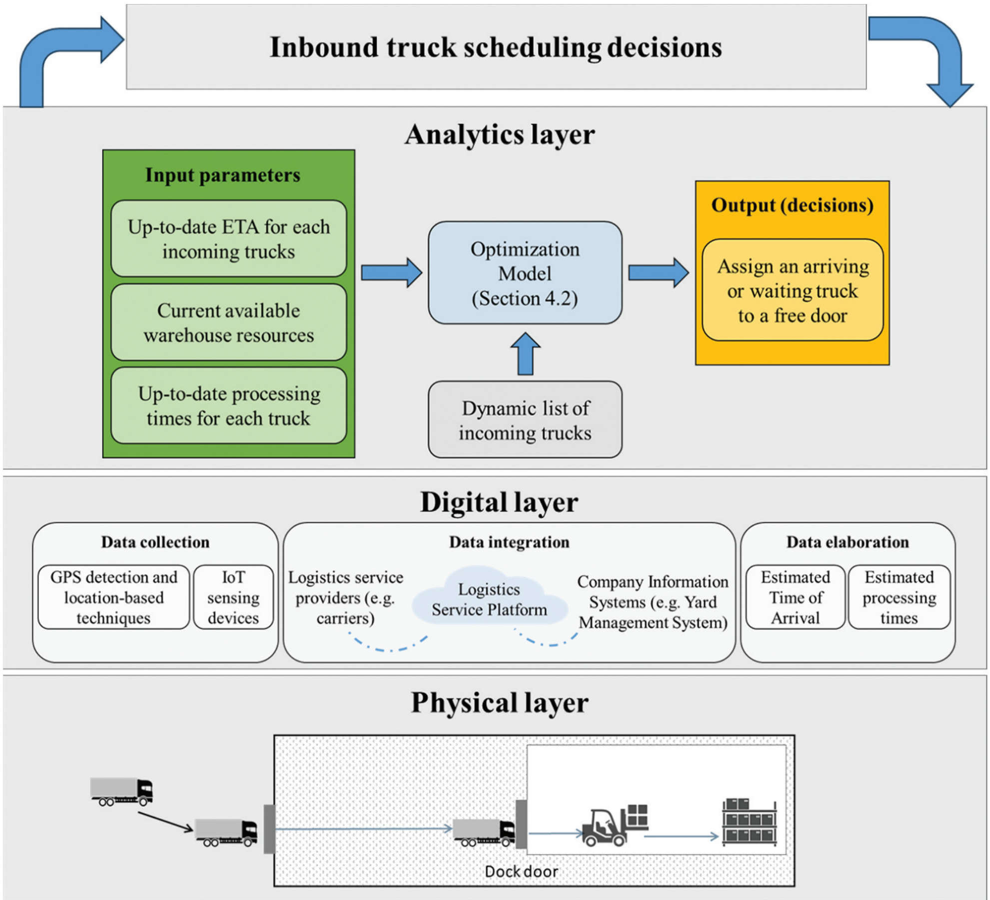

Figure 2. ETA-based reactive truck scheduling approach.

facility's working day T is divided into periods $t \in T = \{1, \ldots, T\}$, which can vary in length depending on the rescheduling frequency. At each rescheduling point, the trucks considered are those not yet arrived from the current rescheduling point to the end of the working day. Various strategies can be employed to set the rescheduling frequency. Different well-known strategies for rescheduling can be adopted, such as continuous, periodic, event-driven, or hybrid rescheduling point-based (Vieira et al., 2003). Additionally, the rescheduling frequency may differ from the frequency with which the new schedule is actually shared with the actors involved in the inbound transportation process and implemented, i.e. managers of the logistics service providers for the transportation and warehousing activities, truck drivers, and warehouse operators. Companies can determine the most appropriate strategy for identifying and sharing a new schedule based on the characteristics of their internal processes and the external context in which they operate (e.g. the effort required to collect high-quality input parameters, the characteristics of their logistics service providers, the type of collaboration and integration with them, and the level of responsiveness and adaptability of their internal processes).

4.2. Generating a new truck schedule: the optimization model

As mentioned in section 4.1, the new truck schedule is generated through optimization. The truck scheduling problem is framed as follows.

Consider a receiving facility that has an unloading capacity constrained by some inbound resources (i.e. doors or operator teams in charge to perform the unloading operations) indexed by $r \in R = \{1, \ldots, R\}$ to serve a set of I trucks during the working day, indexed by $i \in I = \{1, \ldots, I\}$. Trucks might require distinct processing times due to the characteristics of the facility (e.g. unloading operator team, the distance between the door, and the storage area) and the content of the truck. We, therefore, assume that each truck has its own specific processing time at a given resource, denoted as p_i^r. We also assume resources with exclusive service mode, meaning that they are dedicated to unloading activities only. Each resource can serve any truck.

The objective of the optimization model is to improve the scheduling performance by reducing trucks total waiting time throughout the working day. The model takes in input (i) the real-time truck ETAs, ETA_i^t, (ii) the truck processing times, p_i^r, which include the unloading time and the time to free the bay after the truck has been unloaded, and (iii) the current status of resources for unloading. It then assigns to each upcoming truck a service order, namely, it gives each truck the optimal position in the schedule, as well as the optimal allocation to a resource so that the expected sum of waiting times at the certain rescheduling point of the I trucks served from t to the end of the warehouse working day, SWT^t, is minimized. As shown in equation (1), SWT^t represents the sum of the expected waiting time of each truck i, wt_i^t.

$$SWT^t = \sum_t^T \sum_i^I wt_i^t \tag{1}$$

At the generic rescheduling point t and for the generic truck i, the expected waiting time, wt_i^t, is computed as the difference between the trucks service time, s_i^t, representing the planned time the truck starts being served by the operators at the assigned dock, and the truck ETA, ETA_i^t, as the best proxy of truck expected arrival time, as displayed in equation (2).

$$wt_i^t = s_i^t - ETA_i^t \tag{2}$$

We adopted the mathematical model formulation presented by Konur and Golias (2013b), and we adapted it to fit our problem. We therefore set the minimization of trucks total waiting time throughout the working day as the optimization model objective instead of the minimization of the total service costs, and we considered trucks ETA instead of deterministic arrival times. The mathematical formulation of the optimization model is provided as follows.

