The Orchestra of Movement
Polycentric Management in Multimodal Transport

Parmaksizoglou, I.A.

DOI
10.4233/uuid:1e22c336-8af1-46f9-9aa1-19a03c77b83f

Publication date
2026

Document Version
Final published version

Citation (APA)
Parmaksizoglou, I. A. (2026). *The Orchestra of Movement: Polycentric Management in Multimodal Transport*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:1e22c336-8af1-46f9-9aa1-19a03c77b83f

POLYCENTRIC MANAGEMENT IN MULTIMODAL TRANSPORT

Ilias Alexandros Parmaksizoglou

The Orchestra of Movement

Polycentric Management in Multimodal Transport

THE ORCHESTRA OF MOVEMENT

POLYCENTRIC MANAGEMENT IN MULTIMODAL TRANSPORT

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus, prof. dr. ir. H. Bijl,
chair of the Board for Doctorates
to be defended publicly on
Thursday 29 January 2026 at 10:00 o'clock

by

Ilias Alexandros PARMAKSIZOGLOU

Master of Science in Operational Research with Data Science,
University of Edinburgh, United Kingdom
born in Athens, Greece

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus,	chairperson
Prof. dr. ir. J.M. Hoekstra,	Delft University of Technology, *promotor*
Dr. O.A. Sharpans'kykh,	Delft University of Technology, *copromotor*
Dr. A. Bombelli,	Delft University of Technology, *copromotor*

Independent members:

Prof. dr. W. Dewulf	University of Antwerp, Belgium
Prof. dr. A. Lange	Frankfurt University of Applied Sciences, Germany
Dr. B. Atasoy	Delft University of Technology
Prof. dr. ir. L. A. Tavasszy	Delft University of Technology
Prof. dr. ir. M. Mulder	Delft University of Technology, reserve member

This dissertation has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 953618, as part of the ORCHESTRA project.

Keywords: Multimodal Transport, Polycentric Management, Multi-Agent Systems, Collaborative Decision-Making, Scheduling, Optimization, Heuristics

Printed by: Ipskamp Printing

Cover by: Ilias Alexandros Parmakizoglou

ISBN 978-94-6384-898-5

An electronic copy of this dissertation is available at
https://repository.tudelft.nl/.

Change what you can, manage what you can't.

Raymond McCauley

CONTENTS

Acknowledgements

Four years ago, I had the opportunity to move to a new country to work on the topic of multimodal transportation in what felt like a true culmination of my academic journey. Four years later, and more than 150 pages of written text that do not feel like enough, I can say that the experience has been an absolute privilege.

None of this would be possible without Dr. Alessandro Bombelli and Dr. Alexei Sharpanskykh. I thank both for helping me navigate the PhD journey, taking time to review my writings, coping with my at times unorthodox ideas, and providing tough but fair feedback when it was needed. Collaborating with them has been the greatest professional lesson I have learned, and any researcher I am today is undoubtedly a product of that experience. I would also like to thank my promotor, Prof. Jacco Hoekstra, for the invaluable guidance in realizing this thesis effectively, as well as Dr. Bruno Santos for their support during the earlier stages of my research.

There are too many colleagues to thank individually, so I would like to express my gratitude in advance to all my fellow PhD students, postdocs, and colleagues from ATO and later O&E. Most importantly, I am particularly thankful to many of you for letting me terrorize you with countless *Blood on the Clocktower* gaming sessions. Special thanks go to Iordanis for the much-needed Greek support throughout the PhD and for helping me translate what life at TU Delft really means, especially during the initial period of lockdowns and extensive remote work. Thanks to all other PhDs/PostDoc, Hao, Prashant, Malte, Simon, Matt, Mike, Haonan, Joao, Ingeborg, Wenhua, Marie, Juseong, Gülçin, Chengpeng, Mahdi, Karim, Sam, Phillipe, Daniel, Fynn, Sara, Mihai, Marta, and Pieter-Jan, for making the workplace such an inspiring and enjoyable environment.

Outside of TU Delft, there are many friends to thank for their support throughout the past years. I'll try to name everyone and tempt fate, but if I accidentally forget someone, don't worry—it's either because I'm forgetful or you didn't pull your weight in the last four years (just kidding, mostly!). I am grateful to my high school friends, who have stayed in touch over the past twelve years, despite living in different countries: Michael L., Stelios, Kosmas and Michael G. Special thanks also go to friends from Greece: Adrikos, Paschalis, George, Michael A., and Nikos. The Greek community in the Netherlands has also been a source of great support, and I am particularly thankful to Savina, Thanasis, Iasonas, Melina, Adonis, Natalia, Menios, Anna, Dimitris and Anna-Maria.

I would like to thank all my family and specifically my grandma, who learned to use video calls so she could stay connected with me and my brother after we moved away from Greece. I also thank my brother, Anastassis, for his encouragement over the years, and my parents for all of their support. I deeply realize that I am extraordinarily privileged to be in the position I am today, and that this would not have been possible without them. Last, I thank Elena for her endless patience and for making this journey feel shared rather than faced alone. I genuinely can't wait for the next journeys.

Summary

The demand for transport services has been steadily increasing over the past decades, a trend that shows no indication of slowing down, as the global population continues to rise. Combined with the ongoing urbanization trend and car-dependence of modern societies, it is expected that the average person will spend significantly more time stuck in traffic compared to the past. It becomes evident that traffic congestion constitutes one of the major challenges of this century and that a shift towards alternative modes of transport is needed.

Promoting multimodality has been a key strategy to reduce car dependence. Multimodal transport refers to the use of a combination of modes for a single journey. Multiple initiatives related to multimodality have been proposed, such as Mobility as a Service, most of them user-centric. However, there is significant need for support for policymakers and traffic managers as well. It is clear that within a multimodal transport ecosystem, modes can no longer operate with a siloed approach—only focusing within their respective mode or domain—and that there is a need for traffic management in a multimodal manner.

This dissertation explores multimodal traffic management through the lens of polycentric governance. Polycentric systems involve decentralized, interacting, and sometimes overlapping decision-making units that this dissertation maps to multimodal transport stakeholders and explores their coordination through processes of competition, cooperation, and conflict resolution. This form of coordination is defined as *traffic orchestration*, and its implementation though the novel stakeholder role of Traffic Orchestrator, across an array of multimodal transport settings is the main objective of this thesis. To achieve that, the use of distributed methods and in particular multi-agent systems as the key methodological approach is selected, due to the clearly non-centralized nature that polycentric systems necessitate.

Multimodal settings are explored in the form of two transport scenarios. The first scenario relates to seaport terminal operations and the second related to airport passenger accessibility. The port-centric focus of this dissertation is a deliberate design choice, as ports serve as key hubs of multimodal activity.

To study polycentricity, a first goal of this dissertation was to explore how competition can be leveraged for traffic management and coordination of stakeholders. To that end, in **Chapter 2** focus was given on the problem of truck congestion at seaport terminals due to unregulated truck arrivals. A system was proposed that uses the interdependence of transport services for access at the terminal, through a competitive mechanism acting as a demand management tool. An auction, managed by an orchestrator, implements an incentive compatible and truthful pricing policy that limits the supply of access rights per time-window and asserts that service providers must participate to secure access in the terminal. Results show that the application of the mechanism can have a significant effect in reducing congestion at the terminal, while also asserting that operational requirements of the transport services providers are also respected to promote adoption.

A second goal was to explore how collaboration between modes can be successfully utilized. Building on the same freight transport scenario, in **Chapter 3** focus was given on the synchronization of modes arriving at a seaport. In particular, the timing interdependence of vessels and trucks accessing the terminal was explored through a multi-agent, multi-objective model, coordinated by an orchestator. This model aimed at mapping stakeholder interactions to increase cooperation, by generating common ground solutions related to truck scheduling and berth allocation. In the center, of this model was the development of a novel algorithm inspired by prioritized planning, aiming at exploring different priority structures. The proposed approach was shown to be very efficient in locating diverse results, in comparison with other approaches in the literature.

Apart from focusing on how to leverage polycentricity for better managing transport service providers, it was essential to examine the interactions between traffic orchestrators responsible for managing traffic within their respective domains. In **Chapter 4**, the focus shifts to the passenger scenario, and the conflicts arising in disruption management efforts for airport passenger access are explored. A case where passengers are affected by a disruption in the surface access system is studied, and the application of measures such as delaying flights and rerouting passengers is examined. Two orchestrators—one for the airside domain and one for the landside domain—engage in multi-agent negotiation to decide on the combination of measures taken to address the disruptions involved. Simulation results show the merits of the method in reducing delays and distributing costs related to disruption management across domains.

Finally, in **Chapter 5** the focus shifts away from orchestrations and towards the development of new tools supported by orchestration to facilitate multimodal transport. In particular, the exploration of a new mobility service for airport access is proposed that aims to bridge the gap between the first-mile of users accessing the airport and their available public transport. Using a formalism based on Distributed Constraint Optimization, a method to leverage existing taxi infrastructure to feed the public transport is explored for users in danger of losing their flights. The effect of the proposed demand response transport service in reducing missed flights is shown, contingent on different set of criteria selected by the taxi agents.

In conclusion, this research introduces traffic orchestration as a framework for multimodal transport coordination and demonstrates its application in port-centric contexts. The findings suggest that Traffic Orchestrators can improve efficiency and integration in multimodal systems, but their effectiveness depends on stakeholder collaboration, data availability, and governance structures. As transport networks evolve, the need for orchestration will likely increase, especially in systems where central control is neither feasible nor desirable. Overall, traffic orchestration offers a promising path toward more adaptive, equitable, and sustainable multimodal transport management.

1 Introduction

The need for transport services within the European Union (EU) has been rising steadily since the early 2000s, for both passenger and freight transport. It is anticipated that this trend will continue, with passenger and freight transport volumes increasing by more than 20% by 2050 relative to current levels [1]. However, despite the rise in traffic volumes, projections related to modal splits paint a very similar car-dependent picture with respect to the future of mobility by 2050, as illustrated by Figure 1.1. In fact, it is estimated that under current expected mobility patterns, the average urban resident is expected to spend 106 hours a year stuck in traffic by 2050, which is more than three times the amount of time reported in 2012 [2].

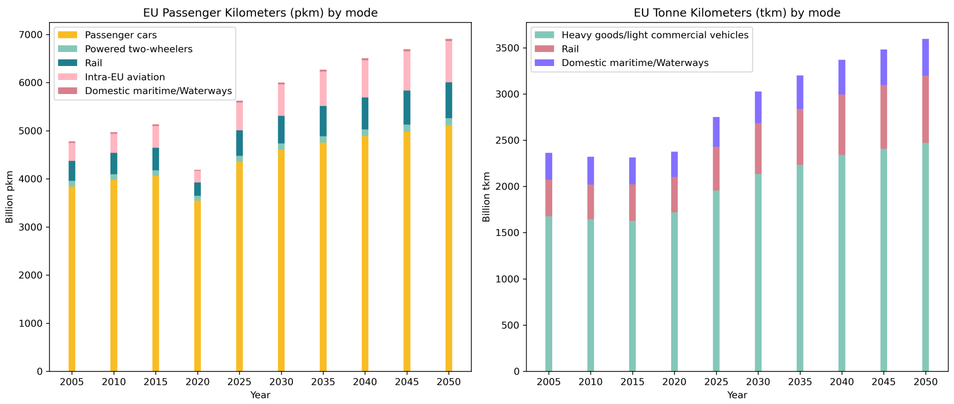


Figure 1.1: Passenger and Freight transport volumes in the European Union Reference Scenario 2050

To tackle the issue of car-dependence, the advancement of multimodal transport solutions is crucial. Multimodal transport is the process of moving people and goods through a combination of at least two modes of transport to combine the advantages of various modes while avoiding their limitations [3]. In the literature, multiple concepts related to multimodal transport have been proposed to offer users more flexible and sustainable mobility. Examples include Mobility as a Service (MaaS) [4] for passenger transport and synchromodality for freight transport [5]. MaaS platforms integrate different transport services, such as ride-hailing, bike sharing, and public transport (PT), into a single digital interface that enables users to plan, book, and pay for multimodal trips, thereby reducing the need for private vehicles. Synchromodal approaches allow logistics providers to choose between modes, such as rail, barge, and truck, in real time depending on factors such as cost, network availability, or environmental impact, without altering the original shipment booking.

The push for multimodality has been heavily motivated by its perceived environmental benefits [6]. These include lowering demands on limited resources such as urban space, clean air, and quiet, due to decreased reliance on private vehicle use [7]. Multimodal travelers typically make greater use of public and active transport modes while relying less on private cars [8], and in areas where multimodal options are more prevalent, trends show a corresponding decline in private car ownership [9]. The evidence suggests that promoting multimodality can support a transition from an ownership-oriented transport system to one focused on access, which can have substantial benefits for lowering energy use and carbon emissions [10].

While multimodal mobility is increasingly recognized as essential for sustainable transport, current approaches to implementation remain fragmented, having been developed by different actors over time and often without a unified traffic management perspective [7, 11], which has traditionally operated in a uni-modal manner. As transport services have expanded, this single-mode approach is gradually becoming insufficient. Managing traffic effectively across a network of transport modes requires coordination that goes beyond traditional practices [12]. Nevertheless, numerous obstacles still hinder the implementation of multimodal coordination. The first and most crucial issue to overcome is the current, limited exchange of real-time traffic data between modes of transport [13]. For example, a road traffic control center cannot proactively manage overflow traffic caused by passengers switching modes during disruptions if it does not have timely information on train delays. Additionally, different stakeholders, such as PT companies, private transport providers, and traffic authorities, often have different rules, priorities, and institutional limits [14]. For example, traffic regulations or safety standards can vary significantly between road and air systems, making coordinated disruption responses or integrated control strategies difficult. Additional examples of barriers include the absence of standards in data formats for facilitating data sharing, privacy issues, and a lack of trust among competing modes and service providers.

To address these challenges is essential to move beyond centralized and single-mode transport management approaches. A governance concept suitable to address the diverse needs of multiple stakeholders is that of polycentricity. Polycentric systems are composed of “(1) many autonomous units formally independent of one another, (2) choosing to act in ways that take account of others, and (3) engaging in processes of collaboration, competition, and conflict resolution" [15]. Polycentric systems are typically seen as well-suited for managing common-pool resources, where the resource environment or domain is characterized by an open-access problem [16]. An open access problem occurs when resources are available to multiple users, however in absence of adequate regulation and coordination, the system's effectiveness decreases. A common example of the problem is observed in fisheries, where fishermen are motivated to catch as many fish as possible, as failure to do so allows others to exploit the resource, despite the practice depleting the resources in the long term. Similarly, an open-access problem in transport arises when urban road networks become congested during peak hours, even though alternative routes or modes are available, due to lack of coordination.

The main objective of this thesis is exploring coordination of independent transport actors around shared goals, through methods based on polycentric principles. This form of coordination is termed as traffic orchestration and formally defined as follows:

The coordinated management of transport resources within a single mode to leverage advantages across multiple modes, ultimately optimizing the performance of the entire transport system.

1.1. Orchestration in Multimodal Transport

The necessity to move beyond isolated, uni-modal solutions and embrace a more integrated perspective in transport management is also supported by proposed roadmaps and legislation. The Strategic Transport Research and Innovation Agenda by the EU [17] emphasizes the need for network-wide traffic management systems that incorporate flexible administrative boundaries across transport modes and domains. While recent decades have seen significant progress in physical and infrastructural integration [18], operational and strategic coordination across transport modes warrants further research. This gap highlights the opportunity to redefine traffic management by focusing on the interactions of the involved stakeholders and modes to apply traffic orchestration.

Key stakeholders within a multimodal transport system include Transport Service Providers (TSPs) and Network Users (NUs). TSPs deliver passenger and freight transport services, and include PT agencies, bus companies, railways, airlines, and logistics firms. TSPs must also coordinate with other stakeholders, sharing information to align with broader network strategies [19]. NUs include passengers and freight shippers whose transport needs generate demand. Their choices shape transport services, influencing routing, capacity, and traffic conditions. This thesis also capitalizes on a new stakeholder role, the Traffic Orchestrator (TO) [20], which is responsible for managing traffic flows within a specific transport domain or mode. The TO functions as a coordinating entity responsible for smooth traffic flows, while considering the performance of the overall system [21]. A transport system can have multiple TOs who must also coordinate with each other to prevent local decisions from causing wider system inefficiencies.

This theses is introducing the TO role in different domains and contexts within a multimodal transport system. While this could be explored in various domains, ports offer a natural starting point, as hubs where multiple modes intersect. The

1

responsibilities of TOs also can align with current responsibilities of port managers, such as those performed by terminal operators in seaports and duty managers in airports, and also engage in coordination across multiple actors but not necessarily transport modes. This coordination relies heavily on joint planning and digital integration among stakeholders to enable smooth intermodal flows [22] as decisions taken by ports at the local level influence the performance of broader transport corridors [23]. Moreover, ports have been shown to exhibit several key polycentric design features [24].

Within the following sections, the current state of multimodal integration in the transport sector is examined to motivate the need for traffic orchestration (Section 1.1.1), and highlight the limitations that justify the proposed approach (Section 1.1.2). Then, distributed planning approaches to support traffic orchestration are examined, to provide a methodological basis for this dissertation (Section 1.1.3).

1.1.1. INTEGRATED PLANNING FOR MULTIMODAL TRANSPORT MANAGEMENT

Although research on multimodal traffic management remains relatively limited [25], the literature provides several examples that investigate multimodal integration from an operational perspective across various transport contexts. While not an exhaustive list, several key examples are identified, which are summarized in Table 1.1.

Table 1.1: Case Studies on Integrated Management in Transport

Topic	Transport Type	Modes	References	Planning Type	Port focus	Explored in Thesis
Dedicated Bus Lanes	Passenger	Car, Bus	[26–29]	Strategic	✗	✗
Demand Responsive Transit	Passenger	Car, Rail, Bus	[30–32]	Tactical / Operational	✓	✓
Park and Ride	Passenger	Car, Rail, Bus	[33–36]	Strategic / Tactical	✓	✗
Air-Rail Integration	Passenger	Air, Rail	[37–40]	Tactical / Operational	✓	✓
Hub Location Problems	Freight	Truck, Rail, Sea	[41–43]	Strategic	✓	✗
Port Hinterland Connections	Freight	Sea, Rail, Road	[23, 44]	Strategic / Tactical	✓	✗
Truck Appointment Systems	Freight	Truck, Rail, Sea	[45–51]	Tactical / Operational	✓	✓

PASSENGER TRANSPORT

A common example of multimodal integration is the establishment of Dedicated Bus Lanes (DBLs). A DBL is a strategic planning measure that prioritizes transit vehicles along specific road corridors by separating them from general traffic, enabling more efficient movement through congested areas. Their implementation affects multiple transport modes, as allocating road space to buses can improve PT performance but may also reduce road capacity for private vehicles. The selection of DBL locations is a complex task, often addressed through bi-level optimization models that account for both system-level objectives, such as bus frequency, and user-level objectives, such as reduced travel time in multimodal networks [26–28]. DBLs are fundamentally strategic, long-term infrastructure interventions in an urban, non-port-centric context. Nonetheless, recent studies have started to incorporate dynamic traffic conditions and operator responses to better align DBL planning with multimodal behavior and congestion in a dynamic way [29].

Multimodal integration in passenger transport is often studied through the combination of private car use with public rail or bus services, such as Demand-responsive transport (DRT) and Park and Ride (P&R) systems. DRT services predominantly focus on areas with limited PT connectivity and use passenger cars, vans, or small buses to offer transport, in response to passenger requests [31]. In practice, DRT often serves as a first/last-mile connector, linking travelers' origins or destinations with mainline bus or rail stations [32]. P&R systems aim to incentivize drivers to leave their cars at designated lots, typically integrated with major hubs, and continue by PT [34]. The aim is to incentivize car users to shift to PT [33], thereby alleviating congestion and reducing environmental impacts [35]. There are several parallels between DRT and P&R. Both systems share a hub-centric focus, as they aim to consolidate and coordinate access to major nodes within the transport network. They also aim to improve accessibility, reduce urban congestion, and encourage a shift toward more sustainable transport modes, serving as effective transport demand management strategies, particularly in low-density or peri-urban areas where traditional transit options are limited.

Another important case is the integration of air-rail transport systems. Air–rail integration involves coordinating flight and train networks so that they complement each other, offering seamless transfers for passengers. This approach is especially valuable during disruptions or capacity constraints, as it highlights the advantages of combining air and rail services and the importance of real-time information sharing among stakeholders [39]. Research highlights that close cooperation between airlines, rail operators, and airports can maintain traveler connectivity during disruptions, for example by re-routing passengers via high-speed rail when flights are delayed or canceled [40]. To fully capitalize on air-rail synergies, attention is also often given to airport terminal processes and ground connections [52] with respect to integration. Simulation studies suggest that prioritizing delayed rail-to-air transfer passengers in security or boarding queues can significantly reduce missed flight connections and total passenger delay times [38]. Finally, providing easy connections through integrated ticketing, dedicated shuttle buses, and coordinated schedules also makes intermodal transfers more reliable and increases passenger satisfaction [53].

In this dissertation, focus is given on DRT and air–rail integration as representative applications for multimodal orchestration in passenger transport, as they align more closely with the tactical and operational focus of the TO. This choice also reflects the port-focused nature of the study. P&R schemes, while relevant to multimodal integration, often require long-term strategic planning and capital-intensive infrastructure investments [36], making them less compatible with the scope of this research. Similarly, DBLs are strategic infrastructure interventions designed primarily for urban settings, with limited operational flexibility and weak alignment with the TO's role in localized, cross-modal coordination.

FREIGHT TRANSPORT

A significant challenge in freight transport relates to determining optimal hub locations. Hub Location Problems (HLP) involve determining the strategic placement of hub facilities in a transport network to consolidate shipments across multiple modes, enabling efficient bundling of flows [41]. Hubs serve as critical nodes for transshipment, hence determining optimal placement can often lead to significant reductions in overall transport costs and facilitates smooth modal transfers [42]. By acting as modal interfaces, hubs support synchronized operations across transport modes and help harmonize time schedules, vehicle capacities, and handling requirements.

Closely related is the topic of port–hinterland connectivity, which addresses how seaports interface with inland terminals via road, rail, and inland waterways. The literature has extensively examined this dimension through studies on dry ports, intermodal corridors, and inland connectivity, emphasizing their role in expanding port reach and operational efficiency [23]. Recent studies in hinterland freight transport emphasize the integration of strategic decisions, such as node selection and commodity flow assignment, into the planning process, balancing profit-oriented objectives with network design and using synchromodality to enable dynamic replanning and flexible coordination under operational uncertainty [44]. This integrative perspective shows how multimodal connectivity transcends simple modal linkages to embrace a coordinated network-level optimization of flows, assets, and information.

Finally, a common and practical example of multimodal integration in freight transport is the coordination of trucks at container terminals through Truck Appointment Systems (TAS). These systems help synchronize truck arrivals with terminal operations, reducing congestion, minimizing waiting times, and enhancing the overall efficiency of the modal transfer process [54]. By regulating and spreading out truck arrivals, appointment systems smooth out gate demand, reducing queue times and congestion at terminal entrances. Researchers have also associated the adoption of TAS with benefits beyond congestion reduction, including decreased pollution in terminals [46] and improvements in other aspects of port terminal planning. These include improved synchronization of handling components, such as storage allocation and quay crane management [55], reduction of empty trips made by yard trucks [47] and faster container re-handling operations [48]. The benefits of appointment systems extend beyond road transport by facilitating the seamless movement of goods, such as rail and inland waterways [49]. Vessel-truck coordination via appointment systems in particular has emerged as a key strategy for improving operational efficiency at container terminals. Recent studies have suggested aligning truck slots with vessel schedules, using vessel-dependent appointment models to enhance synchronization between landside and seaside operations [50, 51].

HLPs are closely linked to multimodal integration, involving strategic, long-term decisions on infrastructure placement and investment [43]. However, these capital-intensive, long-horizon decisions lie beyond the operational and tactical focus of this thesis. Port–hinterland connectivity is broad and complex, creating large domains that often limit direct responsibility and potential influence of a

TO, which is the main reason why the topic is not explored here. Instead, this dissertation focuses on TAS as a clear example of multimodal integration at the tactical level. These systems enable effective coordination by providing a structured, transparent interface for stakeholders, offering a practical foundation for multimodal orchestration within the port terminal ecosystem that aligns with the scope of this research.

1.1.2. Challenges

Although several examples demonstrate the potential of integrated planning to enhance multimodal operations, implementation in practice remains highly challenging. A number of barriers continue to hinder effective coordination, as outlined in the following paragraphs.

One of the most critical challenges in traffic orchestration is the fragmentation and often conflicting interests among stakeholders within multimodal transport systems [56]. Service providers, infrastructure managers, and public authorities, frequently pursue conflicting objectives, such as maximizing ridership, optimizing profits, or minimizing operational risk. These differing agendas can discourage the level of collaboration and data sharing necessary for coordinated decision-making. In the absence of clearly defined incentive structures or trusted intermediaries, stakeholders may be reluctant to disclose operational data, fearing loss of strategic advantage or reduced autonomy.

Reluctance to change is also a significant issue. Encouraging travelers and freight operators to adopt new routines, such as using P&R facilities, engaging with DRT, or shifting to less congested modes, requires more than operational integration. Travelers prefer personal vehicles for their convenience and flexibility and studies suggest that those who have the option to drive generally require strong incentives to adopt PT alternatives [57]. This highlights the need for outreach strategies, pricing mechanisms for congestion control, and service-level improvements that make multimodal travel attractive.

Finally, the structural complexity of multimodal systems makes orchestration technically demanding [3]. Each transport mode, operates under its own technical standards, regulatory frameworks, and scheduling constraints. This results in systems that are optimized individually but not collectively. Thus, it is crucial for traffic orchestration to reconcile priorities among different modes. For example, road networks often emphasize fluidity and throughput, while air transport prioritizes safety and regulated capacity. Coordination between modes is contingent on harmonizing priorities and pushing a shift toward shared goals, supported by interoperable solutions.

However, a large number of traditional engineering models and algorithms related to traffic management are based on control and centralization [58] and remain grounded in a design-time logic that struggles to accommodate the complexity of modern mobility patterns [59]. Because of the challenges previously mentioned, it is becoming more and more clear that these traditional, centralized methods are not useful at handling the complexity, diversity, and shifting nature of mobility. As they depend on fixed structures and top-down hierarchical control, they can't respond quickly and effectively to the changing and interdependent needs of modern transportation systems. Instead, there is a pressing need for distributed strategies that support adaptive coordination among diverse actors and transport modes. Such approaches are better aligned with the inherently distributed nature of the transport ecosystem.

1.1.3. DISTRIBUTED METHODS FOR TRAFFIC ORCHESTRATION

Decentralization and multi-actor approaches in transport have been extensively studied in recent decades. However, in the specific context of multimodal traffic management, practical applications of coordinated decision-making remain limited. Understanding how effective coordination can be achieved through orchestration in such settings requires a closer look at the three fundamental processes of polycentric systems: competition, collaboration, and conflict resolution.

Multi-agent systems (MAS) provide a suitable distributed approach for capturing these processes. MAS enable the simulation, analysis, and distributed optimization of autonomous decision-making entities and capture the dynamic properties and interactions between them. MAS offer several advantages for transport applications, including providing a natural and intuitive problem-solving paradigm for active entities, avoiding the need for centralized solutions that cannot capture all necessary details, and offering an appropriate framework for modeling heterogeneous systems [60].

In multimodal transport systems, conflict resolution is an important component of stakeholder coordination, as conflicts arise from differing objectives, shared constraints, and overlapping responsibilities between stakeholders. Effective coordination requires accurate representation of stakeholders' goals and their interdependencies, which may involve resources, timing, and tasks. For example, resource interdependence can arise when multiple freight shippers, i.e., NUs, rely on limited terminal capacity or rail slots managed by different operators [61]. Similarly, temporal interdependence arises in the PT network, when NUs depend on the precise coordination of schedules between different operators, to enable timely and seamless transfers [62]. While resolving such issues can be often attributed to lack of data exchange, addressing these interdependencies requires more than just information sharing. Interacting agents are actively engaged in competitive or collaborative scenarios [63], where effective coordination strategies can be utilized to align actions and resolve conflicts to mitigate issues caused by such interdependencies.

In the context of traffic orchestration, competition can be used to regulate the interaction among transport actors who seek access to limited shared resources, under conditions where not all requests can be simultaneously satisfied. To model competition in multimodal transport systems, a commonly studied distributed approach is the use of auctions. An auction is a market mechanism governed by a clear set of rules that determine resource allocation and pricing based on bids submitted by participants [64]. Auctions have been used in transport settings to manage congestion and regulate access to limited resources, such as slot allocation for airlines [65]. Similar applications can be found in other areas, including car-sharing [66] and berth allocation at marine terminals [67]. Another way to apply coordination in a competitive setting is through negotiation, a process through which agents with different goals or preferences reach a joint decision by exchanging proposals. In competitive settings, negotiation acts as a form of communication between agents and enables them to coordinate their actions without centralized control. Negotiation among multiple agents in the air transport sector has been studied to assess system performance, particularly in relation to the level of decision-making autonomy and the effectiveness of coordination between stakeholders [68]. Negotiation-based coordination to allocate airport resources among competing airlines was also used to demonstrate improved efficiency and adaptability in dynamic scheduling scenarios [69].

Coordination in a cooperative setting is largely related to planning for the associated challenge and typically categorized into two approaches: unthreaded planning and interleaved planning [70]. Unthreaded planning considers planning and coordination as sequential and independent processes. On the other hand, interleaved planning combines the planning and coordination activities and is especially suitable for tasks involving group goals, as agents collaboratively explore the search space to construct a solution plan. In collaborative multimodal transport settings, multi-agent planning optimization techniques can play a crucial role in aligning the goals of different actors and resolving trade-offs between competing objectives. Multi-Objective Optimization (MOO) is one such method that can be categorized as unthreaded planning, as the system first generates a set of possible plans, and then applies optimization techniques to evaluate and select the most suitable ones based on multiple criteria. Examples of MOO in multimodal transport focus on balancing criteria such as minimizing waiting time, emissions, and vessel departure times in coordination between vessels in port areas [71]. Approaches of interleaved planning include Distributed Constraint Optimization (DCOP) and Prioritized Planning. DCOP uses information exchange between agents at a local level to coordinate towards an overall system objective. This method has already been applied in various transport domains, such as traffic flow problems [72]. Prioritized Planning is also a widely adopted method for addressing collaboration problems within the field of MAS, commonly applied in problems such as Multi-Agent Path Finding (MAPF) [73], where agents operate based on predefined priority orders. Exploring alternative priority structures, for example across modes, can provide valuable insights into more efficient traffic orchestration.

1.2. Research Questions

This dissertation explores traffic orchestration within a multimodal transport system and the role of the TO in applying targeted measures within a single mode or domain, while maintaining awareness of system-wide effects. The TO is central, as it can operationalize the core principles of traffic orchestration in complex, multi-actor scenarios, centered around integrated planning for multimodal transport. In this dissertation, orchestration is studied with a port-centric perspective, limiting the study to processes concerning seaports and airports. As natural hubs of multimodal activity, ports offer a concrete starting point for implementing orchestration in practice. Within the studied port environments, the application of polycentric management to regulate traffic by the TO is a main focus. The TO leverages polycentricity by actively engaging with stakeholders, in processes of collaboration, competition, and conflict resolution, with the purpose of facilitating coordination across stakeholders. Given the presence of multiple actors with differing agendas, it is considered critical to explore coordination through non-centralized, distributed decision-making mechanisms. Therefore, all the above components collectively shape the overarching question behind this thesis, which is to address the following research question (RQ):

How can polycentricity be leveraged to implement orchestration in port-centric multimodal transport systems?

Addressing the main question requires placing particular emphasis on the orchestrator's interactions with other stakeholders, such as TSPs, NUs, and other orchestrators. These interactions shape how decisions are made collectively, how priorities are balanced, and how coordination can be applied across domains and modes. Building on the conceptual foundation of polycentricity established in the previous sections, interactions among stakeholders can be characterized by both competitive and cooperative dynamics, under normal and disruptive operational conditions. To that end, it is clear that the main question must be explored from multiple perspectives. Thus, it is further divided into four supporting research questions, structured around key characteristics of the orchestration setting: the number of orchestrators involved, the number of transport modes considered, the operational conditions and coordination type, and the integrated management problem being studied, as follows:

RQ1: **How to apply orchestration for congestion management among competing Transport Service Providers within a single mode?**

The first RQ investigates how traffic orchestration can be effectively implemented within a single transport mode, with a particular focus on how competition is managed among stakeholders operating in the same domain. This question is a result of the limited studies on how interactions among TSPs can be utilized to reduce traffic in port settings and how the TO can leverage competition as a transparent and fair measure to manage congestion effectively.

RQ2: **How can multimodal collaboration between Transport Service Providers and Vessel Operators be realized through orchestration by a single orchestrator?**

Next, the focus shifts to interactions between multiple transport modes, emphasizing collaboration within a system managed by a single orchestrator. This question aims to explore the potential of novel approaches, such as diverse prioritization techniques tailored to the specific needs of different transport modes in port areas, facilitated by a TO steering the system to favorable outcomes based on cooperation.

RQ3: **How can different orchestration measures, realized by multiple orchestrators affect system recovery from disruptions of airport multimodal accessibility?**

Furthermore, the concept is expanded to multiple orchestrators, as it becomes particularly relevant in scenarios where disruptive occurrences lead to conflicts. The effects of multiple actors working together to recover from disruptions in airport multimodal accessibility remain underexplored, particularly concerning distributed decision-making and conflict management.

RQ4: How can the novel concept of demand responsive transport services enhance orchestration to improve airport multimodal accessibility?

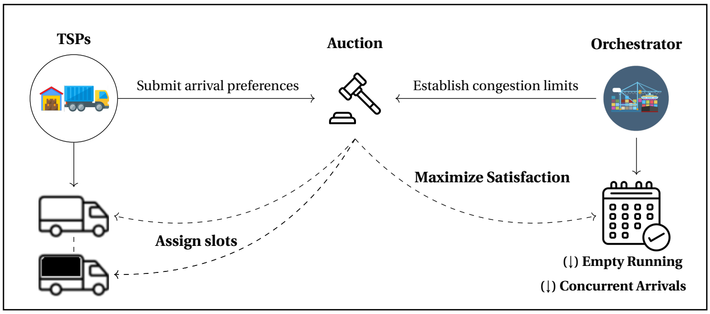
Finally, the exploration of new transport services is explored, through use of distributed methods. The integration of DRT services into multimodal systems is an emerging area with limited research that can be facilitated from orchestration. Enhancing airport accessibility is specifically explored, as existing studies mainly consider demand response in isolation or urban contexts without linking it to broader coordination frameworks.

1.3. Research Methodology

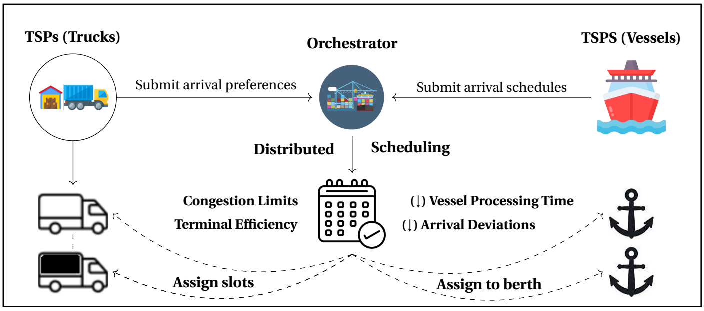
Building on the conceptual foundation established in the previous sections, this thesis adopts a methodology based on distributed approaches. To that end, MAS is selected as the overarching modeling paradigm to capture the dynamic behavior of autonomous stakeholders involved in traffic orchestration and their interaction. However, centralization remains deeply embedded in the operational reality of transport systems [59]. Thus, a turn to a fully distributed system might prove impractical and difficult to implement in a real-world scenario. Therefore, a hybrid approach which integrates centralization aspects in distributed systems is often considered. In such cases, centralization typically concerns enhancing the decision-making capacity of the TO and remains limited. The TO may apply centralized control to compensate for the absence of established norms, such as imposing limits with respect to certain conditions, but not take unilateral decisions with respect to traffic management.

Coordination between stakeholders and modes is modeled with multiple methods such as auctions and negotiation to model competitive resource allocation, and optimization techniques like prioritized planning and DCOP to support collaborative, goal-aligned decision-making. The effect of orchestration is investigated though a variety of case studies, as elaborated in Table 1.2. Two scenarios will be examined, one centered on freight transport and port terminal operations and the other on passenger transport and airport access in a multimodal manner. Beyond the type of scenario, the case studies are also differentiated by the number of transport modes and orchestrators involved. A structured approach is taken for the case studies, for different levels of orchestration as depicted in Figure 1.2.

