# A robust optimization approach for platooning of automated ground vehicles in port hinterland corridors

Pourmohammad-Zia, Nadia; Schulte, Frederik; González-Ramírez, Rosa G.; Voß, Stefan; Negenborn, Rudy R.

**DOI**
10.1016/j.cie.2023.109046

**Publication date**
2023

**Document Version**
Final published version

**Published in**
Computers and Industrial Engineering

Computers & Industrial Engineering 177 (2023) 109046

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

# A robust optimization approach for platooning of automated ground vehicles in port hinterland corridors

Nadia Pourmohammad-Zia [a], Frederik Schulte [b], Rosa G. González-Ramírez [c,*], Stefan Voß [d], Rudy R. Negenborn [b]

[a] Department of Hydraulic Engineering, Delft University of Technology, The Netherlands
[b] Department of Maritime and Transport Technology, Delft University of Technology, The Netherlands
[c] Faculty of Engineering and Applied Sciences, Universidad de Los Andes, Chile
[d] Institute of Information Systems, University of Hamburg, Germany

ARTICLE INFO

*Keywords:*
Platooning
Automated ground vehicles
Port hinterland corridors
Bi-objective optimization
Robust optimization
Emission reduction

ABSTRACT

Modern ports face significant challenges as strategic nodes of global supply chains, being responsible for the coordination of inbound and outbound flows at deep-sea and in hinterland transport corridors. Digitization and the adoption of disruptive technologies can help ports to tide over operational challenges. Automated Ground Vehicles (AGVs) are an integral part of operations at many modern ports, especially inside container terminals. With the shift to automated transport outside of the terminal areas, these AGVs may form platoons to establish an efficient port hinterland transport corridor. In this work, we propose a new robust optimization approach to assess the time and cost-efficiency of applying such AGV platoons in a container pickup and delivery problem. We develop a bi-objective mixed-integer programming model, which simultaneously minimizes time and cost elements, and also considers emissions. Each transportation task can be carried out by AGVs or conventional trucks, while the number of available vehicles for each mode is uncertain (as they are used to connect different modalities of container transport). The robust optimization model is based on an ellipsoidal uncertainty set to handle this uncertainty and an augmented epsilon constraint method to obtain Pareto-optimal solutions for this multi-objective problem. The developed framework is evaluated in two case studies: the Port of Rotterdam in The Netherlands and the Port of Valparaíso in Chile, with different traveling distances in corridors to a dry port (200 km) and a pre-terminal (11 km), respectively. The results indicate that the new direct delivery scheme by AGV platoons is significantly more cost- and time-efficient than the benchmark and provides a low-carbon emission transportation mode. While the benefits of decreased dwell times (56% on average) and carbon emissions (on average by 10%) are similar for short and long traveling distances, the savings in cost increase (from 4.9% to 8%) with the increased distance in the Rotterdam case.

## 1. Introduction

Modern ports face significant challenges as strategic nodes of global supply chains. The related efficiency and flexibility requirements have been highlighted by the disruptions during the COVID-19 pandemic and the subsequent recovery phases. In such an environment, the coordination of inbound and outbound flows at deep-sea and in hinterland transport corridors is a challenging task. As highlighted in earlier research (Daduna & Stahlbock, 2020), hinterland transport is a typical bottleneck, in which the lack of coordination results in long truck queues at the gates of the port terminals, which translates into emissions, congestion, and negative impacts on the port cities. Therefore, a critical challenge for ports is the coordination of land-side operations required for the pre- and end-haulage of cargo. Furthermore, road transport is the transport mode that generates more emissions than rail and inland waterways, making the decarbonization of the freight transport sector one major concern (Ambra et al., 2019).

The application of autonomous driving is well-established in closed environments such as port terminals, warehouses, and industrial plants (Pourmohammad-Zia, Schulte, & Negenborn, 2020). Automated vehicles have been used at ports for decades in the transport of cargo during the loading and unloading transfer operations. However, hinterland and drayage transport of cargo has not been automatized yet, due to the challenges that an open and uncontrolled environment implies.

* Corresponding author.
*E-mail addresses:* N.PourmohammadZia@tudelft.nl (N. Pourmohammad-Zia), f.schulte@tudelft.nl (F. Schulte), rgonzalez@uandes.cl (R.G. González-Ramírez), stefan.voss@hamburg.de (S. Voß), R.R.Negenborn@tudelft.nl (R.R. Negenborn).

https://doi.org/10.1016/j.cie.2023.109046

Available online 31 January 2023

There are some initiatives in place to aid the adoption of automated vehicles and in general, to foster more efficient freight transportation and counteract the shortage of truck drivers. For instance, the *Container Exchange Route* initiative promoted by the Port of Rotterdam Authority, is a closed track of about 17 km long for the transportation of containers between locations in the Maasvlakte area (Port of Rotterdam, 2022). The first transports over the track are expected to take place by the end of 2023. Although this track is intended to be used by manned vehicles, in the future it may be possible to test autonomous vehicles as it is currently evaluated in the Port of Hamburg. Under a four-year pilot project subsidized by the European Union (MODI project), Hamburg is the first city that will be testing autonomous truck transport from the motorway to the terminal area of the Port of Hamburg. This was facilitated by the ITS strategy (Intelligent Transport System), as the test track will be used based on the ITS-G5 technology. Furthermore, the vehicles will be tested on motorways between Rotterdam in the Netherlands and Moss in Norway (Hamburg News, 2022). Although there are some initiatives such as those mentioned above, most roads are not yet ready and are not expected to be ready in the short or mid-term to be safely used by Automated Ground Vehicles (AGVs). Accordingly, platooning can be considered as a transition step for the early adoption of automated vehicle technology such as AGVs, and as a transport mode with the potential to reduce the environmental impact of freight transportation (Boysen et al., 2018).

Truck platooning links two or more trucks in a convoy by connectivity technology and automated driving support systems. A leading human-driven truck is followed by the rest of the vehicles that do not necessarily need drivers and automatically adapt to changes in the leader's movement. Platooning is an emerging and promising alternative transportation mode as an intermediate solution on the way from human-operated vehicles to full automation in road transport (Carbaugh et al., 1998), and platoon coordination is a complex problem that may involve different uncertainties (Johansson et al., 2021). Driving closely together reduces fuel consumption as it improves the aerodynamics of the vehicles in the platoon, which also translates into emission savings (Bergenhem et al., 2012). Moreover, earlier work on hinterland transportation has demonstrated that collaborative transportation (which is naturally required for platooning) is an effective means to reduce empty runs as well as related costs and emissions (Schulte et al., 2017). Considering the above, platooning has the potential to reduce costs and emissions while enabling more efficient use of road capacity.

The implementation of AGVs for a direct transfer of cargo from the vessel (thereby avoiding the traditional storage option) has received limited attention in the literature. However, this strategy could hold several advantages, specifically for those ports in which yard space is a scarce resource. Fig. 1 illustrates the traditional transferring of cargo processes in a container terminal compared to an alternative mode using platoons. In a traditional approach, a container is unloaded off the vessel and temporarily stacked in the yard, and then picked up by an external carrier that transports it to its destination in the hinterland. Alternatively, a container, unloaded from the vessel, may directly be transported by AGV platoons, thus avoiding additional storage and loading operations. The coordination of landside and seaside operations and their different modalities is challenging. However, when only a certain subset of containers is considered, such as empty containers or those containers that are stored in bonded warehouses, the potential gains make it a viable option to explore this alternative and thus also avoid additional handling operations for this subset of containers.

In this work, we propose a new robust optimization approach to assess the time and cost-efficiency of applying such AGV platoons in a container pickup and delivery problem. In this case, import containers unloaded from a vessel are directly transported to a dry port or other locations in the hinterland, avoiding the stacking of the containers in the yard. To this end, we develop a bi-objective mixed-integer programming model, which simultaneously minimizes time and cost elements for the best combination of AGV platoons and conventional trucks. In order to obtain more environmentally friendly results, emission reduction is taken into account by considering the emission penalty as a component of the cost-related objective function. Each transportation task may either be carried out by AGVs or conventional trucks, and the number of available vehicles for each mode faces uncertainty because they may be used by different parties to connect different transport modalities in the container terminal and the port hinterland corridor.

The robust optimization approach (Ben-Tal et al., 2009; Caserta & Voß, 2019) builds on an ellipsoidal uncertainty set, and the augmented epsilon constraint method is adopted to handle the uncertainty and obtain Pareto optimal solutions, respectively. The proposed framework is illustrated in two case studies: the Port of Rotterdam in The Netherlands and the Port of Valparaíso in Chile. We consider the transportation of containers between the port and a dry port in the hinterland in both cases. The case study of the Port of Rotterdam outlines a long traveling distance to the dry port in the logistic hub Venlo (200 km distance), while the case of the Port of Valparaíso represents a short traveling distance to the pre-terminal ZEAL (11 km distance). This allows us to contrast the benefits of platoons for short and long traveling distances. In this work, we intend to evaluate the dual use of AGVs in terminal operations and hinterland platooning, as an explorative study. Since there is almost no prior work on this particular question, let alone any real-world data on the viability of using terminal AGVs for hinterland platooning, the robust optimization approach under explicit consideration of AGV unavailability is chosen to provide sufficient insight into the underlying economic trade-off. The uncertainty related to the number of containers as well as its impact on port operations, on the other hand, is much better understood. Therefore, we consider different scenarios to model this uncertainty in our problem.

The remainder of this paper is organized as follows: Section 2 provides an overview of the related literature and existing gaps. The proposed model is introduced in Section 3 and the solution procedure is outlined in Section 4. Section 5 illustrates two case studies for our problem, including numerical results, a sensitivity analysis, and managerial insights derived from the experiments. Finally, the paper is concluded, and future research directions are presented in Section 6.

## 2. Literature review

Automated technology has been a key factor to support international trade growth, and several container terminals worldwide have been automatized at a certain level. In this regard, Kon et al. (2020) present a survey of the current trends and conclude that the adoption of automated equipment and technology in a container terminal minimizes the inefficiencies of container handling by reducing total travel times of the transport of containers and lowering operational costs. Moreover, inter-terminal transportation and the application of AGVs in this area have been investigated (Heilig & Voß, 2017; Tierney et al., 2014). Among the different automated equipment for container handling, AGVs have been implemented for the horizontal transport of containers during the loading and unloading operations, transporting containers between the quay and the yard. Platooning has emerged as a promising technology that not only offers significant fuel savings but also prepares the ground for increased autonomy in freight transportation (Janssen et al., 2015). Research developments in the area date back to the early 1980s, when Van Aerde and Yagar (1984) provided one of the initial related studies. A large part of the relevant literature has been devoted to technical and technological aspects of platooning, including string sequence and stability, signal timing, longitudinal trajectory control, speed profile, connectivity issues, obstacle avoidance, and vehicle-to-vehicle communications.

As emphasized by Gerrits et al. (2019) and Pourmohammad-Zia, Schulte, Souravlias, and Negenborn (2020) studies on the operational side of platooning, such as planning, routing, and scheduling, are still scarce in the logistics literature. A first attempt to explore the benefits

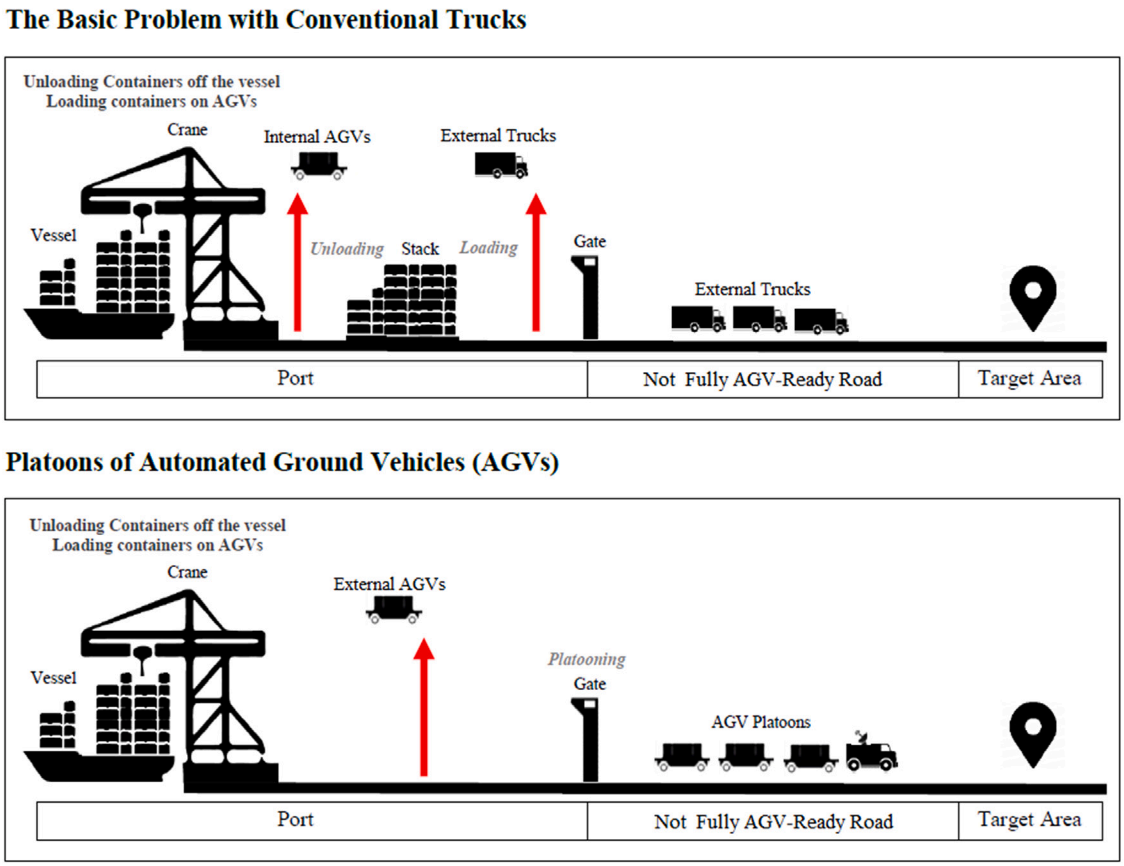


**Fig. 1.** The container drayage process with conventional trucks and AGV platoons in port hinterland corridors.

of platooning is presented by Larsson et al. (2015). The main objective is to maximize fuel savings while considering the formation and routing of the platoon. For the same platooning problem, an improved model is developed in Larson et al. (2016). This approach significantly reduces the problem size, thereby enabling to handle realistic instances more efficiently. Different aspects of the platoon formation problem are analyzed in Boysen et al. (2018). Their computational analysis shows that the benefits of platooning on fuel consumption depend significantly on the number of platoon partners, restrictions on the platoon length as well as the size of the delivery time-windows.