$$\text{minimize}\, SWT^t = \sum_t^T \sum_i^I wt_i^t = \sum_t^T \sum_i^I \left(s_i^t - ETA_i^t\right) \tag{3}$$

$$\text{s.t.} \sum_{r \in R} x_i^r = 1 \forall i \in I \tag{4}$$

$$f_i + \sum_{a \in I: a \neq i} y_{a,i} = 1 \forall i \in I \tag{5}$$

$$l_i + \sum_{a \in I: a \neq i} y_{i,a} = 1 \forall i \in I \tag{6}$$

$$f_a + f_b \leq 3 - x_a^r - x_b^r \forall r \in R, \forall a, b \in I, a \neq b \tag{7}$$

$$l_a + l_b \leq 3 - x_a^r - x_b^r \forall r \in R, \forall a, b \in I, a \neq b \tag{8}$$

$$y_{a,b} - 1 \leq x_a^r - x_b^r \leq 1 - y_{a,b} \forall r \in R, \forall a, b \in I, a \neq b \tag{9}$$

$$s_i^t \geq \sum_{a \in I} s_a y_{a,i} + \sum_{r \in R} \sum_{a \in I: a \neq b} p_i^r x_r y_{a,i} = 1 \forall i \in I \tag{10}$$

$$s_i^t \geq ETA_i^t \forall i \in I \tag{11}$$

$$x_i^r \in \{0, 1\}, \forall r \in R, \forall i \in I \tag{12}$$

$$y_{a,b} \in \{0, 1\}, \forall a, b \in I, a \neq b \tag{13}$$

$$f_i \in \{0, 1\}, \forall i \in I \tag{14}$$

$$l_i \in \{0, 1\}, \forall i \in I \tag{15}$$

The objective function that aims to minimize the expected sum of truck waiting times is given in (3). Let x_i^r denote a binary variable such that $x_i^r = 1$ if truck i is assigned to resource r and $x_i^r = 0$ otherwise. Constraints (4) makes sure that one truck is assigned to one and only resource. Supposing that $x_a^r = x_b^r = 1$ such that $a,b \in I$ and both a and b will be processed by resource r, a binary variable $y_{a,b}$ is defined such that $y_{a,b} = 1$ if truck a is the immediate predecessor of truck b and $y_{a,b} = 0$ otherwise. Constraints (5) and (6) ensure that each truck either is processed as the first truck or has a predecessor, and each truck either is processed as the last truck or has a successor. The variables $f_i$and l_i are auxiliary binary variables such that $f_i = 1$ if truck i is processed as the first truck at the resource it is assigned to and $f_i = 0$ otherwise, and $l_i = 1$ if truck i is processed as the last truck at the resource it is assigned to and $l_i = 0$ otherwise. Constraints (7) and (8) make sure that each inbound resource has at most one first truck and each inbound resource has at most one last truck. Constraints (9) ensures that a truck cannot be a predecessor or successor of another assigned to a different door. Constraints (10) makes sure that a truck cannot be received before the predecessor processing is over. Constraints (11) ensures that a truck assignment to the door cannot be before its ETA. Finally, constraints (12)–(15) define binary variables.

5. Applying the ETA-based reactive truck scheduling approach: the case of a grocery retailer

5.1. Empirical study: case description and approach setting

An evaluation of the application potential and obtainable benefits of the ETA-based reactive truck scheduling approach is proposed by the mean of its application to a real case conducted in collaboration with one of the Italian largest grocery retailers, with reference to its largest distribution center located in the North of Italy.

The reference warehouse performs unloading operations in a 9-hour shift (from 6:00 to 15:00), with dedicated operator teams. The operators in charge of performing the unloading operations represent the most relevant constraint for the management of the scheduling activities, as the number of available operators is lower than the total number of doors dedicated to the unloading activities. Every day a different number of operators is assigned to the unloading activities, according to the expected number of incoming trucks. The company is experiencing an increase in the time trucks wait in the warehouse yard before being unloaded. This further increases when truck arrivals are concentrated. In such a context, the ETA-based reactive truck scheduling approach could improve their truck unloading performance by synchronizing the unloading and put-away activities. The company predicts the travel time of their fleet and then derives the trucks ETA. The main input of the ETA forecast model the company used includes (i) the historical data about deliveries and truck arrival times specific to each customer and carrier, (ii) the appointment time of the truck at the receiving facility, (iii) the observed driving and rest hours, (iv) the real-time traffic, (v) the weather, (vi) driving bans, and (vii) receiving facility location-specific data (e.g. facility coordinates). The forecast model was trained with 2.7 million historical shipments, resulting in a 4% error – computed as the average difference between the ETA and the truck ATA – considering ETA estimates 10 hours before the actual arrival time, and even lower for following estimates, closer to the actual arrival time. Information about ETA accuracy and estimation are provided in Appendix A.

When applying the ETA-based reactive truck scheduling approach, it is necessary to define the time interval between two consecutive rescheduling points. To understand when to perform the rescheduling, thus when to collect the new ETA estimation, a comparison was performed between the average service time needed for trucks unloading for the retailer (i.e. 81 min) and the accuracy of the ETA estimation model adopted by the company (see Table A1 in Appendix A). When trucks are between one and five hours from their arrival, the ETA accuracy is enough to ensure, on average, an absolute error below the average service time and mainly lower than one hour. In this context, the retailer facility could try to set a draft of resources allocation at lower grain. Data show a better and steady accuracy of the ETA information within one hour from the trucks ATA. This makes it possible to use this ETA for creating the truck schedules. Moreover, a scheduling horizon of one hour allows taking into account warehouse capacity constraints in terms of the time needed to reallocate resources in the facility. Thus, the rescheduling frequency for the retailer has been set to one hour. A time window of an hour has been also considered to set a frozen period in which the current schedule can not be subjected to a rescheduling due to the company constraints in adjusting the warehouse capacity. These latter assumptions imply that the truck schedule between rescheduling point t and rescheduling point t+1 (i.e. from 8:00 to 9:00) cannot be changed, meaning that further truck delays or early arrivals will be considered at the next rescheduling point. Only the trucks scheduled after t+1 might be subjected to rescheduling.