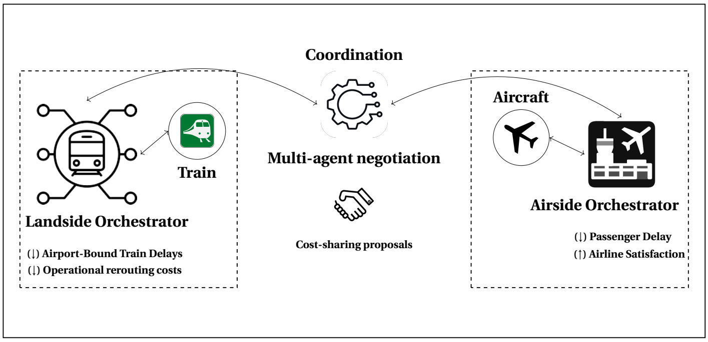
Case study A is based on the freight scenario and examines the regulation of truck arrivals at the port terminal to reduce congestion by introducing the orchestration concept in a system with a single mode and a single orchestrator. Elements of competition among TSPs are leveraged as an orchestration mechanism aiming at reducing congestion incurred by trucks competing for access rights at a multimodal



(a) Orchestration of a single mode in a port setting via auction (↓ signals minimization)



(b) Orchestration of multiple modes in a port setting via distributed scheduling (↓ signals minimization)



(c) Multiple orchestrators interacting in a multimodal context (↓ signals minimization, ↑ signals maximization)

Figure 1.2: Diverse settings of applied orchestration

Table 1.2: Degrees of freedom for examined case studies

Case Study	**Orchestrators**	**Modes**	**Transport Scenario**	**Research Question**
A	1	Truck	Freight	1
B	1	Truck, Vessel	Freight	2
C	2	Train, Bus, Aircraft	Passenger	3
D	*Support Tool*	Train, Bus, Metro, Taxi, Tram, Aircraft	Passenger	4

port terminal. The case study is building on the concept of appointment scheduling [54] as a way to support multimodal integration and propose a polycentric approach using a Vickrey-Clarke-Groves (VCG) auction mechanism [74]. The TO acts as the system's independent auctioneer that leverages the interdependence of trucking companies with respect to access, while maintaining certain centralized elements in the auction design, particularly regarding the determination of arrival quotas. The goal is to improve truck scheduling, promote fair bidding, and build communication channels and flexible rules between Marine Terminal Operators (MTOs) and Licensed Motor Carriers (LMCs).

In Case Study B, the focus remains on the freight scenario, but now the introduction of interactions across multiple modes are considered, again with a single orchestrator. Building on Case Study A, elements of appointment scheduling are incorporated with the concept of Vessel Dependent Time Windows [75] to introduce a collaborative, multi-actor approach that synchronizes vessel berth allocation with truck appointment scheduling through data sharing and terminal-level coordination. The TO is now significantly more involved in decision-making, leveraging the timing interdependence among different modes, but also representing the terminal's requirements and having the ability to reject solutions that do not meet terminal-imposed criteria, such as capacity constraints. It however, has no clear objective w.r.t, to a desired solution. The proposed approach moves away from competition and focuses on enhancing collaboration across modes. A new methodology, inspired by Prioritized Planning [76] and MOO, is developed to enable distributed scheduling between trucking companies and vessel operators.

In Case Study C, the focus shifts on the passenger transport scenario and multiple orchestrators are introduced to a system with multiple modes. In particular, the problem of air-rail integration is tackled by simulation focusing on optimizing policies among different orchestrators during disruptions affecting airport landside accessibility. In this case, TOs of different domains are fully engaged in competition and collaboration by formulating contrasting objectives between orchestrators such as minimizing operational costs and passenger delays. The approach highlights how targeted measures like and tactical flight delays [77] can improve efficiency during

1

periods of disruption.

Finally, in Case Study D the potential impact of traffic orchestration on transport operations is explored by introducing a DRT service. The proposed service enhances accessibility in PT networks by serving users in remote areas, especially those with extended first-mile connections to airports. It also relies on centralization of information at the TO level with respect to passenger access. Using a DCOP formalism [72], taxis are optimized for ride-sharing and integrated with PT, reducing users' travel time while efficiently linking them to major transport hubs.

1.4. THESIS OVERVIEW

In **Chapter 2**, RQ1 is addressed, where the benefits of orchestration within a single mode are explored. **Chapter 3** acts as an extension to the first case study but focusing on the collaborative aspect of orchestration, in order to answer RQ2. In **Chapter 4**, the shift to the passenger transport scenario aims to increase complexity of the system by introducing multiple orchestrators and analyzing interactions between them in order to answer RQ3. **Chapter 5** explores the impact of traffic orchestration through the development of a new transport services to address RQ4. Finally, **Chapter 6** concludes this thesis by evaluating and reflecting on the obtained outcomes for the research questions of the thesis. This chapter also offers directions for future research.

While each chapter is designed to stand on its own, readers are encouraged to begin with **Chapter 1** before proceeding further. **Chapter 2** should ideally be read prior to **Chapter 3**, as it provides foundational context. **Chapters 4** and **5** are more self-contained and can be read independently. Figure 1.3. presents a visual overview of the thesis structure, highlighting the suggested reading order.

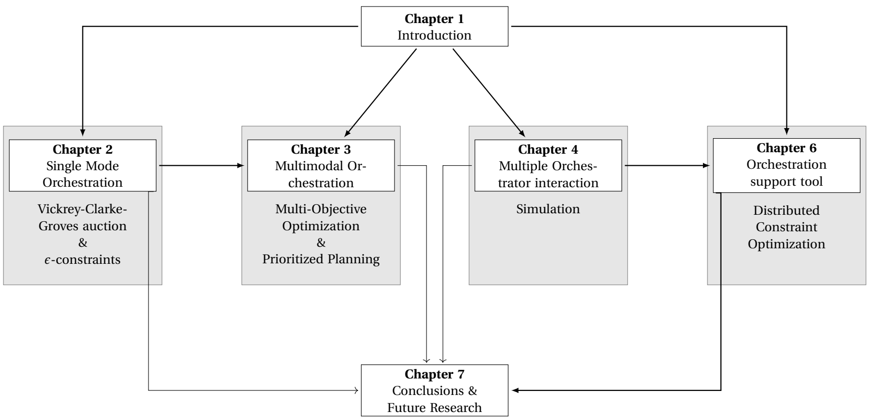


Figure 1.3: Thesis Outline

2

Single mode orchestration among competing Transport Service Providers

Chapter 2 introduces the concept of orchestration for a single mode within a port environment. In particular, the problem of truck congestion at marine terminals is studied, due to the unregulated arrival of Licensed Motor Carriers. This problem highlights the resource interdependence of different Transport Service Providers, with respect to access rights for entering the terminal. To deal with this issue, the Traffic Orchestrator is introduced as a coordinating entity leveraging polycentricity by introducing a competitive mechanism to regulate access among TSPs.

The proposed approach addresses the problem through the framework of truck appointment scheduling, a frequent congestion control mechanism for marine terminals. An auction mechanism that allocates truck slots equitably and emphasizing transparency is introduced to ensure efficient resource use. The system is partially distributed, with the derivation of schedules determined exclusively by the TSPs preferences, but with the TO introducing certain norms, ensuring certain conditions are met with respect to terminal efficiency.

First, Section 2.1 and Section 2.2 provide an overview of the problems faced by marine terminals and the state of the art regarding truck appointment system models and algorithms. Section 2.3. and Section 2.4 define the main problem statement and methodology for designing the TAS and auction mechanism. An experimental campaign is then undertaken in Section 2.5 to assess the added value of the proposed approach, followed by conclusions and future research avenues in Section 2.6.

This chapter is based on the following research article: Parmaksizoglou, I.A.; Bombelli, A.; Sharpanskykh, A. A Novel Auction-Based Truck Appointment System for Marine Terminals. Logistics 2024, 8, 40. https://doi.org/10.3390/logistics8020040

2.1. Introduction

The continuously increasing growth of international maritime trade over the past three decades has resulted in a significant upsurge in the volume of cargo being transported. Cargo terminals, serving as exchange hubs for freight from one leg of the multimodal chain to another, are under growing strain as the yearly cargo throughput across ports has exceeded 10 billion, according to a recent review by [78]. Nevertheless, the maritime freight industry encounters significant challenges, some of which are distinct from those in other modes of transport. These challenges include port terminal congestion, labor strikes, adverse weather conditions, shortages of shipping containers, and delays in customs procedures [79, 80]. From an operational standpoint, port congestion in maritime terminals is a significant issue primarily driven by the unpredictability and increased flow of truck arrivals, potentially resulting in substantial delays and environmental harm if not effectively managed. This congestion not only leads to operational inefficiencies, strained community relations, and sustainability concerns but also erodes the port's competitive edge. This problem has also been exacerbated by the adoption of multimodality. Multimodality has contributed to expanding the global reach and reliability of freight transport, but it has also resulted in an increase in drayage operations in ports, i.e., the transport of cargo over short distances via ground. An example of such operations is the transport of cargo from the port terminal to a close depot, in order to facilitate modal change, in the overall multimodal cargo delivery process. Coordinating between different modes of transport is essential to alleviate congestion in marine terminals as it enables seamless transfer of cargo, reduces dwell times, and optimizes the use of available infrastructure and resources, ultimately improving the efficiency and sustainability of the entire supply chain.

A common measure to mitigate congestion used by ports is the implementation of a Truck Appointment System (TAS). A TAS has the primary goal of reducing gate congestion at port terminals by flattening the gate activity to an efficient and harmonious level [54]. Under more common TAS implementations, port operators indicate available time windows with a fixed amount of appointments for trucks accessing terminals; hence, a port operator practically regulates the arrival rates of incoming trucks. This provides substantial benefits to all stakeholders, with port operators having a more robust and efficient environment to coordinate, logistics companies being able to better schedule itineraries, and truckers experiencing milder delays in terminal gate queues.

TASs have been the subject of active research since the beginning of the century, with most implementations aimed at modifying external truck arrival patterns to align them with available resources and terminal-imposed quotas [46, 81]. Although TASs offer significant benefits, they also present some limitations. One of the most significant issues is the lack of transparency in their design, leading to a gap in trust between the involved partners, particularly from Licensed Motor Carriers (LMCs) operating the trucks toward Marine Terminal Operators (MTOs). This trust gap mainly arises from concerns about how appointment quotas are established, whether special quotas exist for specific customers, and the determination of fees [45]. Limited flexibility within the design of TASs is another major issue. All actors involved in the system desire flexibility, with MTOs seeking more flexibility from carriers in terms of service availability within the day. On the other hand, LMCs are seeking more flexibility in appointment rescheduling and the ability for multilayered planning, such as piggybacking appointments to schedule double moves. In the context of truck scheduling, a double move is a delivery to a warehouse followed by a pickup from the same warehouse, in order to reduce the number of empty truck trips and trucks used. The reduction in empty truck trips, particularly in truck scheduling, has not been extensively studied in the development of TASs [47].

To that end, the primary goal of this study is the development of a TAS that addresses these two gaps in current implementations. In order to increase transparency and flexibility, inspiration is taken from polycentric systems of governance as a way to manage common pool resources for competing actors in a decentralized manner. A polycentric system is defined as a system of "many autonomous units formally independent of one another, choosing to act in ways that take account of others, through processes of collaboration, competition, and conflict resolution" [15]. A polycentric system has harmonized rules based on local conditions and affirmation that those affected by the rules can participate in modifying them [16]. Mapping relationships between all involved actors is necessary under a polycentric system in order to create arbitration mechanisms for conflict resolution and collaboration and enable the system to self-organize. Collaboration has been identified in the literature as one of the key drivers to improve supply chain operations [82, 83], but its actual implementation is constantly facing setbacks due to acceptance issues by stakeholders at the same level of the supply chain. However, a port environment is increasingly suitable for such a collaborative form of management, as it is already partly polycentric [24].

In the context of a TAS, the use of an auction is proposed to act as a capacity balancing mechanism that adheres to polycentric principles for the determination and scheduling of truck activities. The common resource at stake in the proposed auction is the right of trucks to access the terminal during a specific time of day. The proposed auction acts as a demand-varying toll during peak periods to alleviate congestion. This approach ensures that the appointment process is determined equitably but also incentivizes logistics companies (and by extension LMCs) to be more flexible, since their inflexibility could result in additional costs. Moreover, to promote flexibility by MTOs, the optimization of carrier-specific criteria in the TAS design is incorporated, namely the maximization of double moves. The proposed optimization strategy satisfies the polycentric system's requirement that those impacted by the rules (carriers, shippers, truck drivers, etc.) have a say in modifying them, leading to more equitable coordination and synchronization of arrivals. The TAS is designed with a focus on the truck hauling process, which is crucial for logistics companies and LMCs. This emphasis can help boost acceptance of the developed system among these stakeholders, while also providing opportunities for both parties to show flexibility.

The contribution of this study is twofold. To the best of the authors' knowledge, for the first time, an auction mechanism for collaborative truck arrival management at a marine terminal is presented. A negotiation protocol that governs participants' interaction (LMCs and MTOs) is defined, as well as a Winner Determination Problem (WDP) formulated as a Mixed-Integer Linear Programming (MILP) model and a pricing rule that enforces sincere bidding. Secondly, by means of an experimental framework, an exploratory analysis is performed aiming at finding common ground solutions between MTO and LMC interactions as a way to highlight opportunities for collaboration.

2.2. Literature Review

2.2.1. Truck Appointment Systems

The last two decades have seen significant growth in the literature on TASs, with a primary focus on developing optimization models for managing truck arrivals based on terminal-related objectives. A main aspect of most TAS implementations is the minimization of deviation from the preferred arrival time of external trucks. For example, a simulation–optimization model as a way to minimize inconvenience incurred by deviation from preferred arrival times in parallel with truck turnaround times was proposed by [48]. However, the problems and consequences of port congestion are multifaceted; hence, many different TAS implementations have been proposed to mitigate its specific issues. In particular, associating the allocation of straddle carriers to different transport modes using data on preferred arrival times of external trucks obtained from a TAS through a MILP model was studied in [49]. The main objective of this model was the minimization of terminal-related delays. The study conducted by [84] also delved into aspects of port logistics beyond the arrival of external trucks. To minimize waiting times for both external and internal trucks, they proposed a nonstationary queuing theory model that focuses on improving the gate and yard operations. The optimization of the container relocation process through a truck scheduling framework was considered by [85]. The authors developed a proactive decision support system aimed at minimizing terminal-related delays that takes into account essential parameters such as company preferences, yard schedules, and terminal quotas.

A specific aspect of port logistics often addressed by TASs is the optimization of drayage operations. Drayage is defined as “the transport of goods over a short distance, typically from a port to a nearby warehouse or distribution center, by trucks or other vehicles”. The implementation of a TAS that can lead to reduced operational time in the drayage problem across various logistics companies was explored in [81, 86] through a purely centralized approach that considers both MTO and LMC interests. The effect on drayage was also considered by [47]; however, focus was given to the minimization of “empty running” within terminals as a way to reduce emissions within a marine terminal. Empty running refers to the “transport of empty vehicles after they have been unloaded at their destination”. Similarly focus was given on reducing empty truck trips to boost port operations by minimizing turnaround time while also optimizing truck deviation from preferred arrival time using a combined data-mining and optimization approach in [87].

The need for collaboration among actors in the development of TASs is evident in increasing both transparency and flexibility by all actors. The effect of cooperation was explored in [88] through the development and evaluation of forwarder-focused, terminal-focused, and cooperative models that were evaluated through a Monte Carlo simulation. A decentralized negotiation process was proposed by [89] as a way to establish a collaborative appointment process between tracking companies and terminals. In [90], the authors continued the work to propose an iterative collaborative scheme with embedded pricing mechanisms. The use of pricing as a way to achieve system optimal appointments was first studied by [91], who suggested a methodology to create time-varying tolls to smooth arrivals in port areas. A two-phase optimization approach was used that first determined the arrival pattern that led to system optimality. Then, the desirable pattern of time-varying tolls with respect to the terminal operator was determined in order to shift arrivals to the system optimum. However, the introduction of collaboration within TASs can also lead to the adoption of revenue-neutral congestion measures, like tradable permits, as explored by [92], which do not have the penalizing nature of the implementation of a toll mechanism. The use of pricing for determining port access acts as a major inspiration for the auction-based TAS developed in this study.

2.2.2. AUCTIONS FOR DEMAND CAPACITY BALANCING

To the best of the authors' knowledge, no previous academic literature has utilized an auction-based mechanism to manage arrivals within a TAS framework. However, auctions have been examined for demand capacity balancing in various transport-related problems, such as slot allocation for airlines in airport terminals, development of innovative urban mobility schemes, the shipping sector, and supplier selection in supply chain optimization. In [93], it was first suggested to utilize a sealed bid combinatorial auction to assign airport time slots to competing airlines. As the goal is to maximize demand satisfaction in the face of a capacity problem, the proposed auction requires the inclusion of contingency bids. A case study for Hartsfield Atlanta International Airport [94] explored the use of a combinatorial clock auction to enhance the use of airport time slots by maximizing passenger throughput while ensuring safety capacity, thereby reducing congestion and delays. The use of a Walrasian Auction to match supply and demand was explored in [95], while the use of an ascending-bid multiunit auction was explored by [96]. In [65] a quantity-contingent auction to allocate airport departure and arrival slots, while imposing constraints on market power was proposed. A quantity-contingent auction is a type of auction mechanism where bidders submit bids for a specific quantity of a good or service, and the auctioneer selects the winners based on their submitted quantity and the prevailing price. To ensure truthful bidding, the authors chose to use Vickrey–Clarke–Groves (VCG) prices [74], which are known for being incentive-compatible, i.e, every participant can obtain the best possible outcome for themselves by behaving in accordance with their true preferences.

In the context of supply chain optimization, a two-stage auction mechanism for selecting third-party logistics (3PL) suppliers in fourth-party logistics (4PL) operations was proposed in [97], incorporating 3PL suppliers' attributes for risk aversion as the first step for multicriteria decision making. With respect to the berth allocation problem within a marine terminal, an exploratory analysis of different auctions was performed in [67], focusing on profit maximization of the terminal. Under a similar setting, an implementation of a VCG auction for the problem of loading/unloading of ships was proposed by [98], as an improvement to the First-Come-First-Serve approach. The same scheduling problem was addressed by [99], who applied a multiperiod combinatorial auction able to handle large-scale instances of ship arrivals. Considering urban mobility, the use of a permit scheme to promote ride-sharing through a specific area was proposed in [100]. Permits were distinguished to users that drive alone, use ride-sharing, or use public transport, and they could only be acquired through the auction mechanism with a VCG pricing policy. A VCG mechanism for a car-sharing system with an embedded auction supporting multiple bids by users was also proposed in [66]. The shared parking problem was addressed by [101], through the development of two incentive-compatible double auctions. In general, the use of VCG is predominant within the literature and acts as a motivating factor for applying it within the developed TAS framework.

2.3. Problem Definition

This study focuses on tackling the issue of truck scheduling at a marine terminal through the creation of a TAS, with a particular emphasis on planning and managing the truck hauling process. Transporting goods and cargo through trucks involves moving them across various sites, such as distribution centers, customer sites, and port terminals, making the truck hauling process a crucial component of logistics and transport operations. Ensuring the smooth execution of this process is vital for companies in these industries. To achieve this, companies need to coordinate various tasks, such as scheduling, cargo loading and unloading, drayage, and packing. By doing so, these companies can enhance their operational efficiency and improve customer satisfaction. For the purposes of this study, customers are defined as either shippers, who are responsible for organizing and transporting goods from one location to another, or consignees, who are the intended recipients of the goods.

In this method, all incoming truck arrivals are associated with two distinct types of jobs: imports and exports. Export jobs are referred to as “pickup jobs”, since they require the pickup of goods from the shipper prior to travel to the terminal (to be exported). Conversely, import jobs are referred to as “delivery jobs”, since they involve the delivery of goods to the consignee after accessing the terminal. The available job types considered in the TAS are visually depicted in Figure 2.1. A delivery job comprises traveling to the terminal, gate clearance, loading, transport to the consignee, and unpacking, whereas a pickup job involves traveling to the shipper, packing, transport to the terminal, gate clearance, and unloading. The time cost of returning to the original depot is not factored in for either job type. It is evident from the figure that empty trucks are used for at least a portion of the transport process for both job types, resulting in a potentially higher number of trucks being required for a given set of jobs. To address this issue, a double move can be performed if a pickup and delivery job can be performed sequentially. Only cases where a delivery job follows a pickup job are considered, but not the other way around. This allows a single truck to be used for two jobs, without the need for additional transport costs.

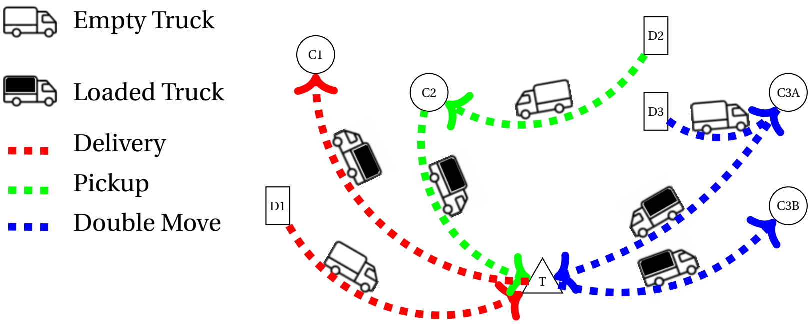


Figure 2.1: Schematic representation of different job types: Job 1 (red) is a delivery job from terminal T to consignee C1, originating from depot D1. Job 2 (green) is a pickup job from shipper C2 to terminal T, starting at depot D2. Job 3 (blue) is a double move by a truck starting from depot D3 that first visits shipper C3A and then consignee C3B.

The design goal is to create a TAS that optimizes the order of truck arrivals at the terminal gate based on requested job activities. The aim is to maximize the satisfaction of logistics companies and improve terminal conditions for all stakeholders. To achieve this, a transparent auction mechanism determined through system-wide utility optimization is proposed. Additionally, the impact of flexibility is measured and a collaboration framework among companies to explore solutions that are agreeable to all parties involved is initiated. The final TAS is realized through a specific methodological framework, which is detailed in Section 2.4.

2.4. METHODOLOGY

This section presents the methodological framework used to define the auction-based TAS. First, all the necessary concepts and processes to operate the TAS are explained, starting with the various components of the auction mechanism, including the main sets, parameters, and assumptions of the model (described in Section 2.4.1), the WDP formulated as a MILP (explained in Section 2.4.2), and the incentive-compatible price rule (elaborated in Section 2.4.3). To ease understanding, Figure 2.2 presents an overview of the processes that are part of the appointment system.

The process begins with companies initializing their job costs by utilizing inputs such as their depot and customer locations, along with associated deadlines for each job. This step is essential in determining lower and upper time limits for each job and overall drayage costs, as well as the flexibility of each job. Once these inputs are established, the company can proceed by submitting slot requests for each job they intend to perform during the day. A slot is the right of access for a truck within

2

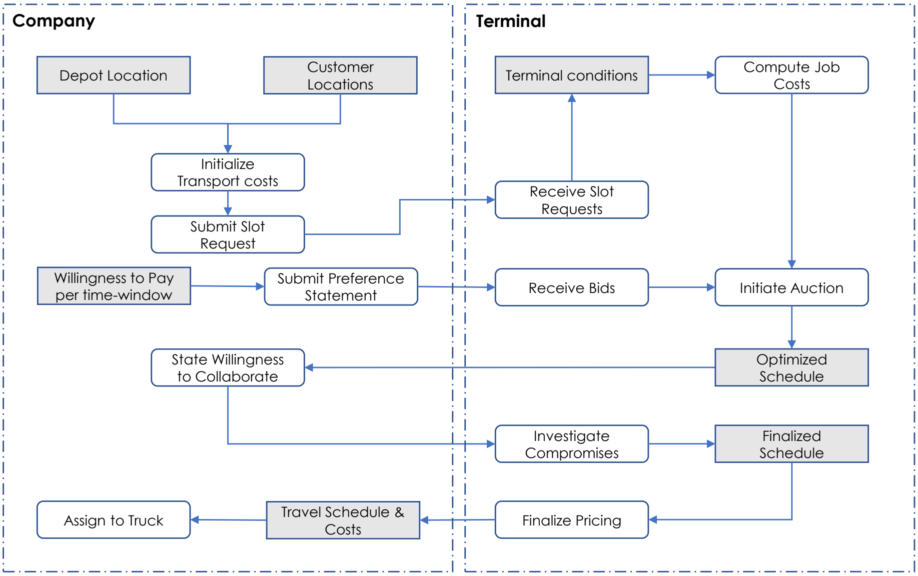


Figure 2.2: Underlying processes and inputs/data of the developed Truck Appointment System. Processes are denoted by rounded white rectangles, while data are denoted by gray rectangles.

a specific time period for a given time window, ranging from the time of arrival at the terminal to the time of gate clearance. The slot request is similar to an appointment process used by current TAS implementation and requires the company to provide designated information, such as the truck's plate number, trucker ID, booking number, and, in this particular case, the lower and upper time bounds for job execution, along with the computed transport costs from the previous step. The transport costs primarily pertain to the duration it takes for trucks to arrive at the terminal, without requiring reference to any internal trucking details. The stated lower and upper time limits offer the chance for companies to be rewarded by showing flexibility in planning their jobs. Tighter bounds increase the chances of a company being serviced within a specific time window but also increase time costs or may result in determining no feasible assignment for that job. Looser bounds, on the other hand, can result in lower time costs and increased chances of a successful job assignment. In parallel with this, companies must also submit a preference statement, indicating their willingness to pay for acquiring a slot at a different time window for any truck. In contrast to the slot request, the preference statement is submitted once for all company jobs and is essentially equivalent to the bids that a company may submit for each slot. The willingness to pay may vary from high values during periods of increased desirability for a company, to zero, which indicates that the company would only use the service at no charge during this time window. Reasonably, a negative willingness to pay is not considered. The statement of preference essentially shapes the market dynamics that will determine the outcome of the auction. Due to its aggregated structure, crafting the preference statement will require careful consideration by each company.

At an appropriate time before the considered time horizon, e.g., a day in advance, the terminal receives slot requests for all potential jobs and associated bids for that day per com pany. Initially, the terminal operator must finalize the job time costs by accounting for terminal-related operations based on local conditions, such as loading and mounting, which may result in some jobs being dismissed from consideration within the TAS, based on stated job limits. After that, the MTO can initiate the auction and provide an optimized schedule, which is then sent back to the companies. After receiving the schedule, each company needs to indicate their level of willingness to collaborate by specifying the percentage by which they are willing to accept a suboptimal solution as the final schedule, provided it contains characteristics that are desirable for both the MTOs and LMCs. This willingness to collaborate is essential as it provides a way for both parties to show flexibility and enables the synchronization of truck transport under multiple layers of planning. In this study, the increased time interval between any two different jobs is considered a characteristic that the MTOs aim to incorporate into the schedule, while the increased occurrence of double moves in the schedule is desirable for the LMCs. Once the terminal receives collaboration-related input, it can use a precommunicated strategy, such as taking the average or geometric mean across companies' percentages to investigate compromises and finalize the schedule for that day. Then, the final pricing for each slot assigned to a company is determined, taking into consideration the effect of collaboration in the pricing, and communicated to the company. while each company can assign a truck to a job, or multiple jobs in case of a double move.

Overall, the proposed TAS operates under the assumption that the terminal holds the authority to determine final truck schedules. Nevertheless, it takes a proactive approach by establishing a collaborative environment and clear communication protocols for trucking companies to contribute to the decision-making process. However, scheduling should consider external factors affecting trucking companies and existing relationships with terminals. Terminals can address this by temporarily using a TAS in a limited manner and reserving dedicated slots for specific clients, though this may reduce overall capacity for other companies. It is worth noting that this study does not delve into these special relationships, as their impact on the model's development could be deemed insignificant.

2.4.1. SETS, PARAMETERS, AND ASSUMPTIONS

The main sets and parameters involved in model development are presented here. All inputs involved are listed in Table 2.1. In the rest of this study, we use calligraphic, uppercase, and lowercase letters for sets and subsets, parameters, and decision variables, respectively.

First, a set of logistics companies $\mathscr{C} = \{1, 2, \ldots, c, \ldots, C\}$ are defined that carry out drayage operations on a marine cargo terminal during a given time horizon TH defined by a start-time T_{in} and an end-time T_{fin} so that $TH = T_{fin} - T_{in}$. TH

2

is divided into time windows of arbitrary but fixed length WL, determined by the terminal operator, and represented as $\mathscr{W} = \{1, 2, \ldots, w, \ldots, W\}$. For the sake of clarity, the first time window ranges from T_{in} to $T_{in} + WL$ and the last one from $T_{fin} - WL$ to T_{fin}. The terminal has predefined requirements that depend on the time window length, such as a quota TQ, which sets the maximum number of slots that can be auctioned per time window. Each company has a specific demand for slots during the designated time period and certain preferences for particular time windows. Unlike prior implementations of TAS that necessitated the binary declarations of preferred arrival time windows, the right of access is purely determined by each company's willingness to pay for the procurement of a single slot for a time window $w \in \mathscr{W}$. To simplify the analysis, the following assumption is used, based on the information obtained from the preference statement:

Table 2.1: Sets, subsets, and parameters used in the TAS framework.

Sets and Subsets	
$\mathscr{C}$	Set of companies, indexed by c
$\mathscr{D}$	Set of delivery jobs, indexed by j
$\mathscr{F}$	Set of trucks, indexed by f
$\mathscr{J}$	Set of jobs ($\mathscr{J} = \mathscr{P} \cup \mathscr{D}$), indexed by j
$\mathscr{L}$	Set of phases, indexed by l
$\mathscr{P}$	Set of pickup jobs, indexed by j
$\mathscr{W}$	Set of time windows, indexed by w
$\mathscr{D}_c$	Subset of delivery jobs of company c
$\mathscr{F}_c$	Subset of trucks owned by company c
$\mathscr{J}_c$	Subset of jobs ($\mathscr{J}_c = \mathscr{P}_c \cup \mathscr{D}_c$) of company c
$\mathscr{M}_j$	Subset of delivery jobs that can follow pickup job j in a double move
$\mathscr{P}_c$	Subset of pickup jobs of company c
Parameters	
$A_{j,l}$	Time needed for phase l of job j
$B_{c,w}$	Bid of company c for a single slot at time window w
LB_j, UB_j	Lower and upper bounds for jobs j
TH	Duration of time horizon (minutes)
TQ	Terminal quota (trucks)
$V_{c,w}$	Willingness to pay for a single slot of company c at time window w
WL	Duration of time window (minutes)

Assumption 2.1 *The willingness to pay $V_{c,w}$ is represented by the bid $B_{c,w}$ made by company c for the acquisition of a single slot in time window w.*

Assumption 1 is not trivial, and it is important to enforce it through the use of incentive-compatible price rules (Section 2.4.3) like VCG [74] to ensure the sincerity of the bidders. In the context of the TAS, bids also indicate user satisfaction from the procurement of a slot for a specific job, again under the assumption of truthful bidding.

Given that company c's bid for a slot in a single time window w is represented by its willingness to pay, it can be assumed that the bid of a company for any of its jobs is equal to its bid for a slot in a single time window, which can be expressed as follows:

$$B_{j,w} = B_{c,w} \;\forall\; c \in \mathscr{C},\; w \in \mathscr{W},\; j \in \mathscr{J}_c \tag{2.1}$$

Jobs must be assigned to a truck operated by the associated company. The available fleet of trucks for job execution is represented as $\mathscr{F} = \{1, \ldots, f, \ldots, F\}$, and each company in the system has its own fleet of available trucks $\mathscr{F}_c \subseteq \mathscr{F}$.

Assumption 2.2 *The number of trucks in fleet $\mathscr{F}_c$ for company c can always cover the number of jobs $\mathscr{J}_c$ that the company operates.*

Assumption 2 can be relaxed by allowing a reduced fleet of trucks in some companies for a given set of jobs and thus making mandatory the assignment of double moves at these companies. However, refraining from that in the analysis, a system-wide approach is utilized when exploring the reduction in the number of trucks in the terminal, essentially enforcing the amount of double moves to a minimum feasible value. To formulate enforcement of double moves, the subset $\mathscr{M}_j$, which contains the candidate delivery jobs to follow pickup job j, is defined. It follows that $\mathscr{M}_j = \emptyset \;\forall j \in \mathscr{D}$, as a delivery job, cannot be the first job of a double move, as described in Section 2.3.

Assumption 2.3 *Subset $\mathscr{M}_j$ for $j \in \mathscr{P}_c$ contains jobs belonging to company $c \in \mathscr{C}$, as double moves are only possible between jobs operated by the same company.*

Assumption 3 is operationally justifiable, as a job can only be completed by the company that owns it. Relaxing this assumption could further increase the number of double moves within the marine terminal. However, it requires horizontal collaboration across different companies in the form of job exchange. This further entails sharing potentially sensitive information with competitors such as slot requests, which may be unrealistic. As already defined, within a slot request all the crucial information that ensures the successful execution of a job is provided by the company such as the lower bound LB_j and upper bound UB_j, signaling the earliest possible time for job launch and the latest possible time for job completion. Slot requests also contain information that defines the phase l of a job j and job-related time needed $A_{j,l}$.

Assumption 2.4 *We define for each job a set of three phases $\mathscr{L} = \{1,2,3\}$ related to pregate routing ($l = 1$), gate clearance ($l = 2$), and after-gate routing ($l = 3$), and we define the associated job- and phase-specific time cost $A_{j,l}$.*

Assumption 4 aggregates customer-specific time costs (e.g., transport time to the terminal) with terminal-related time costs (e.g., unloading time of a container) to a specific position within the time horizon of a job, as described in the *Compute Job Costs* process in Figure 2.2. For this case study, these time costs are considered deterministic and known a priori to TAS assignment.

2.4.2. WINNER DETERMINATION PROBLEM

Upon receiving all slot requests and preference statements from the different companies, the terminal can determine all job-related times based on expected terminal conditions and initiate the auction. A single-round sealed bid auction is used, with a WDP that maximizes users' satisfaction based on stated willingness to pay while establishing a feasible schedule based on slot request. To represent decisions made by the TAS, necessary decision variables are defined in Table 2.2.

Table 2.2: Decision variables for the Winner Determination Problem.