A related idea to platooning is the road trains or multi-trailer trucks (MTT). An MTT consists of several container-carrying trailers that can generally transport up to five 40-foot containers and is not automated, requiring a human to drive a tractor unit that pulls the trailer (Tierney et al., 2014). Although platooning and MTTs share similarities from a modeling perspective, the technology significantly differs. An MTT is less flexible than an AGV that can perform different transport operations, as it is considered in the approach proposed in this manuscript. Furthermore, the coupling time of the tractor unit to the trailer can result in a slower turn-around time for the vehicles than AGVs, as it is explained by Duinkerken et al. (2007). Another important distinction is that an MTT requires more space as the trailers are coupled, while AGVs are more flexible and only need a space for platoon formation. The versatility of an AGV to carry out transport operations in the port terminal, or transporting the container to a dry port or other terminals by means of platooning, is one of the advantages presented by the proposal of this manuscript.

Before presenting an overview of the existing literature, it is important to refer to preliminary research presented by the authors of this manuscript as conference proceedings, and the main differences with this work (Pourmohammad-Zia, Schulte, & Negenborn, 2020; Pourmohammad-Zia, Schulte, Souravlias, & Negenborn, 2020). Pourmohammad-Zia, Schulte, and Negenborn (2020) investigate a platform-based container transportation problem between a port and an industrial, considering two transport modes. Truck or an automated vehicle. A mathematical model is proposed with the aim to assign vehicles to transport services. As there is an interactive decision-making process between the carriers and the platform, this is modeled as a two-level constrained Stackelberg competition and transformed into a one-level MIP model. The main differences with this work are related to the problem setting and the solution methodologies. Previous research considers that freight transportation is performed by multiple carriers between the port and an industrial zone and a single objective function is considered (minimizing total costs). In this work we are considering drayage services between the port and a dry port, we are assuming that the available number of vehicles for each delivery mode is uncertain and modeling the problem as a bi-objective MIP model. On the other hand, the same problem as in this manuscript is considered by Pourmohammad-Zia, Schulte, Souravlias, and Negenborn (2020). The main differences with this work are related to the modeling and solution methodologies. In previous research, a bi-objective MIP problem is defined, minimizing dwell times and costs as the objective functions. This work considers the same objectives, but emissions are directly modeled as a cost, while the previous research performs an independent analysis of the solutions found. Another difference is that the previous model assumes deterministic variables. In contrast, in the current model, the available number of vehicles is stochastic and a robust optimization approach is considered as a solution methodology.

Tables 1 and 2 provide a general overview of the existing literature related to truck platooning and AGV scheduling for freight transportation. Seven categories are considered here. Table 1 presents four of such categories that correspond to the Decision Problem, Modeling Approach; Solution Approach, and Uncertainty. Table 2 presents the last three categories, involving: Objective Function, Scope, and Features.

**Table 1**
Overview of the existing literature (Part I).

| | Decision | | Modelling | | | Solution | | Uncertainty | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scheduling | Routing | Analytical | Mathematical programming | Markov chains | Exact | Approximate | Simulation | Stochastic | Robust | Deterministic |
| Nishimura et al. (2005) | | ✓ | | ✓ | | | ✓ | | | | ✓ |
| Duinkerken et al. (2007) | | ✓ | | | | | | ✓ | ✓ | | |
| Tierney et al. (2014) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Cordeau et al. (2015) | | ✓ | | | | | ✓ | ✓ | ✓ | | |
| Larsson et al. (2015) | | ✓ | ✓ | ✓ | | ✓ | ✓ | | | | ✓ |
| Larson et al. (2016) | | ✓ | ✓ | | | ✓ | | | | | ✓ |
| Zhang et al. (2017) | ✓ | ✓ | | ✓ | | | ✓ | | | | ✓ |
| Boysen et al. (2017) | ✓ | | ✓ | | | ✓ | | | | | ✓ |
| Tschöke and Boysen (2018) | ✓ | | | ✓ | | | ✓ | | | | ✓ |
| Boysen et al. (2018) | ✓ | | ✓ | ✓ | | ✓ | | | | | ✓ |
| Luo et al. (2018) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Larsen et al. (2019) | ✓ | | | ✓ | | | ✓ | | | | ✓ |
| Abdolmaleki et al. (2019) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Scherr et al. (2019) | ✓ | ✓ | | ✓ | | ✓ | | | | | ✓ |
| Luo and Larson (2020) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Hirata and Fukaya (2020) | | | ✓ | | | ✓ | | | | | ✓ |
| Xiong et al. (2020) | | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | |
| You et al. (2020) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Chen et al. (2020) | ✓ | | | ✓ | | ✓ | | | | | ✓ |
| Zhong et al. (2020) | ✓ | | | ✓ | | | ✓ | | | | ✓ |
| Zheng et al. (2020) | ✓ | | | ✓ | | ✓ | | | | | ✓ |
| Shouwen et al. (2020) | ✓ | ✓ | | ✓ | | ✓ | ✓ | | | | ✓ |
| Zhang et al. (2020) | | ✓ | | ✓ | | | ✓ | | | | ✓ |
| Pourmohammad-Zia, Schulte, and Negenborn (2020) | ✓ | | | ✓ | | ✓ | | | | | ✓ |
| Pourmohammad-Zia, Schulte, Souravlias, and Negenborn (2020) | ✓ | | | ✓ | | ✓ | | | | | ✓ |
| Xue et al. (2021) | ✓ | ✓ | | ✓ | | | ✓ | | | | ✓ |
| Repoux et al. (2021) | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | ✓ |
| Scholl et al. (2022) | ✓ | | | ✓ | | | ✓ | | | | ✓ |
| Caballero et al. (2022) | | ✓ | | ✓ | | | ✓ | | | | ✓ |
| Scherr et al. (2022) | | ✓ | | ✓ | | ✓ | | | ✓ | | |
| This work | ✓ | | | ✓ | | ✓ | | | | ✓ | |

The overview of the literature presented in Table 1 reveals that in terms of the decision problem, the contributions are similarly focused on routing and scheduling problems and there are some that deal with the two decision problems such as (Abdolmaleki et al., 2019; Luo & Larson, 2020; Luo et al., 2018; Scherr et al., 2019; Shouwen et al., 2020; Xue et al., 2021; You et al., 2020; Zhang et al., 2017). This manuscript, as well as previous research (Pourmohammad-Zia, Schulte, & Negenborn, 2020; Pourmohammad-Zia, Schulte, Souravlias, & Negenborn, 2020), is focused on solving only the scheduling problem. On the other hand, most of the contributions consider a mathematical programming or analytical approach in terms of modeling, and few consider an analytical approach or Markov chains (Boysen et al., 2018, 2017; Hirata & Fukaya, 2020; Larson et al., 2016; Larsson et al., 2015; Xiong et al., 2020). With respect to the solution methodologies, there is a relatively similar number of exact and approximate approaches. In this manuscript and in previous research (Pourmohammad-Zia, Schulte, & Negenborn, 2020; Pourmohammad-Zia, Schulte, Souravlias, & Negenborn, 2020), only an exact approach is considered. As shown in the table, most of the papers have proposed deterministic models, and only five of them deal with uncertainty (Cordeau et al., 2015; Duinkerken et al., 2007; Repoux et al., 2021; Scherr et al., 2022; Xiong et al., 2020), as it is done in our research. In terms of the uncertainty approach, this is the only paper proposing a robust optimization approach. A mathematical programming model is proposed, based on a network flow formulation and explicitly considers the underlying uncertainty of the problem.

As Table 2 suggests, concerning the objective function, the contributions have considered optimizing both time and costs, including fuel consumption. However, no paper has considered emissions. On the other hand, all of the research works have taken a single objective, and only (Pourmohammad-Zia, Schulte, Souravlias, & Negenborn, 2020) and the present work have applied a multi-objective structure. In terms of the scope, a very confined part of the literature on platooning is related to inter-terminal and hinterland transport operations, which is the focus of this manuscript. Inter-terminal problems have been addressed by Duinkerken et al. (2007), Tierney et al. (2014), Zheng et al. (2020), and hinterland transport by Pourmohammad-Zia, Schulte, and Negenborn (2020), Pourmohammad-Zia, Schulte, Souravlias, and Negenborn (2020), Scholl et al. (2022), Xue et al. (2021), You et al. (2020). Seven out of the thirty contributions are focused on port terminals, considering hence, a closed area to operate the automated vehicles. The rest of the reviewed articles are not oriented to port operations, focused on either rail terminals or a heterogeneous vehicle network. In this manuscript, the scope of the problem is related to both inter-terminal and hinterland transport. A heterogeneous vehicle network that confines the AGVs' application to restricted AGV-ready areas is heeded by only nine papers, including this manuscript. We can also observe that contributions related to MTTs are scarce and some of them are associated with the horizontal transport of containers in a rail terminal, while only one considers the inter-terminal transportation (Duinkerken et al., 2007). MTTs are considered neither in this manuscript, which is focused only on platoons and AGVs. When dealing with inter-terminal or hinterland transportation, most of the contributions consider both AGVs and Platoons, with the exception to You et al. (2020) that considers only AGVs.

**Table 2**
Overview of the existing literature (Part II).

| | Objective function | | | | | Scope | | | | | Features | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Time | Cost | Emission | Single-objective | Multi-objective | Inter terminal | Hinterland | Port-terminal | Rail-terminal | HVN* | Platoon | AGV | MTT** |
| Nishimura et al. (2005) | | ✓ | | ✓ | | | | ✓ | | | | | ✓ |
| Duinkerken et al. (2007) | ✓ | | | ✓ | | ✓ | | | | | | ✓ | ✓ |
| Tierney et al. (2014) | ✓ | | | ✓ | | ✓ | | ✓ | ✓ | | | ✓ | |
| Cordeau et al. (2015) | ✓ | | | ✓ | | | | ✓ | | | | | ✓ |
| Larsson et al. (2015) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Larson et al. (2016) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Zhang et al. (2017) | ✓ | ✓ | | | | | | | | | ✓ | | |
| Boysen et al. (2017) | ✓ | | | ✓ | | | | | ✓ | | | | ✓ |
| Tschöke and Boysen (2018) | ✓ | | | ✓ | | | | | ✓ | | | | ✓ |
| Boysen et al. (2018) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Luo et al. (2018) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Larsen et al. (2019) | ✓ | ✓ | | ✓ | | | | | | | ✓ | | |
| Abdolmaleki et al. (2019) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Scherr et al. (2019) | | ✓ | | ✓ | | | | | | ✓ | ✓ | ✓ | |
| Luo and Larson (2020) | | ✓ | | ✓ | | | | | | | ✓ | | |
| Hirata and Fukaya (2020) | ✓ | | | ✓ | | | | | | | ✓ | | |
| Xiong et al. (2020) | ✓ | ✓ | | | | | | | | | ✓ | | |
| You et al. (2020) | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | ✓ | | |
| Chen et al. (2020) | ✓ | | | ✓ | | | | ✓ | | | | ✓ | |
| Zhong et al. (2020) | ✓ | | | ✓ | | | | ✓ | | | | ✓ | |
| Zheng et al. (2020) | ✓ | | | ✓ | | ✓ | | ✓ | ✓ | | | ✓ | |
| Shouwen et al. (2020) | ✓ | | | ✓ | | | | ✓ | | | | ✓ | |
| Zhang et al. (2020) | | | | | | | | | | | | | ✓ |
| Pourmohammad-Zia, Schulte, and Negenborn (2020) | | ✓ | | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | |
| Pourmohammad-Zia, Schulte, Souravlias, and Negenborn (2020) | ✓ | ✓ | | | ✓ | | ✓ | | | ✓ | ✓ | ✓ | |
| Xue et al. (2021) | | ✓ | | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | |
| Repoux et al. (2021) | ✓ | | | ✓ | | | | | | ✓ | ✓ | ✓ | |
| Scholl et al. (2022) | | ✓ | | ✓ | | | ✓ | | | | ✓ | | |
| Caballero et al. (2022) | | ✓ | | ✓ | | | | | | ✓ | ✓ | | |
| Scherr et al. (2022) | | ✓ | | ✓ | | | | | | ✓ | ✓ | ✓ | |
| This work | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | |

(HVN*): Heterogeneous Vehicle Network; (MTT**): Multi-Trailer-Truck

To put the related literature in a nutshell, despite the increasing interest in platooning, there is limited research in the freight transportation sector and particularly port-related operations. This provides opportunities, especially for new decision-making approaches investigating its role in a wide spectrum of logistics applications. So far, platoon formation, scheduling, and routing problems have claimed most of the research attention, while the role of platooning as a transfer mode for port-hinterland and inter-terminal transportation still remains widely unexplored. More precisely, only three contributions consider a heterogeneous vehicle network (that confines the application of AGVs to restricted AGV-ready areas) and thereby apply platooning as a transfer mode in non-AGV-ready areas. From those references, two are related to port transport operations and one (Scherr et al. (2019)) to last-mile distribution. Moreover, up to now, fuel costs have been the main focus of platooning problems. Considering other objectives will reveal the impact of platooning on additional aspects, thereby unlocking its full potential.