5.2. Empirical study: impacts evaluation

In this section, the impacts stemming from the adoption of the developed ETA-based reactive truck scheduling approach are shown. The optimization model described in section 4.2 was considered. A GA heuristic was used to solve the optimization model. It was structured according to three stages: (i) chromosomal representation (encoding), (ii) reproduction, and (iii) fitness function evaluation and selection process. These are detailed in Appendix B. The fitness function consists of minimising the truck waiting times wt_i^t (equation 3). The impacts were benchmarked against the performance of the current truck scheduling approach used by the company, i.e. the FCFS rule, which is commonly considered as benchmark approach (e.g. Tappia et al., 2024). To perform the comparison, the performance indicator waiting time reduction, determined by the expression $RWT = \frac{(SWT_{FCFS} - SWT_{ETA-based})}{SWT_{FCFS}}$ %, was calculated. The RWT shows the reduction in the sum of the waiting time obtained with the developed approach, $SWT_{ETA-based}$, with respect to the one obtained with the FCFS, SWT_{FCFS}. First, the maximum benefits of exploiting ETA information on truck arrival times for truck scheduling were explored. To evaluate the maximum benefits achievable, the approach was assessed considering 'perfect information' (section 4.2.1). Then, to assess the impact of ETA accuracy and truck arrival rate on the performance of the proposed approach, further numerical experiments were conducted, relaxing the assumption of perfect information (section 4.2.2 and section 4.2.3). In all the experiments, ETAs have been estimated based on the performance of the actual forecast model used by the company. Data used include data about truck ATA and data about the ETA accuracy, σ^2, varying according to the different distances between t and ATA. Refer to Appendix A for details on ETA accuracy and estimation.

A sample of eight days corresponding to 547 trucks was considered for evaluating the performance of the ETA-base reactive truck scheduling approach; each day was divided into nine periods of an hour, corresponding to eight rescheduling points, and each day was characterized by the following input: (i) trucks actual arrival times, (ii) trucks processing times, and (iii) number of resources dedicated to unloading. The genetic algorithm is run on a computer with 16 GB of RAM and an Intel Core i7- 507 9700 processor with 3 GHz. To improve results robustness, ten independent runs have been performed for each day, and the results have been average out.

5.2.1. Performance assessment with perfect information

To evaluate the maximum benefits achievable, the ETA-based reactive truck scheduling approach was assessed considering 'perfect information', i.e. ETA always equals the ATA and is assumed known at the facility at the beginning of the day.

Figure 3 presents the performance of the FCFS approach, the ETA-based reactive truck scheduling approach, and the RWT obtained in the considered days. Results show that the proposed approach outperforms the current truck scheduling system of the case company, displaying an improvement in the RWT from 24% to 52% depending on the day. The application of the ETA-based reactive truck scheduling approach allows reducing the average sum of the trucks waiting time per day from 3,451 min (approximately 57 h) to 2,051 min (approximately 34 hours) with respect to the FCFS approach, corresponding to an average of 38% RWT. The average truck waiting time decreases from 57 min to 34 min per truck, corresponding to a 40% reduction. This reduction contribute to an improvement of the entire system performance, as well as the truck waiting time and less congestion in the yard. In particular, resources and space utilization in the yard increase, as well as the door occupancy. This promises not only economic savings but also improvements in environmental and social sustainability, thanks to reduced emissions of waiting trucks and drivers' stopover time.

Additionally, the scheduling stability was investigated. In particular, we compare the truck entry time as defined by the ETA-based truck scheduling approach with the time slot booked by the driver. It turned out that 96% of the trucks analysed were served before the end of their unloading slot, with 76% of the trucks that were served within their booked unloading slot and 20% of the trucks that were served before the beginning of their unloading window.

5.2.2. Impact of ETA accuracy variation

The accuracy of ETA information σ^2 impacts the performance of the approach: less accurate ETA could downgrade the approach optimization performance, eventually leading to inefficient scheduling choices in terms of the truck waiting time reduction.

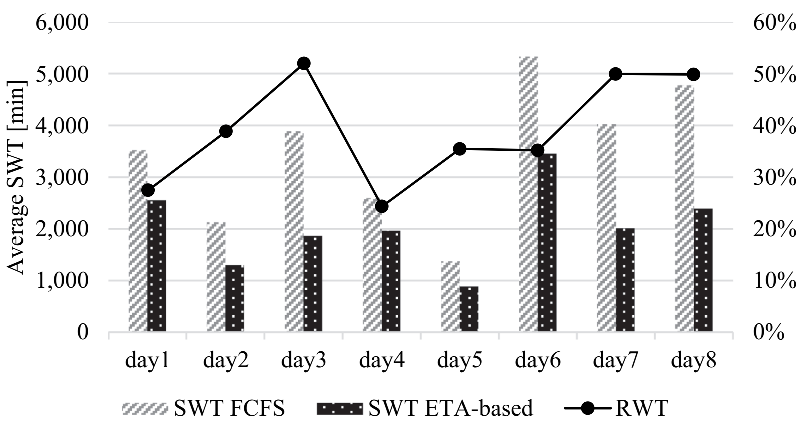

Figure 3. Comparison between the performance of the FCFS scheduling and the ETA-based reactive truck scheduling approach.

To assess the impact of ETA accuracy on the developed approach, ETAs for each truck have been estimated, by adding an error to the truck ATA. Different σ^2 of ETA errors were considered, ranging from 'perfect information', i.e. $\sigma^2 = 0$ to $2\sigma^2$, where σ^2 represents the accuracy of the ETA estimation model adopted by the company, with a step of 0.1 (Figure 4). Each level was tested against the eight selected days to improve results robustness to specific characteristics of a single day. Results were then averaged.

Results show the performance of the FCFS approach, the ETA-based reactive truck scheduling approach, and the corresponding RWT obtained under the different ETA accuracy levels included in the analysis. Considering the ETA accuracy of the estimation model adopted by the company, σ^2, the average sum of truck waiting times per day decreases from 3,451 min (approximately 57 hours) to 2,418 min (approximately 40 hours), with respect to the FCFS, corresponding to an average of 30% RWT. Results proved that the approach always outperforms the FCFS in reducing the truck waiting times, even when ETA accuracy is lowered. Downgrading the ETA accuracy from perfect information to $2\sigma^2$ increases the sum of the truck waiting times per day by 28% (from 2,018 min to 2,580 min). The benefit of the truck waiting time reduction gets worse with the increase of the ETA accuracy, as suggested by the RTW indicator, which improves from 25% in the worst case (i.e. ETA accuracy = $2\sigma^2$) to 42% in the best case (i.e. $\sigma^2 = 0$).