$s_{j,l}$	Continuous variable in $\mathbb{R}$. Start time of phase l (in minutes) for job j. For example, with $s_{5,2}$ the start time of the gate clearance phase $(l = 2)$ of the fifth truck $(j = 5)$ is mapped
$a_{j,w}$	Binary variable, equal to 1 if job j is scheduled to access the gate within time window w
f_{j_1,j_2}	Binary variable, equal to 1 if job j_1 is scheduled to access the gate before job j_2
b_{j_1,j_2}	Continuous variable in $\mathbb{R}_{\geq 0}$. Absolute temporal difference in scheduled access between jobs j_1 and j_2
$v_{j,f}$	Binary variable, equal to 1 if job j uses truck f
$d_{j,f}$	Binary variable, equal to 1 if delivery job j uses truck f to execute a double move
m_f	Binary variable, equal to 1 if truck f performs a double move

Using the described decision variables and the inputs described in Section 2.4.1, the WDP of the single-round auction is formulated as follows:

$$\max \sum_{j \in \mathcal{J}} \sum_{w \in \mathcal{W}} B_{j,w} a_{j,w} \tag{2.2}$$

subject to:

$$s_{j,1} \geq LB_j + TH\left(\sum_{w\in\mathcal{W}} a_{j,w} - 1\right) \qquad \forall j \in \mathcal{J} \tag{2.3}$$

$$s_{j,2} \leq WL(w+1) + TH(1 - a_{j,w}) \qquad \forall j \in \mathcal{J}, w \in \mathcal{W} \tag{2.4}$$

$$s_{j,2} \geq WLw - TH(1 - a_{j,w}) \qquad \forall j \in \mathcal{J}, w \in \mathcal{W} \tag{2.5}$$

$$s_{j,3} + A_{j,3} \leq UB_j - TH\left(1 - \sum_{w\in\mathcal{W}} a_{j,w}\right) \qquad \forall j \in \mathcal{J} \tag{2.6}$$

$$\sum_{j\in\mathcal{J}} a_{j,w} \leq TQ \qquad \forall w \in \mathcal{W} \tag{2.7}$$

$$s_{j,1} + A_{j,1} = s_{j,2} \qquad \forall j \in \mathcal{P} \tag{2.8}$$

$$s_{j,1} + A_{j,1}\left(1 - \sum_{f\in\mathcal{F}} d_{j,f}\right) = s_{j,2} \qquad \forall j \in \mathcal{D} \tag{2.9}$$

$$s_{j,2} + A_{j,2} = s_{j,3} \qquad \forall j \in \mathcal{J} \tag{2.10}$$

$$v_{j,f} + m_f \leq 1 + \sum_{w\in\mathcal{W}} a_{j,w} \qquad \forall j \in \mathcal{J}, f \in \mathcal{F} \tag{2.11}$$

$$v_{j,f} + m_f \leq 2 - \beta(1 - d_{j,f}) \qquad \forall j \in \mathcal{D}, f \in \mathcal{F} \tag{2.12}$$

$$v_{j,f} + m_f \geq 2d_{j,f} \qquad \forall j \in \mathcal{D}, f \in \mathcal{F} \tag{2.13}$$

$$\sum_{f\in\mathcal{F}_c} v_{j,f} = 1 \qquad \forall c \in \mathcal{C}, j \in \mathcal{J}_c \tag{2.14}$$

$$\sum_{j\in\mathcal{J}} v_{j,f} \geq 2m_f \qquad \forall f \in \mathcal{F} \tag{2.15}$$

$$\sum_{j\in\mathcal{J}} v_{j,f} \leq 1 + m_f \qquad \forall f \in \mathcal{F} \tag{2.16}$$

$$s_{j_1,2} - s_{j_2,2} \leq TH(1 - f_{j_1,j_2}) \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.17}$$

$$f_{j_1,j_2} + f_{j_2,j_1} = 1 \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.18}$$

$$b_{j_2,j_1} \leq s_{j_2,2} - s_{j_1,2} + 2TH(1 - f_{j_1,j_2}) \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.19}$$

$$b_{j_2,j_1} \geq s_{j_2,2} - s_{j_1,2} - TH(1 - f_{j_1,j_2}) \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.20}$$

$$b_{j_1,j_2} = b_{j_2,j_1} \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.21}$$

$$s_{j_2,2} - s_{j_1,3} \leq TH(1 - m_f) + A_{j_1,3} \qquad \forall c \in \mathcal{C}, j_1 \in \mathcal{P}_c, j_2 \in \mathcal{M}_{j_1}, f \in \mathcal{F}_c \tag{2.22}$$

$$s_{j_2,2} - s_{j_1,3} \geq -TH(1 - m_f) + A_{j_1,3} \qquad \forall c \in \mathcal{C}, j_1 \in \mathcal{P}_c, j_2 \in \mathcal{M}_{j_1}, f \in \mathcal{F}_c \tag{2.23}$$

$$v_{j_1,f} + v_{j_2,f} \leq 1 \qquad \forall c \in \mathcal{C}, j_1 \in \mathcal{P}_c, j_2 \in \mathcal{J} \setminus \mathcal{M}_{j_1}, f \in \mathcal{F}_c \tag{2.24}$$

$$a_{j,w} \in \{0,1\} \qquad \forall j \in \mathcal{J}, w \in \mathcal{W} \tag{2.25}$$

$$f_{j_1,j_2} \in \{0,1\} \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.26}$$

$$v_{j,f} \in \{0,1\} \qquad \forall j \in \mathcal{J}, f \in \mathcal{F} \tag{2.27}$$

$$d_{j,f} \in \{0,1\} \qquad \forall j \in \mathcal{D}, f \in \mathcal{F} \tag{2.28}$$

$$m_f \in \{0,1\} \qquad \forall f \in \mathcal{F} \tag{2.29}$$

$$s_{j,l} \in \mathbb{R}_{\geq 0} \qquad \forall j \in \mathcal{J}, l \in \mathcal{L} \tag{2.30}$$

$$b_{j_1,j_2} \in \mathbb{R}_{\geq 0} \qquad \forall j_1 \in \mathcal{J}, j_2 \in \mathcal{J} \setminus \{j_1\} \tag{2.31}$$

The objective formulated in Equation (2.2) maximizes the collective value placed on slots by individuals involved in the auction. This objective could alternatively be understood as optimizing user satisfaction or the effectiveness of the system's allocation. Constraints (2.3)–(2.6) enforce the assignment of each job to a specific time window while guaranteeing that such an assignment is made only when the lower Equation (2.3) and upper Equation (2.6) time bounds are not violated. Additionally, in constraint (2.7), a total limit of assignments per time window based on the quota TQ set by the terminal is imposed. Constraints (2.8)–(2.10) ensure that the phases of a job are executed sequentially. However, since a job may be performed as part of a double move with a different starting phase than the planned one, an indicator variable $d_{j,f}$ is introduced to signal such an occurrence. If the indicator variable $d_{j,f}$ is set to 1, the starting phase of the job becomes equal to phase 2 Equation (2.9). With constraint (2.11), the assignment of a job to a specific time window is linked to an assignment within a truck and possibly a double move. With constraints (2.12)–(2.13), the decision variables $v_{j,f}$ and m_f are forced to be unitary if decision variable $d_{j,f}$ is unitary, and it is also enforced that at least one of them is zero otherwise. For constraint (2.12), β is denoted as a small value close to zero so that $v_{j,f}$ and m_f cannot be both unitary if $d_{j,f}$ is zero. Constraints (2.14) ensure that each job j is assigned to a truck owned by the company in charge of j. Constraints (2.15)–(2.16) force that two jobs should be assigned to a truck if m_f is unitary. Constraints (2.17) ensure that $s_{j_2,2} \geq s_{j_1,2}$ if j_1 is scheduled to be serviced at the gate before j_2. Constraints (2.18) ensure that either j_1 precedes j_2 or vice versa. Using indicator f_{j_1,j_2}, the absolute temporal difference in these two jobs concerning gate access can be computed via constraints (2.19)–(2.21). Constraints (2.22)–(2.24) assert that when a truck is performing a double move, the delivery job can start immediately after the end of the pickup job and that only appropriate jobs are considered. Finally, Constraints (2.25)–(2.31) define the nature of the decision variables. In particular, with $\mathbb{R}_{\geq 0}$, the set of non-negative real numbers is defined.

The WDP establishes the optimized schedule from the perspective of revenue maximization and by extension social optimum, since we operate under the assumption that bidders state their true valuations for gaining access to the port. Concerning terminal-imposed requirements, the only existing parameter is that of time window quota, representing the maximum productivity rate of a terminal during a time window. As previously described, the optimized schedule is shared with logistics companies, and their willingness to collaborate is requested to identify opportunities for compromise. The proposed methodology involves optimizing the schedule through the inclusion of two additional conditions that complement the primary outcome and introduce collaboration in the system. These conditions could be included as part of the objective function to maximize, as they represent criteria that are desirable in the resulting schedule. However, the use of a single-objective metric is preferred for the WDP when dealing with an auction mechanism. Hence, the use of the well-known ϵ-constraint method for multiobjective optimization problems is exploited. This method involves reformulating the additional conditions as constraints to create a single objective function with multiple objective criteria [102], where the right-hand side of the additional constraint is changed to provide a range of solutions. Because more stringent requirements on the additional constraint negatively affect the solution quality, the set of solutions can then be mapped in a Pareto-front fashion. This is paramount when dealing with external actors characterized by contrasting needs. The specific constraints for the developed WDP are defined as follows.

Definition 2.1 *ϵ-constraint #1—Temporal Difference; Assignment of jobs is restricted to a minimum time difference ϵ_{td} between any two nonidentical jobs.*

$$b_{j_1,j_2} \geq \epsilon_{td} \cdot f_{j_1,j_2}, \ \forall j_1 \in \mathscr{J}, j_2 \in \mathscr{J} \setminus \{j_1\} \tag{2.32}$$

Definition 2.2 *ϵ-constraint #2—Double Moves; At least a minimum number of double moves ϵ_{tr} should occur within a day.*

$$\sum_{f \in \mathscr{F}} m_f \geq \epsilon_{tr} \tag{2.33}$$

The ϵ-constraint #1 is primarily beneficial for the terminal, but it can also be argued that enforcing this constraint is advantageous for LMCs because the increased time gap between jobs can function as a slack to absorb minor delays. Similarly, while ϵ-constraint #2 is focused on LMCs, enforcing this requirement can increase the desirability of the terminal. To apply the ϵ-constraints, the maximum values for ϵ_{tr} and ϵ_{td} (explained in Section 2.5) that allow feasible solutions must be established and iterate over user-defined feasible values. However, the final schedule is based on the average willingness to collaborate, representing the maximum allowed drop in revenue after applying the ϵ-constraints. For example, if the average willingness to collaborate is 10%, the search for solutions with increased ϵ_{tr} and ϵ_{td} will not include any objective values that are not at least 90% of the original solution. Overall, the application of ϵ-constraints #1 and #2 will result in revenue that is less than or equal to the optimized solution generated by the WDP. Nonetheless, by implementing effective pricing rules, this trade-off can be leveraged.

2.4.3. PRICING POLICY

After computing a job assignment strategy via the WDP, it is essential to implement a rule for determining the payment for each job per time window. This pricing rule must be unambiguous to all auction participants before the start of the auction. Ideally, the pricing rule should satisfy two criteria: individual rationality, meaning that the price paid should be equal to or less than the maximum amount each participant is willing to pay for a truck to acquire a slot within a specific time window, and incentive compatibility, meaning that participants will have an incentive to place truthful bids during the auction. As stated in Section 2.4.1, each company has a private value $V_{c,w}$ for acquiring a single slot at a specific time window, representing their willingness to pay. To ensure an efficient combinatorial auction design, it is crucial to establish prices for the allocated resources that encourage bidders to set their bid prices ($B_{c,w}$) equal to the values they have assigned to the resources ($V_{c,w}$), as stated in Assumption 1. The first-price policy, where bidders pay the initial bid amount, does not prevent speculative behavior and is not incentive-compatible. As an alternative, the VCG policy (also called the second-price policy) is commonly used because it has been extensively shown to be effective in the literature. The VCG policy is incentive-compatible and has been proven to be effective for many variant WDPs [65].

Let us define R^* as the maximized revenue determined from the WDP without any ϵ-constraints. $R^*(w)_N^M$ is further distinguished as the partial maximized revenue acquired in time window w by auctioning M slots across N companies. Then, the general equation for a VCG payment $pay_{c,w}$ of company $c \in \mathscr{C}$ per time window w is expressed in Equation (2.34):

$$pay_{c,w} = R^*(w)_{-(c)}^M - R^*(w)_N^{-(c)} \tag{2.34}$$

$R(w)_{-(c)}^M$ represents the system's optimal outcome for the WDP if the bid Bc, w for that time window is assumed to be zero. On the other hand, $R(w)_N^{-(c)}$ refers to the optimal outcome of the WDP excluding the revenue from bid $B_{c,w}$. Essentially, a VCG payment is equal to the opportunity cost or marginal harm caused to other participants. When the sum of bids of the second-best combination is equal to the current best without the selected company, the price they will pay will be the same as their original bid. In all other cases, the price paid by the selected participant will be lower, thus also proving individual rationality. In the end, the utility $u_{c,w}$ gained by each company c for a slot at time window w is equal to

$$u_{c,w} = V_{c,w} - pay_{c,w} \tag{2.35}$$

The computation of VCG prices requires solving the WDP $|\mathscr{C}| \times |\mathscr{W}|$ times, which can be computationally challenging in practice. A simpler alternative is to use the second-price rule, where each company pays the bid equal to the second-highest bid after their own. In the context of the TAS, a different rule to reduce complexity is adopted. Since revenue maximization is not the main goal of MTO, but rather congestion mitigation, an arbitrary congestion limit c_l for each time window is established. If the limit is exceeded in the assignment obtained from the WDP, that time window is considered congested, and the fees are determined via the VCG process as described above. However, if the limit is not exceeded, all fees related to that time window are considered to be zero, and no computation of VCG prices is required. This significantly reduces the amount of prices to be computed.

To make the implementation of the ϵ-constraints more desirable, the pricing mechanism needs to be modified to account for the cost of collaboration. The pricing mechanism should consider the decrease in user satisfaction represented by revenue R^*, resulting from the introduction of these constraints. When ϵ-constraints are introduced (as described in Section 2.4.2), the difference in utility $L_{c,w}$ per company and time window compared with the original assignment is computed among different combinations of ϵ-constraints, and discounted/added to the updated prices to reflect the incurred inconvenience and benefit. The pricing policy is described in Algorithm 1. The pricing policy used in the TAS implementation is not budget-balancing across iterations, which implies that the total payments may not match the solution obtained by the original WDP. Nonetheless, this characteristic can also prove desirable for trucking companies as it can relate to a direct way of remuneration in case of incurred inconvenience.

Algorithm 1: Pricing Policy

```
Data: Initial Schedule a'_{j,w} ; Final Schedule and Revenue a*_{j,w}, R* ; Bids B_{c,w}
Result: Prices pay_{c,w} and utilities u_{c,w} per company for each time window
for w ∈ 𝒲 do
    for c ∈ 𝒞 do
        pay_{c,w} = 0
        if Σ_{j∈𝒥} a_{j,w} ≥ c_l then
            Calculate R*(w)^M_{-(c)} by setting B_{c,w} = 0 and resolving WDP for final
             ε_td, ε_tr
            R*(w)^{-(c)}_N = R* − Σ_{j∈𝒥𝒞} a*_{j,w} · B_{c,w}
            L_{c,w} = Σ_{j∈𝒥𝒞} a'_{j,w} · B_{c,w} − Σ_{j∈𝒥𝒞} a*_{j,w} · B_{c,w}
            pay_{c,w} = R*(w)^M_{-(c)} − R*(w)^{-(c)}_N − L_{c,w}
            u_{c,w} = B_{c,w} − pay_{c,w}
        end
    end
end
```

2.5. EXPERIMENTS

In this analysis, the practicality and applicability of the developed model and solution methodology are validated. Specifically, both the scalability of the approach under increased problem sizes and also its ability to accurately serve users in a way that the social optimum is maximized is tested. To this end, the TAS is benchmarked under randomly generated instances that incorporate real-life characteristics. These instances were created for a hypothetical terminal, which was required to coordinate truck scheduling operations with 10 logistics companies in the surrounding area. The specific demand per company varied across the examined instances, but it was generally assumed that each company would send between 5–15 trucks per day. This demand level was consistent with that of a medium-sized freight terminal, as indicated by insights gathered from expert interviews. The terminal was assumed to operate for 10 h each day (e.g., 7:00 AM–5:00 PM), which translates into a planning horizon of 600 min such that $T = [0, 600]$. The planning horizon T is then divided into a total of 10 time windows with WL = 60 min. Appointment quotas for each time window were considered to be flat and set to a maximum of 15 trucks. Jobs were randomly generated to be either related to pick-up or deliveries.

Under the assumption that the depots of origin of the logistics companies were located in close proximity to the port, the travel time in minutes from depot to terminal is distributed using the following uniform distribution $\mathcal{U}(10, 30)$. However, transport time costs from the terminal/depot to consignees/shippers were expected to be more time-consuming, so sampling from $\mathscr{U}(30,90)$ was utilized. To determine the time costs associated with terminal operations, examples from the literature are referenced. Mounting and unmounting times were assumed to last 5 min [103], while packing/unpacking times at the customer end were uniformly distributed as $\mathscr{U}(5,60)$ [104]. Thus, the time costs related to accessing the terminal were calculated based on depot-to-terminal transport costs for deliveries and depot-to-consignee transport costs, packing, and consignee-to-terminal costs for pickups. Likewise, time costs related to accessing the terminal after gate clearance were determined based on mounting, depot-to-shipper transport, and unpacking costs for deliveries, while pickup costs were calculated based on unmounting time costs. The gate clearance time costs were set to a minimum of 2 min [105].

For each job, an assumed range of flexibility from 60 to 240 min, measured in half-hour intervals, per company is used. To establish the lower and upper time bounds, the total job costs are combined with each company's flexibility to determine the feasible makespan for job execution. This makespan was then aligned with the time window where the company's willingness to pay was the highest to establish a clear timeline for job execution. The assumed willingness to pay of each company was set to vary between €0 and €20, which was determined based on the possibility that a company may not want to bid for a slot at all or may be willing to bid slightly higher than examples of currently applied surcharges (€15) for booking slots during congested time windows using a First-Come-First-Serve policy [106]. As slot requests fluctuate throughout the day and willingness to pay for a slot is the main determinant of this fluctuation in this approach, it is hypothesized that the willingness to pay for a slot is either uniformly distributed ($\mathbb{P}_1$) across the day or higher on average during midday ($\mathbb{P}_2$), which indicates greater demand (peak hour) during that time. This will help in benchmarking the TAS under different demand scenarios.

Focusing on algorithmic specifications, Gurobi 11.0.0 [107] was used to solve all MILP models. Unless differently specified, the numerical results were obtained using an Intel Xeon Gold 6226R CPU. All necessary transformations of input for the pricing mechanism and VCG policy were conducted in Python. In all instances, we imposed a time limit of one hour to also validate the applicability and scalability of the approach.

In Tables 2.3 and 2.4, the results for instances of $\mathbb{P}_1$ and $\mathbb{P}_2$ slot preferences are presented without any application of ϵ-constraints. The initial column displays the instance label, while the second column presents the number of jobs, which indicates the problem size. In the third and fourth columns, the objective function and computational time are reported, while the fifth and sixth columns indicate the elapsed time to reach the best solution and the deviation from the theoretical optimal. The last two columns present the final outcomes from the application of the auction. Specifically, they show the number of trucks that were assigned a slot within an examined instance and the total number of auctioned slots within congested time windows. The increase in problem size leads to an increase in computation time and the percentage of unserved trucks. This trend is observed in both distribution patterns of slot preferences, but it is more pronounced in pattern $\mathbb{P}_2$, where preferences tend to be concentrated in the middle of the day. In the worst-case scenario (Instance 12_$\mathbb{P}_2$), only 79% of trucks were served via the appointment system. In terms of computational time, all but one instance with $\mathbb{P}_1$ preferences proved optimality in less than 30 min and reached the optimal solution in less than 2 min. However, this was not the case for $\mathbb{P}_2$, where optimality was not always proven in instances with more than 70 jobs, although the best solution was generally reached in under ten minutes. This highlights potential issues in days with demand concentration at specific time windows. Nevertheless, solutions within 5% of the theoretically optimal solution were achieved in all but two instances during the one-hour runtime. Given that the time to reach the best solution was relatively short, a heuristic was not considered necessary. Finally, it was observed that the objective values between patterns varied significantly, indicating that revenue maximization in the WDP is linked to the concentration of arrivals within a given day.

Table 2.3: Key performance indicators from the application of TAS for $\mathbb{P}_1$ slot preferences.

Instance	No. Jobs	Obj.Value (€)	Sol.Time (s)	Time to Best (s)	Gap (%)	Served Trucks	Auctioned Slots
1_$\mathbb{P}_1$	40	593.7	3	1	0.0000	40	25
2_$\mathbb{P}_1$	45	714.9	2	1	0.0000	45	26
3_$\mathbb{P}_1$	50	789.8	5	3	0.0000	50	37
4_$\mathbb{P}_1$	55	812.8	22	6	0.0000	54	39
5_$\mathbb{P}_1$	60	895.0	11	2	0.0000	59	43
6_$\mathbb{P}_1$	65	1016.6	21	12	0.0000	64	56
7_$\mathbb{P}_1$	70	1060.0	144	15	0.0000	70	60
8_$\mathbb{P}_1$	75	1079.5	144	20	0.0000	70	61
9_$\mathbb{P}_1$	80	1277.1	26	12	0.0000	80	72
10_$\mathbb{P}_1$	85	1259.7	182	81	0.0000	82	68
11_$\mathbb{P}_1$	90	1258.8	1451	48	0.0000	85	69
12_$\mathbb{P}_1$	95	1292.9	1565	58	0.0000	88	70
13_$\mathbb{P}_1$	100	1455.4	3600	69	0.11	96	82

Figure 2.3 presents a Gantt chart illustrating the scheduling of 20 jobs under $\mathbb{P}_1$ slot preferences for the latter half of the observed day utilizing the TAS system. The visualized Gantt chart corresponds to results related to Instance 3_$\mathbb{P}_1$, as reported in Table 2.3. Across all case studies, there are 10 companies denoted by letters A to J, yet only four have jobs within the time windows 5 to 10 in this particular case. Each row in the Gantt chart depicts the schedule of a truck, which can either be a single job (e.g., truck T20 only performs job J19) or two jobs (e.g., truck T1 performs job J0 and J2 as a double move). It serves as a visual representation of the job schedule throughout the day, with the black vertical line indicating the gate access time. This scenario corresponds to a WDP achieving the maximum possible revenue, as evidenced in Tables 2.3 and 2.4, without incorporating ϵ-constraints by default. Upon visual inspection, it becomes evident that some trucks tend to

Table 2.4: Key performance indicators from the application of TAS for $\mathbb{P}_2$ slot preferences.

Instance	No. Jobs	Obj.Value (€)	Sol.Time (s)	Time to Best (s)	Gap (%)	Served Trucks	Auctioned Slots
1_$\mathbb{P}_2$	40	456.8	26	2	0.0000	40	29
2_$\mathbb{P}_2$	45	499.6	51	4	0.0000	45	34
3_$\mathbb{P}_2$	50	549.8	52	5	0.0000	50	37
4_$\mathbb{P}_2$	55	537.8	171	8	0.0000	51	37
5_$\mathbb{P}_2$	60	695.4	123	10	0.0000	60	53
6_$\mathbb{P}_2$	65	631.4	400	35	0.0000	62	52
7_$\mathbb{P}_2$	70	717.9	3600	660	1.05	68	63
8_$\mathbb{P}_2$	75	681.5	3600	100	2.68	67	61
9_$\mathbb{P}_2$	80	836.3	3600	116	2.51	72	66
10_$\mathbb{P}_2$	85	752.6	3600	153	2.72	71	66
11_$\mathbb{P}_2$	90	934.2	3600	262	4.5	78	69
12_$\mathbb{P}_2$	95	883.6	3600	343	10.4	75	70
13_$\mathbb{P}_2$	100	941.4	3600	262	12.6	82	81

cluster together in close proximity, resulting in scenarios where users may have limited time flexibility, while certain time periods remain notably vacant (e.g., Window 6). For example, company H has jobs clustered very close to each other. This might not pose operational issues in low-demand periods but may be very detrimental to port performance in high-demand periods. Interestingly, the use of double moves may be determined as an optimal solution even without applying the ϵ-constraints for collaboration. To identify solutions with even more favorable attributes, an exploratory analysis is employed involving the utilization of ϵ-constraints, as discussed in Section 2.4.2. To determine the generation of candidate ϵ-constraint solutions, which can be computationally expensive, the limits for double moves (ϵ_{tr}) and temporal difference (ϵ_{td}) are initially established in the tables. A maximum of 10 double moves is determined by solving the original instances with a modified objective function that prioritizes double move maximization. For the temporal difference, an arbitrary 5 min limit is considered to be reasonable. This approach allowed for quick identification of solutions that can be used as a starting point for all other instances. Next, alternative assignments with set ϵ-constraints are computed, beginning from the highest possible double move and temporal difference of 5 min and decreasing iteratively, until pinpointing a solution that matches the optimal solution in the base scenario.

Figure 2.4 shows that the application of ϵ-constraints does not necessarily have a negative impact on the optimal solution, but it is consistently equal to or less than the optimal solution. For example, in Instance 3_$\mathbb{P}_1$, imposing constraints of a minimum temporal difference of 5 min and at least six double moves results in a TAS with the same level of user satisfaction as the base scenario. However, for Instance 3_$\mathbb{P}_2$, applying the same constraints leads to a drop of nearly 10% compared with the base scenario, resulting in a revenue loss of approximately EUR 49 (from EUR 549.8

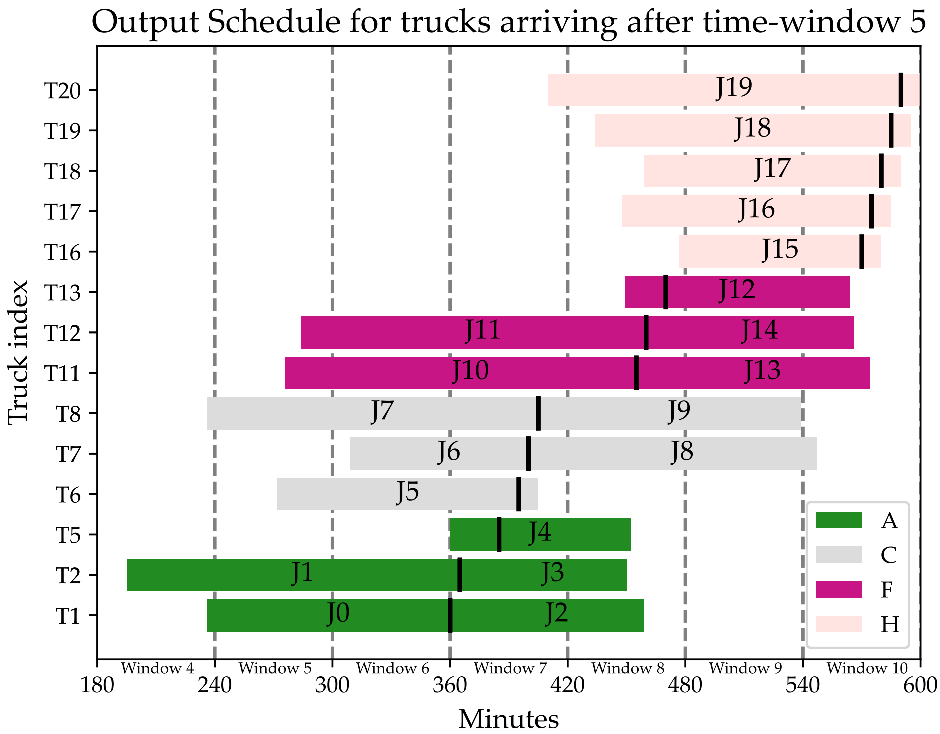


Figure 2.3: Partial schedule for Instance 3_$\mathbb{P}_1$ without application of ϵ-constraints. The black vertical line indicates truck arrival at the gate.

to EUR 505.5). To balance the competing objectives of decreasing user satisfaction and increasing ϵ-constraint parameters, the concept of willingness to collaborate is introduced in Section 2.4. This metric denotes the maximum acceptable reduction in performance during the ϵ-constraint analysis, and is arbitrarily set at 10%. Thus, only solutions that are at least 90% in value of the original solution were considered in this analysis. Based on this criterion, four solutions were excluded in both cases because they prioritized maximizing the number of double moves or temporal difference over user satisfaction. Lastly, the impact of pricing on the participating companies for Instance 3_$\mathbb{P}_2$ is demonstrated in a case with concentrated arrivals where the ϵ-constraints method is already utilized, in Table 2.5. Notably, all companies were assigned their desired slots during the observed day. In the base scenario, the total revenue collected from the auctioning of 37 slots was EUR 315, resulting in an average of EUR 8.5 per slot auctioned. Based on the WDP results, the average slot valuation was EUR 10 per slot, which again highlights the individual rationality in the auction. Under imposing of ϵ-constraints, the solution provided by $\epsilon_{tr} = 10$ and $\epsilon_{td} = 4$ is selected, as it is the one closest to the cut-off rate of 90% from the optimal solution (specifically at 91%). In this case, the second prices derived

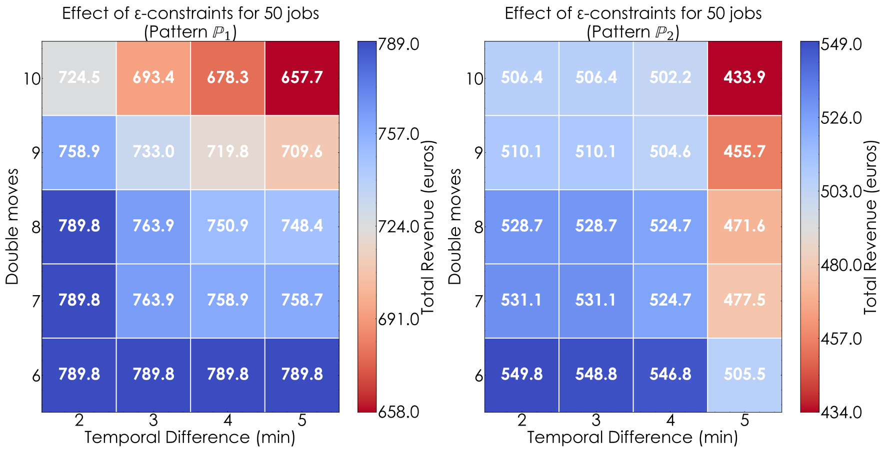


Figure 2.4: Effect of ϵ-constraints for Instances 3_$\mathbb{P}_1$ and 3_$\mathbb{P}_2$ (50 jobs).

from the auction resulted in revenue almost similar to the first case (EUR 311), but after adjusting for the lost utility of the affected companies, the price dropped to EUR 267 for 36 slots, resulting in EUR 7.4 per slot on average. The ratio of utility to final price for both cases is 1.75 in the base scenario and 1.88 in the solution that includes ϵ-constraints. This indicates that, on average, spending a euro in the second case results in a higher gain in utility.

Table 2.5: Breakdown of auction result for Instance 3_$\mathbb{P}_2$.

	Paid Slots	**Total Utility**	**Sec. Price**	**Double Moves**	**Paid Slots**	**Total Utility**	**Sec. Price**	**Adj. Prices**	**Double Moves**
Comp.		**No ϵ-constraints**					$\epsilon_{td} = 4, \epsilon_{tr} = 10$		
A	4	60	13	0	5	47	16	4	2
B	5	54	46	0	5	55	46	47	0
C	5	48	47	0	5	48	47	47	2
D	5	52	32	0	5	35	32	15	2
E	5	79	71	0	5	76	71	68	0
F	5	16	16	0	3	24	10	18	2
G	2	62	28	0	1	39	18	0	2
H	0	40	0	0	0	40	0	0	0
I	3	58	13	0	4	59	22	23	0
J	3	83	49	0	3	79	49	45	0

2.6. Discussion

This study presented a new formulation for a TAS inspired by principles of polycentric management to enhance transparency and flexibility during scheduling.

Transparency is achieved by designing a clear auction mechanism that prioritizes user satisfaction and focuses specifically on the crucial operation of truck hauling. To satisfy the aim of enhancing flexibility for both MTOs and LMCs, a procedure to investigate solutions that meet the desired criteria of both parties without disrupting their operations significantly is developed. To accommodate terminals, the exploration of solutions with bigger gaps between jobs is performed so that they can distribute their operations more evenly. Meanwhile, LMCs gain more flexibility by providing them with schedules that allow for double moves, leading to reduced resource utilization.

The developed model allowed for the evaluation of the effect of the TAS on drayage operations with and without collaborative parameters in the process. Experimental results indicate that (1) as the problem size grows, the time required to find a solution increases considerably, but high-quality solutions are obtained quickly nonetheless; (2) the objective function can vary significantly based on the pattern of arrival preferences examined, indicating that application of the mechanism may be more appropriate under a day-by-day manner; (3) assuming revenue maximization, the TAS can service an average of 96% of trucks across various instances within their defined limits and terminal imposed parameters in the base scenario; (4) exploration of collaborative parameters can be accelerated when using the base solution as a warm-start; and (5) under the inclusion of collaboration, the applied pricing policy that incorporates a price reduction due to collaboration-related inconvenience results in greater utility for trucking companies on average.

Nevertheless, the partially decentralized nature of this approach comes with several inherent limitations. Firstly, the auction-based method could potentially lead to uneven resource distribution, based on the financial strength of the involved parties. This might result in certain participants obtaining more favorable time slots or resources, leaving others to grapple with congestion or delays, but this effect can be remedied through the inclusion of market power constraints [65]. Moreover, this decentralized setup presents fewer chances for direct optimization due to reduced control by the MTOs. It is also worth acknowledging that implementing this approach in a real-world scenario might encounter substantial resistance to change, particularly from participants who are accustomed to conventional methods. Overall, this marks the first attempt to develop a transparent and flexible TAS. Therefore, in order to facilitate a more practical implementation of the proposed method, it may be necessary to conduct additional refinement of the assumptions used in the model. For example, modifying Assumption 2 to better reflect fleet size limitations might require model enhancements to preemptively incentivize more double moves for better fleet utilization. Additionally, a more detailed mapping of internal port operations (such as rehandling) would further enhance the practical relevance of the TAS and overall benefit to the involved stakeholders.

In subsequent studies, attention will be directed towards modeling and enabling collaboration between stakeholders in the port area. As TAS remains the clearest form of communication between port terminals and companies, it can act as a foundation for developing a multiagent system with all involved parties that can fully support collaboration. Additionally, in this study, utilities of agents from acquiring a slot were generated randomly and merely treated as input for the auction. A dedicated study that clearly maps the derived utility of a company could pave the way to a better understanding of the decision making behind logistics companies and lead to the adoption of further measures of demand management for port terminals. Simultaneously, while the proposed TAS is adept at managing demand for medium-sized terminals, such as the one it was initially designed for, scaling its application to larger terminals can be facilitated by the development of a specialized heuristic. Finally, introducing uncertainty within the developed models will greatly improve the quality of the solutions. The utilization of stochastic recourse programming and scenario generation could improve the robustness of the derived schedules under uncertainty. Overall, it is clear that auction-based scheduling algorithms hold significant potential for resolving conflicts for TAS. It will be interesting to observe how this approach continues to develop in the future.

3

MULTIMODAL COLLABORATION IN A MARINE TERMINAL UNDER A SINGLE ORCHESTRATOR

Chapter 3 extends the concept of orchestration in ports for multiple modes, still under the coordination of a single orchestrator. Now, the problem shifts to synchronization of vessel arrivals with truck arrivals to reduce congestion both on the seaside and landside. The examined problem now explores the temporal interdependence of Transport Service Providers like shipping carriers and logistics firms. The Traffic Orchestrator's task within this problem is to leverage cooperation between two modes with shared agendas, by introducing a system to cater to both actors' preferences.

To model the problem a multi-agent, multi-objective model that facilitates the tactical planning of vessel berth allocation and truck appointment scheduling is developed. The proposed system is based on the interleaved planning approach, with a single orchestrator assessing trade-offs related to port terminal operations based on the preferences of multiple actors. The multi-agent system is supported by a novel methodology centered on prioritized planning developed to support in the identification of more and better common ground solutions.

First, Section 3.1 and Section 3.2 provide an overview of examined problem and motivation for the modeling approach chosen. Section 3.3 defines the main decision-making between agents in the proposed system and Section 3.4 explains the solution algorithms employed. A case study for a medium sized terminal is undertaken in Section 3.5 to assess the performance of the developed algorithm, followed by a discussion of results in Section 3.6.

This chapter is based on the following research article: Parmaksizoglou, I. A., Bombelli, A., & Sharpanskykh, A. (2025). A Multi-Agent Optimization Approach for Multimodal Collaboration in Marine Terminals. Logistics, 9(3), 110. https://doi.org/10.3390/logistics9030110

3

3.1. Introduction

The unprecedented growth of international maritime trade over the last three decades has resulted in significantly increased cargo volumes, heavily affecting marine terminals operations globally. Ports face daily issues such as congestion, air pollution, and delays that hinder their effectiveness and competitiveness. During peak hours, irregular truck arrivals and equipment shortages on the landside as well as increased vessel traffic on the seaside exacerbate these problems and highlight operational inefficiencies. These problems can create a domino effect on other port activities, further reducing productivity [108].

Port operations inherently involve a multimodal aspect because they serve as critical hubs where different transportation modes, such as maritime, road, rail, converge to facilitate the movement of goods. Hence, the aforementioned issues can be addressed by enabling terminals' transition towards an advanced multimodal transport system that leverages digital technologies and cooperation across stakeholders. Achieving coordination within multimodal systems requires streamlining administrative boundaries, fostering flexible and polycentric forms of management across modes, and increasing system resilience as emphasized by the Strategic Transport Research and Innovation Agenda [17]. Effective coordination is crucial because of the diverse and often conflicting goals of different stakeholders, varying private and public values, and differing preferences that must be harmonized to optimize the overall system performance.

Coordination among stakeholders in a multimodal marine terminal can be achieved across strategic, tactical, and operational levels. At the strategic level, stakeholders including shipping lines, terminal operators, and logistics companies, can engage in collaborative planning to align long-term goals and investments. At the tactical level, coordination can be enhanced through data sharing among stakeholders and collaborative decision support systems that facilitate day-to-day operational decisions concerning interrelated activities, such as berth allocation, truck scheduling and, cargo processing. Tactical planning assumes some degree of information system integration and many ports already use systems such as Port Community Systems (PCS). Operational coordination further involves real-time decisions and the interplay of various actors, including not only terminal operators and carriers but also port authorities, tug services, pilots, truck companies, and shippers.

This study focuses on the coordination of multimodal terminal operations at a tactical level, an area previously explored in works such as [49, 109]. However, these studies often rely on a fixed set of rules and centralize decision-making around a single actor. This overlooks the inherently distributed nature of coordination in multimodal terminals, where numerous independent stakeholders operate with distinct objectives, constraints, and procedures. Additionally, terminal planning is typically multi-objective, further complicating coordination and raising critical questions about how to ensure fairness and transparency in decision-making processes, issues that remain insufficiently addressed in the literature [45]. These observations highlight a clear gap, namely the lack of distributed modeling approaches that reflect the autonomy of different actors while enabling fair, multi-objective coordination in port terminal operations.

To address this, the study sets as its main objective developing a novel approach to model collaboration among terminal stakeholders in a distributed manner using a Multi-Agent System (MAS) framework. This approach aims to tackle the challenge of synchronizing vessel arrivals with truck scheduling in order to reduce delays and congestion in a coordinated manner. In addition, the study seeks to support fair and transparent multi-objective decision-making by applying Pareto optimality, and to develop an effective solution method that combines prioritized planning with neighborhood search to enhance computational performance. This combination of distributed coordination, multi-objective fairness, and optimization represents a novel and comprehensive approach not yet explored in existing terminal operations literature.

The proposed system models stakeholder collaboration through a MAS approach, integrating data (e.g., arrival schedules) from actors (e.g., logistics companies) and modes (e.g., vessels, trucks) to facilitate distributed, multi-objective planning. Pareto optimal solutions are sought to promote fairness among actors, with the terminal acting as an external coordinator responsible for the orchestration of different agents. A novel algorithm is developed based on prioritized planning in combination with a neighborhood search heuristic algorithm to enhances solution quality. The algorithm's performance is benchmarked against established multi-objective optimization algorithms, demonstrating its ability to produce more Pareto front contributions and increased hypervolume in a range of simulated terminal scenarios.