As previously highlighted, none of the reviewed contributions propose a multi-objective optimization approach, and, to address uncertainty, this work is the only one that proposes a robust optimization approach. As emphasized by Gabrel et al. (2014), robust optimization aims to protect the decision-maker against parameter ambiguity and stochastic uncertainty and the main paradigm relies on worst-case analysis in which a solution is evaluated considering the realization of the most unfavorable uncertainty. In this regard, computing the worst-case analysis may consider a finite number of scenarios based on historical data, or continuous, convex uncertainty sets such as polyhedra or ellipsoids. In this manuscript, the proposed solution methodology considers ellipsoidal uncertainty sets proposed by Ben-Tal and Nemirovski (1999, 2000) to account for uncertainty in the number of available vehicles. According to Ben-Tal et al. (2009), an ellipsoidal set may be used to reduce the conservatism when the real-life uncertainty is a box, while still maintaining a large probability of constraint satisfaction. Bertsimas and Sim (2004) analyze the complexity and practical efficiency of this approach and showed that general ellipsoidal uncertainty sets are NP-Hard even though the nominal problem can be polynomially solved. Hence, approximation techniques based on piecewise linearization are employed to tackle such problems (Beyer & Sendhoff, 2007), which is also done in this manuscript. This methodology has been applied to tackle uncertainty issues of several operations management problems, such as retailer-supplier flexible contracts with uncertain demand that is only known to reside in some uncertainty set (Ben-Tal et al., 2005); network design problems with uncertainty either on demand or cost (Gao & Ryan, 2014; Mudchanatongsuk et al., 2008); evacuation planning transportation planning with demand uncertainty (Yao et al., 2009); facility location problems (Baron et al., 2011); vehicle routing problems (Pelletier et al., 2019; Sungur et al., 2008); among others. For comprehensive reviews of different approaches to tackle uncertainty under a robust optimization approach, the reader can refer to Beyer and Sendhoff (2007), Lu and Shen (2021).

**Table 3**
Dwell time in two delivery modes.

| Dwell time | |
|---|---|
| Delivery by AGV ($n = 1$) | Delivery by Truck ($n = 2$) |
| Loading containers on AGVs ($t_1$) | Loading containers on AGVs ($t'_1$) |
| Traveling to platooning area ($t_2$) | Traveling to stack ($t'_2$) |
| Waiting for platoon formation ($t_3$) | Unloading containers off the AGVs ($t'_3$) |
| Forming platoons ($t_4$) | Stacking ($t'_4$) |
| Traveling to gate ($t_5$) | Loading containers on external trucks ($t'_5$) |
| | Traveling to gate ($t'_6$) |

## 3. Model development

### 3.1. Problem description

The proposed framework outlines pre- and end-haulage container transportation, precisely the full container pickup and delivery problem between a port and its hinterland depot or adjacent dry port referred to as the target area in our paper. After unloading a vessel in the traditional terminal process, the import containers are moved to the stack, where they wait for the rest of their delivery journey. We assume that a subset of these containers can be directly delivered to their target area without requiring stacking as a buffer. That is, these containers do not need intermediary processes before the delivery, their release time are close to each other, and their delivery time-windows at the target-zone opens in near time. After being unloaded off the vessel, these containers can be loaded on the AGVs and directly head to their final destination. Therefore, for this subset of the containers, denoted as $K_D$ in our model, two delivery modes can be applied, including the direct delivery by AGVs in platoons ($n = 1$) and the conventional trucks with traditional stacking procedure ($n = 2$). After delivering these containers to the target area, the export containers, denoted as $K_P$, are picked up by the vehicles on their way back to the port. The idea is to investigate if the proposed direct pickup and delivery scheme for the set of containers $K = K_D \cup K_P$ can bring savings in time and cost to the system.

A key feature of this direct delivery scheme is eliminating some loading-unloading activities and waiting times. Therefore, the model considers one journey at a time and multiple journeys are independent of each other. More precisely, if we consider multi-trip structure in our problem, a part of the containers should wait at stack until the previous journey of the fleet is completed, which is in contrast with the main purpose of the proposed direct delivery scheme. We consider an import-oriented port suggesting that the number of import containers is higher than that of export containers and define a set of dummy export containers such that $|K_D| = |K_P|$. In this way, it is guaranteed that the vehicles carrying import containers will return to the port delivering the export containers.

The transportation network is considered to be heterogeneous. The port and the target area are ready for the application of automated driving, while the linking road segment that connects these two areas is not suitable for AGVs. Therefore, the AGVs have to join a platoon with a human-driven leader to move within this linking road segment. The set of potential platoons is distinguished by $P$, the size of which shows the number of available leading vehicles and their drivers. A part of internal AGVs managed by port authorities are assigned to the proposed direct delivery scheme (known as external AGVs). The available numbers of vehicles for each delivery mode are not deterministic and belong to an uncertainty set. That is because these vehicles may be used to carry out other transportation tasks in different situations. For instance, the AGVs may serve as internal port vehicles to transfer the containers between the quayside and stack, which affects the number of available AGVs for the direct delivery scheme.

Import containers' dwell-time is understood as the time taken for the containers to be loaded onto the external vehicles leaving the container terminal. The elements of dwell-time for each delivery mode are represented in Table 3. $t_1$, $t_2$, $t_4$, $t'_1$, $t'_2$, $t'_3$, $t'_5$, and $t'_6$ are fixed known parameters, whereas $t_3$ and $t'_4$ are variables that will be determined in the model.

Decreasing the dwell time is highly important as it is a key performance indicator in ports. Additionally, reducing the idle time of the vehicles is of great significance due to the negative impact of their underutilization. As Table 3 suggests, despite the dwell-time, the idle time of the AGVs can be potentially higher compared to conventional trucks. This is why we have simultaneously taken the dwell-time and waiting times as our time-related objective function. On the other hand, decreasing the time can come at the price of higher costs, diminishing the benefits of the proposed structure. Accordingly, this research aims to specify optimal delivery modes and schedules that minimize dwell and idle time elements as well as the related costs.

### 3.2. Mathematical formulation

The problem is modeled on a directed graph $G = (V, A)$ where $V$ is the set of vertices and $A$ is the set of arcs. $V = \{ID\} \cup S_1 \cup S_2 \cup \{FD\}$ includes the initial origin ($ID$) and its copy as the final destination ($FD$), the destination of import containers in the target area ($S_1$) and the origin of export containers in the target area ($S_2$). The set of admissible arcs is defined as: $A = \{(i,j)|i,j \in V, i \neq j, (i,j) \in A_1 \cup A_2 \cup A_3\}$ where: $A_1 = \{(i,j)|i = ID, j = S_1\}$, $A_2 = \{(i,j)|i = S_1, j = S_2\}$, $A_3 = \{(i,j)|i = S_2, j = FD\}$

The remainder of the notations used to formulate the model of our problem is listed as follows.

**Notations**

**Parameters**

| | |
|---|---|
| $U_B$ | Maximum allowed number of AGVs in a platoon |
| $L_B$ | Minimum allowed number of AGVs in a platoon |
| $T_i^n$ | Service time at vertex $i$ for delivery mode $n$ |
| $TR_{ij}^n$ | Travel time of arc $(i,j)$ for delivery mode $n$ |
| $RT^k$ | Release time of container $k \in K_D$ |
| $TA_i^k$ | Lower bound for admissible delivery time for container $k$ at vertex $i$ |
| $TB_i^k$ | Upper bound for admissible delivery time for container $k$ at vertex $i$ |
| $\tilde{AV}^n$ | Available vehicles of mode $n$ (belonging to the uncertainty set $\zeta$ ) |
| $CT^n$ | Unit fuel consumption cost of mode $n$ ($CT^p$ respective cost for platoon $p$) |
| $CL^n$ | Driver wage for mode $n$ ($CL^1 = 0$ and $CL^p$ respective cost for platoon $p$) |
| $CA^n$ | Acquisition cost for vehicles of mode $n$ ( $CA^p$ respective cost for platoon $p$) |
| $CE$ | Emission penalty cost per gr, that is charged by the government |
| $e_{ij}^n$ | Energy consumption of the vehicle of mode $n$ for traveling arc $(i,j)$ |
| $ce_{ij}^n$ | Carbon emission of the vehicle of mode $n$ for traveling arc $(i,j)$ |
| $ep_{ij}$ | Energy consumption of a platoon leader for traveling arc $(i,j)$ |
| $cep_{ij}$ | Carbon emission of a platoon leader for traveling arc $(i,j)$ |
| $m_1 \dots m_9$ | Lower bounds for the left-hand side of the respective constraints |
| $M_1 \dots M_5$ | Upper bounds for the left-hand side of the respective constraints |
| $w_1 \dots w_3$ | The weights, projecting the relative importance of the time components |

**Variables**

| | |
|---|---|
| $y^{kn}$ | 1: if the import container $k \in K_D$ is transported by a vehicle of mode $n$<br>0: otherwise |
| $z^{kn}$ | 1: if the export container $k \in K_P$ is transported by a vehicle of mode $n$<br>0: otherwise |
| $x^{kln}$ | 1: if the vehicle of mode $n$ carries the export container $l \in K_P$ after delivering the import container $k \in K_D$<br>0: otherwise |
| $\varphi_p$ | 1: if platoon $p$ is formed<br>0: otherwise |
| $\upsilon_p^k$ | 1: if the AGV carrying container $k \in K_D$ joins platoon $p$<br>0: otherwise |
| $u_p^k$ | 1: if the AGV carrying container $k \in K_P$ joins platoon $p$<br>0: otherwise |
| $ST_i^{kn}$ | Time when the vehicle of mode $n$ carrying container $k$ starts to service vertex $i$ |
| $LT_i^{kn}$ | Time when the vehicle of mode $n$ carrying container $k$ leaves vertex $i$ |
| $t_3^k$ | Waiting time of AGV carrying container $k \in K_D$ to join its platoon at the gate |
| ${t'_4}^k$ | Stacking time of container $k \in K_D$ |
| $DT^{kn}$ | Dwell-time of container $k \in K_D$ transported by a vehicle of mode $n$ |
| $TW^{kn}$ | Waiting time of the AGV carrying container $k \in K_P$ to join a platoon at the target area ($TW^{k2} = 0$ ) |
| $TO^{kn}$ | Waiting time of the vehicle of mode $n$ carrying container $k \in K$ to start its service at the target area |
| $STP_{ip}$ | Time when platoon p starts to service vertex i |

Then, the proposed multi-objective optimization model is formulated as:

$$Min\, F_T = \sum_{n=1,2}\sum_{k\in K_D} w_1 DT^{kn} + \sum_{n=1,2}\sum_{k\in K} w_2 TO^{kn} + \sum_{n=1,2}\sum_{k\in K_P} w_3 TW^{kn} \tag{1}$$

$$\begin{aligned} Min\, F_C = & \sum_{n=1,2}\sum_{k\in K_D}\sum_{(i,j)\in A} CT^n e_{ij}^n y^{kn} + \sum_{n=1,2}\sum_{k\in K_D} (CL^n + CA^n)\, y^{kn} \\ & + \sum_{n=1,2}\sum_{k\in K_D}\sum_{(i,j)\in A} CE\, ce_{ij}^n y^{kn} + \sum_{p\in P}\sum_{(i,j)\in A} CT^p ep_{ij}\, \varphi_p \\ & + \sum_{p\in P}(CL^p + CA^p)\, \varphi_p + \sum_{p\in P}\sum_{(i,j)\in A} CE\, cep_{ij}\, \varphi_p \end{aligned} \tag{2}$$