While a decrease in the performance of the approach is expected as the ETA accuracy is lowered, these results suggests that a good share of benefits – more than a 20% trucks waiting time reduction – can be achieved even when the predictive performance of the ETA model is downgraded by a 100%, compared to the reference model (i.e. $2\sigma^2$). These results in a support for companies when making-decisions about how to invest in advanced models for the ETA prediction. They could also support the deployment of the approach in companies, since if the accuracy of the predictive model is not sufficient, the combination of this information with a periodic rescheduling approach that keeps part of the schedule frozen could also lead to reduced scheduling performance than simpler rules such as FCFS.

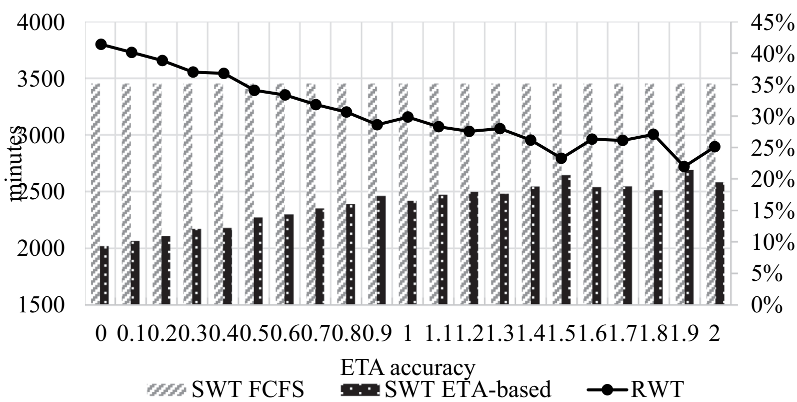

Figure 4. ETA-based reactive truck scheduling approach performance considering ETA accuracy.

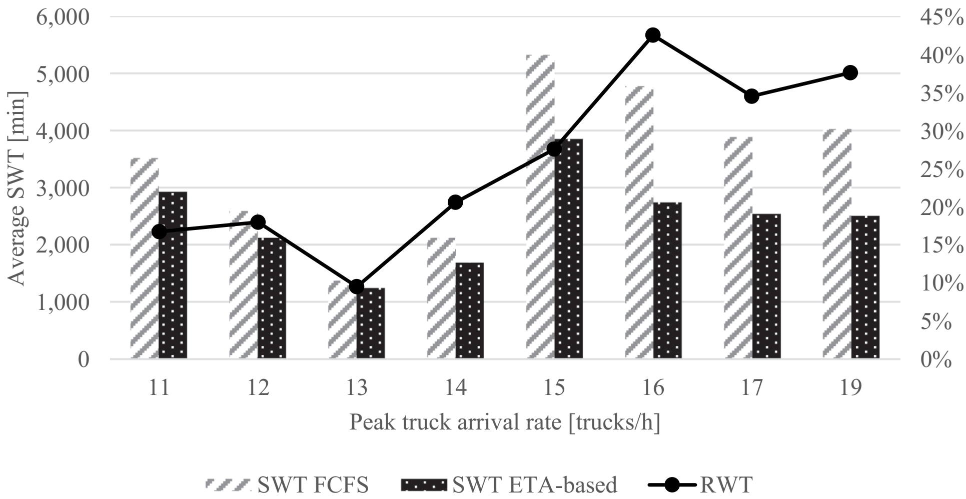

Figure 5. Eta-based reactive truck scheduling approach performance considering peak truck arrival rate.

5.2.3. Impact of peak truck arrival rate

The impact of different levels of peak truck arrival rate on the performance of the developed approach was assessed. A higher arrival rate represents a status of high workload for the unloading resources (Zhen, 2016); thus, it is expected to affect the approach performance: in case of a high truck arrival rate, knowing in advance the expected truck arrival time could improve the peak management. To run these experiments, the ETA accuracy level has been set equal to the one of the estimation model adopted by the company, i.e. σ^2. Figure 5 shows the performance of the FCFS approach, the ETA-based reactive truck scheduling approach, and the *RWT* obtained in days with different peak truck arrival rates. Results show that the ETA-base truck scheduling approach performance improved as the facility workload increases: the *RWT* indicator raise from 17%, corresponding to a day with a low peak truck arrival rate (i.e. 11 trucks/day), to 38%, corresponding to a day with high peak truck arrival rate (i.e. 19 trucks/day). These refer to an improvement brought by the ETA-based reactive truck scheduling approach with respect to the FCFS approach performance of 591 min (approximately 10 hours) – from 3,517 min to 2,926 min – in case of low peak truck arrival rate and of 1,517 min (approximately 25 hours) – from 4,023 min to 2,506 min – in case of high peak truck arrival rate. It should be noted that, due to the distribution of truck arrivals during the day, the benefits do not linearly increase with the peak truck arrival rate. For instance, the day showing a peak truck arrival rate equal to 13 trucks/hour is characterized by a relatively low number of trucks arriving in the time period just before and after the peak hour. Conversely, the day showing a peak truck arrival rate equal to 16 trucks/hour is characterized by an increased arrival rate in the time period just before the peak hour.

This result provides insights on the impact of the approach based on the truck arrival time distribution, and it can be used by companies to understand which are the periods during the day in which the implementation of the proposed approach is required to avoid congestion and, therefore, to set the rescheduling frequency accordingly.

6. Discussion

This research explores the use of ETA information for improving truck scheduling. In doing so, it proposes a new managerial approach that integrates ETA in truck scheduling to reduce the waiting times of trucks, i.e. the ETA-based reactive truck scheduling approach, and tests its impact on a real case. The ETA-based reactive truck scheduling approach is a managerial approach that exploits real-time information about trucks' ETA to determine the optimal truck scheduling that minimizes the sum of trucks waiting time during the facility working day.