3.2. Problem description and modeling approach

3.2.1. Problem Description

Scheduling operations for multimodal freight transport in a synchronized manner involves effectively addressing the needs and objectives of multiple stakeholders with contrasting agendas. In this study, the problem revolves around the interactions between three distinct actors forming a multimodal chain, in an environment similar to the one depicted in Figure 3.1.

The examined problem centers on synchronizing two interdependent processes: truck scheduling through an appointment system and berth allocation for inbound vessels. These processes share limited terminal resources and must be planned fairly and efficiently in a distributed environment where actors have conflicting objectives. Within this problem, the first actor is the vessels, which generate traffic from the seaside and expect quick access to a compatible berth and timely exit from the port to continue to subsequent destinations. The second actor is the logistics companies, which generate landside traffic by dispatching trucks to the terminal to pick up or deliver cargo associated with the incoming vessels. The decision making of logistics companies is centered around reducing their deviation cost from their desired processing time-period arising from potential delays in vessel arrivals and departures or truck congestion. Finally, the terminal is acting as an intermediate point in the multimodal chain, orchestrating the transition between different transportation modes and processing the demand. The terminal is also expected to ensure that

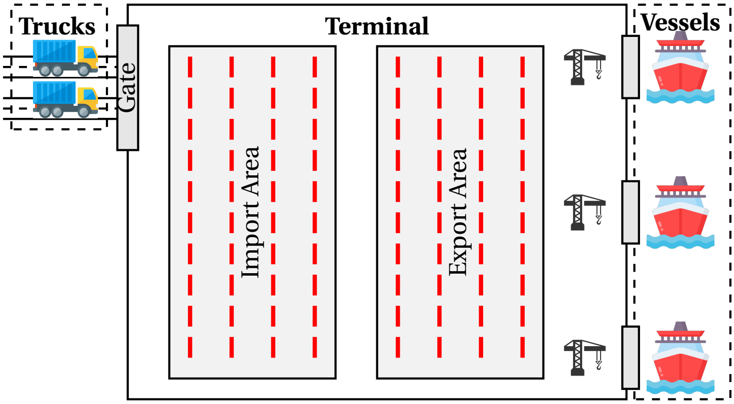


Figure 3.1: Terminal layout for examined supply chain.

certain service levels are maintained by tracking Key Performance Indicators (KPIs). Such KPIs include the maximum arrival rate of trucks per hour, cargo levels in the storage areas, as well as limits related to resources such as internal vehicles to perform drayage operations.

The system's actors are interconnected since they share resources such as berths, cargo handling equipment, and arrival windows. The requirement to synchronize processes among several stakeholders, who can have competing goals and little knowledge of one another's operations, further emphasizes the distributed aspect and need for distributed modeling methodology for this problem. Building on this, we further segment the problem setting it into two interrelated distinct tasks: (1) truck scheduling at marine terminals, which is relevant for logistics companies; and (2) berth allocation for inbound vessels, which directly impacts the vessels. Given the terminal's pivotal role as a coordinator, its own operations are affected by aspects of both tasks.

Truck scheduling at marine terminals

Uncoordinated arrivals of trucks in marine terminals is a major problem caused by the unpredictability and rising volume of truck arrivals. A widely adopted solution to this problem in the literature is the implementation of a Truck Appointment System (TAS) [110]. Appointment systems are designed to reduce the impact of concurrent influx of arrivals by limiting the number of trucks admitted each time-period. A time-period is the temporal interval used to measure access rights in an appointment system (e.g., 1 hour). TAS are often considered mandatory [91] for all trucks entering the port. This study also assumes a mandatory appointment system, where all logistics companies must request specific slots for their trucks. A slot grants a truck the right to access the terminal within a designated time-period. The proposed system, however, does not operate on a simple First-Come, First-Serve (FCFS) basis. Decentralization has been proposed as a way to enable collaborative appointment scheduling between trucking companies and terminals [89]. Inspired by this concept, our work adopts a similar philosophy. In line with [111], the proposed system arbitrates between conflicting truck requests based on company preferences, with the overall objective of minimizing the maximum deviation cost from the original requests for all logistics companies.This objective introduces fairness in truck scheduling operations among different logistics companies. Fairness is introduced though an arbitration process that aims to reduce the incurred deviations per company.

Trucks are anticipated to enter the marine terminal to fulfill specific tasks. These tasks can be categorized into pickup tasks, involving the retrieval of cargo from the terminal, and delivery tasks, which entail transporting cargo to be exported through the terminal. The complexities of truck drayage within a marine terminal vary with the type of task [81]. In this study, all scheduled tasks are assumed to be related to a vessel's arrival at the terminal. This operational framework aligns with the principles outlined in [75], wherein the concept of vessel-dependent time-windows is introduced. A Vessel-Dependent Time-Window (VDTW) is defined as a set of time-periods during which specific trucks, based on their tasks, are granted terminal access. Separate time-windows are designated for pickups and deliveries: delivery jobs are expected to be scheduled near the vessel's arrival, while pickup jobs occur after the vessel has unloaded its cargo. This study omits any interactions between trucks performing different jobs, similar to [112], with aspects such as minimizing empty runs [47, 111] not being considered.

Berth allocation for inbound vessels

The Berth Allocation Problem (BAP) is a well-established topic in operations research. It involves optimizing the assignment of berthing locations and time slots to arriving vessels at the quay, taking into account relevant constraints [113]. A crucial objective is often minimization of vessel waiting and exit times through optimal berth assignments. Approaches to BAPs can be classified as proactive, reactive, or hybrid [114]. Our approach is classified as proactive, as it is fully embedded in the planning phase. For the purposes of this study, the vessel arrival schedule is assumed to be deterministic and fixed, and is examined over a full week in a tactical planning context, following a similar setup to [115]. The occurrence of delays and any other disruptions is not studied. In contrast to previous studies on VDTWs [116], a bidirectional impact between VDTWs and berth planning is assumed, indicating mutual influence between the two. This suggests that immediate access to the terminal from the seaside is not guaranteed, as congestion may occur due to vessels occupying berths with active VDTWs, which can make mooring impossible during specific time-periods and incur waiting times. Immediate access may be also hindered, if it leads to high deviation costs for logistics companies. Berth size and vessel compatibility are also considered, implying that not all vessels can use all berths. Finally, vessel exit times depend on factors such as berth productivity, which is influenced by the number of quay cranes, available internal vehicles, and the drayage time costs within the terminal. To model the intricacies of cargo handling by the terminal and its effect on vessel departure, a macroscopic approach is used to determine productivity rates, as previously proposed by [117]. This approach computes the processing time for loading and unloading vessels based on terminal resources and cargo levels, while also measuring the conditions of import and export areas and the demand for internal vehicles. This study does not incorporate vessel-specific weights or priority levels, to differentiate between vessel types such as motherships and feeders. Additionally, transshipment activities and multimodal transport connections, which can significantly influence vessel turnaround times, are not explicitly modeled. These simplifications were made to focus on the core coordination mechanisms under controlled assumptions. Extending the problem to account for vessel heterogeneity and broader port operations however does not contrast with the selected approach to model the problem.

3.2.2. Modeling approach

To the best of the authors' knowledge, the defined problem setting has not been previously studied. An important difference with existing literature is that vessels may be delayed to reduce truck congestion at the landside. Therefore, to select an appropriate solution methodology, inspiration was drawn from problems in the literature that share similar features. The MAS modeling paradigm is considered highly suitable for this problem because of the involvement of multiple autonomous yet interdependent stakeholders, each with distinct goals and incomplete information about others. Previous approaches to modeling container terminal operations using MAS are well-documented in the literature. For example, [118] introduces a micro-level MAS framework for container terminals, while [119] examines MAS-based coordination of barge and terminals to improve hinterland transport planning. Likewise, [117] focuses on the coordination of internal trucks to manage cargo unloading operations. However, the previous models have a more limited scope, as agents only represent internal terminal functions without addressing stakeholder coordination and multimodal collaboration.

A closely related problem from MAS that inspires our modeling approach is the Multi-Agent Pickup and Delivery Problem (MAPD), which shares several design similarities. Multi-agent pickup and delivery is the problem of allocating tasks for agents and finding shortest paths without collisions. Both involve multiple interrelated agents, each with its own objectives and limited knowledge of others' plans, creating potential conflicts in decision-making. Additionally, both problems take into account dynamic scheduling and time constraints, which can disrupt planned operations. Finally, resource sharing and coordination are critical in both cases, as agents must efficiently allocate and manage shared resources to optimize overall system performance while balancing individual priorities. Solving MAPD problems often involves prioritization techniques and heuristics to enhance optimization. For instance, [120] applies prioritized planning to develop efficient paths, combined with Large Neighborhood Search (LNS) for iterative solution improvement. Similarly, [121] integrates task deadlines into a priority-based framework, using bounding and pruning techniques to maximize task assignments. [76] also leverages prioritization to ensure collision-free routes when assigning multiple goals to agents, striking a balance between managing conflicting objectives and task completion, with LNS aiding the search process. A key difference between the examined problem and MAPD problems is the less apparent presence of a unified optimization goal, in the latter case. While MAPD studies typically involve independent agents working toward system-wide optimization, the examined problem lacks a clear, single optimization goal due to the varying, sometimes conflicting, objectives of different stakeholders. This complexity necessitates balancing these competing interests rather than pursuing a single objective, often addressed in the literature through multi-objective representations.

Multi-objective optimization is a common approach in scheduling operations with multiple, possibly conflicting goals, which is a key characteristic of the examined problem. Examples include job shop scheduling [122], timetabling [123], and machine scheduling [124]. In supply chain-related problems with multiple objectives, examples include truck scheduling in cross-docking centers, where the focus is on maximizing reliability against breakdowns while minimizing outbound truck tardiness [125], ship scheduling in congested marine terminals, balancing environmental, economic, and social objectives [126], and integrated terminal management, minimizing ship service times and yard crane operational costs [127]. The standard methodology for solving these problems are multi-objective evolutionary algorithms (MOEAs), like NSGA-II [128] and SPEA2 [129].

This study introduces an approach inspired by both MOEAs and MAS to facilitate collaborative scheduling in multimodal terminal operations by utilizing distributed agents to enable multi-actor decision-making to tackle the issues outlined in Section 3.2.1. The use of priorities is also exploited to guide the optimization of the system based on KPIs. Each agent is guided by its own decision making model. Identification of conflicts and compromise solutions for the interacting agents is performed through terminal coordination and optimization with either existing MOEAs or a novel solution methodology inspired from prioritized search.

3.3. MODEL FORMULATION

The problem statement involves three distinct actor groups, each with specific requirements and objectives, which are modeled as decision-making agents within a MAS. The first group, consisting of vessels, is represented by the **berth allocation agent**, which seeks to minimize both waiting times and processing times for the vessels, by ensuring a berth allocation for timely mooring and cargo handling. The second group, comprising logistics companies, is represented by the **truck arrival management agent**, aiming to incur reduced deviation costs by aligning truck arrivals with their preferred time-periods and optimizing pickup and delivery schedules. Lastly, we define the **terminal processes agent** that acts as an independent coordinating agent, responsible for overseeing the system processes and verifying the feasibility of all solutions by balancing the needs of the vessels and logistics companies, while maintaining smooth terminal operations. While the framework features a terminal coordinator, its function is not to dictate actions but to facilitate information exchange and conflict resolution between agents. The coordinator acts as a neutral intermediary, identifying conflicts over shared resources and enabling agents to adjust their plans in order to identify mutual beneficial solutions. This design ensures that the decentralized nature of the MAS is preserved, with coordination achieved through adaptation rather than central control.

The proposed approach assumes that agents collaborate by exchanging solutions, represented by their associated costs, in order to converge on a mutually acceptable outcome. While this assumption facilitates the exploration of coordinated decision-making, it may not fully reflect the current business priorities or operational constraints faced by terminal stakeholders. In particular, the model does not explicitly account for the asymmetry of power among actors, such as the disproportionate influence of shipping lines compared to smaller logistics providers or trucking companies. Although this imbalance is partially captured by the sequential structure of the multi-agent system, where vessels act first, the broader institutional and governance issues surrounding stakeholder inequality and trust remain beyond the scope of this study. Instead, the primary objective is to assess the viability and effects of different coordination and prioritization mechanisms in cargo handling. Demonstrating the value of such mechanisms is a necessary first step toward future work that may address practical barriers to collaboration, including data sharing, trust, and power imbalances.

The overall goal of the MAS is to determine Pareto optimal solutions by deploying search algorithms that take into account all requirements set by the involved agents. In subsection 3.3.1, the berth allocation agent is described, followed by the truck arrival management agent in subsection 3.3.2, and by the terminal processes agent in subsection 3.3.3. Given the involved agents are interrelated, many parameters and variables are shared across them. For conciseness, these parameters and variables will be introduced only when they first appear in the tables within this section. In Figure 3.2, a schematic representation illustrates the interactions among variables, parameters and processes (to be introduced in the following sections) within the proposed MAS.

3.3.1. Berth Allocation Agent

The berth allocation agent is responsible for vessel related operations. All sets, parameters and variables necessary to describe this agent are listed in Table 3.1. Allocation of berths to each vessel v is defined by variable x_v, while priority of vessels per berth y_b is an ordered set consisting of all vessel indices assigned to that berth, from higher to lower priority. A vessel v is granted access for mooring at time unit m_v and based on allocated berth x_v the processing time p_v for loading/unloading operations can be defined. Within the interval $[m_v, m_v + p_v]$, the berth is considered occupied, with $m_v + p_v$ representing the exit time of the vessel from the berth. The processing and mooring times for each vessel are measured in time-units (e.g., one minute) within the considered planning period.

With respect to the berth compatibility, each vessel v is characterized by a vessel length L_v. Similarly, each berth b is assigned a maximum vessel length M_b that it can service. Smaller vessels can use berths designed for larger vessels, but the reverse is not possible. Assignment of a larger vessel to an incompatible berth will result in an arbitrarily large processing time p_v. Finally, the existence of priorities

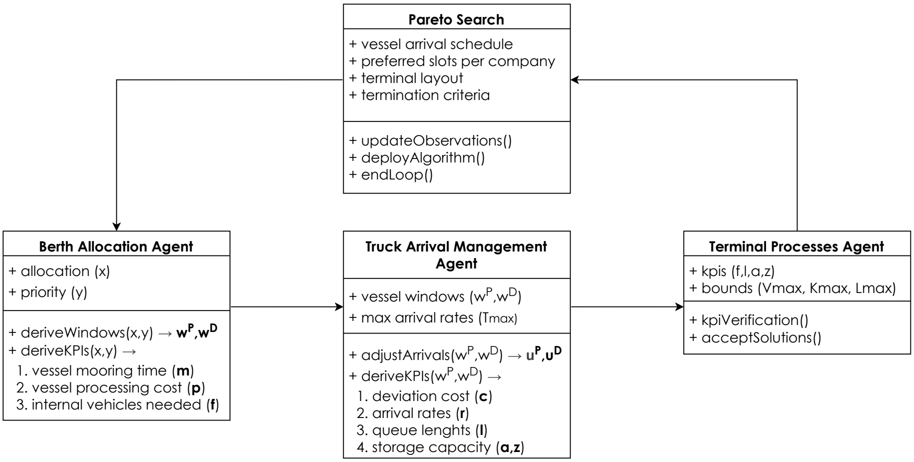


Figure 3.2: Representation of agent interactions.

as established by y_b asserts that no vessel with higher priority for the same berth should experience delays due to a vessel with lower priority. Let $y_A = [v_0, v_1, \ldots, v_n]$ be the ordered list of vessels assigned to berth A, where $n = |y_A| - 1$. For each $i \in \{0, \ldots, n-1\}$, the following condition must hold:

$$m_{y_A^i} < m_{y_A^{i+1}} \quad \vee \quad m_{y_A^i} > m_{y_A^{i+1}} + p_{y_A^{i+1}} \tag{3.1}$$

where $m_{y_A^i}$ denotes the mooring (start) time of vessel y_A^i, and $p_{y_A^i}$ is its processing time. This essentially ensures that a vessel with higher priority will never be delayed by a lower-priority vessel, although a lower-priority vessel may still be served earlier if it does not interfere with the higher-priority vessel's schedule (as shown in the right hand side of Condition 3.1). The relationship between priority y and mooring time m is furhter explained with an example, in Figure 3.3.

Processing time of cargo is the main determinant of the vessels' exit time from the terminal. For this particular problem, a vessel is considered to carry only cargo in the form of Twenty-foot Equivalent Units (TEUs). Cargo is either designated for exports (E_v) and must be loaded onto vessel v, or it is designated for imports (I_v) and must be unloaded from vessel v. The amount of TEUs to be processed evidently affects the processing time but so does the productivity of the assigned berth, as each berth has a specific number of available quay cranes C_b, and TEUs that can be processed per time-period based on mode S^S and S^B. When in single mode (S^S), cranes will exclusively load or unload cargo with no overlap. When in double mode (S^B), loading of containers can take place in parallel to unloading and vice-versa. Derivation of processing times for vessels follows a process similar to [117] as follows:

Table 3.1: Sets, parameters and variables used by the berth allocation agent.

Sets	
$\mathscr{B}$	Set of Berths, indexed by b
$\mathscr{I}$	Set of time-periods, indexed by i
$\mathscr{V}$	Set of Vessels, indexed by v
Parameters	
A_v	Expected arrival time of vessel v, measured in time-units
C_b	Number of quay cranes in berth b
E_v	Amount of export cargo for vessel v, measured in TEUs
I_v	Amount of import cargo for vessel v, measured in TEUs
L_v	Length of vessel v, measured in meters
M_b	Maximum vessel length a berth b can service, measured in meters
s^B	Amount of processed cargo by a crane in double mode during a single time-unit, measured in TEUs per time-unit
s^S	Amount of processed cargo by a crane in single mode during a single time-unit, measured in TEUs per time-unit
W	Number of time-units in a single time-period
Variables	
d_v^S	Amount of processed cargo in single mode for vessel v, measured in TEUs
d_v^B	Amount of processed cargo in double mode for vessel v, measured in TEUs
m_v	Mooring time of vessel v, measured in time-units
p_v	Processing time of vessel v, measured in time-units
p_v^B	Processing time of vessel v in double mode, measured in time-units
p_v^S	Processing time of vessel v in single mode, measured in time-units
w_v^D	Set of time-periods $i \in \mathscr{I}$ during which cargo deliveries for vessel v can occur
w_v^P	Set of time-periods $i \in \mathscr{I}$ during which cargo pickups for vessel v can occur
x_v	Assigned berth for vessel v, taking values $b \in \mathscr{B}$
y_b	Ordered set designating vessel priority for berth b, taking values $v \in \mathscr{V}$

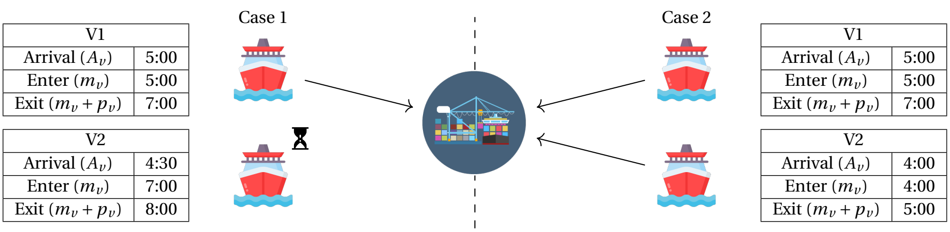


Figure 3.3: Two cases of execution of vessel schedules approaching the same berth with V1 having priority over V2. V1 has a 2-hour processing time, while V2 has a 1-hour processing time. In Case 1, V2 arrives 30 minutes before V1 but must wait due to V1's priority. In Case 2, V2 arrives an hour earlier and can be served by 5:00, when V1 arrives, despite the lower priority.

$$d_v^B = \min(I_v, E_v) \qquad \forall v \in \mathcal{V} \tag{3.2}$$
$$d_v^S = |I_v - E_v| \qquad \forall v \in \mathcal{V} \tag{3.3}$$
$$p_v = p_v^S + p_v^B \qquad \forall v \in \mathcal{V} \tag{3.4}$$
$$p_v^S = \frac{d_v^S}{S^S \cdot C_{x_v}} \qquad \forall v \in \mathcal{V} \tag{3.5}$$
$$p_v^B = \frac{2d_v^B}{S^B \cdot C_{x_v}} \qquad \forall v \in \mathcal{V} \tag{3.6}$$

where d_v^S is the amount of TEUs to be processed in single mode and d_v^B the amount of cargo to be processed in double mode. Processed cargo in a specific mode is calculated in Equations (3.2)-(3.3) asserting that as many TEUs as possible will be processed in double mode and the rest in single mode. Then, the processing time is defined in Equation 3.4, contingent on the individual processing times per crane mode as defined in Equations (3.5)-(3.6).

Depending on whether a vessel has more TEUs to load than unload, double mode processing will occur before/prior than single mode. When there are more TEUs to be loaded to the vessel than unloaded, the vessel will first be processed in double mode. This ensures that unloading will finish before loading, leaving more time for the truck pickup related windows. Conversely, when there are more TEUs to be unloaded than loaded the vessel will first be processed in single mode. This ensures loading does not start earlier than needed, thus allowing more time for deliveries to arrive later.

The processing mode also impacts the time-windows w_v^D and w_v^P for each vessel, which take values $i \in \mathcal{I}$. A time-period i represents a set of time-units within the examined working week (e.g., all minutes in a single hour). The time-unit indicating the start of cargo loading is associated with the last possible time-period for delivery jobs, establishing the upper bound of w_v^D. In contrast, the time-unit marking the completion of cargo unloading designates the first possible period of w_v^P. Deliveries are assumed to occur at any time before the upper bound of w_v^D, and pickups after the lower bound of w_v^P, although they are generally expected to take place within 12 hours of the respective bounds.

Overall, the decision-making agent responsible for berth allocation aims to minimize the waiting and processing times for all vessels. Its objective function (termed the vessel_process function), subject to the requirements outlined earlier, is defined as:

$$\text{vessel\_process}(x, y) = \sum_{v \in \mathcal{V}} (m_v - A_v + p_v) \tag{3.7}$$

3.3.2. TRUCK ARRIVAL MANAGEMENT AGENT

The truck arrival management agent is responsible for operations related to logistics companies and trucks. All sets, parameters and variables necessary to describe this agent are listed in Table 3.2. Each truck that accesses the terminal is considered to be dependent on a vessel $v \in \mathcal{V}$ and owned by a Logistics Company $l \in \mathcal{L}$. Additionally, each truck has a distinct job type as either a pickup, or a delivery. A single truck is assumed to carry one TEU within the terminal and each truck has its own preferred arrival time-period $i \in \mathcal{I}$. The sum of preferred arrival time-periods define $T^D_{l,v,i}$ as the number of trucks that company l prefers to send for delivery jobs related to vessel v during time-period i. Similarly, $T^P_{l,v,i}$ represents the preferred number of trucks for pickup jobs. The stated preferred arrival periods for trucks simulate the appointment process in the proposed model.

Table 3.2: Sets, parameters and variables used by the truck arrival management agent.

Sets	
$\mathcal{L}$	Set of Logistics Companies, indexed by l
Parameters	
$T^D_{l,v,i}$	Number of preferred trucks arrivals for deliveries by company l for vessel v in period i
$T^P_{l,v,i}$	Number of preferred trucks arrivals for pickups by company l for vessel v in period i
T_{max}	Maximum arrival rate for trucks per time-period
Λ_l	Deviation cost factor per company l
Variables	
c_l	Deviation cost incurred to logistics company l, measured in monetary units
r_i	Number of cumulative truck arrivals in period i
r^D_i	Number of cumulative truck arrivals in period i, related to delivery jobs
r^P_i	Number of cumulative truck arrivals in period i, related to pickup jobs
$u^D_{l,v,i}$	Number of truck arrivals by company l for vessel v in period i, related to delivery jobs
$u^P_{l,v,i}$	Number of truck arrivals by company l for vessel v in period i, related to pickup jobs

Each company is assumed to be characterized by a deviation factor Λ_l. This deviation factor represents how averse a company is to deviations from their preferred schedule. When the preferred arrival schedule is deemed infeasible a cost c_l is calculated as described in Equation 3.8.

$$c_l = \sum_{i \in \mathcal{I}} n_i \cdot \exp\left(\Lambda_l * d_i\right) \tag{3.8}$$

where n_i denote the amount of trucks that need to be deviated at a specific time-period for a logistic company and d_i is the time-period difference between period i and the first feasible time-period. The exponential factor is selected to discourage assignments that differ to a large extent from trucks preferred arrival period. A preferred arrival schedule may be deemed infeasible in two particular cases. The first cases relates to the timing of truck arrivals not aligning with the vessel's arrival and handling processes. We denote this form of infeasibility as *hard*. In this case, the preferred arrival schedule can be accepted by the truck arrival management agent, given the berth allocation agent's solution w_v^P, w_v^D, if the following conditions hold:

$$\begin{cases} T^D_{l,v,i} = 0 & \forall i \notin w_v^D \\ T^P_{l,v,i} = 0 & \forall i \notin w_v^P \end{cases} \tag{3.9}$$

Such infeasibility requires correction by incurring costs to logistics companies and rescheduling the trucks to the next feasible period. For instance, if trucks are planned for pickup in time-period 5 but the vessel moors in time-period 6 and finishes unloading by time-period 8, the trucks must be rescheduled to time-period 9, i.e., the earliest time-period when pickup can occur. Hard deviations are calculated using Algorithm 2.

The second case of schedule infeasibility concerns the maximum arrival quota per time-period (T_{max}). In this scenario, deviations are required to reduce arrivals to T_{max}, ensuring compliance with constraints set by the terminal processes agent. This type of infeasibility is classified as *soft*, as it does not imply an infeasible schedule but instead affects terminal productivity. To address soft deviations, Algorithm 3 is applied, as illustrated through a graphical example in Figure 3.4.

The algorithm begins by identifying congested periods and sorting them from the most to the least congested. In Figure 3.4, we consider an example where the maximum arrival quota per time-period is set at 100 trucks and only one time-period needs correction. In this context, time-period 2 exceeds this limit by having 30 more trucks arrivals than the set limit, indicating a soft violation. For each period i with a soft violation, if traffic is higher in the prior period $i-1$ over the subsequent $i+1$, pickup jobs are selected for deviation to time-period $i+1$, as slightly delaying a pickup is allowed by our strategy. If traffic is higher in the subsequent period $i+1$ over the prior $i-1$, delivery jobs are selected for deviation to time-period $i-1$, as slightly anticipating delivery jobs is allowed by our strategy as well. If adjacent periods have equal traffic, deviations alternate between pickups and deliveries. In the given example, time-period 3 initially has a lower arrival rate than time-period 1, prompting the rescheduling of five pickups from time-period 2 to time-period 3. After the initial five shifted trucks, the arrival rate of time-period 3 matches that of time-period 1, prompting the rescheduling to alternate between periods 1 and 3. As a result, 10 deliveries are shifted to time-period 1, and 10 more pickups are moved to time-period 3 leading to a total of 15 pickups delayed to time-period 3, bringing both periods to the T_{max} quota. As indicated by Algorithm 3, if both neighboring periods reach T_{max}, the adjustment window is extended by one additional period to time-periods $i-2$ and $i+2$. In this example, the remaining five trucks needing rescheduling from time-period 2 are shifted to time-period 4, after extending the adjustment window by one additional period.

This process ensures that deliveries are never shifted to later periods, nor pickups

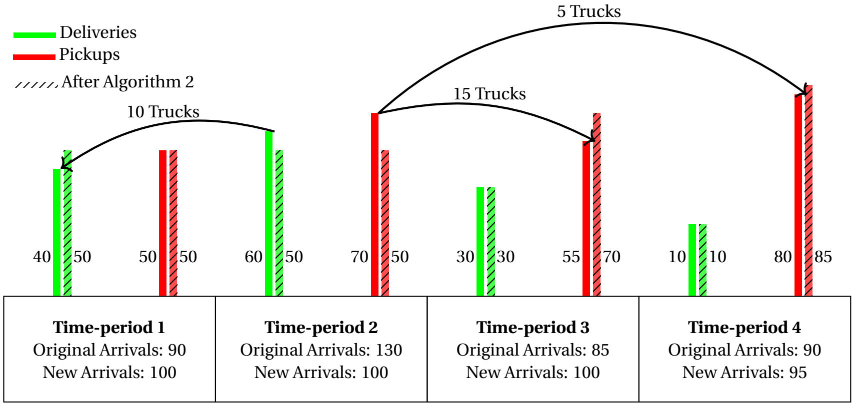


Figure 3.4: Transformation of arrival rates after Algorithm 2

to earlier ones, as such changes may cause hard violations. The algorithm thus maintains schedule feasibility while optimizing terminal productivity by managing soft deviations efficiently. Hard deviations are addressed first, followed by soft deviations. To reduce the arrival rates, the *minmax* rule is used to minimize the maximum deviation cost per logistic company, including the deviation cost already incurred by hard deviations. Deviations are selected in a way that the company incurred the least cumulative cost is being selected for each truck deviation. The algorithm computing the soft deviation costs is provided in Algorithm 3.

Overall, the truck arrival management agent aims to minimize the amount of incurred deviation costs towards the logistics companies. Its objective function, subject to the requirements outlined by Algorithms (2),(3) is defined as:

$$\text{incur\_deviations}(w^D, w^P, T_{max}) = \min \sum_{l \in \mathscr{L}} c_l \tag{3.10}$$

3.3.3. Terminal Processes Agent

The terminal processes agent is responsible for operations related to the terminal and overall coordination of the system. All parameters and variables associated with the Terminal are listed in Table 3.3.

The terminal's decision-making is centered around managing requirements related to congestion, space, and available equipment. Four key metrics are considered: arrival rates, constrained by the maximum limit T_{max} (addressed in the previous section); queue length at the gate, limited by L_{max}; cargo space in import and export areas, constrained by K_{max}; and internal vehicles used, limited by V_{max}.

To model truck arrivals at the gate a non-homogeneous Poisson distribution for the derived arrival rates r by the truck arrival management agent is used. Service times are treated as independent and identically distributed, consistent with the M/G/k queuing model, for k lanes as in existing literature [130, 131]. To handle cases

3

Algorithm 2: hard($T^D, T^P, \Lambda, w^D, w^P$)

```
u^P ← T^P
u^D ← T^D
for l ∈ 𝓛 do
    for v ∈ 𝒱 do
        for i ∈ 𝓘 do
            if i ∉ w^D_v ∧ T^D_{l,v,i} > 0 then
                d ← i − max(w^D_v)
                u^D_{l,v,i−d} ← u^D_{l,v,i} + u^D_{l,v,i−d}
                c_l ← c_l + u^D_{l,v,i} ∗ exp(Λ_l ∗ d)
                u^D_{l,v,i} ← 0
            end
            else if i ∉ w^P_v ∧ T^P_{l,v,i} > 0 then
                d ← min(w^P_v) − i
                u^P_{l,v,d+i} ← u^P_{l,v,i} + u^P_{l,v,d+i}
                c_l ← c_l + u^P_{l,v,i} ∗ exp(Λ_l ∗ d)
                u^P_{l,v,i} ← 0
            end
        end
    end
end
for i ∈ 𝓘 do
    r_i ← Σ_{l∈𝓛} Σ_{v∈𝒱} u^P_{l,v,i} + u^D_{l,v,i}
end
return u^P, u^D, r, c
```

Algorithm 3: soft$(u^P, u^D, r, c, \Lambda)$

$I = argsort(r_i)$
for $i \in \mathcal{I}$ **do**
  if $r_i > T_{max}$ **then**
    $n_d \leftarrow r_i - T_{max}$; $D \leftarrow 1$
    while $n_d > 0$ **do**
      if $r_{i-D} > r_{i+D}$ **then**
        $y \leftarrow \{l, \ \forall l \in \mathcal{L}, v \in \mathcal{V} | u^P_{l,v,i} > 0\}$
        $choice \leftarrow argmin(\{c_l, \ \forall l \in y\})$
        if $r_{i+D} = T_{max}$ **then**
          $D \leftarrow D + 1$
        end
        $c_{choice} \leftarrow c_{choice} + \exp(\Lambda_l * D)$
        $u^P_{l,v,i} \leftarrow u^P_{l,v,i} - 1$
        $u^P_{l,v,i+D} \leftarrow u^P_{l,v,i+D} + 1$
        $r_{i+D} \leftarrow r_{i+D} + 1$
      end
      else
        $y \leftarrow \{l, \ \forall l \in \mathcal{L}, v \in \mathcal{V} | u^D_{l,v,i} > 0\}$
        $choice \leftarrow argmin(\{c_l, \ \forall l \in y\})$
        if $r_{i-D} = T_{max}$ **then**
          $D \leftarrow D + 1$
        end
        $c_{choice} \leftarrow c_{choice} + \exp(\Lambda_l * D)$
        $u^D_{l,v,i} \leftarrow u^D_{l,v,i} - 1$
        $u^D_{l,v,i-D} \leftarrow u^D_{l,v,i-D} + 1$
        $r_{i-D} \leftarrow r_{i-D} + 1$
      end
      $r_i \leftarrow r_i - 1$
      $n_d \leftarrow n_d - 1$
    end
  end
end
return u^P, u^D, r, c

Table 3.3: Parameters and variables used in the model used by the terminal processes agent.

Parameters	
G^B	Amount of processed cargo by an internal vehicle when crane is in double mode in one period, measured in TEUs
G_I^S	Amount of processed cargo by an internal vehicle when crane is in single mode and heading to import area in one period, measured in TEUs
G_E^S	Amount of processed cargo by an internal vehicle when crane is in single mode and heading to export area in one period, measured in TEUs
K_{max}	Maximum cargo that can be stored in import/export areas, measured in TEUs
L_{max}	Maximum queue length in the gate area
V_{max}	Maximum number of internal vehicles that can be used to process cargo
Variables	
a_i	Processed cargo in export area in time-period i, measured in TEUs
e_v^S	Amount of internal vehicles to process cargo in single mode for vessel v
e_v^B	Amount of internal vehicles to process cargo in double mode for vessel v
f_i	Amount of internal vehicles needed to process cargo in time-period i
$h_{v,i}^S$	Processed cargo in single mode in time-period i related to vessel v, measured in TEUs
$h_{v,i}^B$	Processed cargo in double mode in time-period i related to vessel v, measured in TEUs
l_i	Queue length formed in time-period i
z_i	Processed cargo in import area in time-period i, measured in TEUs

when arrival rates exceed service rates, the stationary backlog-carryover method is used [132, 133], which allows queues to build up in overloaded periods and waiting jobs can be transferred to a subsequent period. The derivation of equations to determine the queuing approximation for l can be found in 3.6.

Cargo is updated based on the actual pickup and delivery rates r^P and r^D, as provided by the truck arrival management agent and is also contingent in the processing modes followed as explained in subsection 3.3.1. For clarity of the formulations in Table 3.4, subsets relating to specific moments in the cargo handling process are formulated measured in time-periods. Essentially, the time-periods that a vessel will process cargo in either single or double mode are isolated based on the mooring time and processing time derived by the berth-allocation agent. As previously discussed, based on whether there are more imports or exports, a different sequencing of cargo processing is performed. The total TEUs in import (z) and export areas (a) can then be computed based on Equations (3.11)-(3.18). For a specific vessel, cargo processing may begin after an associated time-period has started and conclude before a period ends. Equations (3.11)–(3.14) define the actual amount of cargo processed for each period within the subsets outlined in Table 3.4, based on the mooring and processing times of the vessel. Three cases are thus possible: cargo processing starting partway through an involved period, cargo

Table 3.4: Subsets used in the model, specific to the Terminal.