*Subject to*:

$$\sum_{n=1,2} y^{kn} = 1 \qquad \forall k \in K_D \tag{3}$$

$$\sum_{n=1,2} z^{kn} = 1 \qquad \forall k \in K_P \tag{4}$$

$$\sum_{k\in K_D} y^{kn} \leqslant A\tilde{V}^n \qquad \forall n = 1,2 \tag{5}$$

$$\sum_{k\in K_P} z^{kn} = \sum_{k\in K_D} y^{kn} \qquad \forall n = 1,2 \tag{6}$$

$$y^{k1} = \sum_{p\in P} \upsilon_p^k \qquad \forall k \in K_D \tag{7}$$

$$z^{k1} = \sum_{p\in P} u_p^k \qquad \forall k \in K_P \tag{8}$$

$$\sum_{k\in K_D} \upsilon_p^k \le U_B\, \varphi_p \qquad \forall p \in P \tag{9}$$

$$\sum_{k\in K_D} \upsilon_p^k \ge L_B\, \varphi_p \qquad \forall p \in P \tag{10}$$

$$\sum_{k\in K_P} u_p^k \le U_B\, \varphi_p \qquad \forall p \in P \tag{11}$$

$$\sum_{k\in K_P} u_p^k \ge L_B\, \varphi_p \qquad \forall p \in P \tag{12}$$

$$ST_{ID}^{k1} = (RT^k + t_1 + t_2)y^{k1} \qquad \forall k \in K_D \tag{13}$$

$$ST_{ID}^{k2} = (RT^k + t'_1 + t'_2 + t'_3 + t'_5 + t'_6)y^{k2} + {t'_4}^k \qquad \forall k \in K_D \tag{14}$$

$$LT_{ID}^{k1} = ST_{ID}^{k1} + t_3^k + (t_4 + t_5)y^{k1} \qquad \forall k \in K_D \tag{15}$$

$$LT_{ID}^{k2} = ST_{ID}^{k2} \qquad \forall k \in K_D \tag{16}$$

$$STP_{ip} = \max_{k\in K_D}(ST_i^{k1}\upsilon_p^k) \qquad \forall i \in \{ID\} \cup \{S_1\}, p \in P \tag{17}$$

$$STP_{ip} = \max_{k\in K_P}(ST_i^{k1}u_p^k) \qquad \forall i \in \{S_2\} \cup \{FD\}, p \in P \tag{18}$$

$$t_3^k = \sum_{p\in P}(STP_{IDp} - ST_{ID}^{k1})\upsilon_p^k \qquad \forall k \in K_D \tag{19}$$

$$x^{kln} \le y^{kn} \qquad \forall k \in K_D, l \in K_P, n = 1,2 \tag{20}$$

$$x^{kln} \le z^{ln} \qquad \forall k \in K_D, l \in K_P, n = 1,2 \tag{21}$$

$$\sum_{k\in K_D}\sum_{l\in K_P} x^{kln} = \sum_{k\in K_D} y^{kn} \qquad \forall n = 1,2 \tag{22}$$

$$\sum_{k\in K_D} x^{kln} \le 1 \qquad \forall l \in K_P, n = 1,2 \tag{23}$$

$$\sum_{l\in K_P} x^{kln} \le 1 \qquad \forall k \in K_D, n = 1,2 \tag{24}$$

$$TW^{k1} = \sum_{p\in P}(STP_{S_2p} - ST_{S_2}^{k1})u_p^k \qquad \forall k \in K_P \tag{25}$$

$$TW^{k2} = 0 \qquad \forall k \in K_P \tag{26}$$

$$ST_{S_1}^{kn} \ge (LT_{ID}^{kn} + TR_{IDS_1}^n)y^{kn} \qquad \forall k \in K_D, n = 1,2 \tag{27}$$

$$LT_{S_1}^{kn} = ST_{S_1}^{kn} + T_{S_1}^n y^{kn} \qquad \forall k \in K_D, n = 1,2 \tag{28}$$

$$ST_{S_2}^{kn} \ge (LT_{S_1}^{kn} + TR_{S_1S_2}^n)x^{kln} \qquad \forall k \in K_D, l \in K_P, n = 1,2 \tag{29}$$

$$LT_{S_2}^{kn} = ST_{S_2}^{kn} + T_{S_2}^n z^{kn} + TW^{kn} \qquad \forall k \in K_P, n = 1,2 \tag{30}$$

$$ST_{FD}^{kn} \ge (LT_{S_2}^{kn} + TR_{S_2FD}^n)z^{kn} \qquad \forall k \in K_P, n = 1,2 \tag{31}$$

$$LT_{FD}^{kn} = ST_{FD}^{kn} + T_{FD}^n z^{kn} \qquad \forall k \in K_P, n = 1,2 \tag{32}$$

$$TO^{kn} = ST_{S_1}^{kn} - (LT_{ID}^{kn} + TR_{IDS_1}^n)y^{kn} \qquad \forall k \in K_D, n = 1,2 \tag{33}$$

$$TO^{ln} = ST_{S_2}^{ln} - (LT_{S_1}^{kn} + TR_{S_1S_2}^n)x^{kln} \qquad \forall k \in K_D, l \in K_P, n = 1,2 \tag{34}$$

$$DT^{k1} = (t_1 + t_2 + t_4 + t_5)y^{k1} + t_3^k \qquad \forall k \in K_D \tag{35}$$

$$DT^{k2} = (t'_1 + t'_2 + t'_3 + t'_5 + t'_6)y^{k2} + {t'_4}^k \qquad \forall k \in K_D \tag{36}$$

$$TA_i^k y^{kn} \le ST_i^{kn} \le TB_i^k y^{kn} \qquad \forall i \in \{ID\} \cup \{S_1\}, k \in K_D, n = 1,2 \tag{37}$$

$$TA_i^k z^{kn} \le ST_i^{kn} \le TB_i^k z^{kn} \qquad \forall i \in \{S_2\} \cup \{FD\}, k \in K_P, n = 1,2 \tag{38}$$

$$\upsilon_p^k, u_p^k, \varphi_p, y^{kn}, z^{kn}, x^{kln} \in \{0,1\} \qquad \forall p \in P, k \in K, n = 1,2 \tag{39}$$

$$ST_i^{kn}, LT_i^{kn}, TW^{kn}, TO^{kn}, STP_{ip}, t_3^k, {t'_4}^k, DT^{kn} \ge 0 \qquad \forall i \in V, p \in P, k \in K, n = 1,2 \tag{40}$$

The objective function (1) minimizes the dwell-time of the containers and the idle time of the vehicles of two modes, including the waiting time of the vehicles carrying import containers to start their service at the target area and the waiting time of the AGVs to join their platoon. In the objective function (2), the total cost of the system is minimized, which involves transportation, labor wage, vehicle acquisition, carbon emission penalty, and platoon formation costs. Platoon formation cost expresses the charge of assigning a human-driven leading vehicle and its driver to each string. It involves the transportation cost of the platoon leaders, as well as their drivers' wages, acquisition costs, and emission penalty costs. Constraints (3) guarantee that each import container is delivered by one of the delivery modes. Constraints (4) express the same principle for the export containers. Constraints (5) ensure that the limits on the available numbers of AGVs and trucks, which are random variables, are respected. Constraints (6) guarantee the vehicles of each transportation mode that deliver the import containers to the target area, pick up the export containers and go back to the port. Constraints (7) imply that an AGV can leave the port only if it joins a platoon. Constraints (8) ensure that an AGV leaving the target area joins a platoon, too. Constraints (9)–(12) specify the number of allowed AGVs in a platoon and also indicate that AGVs can join a platoon if that platoon is formed. Since making a platoon of one vehicle is meaningless, the lower bound on the platoon size is usually taken as two.

Constraints (13) and (14) determine the service start time of the vehicles of the two modes, that is, when the vehicle arrives at the gate of the container terminal. The time that the vehicles of two modes leave the gate is specified by Eqs. (15) and (16). Constraints (17) and (18) determine the service start time of each platoon at each vertex, which is the time when all of the vehicles in the platoon have started their service at that vertex. The waiting time of each AGV for forming a platoon at the gate is obtained by constraints (19). Constraints (20)–(24) check if a vehicle that delivers a specific import container $k$ transports a particular export container $l$. Constraints (25) specify the waiting time of each AGV for forming a platoon at the target area, and constraint (26) indicates that this value is zero for the trucks. Service time and leaving time at different vertices are obtained through constraints (27)–(32). Constraints (33) and (34) specify the waiting time of the vehicles of each delivery mode to start their service at the target area. Dwell-time of the containers of each delivery mode is obtained by Eqs. (35) and (36). Admissible service time-windows are introduced in constraints (37) and (38). Finally, constraints (39) and (40) specify the type of the decision variables.

Eqs. (17)–(19), (25), (27),(29), (31), (33), and (34) are non-linear, which are linearized as follows:

$$STP_{ip} - ST_i^{k1} \geq m_1(1 - v_p^k) \qquad \forall i \in \{ID\} \cup \{S_1\}, p \in P, k \in K_D \tag{41}$$

$$STP_{ip} - ST_i^{k1} \geq m_2(1 - u_p^k) \qquad \forall i \in \{S_2\} \cup \{FD\}, p \in P, k \in K_P \tag{42}$$

$$t_3^k + ST_{ID}^{k1} - STP_{IDP} \leq M_1(1 - v_p^k) \qquad \forall p \in P, k \in K_D \tag{43}$$

$$t_3^k + ST_{ID}^{k1} - STP_{IDP} \geq m_3(1 - v_p^k) \qquad \forall p \in P, k \in K_D \tag{44}$$

$$t_3^k \leq M_2 \sum_{p \in P} v_p^k \qquad \forall k \in K_D \tag{45}$$

$$TW^{k1} - STP_{S_2p} + ST_{S_2}^{k1} \leq M_3(1 - u_p^k) \qquad \forall p \in P, k \in K_P \tag{46}$$

$$TW^{k1} - STP_{S_2p} + ST_{S_2}^{k1} \geq m_4(1 - u_p^k) \qquad \forall p \in P, k \in K_P \tag{47}$$

$$ST_{S_1}^{kn} - LT_{ID}^{kn} - TR_{IDS_1}^n \geq m_5(1 - y^{kn}) \qquad \forall k \in K_D, n = 1, 2 \tag{48}$$

$$ST_{S_2}^{kn} - LT_{S_1}^{kn} - TR_{S_2S_2}^n \geq m_6(1 - x^{kln}) \qquad \forall k \in K_D, l \in K_P, n = 1, 2 \tag{49}$$

$$ST_{FD}^{kn} - LT_{S_2}^{kn} - TR_{S_2FD}^n \geq m_7(1 - z^{kn}) \qquad \forall k \in K_P, n = 1, 2 \tag{50}$$

$$TO^{kn} - ST_{S_1}^{kn} + LT_{ID}^{kn} + TR_{IDS_1}^n \leq M_4(1 - y^{kn}) \quad \forall k \in K_D, n = 1, 2 \tag{51}$$

$$TO^{kn} - ST_{S_1}^{kn} + LT_{ID}^{kn} + TR_{IDS_1}^n \geq m_8(1 - y^{kn}) \quad \forall k \in K_D, n = 1, 2 \tag{52}$$

$$TO^{ln} - ST_{S_2}^{ln} + LT_{S_1}^{kn} + TR_{S_1S_2}^n \leq M_5(1 - x^{kln}) \; \forall k \in K_D, l \in K_P, n = 1, 2 \tag{53}$$

$$TO^{ln} - ST_{S_2}^{ln} + LT_{S_1}^{kn} + TR_{S_1S_2}^n \geq m_9(1 - x^{kln}) \; \forall k \in K_D, l \in K_P, n = 1, 2 \tag{54}$$

Constraints (17) and (18) are linearized by the constraints (41) and (42), respectively. Constraints (43)–(45) are linearized versions of constraints (19). Constraints (25) are linearized by constraints (46) and (47). Constraints (48), (49), and (50) are linearized versions of constraints (27), (29), and (31), respectively. Finally, constraints (33) and (34) are linearized by constraints (50)–(54).

## 4. Solution approach

### 4.1. Robust optimization

In order to reflect a more practical setting, the number of available vehicles of each mode is considered uncertain in our model. There exist several approaches to handling uncertainty in optimization problems. Among those is robust optimization, whose good performance in facing uncertainty has long been outlined. We confine these uncertain availability parameters to vary within a predetermined uncertainty set $\zeta$. This is in place of taking a hypothetical probability distribution, which may not be applicable in related problem settings (Caserta & Voß, 2019). The box uncertainty set is the most widely applied uncertainty set in robust optimization due to its computational simplicity. On the other hand, it allows for highly conservative solutions where all random variables can take the values of the worst-case scenario. The ellipsoidal uncertainty set resolves this issue by cutting out unlikely scenarios at the price of higher computational complexity compared to the box and polyhedral uncertainty sets. The ellipsoidal uncertainty set has been successfully applied in a wide variety of problems and is formulated as:

$$\zeta^E = \{\tilde{\alpha} \in R^q \mid (\tilde{\alpha} - \bar{\alpha})^T \Sigma^{-1} (\tilde{\alpha} - \bar{\alpha}) \leq \Omega^2\} \tag{55}$$

Where $\tilde{\alpha}$ is the uncertain vector, $q$ is linked to the size of the vector, $\bar{\alpha}$ is the vector of nominal values (usually taken as the average over the past historical records), $\Sigma$ is the covariance matrix, and $\Omega$ is the safety parameter that reflects the attitude of the decision-maker towards risk. As $A\tilde{V}^n$ is a vector of size one in our problem, $\zeta^E$ is decreased to:

$$\zeta^E = \{A\tilde{V}^n \in R \mid \frac{(A\tilde{V}^n - A\bar{V}^n)^2}{{\sigma_n}^2} \leq \Omega^2\} \tag{56}$$

For a robust optimization approach, we capture the worst condition that can take place based on the values of $A\tilde{V}^n$. Then, constraints (5) are reformulated as:

$$\sum_{k \in K_D} y^{kn} \leq \min_{A\tilde{V}^n \in \zeta^E} \{A\tilde{V}^n\} \qquad \forall n = 1, 2 \tag{57}$$

By applying Karush-Kuhn–Tucker conditions on the right-hand side of constraints (57), we have:

$$A\tilde{V}^n = A\bar{V}^n - \Omega\sigma_n \tag{58}$$

Then, the robust counterpart of constraints (57) is:

$$\sum_{k \in K_D} y^{kn} \leq A\bar{V}^n - \Omega\sigma_n \qquad \forall n = 1, 2 \tag{59}$$

Accordingly, constraints (5) are replaced with the new constraints (59).