6.1. Theoretical contributions

The managerial approach proposed enriches previous literature on truck scheduling by studying a new way to deal with uncertainty in truck arrival time. As it includes rescheduling, the ETA-based reactive truck scheduling approach presents the same benefits as reactive approaches for truck scheduling, compared to proactive ones. Unlike extant reactive approaches, which take into account early or late truck arrivals only when the truck reaches the facility, the ETA-based reactive truck scheduling approach allows acting in advance on arrival times uncertainty by exploiting predictive information about all the incoming trucks, dynamically adjusting the schedule according to the expected trucks arrival times. Being ETA predictive, it allows improving the optimization performance as all the incoming trucks can be scheduled, while extant reactive approaches could only optimize trucks already arrived at the receiving facility (Cekała et al., 2015). The empirical evidence provided strengthened and confirmed the results of previous studies about the utility of ETA information in improving facility operations resource efficiency (Hill & Böse, 2017). Our results confirm that the ETA-based reactive truck scheduling approach can be more efficient than the most commonly used reactive approach (i.e. FCFS) in reducing the total truck waiting times (up to 52% reduction in the case considered). Despite this result being case-specific as it depends on the ETA forecast model adopted by the company, the analysis conducted on the impact of ETA accuracy variations proved that the approach always outperforms the FCFS even when ETA accuracy is lowered. Results of the analysis conducted on the peak truck arrival rate further strengthen the evidence of the benefit of the approach, proving its ability to efficiently manage truck arrival peaks, with the case showing better *RWT* performance in days with a higher number of trucks arriving at the peak hours.

By showing which relation exists between ETA accuracy and the benefits generated, this study also provides relevant insights into the ETA modeling literature. Being ETA information 'primarily seen as an instrument for early support for operational decision-making problems' (Balster et al., 2020, p. 415), having a benchmark for ETA accuracy could support further research on ETA estimations model development and application.

This research also contributes to Industry 4.0 literature by evaluating a new data-driven approach supporting decision-making. Being a recent research field, literature has just started understanding how to apply 4.0 concepts (Dhiaf et al., 2021). While authors discussed the potential benefits (Bhattacharya et al., 2010) and how to measure (Pessotto Almeida et al., 2022) and capture them (Ferrari et al., 2021), few studies exist about their quantification (e.g. Zhao et al., 2020). Studying how to exploit data availability and integrate data analysis into extant logistics processes and providing the quantification of the related benefits could help companies fully exploit Industry 4.0 potential (Aron et al., 2023; Dhiaf et al., 2021).

6.2. Managerial implications

This research proposes a new managerial approach that could help companies in improving the efficiency of the unloading processes by exploiting ETA information. Starting from an initial schedule, the ETA-based reactive truck scheduling approach suggests companies to reschedule the truck service order according to the real-time ETA information. These are captured immediately before each rescheduling to benefit from up-to-date information about travel times and delays.

To function the managerial approach proposed requires some prerequisites for its application in practice. First, the approach requires that companies equip themselves with technologies that can compute the ETA. These include technologies that track the trucks to provide real-time locations, technologies for data analysis, and technologies for system integration between the carrier and the receivers, and between the receiver's information systems supporting the logistics processes affected by the proposed approach, i.e. the Yard Management System, the Transportation Management System, and the Warehouse Management System. The latter becomes necessary in contexts where the receiving facility is working with mixed fleets, both owned and outsourced, to have access to ETA information for all the incoming trucks. Technologies for truck locations and data analytics exist and are often already in place. Most of the new trucks are provided with telematics that tracks all the relevant information, including location in real-time; truck location can also be retrieved from the drivers' smartphone. Supply chain visibility players are nowadays offering technologies to compute ETA for fleets, and ETA is becoming a quite common service offered by carriers. Providing ETA data in real time to the receiving facility might be more complex, since issues such as privacy might prevent the carrier from sharing ETA information with its business partners. While technologies exist for systems integration, their development could be influenced by relationships among the actors, and partnership might ease the willingness to exchange information. Second, the approach requires the trucks processing time as input parameter, to enable the generation of a new informed scheduling. These can be derived from standard or historical data of the time required to process a single unit load of specific products combined with the Despatch Advice (DESADV), which gives information about the in-transit shipments, or based on the current status of ongoing activities and warehouse workforce. Third, the application of the model could also require a rearrangement of warehouse processes that have to ensure the flexibility required to fit the new scheduling system. In this sense, a company that wishes to apply the new managerial approach should perform an analysis of the warehouse processes of the average processing time of trucks and of the accuracy of the ETA model to set the correct rescheduling frequency. At last, a thorough assessment of the costs is required, including the phase of fine-tuning for obtaining and integrating accurate input data as well as training for operators in adapting their decision-making process to integrate the model output.

The ETA-based reactive truck scheduling approach could impact different actors. First, it offers warehouse managers a new managerial approach to perform truck scheduling under uncertainty in truck arrival times based on Industry 4.0 concepts towards the synchronization of logistics flows. Warehouse managers could use this approach to cope with late and early trucks more effectively and efficiently than extant instruments, thanks to the predictive visibility offered by ETA information. Additionally, the reduction in the truck waiting times offered by the ETA-based reactive truck scheduling approach could allow warehouse managers to both offer a better service level to transportation providers and reduce the penalties connected to truck waiting times. Our approach could entail a better synchronization between transport and warehouse activities (and supply chain actors) and higher efficiency by improving activity planning and resource utilization since it defines an initial schedule at the beginning of the day and offers anticipated visibility in schedule changes. The adoption of the ETA-based reactive truck scheduling approach also provides benefits for yard managers, since it lowers the number of trucks waiting to be unloaded, by reducing the average truck transit time inside the receiving facility yard. Indeed, both early and late trucks have to wait for docking; this may cause congestion, which results in longer operations time (Xi et al., 2020). Carriers and transportation companies could also benefit from the reduction in the total truck waiting time offered by the ETA-based reactive truck scheduling approach, since it contributes to improving their resource (e.g. trucks and drivers) efficiency. This is particularly relevant in today's context, since improving resource utilization could be a possible way to mitigate the persistent driver shortage faced by the logistics industry.

By reducing truck waiting time, our approach could also contribute to improving environmental sustainability, especially for temperature-controlled industries, where substantial amounts of energy are required to not shorten the products' shelf-life. Social sustainability could also be pursued by our approach: since waiting on-site could trigger overtime or long working hours, and considering the fact that warehouse yards may not be a safe workplace, their reduction contributes to improve the safety and work-life balance of drivers (Kubo et al., 2021).

Finally, we note that our model is computationally efficient, only taking a - fraction second per rescheduling, (e.g. in the real case analyzed, characterized by an average number of trucks per day equal to 61, the genetic algorithm found a solution in less than one minute), which renders it amenable for implementation in companies. Finally, our approach can be adjusted according to the specific facility configuration.