Subsets	
$S_v^1 = \left\{ \left\lfloor \frac{m_v}{W} \right\rfloor, \left\lceil \frac{m_v + p_v^S}{W} \right\rceil \right\}$	Time-periods associated with start of mooring until the end of first processing in single mode for vessels v with $I_v \geq E_v$. If $I_v < E_v$, $S_v^1 = \emptyset$
$S_v^2 = \left\{ \left\lfloor \frac{m_v + p_v^S}{W} \right\rfloor, \left\lceil \frac{m_v + p_v}{W} \right\rceil \right\}$	Time-periods associated with end of first processing in single mode to exit time for vessels v with $I_v \geq E_v$. If $I_v < E_v$, $S_v^2 = \emptyset$
$S_v^3 = \left\{ \left\lfloor \frac{m_v}{W} \right\rfloor, \left\lceil \frac{m_v + p_v^B}{W} \right\rceil \right\}$	Time-periods associated with start of mooring until the end of first processing in double mode for vessels v with $I_v < E_v$. If $I_v \geq E_v$, $S_v^3 = \emptyset$
$S_v^4 = \left\{ \left\lfloor \frac{m_v + p_v^B}{W} \right\rfloor, \left\lceil \frac{m_v + p_v}{W} \right\rceil \right\}$	Time-periods associated with end of first processing in double mode to exit time for vessels v with $I_v < E_v$. $I_v \geq E_v$, $S_v^4 = \emptyset$
$\mathscr{I}^* = \mathscr{I} \setminus \{\mathscr{I}_0\}$	Time-periods excluding first period

processed throughout the entirety of a period, and cargo processing concluding before a period ends. The use of arrival rates in Equations (3.16) and (3.18) is appropriate for measuring TEUs, as it is assumed that each arriving truck carries a single TEU. Both cases assume an empty storage area at the start of the working week and storage capacity at the import and export areas is considered finite for a maximum K_{max} TEUs.

$$h^S_{v,i} = \frac{\min\left(W \cdot i - m_v, m_v + p^S_v - W(i-1), W\right) \cdot d^S_v}{p^S_v}, \qquad \forall i \in S^1_v, \forall v \in \mathcal{V} \tag{3.11}$$

$$h^B_{v,i} = \frac{\min\left(W \cdot i - m_v + p^S_v, m_v + p_v - W(i-1), W\right) \cdot d^B_v}{p^B_v}, \qquad \forall i \in S^2_v, \forall v \in \mathcal{V} \tag{3.12}$$

$$h^B_{v,i} = \frac{\min\left(W \cdot i - m_v, m_v + p^B_v - W(i-1), W\right) \cdot d^B_v}{p^B_v}, \qquad \forall i \in S^3_v, \forall v \in \mathcal{V} \tag{3.13}$$

$$h^S_{v,i} = \frac{\min\left(W \cdot i - m_v + p_v B, m_v + p_v - W(i-1), W\right) \cdot d^S_v}{p^S_v}, \qquad \forall i \in S^4_v, \forall v \in \mathcal{V} \tag{3.14}$$

$$z_0 = 0 \tag{3.15}$$

$$z_i = z_{i-1} - r^P_i + \sum_{v \in \mathcal{V} | i \in S^1_v} h^S_{v,i} + \sum_{v \in \mathcal{V} | i \in S^2_v} h^B_{v,i} + \sum_{v \in \mathcal{V} | i \in S^3_v} h^B_{v,i} + \sum_{v \in \mathcal{V} | i \in S^4_v} h^S_{v,i}, \qquad \forall i \in \mathcal{I}^* \tag{3.16}$$

$$a_0 = 0 \tag{3.17}$$

$$a_i = a_{i-1} - r^D_i + \sum_{v \in \mathcal{V} | i \in S^1_v} h^S_{v,i} - \sum_{v \in \mathcal{V} | i \in S^2_v} h^B_{v,i} - \sum_{v \in \mathcal{V} | i \in S^3_v} h^B_{v,i} - \sum_{v \in \mathcal{V} | i \in S^4_v} h^S_{v,i}, \qquad \forall i \in \mathcal{I}^* \tag{3.18}$$

Finally, a maximum number of internal vehicles V_{max} is considered available. The amount of TEUs a vehicle can process within a single period is defined as G^B for double mode, G^S_I for single mode moves towards the import area and G^S_E for the export area. Building on that, Equations (3.19)-(3.21) defines the amount of vehicles needed per processing mode and vessel for the processing times of vessels as defined by the berth allocation agent. These equations establish the amount of vehicles needed to match the productivity of the used mode and cranes. Then, the total number of internal vehicles f_i needed can be computed from Equation 3.22.

$$e^S_v = \frac{d^S_v \cdot W}{p^S_v \cdot G^S_E}, \qquad \forall v \in \mathcal{V} \mid E_v > I_v \tag{3.19}$$

$$e^S_v = \frac{d^S_v \cdot W}{p^S_v \cdot G^S_I}, \qquad \forall v \in \mathcal{V} \mid I_v > E_v \tag{3.20}$$

$$e^B_v = \frac{d^B_v \cdot W}{p^B_v \cdot G^B}, \qquad \forall v \in \mathcal{V} \tag{3.21}$$

$$f_i = \sum_{v \in \mathcal{V} | i \in S^1_v} e^S_v + \sum_{v \in \mathcal{V} | i \in S^2_v} e^B_v + \sum_{v \in \mathcal{V} | i \in S^3_v} e^B_v + \sum_{v \in \mathcal{V} | i \in S^4_v} e^S_v, \qquad \forall i \in \mathcal{I} \tag{3.22}$$

Overall, the terminal processes agent has no explicit optimization goal, thus its decision-making is represented by a simple constraint satisfaction function termed terminal_constraints(r), which checks whether variables f, z, a, l that are directly related to r remain below upper bounds, returning False if any are violated.

3.4. Solution Methodology

Searching for Pareto optimal solutions that improve and satisfy the individual objectives of all agents depends on an efficient search algorithm as previously signaled in Figure 3.2. Due to the problem's complexity, nonlinearity, and large solution space, metaheuristic methods are used. We consider multi-objective evolutionary optimization algorithms and a novel technique that combines prioritized planning with neighborhood search for developing the search algorithm. These methods balance conflicting objectives and refine solutions locally based on the requirements and functions defined in Section 3.3. Specifically, the vessel_process and incur_deviation must be minimized, while the terminal_constraints functions must be satisfied during the solution process.

3.4.1. Multi-objective evolutionary algorithms

A common approach to solving multi-objective optimization problems involves population based algorithms that utilize evolutionary computation. Multi-Objective Evolutionary Algorithms (MOEAs) can efficiently generate a diverse set of trade-off solutions, focusing on convergence, diversity, and coverage of the examined solution space. These algorithms form the foundation of multi-objective optimization problems and have been extensively studied in the literature. To solve the problem presented in this study using MOEAs, the employed methodology, detailed in Figure 3.5, employs the following steps:

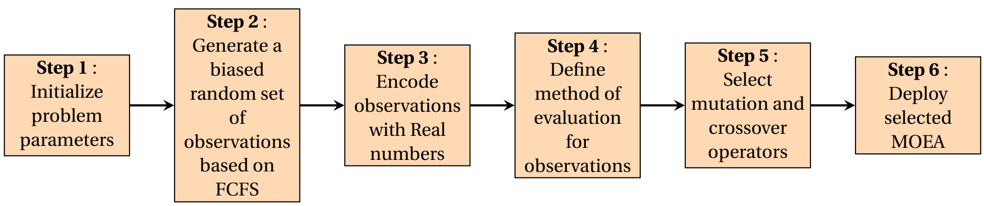


Figure 3.5: Methodology employed for use of Multi-Objective Evolutionary Algorithms.

Step 1: **Initialize Problem Parameters** - This includes determining the number of vessels, available berths, logistics companies involved, and specific requirements such as vessel-to-berth compatibility.

Step 2: **Generate Initial Set of Solutions** - An initial set of solutions of berth allocation x and priority of vessels y per berth is generated and evaluated by assigning a simple FCFS priority based on the chronological arrival times of vessels, and then a random assignment of berths for each vessel, provided that the allocation is feasible with respect to vessel-to-berth compatibility. The generated x and y are defined as observations of the search algorithm.

Step 3: **Encoding of Observations** - To facilitate the search process, observations of x and y must be encoded in a form that makes it easy to apply operators. To that end, we utilize real-encoding. For each vessel, a real number is generated randomly within the range from 0 to the total number of berths $|\mathscr{B}-1|$. The integer part of this number indicates the assigned berth for the vessel, while the fractional part represents the vessel's priority among those allocated to the same berth. Vessels with the same integer part are sorted based on their fractional values to establish priority order. The chromosome structure is further illustrated in Figure 3.6.

V1	V2	V3	V4	V5	← Vessel Index
0.15	1.12	0.04	1.04	1.06	← Generated Real
A	B	A	B	B	← Berth Allocation
2	3	1	1	2	← Vessel Priority

Figure 3.6: Encoded chromosome with Reals.

Step 4: **Define evaluation method** - The model defined in Section 3.3 must satisfy constraints during fitness evaluation. To handle constraint violations, hard constraints are transformed into soft constraints by adding high penalties to the objective value when violations occur. To compute the costs across agents, the vessel_process, incur_deviation and terminal_constraints(r) functions are deployed.

Step 5: **Select crossover and mutation operators** - Generating diverse observations is crucial for the effectiveness of MOEAs as it helps explore a broader solution space and avoid premature convergence. To achieve this diversity, crossover and mutation operators are employed. For real-valued representations, a common crossover method is Simulated Binary Crossover (SBX). The SBX operator mimics the behavior of binary crossover for integers and is defined mathematically as follows:

$$x_i^{(1)} = \frac{1}{2}\left[(x_i^{(1)} + x_i^{(2)}) - \beta \cdot (x_i^{(2)} - x_i^{(1)})\right] \tag{3.23}$$

$$x_i^{(2)} = \frac{1}{2}\left[(x_i^{(1)} + x_i^{(2)}) + \beta \cdot (x_i^{(2)} - x_i^{(1)})\right] \tag{3.24}$$

$$\beta = \begin{cases} (2u)^{1/(\eta_1+1)}, & \text{if } u \le 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{1/(\eta_1+1)}, & \text{if } u > 0.5 \end{cases} \tag{3.25}$$

where $u \sim \mathscr{U}(0,1)$ and $\beta > 0$. Variable β is drawn from a beta distribution with an η_1 index of user defined distribution to introduce variability in the crossover process. For mutation, polynomial mutation is commonly used. This method introduces small changes to individuals by altering their values with a polynomial distribution. The mutation operation is defined as:

3

$$x_i' = x_i + \delta \cdot (x_{i,\text{upper}} - x_{i,\text{lower}}) \tag{3.26}$$

where δ is a polynomially distributed random variable and η_2 is a distribution index that controls the mutation magnitude:

$$\delta = \begin{cases} \left(\frac{2\cdot\mathscr{U}(0,1)}{1+\eta_2}\right)^{\frac{1}{\eta_2+1}} - 1, & \text{if } \mathscr{U}(0,1) \le 0.5 \\ 1 - \left(\frac{2\cdot(1-\mathscr{U}(0,1))}{1+\eta_2}\right)^{\frac{1}{\eta_2+1}}, & \text{if } \mathscr{U}(0,1) > 0.5 \end{cases} \tag{3.27}$$

For all MOEAs these two operators were utilized with $\eta_1 = 15$ and $\eta_2 = 20$ for SBX and polynomial mutation respectively.

Step 6: **Deploy Selected MOEAs -** As previously established in subsection 3.2.2, the common benchmark algorithms NSGA-II [128] and SPEA2 [129] are used.

3.4.2. Prioritized search

MOEAs are relatively straightforward to implement and can effectively yield a satisfactory set of solutions for multi-objective optimization problems. However, achieving the set of all Pareto efficient solutions can be challenging due to the problem's complexity and high dimensionality. A significant drawback is the excessive generation of redundant observations, as the operators used to create new solutions focus on diversity but lack a robust mechanism to incorporate local knowledge into the search process. For example, certain berths may be incompatible with specific vessels, yet the search algorithm evaluates these infeasible solutions, which, despite incurring minimal computational cost, detracts from overall optimization efficiency. To address these limitations, we propose a novel algorithm based on prioritized planning, which utilizes local knowledge to minimize redundancy and improve solution quality. Our approach employs a *search algorithm*, as described in Algorithm 5, to determine the priority list y. Subsequently, the berth allocation variable x is assigned sequentially for each vessel according to y, leveraging *priority trees*, as outlined in Algorithm 4.

Algorithm 4: priority_tree(y,swap)

```
$sols$, OPEN ← ∅, ∅
ROOT ← { BA^c : 0, TAM^c : 0, C : {$b$ : ∅ | $b \in \mathscr{B}$}, x : ∅ }
insert OPEN in ROOT
for v ∈ y do
    children ← ∅
    while OPEN do
        curr ← state from OPEN with index 0
        remove OPEN from curr
        $b_{p_v}, b_{c_v}$, trees ← ∞, ∞, ∅
        for b ∈ $\mathscr{B}$ do
            if $L_v \leq M_b$ then
                $p_v, m_v$ ← vessel_process(curr, b)
                $c_v, r$ ← hard(curr, $m_v$)
                if $p_v < b_{p_v}$ and $c_v < b_{c_v}$ then
                    $b_{p_v}, b_{c_v} \leftarrow p_v, c_v$
                    trees ← [$p_v, c_v, m_v, r, b$]
                end
                else if $p_v < b_{p_v}$ then
                    $b_{p_v} \leftarrow p_v$
                    add [$p_v, c_v, m_v, r, b$] in trees
                end
                else if $c_v < b_{c_v}$ then
                    $b_{c_v} \leftarrow c_v$
                    add [$p_v, c_v, m_v, r, b$] in trees
                end
            end
        end
        if length(trees) > 1 then
            update v in $swap$ by 1
        end
        if length(trees) > $k$ then
            keep $k$ trees with lowest total cost
        end
        for br ∈ trees do
            child ← { BA^c : curr[BA^c] + br[$p_v$], TAM^c : curr[TAM^c] + br[$c_v$], C : curr[C], x : curr[x], A : br[$r$] }
            add br[$m_v$] in child[C][br[b]]
            add br[$b$] in child[x]
            add child in children
        end
        for child ∈ children do
            insert child in OPEN
        end
    end
    for child ∈ children do
        update child with soft(child)
        if terminal_constraints(child[A]) then
            insert child in sols
        end
    end
end
return $sols, swap$
```

3

Algorithm 5: priority_search(y,end,pb,pt)

```
ledger ← { BA : {s : ∅, b : ∞},
           TAM : {s : ∅, b : ∞} }
swap ← [1 | ∀ i ∈ 𝒱]
front, candidates ← ∅, ∅
while True do
    sols, swap ← priority_tree(y, swap)
    non_dominated ← ∅
    add sols in candidates
    n ← |candidates|
    for i ∈ candidates \ {candidates[n]} do
        dominated ← False
        for j ∈ candidates \ {candidates[0]} do
            if i ≠ j and is_dominated(i, j) then
                dominated ← True
                break
            end
        end
        if not dominated then
            add(i) in non_dominated
        end
    end
    add non_dominated → front
    for f ∈ front do
        if ledger[BA][b] > f[BA^c] then
            ledger[BA] ← {s : f, b : f[BA^c]}
        end
        if ledger[TAM][b] > f[TAM^c] then
            ledger[TAM] ← {s : f, b : f[TAM^c]}
        end
    end
    Define u ∼ Uniform(0, 1)
    if u < pb then
        select y from ledger[BA][sol]
        apply destroy operator on y
        update y with a repair operator
    end
    else if u < pt then
        select y from ledger[TAM][sol]
        apply destroy operator on y
        update y with a repair operator
    end
    else
        select y from current front
        update y with a random operator
    end
    if end then
        break
    end
end
return front
```

PRIORITY TREES

In constructing a priority tree we begin with a given priority list y and try to define the berth allocation $x_v \ \forall v \in \mathcal{V}$. To define x we assume that each vessel consistently selects a berth using a greedy approach, i.e., the one that minimizes any of the associated costs, always considering local conditions such as berth occupancy caused by other vessels. Each vessel is associated with a processing cost p_v, and an incurred deviation cost for companies, c_v, based on the selected berth. Given that the problem has two distinct objectives to minimize, different berth allocations may optimize different criteria. To address this, the algorithm may consider multiple berth allocations. When two different berths perform better for one objective but worse for the other, a branch occurs as no solution dominates the other.

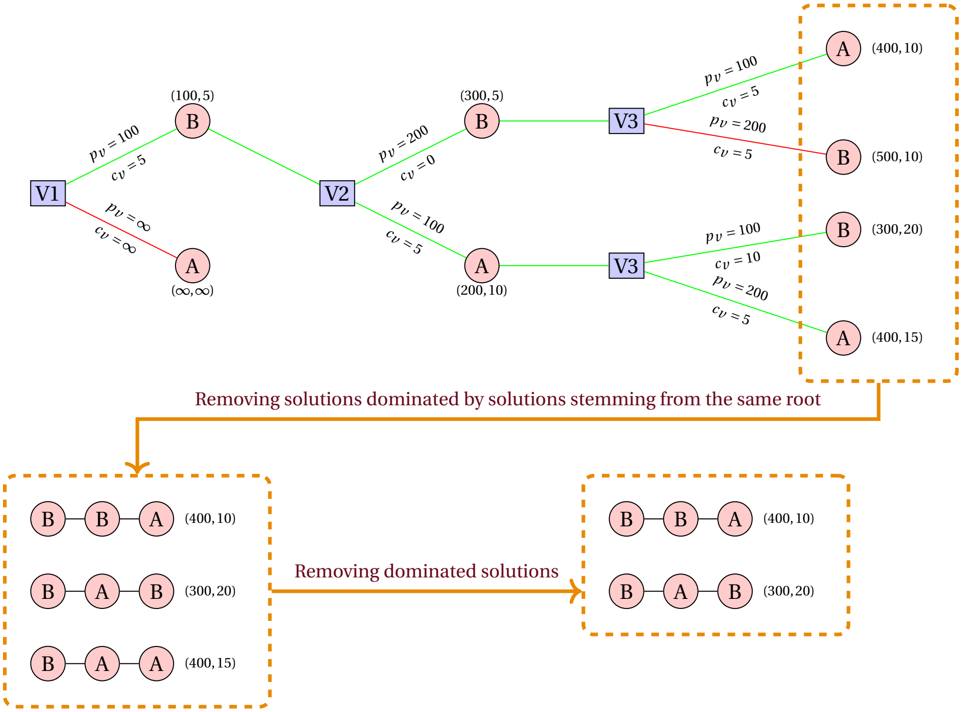


Figure 3.7: Schematic representation of the branching process to create priorities

In Figure 3.7, an example for the formation of priority trees is illustrated with three vessels and priorities V1 > V2 > V3. For vessel V1, berth B is selected since it is the greedy solution compared to the infeasible solution of berth A which yields an infinite cost. For vessel V2, both berths yield minimum values for different costs, with berth A minimizing the total sum of p_v and berth B minimizing the total sum of c_v, resulting in new branches. For vessel $V3$, two branches and four allocations must be evaluated, and only greedy solutions must be kept. Allocation $B-B-B$ is disregarded because, for V3, allocation $B-B-A$ performs better in both objectives, thereby dominating solution $B-B-B$. Allocations $B-A-A$, $B-A-B$, and $B-B-A$ are part of the final output of this process, but it is noted that allocation $B-A-A$ is dominated by allocation $B-B-A$. This branch is dominated across all solutions, but not within solutions stemming from its root, thus is discarded at a later stage, as indicated by Figure 3.7.

We generally aim to retain non-dominated solutions originating from the same root, as they may lead to better final outcomes under the current priority constraints when examining vessels further down the priority list. However, this approach introduces significant redundancy, which can negatively affect performance as the number of vessels increases. To mitigate this, we apply a simple rule: we always keep at most the top k solutions. These are selected based on minimizing the sum of the two cost components. If, at any point, the number of branches from a root exceeds k, the least favorable solutions are discarded.

Algorithm 4 describes the process of creating priority-based trees, as visualized in Figure 3.7, for a given ordered priority y. We also introduce the concept of an archive $swap$, used to store indices of vessels where the greedy decision for berth allocation results to a branch, as shown in Figure 3.7. Information related to costs for the Berth Allocation Agent, Truck Arrival Management Agent, and occupancy constraints for the associated berths are stored in the ROOT dictionary (Algorithm 4, Line 2) and are updated for any given priority. Proceeding iteratively for every vessel $v \in y$, the processing time of each vessel and its impact on the vessel schedule is first computed (Algorithm 4, Line 12) using the *vessel_process* function. All possible berth allocations are evaluated iteratively, provided they are compatible with the vessel size (Algorithm 4, Line 11). Current best berth allocation for vessel processing and incurred deviation are stored in variables b_{p_v}, b_{c_v}. Vessel processing costs are calculated for a single vessel, and conflicts with vessels of subsequent priorities are checked by updating the “curr" dictionary. Then, the hard deviation cost to the logistics companies caused by this vessel (c_v) and any effect to the current arrival rates applied to logistics companies is computed by Algorithm 2 (Algorithm 4, Line 13).

Based on the cumulative c_v and p_v, all potential branches relating to a greedy allocation are stored as previously explained (Algorithm 4, Line 14-22). When multiple branches are created, the vessel causing the split updates the archive ($swap$) (Algorithm 4, Line 24). The archive is used to guide exploration of different priorities around this vessel, later in the search process. Subsequently, occupancy constraints and current costs per agent are updated for all branches (Algorithm 4, Line 27-31). Finally, after processing all vessels, the derived branches are added to the found solutions, after being updated to account for soft violations as per Algorithm 3, if they do not violate any terminal related constraints (Algorithm 4, Line 32-37) such as maximum queue list and storage capacities.

Search Algorithm

A search strategy is proposed that takes elements from neighborhood search to efficiently explore the solution space for different applied vessel priorities. Algorithm 5 is employed to search for non-dominated priorities by systematically refining the solution space through a combination of exploration and exploitation strategies. Below are the key steps of the search algorithm:

1. **Initialization:** The algorithm begins with an intuitively promising priority strategy. We utilize FCFS for the examined vessels and create the priority trees as previously explained in (Algorithm 4). Two termination criteria, collectively denoted as *end*, are considered:
   - A pre-specified maximum number of iterations.
   - Convergence to a certain Pareto front satisfying solution quality thresholds.

2. **Updating the Pareto Front:** At each iteration, dominated solutions derived from the priority trees are discarded to create the current best Pareto front (Algorithm 5, Lines 6-17).

3. **Exploration and Exploitation:** The algorithm uses exploration and exploitation to refine and diversify the solution space (Algorithm 5, Lines 18-34):
   - **Exploitation:** A ledger maintains the best feasible priorities and allocations for each decision-making agent (Algorithm 5, Lines 18–22). To intensify the search near high-quality solutions, we apply a destroy-and-repair strategy: part of a solution is perturbed and then heuristically reconstructed (Algorithm 5, Lines 23–33). The process is applied to the current best solution of either the TAM or BA agent, chosen at random from the ledger. A destroy operator is followed by a repair operator, both selected randomly. The available operators are:

     Destroy operators apply targeted changes:
     - `random_subsequence_removal`: removes a contiguous block of n elements and then apply local reordering.
     - `random_position_removal`: removes k elements from random positions for broader variation.

     Repair operators restore priority structure:
     - `random_reinsertion`: reinserts removed elements at random positions to promote diversity.
     - `greedy_reinsertion`: reinserts each element in a weighted manner influenced by the $swap$ archive.
   - **Exploration:** To diversify the search space and avoid local optima, we apply a set of local operators that modify candidate solutions. One operator is selected at random in each iteration. The following operators are used:

     a) `insert` – Inserts a random vessel into a different position in the sequence. To guide the exploration we use the $swap$ archive as a weight for vessel selection.

     b) `shuffle` – Randomly shuffles a small segment of consecutive vessels.

   c) `reverse` – Reverses the order of a selected segment in the sequence.
   d) `relocate` – Moves a segment of vessels to a different position.
   e) `two_opt` – Swaps two non-overlapping segments.

4. **Sampling Strategy:** A specific sampling strategy is employed to balance exploration and exploitation throughout the iterations in our experiments:
   - When exploiting, the decision to select a priority for a specific decision-making agent is made uniformly, with probabilities for berth allocation and truck arrival management set equally ($p_b = p_t$).
   - During the first 80% of iterations, the algorithm allocates 20% of iterations to exploitation and 80% to exploration ($p_b = p_t = 0.1$).
   - For the final 20% of iterations, the balance shifts, with 80% of iterations focused on exploitation and 20% on exploration ($p_b = p_t = 0.4$).

Ultimately, the best observed Pareto front is returned as the output of Algorithm 5.

Scalability & Parallelization

The prioritized search algorithm, while reducing the solution space, can increase computational costs due to the need to form trees and perform computationally expensive operations, such as those in Algorithm 2, for each vessel individually. This computational cost grows with the number of vessels and berths, making single priority evaluations significantly more expensive. This issue is partially addressed by reducing redundancy of examined branches (Algorithm 4, Lines 25–26), where only the top k priority vectors per branch are retained. In our experiments, we used $k = 10$ to balance performance with computational efficiency. Scalability concerns related to increased vessel and berth numbers are further addressed through the evaluation in subsection 3.5.2.

Another way to speed up computation, unlike MOEAs, which rely on iterative learning across generations, is through the parallelizable nature of Algorithm 5, which offers a practical advantage in large-scale problem settings. We propose a simple parallelization approach where multiple processes start from different priority strategies close to FCFS and independently follow the steps outlined in the previous section related to the search algorithm. This allows multiple processes to concurrently evaluate different priorities, significantly increasing the search capacity of the algorithm. However, without guidance some processes may get stuck in suboptimal solutions while others progress more effectively. To address this, we ensure that the best current observation from any individual process, with respect to a specific agent, is used to update the ledger (as defined in Algorithm 5) across all processes. The ledger helps guide processes stuck in poor regions of the solution space back toward the current optimum by recording and exploiting promising solutions. Since the ledger serves as the minimal form of communication across processes and can be updated asynchronously, the communication overhead remains negligible. The search process terminates once all processes complete their final iterations, ensuring that the prioritized search strategy maintains a comparable number of iterations across processes to MOEAs, even as the number of vessels or berths increases.

3.5. CASE STUDY

3.5.1. GENERATION OF TEST INSTANCES

The developed model and solution methodologies were tested for a medium-sized terminal in Norway over one week, with time-units measured in minutes and aggregated into hourly time-periods. A medium-sized terminal typically processes approximately 500,000 to 1,000,000 TEUs per year, which corresponds to around 10,000 to 20,000 TEUs per week [134]. The instances in this study are characterized by three distinct factors.

1. the number of vessels approaching the terminal during the examined working period.
2. the number of available berths for these ships.
3. the level of incoming truck traffic to the terminal.

We report the values used for these three factors in all numerical experiments, together with other important parameters, in Table 3.5.

Table 3.5: Summary of Test Data

Factors	**Levels**
Level of truck traffic	Low, Medium, High
Number of berths available	2, 3, 4
Number of quay cranes per berth	1, 2, 3
Number of logistics companies	50
Number of vessels approaching the terminal	20, 25, 30, 35, 40, 45, 50
Number of TEUs per time-period per mode (S^B, S^S)	50 (double), 31 (single)
Terminal Parameters: ($K_{\max}$, $T_{\max}$, $L_{\max}$, $V_{\max}$)	2000 TEUs, 250 trucks, 20 trucks, 50 vehicles
Vessel Categories (based on length)	<100m, 100m-200m, >200m

For the generated vessels, the expected arrival time A_v is considered deterministic and known, while the length L_v follows a uniform distribution within their respective vessel categories. The cargo amounts I_v and E_v are correlated with the size of the vessel. They are also proportional to incoming traffic obtained from loop detector data for heavy vehicles that were gathered in a road axis adjacent to the examined terminal. These were transformed to preferred pickup T^P and delivery slots T^D.

Truck traffic is distributed among 50 logistics companies, each with a deviation cost factor Λ_l drawn from $\mathscr{U}(0,1)$. Trucks are assigned randomly to vessels based with a constraint ensuring trucks are within 12 time-periods of the vessel's arrival. The assignment to I_v and E_v depends on whether the sampled window is before or after the vessel's arrival. Overall, traffic volumes varied from 3,773 to 4,449 trucks in low-traffic instances, 10,661 to 14,705 in medium traffic, and 17,275 to 21,748 in high-traffic scenarios.

Regarding the terminal geometry, the terminal features between two to four berths. With two berths, one is dedicated to vessels smaller than 100 meters, while the other accommodates vessels of all sizes. When three or four berths are available, additional berths serve vessels up to 200 meters in length. The berth for vessels under 100 meters is equipped with a single quay crane, whereas the larger berths each have two or three quay cranes. Travel time from any berth to the import area is five minutes, while travel time from the berth to the export area is four minutes. The travel time between the import and export areas is set at one minute.

Regarding terminal productivity parameters, the crane throughput is set to 50 TEUs per period in double mode (S^B) and 31 TEUs per period in single mode (S^S). Loading and unloading times for internal trucks are each set to one minute. Gate terminal productivity is 50 trucks per lane per period, with a total of two lanes available both of which can be used for pickup and deliveries. Finally, regarding terminal operational parameters, the maximum truck arrival rate per period ($T_{\max}$) is set to 125 trucks per lane. The maximum storage capacity in both the import and export areas ($K_{\max}$) is 2000 TEUs. The maximum allowable queue length at any time ($L_{\max}$) is 20 trucks, and the maximum number of internal trucks in use at any time ($V_{\max}$) is 50.

3.5.2. Results & Discussion

The numerical campaign revolved around six core instances. Each instance is characterized by an identifier in the form $\alpha - \beta - \gamma$, where α represents the number of vessels approaching the terminal, β represents the number of berths available, and γ represents the level of truck traffic. For example, instance 25-2-low represents an instance with 25 vessels, 2 berths, and low traffic. All numerical results were generated on an Intel Xeon Gold 6226R with 48 CPU cores and 192 GB of RAM. Both algorithms were implemented in Python, with the MOEAs employed using the existing pymoo package [135]. Each instance was executed for 5,000 iterations, consisting of 25 generations with a population of 200 for the evolutionary algorithms, and 20 processes each with 250 iterations for the prioritized search. The parameters for exploration, crossover, and mutation for both algorithms have been previously described in Section 3.4. To assess the robustness of the algorithms against stochastic variations, each instance was solved 5 times for each algorithm presented by changing each time the random seed.

In Table 3.6, a comprehensive set of metrics evaluating the performance of each algorithm is presented. Specifically, the table includes Pareto front contributions (PF), hypervolumes (HV), algorithm runtime in seconds, and iterations to the best Pareto front (ITB). The hypervolume measures the volume of the objective space that is dominated by the obtained set of non-dominated solutions and bounded by a predefined reference point. The reference point is selected just beyond the worst performance observed across all examined algorithms. Specifically, for each instance, it is defined by the maximum values of the Berth Allocation and Truck Arrival Management objectives observed in the proposed fronts across all solution methods. An algorithm with a larger hypervolume over the other indicates a better spread and convergence of the Pareto front approximation toward the true Pareto front.

For these metrics, the average, minimum, and maximum values across the 5 runs are presented. The selection of five runs was made after confirming that the coefficient of variation related to hypervolumes had stabilized after five runs. It is important to note that the true Pareto front is unknown; therefore, the solutions are assessed based on the best results obtained across all solution algorithms. Finally, the combined performance of each algorithm, aggregated from all runs, is reported in the “Comb." row for each instance.

Table 3.6: Comparison of Algorithms

Algorithms		NSGA-II				SPEA2				Prioritized Search			
Instance	Stats	PF	HV	Runtime	ITB	PF	HV	Runtime	ITB	PF	HV	Runtime	ITB
20-2-low	Avg.	6.1	3.8×10^{3}	1315	3178	5.8	3.8×10^{3}	1318	2933	5	3.8×10^{3}	872	2604
	Max	7	3.8×10^{3}	2012	4800	7	3.8×10^{3}	2045	3800	7	3.8×10^{3}	1068	3540
	Min	4	3.7×10^{3}	894	2200	3	3.6×10^{3}	929	2000	3	3.6×10^{3}	734	500
	Comb.	7	3.8×10^{3}	-	-	7	3.8×10^{3}	-	-	7	3.8×10^{3}	-	-
25-2-low	Avg.	2	2.5×10^{4}	1750	3933	2	2.5×10^{4}	1483	4489	3	2.2×10^{3}	1252	1780
	Max	2	2.5×10^{4}	2517	5000	2	2.5×10^{4}	2480	5000	5	2.5×10^{4}	1439	4080
	Min	0	2.4×10^{4}	1219	2200	1	2.4×10^{4}	1108	3400	0	1.8×10^{4}	1113	320
	Comb.	2	2.5×10^{4}	-	-	2	2.5×10^{4}	-	-	6	2.5×10^{4}	-	-
30-2-low	Avg.	2	1.4×10^{4}	1902	4889	1	1.5×10^{4}	1856	4778	3	1.8×10^{4}	1387	3581
	Max	7	1.7×10^{4}	2945	5000	4	1.7×10^{4}	2959	5000	5	1.9×10^{4}	1518	4880
	Min	0	1.1×10^{4}	1326	4400	0	1.4×10^{4}	1346	4000	1	1.7×10^{4}	1209	1240
	Comb.	12	1.7×10^{4}	-	-	6	1.7×10^{4}	-	-	13	2.0×10^{4}	-	-
25-3-medium	Avg.	0	0.9×10^{8}	2110	4960	0	0.9×10^{8}	2069	5000	4	1.2×10^{8}	974	4368
	Max	0	1.0×10^{8}	2120	5000	0	1.0×10^{8}	2091	5000	6	1.2×10^{8}	1186	4840
	Min	0	0.8×10^{8}	2099	4800	0	0.9×10^{8}	2036	5000	1	1.1×10^{8}	815	4080
	Comb.	0	1.1×10^{8}	-	-	0	1.0×10^{8}	-	-	16	1.2×10^{8}	-	-
30-3-medium	Avg.	0	0.1×10^{7}	2664	4840	0	0.1×10^{7}	2635	4866	3.8	0.2×10^{7}	1393	4020
	Max	0	0.1×10^{7}	2772	5000	0	0.1×10^{7}	2660	5000	7	0.2×10^{7}	1845	4900
	Min	0	0.9×10^{6}	2617	4600	0	0.9×10^{6}	2609	4800	1	0.1×10^{7}	1087	2440
	Comb.	0	0.1×10^{7}	-	-	0	0.1×10^{7}	-	-	10	0.2×10^{7}	-	-
35-3-medium	Avg.	0	0.8×10^{8}	3156	4933	0	1.5×10^{8}	3101	4933	4.2	2.3×10^{8}	2602	4756
	Max	0	1.5×10^{8}	3209	5000	0	1.7×10^{8}	3164	5000	11	2.4×10^{8}	2920	4940
	Min	0	0.8×10^{7}	3065	4800	0	1.3×10^{8}	3015	4800	1	2.3×10^{8}	2281	4400
	Comb.	0	1.5×10^{8}	-	-	0	1.7×10^{8}	-	-	17	2.4×10^{8}	-	-
40-4-high	Avg.	0	1.3×10^{8}	2820	5000	0	1.4×10^{8}	2840	5000	14.3	3.2×10^{8}	6949	4933
	Max	0	1.5×10^{8}	2850	5000	0	1.6×10^{8}	3091	5000	20	3.3×10^{8}	7075	4980
	Min	0	1.1×10^{8}	2669	5000	0	1.1×10^{8}	2669	5000	10	3.2×10^{8}	6798	4860
	Comb.	0	1.6×10^{8}	-	-	0	1.7×10^{8}	-	-	43	3.3×10^{8}	-	-
45-4-high	Avg.	0	4.0×10^{9}	4123	5000	0	3.9×10^{9}	3809	5000	13.3	1.1×10^{10}	9138	4920
	Max	0	5.0×10^{9}	4643	5000	0	4.8×10^{9}	4596	5000	21	1.2×10^{10}	9339	4980
	Min	0	3.4×10^{9}	3539	5000	0	2.8×10^{9}	3312	5000	6	1.1×10^{10}	8881	4820
	Comb.	0	5.0×10^{9}	-	-	0	4.8×10^{9}	-	-	40	1.2×10^{10}	-	-
50-4-high	Avg.	0	1.6×10^{12}	4586	5000	0	1.5×10^{12}	3421	5000	9.30	1.7×10^{12}	11777	4953
	Max	0	1.6×10^{12}	5497	5000	0	1.6×10^{12}	3877	5000	24	1.7×10^{12}	12554	4980
	Min	0	1.5×10^{12}	3839	5000	0	1.5×10^{12}	3136	5000	0	1.7×10^{12}	11031	4940
	Comb.	0	1.6×10^{12}	-	-	0	1.6×10^{12}	-	-	28	1.7×10^{12}	-	-

The instances are further analyzed based on the traffic level used, beginning with the low traffic scenarios. For these cases, the performance of the Prioritized Search algorithm was found to be comparable to, or better than that of NSGA-II and SPEA2.

For the 20-2-low instance, NSGA-II showed slightly better consistency in identifying the best observed front, reflected in a higher average of Pareto front contributions. However, variability in both Pareto front contributions and hypervolumes remained marginal across all methods. In the 25-2-low instance, none of the algorithms identified the complete best observed Pareto front in a single run. Nonetheless, Prioritized Search achieved the highest number of Pareto front contributions across all runs. Interestingly, its average hypervolume performance was slightly lower than that of SPEA2 and NSGA-II. In the more complex 30-2-low instance, Prioritized Search further solidified its advantage. It consistently delivered more Pareto front contributions, higher hypervolumes, and faster convergence to the best observed front. While NSGA-II and SPEA2 each contributed only six solutions to the front, Prioritized Search contributed twelve, helping to uncover a front of 21 distinct solutions, underscoring the need for arbitration in such a multi-objective context. It is important to notice that the Prioritized Search algorithm exhibited a clear runtime advantage, being approximately 20-50% faster in runtime and significantly better convergence to the best solution than the evolutionary algorithms. In Figure 3.8, the Pareto fronts identified by the solution algorithms and their overall convergence behavior are illustrated.

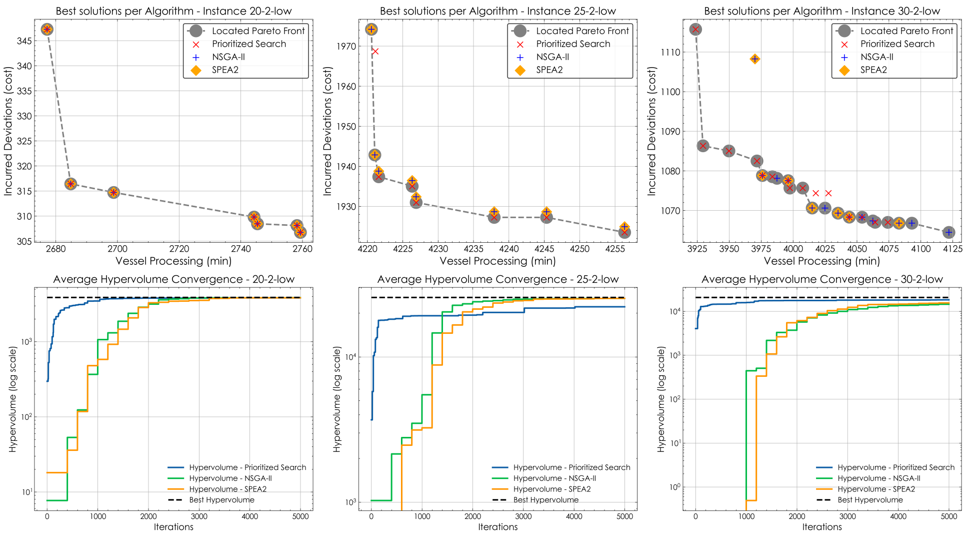


Figure 3.8: Comparison of pareto fronts and convergence across algorithms for instances of low traffic.