### 4.2. Augmented epsilon constraint method

In the proposed bi-objective model, it is impossible to obtain an individual solution that can simultaneously optimize both objective functions. For this reason, the augmented epsilon constraint method is used to achieve Pareto optimal solutions that capture the trade-offs between minimizing cost and time (Mavrotas, 2009). In the considered case with two objectives, this method equals the AUGMECON2 method proposed by Mavrotas and Florios (2013). In this approach, we optimize one of the objective functions using the other as a constraint accompanied by the original constraints of the problem. We take time ($F_T$) as the main objective function and calculate the range of $F_C$ by

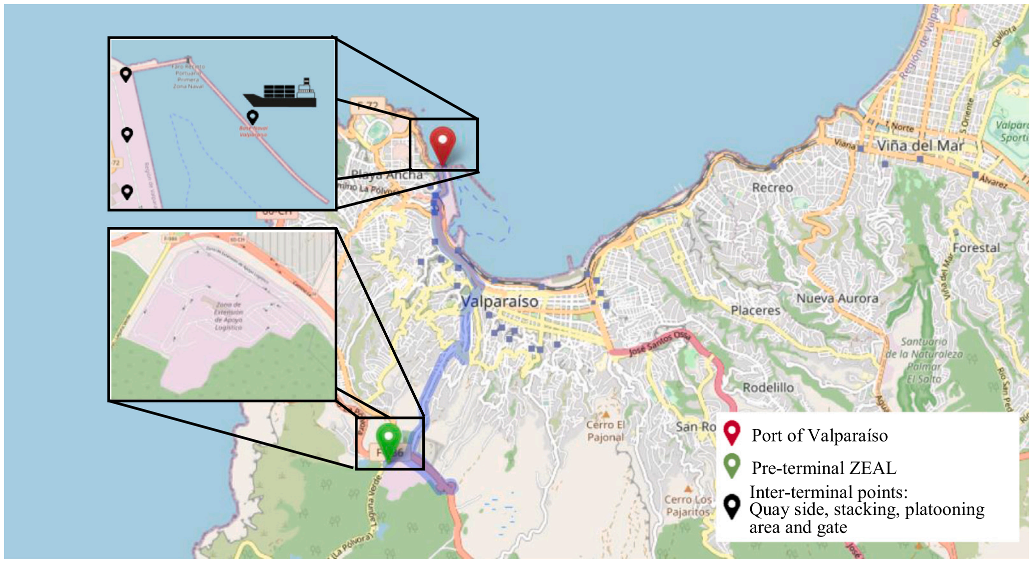


**Fig. 2.** Graphic representation of the Port of Valparaíso–ZEAL case study.

creating the payoff table obtained by the lexicographic optimization of the objective functions. Then, the range of $F_C$ is divided into $k$ equal intervals resulting in $k+1$ grid points for $F_C$. Subsequently, $k+1$ optimization sub-problems are solved to obtain the Pareto front of the problem. The optimization sub-problem for the $l$th grid point is formulated as:

$$Min\, F_T - \varepsilon\left(\frac{S_l}{r}\right) \tag{60}$$

s.t.

$$F_C + S_l = e_l \tag{61}$$

$$Constraints\ (3), (4), (6)\text{–}(16), (20)\text{–}(24), (26), (28), (30), (32), (35)\text{–}(40), (41)\text{–}(54), (59)$$

where $\varepsilon$ is a small number $(10^{-6} - 10^{-3})$ and $e_l$ is obtained as $e_l = ub - \frac{lr}{k}$ (where $ub$ and $r$ are the upper bound and range of $F_C$, respectively).

In order to derive the best compromise solution from the obtained Pareto front, the membership function in fuzzy sets is applied (Tavakkoli-Moghaddam et al., 2015). A linear membership function for each of the objective functions is introduced as:

$$\begin{cases} \mu_m^l = 0 & F_m^l \le F_m^{min} \\ \frac{F_m^{max} - F_m^l}{F_m^{max} - F_m^{min}} & F_m^{min} \le F_m^l \le F_m^{max} \\ 1 & F_m^l \ge F_m^{max} \end{cases} \tag{62}$$

where $m = T, C$ and $l$ indicate the two objective functions and grid points, respectively. Then, the overall membership function is normalized as:

$$\mu^l = \frac{\varpi_1 \mu_1^l + \varpi_2 \mu_2^l}{\sum_{g=1}^{k+1} \sum_{m=1,2} \varpi_m \mu_m^g} \tag{63}$$

where $\varpi_m$ is the weight value of the $m$th objective function. Finally, the solution with the maximum membership function $\mu^l$ is selected as the best compromise solution.

## 5. Numerical results

Our developed structure is illustrated through two case studies: the Port of Valparaíso in Chile and the Port of Rotterdam in The Netherlands. In both cases, we consider the transportation of the containers between the port and a dry port in the hinterland. The traveling distance of the latter case is considerably longer than the former one. This provides us with the opportunity to contrast the benefits of platoons for short and long traveling distances.

The model is a variant of the assignment problem and can be solved for large-size instances in a reasonable time. The MIP model is coded in IBM ILOG CPLEX Optimization Studio 12.7, and the experiments are carried out on a computer with Intel®Core i7-8650U CPU 1.9 GHz, 2.11 GHz, and 7.88 GB memory available.

### 5.1. Experimental settings

In the first case study, we consider full container pickup and delivery between the port of Valparaíso, in particular, the main port terminal TPS (South Pacific Terminal, TPS by its acronym in Spanish) and the pre-terminal ZEAL (Logistics Economic Activities Zone). According to the logistics model of the port of Valparaíso, ZEAL operates under a centralized system in which all trucks should arrive at this pre-terminal, register, and wait until the port terminal authorizes their arrival to the container terminal. Once the truck is called, it travels to the port and either drops off the export container or picks up an import container. ZEAL is located 11 kilometers from the port and was implemented to reduce traffic and congestion of heavy vehicles in the port city of Valparaíso and the two terminals of the port have very limited space.

The second case study illustrates a similar problem between the port of Rotterdam, in particular APM terminals Maasvlakte II (The western part of the seaport) and the logistic hub Venlo, which is an international hub connecting the port to the German hinterland. The hub is located in the southeast of The Netherlands and within 200 km distance from the port of Rotterdam. Figs. 2 and 3 provide a graphic representation of these case studies.

The input parameters of these case studies are defined mainly based on the experience of the authors in past projects with the Port of Rotterdam and Chilean ports like Valparaíso, San Antonio and Arica. Moreover, we incorporated the available information on the websites of each port terminal to get an idea of the current TEU transfer volume and the available equipment. The port of Valparaíso, for instance, provides this information on its website related to seaside planning, that is, it announces the vessels that are expected to arrive and their assignment to berths. Additional information of the route, arrival and departure times of the vessels is obtained from the website of MarineTraffic. We also collected the available statistics to determine the maximum number of quay cranes assigned to a vessel and the maximum number of container movements per quay crane per hour.

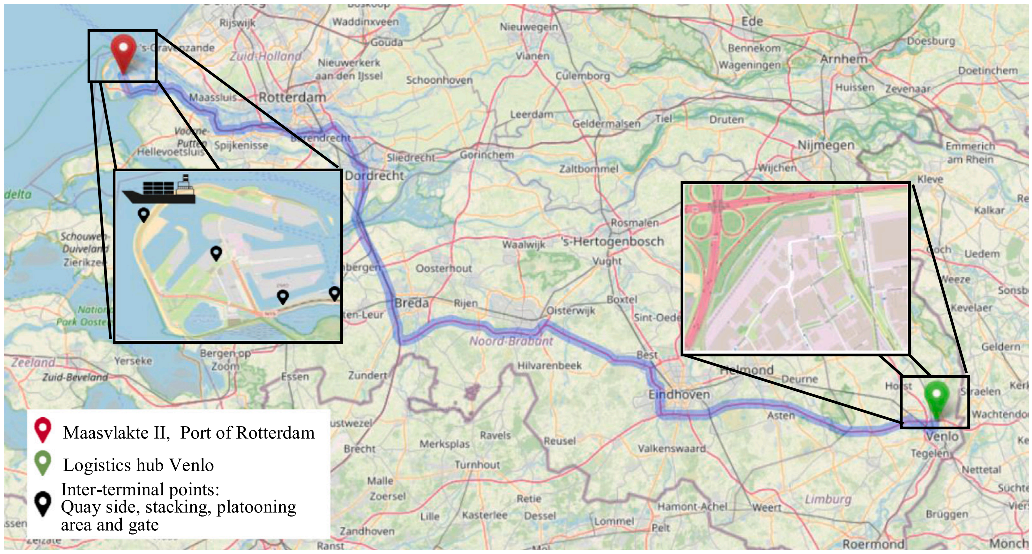


**Fig. 3.** Graphic representation of the Port of Rotterdam–Venlo case study.

We assume that an average-size vessel in the Port of Valparaíso and the Port of Rotterdam, may require unloading around 2000 and 4000 containers, respectively. From those containers, 30% correspond to empty ones that will be transported to empty container depots. 25% and 20% will be directly transported to the hinterland and 11% and 7.5% will need additional time in the port due to administrative requirements, respectively. 30% are transported to bonded warehouses located in the inter-port area in both cases and 20% are transported by barge in the case of the Port of Rotterdam. Finally, 4% (80 containers) and 2.5% (100 containers) are transported to ZEAL and Venlo, respectively.

It is assumed that, on average, a quay crane operator performs 25 movements per hour and that three quay cranes will be assigned to handle the vessel in the Port of Valparaíso. In the case of the Port of Rotterdam, these are 40 movements and five quay cranes. We are assuming that the Port of Rotterdam is more efficient in terms of transferring capacity than Valparaíso and that it has more available quay cranes.

Accordingly, for a vessel that requires unloading 2000 (4000) containers, approximately 26 (20) h will be necessary to serve the vessel in the Port of Valparaíso (the Port of Rotterdam). The unloading sequence is, in general, uncertain and determined according to the way containers are organized in the vessel and the corresponding stowage plan. The planning horizon starts as the first container of the subset is unloaded off the vessel. Hence, unloading of this subset of the containers can start at any time step of the unloading process without impacting the results. Thereby and without loss of generality, we assume 80 (100) containers that will be transported to the ZEAL (Venlo) are positioned in the vessel such that they are among the first 5% of the unloaded containers. That is, their release time, which reflects the order in which the containers are unloaded off the vessel, is distributed over 80 (60) min requiring them to serve these containers in groups of three (five) consecutive containers every 2.4 (1.5) min. The release time values are provided in Tables 4 and 5 for the two cases. The containers are numbered based on their release time in ascending order.

Service time-windows of the import containers at ZEAL and Venlo start (end) based on their release time plus a lower (upper) bound on the required time to arrive there. For the export containers, we take the time-windows of import containers as the basis and add the required time to start loading the export containers after arriving at ZEAL and Venlo. Tables 6 and 7 provide the time-windows of import and export containers for the two case studies.

For the uncertainty set, we let the safety parameter $\Omega$ equal one in both cases (we investigate the impact of changing the $\Omega$ value later). $A\bar{V}^n$ is considered to take integer values uniformly distributed within [70, 85] and [90, 105] for the case of Valparaíso and Rotterdam, respectively. $\sigma_n$ is uniformly distributed within $[1, \frac{A\bar{V}^n}{10}]$, in both cases. Thus, the available vehicles can take any value within the uncertainty set characterized by these parameters. In Table 12, in the first row, we also show how neglecting $\sigma_n$ and taking only the average value would impact the results. Similarly, we also show how varying the level of $\Omega$ affects the results (the level of risk aversion).

Distances are transformed into travel time by considering speeds of 45 km/h for the trucks and 30 km/h for the AGVs in the linking road of the port of Valparaíso to ZEAL and 20 km/h for both modes within the AGV-ready areas. In the second case, these speeds are 75 km/h for the trucks and 55 km/h for the AGVs in the linking road of the port of Rotterdam to Venlo and 25 km/h for both modes within the AGV-ready areas. In a recent research project that was carried out to investigate the potential for the application of AGVs (Pauwels, 2021), the simulation results showed that the driving speed largely impacts the emergency breaks and collisions of AGVs. Platooning and autonomous driving regulations can also put limits on these speeds. It should be noted that these speeds are experimental choices regarding our case and can be varied for different problem settings.

Travel costs are proportional to traveling distance and are higher for the trucks due to higher fuel consumption. The reason is that for vehicles traveling in a platoon, their fuel consumption decreases due to lower air drag. The number of admissible AGVs in a platoon is confined to (2, 4) in both case studies.