7. Conclusions

The present work analyzed a new managerial approach for truck scheduling under uncertainty in truck arrival times aimed to minimize the expected truck waiting times. The approach, called the ETA-based reactive truck scheduling approach, combined the ETA information of incoming trucks with the real-time update offered by a reactive scheduling approach to dynamically generate new optimal schedules that take into account the current trucks delays. This is intended to improve the synchronization between transportation and warehousing activities, thus increasing the efficiency of logistics distribution networks and at the same time address the challenge of redesigning traditional decision-making instruments to take advantage of Industry 4.0 faced by companies. The impact of the approach was assessed through the application to a real case involving one of the largest Italian grocery retailers and benchmarked against the most common reactive truck scheduling approach, i.e. the FCFS rule. Results suggest that the new approach can outperform the FCFS also when ETA accuracy is downgraded, proving its efficiency in reducing the impact of uncertainty in truck scheduling. The benefits improve with a higher peak truck arrival rate, further increasing the utility provided by this new approach.

This work enriches previous literature on truck scheduling by providing a new scheduling approach to deal with truck arrival time uncertainty, which exploits Industry 4.0 concepts. The paper also contributes to Industry 4.0 research field as it sheds light on how data can improve decision making approaches supporting logistics processes, providing an application of 4.0 concepts to truck scheduling. The study also yields practical implications, as the ETA-based reactive truck scheduling approach could benefit facility managers, offering an efficient and effective instrument to cope with truck arrival time uncertainty, warehouse, and yard managers, by reducing truck waiting times and the connected penalties and yard congestion, and carriers, by improving trucks and driver efficiency, wealth, and safety through a reduction in waiting times.

The present paper shows some limitations that open up future research possibilities. The assumption made to develop the model of fixed unloading resources during the day prevented the full model adherence with alternative types of warehouse doors environment or operational characteristics; thus, future research could relax these assumptions to include these and other facility-specific characteristics in new versions of the model. Impacts were assessed against FCFS policy. Although it is widely used by practitioners when performing truck scheduling and by researchers when comparing truck scheduling models (Cekała et al., 2015; Konur & Golias, 2013b), benefits against other scheduling rules can be explored. Future research could also explore the impact of changing the rescheduling frequency, taking into account the impact on both the truck and warehouse resource scheduling. The periodic rescheduling frequency could be compared with the others rescheduling strategies, i.e. event-driven or rescheduling point-based (Vieira et al., 2003). Lastly, an economic evaluation of the system required to use the developed approach and the overall benefits provided to both the carrier and the receiving facility could be carried out to reinforce the results of this work.

Acknowledgments

This research is part of a broader Italian-funded PNRR Research project 'Centro Nazionale per la Mobilità Sostenibile' (CN MOST) – Spoke 10 'Sustainable Logistics'. We would like to thank all partners and companies that have actively contributed to make this research possible.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Acar, K., Yalcin, A., & Yankov, D. (2012). Robust door assignment in less-than-truckload terminals. *Computers & Industrial Engineering*, *63*(4), 729–738. https://doi.org/10.1016/j.cie.2012.04.008

Amini, A., Tavakkoli-Moghaddam, R., & Omidvar, A. (2014). Cross-docking truck scheduling with the arrival times for inbound trucks and the learning effect for unloading/loading processes, prod. *Production and Manufacturing Research*, *2*(1), 784–804. https://doi.org/10.1080/21693277.2014.955217

Aron, C., Sgarbossa, F., Ballot, E., & Ivanov, D. (2023). Cloud material handling systems: A cyber-physical system to enable dynamic resource allocation and digital interoperability. *Journal of Intelligent Manufacturing*, 1–22. https://doi.org/10.1007/s10845-023-02262-6

Balster, A., Hansen, O., Friedrich, H., & Ludwig, A. (2020). An ETA prediction model for intermodal transport networks based on machine learning. *Business & Information Systems Engineering*, *62*(5), 403–416. https://doi.org/10.1007/s12599-020-00653-0

Barbour, W., Martinez Mori, J. C., Kuppa, S., & Work, D. B. (2018). Prediction of arrival times of freight traffic on US railroads using support vector regression. *Transportation Research Part C: Emerging Technologies*, *93*, 211–227. https://doi.org/10.1016/j.trc.2018.05.019

Bhattacharya, M., Chu, C. H., Hayya, J., & Mullen, T. (2010). An exploratory study of RFID adoption in the retail sector. *Operations Management Research*, *3*(1–2), 80–89. https://doi.org/10.1007/s12063-010-0029-z

Boysen, N., & Fliedner, M. (2010). Cross dock scheduling: Classification, literature review and research agenda. *Omega*, *38*(6), 413–422. https://doi.org/10.1016/j.omega.2009.10.008

Buijs, P., Vis, I. F., & Carlo, H. J. (2014). Synchronization in cross-docking networks: A research classification and framework. *European Journal of Operational Research*, *239*(3), 593–608. https://doi.org/10.1016/j.ejor.2014.03.012

Carson John, S. (2002). Model verification and validation. In E. Yiicesan, C.-H. Chen, J. L. Snowdon, & J. M. Charnes (Eds.) *Proceedings of the 2002 Winter Simulation Conference* (pp. 1945–1950). IEEE.

Cekała, T., Telec, Z., & Trawiński, B. (2015). Truck loading schedule optimization using genetic algorithm for yard management. *Lecture Notes in Computer Science*, *9011*, 36–548. https://doi.org/10.1007/978-3-319-15702-3_52

Dhiaf, M. M., Atayah, O. F., Nasrallah, N., & Frederico, G. F. (2021). Thirteen years of operations management research (OMR) journal: A bibliometric analysis and future research directions. *Operations Management Research*, *14*(3–4), 235–255. https://doi.org/10.1007/s12063-021-00199-8

Ferrari, A., Mangano, G., Cagliano, A. C., & De Marco, A. (2021). 4.0 technologies in city logistics: An empirical investigation of contextual factors. *Operations Management Research*, *16*(1), 345–362. https://doi.org/10.1007/s12063-022-00304-5

Flores da Silva, M. R., Sousa Agostino, I. R., & Morosini Frazzon, E. (2023). Integration of machine learning and simulation for dynamic rescheduling in truck appointment systems. *Simulation Modelling Practice and Theory*, *125*, 102747. https://doi.org/10.1016/j.simpat.2023.102747