In the medium traffic instances 25-3, 30-3, and 35-3, the Prioritized Search algorithm consistently outperformed both NSGA-II and SPEA2 across all evaluated metrics. In the 25-3 instance, it was the only algorithm to contribute to the Pareto front, providing 16 non-dominated solutions and achieving the highest average hypervolume about 33% higher than the best-performing evolutionary algorithm. The 30-3 instance showed similar trends, with Prioritized Search contributing 10 solutions, compared to none by the evolutionary algorithms, and achieving an average hypervolume approximately 100% higher. In the 35-3 instance, Prioritized Search again dominated, contributing 17 solutions and reaching an average hypervolume which was over 50% higher than NSGA-II and SPEA2. Runtime analysis indicates that in the most complex case, Prioritized Search required about 10% more computation time on average, but reached its best solutions in 25% fewer iterations, suggesting better efficiency per iteration. In contrast, NSGA-II and SPEA2 not only failed to find high-quality trade-offs but also consumed comparable or greater computational resources. This inefficiency is compounded by their zero contributions to the combined Pareto fronts across all instances. Overall, it demonstrates clear advantages in convergence speed, solution quality, and computational efficiency in medium traffic scenarios, as illustrated in Figure 3.9.

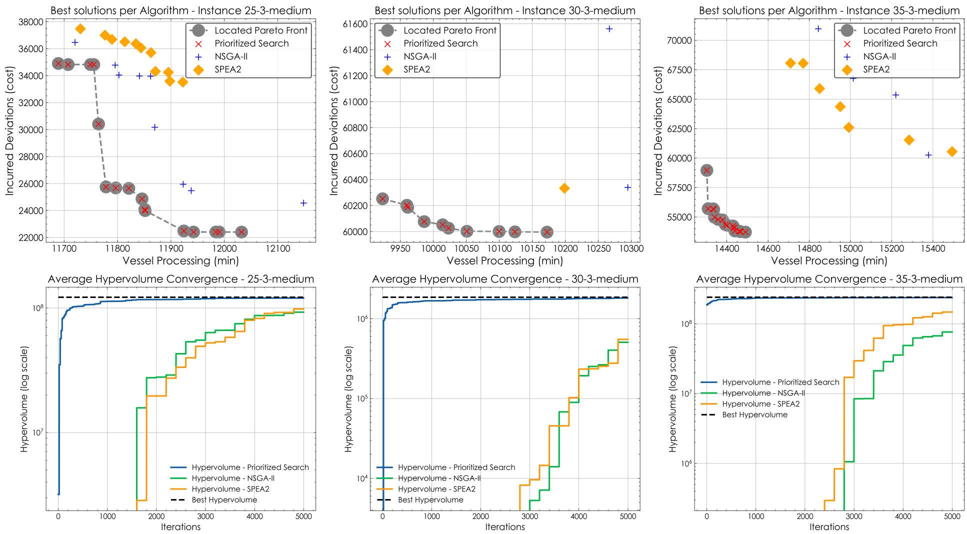


Figure 3.9: Comparison of Pareto fronts and convergence across algorithms for instances of medium traffic.

In the high traffic instances 40-4, 45-4, and 50-4, Prioritized Search again showed a significant advantage over NSGA-II and SPEA2. In all three cases, the evolutionary algorithms failed to contribute any solutions to the combined Pareto fronts, while Prioritized Search contributed 43, 40, and 28 solutions respectively. This dominance is again reflected in its consistently superior hypervolume values, indicating both better spread and convergence toward the optimal front. Although the complexity of the problem increased substantially, Prioritized Search remained effective, continuing to identify well-balanced solutions near the knee of the Pareto front. However, the increase in complexity came with a computational cost, as Prioritized Search exhibited longer runtimes than both NSGA-II and SPEA2 in all three high traffic instances. These findings are visually summarized in Figure 3.10, which highlights the superior performance and robustness of Prioritized Search in demanding high traffic scenarios.

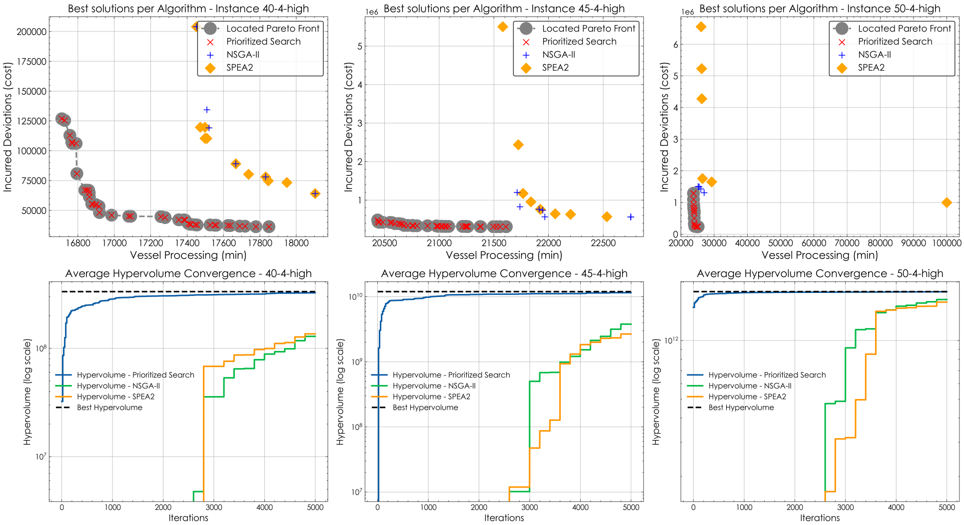


Figure 3.10: Comparison of Pareto fronts and convergence across algorithms for instances of high traffic.

3.6. CONCLUSIONS

This study introduces a novel approach to enhancing stakeholder coordination by synchronizing truck scheduling and berth allocation in a marine terminal. It presents an appointment system for trucks, building on the existing concept of vessel-dependent time-windows but allowing more flexibility for schedule deviations of vessels. A comprehensive model is proposed to facilitate terminal decision-making through orchestration of all interacting actor groups. Through effective terminal coordination, this model generates solutions that benefit all parties involved. Decision-making is achieved by distributed agents, focusing on representing the requirements imposed by different actors related to berth allocation, truck arrival processing and terminal operations. Additionally, the study presents a new multi-agent, multi-objective solution methodology based on Prioritized search for the proposed model, tested against common benchmark algorithms to validate its applicability and effectiveness.

The Prioritized Search method demonstrates increased performance by generating more Pareto front contributions and overall better convergence. Across all traffic scenarios, the Prioritized Search algorithm contributed a total of 180 Pareto-optimal solutions, compared to 21 by NSGA-II and 15 by SPEA2, highlighting a substantial advantage in solution discovery. Moreover, it consistently achieved higher hypervolume reaching up to 100% in medium traffic cases and maintained superior convergence efficiency, reaching the best solutions in 25–50% fewer iterations on average. The average runtime per iteration for medium-traffic instances was approximately 0.5 seconds for NSGA-II and SPEA2, and 0.3 seconds for the Prioritized Search. However, in higher-traffic instances, this increased to around 0.8 seconds for NSGA-II and SPEA2, and 2 seconds for the Prioritized Search. This indicates that while the Prioritized Search is more efficient in less congested scenarios, its runtime scales less favorably under heavier traffic conditions due to the increased complexity of coordinated decision-making. Nonetheless, even at half the number of iterations, the performance of the Prioritized Search in high-traffic instances remained superior, highlighting its effectiveness despite the increased computational cost. The solution algorithm is particularly effective at identifying solutions near the knee of the Pareto front across a range of traffic scenarios, consistently outperforming or matching NSGA-II and SPEA2. Although it incurs higher computational costs, especially in larger instances, this method delivers significantly superior solution quality due to its more focused and efficient exploration of the search space. Notably, it achieves these results while requiring fewer iterations on average, highlighting its ability to converge more quickly to high-quality trade-offs. In a more qualitative manner, the proposed approach highlights the potential of different prioritization techniques in vessel rotation and terminal cargo management through enhanced stakeholder collaboration and coordination.

Although the proposed coordination model yields promising results for medium-sized terminals, its applicability to larger ports merits further exploration. Power asymmetry warrants further investigation, as ports, particularly larger terminals, often have established relationships with specific stakeholders. These dynamics could be captured in the model through negotiation protocols or power-sensitive utility functions that reflect varying levels of influence. The model's modular design facilitates such extensions. Validating the approach in a larger terminal would be a valuable direction for future research but may introduce challenges tied to a broader and more diverse stakeholder base, including data-sharing barriers and conflicting interests, issues more likely in the competitive environment of a major port. Real-world implementation should also address stakeholder reluctance toward oversight by clearly defining operational prerequisites and integration pathways for deploying the system within Port Community Systems. In terms of scalability, the computational cost of the Prioritized Search method, while capable of producing high-quality Pareto solutions, may limit its practicality in real-time or large-scale settings with constrained processing resources. Nevertheless, research avenues exist for improving the scalability of the approach. Another limitation of the current model is its reliance on deterministic vessel arrivals and fixed planning horizons. This reduces its responsiveness to real-world disruptions, such as delays or equipment failures. Furthermore, the model does not yet incorporate real-time data or reflect specific terminal technologies. For instance, in ports where Automated Guided Vehicles (AGV) are deployed, the framework could be extended to represent AGV-based drayage operations.

Building on these limitations, possible extensions would focus on the further refining of the Prioritized Search algorithm. Enhancing the search strategy by incorporating more operators could potentially yield better outcomes through smarter exploration. Additionally, exploring alternative tree formation methods, such as depth-first search, might reduce computational costs associated with priority-based tree operations. An additional consideration would be to treat the terminal as an independent agent with its own objective value taking into account other optimization criteria such as the minimization of empty runs. Applying this approach to a multi-terminal environment, where vessels and trucks may have to rotate between terminals could also introduce new complexities, enhancing our understanding of inter-terminal dynamics. Finally, the impact of dynamic scheduling, introduction of uncertainty in arrivals, and real-time data integration to enhance the adaptability of the proposed approach in disruptions could be also explored as well as the applicability to other domains, such as airport logistics or urban freight systems.

STATIONARY BACKLOG CARRYOVER QUEUING APPROXIMATION

For an expected arrival rate r :

$$r^*_{i+1} = r_{P+1} + b_i, \;\; \forall i \in \mathscr{I} \tag{3.28a}$$

$$r^*_1 = r_1 \tag{3.28b}$$

$$b_i = r^*_i \cdot P_i(b), \;\; \forall i \in \mathscr{I} \tag{3.28c}$$

where b_i represents the expected trucks to be shifted to the next time-period based on the current arrival rate and service time of the gate and r^* is the updated arrival rate. To compute the probability $P_i(b)$ of traffic spilling over to the next-time-window Erlang's loss formula is applied. Parameter μ relates to Avg. gate service time.

$$P_i(b) = \frac{(\frac{r^*_i}{\mu})^k}{k! \cdot \sum_{i=0}^{k} \frac{(\frac{AR^*_i}{\mu})^i}{i!}}, \;\; \forall i \in \mathscr{I} \tag{3.29}$$

To account for the modified arrival rate of trucks AR_i^{MAR} that is expected to be processed in a single time-period the expected utilization rate of the gate $E_i[U]$ is computed as follows:

$$E_i[U] = \frac{r^*_i - b_i}{k \cdot \mu}, \;\; \forall i \in \mathscr{I} \tag{3.30a}$$

$$r_i^{MAR} = k \cdot \mu \cdot E_i[U], \;\; \forall p \mathscr{P} \tag{3.30b}$$

$$\rho_i = \frac{r_i^{MAR}}{\mu \cdot k}, \;\; \forall i \in \mathscr{I} \tag{3.30c}$$

$$l_i = r_i^{MAR} \cdot E_i[W_{M/G/k}], \;\; \forall i \in \mathscr{I} \tag{3.30d}$$

For the computation of the expected queue length within each time-window, the Cosmetatos approximation [136]) is leveraged.

$$E_i[W_{M/G/c}] = CV^2 \cdot E_i[W_{M/M/c}] + (1 - CV)^2 \cdot E_i[W_{M/D/c}], \;\; \forall i \in \mathscr{I} \tag{3.31}$$

This approximation relies on the calculation of the waiting time $E_i[W_m/M/k]$ for the $M/M/k$ queue (service times are exponentially distributed) and the expected waiting time $E_i[W_m/D/k]$ for the $M/D/k$ queue (job service times are deterministic). Precise analytical derivations of queue performance metrics for these two queues are well-documented in [137].

M/M/k queue

$$\pi_{0_i} = \left[\sum_{i=0}^{k-1} \frac{(k\rho_i)^i}{i!} + \frac{(k\rho_i)^k}{k!(1-\rho_i)} \right]^{-1}, \;\; \forall i \in \mathscr{I} \tag{3.32a}$$

$$E_i[W_{M/M/k}] = \frac{\pi_{0_i}\left(\frac{r_i^{MAR}}{\mu}\right)^k \rho_i}{k!(1-\rho_i)^2 \cdot r_i^{MAR}}, \quad \forall i \in \mathscr{I} \tag{3.32b}$$

M/D/k queue

$$n_{c_i} = \left(1 + \frac{(1-\rho_i)(k-1)(4+5k)^{0.5} - 2}{16\rho_i \cdot k}\right)^{-1}, \quad \forall i \in \mathscr{I} \tag{3.33a}$$

$$E_i[W_{M/D/k}] = \frac{E_i[W_{M/M/k}]}{2 \cdot n_{c_i}}, \quad \forall i \in \mathscr{I} \tag{3.33b}$$

4

Multimodal disruption management for airport access under multiple traffic orchestrators

Chapter 4 explores the interaction of multiple orchestrators across transport domains. In particular, the examined problem relates to airport access from a major metropolitan region, under disruptive situations, and the two orchestrators are divided to the landside and airside domain. Apart from introducing multiple orchestrators, the system now more explicitly includes interactions of network users with the traffic orchestrator role. The goal is to propose a disruption management approach for airport access by modeling the interaction of all users involved in the system.

Agent-based simulation is used to capture users' interactions. Building on the simulation, a negotiation-based mechanism is proposed, where each orchestrator negotiates the application of tactical measures, such as flight delays or passenger rerouting. A cooperative approach is also explored that makes use of two different cost sharing rules. Both approaches are evaluated through a case study, demonstrating their effectiveness in improving operations and ensuring fair cost distribution among orchestrators.

First, Section 4.1 introduces the problem of multimodal disruption management. Then, Section 4.2 presents the agent-based simulation used to represent airside and landside dynamics. In Section 4.3, the coordination mechanisms between orchestrators are discussed, while Section 4.4 and Section 4.5 detail the negotiation and cooperation frameworks supporting the decision-making. The proposed approaches are evaluated through a case study in Section 4.6, and key findings are discussed in Section 4.7.

This chapter is based on the following research article: Parmaksizoglou, I.A.; Bombelli, A.; Sharpanskykh, A. Agent-based simulation of passenger-centric disruption management for multimodal airport access, Transportation Research Procedia, 2025

4.1. Introduction

In the aviation sector, this push for integration is especially critical. The European Commission has set a target for 90% of travelers within Europe to complete their door-to-door journey within four hours by 2050 [138], which highlights the need for efficient airport access. Achieving this goal requires the coordination of all transport modes involved [139]. In response, airlines have begun offering integrated ticketing and multimodal options that emphasize seamless connections, such as Lufthansa's partnership with Deutsche Bahn [140]. However, a key challenge remains: securing consensus and collaboration among transport operators by facilitating cross-system data sharing, which is essential to enable seamless door-to-door travel in Europe [141].

The challenge of collaboration is further compounded by the occurrence of disruptions in multimodal transport systems, which relies heavily on effective coordination between different modes. On the airside, Airport Collaborative Decision Making (A-CDM) mitigates disruptions related to delays by using information sharing among aviation stakeholders to enhance predictability and resource use. On the landside, the META-CDM concept has been proposed as a framework to bridge the information-sharing gap between air and land transport during disruptions, and address delays affecting both domains [142]. Enhancing the interchangeability of transport modes has been identified as essential for optimizing disruption management [143]. In the aviation sector, improving operations related to passenger disruption management has been shown to reduce congestion, mitigate environmental impacts, and lower costs [144].

While airside disruptions pose significant challenges on their own, delays affecting air passengers often originate from the landside as well. Seamless integration of air transport with public transportation networks can play a crucial role in minimizing delays, if it allows passengers to adapt quickly. To address airport access disruptions, tactical flight rescheduling has been proposed as a measure for servicing affected passengers [77]. This approach involves strategically delaying certain passengers to accommodate disrupted ones, an approach that may seem counterintuitive, but can lead to cumulative passenger delay minimization when considering rebooking related delays. Ensuring compliance with Air Traffic Management (ATM) parameters as well as broader network impacts of delays must also be considered [37], as flight delay management is a complex issue involving multiple stakeholders, including airlines, airports, and passengers [145].

On the landside, delays caused by changes in the network are more common but can have a severe impact, altering the estimated travel time and, consequently, the arrival time of passengers [146]. To mitigate this, various approaches have been proposed focusing on multimodal rerouting and flexible trajectory updates. [147] proposed a model to facilitate collaboration among mobility schemes and identify optimal transfer points for integrating private vehicles with public transport to alleviate congestion. Additionally, [148] introduced a demand-responsive service leveraging urban taxi infrastructure to improve access in underserved areas, particularly for airport connections. Furthermore, integration of rerouting models into public transport disruption management has been explored by [149].

This study seeks to enhance disruption management for multimodal airport access by improving coordination among stakeholders in passenger airport access, under landside disruptions. To achieve this, we distinguish the problem into two distinct domains and propose a framework that incorporates traffic orchestrators (TOs) for each domain, as outlined by [20]. A TO is considered responsible for traffic management within a well defined transport domain. The framework includes an airside and landside orchestrator, each capable of applying corrective measures to serve passengers during periods of disruptions. Assuming an integrated ticketing solution for train-accessing passengers, this study specifically explores the implementation of tactical flight delays as a corrective measure applied by the airside orchestrator, and the deployment of rerouting strategies, such as directing passengers to alternative transport options like buses, by the landside orchestrator.

An agent-based simulation environment is developed mapping operations related to flight departures, passenger arrivals, transit network updates, and security screening. When a flight is identified as having passengers at risk of missing their flights due to a disruption, corrective measures are established under a game-theoretic framework, where orchestrators negotiate to reach a consensus on the application of measures. Multi-agent negotiation across stakeholders in the aviation sector has been previously explored as a way to evaluate performance based on decision-making levels and coordination capabilities [68, 150]. In our approach, orchestrators engage in iterative one-to-one negotiations to minimize their respective costs. The impact of different strategies employed by the orchestrators is assessed through an experimental evaluation, focusing on the optimization of costs for the orchestrators and their effects on overall airport performance.

4.2. Agent-based Simulation

Given the system under consideration consists of multiple autonomous, coordinating entities, the multi-agent system modeling and simulation paradigm is well-suited for representing and analyzing its dynamics. The proposed agent-based model is illustrated in Figure 4.1, with a detailed breakdown of all associated agents provided in the following chapters.

4.2.1. Environment

To model the operations of the examined airport, inputs are required on passenger behavior, flight schedule, airport conditions, and the transit network serving the airport. All modeling decisions regarding the simulated processes were made in consultation with the examined airport's accessibility managers [151]. Establishing modal splits for incoming passengers is a main environmental input. These vary depending on the time of day, as detailed in Table 4.1. Peak hours (7:00–9:00, 16:00–19:00) correspond to the highest arrival activity, shoulder hours to moderate activity between peak periods, and off-peak hours to lower activity. Transit schedules for buses and trains are integrated using publicly available General Transit Feed Specification (GTFS) data for the examined date [152]. Passenger arrival is also contingent on carrier and destination type, as it strongly influences the expected

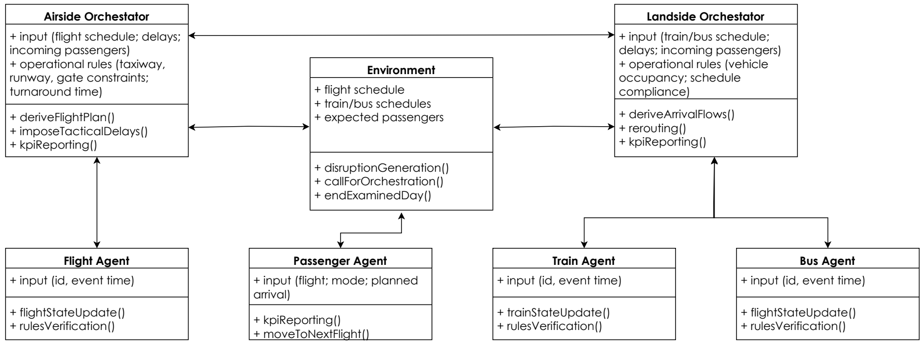


Figure 4.1: Schematic representation of the agent-based simulation model.

safety margin for a passenger, which indicates how much in advance we expect a passenger to arrive in the airport, compared to their scheduled departure time, as listed in Table 4.2.

Table 4.1: Modal share during different time periods.

Time Period	Bus	Car	Taxi	Train
Peak Hours	15%	45%	10%	30%
Shoulder Hours	10%	60%	10%	20%
Off-Peak Hours	10%	60%	20%	10%

Table 4.2: Expected safety margin prior to flight departure.

Carrier	Domestic	Non-Schengen	Schengen
Legacy	2 hr	3 hr	2 hr
Low-Cost	1.5 hr	2 hr	1.5 hr
Leisure	1.5 hr	2 hr	1.5 hr

Data on carriers, arrivals/destinations, aircraft types, and scheduled departure/arrival times for the examined date are collected from publicly available flight records [153]. Passenger volumes for specific flights were provided by the airport. Additionally, airport capacity limits are set as operational constraints. A maximum of 77 aircraft can be accommodated at the gates, a two-runway configuration is present, and a taxiing network capacity of 15 aircraft. Finally, the airport is equipped with 20 X-ray machines, though not all are operational at all times. Their availability varies by period: 20 during peak hours, 10 during shoulder hours, and 5 during off-peak hours.

4.2.2. PASSENGER AGENTS

In the absence of exact data, approximation methods are used to generate the arrival times of passenger agents. Each passenger agent is assigned a mode and a flight as part of its characteristics, which influences their arrival time. We consider that passenger arrivals for a specific flight follow a normal distribution, with the mean centered around the flight departure time minus the arrival safety margin (as listed in Table 4.2), and a standard deviation of 30 minutes. This aligns with recent examples of existing literature [154] and consultations with the airport. Transfer passengers are treated as departing passengers, with their arrival time matching their flight's arrival time. For passengers arriving via a public transit mode, generated agent arrival times, are also linked to the airport's transit network, ensuring that their arrival corresponds to an available service line within their mode.

After arrival, passenger agent's processing time and waiting in security queues are approximated using the stationary backlog carryover approach [132]. Once screened, an agent's state changes to either “safe" or at “risk". Non-Schengen passengers are safe if they have 45+ minutes before departure, and others are safe with 30+ minutes. Passenger agents with an at risk classification due to a disruption, may trigger corrective measures by the orchestrator agents.

4.2.3. BUS & TRAIN AGENTS

Passenger agents traveling by bus or train update the capacity of the corresponding line of a Train or Bus agent servicing their connection to the airport. These agents fall under the domain of the landside orchestrator and are sensitive to updates related to changes in the GTFS input (e.g., due to a disruption), based on interactions with the landside orchestrator. Operationally, a train line has a maximum capacity of 230 passengers, while a bus line has a maximum capacity of 55 passengers. As passengers are simulated, both bus and train agents update their capacity to ensure compliance with these limits. If a passenger attempts to board a line at maximum capacity, the bus or train agent will reschedule them to the next available service.

4.2.4. FLIGHT AGENTS

These agents fall under the domain of the airside orchestrator. Flight agents are activated according to the schedule of the examined environment and are continuously updated to reflect real-time changes in airport operations. The flight agent's state transitions through various phases such as waiting, taxiing, takeoff/landing, and arrived/departed, while interacting with airport infrastructure to ensure compliance with operational constraints for gate, taxiway and runway utilization set by the environment. The two-runway configuration also requires a 2-minute separation between consecutive aircraft, and one runway dedicated exclusively to departures and the other to arrivals. Taxiing time is dynamically adjusted based on congestion, ranging from a minimum of 5 minutes on an empty taxiway to a maximum of 15 minutes under full congestion. Any flight agent that may violate these conditions is delayed. Additionally, turnaround time constraints are imposed mandating a minimum gap of 45 minutes between a flight's arrival and departure; if this is violated, the agent is delayed accordingly.

4.2.5. Orchestrator agents

Orchestrators oversee the activation of agents within their domain, ensuring compliance with operational constraints and reporting KPIs, such as delays. They are primarily responsible for implementing corrective measures during disruption than can lead to the adjustment of other agents' conditions. An airside orchestrator can directly impact the flight schedule of all flight agents by imposing tactical delays on individual flights, while a landside orchestrator can alter the capacity conditions of bus and train agents by rerouting passengers. Each orchestrator has its own objective function guiding its decision-making, which may consider multiple aspects. Orchestrators do not have explicit knowledge of each other's objective functions. The selection of appropriate measures is achieved by orchestrators trying to optimize their objectives through coordination between them.

4.3. Coordination

During the simulation, when a flight is identified as having at-risk passenger agents due to a disruption, orchestrator imposed measures are explored. In the examined framework, a disruption may involve a sudden cancellation of multiple train lines to the airport, leading to increased congestion and a supply-demand imbalance for this mode of transport. Coordination between TOs in the proposed system follows the process outlined in Figure 4.2.

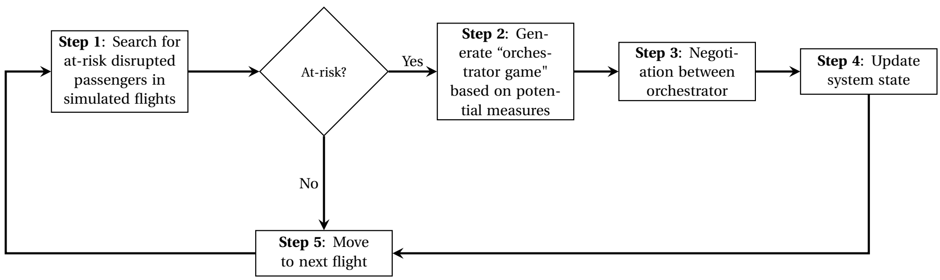


Figure 4.2: Coordination Strategy for traffic orchestration.

To determine which measures can be applied to mitigate disruption issues, we develop the "orchestrator game". In this game, the airside orchestrator can take actions related to tactical flight delays, while the landside orchestrator takes actions on multimodal rerouting. Effects of each action are highly correlated. For example, rerouting certain number of passengers may not be possible without a specific tactical delay applied, or a tactical delay may make rerouting of passengers redundant, as the passenger agents' would no longer be classified as at risk. This has a direct effect on incurred costs of orchestrators.

We associate costs for the airside orchestrators with the cost of unpunctuality. This is the implied revenue losses for an airline resulting from a departure delay, also referred as the “soft" cost of passenger delay [155]. Monetary values used to estimate these costs, are based on aircraft type, delay duration, and the number of affected passengers [156]. Regardless of cost, tactical delays must remain limited to avoid adverse effects, particularly on transfer passengers. Thus, the maximum tactical delay is capped at 30 minutes.

During a disruption, the landside orchestrator seeks to identify rerouting opportunities for at-risk passengers. Selecting passengers to reroute is also contingent on the state of the simulation, ensuring that potential options are not at capacity. Naturally, rerouting incurs a cost equivalent to the fare of the alternative mode of transport, set at 15€ for this simulation. As the amount of passengers that need to be rerouted is contingent on the applied tactical delay as well, we use an iterative approach with a five-minute step starting from 0 to 30 minutes to create a cost matrix for these measures.

4

Finally, there is the cost of rebooking passengers that missed their flights. Under the proposed integrated ticketing solution, orchestrators are assumed to bear responsibility for this, to boost seamlessness of the door-to-door journey experience. We also make use of the [156] report to associate costs of rebooking a passenger based on flight type (short-haul, mid-haul or long-haul). To determine cost-sharing for rebooking costs during a network disruption, an ad-hoc mechanism is introduced. If the airside orchestrator takes no action, the costs are shared equally. Since the disruption originates on the landside, it is deemed unfair to allocate more than 50% of the cost to the airside, even in the absence of any intervention. However, for each tactical delay applied by the airside orchestrator, its share of rebooking costs is progressively reduced. Once a tactical delay of 15 or more minutes is imposed, the airside's cost share is reduced to zero.

Table 4.3: Cost distribution for different tactical delays and rerouting scenarios.

Airside	**Landside**		
	$Y = 0$	$Y = 1$	$Y = 2$
$X = 0, \delta = 0$	(1250,1250,0)	-	-
$X = 5, \delta = 5$	(866,833,5)	(783,682,6)	(700,530,7)
$X = 10, \delta = 10$	(966,184,9)	(900,15,10)	-
$X = 15, \delta = 15$	(1400,250,9)	(1400,15,10)	-
$X = 20, \delta = 30$	(3150,0,10)	-	-
$X = 25, \delta = 60$	(5400,0,10)	-	-
$X = 30, \delta = 90$	(8100,0,10)	-	-

In Table 4.3, an example of the “orchestrator game" is introduced. Each entry in the table is a three-dimensional tuple, defined by an applied tactical delay of X minutes and Y rerouted passengers. The table shows the costs to the airside and landside orchestrators, along with the number of at-risk passengers served by this joint action, included for clarity. Empty cells indicate the infeasibility of a joint action. For this example, we consider a short-haul flight with 100 passengers, 90 of whom are safe and 10 at risk of missing their flight. The rebooking cost of 250€ per passenger, as outlined in [156], applies to short-haul flights, while the soft cost of passenger delay (denoted by δ) varies depending on the delay and the aircraft type (in this case, a B733).

When no action is taken ($X = 0$, $Y = 0$), the cost of rescheduling the 10 at-risk passengers (250€ × 10) is equally shared between the orchestrators. With a 5-minute tactical delay ($X = 5$), 5 passengers are already able to catch their flight, but the airside incurs a soft cost of 450€ for the 90 safe passengers that experience a 5 minute-delay. This is in addition to the shared 1250€ cost for the remaining five passenger that missed their flights. In this case, the airside orchestrator covers one third (416€) of the total cost, while the landside orchestrator bears the remaining two thirds (833€). Furthermore, rerouting a single passenger in this case (X=5, Y=1) reduces the shared cost by 250€, with the airside and landside orchestrators each saving 83€ and 167€, respectively, while the landside incurring an additional 15€ rerouting cost.

The landside orchestrator's optimal action favors longer delays without rerouting (X, Y = (20,0), (25,0), (30,0)), whereas the airside prefers a 5-minute delay with rerouting (X, Y = (5,2)), which also corresponds to a Nash equilibrium, even though some passengers are not served in this scenario. A fully cooperative solution which minimizes the combined costs for the two orchestrators, would result in X, Y = (10,1), but may not be the fairest since it disproportionately burdens the airside orchestrator.

4.4. Negotiation

We use the "orchestrator game" to reach joint actions through negotiation between the two orchestrators. The goal is to develop solutions that not only enhance system performance but also ensure fairness. The components of the proposed negotiation mechanism are as follows:

- **Domain:** Orchestrators negotiate corrective measures by exchanging proposals, determining the extent of applied measures and whether they should be applied individually or in combination.

- **Protocol:** A heuristic-based framework, simulating an alternate-offer protocol is used. In the examined protocol, cost-bargaining enables orchestrators to negotiate to minimize their incurred costs, while preserving their autonomy in decision-making. The alternate-offer protocol is described in Algorithm 6.

- **Utilities:** Each orchestrator's preference profiles are represented through aspirations, linked to incurred costs.
  - *Airside Orchestrator:* Cost of unpunctuality based on incurred delays for passengers, and attributed costs for flight rebooking.

– *Landside Orchestrator:* Cost of rerouting passengers, and attributed costs for flight rebooking.

Algorithm 6: Alternate offer protocol between orchestrators

Input: R, w_A, w_L, $cost_f$, $step$

1 Initialize $r_A \leftarrow 0$, $r_L \leftarrow 0$, $c_A \leftarrow 0$, $c_L \leftarrow 0$
2 **for** each flight f with at-risk disrupted passengers **do**
3   Determine orchestrator game cost matrix ($cost_f$) and extract $best_A, best_L$ based on OF_A, OF_L
4   Set $a_A \leftarrow best_A$, $a_L \leftarrow best_L$, $negotiated\_action \leftarrow \emptyset$
5   **while** $negotiated\_action = \emptyset$ **do**
6   **for** $r = 1$ to R **do**
7   Compute $step_A \leftarrow step \cdot w_A$, $step_L \leftarrow step \cdot w_L$
8   Find best $valid\_pair$ for minimizing $cost_A$ related to airside objective function OF_A
9   **if** $cost_L \leq a_L$ **then**
10                 $negotiated\_action \leftarrow valid\_pair$
11   **break**
12   **end**
13   Find best $valid\_pair$ for minimizing $cost_L$ related to landside objective function OF_L
14   **if** $cost_A \leq a_A$ **then**
15                 $negotiated\_action \leftarrow valid\_pair$
16   **break**
17   **end**
18   Update $a_A \leftarrow a_A + step_A$, $a_L \leftarrow a_L + step_L$
19   **end**
20   **if** $negotiated\_action = \emptyset$ **then**
21   Increase $step$
22   **end**
23   **end**
24   Update $r_A \leftarrow r_A + cost_A - best_A$, $c_A \leftarrow c_A + cost_A$
25   Update $r_L \leftarrow r_L + cost_L - best_L$, $c_L \leftarrow c_L + cost_L$
26   Update w_A, w_L
27 **end**
28 **return** r_A, r_L, c_A, c_L

For each flight f with at-risk passengers, a cost matrix, denoted as $cost_f$, is created to represent the orchestrator game. The actions that minimize each orchestrator's objective functions are computed (Algorithm 6, Line 3) and serve as their initial aspirations. Objective functions can take various forms, and in this study, two approaches are explored: the independent approach, where an orchestrator always suggests the optimal measure from their own perspective, and the cooperative approach, which considers the other orchestrator's costs in their objective function as well. In the cooperative approach, the objective functions incorporate parameters w_A and w_L for airside and landside orchestrator respectively, which represent the extent of concession each orchestrator is willing to make, as follows:

$$OF_A = \text{cost}_A + w_A \cdot \text{cost}_L, \quad OF_L = \text{cost}_L + w_L \cdot \text{cost}_A \tag{4.1}$$

Negotiations take place over a fixed number of rounds, R, during which orchestrators alternate making offers based on their objective functions. In each round, an orchestrator can either accept the offer or propose a counter-offer, continuing until an orchestrator's acceptance condition is met. If a proposal results in a cost that is less or equal to the other orchestrator's aspiration, an agreement is reached, and negotiation concludes. If no agreement is reached within a round, aspirations are increased based on the current step of each orchestrator (Algorithm 6, Line 16). Acceptance conditions are closely tied to the orchestrators' concession parameters (w_A,w_L), as these directly influence how aspirations increase over successive rounds (Algorithm 6, Line 7). If an agreement is not reached within R rounds, the parameter $step$ is updated and the negotiation process is restarted (Algorithm 6, Line 18).

Parameters w_A and w_L may be updated to ensure that the outcomes of previous negotiations influence subsequent rounds. In a setting where agents do not use information over past outcomes, the parameters w_A and w_L simply remain equal. However, we also explore the case where these parameters are adjusted based on orchestrator's regret (r_A, r_L). Regret of each orchestrator is the incurred additional cost over their optimal cost and is updated in the end of each game, in parallel with the total incurred cost (Algorithm 6, Lines 20-21). Specifically, we consider two options: setting w_A and w_L to 0.5 (based on the former case), or updating the values as follows:

$$w_A = 1 - \frac{r_A}{r_A + r_L}, \quad w_L = 1 - w_A \tag{4.2}$$

4.5. Cooperation

In a cooperative setting, agents coordinate to select a joint action that minimizes the total system cost. However, once this socially optimal outcome is selected, the challenge lies in distributing the total cost among the participating orchestrators in a fair and incentive-compatible way. We consider two established cost allocation rules from cooperative game theory: *proportional sharing* and allocation based on the *Shapley value*.