### 5.2. Results

Optimizing the proposed model for the two case studies yields the following results (Table 8). The results indicate that in both case studies, AGVs deliver the majority of the import containers and thereby pick up the export containers. In the Port of Valparaíso–ZEAL (the Port of Rotterdam–Venlo) case, the AGVs join 22 (27) platoons to reach their destination, where nine (15) platoons contain four (four) AGVs, 12 (10) involve three (three) AGVs, and one has (two have) two (two) AGVs. Economically, it is desired to form the minimum number of possible platoons. However, our approach provides a compromise solution out of the Pareto optimal set, simultaneously seeking to minimize time and costs, with a higher priority devoted to time reduction. Precisely, if we had the single objective of cost minimization, the numbers of formed platoons were 18 and 23, each with four AGVs in the first and second case studies, respectively. On the other hand, with a focus on time

**Table 4**
Release time of the import containers in the Valparaíso–ZEAL case (in minutes).

| Import containers | 1–3 | 4–6 | 7–9 | 10–12 | 13–15 | 16–18 | 19–21 | 22–24 | 25–27 |
|---|---|---|---|---|---|---|---|---|---|
| $RT^k$ | 2.4 | 4.8 | 7.2 | 9.6 | 12 | 14.4 | 16.8 | 19.2 | 21.6 |
| Import containers | 28–30 | 31–33 | 34–36 | 37–39 | 40–42 | 43–45 | 46–48 | 49–51 | 52–54 |
| $RT^k$ | 24 | 28.8 | 31.2 | 33.6 | 38.4 | 40.8 | 43.2 | 45.6 | 50.4 |
| Import containers | 55–57 | 58–60 | 61–63 | 64–66 | 67–69 | 70–72 | 73–75 | 76–78 | 79–80 |
| $RT^k$ | 55.2 | 57.6 | 60 | 62.4 | 64.8 | 67.2 | 69.6 | 72 | 74.4 |

**Table 5**
Release time of the import containers in the Rotterdam–Venlo case (in minutes).

| Import containers | 1–5 | 6–10 | 11–15 | 16–20 | 21–25 | 26–30 | 31–35 | 66–40 | 41–45 | 46–50 |
|---|---|---|---|---|---|---|---|---|---|---|
| $RT^k$ | 1.5 | 3 | 7.5 | 9 | 13.5 | 15 | 16.5 | 19.5 | 21 | 22.5 |
| Import containers | 51–55 | 56–60 | 61–65 | 66–70 | 71–75 | 76–80 | 81–85 | 86–90 | 91–95 | 96–100 |
| $RT^k$ | 25.5 | 27 | 34.5 | 36 | 37.5 | 40.5 | 43.5 | 46.5 | 48.5 | 52.5 |

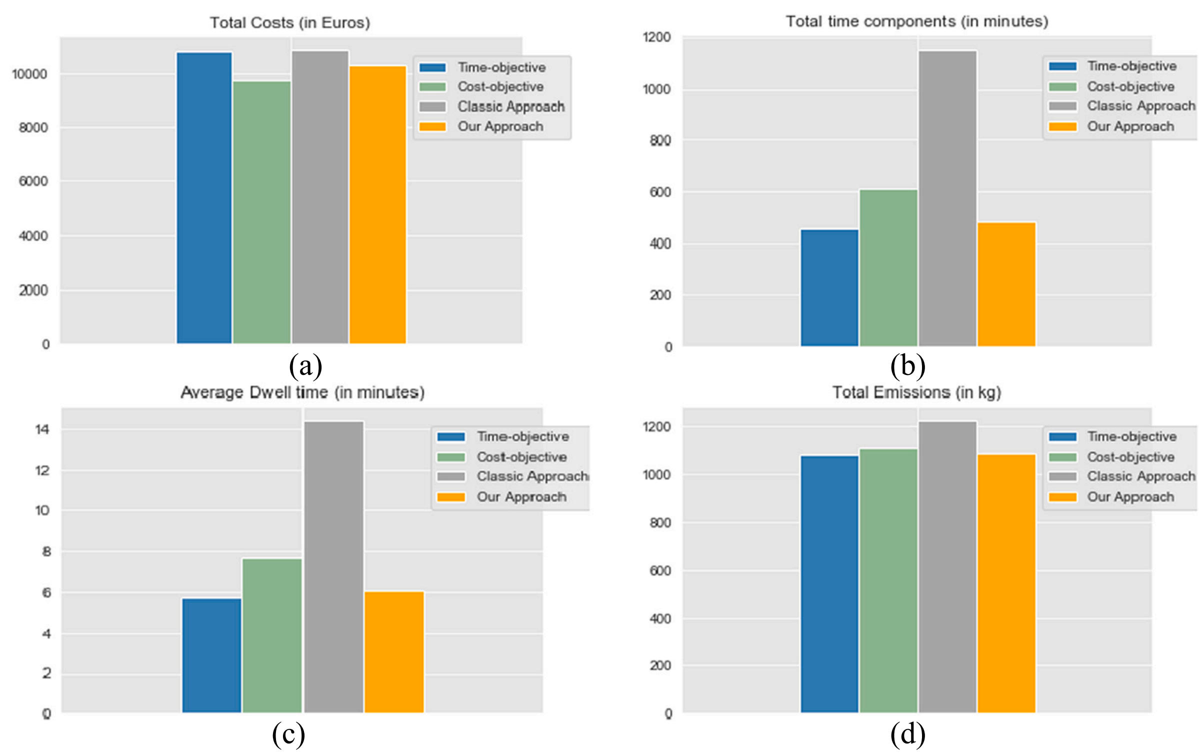


**Fig. 4.** Comparison of (a) Total Costs, (b) Total Time, (c) Average Dwell Time, and (d) Total Emissions in four settings — The Port of Valparaíso–ZEAL.

**Table 6**
Service time-windows in the Valparaíso–ZEAL case (in minutes).

| Import containers | 1–10 | 11–20 | 21–30 | 31–40 | 41–50 | 51–60 | 61–70 | 71–75 |
|---|---|---|---|---|---|---|---|---|
| $TA^k_{S_1}$ | 20 | 28 | 36 | 44 | 52 | 60 | 68 | 76 |
| $TB^k_{S_1}$ | 150.4 | 158.4 | 166.4 | 174.4 | 182.4 | 190.4 | 198.4 | 206.4 |
| Export containers | 1–10 | 11–20 | 21–30 | 31–40 | 41–50 | 51–60 | 61–70 | 71–75 |
| $TA^k_{S_2}$ | 26.9 | 34.9 | 42.9 | 50.9 | 58.9 | 66.9 | 74.9 | 82.9 |
| $TB^k_{S_2}$ | 157.3 | 165.3 | 173.3 | 181.3 | 189.3 | 197.3 | 205.3 | 213.3 |

minimization, 25 platoons were formed, out of which 24 had three AGVs, and one contained two AGVs, for the first case study. This leads to decrease dwell time by reducing the waiting times of AGVs to join a platoon. In the second case study, a focus on time minimization led to 30 platoons, out of which 14 had four AGVs, six involved three, and 10 contained two AGVs. This is while taking the bi-objective approach, allows for considering both objectives and their relative significance and results in applying 22 and 27 platoons.

In comparison to the traditional scheme, the proposed approach not only shortens the dwell time of the import containers by decreasing loading/unloading processes and eliminating stacking but also brings cost savings in terms of lower transportation, labor, and emission penalty costs. This is obtained by the application of AGVs, together with taking a bi-objective approach. Figs. 4 and 5 provide a comparison basis in terms of the value of the two objective functions, as well as the average dwell time of each import container and carbon emissions in four structures, including our proposed one, the single time and cost

**Table 7**
Service time-windows in the Rotterdam–Venlo case (in minutes).

| Import containers | 1–10 | 11–20 | 21–30 | 31–40 | 41–50 | 51–60 | 61–70 | 71–80 | 81–90 | 91–100 |
|---|---|---|---|---|---|---|---|---|---|---|
| $TA^k_{S_1}$ | 166.1 | 169.1 | 172.1 | 175.1 | 178.1 | 181.1 | 184.1 | 187.1 | 190.1 | 193.1 |
| $TB^k_{S_1}$ | 296.6 | 299.6 | 302.6 | 305.6 | 308.6 | 311.6 | 314.6 | 317.6 | 320.6 | 323.6 |
| Export containers | 1–10 | 11–20 | 21–30 | 31–40 | 41–50 | 51–60 | 61–70 | 71–80 | 81–90 | 91–100 |
| $TA^k_{S_2}$ | 172.6 | 175.6 | 178.6 | 181.6 | 184.6 | 187.6 | 190.6 | 193.6 | 196.6 | 199.6 |
| $TB^k_{S_2}$ | 303.1 | 306.1 | 309.1 | 312.1 | 315.1 | 318.1 | 321.1 | 324.1 | 327.1 | 330.1 |

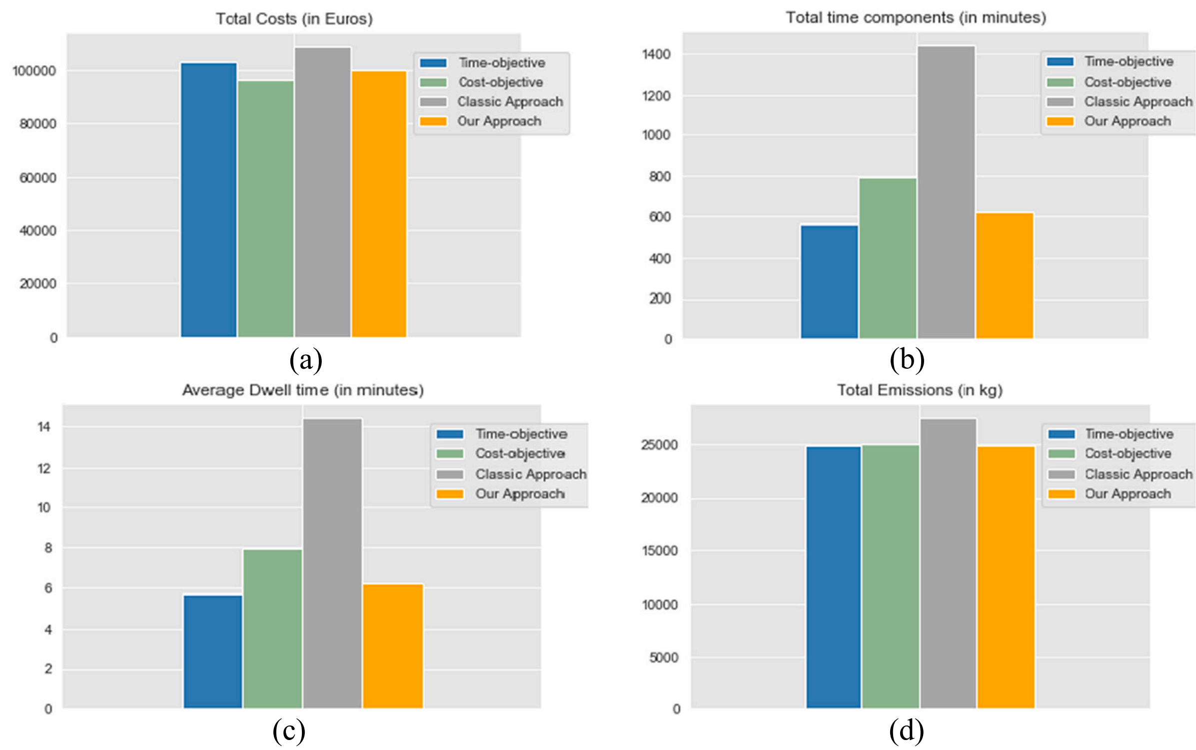


**Fig. 5.** Comparison of (a) Total Costs, (b) Total Time, (c) Average Dwell Time, and (d) Total Emissions in four settings — The Port of Rotterdam–Venlo.

**Table 8**
Results for the two case studies.

| Case | $F_T$ | $F_C$ | $y^{k,n}$ | | | |
|---|---|---|---|---|---|---|
| V-Z | 487.6 | 10 277 | $k = 1$–$74, n = 1$ | 1 | $k = 75$–$80, n = 2$ | 1 |
| R-V | 619.4 | 99 941.89 | $k = 1$–$94, n = 1$ | 1 | $k = 95$–$100, n = 2$ | 1 |
| **Case** | $\sum_n \sum_k DT^{kn}$ | $\sum_n \sum_k TW^{kn}$ | $\varphi_p$ | | | |
| V-Z | 487.6 | 0 | $p = 1$–$22$ | 1 | $p = 23$–$25$ | 0 |
| R-V | 616.4 | 0 | $p = 1$–$27$ | 1 | $p = 28$–$30$ | 0 |
| **Case** | $\sum_n \sum_k TO^{kn}$ | $\sum_n \sum_l TO^{ln}$ | $\sum_k t^k_3$ | | $\sum_k t'^k_4$ | |
| V-Z | 0 | 0 | 31.12 | | 0 | |
| R-V | 0 | 0 | 60 | | 0 | |

V-Z: The Port of Valparaíso–ZEAL , R-V: The Port of Rotterdam–Venlo Case Studies.

objectives, and the classic approach where only conventional trucks are applied.

As Figs. 4 and 5 depict, the proposed scheme is more cost- and time-efficient than the classic approach and provides a more sustainable transportation mode. Switching to the proposed direct delivery scheme leads to a 57% (56%) decrease in the average dwell time of the import containers in the first (second) case study, which is highly desirable as it can boost up the efficiency of container handling at the port of Valparaíso and Rotterdam. While the single "time-objective" approach comes quite close to the bi-objective approach for several performance indicators, it performs clearly worse on costs. Thus, we cannot consider it an equal alternative to the bi-objective approach. Furthermore, a large share of the savings may not require a bi-objective approach. However, the bi-objective approach is the only one that offers balanced and high-quality solutions for all performance indicators considered. The results validate the claim that by applying a bi-objective approach, a compromise solution providing a balance between the two extreme directions (minimizing costs and time) is obtained that, to large extents, holds the advantages of separately minimizing each objective function.

Comparing the benefits of direct delivery by AGVs between the two case studies shows that switching from the classic approach to the proposed scheme leads to almost the same benefits in the two case studies. Expressly, the percentage of reductions in time and carbon emissions are very similar, while the cost saving in the port of Rotterdam–Venlo case is higher. This shows that the cost-efficiency of using AGV platoons gets more intensified as the traveling distance increases. This is not only because of the decreased air drag and, thereby, fuel consumption when traveling in platoons, but also stems from the elimination of the labor costs, which are higher for long traveling distances.