Heidari, F., Zegordi, S. H., & Tavakkoli-Moghaddam, R. (2018). Modeling truck scheduling problem at a cross-dock facility through a bi-objective bi-level optimization approach. *Journal of Intelligent Manufacturing*, *29*(5), 1155–1170. https://doi.org/10.1007/s10845-015-1160-3

Hill, A., & Böse, J. W. (2017). A decision support system for improved resource planning and truck routing at logistic nodes. *Information Technology and Management*, *18*(3), 241–251. https://doi.org/10.1007/s10799-016-0267-3

Khalili-Damghani, K., Tavana, M., Santos-Arteaga, F. J., & Ghanbarzad Dashti, M. (2017). A customized genetic algorithm for solving multi-period cross-dock truck scheduling problems. *Measurement: Journal of the International Measurement Confederation*, *108*, 101–118. https://doi.org/10.1016/j.measurement.2017.05.027

Konur, D., & Golias, M. M. (2013a). Cost-stable truck scheduling at a cross-dock facility with unknown truck arrivals: A meta-heuristic approach. *Transportation Research Part E: Logistics & Transportation Review*, *49*(1), 71–91. https://doi.org/10.1016/j.tre.2012.06.007

Konur, D., & Golias, M. M. (2013b). Analysis of different approaches to cross-dock truck scheduling with truck arrival time uncertainty. *Computers & Industrial Engineering*, *65*(4), 663–672. https://doi.org/10.1016/j.cie.2013.05.009

Ladier, A. L., & Alpan, G. (2016a). Cross-docking operations: Current research versus industry practice. *Omega*, *62*, 145–162. https://doi.org/10.1016/j.omega.2015.09.006

Ladier, A. L., & Alpan, G. (2016b). Robust cross-dock scheduling with time windows. *Computers & Industrial Engineering*, *99*, 16–28. https://doi.org/10.1016/j.cie.2016.07.003
Ladier, A.-L., & Alpan, G. (2018). Crossdock truck scheduling with time windows: Earliness, tardiness and storage policies. *Journal of Intelligent Manufacturing*, *29*(3), 569–583. https://doi.org/10.1007/s10845-014-1014-4
Larbi, R., Gülgün, A., Baptiste, P., & Penz, B. (2011). Scheduling cross docking operations under full, partial and no information on inbound arrivals. *Computers & Operations Research*, *38*(6), 889–900. https://doi.org/10.1016/j.cor.2010.10.003
Leung, E. K. H., Lee, C. K. H., & Ouyang, Z. (2022). From traditional warehouses to physical internet hubs: A digital twin-based inbound synchronization framework for pi-order management. *International Journal of Production Economics*, *244*, 108353. https://doi.org/10.1016/j.ijpe.2021.108353
Liu, X., Chu, F., Zheng, F., Chu, C., & Liu, M. (2021). Parallel machine scheduling with stochastic release times and processing times. *International Journal of Production Research*, *59*(20), 6327–6346. https://doi.org/10.1080/00207543.2020.1812752
Mejía, G., Sarmiento, A., & Guerrero, W. (2023). Truck and Cross-docking scheduling in the flower export sector in Colombia. *Transportation Research Record: Journal of the Transportation Research Board*, *2677*(5), 352–366. https://doi.org/10.1177/03611981221130332
Modica, T., Colicchia, C., Tappia, E., & Melacini, M. (2021). Empowering freight transportation through logistics 4.0: A maturity model for value creation. *Production Planning & Control*, *34*(12), 1149–1164. https://doi.org/10.1080/09537287.2021.1988176
Napoleone, A., Moretti, E., Macchi, M., & Melacini, M. (2023). Synchronisation of material flows in mass-customised production systems: A literature-based classification framework and industrial application. *Production Planning & Control*, *35*(14), 1–19. https://doi.org/10.1080/09537287.2023.2214529
Nasiri, M. M., Ahmadi, N., Konur, D., & Rahbari, A. (2022). A predictive-reactive cross-dock rescheduling system under truck arrival uncertainty. *Expert Systems with Applications*, *188*, 115986. https://doi.org/10.1016/j.eswa.2021.115986
Pessotto Almeida, R., Ayala, N. F., Brittes Benitez, G., Kliemann Neto, F. J., & Frank, A. G. (2022). How to assess investments in industry 4.0 technologies? A multiple-criteria framework for economic, financial, and sociotechnical factors. *Production Planning & Control*, *34*(16), 1583–1602. https://doi.org/10.1080/09537287.2022.2035445
Rajabi, M., & Shirazi, M. A. (2017). Truck scheduling in a cross-dock system with multiple doors and uncertainty in availability of trucks. *Journal of Applied Environmental and Biological Sciences*, *6*, 101–109.
Ronconi, D. P., & Powell, W. B. (2010). Minimizing total tardiness in a stochastic single machine scheduling problem using approximate dynamic programming. *Journal of Scheduling*, *13*(6), 597–607. https://doi.org/10.1007/s10951-009-0160-6
Ruiz, R., & Maroto, C. (2006). A genetic algorithm for hybrid flowshops with sequence dependent setup times and machine eligibility. *European Journal of Operational Research*, *169*(3), 781–800. https://doi.org/10.1016/j.ejor.2004.06.038
Tappia, E., Moretti, E., Mohring, U., & Adan, I. (2024). Part feeding scheduling for mixed-model assembly lines with autonomous mobile robots: Benefits of using real-time data. *International Journal of Computer Integrated Manufacturing*, *M*, 1–16. https://doi.org/10.1080/0951192X.2024.2380276
Van Belle, J., Valckenaers, P., & Cattrysse, D. (2012). Cross-docking: State of the art. *Omega*, *40*(6), 827–846. https://doi.org/10.1016/j.omega.2012.01.005
van der Spoel, S., Amrit, C., & van Hillegersberg, J. (2017). Predictive analytics for truck arrival time estimation: A field study at a European distribution centre. *International Journal of Production Research*, *55*(17), 5062–5078. https://doi.org/10.1080/00207543.2015.1064183
Vieira, G. E., Herrmann, J. W., & Lin, E. (2003). Rescheduling manufacturing systems: A framework of strategies, policies, and methods. *Journal of Scheduling*, *6*(1), 39–62. https://doi.org/10.1023/A:1022235519958

Viet, N. Q., Behdani, B., & Bloemhof, J. (2020). Data-driven process redesign: Anticipatory shipping in agro-food supply chains. *International Journal of Production Research*, *58*(5), 1302–1318. https://doi.org/10.1080/00207543.2019.1629673

Wang, F. Y., Lin, Y., Ioannou, P. A., Vlacic, L., Liu, X., Eskandarian, A., Yisheng, L., Na, X., Cebon, D., Ma, J., Li, L., & Olaverri-Monreal, C. (2023). Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems. In *IEEE Transactions on Intelligent Transportation Systems*, Bilbao. https://doi.org/10.1109/TITS.2023.3305380.