Proportional Sharing This rule allocates the total joint cost $C(N)$ among the participants based on their standalone costs. Let $C(i)$ be the minimum cost that orchestrator i would incur by acting independently, and let $C(N)$ be the cost under the socially optimal joint solution involving all agents. The proportional share x_i for orchestrator i is defined as:

$$x_i = \left(\frac{C(i)}{\sum_{j \in N} C(j)} \right) \cdot C(N) \tag{4.3}$$

This approach is simple and transparent but may lead to unbalanced outcomes, especially when one or more agents have zero standalone cost.

Shapley Value Allocation The Shapley value [157] offers a fairer cost allocation based on the principle of marginal contribution. For a set of agents N, the Shapley value ϕ_i for agent i is defined as the average marginal contribution of i to all possible coalitions:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \cdot [C(S \cup \{i\}) - C(S)] \tag{4.4}$$

The Shapley value computes what each agent contributes on average when joining every possible subset of the group. It satisfies desirable fairness properties such as symmetry, efficiency, and additivity, and ensures that agents who contribute nothing receive nothing, while others are rewarded in proportion to their importance in achieving the total savings. Given the simplicity of this two-player setting, computing the allocation is particularly straightforward.

4.6. EXPERIMENTAL EVALUATION

We generate a case study for Malpensa International Airport (MXP) for June 2022 to test the effect of applying the proposed measures for handling disruptions in the access network. We simulate a series of disruptions occurring on the weekend of 18/6/2022-19/6/2022, which coincides with the busiest weekend of the month. The disruptions occur on either date and during the morning peak (7:00-10:00) or afternoon peak (16:00-19:00). During these periods, we generate either a 50% reduction of service on the most used train line to the airport, or a 30% reduction of service on all train lines servicing the airport. Agent-based simulation is implemented in Python using the Mesa library [158]. We analyzed how the application of corrective measures under three different negotiation strategies:

1. **Independent**; The agents do not use past game information in their decision-making for concessions and optimize independently their own cost (w_A=w_L=0.5).

2. **Cooperative**; Orchestrators use Equation 4.1 to determine the cost of each agent taking each other into account (w_A=w_L=0.5).

3. **Adaptive**; Orchestrators update w_A and w_L based on incurred regret, as stated in Equation 4.2, while maintaining cooperation based on Equation 4.1.

Table 4.4 presents the mean value metrics from the application of different strategies during negotiation after five simulation runs for each disruption. The table reports the costs incurred by both the airside and landside orchestrators, as well as the percentage of missed flights (i.e., the passenger agents that remained at risk after application of measures), total delay incurred by passengers, and located Nash equilbria. In general, we observe that compared to the application of no measures, any negotiation strategy leads to similar results for missed flights and total delay. In the most disruptive case (D8), a decrease of up to 1.4 percent in missed flights is reported, equating to more than 5000 passengers who were able to catch their flights as a result of the corrective measures. Decreases in total delay can also be significant, reaching up to 8 minutes.

Table 4.4: Comparison of different strategies across various instances. Optimal Egalitarian social welfare is highlighted in bold.

	No measures					Independent					Cooperative					Adaptive				
Instance	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash
D1	35825	35825	0.3	14.7	12.8	10693	16256	0.1	13.8	30.4	11839	**12378**	0.1	13.8	28.4	13862	11652	0.1	13.8	28.4
D2	72015	72015	0.6	16.5	13.8	12452	19159	0.1	14.7	44	12999	17392	0.1	14.7	43.6	14886	**16541**	0.1	14.7	41.2
D3	26545	26545	0.3	14.4	12.2	17999	22035	0.3	14.4	20.4	**19122**	17585	0.3	14.4	19.4	20064	17075	0.3	14.4	18.8
D4	154710	154710	1.6	25.6	11.2	28216	48782	0.4	16.5	63.8	30312	40184	0.4	16.6	62	33514	**38189**	0.4	16.6	59.4
D5	112890	112890	1.1	17.2	8	18356	23214	0.2	13.9	47.6	17754	**20752**	0.2	13.9	46.8	17938	21563	0.2	13.9	46.8
D6	124210	124210	0.9	17.9	12.6	16577	26981	0.2	14.9	52.2	17314	21047	0.2	14.8	53.2	18967	**19734**	0.2	14.9	53
D7	44705	44705	0.5	15.7	13.8	25713	37256	0.5	15.4	30	27515	**28745**	0.5	15.4	27	35127	22535	0.5	15.4	26.2
D8	149715	149715	1.9	26	16.2	66417	57146	0.6	18.3	50.8	**47371**	45833	0.5	17.7	49.4	52337	44330	0.5	17.7	49.2

In evaluating the performance of the selected strategies, two key metrics come into play: Utilitarian and Egalitarian social welfare. Utilitarian social welfare seeks to maximize the total sum of costs across all agents, which, in this case, refers to the combined Airside and Landside costs. In contrast, Egalitarian social welfare prioritizes fairness, focusing on the utility of the agent who is worst off. The cooperative strategy performs the best in terms of Utilitarian social welfare, which was expected as it strives to minimize both costs. The adaptive strategy is significantly aligned with the cooperative strategy, showing an average discrepancy of just 3%, whereas the independent strategy exhibits a slightly higher average discrepancy of 12%. When considering Egalitarian social welfare, the cooperative strategy continues to outperform the others in 5 out of the 8 disruption cases and the adaptive strategy performs the best in the remaining three. The discrepancy from the Egalitarian social welfare remains within 2% of the best observed by the cooperative strategy, increases slightly to 7% in the adaptive strategy, and rises significantly to 26% in the independent strategy. Although the independent strategy exhibits a higher discrepancy from the Egalitarian social welfare, it is more effective in prioritizing solutions that align with Nash equilibria. The differences between strategies in terms of Nash equilibria are minimal however, typically varying by just one to three equilibria for cooperative and adaptive strategies.

The adaptive strategy may be slightly underperforming the cooperative strategy, but can offer a fairer solution than the other two strategies, even if it is not generally socially optimal. When analyzing the regret experienced by orchestrators, it becomes clear that the adaptive strategy consistently performs better in stabilizing the maximum regret for both orchestrators. While the independent and cooperative

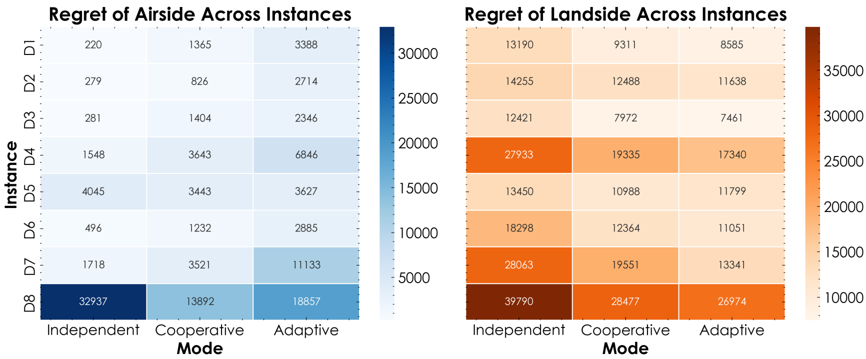


Figure 4.3: Heatmaps for the average regret incurred to both orchestrators.

strategies result in lower regrets for the airside orchestrator, the regret for the landside orchestrator remains disproportionately high, as shown in Figure 4.3. This suggests that the selected measures lead to a slightly more balanced effect on both orchestrators, with minimal impact on airport performance.

To assess the potential effect of cooperation in orchestrator decision-making, we compare outcomes under the two defined payoff allocation schemes: *Proportional* and *Shapley*. Each scheme is evaluated with respect to minimizing the egalitarian additive cost of the objective functions. This is achieved through adaptive concession weights (w_A, w_L), introduced in Equation 4.1 and dynamically updated via Equation 4.2, to incorporate an element of egalitarianism into the decision-making process. Table 4.5 presents key performance indicators for eight instances (D1–D8), including costs attributed to airside and landside orchestrators, percentage of missed flights, total delay, and Nash welfare.

Notably, the Shapley-based scheme results in a more balanced distribution of costs between the orchestrators, consistently reducing the disparity between airside and landside contributions. It also outperforms proportional allocation in consistently identifying the egalitarian social optimum. While the proportional scheme tends to favour the landside orchestrator—since the airside agent generally incurs a higher standalone cost under cooperation—the Shapley value incorporates each orchestrator's marginal contribution, leading to a fairer and more equitable cost-sharing outcome. This improvement is further reflected in the regret experienced by each orchestrator. The Shapley-based approach tends to equalize regret across orchestrators, reducing it for the airside agent and slightly increasing it for the landside one—yet the latter still faces significantly less regret than what the airside orchestrator would experience under proportional sharing. In terms of airport performance, the operational metrics under the fully cooperative approach remain comparable to those of the adaptive cooperative solution identified in the competitive setting. This indicates that cost balancing among orchestrators does not compromise overall airport efficiency. Finally, the number of Nash equilibria identified is slightly lower, but remains close to that of the competitive case. This is expected, as

4

Table 4.5: Comparison of cost allocation strategies across instances. The best (most egalitarian) total cost outcome is highlighted in bold.

	Proportional		**Shapley**		**Metrics**		
Instance	Airside (€)	Landside (€)	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash
D1	19673	4536	**15808**	8401	0.1	13.8	28.6
D2	22233	8157	**18829**	11561	0.1	14.7	43.6
D3	25711	10930	**22373**	14268	0.3	14.4	19.8
D4	43336	26977	**38066**	32247	0.4	16.6	62.0
D5	24126	14262	**21467**	16921	0.2	13.9	46.8
D6	26091	12253	**22871**	15473	0.2	14.9	53.2
D7	43627	11763	**35095**	20295	0.5	15.4	26.4
D8	65673	26846	**54321**	38198	0.5	17.7	48.0

minimizing system-wide costs does not necessarily align with equilibrium outcomes, a phenomenon also observed in the example shown in Table 4.3.

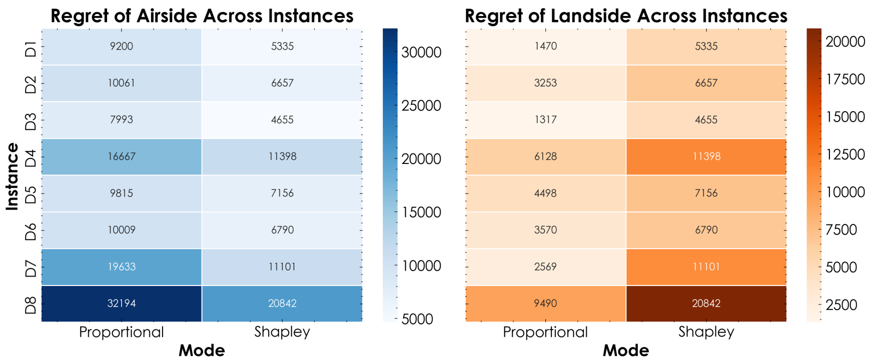


Figure 4.4: Heatmaps for the average regret incurred to both orchestrators under cooperation.

4.7. Conclusions

This study demonstrates how corrective measures, such as tactical flight delays and passenger rerouting, can mitigate disruptions to maintain a seamless passenger experience. The developed agent-based simulation underscored the importance of balanced and adaptive interventions in enhancing airport operational efficiency through the use of negotiation within a TO framework to achieve this. A fully cooperative approach was also studied yielding similar results, which implies that the centralization required for full cooperation is not strictly necessary. Building on these findings, future research could explore extensions such as assessing multi-airport network effects, and incorporating more complex airline and passenger behavioral responses. Additionally, expanding the framework to other transport modes could provide insights into multimodal resilience strategies. By improving coordination among orchestrators, this study provides a basis for more adaptive, integrated and efficient disruption management in airport operations.

5

Transport service design for traffic orchestration support

Chapter 5 shifts focus to innovations facilitated under a system where barriers to traffic orchestration, such as data sharing across modes are easier. An integrated Demand Responsive Transport (DRT) service to improve first-mile accessibility for public transport users traveling to airports is proposed as a support tool for orchestrators. This DRT service is conceived as a support tool operated or commissioned by the TO to improve first-mile access. A multi-agent algorithm based on Distributed Constraint Optimization Problems (DCOPs) is developed to coordinate taxi ride-sharing and determine optimal routing and transfer points. Using real-time data from a routing API, experiments demonstrate the effectiveness of the approach, showing reduced travel times that align with the service's modal share.

First, Section 5.1 introduces the problem context and motivation. Then, Section 5.2 reviews relevant work on multimodal coordination and disruption management. The core methodological contributions are presented in Section 5.3, where we describe the problem formulation, including the DCOP-based structure and the use of a centralized planner to generate options. A case study is presented in Section 5.4 to evaluate the proposed methodology, showcasing the trip generation and experimental scenarios detailed therein. Finally, conclusions and key takeaways are summarized in Section 5.5.

5.1. Introduction

Strengthening mass transit is a strategic goal for many metropolitan cities around the globe. A resilient Public Transit (PT) network facilitates congestion mitigation, reduction of emissions, and can pave the way for a future of seamlessly integrated

This chapter is based on the following research article: Parmaksizoglou, I. A., Bombelli, A., & Sharpanskykh, A. (2023). Design of a Demand Responsive Transport service using Distributed Constraint Optimization for airport access. In 8th International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2023. https://doi.org/10.1109/MT-ITS56129.2023.10241535

mobility. Achieving such future is contingent on improving accessibility in the transport systems. Accessibility has a direct impact on mode choice and the lack of it can lead to increased preference for less sustainable modes and under-utilization of the mass transit network.

Surface access to an airport is a specific type of urban trip where accessibility is significantly important. There have been few studies [159–162] researching surface access, but they mostly focus on factors impacting mode choice. Sustainability studies in aviation often overlook the impact of this type of travel compared to other issues. Nonetheless, access to and from the airport amounts to approximately 8% of the total emissions spent for a complete door-to-door trip [163]. Data from a report of the German Aerospace Center and the European Commission [164] show that utilization of PT for airport access can vary from 40% (Amsterdam Schiphol) to 20% (Barcelona International Airport El Prat). Further increasing the current surface access PT utilization rate can be facilitated by addressing accessibility issues, for example through multimodal coordination.

Coordination across modes can be realized through Demand Responsive Transport (DRT) systems. DRT services can target users that are inclined to use private transport due to low accessibility of their origin. In general, these are users that will not use PT. In this study, a DRT service is proposed for passengers with increased first-mile connections towards an airport. The service is complementary to the main mass transit network and makes use of fixed schedules of a dedicated train line to supply the airport. Candidate users are determined based on real-time traffic and PT information derived from a routing Application Programming Interface (API). Users are matched to taxis that support ride-sharing and optimal sequencing of pick-ups is determined, as well as transfer points for modal change.

The problem of matching users to taxis can inherently benefit from decentralization, as different taxis may have different criteria behind their decision-making and collaboration is not necessarily assumed. Regardless of collaboration across taxis, a system-wide assignment will benefit from scalability under a reduced, decentralized, and localized view of the system. To this avail, we apply a multi-agent perspective modeling the problem as a Distributed Constraint Optimization Problem (DCOP). Expected performance gains of introducing a first-mile-focused DRT service are evaluated through a case study for a major European airport. Overall, the effect of coordination across modes in the system-wide decrease of users' travel time is quantified. Additionally, the applicability of DCOP as a modeling framework is verified and the effect on the solution of different criteria in agents' decision making is assessed.

5.2. Literature Review

Even though the reported statistics vary from airport to airport, private vehicles (self-driving or drop-off) and taxis are a significant part of the modal share for ground access to airports. Travelers to and from airports tend to have a much higher willingness to pay compared to regular urban area trips [159], as there is usually less room for delays. To account for delays, travelers often use safety margins, i.e., an additional buffer time passengers allow in their planning to compensate for unexpected delays. As the trip time to the airport increases, the safety margin increases proportionally [160]. Generally, the out-of- and in-vehicle time of travel are also important factors in travel mode selection, as well as the overall saved time by mode choice and ease of use of the selected transport service. This highlights that multimodality might not be desirable for airport access, as it requires user coordination between modes which generally deteriorates the ease of use. In practice, trips to the airport that contain three or more modal changes are generally avoided [161]. However, airport travelers are in principle in favor of adopting new access modes, such as DRT, especially when they include transit or rail [162].

DRT services can greatly increase accessibility of a PT network. Demand-responsive transport (DRT) is a service for low-population-density areas, using passenger cars, vans, or small buses dispatched in response to passenger requests [165]. The adoption of DRT in urban areas has been explored but not yet implemented [39]. Notwithstanding, the findings suggest that DRT services can have a significant impact in attracting many users compared to other taxi-focused services, especially under a Mobility-as-a-Sevice (MaaS) [4] ecosystem. Efforts have been made to explore integrated DRT services that target both first-mile and last-mile connections, as evidenced by previous studies [166, 167]. However, such efforts have not yet been made specifically for airport access. There is also interest in completely automating DRT services through the integration of autonomous vehicles and public transport [168]. Resource allocation for DRT is crucial and is primarily addressed through the incorporation of ride-sharing techniques, as demonstrated in existing literature [168, 169].

When considering an inherently distributed system such as ride-sharing, different modeling choices on the level of centralization are available. In our context, we want taxis to be partially independent when selecting users, and to have access only to information that is relevant to them, as complete information about the system is often unnecessary for good-quality planning. Therefore, utilizing a distributed formalism such as DCOP can prove to be highly advantageous since it serves as a theoretical framework for multiple agents which must collaborate in making decisions regarding variable values in order to minimize the total cost of constraints or maximize the total utility values [63].

A DCOP consists of a set of agents, variables, domains, and constraints. A variable is controlled by a single agent, while constraints map the cost or utility of a specific variable selection and are by definition soft. Control is distributed, as agents can only assign values to variables they control, and have knowledge only of constraints that are mapped to their variables. However, variables may be constrained by variables owned by other agents by so-called inter-agent constraints that are satisfied through communication between agents. Some crucial DCOP assumptions are that (i) agents communicate only with their neighbors, (ii) each agent knows its variable and domain along with its neighbors, and (iii) each agent knows the cost function involving its own variables, not those of other agents. We refer readers to reference [72] for a thorough overview of the DCOP formalism. Given their broad applicability spectrum, DCOPs have been applied to many different fields such as disaster management and coordination [170], scheduling [171], vessel rotation planning [172], and traffic flow control [173] problems.

5.3. Problem Formulation

5.3.1. Distributed Constraint Optimization Formalism

The problem of matching taxis to users bares parallels with the Vehicle Routing Problem (VRP) [174], and more specifically the multi-depot VRP [175], both well-known NP-hard problems. In the proposed approach, taxis can be considered as “mobile" depots servicing users as efficiently as possible. In classic VRP formulations, the main goal of the planning is the minimization of the overall traveled distance. Our objective is different, as in this study the primary goal is to minimize the traveling time of users while guaranteeing timely access to target transit points. With *transit point*, we mean a specific location of the transport network when modal change occurs. In our context, this is a train station where taxi users are dropped off to shift mode and continue their journey to the airport.

5

We modeled the taxi-dispatching problem in a DCOP fashion as follows. Firstly, we consider that users originate from a set of total n origins $\mathcal{O} = \{o_1, o_2, .., o_n\}$. Multiple users may originate from a single origin to enable realistic planning for cases of users traveling together (e.g., families, etc.). Users have a desired arrival time at the airport, but the selection of the best transit point is decided exclusively by the planner. With regards to agents, we consider a finite number of m taxi agents defined as set $\mathcal{T} = \{t_1, t_2, t_3 .., t_m\}$. Taxis have a standard maximum capacity c_t and an origin o_t, indexed by $t \in \mathcal{T}$. The cost of a complete trip via taxi, shared or not, is considered known and includes waiting time for pick-up. Finally, a PT agent is defined, representing assignment via mass transit as an alternative to taxis. Users originating from $o \in \mathcal{O}$ who cannot be serviced by the DRT service are assumed to use PT to reach a transit point with a first-mile cost for origin o equal to FM_o. In addition, agents are also characterized by the following features that define user and trips compatibility:

1. view ($\mathcal{V}_t$): the set of user origins visible to the taxi agent ($\mathcal{V}_t \subseteq \mathcal{O}$). This is defined by assigning to each agent a certain radius of service measured from its origin. For the PT agent, we set the radius to ∞, hence $V_{PT} = \mathcal{O}$ as all users are visible;

2. first-mile bound: the minimum time FM_o that a user would experience if using PT to qualify for inclusion in the DRT service for a specific agent. For the PT agent, the bound is set to zero;

3. lead-time: the amount of time in advance that an agent becomes aware of users requesting a trip, before the departure of the earliest scheduled dedicated service compatible with the user preferred arrival time. For the PT agent, lead-time is set to ∞;

4. local view ($\mathcal{LV}_t$): the set of users $\mathcal{LV}_t \subseteq \mathcal{V}_t$ satisfying all the aforementioned criteria for agent t.

We now formalize the DCOP as a tuple $<\mathscr{A},\mathscr{X},\mathscr{D},\mathscr{C}>$, where

1. $\mathscr{A} = \{PT, a_1, a_2, ..., a_m\}$ is the set of agents;
2. $\mathscr{X} = \{x_{a,j}\ \forall a \in \mathscr{A}, j \in \mathscr{LV}_a\}$ are variables owned by an agent a and relate to an origin j in their local view;
3. $\mathscr{D} = \{d_{a,j} = \left[d^L_{a,j}, d^U_{a,j}\right]\ \forall a \in \mathscr{A}, j \in \mathscr{LV}_a\}$ is a set of finite domains for the variables such that $x_{a,j}$ takes values in $d_{a,j}$, with $d^L_{a,j}$ and $d^U_{a,j}$ being, respectively, the lower and upper bound. In this problem, all variables take binary values, hence all domains equal to $d_{a,j} = \{0,1\}$;
4. $\mathscr{C} = \{c_1, ..., c_z\}$ is a set of z soft constraints, where each constraint maps to utility functions $c_z : \mathscr{D} \rightarrow \mathbb{R}_{\geq 0}$ that define the cost for a specific choice of variables.

The following DCOP constraints must be satisfied:

1. each origin o must be assigned to exactly one taxi or the PT agent. This is always an inter-agent constraint for taxi agents, as any variable relating to a user origin that they own is also visible to the PT agent. Hence, the PT agent is a neighboring agent to all taxis that can see at least a single origin. Communication might be needed between more taxi agents to determine assignments. This is a hard constraint that maps to an infinite cost if violated

$$\sum_{a \in \mathscr{A}_o} x_{a,o} = 1\ \forall o \in \mathscr{O}$$

   where $\mathscr{A}_o$ is the subset of agents that see origin o;

2. for each agent a, a combination of user origins within its local view has an associated cost, which relates to total travel time of users assigned to that agent, including waiting times for drop-off and pick-up. In practice, not all combinations are available and feasible, but only an agent-specific set $\mathscr{Z}_a$ of the N_b best that are returned through pre-processing via centralized planner. Hence, for a valid selection of users we have

$$\text{evaluate}(x_{a,1}, ..., x_{a,n}) = c_{a,z}\ \forall a \in \mathscr{A} \setminus \{PT\},\ z \in \mathscr{Z}_a$$

   where $x_{a,i}$ is unitary if user i is considered in the evaluated combination z for agent a consistently with the previous definition of set $\mathscr{X}$;

3. for scaling issues, the evaluate constraint is omitted for the PT agent due to the potential number of combinations. Instead, a more direct approach is followed

$$x_{PT,o} = 1 \implies c_{PT,1} = FM_o\ \forall o \in \mathscr{O}$$

$$x_{PT,o} = 0 \implies c_{PT,1} = 0\ \forall o \in \mathscr{O}$$

   where parameter c can only take a single user combination (hence $z = 1$ is the only possible second index in $c_{PT,z}$).

Minimization of cost c for each agent a by selecting optimal combinations z is the ultimate goal of the DCOP.

5.3.2. CENTRALIZED PLANNER

To compute the evaluate constraint, a centralized planner creates combinations of users and determines the optimal pick-up order, transit point selection, and the total cost for each individual taxi. The cost is the aggregated travel time of all users part of the trip. To facilitate modal change, all arrival times to a transit point should be earlier than the scheduled train departure, considering a pre-defined transfer buffer. Routing information is derived from a designated Application Programming Interface (API) [176], providing historical and real-time information for both PT schedules and routes. A travel timetable is constructed from the API for the Origin-Destination (O-D) matrix containing the agent origin locations, origins of users in the local view of the agent, and all possible transit points. The cost of each combination for all agent is determined via a Mixed Integer Linear Programming (MILP) model that maximizes occupancy of a taxi agent while minimizing travel costs. A pool of the N_b best solutions is sought, as selecting just the best agent-specific solution does not necessarily yield system-wide optimality. In Table 5.1, the sets, parameters, and decision variables of the MILP are provided.

Table 5.1: Sets, parameters, and decision variables of the centralized planner.

Sets	
$\overline{\mathcal{O}}$	Set of origins, indexed by i
Parameters	
$T_{i,j}$	Travel time cost from $i \in \overline{\mathcal{O}}$ to $j \in \overline{\mathcal{O}}$
G_i	Latest time to drop-off users at transit point $i \in \overline{\mathcal{O}}$. Greater than zero only for $i \in \mathcal{O}_{TP}$
N_i	Number of persons in $i \in \overline{\mathcal{O}}$. Greater than zero only for $i \in \mathcal{V}_t$
P_i	Processing time of node $i \in \overline{\mathcal{O}}$
max_p	Maximum allowed pick-ups
rwd	Reward of selecting a trip
Cap	Agent capacity
Decision Variables	
$z_{i,j}$	Binary variable, equal to 1 if a trip originating from i towards j is active
t_i	Continuous variable, defining arrival time at node i

Inheriting notation from Sec. 5.3.1, we define the set of origins that can be visited by taxi $t \in \mathcal{T}$ as $\overline{\mathcal{O}} = o_t \cup \mathcal{V}_t \cup \mathcal{O}_{TP}$, where $\mathcal{O}_{TP}$ is the set of transit point origins. A feasible routing for taxi t starts in o_t, visits a subset of users $\mathcal{V}_t$, and ends in one element of $\mathcal{O}_{TP}$. We solve the MILP specific to taxi $t \in \mathcal{T}$ as follows

$$\max \sum_{i\in\overline{\mathcal{O}}} \sum_{j\in\overline{\mathcal{O}}} rwd \cdot N_i \cdot z_{i,j} - T_{i,j} \cdot z_{i,j} \tag{5.1}$$

s.t.

$$\sum_{j\in\mathcal{V}_t} z_{o_t,j} = 1 \tag{5.2}$$

$$\sum_{j\in\mathcal{V}_t\cup\mathcal{O}_{TP}} z_{j,o_t} = 0 \tag{5.3}$$

$$\sum_{i\in\mathcal{V}_t} \sum_{j\in\mathcal{O}_{TP}} z_{i,j} = 1 \tag{5.4}$$

$$\sum_{i\in\mathcal{O}_{TP}} \sum_{j\in\overline{\mathcal{O}}} z_{i,j} = 0 \tag{5.5}$$

$$t_j \geq t_i + P_i + T_{i,j} - (1 - z_{i,j})M \qquad \forall i \in \overline{\mathcal{O}}, j \in \overline{\mathcal{O}} \tag{5.6}$$

$$t_i \leq \sum_{j\in\mathcal{V}_t} z_{j,i} \cdot G_i \qquad \forall i \in \mathcal{O}_{TP} \tag{5.7}$$

$$\sum_{i\in o_t\cup\mathcal{V}_t\setminus\{j\}} z_{i,j} = \sum_{i\in\mathcal{V}_t\cup\mathcal{O}_{TP}\setminus\{j\}} z_{j,i} \qquad \forall j \in \mathcal{V}_t \tag{5.8}$$

$$\sum_{j\in o_t\cup\mathcal{V}_t\setminus\{i\}} z_{j,i} \leq 1 \qquad \forall i \in \mathcal{V}_t \tag{5.9}$$

$$\sum_{j\in\mathcal{V}_t} z_{o_t,j} + \sum_{i\in\mathcal{V}_t} \sum_{j\in\mathcal{V}_t\setminus\{i\}} z_{j,i} \leq max_p \tag{5.10}$$

$$\sum_{j\in\mathcal{V}_t} N_j \cdot z_{o_t,j} + \sum_{i\in\mathcal{V}_t} \sum_{j\in\mathcal{V}_t\setminus\{i\}} N_j \cdot z_{i,j} \leq Cap \tag{5.11}$$

$$z_{i,j} \in \{0,1\} \qquad \forall i \in \overline{\mathcal{O}}, j \in \overline{\mathcal{O}} \tag{5.12}$$

$$t_i \in \mathbb{R}_{\geq 0} \qquad \forall i \in \overline{\mathcal{O}} \tag{5.13}$$

The objective function 5.1 is defined as the weighted number of users part of the assignment minus the expected travel time for servicing such users. A preference is given to solutions that increase taxi ridership through the rwd parameter, but cost minimization is also included to guarantee optimal sequencing of users and transit point selection for drop-off. In general, a rwd greater than the lead-time of the agent will always prioritize occupancy maximization. Constraints 5.2-5.3 restrict the routing to ensure that exactly one trip will originate from the taxi start location and that there will never be a trip towards it. Similarly, constraints 5.4-5.5 ensure that the routing ends in a transit point and prevent trips from originating from a transit point. In constraint set 5.6, time precedence constraints are imposed. P_i is greater than zero only for $i \in \mathcal{V}_t$ and represents boarding time. Without loss of generality, we set t_{o_t} equal to the earliest time a taxi can perform a trip and P_{o_t} equal to zero. M is a big-M that can be set equal to $\max_{i\in\mathcal{O}_{TP}} G_i$. Constraint set 5.7 enforces that the visited transit point $i \in \mathcal{O}_{TP}$ is accessed no later than the time upper bound G_i (related to train departure). Constraint 5.8 is a flow conservation constraint for all user nodes, while constraint 5.9 enforces that a taxi can visit a user either from its starting location o_t or from a previously visited user. In constraints 5.10-5.11 we respectively ensure that the selected trips to users are fewer than the pre-defined number of allowed pick-ups and impose that the capacity constraint of a taxi is not violated. A number of maximum three pick-ups was considered realistic. Finally, in constraint sets 5.12-5.13 the domain of the decision variables is defined.

5.4. Case Study & Results

5.4.1. Trip Generation

A case study is presented that focuses on Milano Malpensa Airport (MXP). MXP currently features a PT share for ground access to the airport, mainly through rail and various shuttle services, that is compatible with other European airports. Notwithstanding, MXP targets to increase such percentage by 2035 to reduce road congestion and increase environmental sustainability. Approximately 50% of the airport's traffic is generated from the Milano metropolitan area. A dedicated train line (Malpensa Express) and various shuttle services (Malpensa Bus, Malpensa Shuttle) are the main PT providers servicing the airport.

To simulate demand towards MXP, historical data were utilized based on recorded outbound passengers for the month of June 2022. 50% of recorded demand was considered, consistently with the average percentage stemming from Milano. We divided a day into 48, 30-minute time periods and users were assigned to expected clusters of arrival to the airport. We used a normal distribution with a mean of four clusters (2 h) before the flight departure cluster and a variance of two clusters. Modal choices were assigned randomly based on reported modal splits for ground access to the airport.

To determine origins of passengers, demographic characteristics of Milano were used. The city is clustered into 88 districts with unique social and cultural identity [177], also called Nuclei di Identità Locale (NILs). Given this zonal structure, population records [178] were used to determine the likelihood of a user group to originate from a specific district. In Fig. 5.1, the generated spatial distribution of origins, for a specific arrival cluster of users, is presented.

After determining all trip characteristics, groups were split into modes based on historical data for ground access to MXP. An estimated 17% of arrivals are considered to use the dedicated train line. Access to the train line was assumed to occur via other PT modes (e.g., metro, tram, or bus). For this subset of users the travel time spent on the first-mile, the optimal mode of transport, and the optimal transit point were computed via the designated API, based on their desired arrival cluster at the airport.

5.4.2. Experiments

In total, 24 instances were generated for three distinct clusters of arrivals M, N, and A, standing respectively for Morning, Noon, and Afternoon peaks. Instances were based on global agent-imposed criteria, to test the performance of the DRT service. For all instances, we experimented with two different radii for the agents' view (2 and

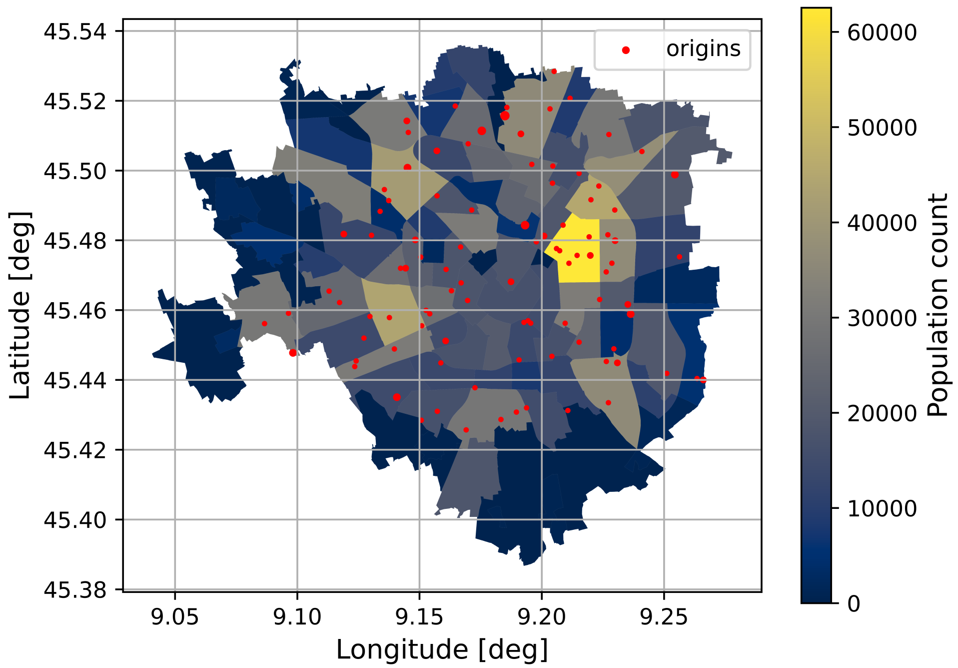


Figure 5.1: Generated origins for Public Transport arrivals in the [8:00-8:30] interval and demographic characteristics for the 88 NILs

4 km). The starting locations of the taxis were generated based on NIL demographic characteristics and taxi cab stands, acquired through OpenStreetMaps [179]. The first-mile bound was set to either 30 or 40 minutes. It is noted that the average first-mile is approximately 30 minutes. Finally, a 30-minute lead-time was imposed and either 4 or 8 taxis were made available. The peak day of the first week of June 2022 was selected to simulate airport arrivals. Cluster M [8:30-9:00] relates to the peak of passengers by train (131 passengers) for that day, Cluster N [12:30-13:00] is close to the daily average per time period (63 passengers), while Cluster A [15:30-16:00] defines the afternoon peak (91 passengers). We unequivocally define an instance by listing, in sequence, the radius view, the first-mile bound, the number of taxis available, and the reference cluster. For example, instance 2_30_4_A relates to a view of 2 km, a first-mile bound of 30 minutes, and 4 available taxis for the time period [15:30-16:00]. In Fig. 5.2, the agent interaction with the environment for the described instance is shown as well as the optimal assignment after model execution.

The numerical results were obtained using a personal laptop running Windows with a 4-core Intel i7-1185G7 and 16 GB of RAM. Frodo 2.18.1 [180] was used to model the DCOP and solve it with the DPOP [181] algorithm. Solution time across all instances was below 15 seconds. The centralized planner was implemented in Python and solved with Gurobi [107]. A maximum pool of ten N_b best solutions per

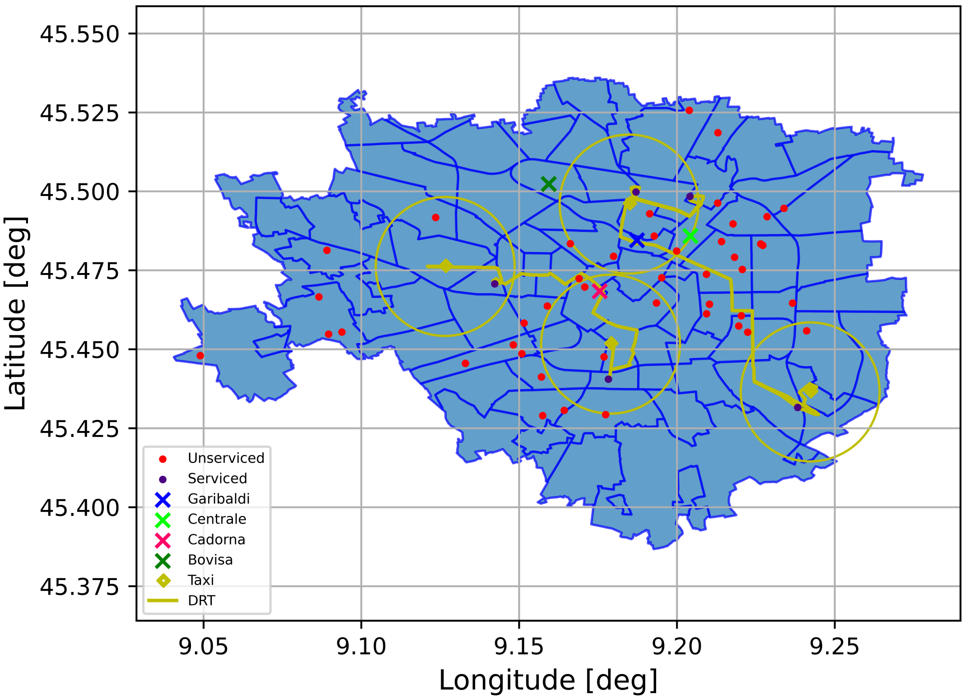


Figure 5.2: Taxi assignment for Instance 2_30_4_A

agent was used for constraint generation. Generating constraints for all agents with the centralized planner was more time-consuming, but it never exceeded 8 minutes for a single instance. Parallelization of this process would cut the running time to less than two minutes. In Table 5.2, a summary of the reported results by the generated instances is presented.