The maximum number of allowed AGVs in a platoon has an impact on platooning benefits. To study this impact, a sensitivity analysis on this parameter is required. Table 9 provides optimal solutions of the problem for different values of $UB$ for the first case study. The same pattern of changes is observed in the second case study.

As suggested by Table 9, the total cost of the system increases by decreasing $UB$. This is because by reducing the value of $UB$, the

**Table 9**
The impact of the maximum number of allowed AGVs in a platoon in the Valparaíso–ZEAL case.

| $UB$ | $F_T$ | $F_C$ | Number of AGVs | Number of trucks | Number of platoons | Average dwell time |
|---|---|---|---|---|---|---|
| 2 | 682 | 11 821 | 50 | 30 | 25 | 8.53 |
| 3 | 485.2 | 10 684.01 | 72 | 8 | 24 | 5.89 |
| **4** | **487.6** | **10 298.87** | **74** | **6** | **22** | **6.095** |
| 5 | 494.79 | 10 049.08 | 74 | 6 | 20 | 6.18 |
| 6 | 497.8 | 9878.68 | 74 | 6 | 18 | 6.21 |

platooning option gets more expensive, as the same platoon can contain fewer AGVs. Therefore, more platoons need to be formed, and fewer AGVs are applied. This is while changes in $UB$, do not lead to a recognizable pattern in the total time. By decreasing $UB$, and thereby using fewer AGVs, the dwell time of the containers shipped by trucks increases. On the other hand, the reduction in $UB$ can also decrease the waiting time of the AGVs for making platoons at Valparaíso. So, the change in the value of $F_T$ depends on the two contradictory factors. For instance, by changing $UB$ from four to three, two more trucks are used that will have larger dwell times. Alternatively, the waiting time for making platoons ($t_3^k$) decreases as three containers are unloaded simultaneously, and their release times are the same. The decrease in $t_3^k$ is larger than the impact of two additional trucks. So, the average dwell time and total time decrease.

One may expect an increase in the number of applied AGVs with an increase in $UB$. The reason why this is not observed in Table 9 is that the number of available AGVs is restricted to 74 in our case. So, if this value was larger, an increase in the application of AGVs was expected.

The platoon formation cost, which is associated with assigning a human-driven vehicle to each platoon as the leader, is expected to have an impact on the platooning benefits. To study this impact, a sensitivity analysis on this parameter is carried out, the result of which is provided in Table 10 for the second case study. The same pattern of changes is observed in the first case study.

As suggested by Table 10, decreasing the platoon formation cost makes platooning more attractive. Then, the number of applied AGVs and the number of formed platoons can increase (here, we had the maximum number of available AGVs applied). An increase in the number of platoons results in fewer AGVs in some platoons, decreasing the waiting time for these AGVs to form the platoon. Therefore, the dwell time of the containers and both objective functions undergo a reduction.

In order to deep dive into the features of our proposed model, it is also essential to analyze the impact of time windows on the optimal solutions. Table 11 provides optimal solutions obtained by varying time-windows $\forall\ k\ and\ l\ =\ 61\text{–}80$ for the first case study. The same pattern of changes is observed in the second case study.

By shifting the service time-windows to 30 min later, the idle time of the AGVs increases. That is because the vehicles need to wait longer for the delivery time-window to be open. The optimal transportation mode is still the same; hence, the system's total cost undergoes no changes. As the time-window shifts 60 min later, it is not optimal to use AGVs for those 20 containers ($\forall\ k\ and\ l = 61\text{–}80$) anymore, and conventional trucks are applied instead. Accordingly, the total cost increases. It is noteworthy that we have put a higher priority on time components, and that is why the transportation mode switches to decrease idle times despite higher costs. These 20 containers will wait on average 38.5 min in the stack before leaving the port. By shifting the time-windows later than 60 min, the stacking time increases. These results convey an important insight: As the delivery time-window shifts later, direct delivery by AGVs loses its efficiency due to longer idle times at the destination.

In order to get better insights into the complexity of the formulated model, the time taken to obtain the optimal solutions for different instance sizes is derived. A weighted sum of the two objective functions

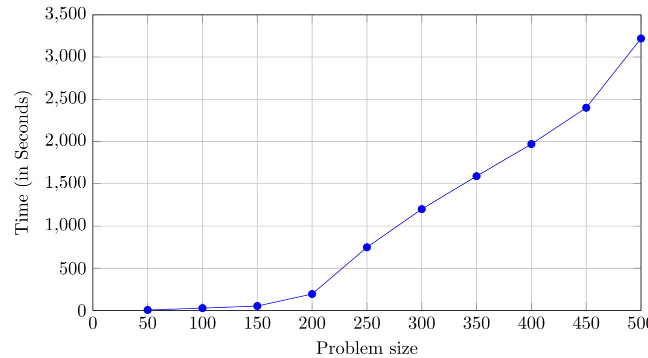


**Fig. 6.** CPU time taken to obtain optimal solutions (in seconds).

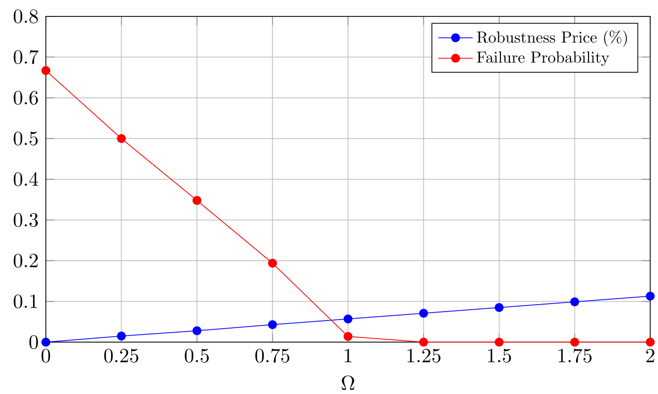


**Fig. 7.** The price of robustness and the reliability of the robust solutions.

is taken as the objective function, and the problem size is varied between 50 and 500 containers. Fig. 6 depicts the run time for these problem sizes.

As the figure depicts, the problem is solved for large instances in a reasonable time. As an instance, the CPU time for solving the problem of 500 containers is less than an hour.

### 5.3. Robustness evaluation

In robust optimization, evaluating the robustness price versus the reliability of the robust solutions is of great significance. We applied the ellipsoidal uncertainty set as it is less conservative in comparison to the box uncertainty set. Therefore, our approach guarantees the feasibility of the optimal solutions for every realization of the uncertain parameters as long as they belong to the ellipsoidal uncertainty set. However, after observing the real parameters, one may realize that the values belong to a box (Caserta & Voß, 2019). Therefore, the following analysis is carried out:

Taking the values of $A\bar{V}^n$ and $\sigma_n$, 1000 realizations of $A\tilde{V} = [A\tilde{V}^1, A\tilde{V}^2]$ are randomly generated within $[A\bar{V}^n - \sigma_n, A\bar{V}^n + \sigma_n]$. Then, the failure probability and robustness price are calculated for different $\Omega$ values, the results of which are provided in Table 12.

Fig. 7 provides a graphical representation of these results. The same behavior is distinguished in both case studies, and thereby, we only provide the results of the Rotterdam–Venlo case here. The price of robustness measures the relative increase in the objective function by switching to robust optimization from the nominal approach where the uncertain parameter is replaced with its average value.

Since $\Omega$ projects a measure of risk aversion, as it increases, we observe an increase in the price of robustness due to the increase in the objective function and a decrease in the probability of failure. Accordingly, the minimum reliability and minimum robustness price

**Table 10**
The impact of platoon formation cost in the Rotterdam–Venlo case.

| Platooning cost | $F_T$ | $F_C$ | Number of AGVs | Number of trucks | Number of platoons | Average dwell time |
|---|---|---|---|---|---|---|
| −50% | 592.4 | 97 656.33 | 94 | 6 | 30 | 5.82 |
| −25% | 610.4 | 98 398.83 | 94 | 6 | 29 | 6.1 |
| **0%** | **619.4** | **99 941.89** | **94** | **6** | **27** | **6.19** |
| +25% | 627.62 | 102 034.95 | 91 | 9 | 25 | 6.28 |
| +50% | 641.74 | 103 778.01 | 89 | 11 | 24 | 6.41 |

**Table 11**
The impact of time-windows on the optimal solutions in the Valparaíso–ZEAL case.

| Changes | $F_T$ | $F_C$ | $\sum_n \sum_k TO^{kn}$ | $\sum_k t_4'^{\,k}$ | Number of AGVs | Number of trucks |
|---|---|---|---|---|---|---|
| **0 ′** | **487.6** | **10 298.87** | **0** | **0** | **74** | **6** |
| +30 ′ | 750.49 | 10 298.87 | 148.87 | 41.9 | 74 | 6 |
| +60 ′ | 1406.9 | 10 814 | 0 | 770.87 | 60 | 20 |
| +90 ′ | 2006.9 | 10 814 | 0 | 1370.87 | 60 | 20 |
| +120 ′ | 2606.9 | 10 814 | 0 | 1970.87 | 60 | 20 |

**Table 12**
The price of robustness and the reliability of the robust solutions.

| $\Omega$ | Robustness price (%) | Failure probability |
|---|---|---|
| 0 | 0 | 0.667 |
| 0.25 | 0.015 | 0.5 |
| 0.5 | 0.028 | 0.348 |
| 0.75 | 0.043 | 0.194 |
| 1 | 0.057 | 0.004 |
| 1.25 | 0.071 | 0 |
| 1.5 | 0.085 | 0 |
| 1.75 | 0.099 | 0 |
| 2 | 0.113 | 0 |

are obtained for $\Omega = 0$. As Table 12 projects, the results of the nominal approach ($\Omega = 0$) fail to meet feasibility in 67% of the realizations. This shows that neglecting uncertainty can lead to considerable losses in the system. A sharp decrease in the failure probability is observed by the increase of $\Omega$, such that altering it from 0 to 1 decreases the failure probability by almost 66%. By taking the desired reliability value as an input, one can specify the value of $\Omega$ that meets this reliability.

### 5.4. Managerial insights

The experiments conducted for the two case studies let us derive several insights for the future management of AGVs at ports and in logistic networks in the hinterland of ports.

- It was shown that the application of AGV platoons for direct delivery provides a more cost-efficient and sustainable connection between the port and the hinterland.
- Additionally, this new transportation mode brings considerable reductions in the dwell time of the containers by eliminating stacking and several loading/unloading processes. Average container dwell time is a performance measure for the ports, and its reduction is highly desirable as it decreases container traffic and congestion. Accordingly, our proposed transportation solution is expected to be a suitable option for the port authorities, specifically when they face congestion and limited space (as, e.g., in Valparaíso) in the port and at their container terminals.
- By using the robust planning approach, the failure probability is reduced by 66% (i.e., the failure probability in the non-robust approach) without a significant increase the robustness price. That is, if the robust optimization approach is applied, the dual use of AGVs in the port and hinterland is a reliable transport concept and this reliability does not come at a significant additional cost.
- We observed that the maximum admissible number of AGVs in a platoon plays a key role in platooning decisions. This emphasizes the impact of platooning regulations, as a first step, on the widespread application of automated driving in open areas.
- The results also imply that if platoon formation costs are managed, the benefits of applying AGVs in terms of costs and time are even higher. This suggests that, by platooning getting cheaper due to technological developments in the future, one can expect their widespread application in drayage operations due to their notable benefits.
- Cost savings of switching to AGV platoons become more significant as the traveling distance increases. On the other hand, it should be noted that the traveling speed of AGVs is lower than conventional trucks, resulting in their longer traveling times. When considering remote destinations, the travel time difference between the two transportation modes needs to be highlighted. Then, if there exists a strict limitation on the number of available AGVs for other transportation tasks, direct delivery by AGVs may not be a good option for long traveling distances. Accordingly, if the decision-makers face multiple destinations for applying the proposed direct delivery scheme, their choice highly depends on the number of available AGVs for the remaining transportation tasks and the relative importance of the proposed direct delivery benefits.

## 6. Conclusions and future research

AGV platoons, as the first step towards automated driving in open port hinterland corridors, can be applied to establish efficient links between the port and hinterland. This work proposes a robust optimization approach that allows us to evaluate the time and cost-efficiency of applying such AGV platoons in a container pickup and delivery problem between ports and their hinterland. We propose a bi-objective mixed-integer programming model, which simultaneously minimizes time and cost elements. Emissions are taken into account to derive more sustainable results, and the number of available vehicles faces uncertainty as multi-purpose vehicles connecting land- and seaside modalities. To handle this uncertainty, we propose a robust optimization approach, adopting an ellipsoidal uncertainty set. And to obtain Pareto optimal solutions for the bi-objective problem, we develop an augmented epsilon constraint method. We have found that AGV platoons indeed offer a significant potential to reduce costs (on average by 8%), dwell time (on average by 56%), and emissions (on average by 10%).

In this way, this study transfers the platooning concept to port hinterland corridors. It explores the potential of AGV platoons as time-efficient, economical, and sustainable transportation modes between ports and their hinterland in transport corridors with different characteristics, instead of only using AGVs inside container terminals. Our results provide the first evidence for the advantages of this concept in terms of reduced dwell time, savings in cost, and lower carbon emissions. Hence, the results of this work contribute to advancing research and innovative solutions for synchromodal transport planning. In the long run, these findings may motivate further case studies and alternative concepts of AGV platoons in port-hinterland corridors, as well as gradual infrastructural investments that could allow us to scale up the approach.