Xi, X., Changchun, L., Yuan, W., & Loo Hay, L. (2020). Two-stage conflict robust optimization models for cross-dock truck scheduling problem under uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, *144*, 102123. https://doi.org/10.1016/j.tre.2020.102123

Xu, B., Liu, X., Li, J., Yang, Y., Wu, J., Shen, Y., & Zhou, Y. (2022). Dynamic appointment rescheduling of trucks under uncertainty of arrival time. *Journal of Marine Science and Engineering*, *10*(5), 695. https://doi.org/10.3390/jmse10050695

Yu, V. F., Sharma, D., & Murty, K. G. (2008). Door allocations to origins and destinations at less-than-truckload trucking terminals. *International Journal of Industrial and Systems Engineering*, *2*(1), 1–15. https://dor.isc.ac/dor/20.1001.1.17358272.2008.2.1.1.4

Zafarzadeh, M., Wiktorsson, M., & Baalsrud Hauge, J. (2023). Capturing value through data-driven internal logistics: Case studies on enhancing managerial capacity. *Production and Manufacturing Research*, *11*(1), 2214799. https://doi.org/10.1080/21693277.2023.2214799

Zhang, Z., Gong, X., Song, X., Yin, Y., Lev, B., & Zhou, X. (2024). An effective two phase heuristic for synchronized seru production scheduling and 3PL transportation problems. *International Journal of Production Economics*, *268*, 109126. https://doi.org/10.1016/j.ijpe.2023.109126

Zhang, Z., Zheng, L., Li, N., Wang, W., Zhong, S., & Hu, K. (2012). Minimizing mean weighted tardiness in unrelated parallel machine scheduling with reinforcement learning. *Computers & Operations Research*, *39*(7), 1315–1324. https://doi.org/10.1016/j.cor.2011.07.019

Zhao, Z., Zhang, M., Xu, G., Zhang, D., & Huang, G. Q. (2020). Logistics sustainability practices: An IoT-enabled smart indoor parking system for industrial hazardous chemical vehicles. *International Journal of Production Research*, *58*(24), 7490–7506. https://doi.org/10.1080/00207543.2020.1720928

Zhen, L. (2016). Modeling of yard congestion and optimization of yard template in container ports. *Transportation Research: Part B Methodological*, *90*, 83–104. https://doi.org/10.1016/j.trb.2016.04.011

Appendices

Appendix A

The potential sources of ETA errors include the model used for its computation and exogenous variables that might not be controlled nor measured such as driver's behaviours and the productivity at each facility in which the truck must stop. Since many dynamic factors must be considered, the ETA becomes rapidly obsolete, and it is constantly updated along the trucks trips. By analysing the data about the real case company's model for ETA estimation, we noticed that when the truck got closer to the destination, the error between the ETA and the ATA decreased. Table A1 reports the average variance, σ^2, in minutes of the ETA errors, computed at different time distance from the trucks ATA. This analysis helped understanding the accuracy of the ETA estimation reference model. On average, the error in the estimation decreases by around 4 times as the truck gets closer to its arrival.

For each truck, a set of ETAs was estimated by adding an error to the truck ATA, assumed as normally distributed with mean equal to 0 and variance equal to σ^2. Given the dynamic nature of its inputs, ETA accuracy improves as it gets closer to the destination; thus, different ETAs were associated to the same truck, one for each rescheduling point. Figure A1 presents an example of truck ETA estimation.

Table A1. Average ETA errors variance σ^2.

Time before ATA [min]	σ^2
0–10	13.68
11–20	21.85
21–30	22.42
31–40	21.54
41–50	20.04
51–60	21.47
61–70	26.61
71–80	25.95
81–90	27.82
91–100	33.15
101–120	61.472
121–140	64.6
141–160	71.043
161–180	75.718
181–200	84.881
201–220	93.823
221–240	101.558
241–260	98.753
261–280	112.523
281–300	115.668
301–400	133.807
401–500	148.937
501–600	117.674

Truck 47	**ATA = 14:01**									
Rescheduling point	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00
ETA	***13:57***	***13:52***	***13:59***	***14:05***	***14:04***	***14:05***	***13:59***	***14:00***	***14:02***	-
σ^2	*78.61*	*78.61*	*68.04*	*68.04*	*59.74*	*44.54*	*36.16*	*21.47*	*13.68*	-

Figure A1. ETA estimation for truck with ID 47.

Appendix B

The GA heuristic used to solve the optimization model of the ETA-based reactive truck scheduling approach was structured according to the stages: (i) chromosomal representation (encoding), (ii) reproduction, and (iii) fitness function evaluation and selection process. These are detailed as follows. Encoding is the process of chromosomes representation; chromosomes must be designed to correspond to a feasible solution of the optimization problem, i.e. a feasible truck schedule. Since integer chromosome representation is more suitable for scheduling problems (Konur & Golias, 2013b, permutation encoding was adopted (Ruiz & Maroto, 2006), which represents each truck as an integer number, i.e. ID, from 1 to I. Reproduction was performed by applying both crossover and mutation. Similar Block 2-Point Order Crossover (SB2OX) was selected as the reference crossover operator, being designed for permutation encoding. The crossover fraction, meaning the percentage of chromosomes undergoing crossover, was set at 0.1 (Ruiz & Maroto, 2006). Interchange mutation was adopted, coupled with a mutation rate of 0.04. The fitness function was constructed as an analytical model that takes in input a chromosome and computes the expected sum of truck waiting times SWT^t according to its related truck schedule. Chromosomes are then assessed according to their fitness function value to determine how the population will give birth to future generations. Tournament selection was chosen as the reference selection operator (Ruiz & Maroto, 2006).