There exist several interesting directions for future research. As an extension of this work, one may consider a dynamic planning approach, under which it will be necessary to determine not only the transport modes but also the scheduling over a planning horizon. Evaluating the benefits of platoons in comparison to rail or barges will provide further insights into the features of this direct delivery scheme and can be regarded as another fruitful future direction. In order to assess the performance of the proposed approach concerning different metrics, in the long run, a simulation model can be developed that provides clear insights into the long-term efficiency of the proposed direct delivery scheme.

## CRediT authorship contribution statement

**Nadia Pourmohammad-Zia:** Conceptualization, Formal analysis, Methodology, Computational implementation (software), Validation, Writing, Review, Editing. **Frederik Schulte:** Conceptualization, Formal analysis, Methodology, Validation, Writing, Review, Editing. **Rosa G. González-Ramírez:** Formal analysis, Methodology, Validation, Writing, Review, Editing. **Stefan Voß:** Conceptualization, Reviewing. **Rudy R. Negenborn:** Conceptualization, Reviewing.

## Data availability

Data will be made available on request.

## Acknowledgments

This paper is supported by the project “Dynamic Fleet Management (P14-18 — project 3)” (project 14894) of the research program i-CAVE, partly financed by The Netherlands Organization for Scientific Research (NWO), domain Applied and Engineering Sciences (TTW). The third author thanks Fondecyt grant No. 1210735 and the program STIC-AmSud-22-STIC-09.

## References

Abdolmaleki, M., Shahabi, M., Yin, Y., & Masoud, N. (2019). Itinerary planning for cooperative truck platooning. *Social Science Research Network (SSRN)*, 1–32.

Ambra, T., Caris, A., & Macharis, C. (2019). Towards freight transport system unification: reviewing and combining the advancements in the physical internet and synchromodal transport research. *International Journal of Production Research*, *57*(6), 1606–1623.

Baron, O., Milner, J., & Naseraldin, H. (2011). Facility location: A robust optimization approach. *Production and Operations Management*, *20*(5), 772–785.

Ben-Tal, A., El Ghaoui, L., & Nemirovski, A. (2009). *Robust optimization, vol. 28*. Princeton University Press.

Ben-Tal, A., Golany, B., Nemirovski, A., & Vial, J. P. (2005). Retailer-supplier flexible commitments contracts: A robust optimization approach. *Manufacturing & Service Operations Management*, *7*(3), 248–271.

Ben-Tal, A., & Nemirovski, A. (1999). Robust solutions of uncertain linear programs. *Operations Research Letters*, *25*(1), 1–13.

Ben-Tal, A., & Nemirovski, A. (2000). Robust solutions of linear programming problems contaminated with uncertain data. *Mathematical Programming*, *88*(3), 411–424.

Bergenhem, C., Shladover, S., Coelingh, E., Englund, C., & Tsugawa, S. (2012). Overview of platooning systems. In *Proceedings of the 19th ITS world congress*.

Bertsimas, D., & Sim, M. (2004). *Robust discrete optimization under ellipsoidal uncertainty sets, vol. 9*. MIT, Manuscript.

Beyer, H. G., & Sendhoff, B. (2007). Robust optimization–a comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, *196*(33–34), 3190–3218.

Boysen, N., Briskorn, D., & Schwerdfeger, S. (2018). The identical-path truck platooning problem. *Transportation Research, Part B (Methodological)*, *109*, 26–39.

Boysen, N., Scholl, J., & Stephan, K. (2017). When road trains supply freight trains: scheduling the container loading process by gantry crane between multi-trailer trucks and freight trains. *OR Spectrum*, *39*(1), 137–164.

Caballero, W. N., Jaehn, F., & Lunday, B. J. (2022). Transportation labor cost reduction via vehicle platooning: Alternative models and solution methods. *Transportation Science*, *56*(6), 1549–1572.

Carbaugh, J., Godbole, D. N., & Sengupta, R. (1998). Safety and capacity analysis of automated and manual highway systems. *Transportation Research Part C (Emerging Technologies)*, *6*(1–2), 69–99.

Caserta, M., & Voß, S. (2019). The robust multiple-choice multidimensional knapsack problem. *Omega*, *86*, 16–27.

Chen, X., He, S., Zhang, Y., Tong, L. C., Shang, P., & Zhou, X. (2020). Yard crane and AGV scheduling in automated container terminal: A multi-robot task allocation framework. *Transportation Research Part C (Emerging Technologies)*, *114*, 241–271.

Cordeau, J. F., Legato, P., Mazza, R. M., & Trunfio, R. (2015). Simulation-based optimization for housekeeping in a container transshipment terminal. *Computers & Operations Research*, *53*, 81–95.

Daduna, J. R., & Stahlbock, R. (2020). Importance of hinterland transport network structures for seaport container terminals: An update. In *Handbook of terminal planning* (pp. 531–557). Springer.

Duinkerken, M. B., Dekker, R., Kurstjens, S. T., Ottjes, J. A., & Dellaert, N. P. (2007). Comparing transportation systems for inter-terminal transport at the maasvlakte container terminals. In *Container terminals and cargo systems* (pp. 37–61). Springer.

Gabrel, V., Murat, C., & Thiele, A. (2014). Recent advances in robust optimization: An overview. *European Journal of Operational Research*, *235*(3), 471–483.

Gao, N., & Ryan, S. M. (2014). Robust design of a closed-loop supply chain network for uncertain carbon regulations and random product flows. *EURO Journal on Transportation and Logistics*, *3*(1), 5–34.

Gerrits, B., Mes, M., & Schuur, P. (2019). Simulation of real-time and opportunistic truck platooning at the port of Rotterdam. In *Proceedings of the 2019 Winter Simulation Conference* (pp. 133–144).

Hamburg News (2022). Hamburg to become testing ground for driverless lorries. https://www.hamburg-news.hamburg/en/innovation-science/hamburg-become-testing-ground-driverless-lorries. (Accessed 26 December 2022).

Heilig, L., & Voß, S. (2017). Inter-terminal transportation: an annotated bibliography and research agenda. *Flexible Services and Manufacturing Journal*, *29*(1), 35–63.

Hirata, T., & Fukaya, T. (2020). Potential of truck platooning for transporting empty trucks considering intercity freight demand imbalances. *LogForum*, *16*(3), 373–383.

Janssen, G. R., Zwijnenberg, J., Blankers, I., & de Kruijff, J. (2015). *Truck platooning: Driving the future of transportation . TNO whitepaper*. The Netherlands: TNO.

Johansson, A., Nekouei, E., Johansson, K. H., & Mårtensson, J. (2021). Strategic hub-based platoon coordination under uncertain travel times. *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 8277–8287.

Kon, W., Rahman, N. S. F. A., Hanafiah, R. M., & Hamid, S. A. (2020). The global trends of automated container terminal: a systematic literature review. *Maritime Business Review 6*(3), 206–233.

Larsen, R., Rich, J., & Rasmussen, T. K. (2019). Hub-based truck platooning: Potentials and profitability. *Transportation Research Part E: Logistics and Transportation Review*, *127*, 249–264.

Larson, J., Munson, T., & Sokolov, V. (2016). Coordinated platoon routing in a metropolitan network. In *2016 Proceedings of the seventh SIAM workshop on combinatorial scientific computing* (pp. 73–82).

Larsson, E., Sennton, G., & Larson, J. (2015). The vehicle platooning problem: Computational complexity and heuristics. *Transportation Research Part C (Emerging Technologies)*, *60*, 258–277.

Lu, M., & Shen, Z. J. M. (2021). A review of robust operations management under model uncertainty. *Production and Operations Management*, *30*(6), 1927–1943.

Luo, F., & Larson, J. (2020). A repeated route-then-schedule approach to coordinated vehicle platooning: Algorithms, valid inequalities and computation. arXiv e-prints: 2004.13758.

Luo, F., Larson, J., & Munson, T. (2018). Coordinated platooning with multiple speeds. *Transportation Research Part C (Emerging Technologies)*, *90*, 213–225.

Mavrotas, G. (2009). Effective implementation of the $\epsilon$-constraint method in multi-objective mathematical programming problems. *Applied Mathematics and Computation*, *213*(2), 455–465.

Mavrotas, G., & Florios, K. (2013). An improved version of the augmented $\epsilon$-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. *Applied Mathematics and Computation*, *219*(18), 9652–9669.

Mudchanatongsuk, S., Ordóñez, F., & Liu, J. (2008). Robust solutions for network design under transportation cost and demand uncertainty. *Journal of the Operational Research Society*, *59*(5), 652–662.

Nishimura, E., Imai, A., & Papadimitriou, S. (2005). Yard trailer routing at a maritime container terminal. *Transportation Research Part E: Logistics and Transportation Review*, *41*(1), 53–76.

Pauwels, A. (2021). *Safety of automated driving in mixed-traffic urban areas: Considering vulnerable road users and network efficiency*: *Technical report*, TU Delft.

Pelletier, S., Jabali, O., & Laporte, G. (2019). The electric vehicle routing problem with energy consumption uncertainty. *Transportation Research, Part B (Methodological)*, *126*, 225–255.

Port of Rotterdam (2022). Container exchange route (CER). https://www.portofrotterdam.com/en/building-port/ongoing-projects/container-exchange-route-cer. (Accessed 26 December 2022).

Pourmohammad-Zia, N., Schulte, F., & Negenborn, R. R. (2020). Platform-based platooning to connect two autonomous vehicle areas. In *Proceedings of the 2020 IEEE 23rd international conference on intelligent transportation systems* (pp. 1–6).

Pourmohammad-Zia, N., Schulte, F., Souravlias, D., & Negenborn, R. R. (2020). Platooning of automated ground vehicles to connect port and hinterland: A multi-objective optimization approach. In *Proceedings of the 2020 international conference on computational logistics* (pp. 428–442).

Repoux, M., Geroliminis, N., & Kaspi, M. (2021). Operational analysis of an innovative semi-autonomous on-demand transportation system. *Transportation Research Part C (Emerging Technologies)*, *132*, Article 103373.

Scherr, Y. O., Hewitt, M., & Mattfeld, D. C. (2022). Stochastic service network design for a platooning service provider. *Transportation Research Part C (Emerging Technologies)*, *144*, Article 103912.

Scherr, Y. O., Neumann-Saavedra, B. A., Hewitt, M., & Mattfeld, D. C. (2019). Service network design with mixed autonomous fleets. *Transportation Research Part E: Logistics and Transportation Review*, *124*, 40–55.

Scholl, J., Boysen, N., & Scholl, A. (2022). E-platooning: Optimizing platoon formation for long-haul transportation with electric commercial vehicles. *European Journal of Operational Research*, *304*(2), 525–542.

Schulte, F., Lalla-Ruiz, E., González-Ramírez, R. G., & Voß, S. (2017). Reducing port-related empty truck emissions: a mathematical approach for truck appointments with collaboration. *Transportation Research Part E: Logistics and Transportation Review*, *105*, 195–212.

Shouwen, J., Di, L., Zhengrong, C., & Dong, G. (2020). Integrated scheduling in automated container terminals considering AGV conflict-free routing. *Transportation Letters 6*(3), 206–233.

Sungur, I., Ordónez, F., & Dessouky, M. (2008). A robust optimization approach for the capacitated vehicle routing problem with demand uncertainty. *IIE Transactions*, *40*(5), 509–523.

Tavakkoli-Moghaddam, R., Sadri, S., Pourmohammad-Zia, N., & Mohammadi, M. (2015). A hybrid fuzzy approach for the closed-loop supply chain network design under uncertainty. *Journal of Intelligent & Fuzzy Systems*, *28*(6), 2811–2826.

Tierney, K., Voß, S., & Stahlbock, R. (2014). A mathematical model of inter-terminal transportation. *European Journal of Operational Research*, *235*(2), 448–460.

Tschöke, M., & Boysen, N. (2018). Container supply with multi-trailer trucks: parking strategies to speed up the gantry crane-based loading of freight trains in rail yards. *OR Spectrum*, *40*(2), 319–339.

Van Aerde, M., & Yagar, S. (1984). *Capacity, speed and platooning vehicle equivalents for two-lane rural highways*. TRB.

Xiong, X., Sha, J., & Jin, L. (2020). Optimizing coordinated vehicle platooning: An analytical approach based on stochastic dynamic programming. arXiv e-prints: 2003.13067.

Xue, Z., Lin, H., & You, J. (2021). Local container drayage problem with truck platooning mode. *Transportation Research Part E: Logistics and Transportation Review*, *147*, Article 102211.

Yao, T., Mandala, S. R., & Chung, B. D. (2009). Evacuation transportation planning under uncertainty: a robust optimization approach. *Networks and Spatial Economics*, *9*(2), 171–189.

You, J., Miao, L., Zhang, C., & Xue, Z. (2020). A generic model for the local container drayage problem using the emerging truck platooning operation mode. *Transportation Research, Part B (Methodological)*, *133*, 181–209.

Zhang, W., Jenelius, E., & Ma, X. (2017). Freight transport platoon coordination and departure time scheduling under travel time uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, *98*, 1–23.

Zhang, R., Wang, D., & Wang, J. (2020). Multi-trailer drop-and-pull container drayage problem. *IEEE Transactions on Intelligent Transportation Systems*, *22*(9), 5708–5720.

Zheng, H., Jin, C., Luo, X., Negenborn, R. R., & Wang, Y. (2020). Dynamic rolling horizon scheduling of waterborne AGVs for inter terminal transport. In *Proceedings of the 2020 IEEE 16th international conference on control & automation* (pp. 761–766).

Zhong, M., Yang, Y., Dessouky, Y., & Postolache, O. (2020). Multi-AGV scheduling for conflict-free path planning in automated container terminals. *Computers & Industrial Engineering*, *142*, 1–11.