Overall, the application of the DRT service reduces the total first-mile travel time experienced by all users, almost proportionally to the modal share. With modal share, we define the percentile ratio between serviced users by the DRT system and all users in the cluster. This reported reduction is significant, but expected since users that are most likely to be serviced are usually the most affected. The pick-up cost of the taxi, i.e., the traveling time between o_t and the first serviced user, increases with the view radius, but still remains approximately around 10 minutes, consistently with current ride-hailing practices. Increasing the taxi view can lead to a further travel time reduction up to 11% (instances 2_30_8_A and 4_30_8_A), but can even lead to no decrease (instances 2_30_4_N and 4_30_8_N). Increasing the first-mile bound is generally detrimental to system optimality, leading to an increase in travel time between 2 and 12%. However, it can lead to a more equitable assignment that truly targets the most affected users. To account for equitability without sacrificing optimality, manual tuning techniques per agent, like a simple

Table 5.2: Cumulative Table of generated Instances

Instance	Travel Time (min)	Reduction	Sol. Time (s)	Taxis	Modal Share	Avg. Pickup Cost
2_30_4_M	3,919	7.9%	4	4	10.7%	5
2_30_4_N	1,745	9.5%	1	4	13.6%	8
2_30_4_A	2,511	8.6%	1	3	12.2%	4
2_30_8_M	3,720	12.6%	9	7	19.1%	5
2_30_8_N	1,661	13.8%	2	5	20.3%	6
2_30_8_A	2,285	16.9%	4	6	22.2%	4
2_40_4_M	4,079	4.1%	1	3	4.6%	6
2_40_4_N	1,900	1.5%	<1	1	1.7%	9
2_40_4_A	2,714	1.2%	<1	1	1.1%	5
2_40_8_M	4,047	4.9%	1	4	5.3%	6
2_40_8_N	1,877	2.6%	<1	2	3.4%	6
2_40_8_A	2,515	8.5%	<1	3	8.9%	6
4_30_4_M	3,813	10.4%	5	4	13.7%	8
4_30_4_N	1,646	14.6%	2	4	23.7%	9
4_30_4_A	2,511	8.6%	2	3	13.3%	4
4_30_8_M	3,554	16.5%	11	7	22.1%	8
4_30_8_N	1,448	24.9%	4	7	39.0%	9
4_30_8_A	2,187	20.4%	4	6	26.7%	8
4_40_4_M	3,926	7.7%	1	4	9.2%	8
4_40_4_N	1,726	10.5%	1	4	13.6%	11
4_40_4_A	2,689	2.1%	<1	2	2.2%	16
4_40_8_M	3,722	12.5%	2	7	15.3%	8
4_40_8_N	1,678	13.0%	1	6	15.3%	11
4_40_8_A	2,491	9.4%	<1	3	8.9%	9

user scoring function, can adapt to existing situations.

5.5. CONCLUSIONS

The present study focuses on developing a new mobility service to support ground access to the airport. A Demand Responsive Transport (DRT) service was conceptualized that makes use of taxi-dispatching and ride-sharing to target users with long first-mile trips to a set of transit points. These transit points represent stations served by a dedicated train line connecting users to their final destination, i.e., the airport. Distributed constraint optimization was utilized in modeling the proposed service. Experiments show that utilization of the DRT service can lead to a decrease of the system's travel time that is roughly proportional to the increase of the modal share. On average, a 10% reduction of the users' travel time was reported across instances, with an average utilization of only 4 taxis.

Although the study focused on airport-bound trips, the service can be extended to include last-mile connections from the airport. An iterative procedure can be used to optimize pick-ups and deliveries simultaneously and improve taxi allocation. Allocation strategies for taxi positioning based on demand can also be considered. Additionally, the fully cooperative nature of the service can be removed, allowing for different decision-making criteria per agent when selecting users. This would enable the service to be integrated into the competitive environment of existing taxi and ride-sharing services.

6
Conclusions

This thesis addressed the problem of effective coordination through polycentric management for multimodal transport, referred to within this thesis as traffic orchestration. In particular, focus was given on a novel stakeholder role defined as Traffic Orchestrator (TO) and their effect within port-centric systems such as seaports and airports. Such systems were selected to be the focus of this thesis as they presented domains where multiple modes of transport interact and coordination problems naturally arise. This research considered distributed approaches for the multi-actor settings that emerged. This final chapter provides a synthesis of the main findings of this dissertation.

We begin by revisiting the problem statement answered by the main research question that motivated the study and summarizing how it has been addressed. We then outline the four key research questions that guided this research and highlight the main contributions of the work, making a distinction between application-related and methodological contributions. Finally, the limitations of the study and directions for future research are discussed to build upon these findings.

6.1. Problem Statement

With regard to the challenge of implementing multimodal traffic management, the core difficulty lies in coordinating heterogeneous systems, objectives, and stakeholders across both passenger and freight networks. Different transport modes operate under distinct rules, service patterns, capacity limitations, and planning horizons, which makes joint optimization highly complex. To address this problem, this thesis poses the following main research question as follows:

How can polycentricity be leveraged to implement orchestration in port-centric multimodal transport systems?

To answer the main research question, first the notion of polycentricity was defined in the context of multimodal transport/traffic management. Principles of polycentric management were leveraged by identifying processes of conflict resolution, collaboration, and competition in the transport sector. Such processes are naturally occurring within the transport ecosystem and provided the main driver behind the use of polycentricity as a governance framework. In particular, for port-centric systems—which are the main focus of this dissertation—competitive settings can be observed between airlines competing for airport slots; collaborative settings emerge through initiatives like Port Community Systems and Airport collaborative decision-making (A-CDM) systems, which facilitate the exchange of standardized information (e.g. customs clearance); and conflict resolution is a constant necessity, for example during disruption periods. A selection of appropriate cases that capture these elements was performed split between two representative transport scenarios: one aimed at improving operational efficiency in freight transport, and the other focused on enhancing accessibility of airports by incoming passengers.

Within each scenario, tailored mechanisms for enabling collaboration, managing competition, and resolving conflicts among stakeholders, were necessary. As previously stated, the inherently distributed nature of transport, necessitated the use of distributed modeling methods for creating these mechanisms. To that end, the use of Multi-Agent Systems was considered as the most appropriate paradigm to model these mechanisms. MAS were used for coordination of stakeholders within the transport ecosystem, in different contexts and through different distributed optimization approaches. For example, to leverage MAS for competitive settings, auction-based models and multi-agent negotiation were utilized, while under collaborative settings approaches such as Distributed Constraint Optimization and Prioritized Planning were considered as an alternative. Within the examined scenarios, elements of centralization were retained by the TO, in an effort to maintain a certain degree of control. This constitutes that the proposed mechanisms were often not fully distributed but hybrid, a design choice compatible with the current realities of transport operations. Examples of centralized elements include the enforcement of maximum arrivals quotas by the orchestrator in port terminals to assert that the port can process the demand.

Regarding implementing orchestration in the examined scenarios, a central factor was deciding how to use the TO as a stakeholder responsible for guiding interactions among actors within and across transport modes. The goal was to utilize the TO as a coordinator responsible for mapping and exploiting interdependencies between stakeholders. To that avail, it was considered important to analyze the role under multiple instances, including single-orchestrator, and multi-orchestrator environments, as well as single-mode and multimodal setups. By doing so, the study also provides a technical foundation for the operational integration of Traffic Orchestrators into existing transport networks, demonstrating how such agents can improve multimodal traffic management.

6.2. Research Questions

To address the broad problem above, this dissertation was guided by four core research questions, each targeting a specific aspect of polycentricity for traffic orchestration in transport systems. For clarity, these questions are restated below and a reflection related to each research question is provided:

RQ1: How to apply orchestration for congestion management among competing Transport Service Providers within a single mode?

Chapter 2 introduced a Traffic Orchestrator acting as a coordinating entity for managing congestion at port terminals. In particular, the problem of limited access capacity caused by unregulated arrivals, which lead to truck congestion was explored. This presented a key example of resource interdependence within the port environment, in the form of access rights to the terminal shared by the trucks. This interdependence was leveraged by the orchestrator by introducing a competitive mechanism for coordination. The goal of the orchestrator was to facilitate equitable and efficient slot allocation related to truck access rights in a congested port terminal. To that end, a single-round, sealed-bid, second-price auction was employed, in which each transport service provider submitted bids reflecting their preferred time windows through associated valuations. The orchestrator, serving as auctioneer, allocated arrivals slots based on these bids and determined payments using a Vickrey-Clarke-Groves (VCG) pricing rule, ensuring incentive compatibility and truthful bidding. This constituted a quantity control traffic management measure that resulted in the terminal maintaining operational quotas related to truck access per hour. To further support flexibility and incentivize use of the mechanism, the optimization of criteria related to the trucks such as double moves were included to ensure that trucks with concurrent tasks (e.g. pickup and delivery) are guaranteed access for both.

6

RQ2: How can multimodal collaboration between Transport Service Providers and Vessel Operators be realized through orchestration by a single orchestrator?

Chapter 3 presented a model in which a single orchestrator coordinated two stakeholder groups across different modes and transport service providers: vessel operators and trucking companies. In particular, the problem of arrival synchronization between vessels and trucks was explored. This constituted an example of timing interdependence within the port environment, as trucks have to plan their arrivals based on the arrival and departure of the vessels carrying their associated cargo. The orchestrator leveraged this interdependence by introducing a clear collaboration mechanism relating to each actor's goals. The collaboration mechanism was modeled with a multi-agent, multi-objective model that aimed to synchronize vessel berthing with truck arrival schedules. The orchestrator utilized shared information on expected vessel arrivals, terminal gate availability, and provider preferences to explore different arrival schedules for both vessels and trucks in a manner that is satisfactory for all actors. Through information exchange, alignment across operational boundaries imposed by the terminal or orchestrator is also guaranteed. At the core of this approach was a prioritized planning algorithm, which allowed the orchestrator to resolve scheduling conflicts by exploring different priority structures for operations based on system-wide impact and stakeholder preferences. Simulation results demonstrated that the proposed mechanism improved terminal efficiency by generating more collaborative scheduling solutions and identifying better Pareto-optimal trade-offs between competing objectives, compared to conventional multi-objective optimization approaches, such as NSGA-II [128] and SPEA2 [129]. These findings confirmed that a single orchestrator, within a framework of multimodal integration and appropriate collaborative planning algorithms, can effectively facilitate synchronization processes across multimodal operations.

RQ3: How can different orchestration measures realized by multiple orchestrators affect system recovery from disruptions of airport multimodal accessibility?

In Chapter 4, the focus shifted on the interactions of multiple orchestrators within a multimodal setting. Building on a scenario related to airport access, the decision-making process of two orchestrators in handling disruptions was examined. In particular, two orchestrators were introduced: an airside orchestrator, responsible for managing operations related to the airside—such as the arrival and departure of flights and airport operations—and a landside orchestrator, overseeing surface access modes such as buses and trains. In addition, the model includes the network user, in the form of passengers, who make access-related decisions independently. To capture the interactions within the explored scenario, an agent-based simulation approach was taken to represent both the airport's landside access system, key airside processes, and passenger arrivals. The simulation also facilitated the exploration of different scenarios related to disruptions in the access network. To handle the disruptions, each orchestrator operated with limited information and domain-specific control, reflecting the distributed nature of real-world transport systems. Two primary response measures were explored during disruptions: passenger rerouting across alternative landside modes to relieve pressure on affected services and tactical flight delaying, allowing the airside orchestrator to adjust flight departure times in order to better synchronize with issues in landside accessibility. To enable coordinated decision-making, the problem of orchestrator interaction was structured using a game-theoretic formulation, in which each orchestrator acted as an autonomous agent seeking to optimize its own objectives. A negotiation mechanism, guided by a heuristic-based policy, facilitated iterative information exchange and adjustment of operational plans between orchestrators. This allowed the orchestrators to maintain their local priorities while converging on efficient solutions for the network users. An exploration of full cooperation was also performed. Simulation results showed that the tactical measures can have a significant effect on reducing average passenger delays while showing different ways of cost sharing between orchestrators.

RQ4: How can the novel concept of demand-responsive transport services enhance orchestration to improve airport multimodal accessibility?

Chapter 5 shifted the focus from the application of orchestration to an exploration of the types of transport services that orchestration can both enable and be enhanced by. Specifically, the concept of DRT was investigated as a novel and flexible mode within the multimodal transport system. A DRT service for airport access was introduced as an ad hoc mechanism to improve passenger trips towards the airport, particularly in areas underserved by traditional fixed-route transit, within a framework that promotes increased data sharing among modes through orchestrator-based coordination. This case study examined how dispatching of DRT services, such as on-demand taxis and ride-sharing vehicles, can be executed based on evolving system states, increased information-sharing and passenger demand patterns. To support this functionality, the system was modeled using a Distributed Constraint Optimization (DCOP) formulation. In this setting, each taxi and passenger was represented as an autonomous agent with individual objectives and constraints. This approach also allowed for the effective integration of ride-sharing strategies through partial centralization, optimizing vehicle utilization while maintaining passenger satisfaction. The findings illustrate the effect of coordination of existing services on reducing missed flights for involved passengers.

6.3. Limitations and Recommendations

While this dissertation has provided encouraging results regarding the role of orchestration in multimodal transport, several limitations remain. These limitations mainly stem from the modelling assumptions required for the application of the proposed methods in a real-world setting, as well as from the current level of technological readiness of the multimodal transport ecosystem.

1. **Scope limited to port environments:**
   A key decision in the research approach of this dissertation was to limit the scope to port-centric settings, specifically, one seaport and one airport. This decision was motivated by the fact that ports are natural domains of multimodal activity, where coordination problems commonly arise, making them an intuitive starting point for developing a structured methodology for orchestration. This design choice enabled detailed modeling and targeted evaluation but can make it harder to generalize the findings of this research to more complex multimodal transport systems. The main reason behind that is that measures implemented at the port level may lead to network-wide imbalances. For example, tactical flight delays introduced at one airport could have cascading effects on other airports, requiring collaborative decision-making across a wider air transport network. Similarly, it is difficult to draw conclusions from insights gathered in port settings when applied to urban contexts, as in such cases generation of traffic is significantly less restricted and more complex. Thus, a key recommendation for further research should be to examine the orchestration framework in broader settings, evaluating whether mechanisms for collaboration, conflict resolution, and distributed control remain effective and scalable beyond port environments.

2. **Quantitative benchmarking of developed models:**
   While the proposed models and algorithms have been thoroughly tested through case studies, quantitative benchmarking against existing state-of-the-art models has not been extensively performed within this dissertation.

With the exception of the prioritized planning algorithm, which is explicitly tested against standard MOEA algorithms, no formal benchmarking has been conducted elsewhere. The main reasoning behind this is that the developed case studies explore different management processes that have not been previously explored within the state of the art. In addition, benchmarking against current management processes is challenging due to the complexity of their implementation and calibration and due to their multi-stakeholder nature, as well as limited data availability. Thus, decision-making regarding the developed algorithms, such as the choice of the auction mechanism, was positioned primarily through qualitative comparison with the existing literature and identification of research gaps. The models developed in this dissertation are based on distributed optimization algorithms, which complicates fair benchmarking against the predominantly centralized approaches commonly found in the literature for similar management processes, such as truck appointment scheduling. Nonetheless, future work could better focus on a better comparison of centralized against non-centralized solutions in a more explicit way, although it is recommended to maintain a narrow scope aligned with the specific traffic orchestration problems addressed in the testing.

3. **Data availability and quality:**
A key limitation and challenge in the application of orchestration is the importance of information exchange between stakeholders within the transport ecosystem. In the developed models, availability of information is generally assumed and shared. These include information such as stakeholders' preferences in the form of utilities, schedules related to operations, and network user criteria. However, capturing realistic behavioral responses and heterogeneous user preferences remains a significant challenge that would merit dedicated investigation. In practice, the accessibility, quality, and interoperability of such transport data are not guaranteed and can vary significantly across regions, systems, and operators. Thus, due to a lack of data sharing, this dissertation often had to rely on synthetically generated data to simulate realistic conditions. While this allowed for continuing with the development of models, it also raises a potential question with respect to real-world applicability, as the effectiveness of orchestration in operational settings will likely depend on the existence of robust data-sharing agreements between stakeholders. Thus, a key recommendation from this dissertation relates to data management and is split into two different domains. Firstly, it is important to explore the foundation under which data-sharing agreements between stakeholders must be put in place. Secondly, in a more methodological manner, it is important to investigate how orchestration strategies perform under conditions of partial, noisy, or delayed information and explore how techniques such as machine learning could help mitigate these limitations.

4. **Focus on simulation:**
The orchestration mechanisms were often evaluated using agent-based simulations calibrated to realistic operational parameters. While simulations

can fully capture the human, institutional, and regulatory complexities of real-world operations, doing so requires substantial modeling effort and detailed data, which are often difficult to obtain. For instance, organizational resistance, privacy concerns, and contractual constraints may affect implementation. Therefore, empirical validation in real-world operational environments is required to assess stakeholder acceptance, system performance under uncertainty, and the practical feasibility of the proposed orchestration strategies. Future work could focus on testing orchestration strategies in pilot projects and living labs, ideally in collaboration with transport authorities, logistics hubs, or Mobility as a Service (MaaS) operators. These initiatives would offer critical insights into stakeholder acceptance, system performance under uncertainty, and the technical feasibility of orchestration strategies in real-world environments. They would also facilitate the integration of traffic orchestration within regulatory, legal, and standardization frameworks, a critical component for adoption, and generate empirical data that can inform and advance further academic research.

5. **Reliance on tactical planning:**
   Most of the measures applied with respect to traffic orchestration within this thesis are associated with tactical planning operations. These include measures such as slot allocation, appointment schedules, and coordinated responses to disruptions. However, the orchestration concept can support real-time operational planning, but this is deemed out of scope for this dissertation. This decision was primarily made to narrow the focus, yet it could be argued that the potential benefits for operational planning may exceed those observed at the tactical level, highlighting the importance of validating the focus on tactical coordination in this work. Future actions should investigate how the orchestration framework can be extended to support operational control beyond tactical planning, enabling predictive and adaptive orchestration in real time. Potential avenues include dynamic rerouting of vehicles in response to live traffic conditions, continuous rescheduling in appointment systems, and real-time conflict resolution in terminal operations.

6.4. CONTRIBUTIONS

The research findings and innovations of this dissertation translate into two main categories of contributions: methodological contributions, which advance the theoretical frameworks for orchestration in transport systems, and application-related contributions, which demonstrate the potential real-world impacts and usefulness of the proposed approaches. The following section highlights these contributions, clarifying how the findings remain valid despite the previously discussed limitations and elaborating on the key research gaps that each contribution addresses.

6.4.1. Methodological Contributions

- **Auction Method for Congestion Management and Appointment Scheduling:** This research is the first to introduce an auction-based algorithm as an effective approach for managing congestion in port terminals through truck appointment scheduling. The use of distributed methods has been identified as a clear gap in the domain of truck appointment scheduling, as efforts to reduce centralization are considered crucial to increase adoption. The proposed pricing rule for the developed auction is incentive-compatible and encourages truthful bidding from the transport providers. While the rule was not optimized for revenue maximization from the terminal's perspective, it was well-suited for traffic demand management, as it promoted a more equitable and efficient distribution of access during peak periods. The proposed mechanism was also fast for the operational realities of terminal operations, providing optimal solutions in most cases in under one hour. While the developed algorithm does not address market power dynamics and relies on simplified utility modeling due to data availability constraints, these aspects do not undermine the core contribution of this work, as the primary objective was to establish auctions as a viable tool for traffic orchestration, building on the concept of incentive-based data sharing and operating as an effective quantity-control measure.

6

- **Prioritized Planning Algorithm for Stakeholder Coordination:** A prioritized planning algorithm was developed to explore the joint planning of truck scheduling and berth allocation problems. Prioritized planning algorithms, as a form of interleaved planning, have not previously been applied to port terminal operations, and specifically to the combined problem of berth allocation and truck scheduling. Different priority structures, such as delaying the berthing of an arrived vessel in favor of one arriving later, were explored. The use of alternative priority structures was enabled by heuristic operators to perform neighborhood search. The algorithm generated diverse Pareto-efficient solutions by leveraging a multi-agent, multi-objective model that facilitated information sharing between vessels, trucks, and the port terminal, highlighting its potential for improving cooperative decision-making in complex logistics environments. The proposed algorithm outperformed the state-of-the-art for the examined problem due to its efficient exploration of the search space. The algorithm was also optimized for parallelization, a feature exploited in this study.

- **Agent-Based simulation framework for orchestrator interaction modelling:** To evaluate the orchestration concepts, an agent-based simulation model was developed to capture interactions between orchestrators, transport service providers, and network users in an airport setting. Each agent operated with its own objectives, information sets, and decision-making logic. This simulation environment constitutes a contribution, as it integrates the tactical flight rescheduling problem [38] with a passenger access simulation tool that maps the accessibility of an airport from a surrounding metropolitan area [151]. The developed simulation was essential for assessing the feasibility and performance of orchestration strategies during disruption periods. Orchestration strategies were explored by structuring the application of potential control measures within a game-theoretic framework. The negotiation problem between orchestrators was then addressed using a heuristic-based alternate proposal method, enabling agents to iteratively exchange and evaluate plans until mutually acceptable outcomes were reached. Arguably, the outcomes of this study rely purely on simulation results, which may obscure certain operational realities. Living labs and real-world trials can further support the adoption of orchestration, but simulation remains important as a first step, as it can indicate potential benefits that still need to be validated in an operational environment.

- **DCOP approach for transport assignment:**
  Limited use of distributed methods in transportation problems [60] represents a key research gap that is addressed by the development of a DCOP for transport assignment. The use of DCOP supported agent-level flexibility while ensuring that local decisions aligned with broader system needs. The DCOP also allowed DRT agents to autonomously evaluate assignment options based on their own objectives and constraints. DCOP was supported by a centralized planner that created efficient route and passenger allocation suggestions, under the assumption of an orchestrator environment. These suggestions were based on passenger-related criteria such as arrival time and safety margins before flight departure. This hybrid architecture integrated both centralized convenience and agent autonomy, enabling orchestrators to guide assignments without enforcing rigid top-down control. Nonetheless, a key limitation of the DCOP-based approach algorithm lies in its scalability and reliance on behavioral assumptions. This limitation can be further addressed by reducing the algorithm to more localized decision-making centers, which may exacerbate challenges related to achieving globally optimal solutions. However, a key point of this thesis is that true global optima rarely exist in complex transport problems, making locally coordinated, practical solutions the most relevant objective.

- **Hybrid architectures for traffic management:**
  This thesis explores hybrid architectures for traffic management revolving around the TO, who utilizes distributed mechanisms for coordination while also retaining centralized elements to ensure alignment with system-wide constraints. All previous methodological contributions collectively illustrate the development of hybrid architectures for traffic management. The auction and prioritized planning mechanisms make use of distributed decision-making while asserting orchestrator influence to ensure feasibility and system alignment. The agent-based simulation framework abstracts domain-specific decisions to the TO to mitigate conflicts, while the DCOP approach combines centralization of information at the TO level with fully distributed transport assignment. These forms of coordination are valuable because they combine

the advantages of decentralization with the realism required for practical implementation under the operational realities of current traffic management. It's clear that all proposed hybrid architectures center on a case study related to a port environment. Rather than being a limitation, this focus provides a controlled environment in which to design, test, and refine mechanisms that balance distributed decision-making with more oversight. Insights and principles derived from these port-centric studies are highly relevant, as ports share fundamental coordination challenges with other multimodal transport systems, making the findings a foundational step and potentially transferable in different transport contexts.

6.4.2. APPLICATION CONTRIBUTIONS

- **Advances in truck appointment scheduling:**
  Building on the results of Chapter 2, this research placed particular focus on truck appointment scheduling as congestion control mechanisms for traffic orchestration. A market-based framework is proposed for application in port terminals to improve interactions between transport service providers and operators, explicitly incorporating terminal-imposed requirements, such as maximum arrivals per hour, to guarantee operational feasibility, while also accounting for service provider requirements, such as enabling double moves, to enhance the flexibility of the mechanism. The proposed framework highlights a clear way into addressing limitations related to lack of transparency and flexibility in appointment scheduling [54]. It also standardizes the process of distributing available capacity based on demand, using the true value of time expressed by transport service providers, rather than relying on arbitrary service-level agreements. Arguably, the proposed mechanism is well-suited for traffic demand management at the tactical level, as it promotes a more equitable and efficient distribution of access during peak periods through pre-planning. While operational realities related to truck access, such as unexpected delays due to traffic congestion, are not addressed, truck appointment scheduling primarily aims to improve the predictability of operations rather than handle unforeseen events. Consequently, the limitation of focusing orchestration on tactical planning is not considered impactful for the traffic management problem addressed in this work.

- **Advances in multimodal coordination in port terminals:**
  In Chapter 3, coordination across modes was explored through different priority structures as an alternative to commonly used approaches, such as first-come, first-served, for synchronizing port terminal operations. In particular, it was explored how aligning priorities between vessel berthing and truck access can significantly improve overall terminal efficiency. The exploration of different priority structures based on multiple parameters in port terminal operations has been a focal point of interest among researchers [182]. However, research on extending these approaches beyond the vessel perspective to a multimodal context remains limited. To that avail, incorporating truck access represented

6

a natural first step. The synchronization of operations across modes in combination with appointment scheduling demonstrated how well-aligned priorities can lead to improvements in overall terminal efficiency. This can allow vessel operators, terminal managers, and transport service providers to better align their time window allocations, thereby reducing gate and berth congestion and promoting smoother traffic flows during peak periods. Similarly to the issue related to truck appointment scheduling, the reliance on tactical planning is not considered a significant limitation due to the controlled nature of the examined terminal environment. Nonetheless, as this framework also includes seaside operations, delays on the seaside can have a more significant impact on the proposed method due to the disproportionate influence this mode has over the others in the port environment. However, reliance on tactical planning is not considered a hindrance, as extending the concept with stochastic optimization methods [115] has been shown to effectively address such uncertainties, showing that traffic orchestration tools for coordination can remain efficient at the tactical planning level. Additionally, this framework can be particularly beneficial in contexts where vessel dominance is less pronounced, such as in Short Sea Shipping and inland waterway transport.

- **Advances in disruption management for airport access:**
  In Chapter 4, the application of traffic management measures across transport modes to improve passenger airport access during disruptions was explored. A mechanism was proposed for arbitration between airside and landside operators to deal with surface access disruptions. Research on the coordination of landside and airside remains very limited [77], despite the clear benefits for passenger travel experience and its alignment with EU-wide objectives. In the proposed scheme, measures such as rerouting passengers via available shuttle services and tactically adjusting flight schedules to accommodate disrupted passengers are considered by orchestrators from the airside and landside to jointly deal with the disruption. From an application perspective, this contribution is particularly relevant for integrated ticketing schemes between airlines and train operators, which already exist in practice and where seamless service is both expected and demanded by passengers. Nonetheless, the requirement of integrated ticketing is there to assert data availability and sharing among operators. Although this represents a significant limitation for the applicability of this approach, the proposed method signals how further integration between modes can offer practical benefits for users and operators alike, supporting the development of such schemes and serving as a step toward realizing the vision of MaaS.

- **Advances in new mobility solutions:**
  In Chapter 5, focus was given on how DRT services can be effectively integrated into a scenario related to airport access. Under the operational requirement of integrated ticketing, a new concept was proposed for delivering more flexible and user-adaptive mobility service. In the airport case study, DRT vehicles were dispatched based on both user-related criteria, such as short

safety margins before flight departures, and system-oriented objectives, such as maximizing ridership and minimizing overall waiting time. In doing so, DRT supplemented traditional fixed-schedule modes by bridging critical first-mile accessibility gaps for airport passengers. Additionally, the framework allowed vehicle agents to autonomously evaluate and select passengers according to their own criteria, balancing centralized orchestration with local autonomy. This integration represents a key contribution toward the operationalization of innovative mobility solutions. However, it remains contingent on the availability of integrated ticketing, and similar limitations regarding data access and sharing, as highlighted in the disruption management case study, also apply. Finally, as DRT is an emerging area of interest within the transportation community, it is particularly important to consider incorporating additional benchmarking in this context.

6.5. STAKEHOLDER IMPLICATIONS OF TRAFFIC ORCHESTRATION

It is important to understand the effect of traffic orchestration on the main stakeholders of the multimodal transport systems explored in this dissertation. These stakeholders include Network Users (NUs), Transport Service Providers (TSPs), and Traffic Orchestrators (TOs), each of whom experiences different benefits and trade-offs from the implementation of orchestration mechanisms.

With respect to NUs the orchestration benefits are apparent, such as improvements in accessibility, reliability, and service quality across multimodal transport chains. However, to achieve these system-wide benefits, a broader, network-oriented mindset from NUs will be required. This may involve trade-offs for individual users, such as sharing more data, accepting temporary concessions like delays, and prioritizing system efficiency over personal convenience. From a managerial perspective, this implies that user communication, transparency, and particularly incentive design are critical to foster acceptance and adoption of orchestration measures.

For transport service providers, orchestration mechanisms can help fill operational gaps, improve alignment and predictability, and ensure fairness among stakeholders, as demonstrated by the explored case studies. However, achieving these benefits requires the establishment of clear norms and agreements regarding data sharing, operational priorities, and acceptable trade-offs. Transport service providers may need to cooperate, negotiate, and comply with polycentric coordination rules that support overall network performance, even when such actions do not directly align with their individual strategic interests. This highlights the need for formal coordination frameworks and governance structures that balance competition with cooperation.

For traffic orchestrators and public authorities that are assumed to adopt the TO role, ensuring compliance from users and transport service providers is a critical prerequisite. Effectively balancing competition and collaboration within this framework is essential to maintain system-wide efficiency and reliability, as well as incentive design, as was previously discussed. The findings of this thesis demonstrate mechanisms and measures on how orchestrators can regulate system performance without fully centralizing control in relatively idealized environments where information sharing is more present than currently in practice. This information gap is the main barrier to achieving traffic orchestration, and overcoming it is the first priority to realize a more resilient, efficient, and coordinated multimodal transport network.

Abbreviations

3PL	Third-party logistics
4PL	Fourth-party logistics
ABM	Agent-Based Model
AGV	Automated Guided Vehicles
AI	Artificial Intelligence
API	Application programming interface
ATM	Air Traffic Management
BAP	Berth Allocation Problem
CDM	Collaborative Decision-Making
DBL	Dedicated Bus Lanes
DCOP	Distributed Constraint Optimization
DRT	Demand-Responsive Transport
ETA	Estimated Time of Arrival
EU	European Union
FCFS	First-Come, First-Served
GTFS	General Transit Feed Specification
HLP	Hub Location Problems
KPI	Key Performance Indicator
LMC	Licensed Motor Carrier
LNS	Large Neighborhood Search
MaaS	Mobility as a Service
MAPD	Multi-Agent Pickup and Delivery Problem
MAS	Multi-Agent Systems

MILP	Mixed-Integer Linear Programming
MTO	Marine Terminal Operators
MOEA	Multi-Objective evolutionary algorithm
MOO	Multi-Objective Optimization
MXP	Malpensa International Airport
NIL	Nuclei d'Identita Locale
NSGA	Non-dominated Sorting Genetic Algorithm
NU	Network User
OR	Operational Research
P&R	Park and Ride
PCS	Port Community System
P&T	Public Transport
RQ	Research Question
SPEA	Strength Pareto Evolutionary Algorithm
TAS	Truck Appointment Systems
TEU	Twenty-foot Equivalent Unit
TSP	Transport Service Provider
TO	Traffic Orchestrator
VCG	Vickrey-Clarke-Groves
VRP	Vehicle Routing Problem
VDTW	Vessel-Dependent Time-Window
WDP	Winner Determination Problem

List of Figures

6

List of Tables

Bibliography

[1] P. Capros, A. De Vita, N. Tasios, D. Papadopoulos, P. Siskos, E. Apostolaki, M. Zampara, L. Höglund-Isaksson, W. Winiwarter, P. Purohit, H. Böttcher, S. Frank, P. Havlík, M. Gusti, H. Witzke, and K. Fragkiadakis. *EU Energy, Transport and GHG emissions -Trends to 2050, Reference scenario 2013*. Publications Office of the European Union, Dec. 2013. DOI: 10.2833/17897.

[2] W. Lerner, v. F. Audenhove, *et al.* "The future of urban mobility: Towards networked, multimodal cities in 2050". In: *Public transport international* 2 (2012).

[3] L. Alessandretti, L. G. Natera Orozco, M. Saberi, M. Szell, and F. Battiston. "Multimodal urban mobility and multilayer transport networks". In: *Environment and Planning B: Urban Analytics and City Science* 50.8 (July 2022), pp. 2038–2070. ISSN: 2399-8083. DOI: 10.1177/23998083221108190. URL: https://doi.org/10.1177/23998083221108190.

[4] S. Heikkilä. "Mobility as a Service - A Proposal for Action for the Public Administration, Case Helsinki". In: *Mobility as a Service - A Proposal for Action for the Public Administration* (2014).

[5] L. A. Tavasszy, R. Janssen, L. der Lugt, and L. Hagdom. *Verkenning Synchromodaal Transportsysteem*. Delft, The Netherlands, 2010.

[6] X. Fu, D. van Lierop, and D. Ettema. "Is multimodality advantageous? Assessing the relationship between multimodality and perceived transport adequacy and accessibility in different travel contexts". In: *Transportation Research Part A: Policy and Practice* 179 (2024), p. 103893. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2023.103893. URL: https://www.sciencedirect.com/science/article/pii/S0965856423003130.

[7] R. van Nes and P. H. L. Bovy. "Multimodal traveling and its impact on urban transit network design". In: *Journal of Advanced Transportation* 38.3 (2004), pp. 225–241. DOI: https://doi.org/10.1002/atr.5670380302. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/atr.5670380302.

[8] R. Buehler and A. Hamre. "The multimodal majority? Driving, walking, cycling, and public transportation use among American adults". In: *Transportation* 42.6 (2015), pp. 1081–1101. ISSN: 1572-9435. DOI: 10.1007/s11116-014-9556-z. URL: https://doi.org/10.1007/s11116-014-9556-z.

[9] T. Kuhnimhof, R. Buehler, M. Wirtz, and D. Kalinowska. "Travel trends among young adults in Germany: increasing multimodality and declining car use for men". In: *Journal of Transport Geography* 24 (2012), pp. 443–450. ISSN: 0966-6923. DOI: https://doi.org/10.1016/j.jtrangeo.2012.04.018. URL: https://www.sciencedirect.com/science/article/pii/S0966692312001317.

[10] E. Heinen and G. Mattioli. "Multimodality and CO2 emissions: A relationship moderated by distance". In: *Transportation Research Part D: Transport and Environment* 75 (2019), pp. 179–196. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2019.08.022. URL: https://www.sciencedirect.com/science/article/pii/S136192091930118X.

[11] M. Hodson and S. Marvin. "Can cities shape socio-technical transitions and how would we know if they were?" In: *Research Policy* 39.4 (2010), pp. 477–485. ISSN: 0048-7333. DOI: https://doi.org/10.1016/j.respol.2010.01.020. URL: https://www.sciencedirect.com/science/article/pii/S004873331000034X.

[12] European Commission. *Europe on the Move – Sustainable Mobility for Europe: safe, connected, and clean.* May 2018. URL: https://www.eumonitor.eu/9353000/1/j4nvhdfcs8bljza_j9vvik7m1c3gyxp/vkofgxoczgwu.

6

[13] T. Chevallier, J. Lauer, C. Renso, A. Blanco-Justicia, D. De Ryck, and A. Papacharalampous. "Making it easy for transport stakeholders to share mobility data". In: *Transportation Research Procedia* 72 (2023), pp. 2237–2244. ISSN: 2352-1465. DOI: https://doi.org/10.1016/j.trpro.2023.11.711. URL: https://www.sciencedirect.com/science/article/pii/S2352146523010098.

[14] I. Pagoni, M. Gatto, I. Tsouros, A. Tsirimpa, A. Polydoropoulou, G. Galli, and T. Stefanelli. "Mobility-as-a-service: insights to policymakers and prospective MaaS operators". In: *Transportation Letters* 14.4 (2022), pp. 356–364. ISSN: 1942-7867. DOI: https://doi.org/10.1080/19427867.2020.1815141. URL: https://www.sciencedirect.com/science/article/pii/S1942786722004118.

[15] V. Ostrom, C. M. Tiebout, and R. Warren. "The Organization of Government in Metropolitan Areas: A Theoretical Inquiry". In: *American Political Science Review* 55.4 (1961), pp. 831–842. ISSN: 0003-0554. DOI: DOI:10.2307/1952530. URL: https://www.cambridge.org/core/product/00789721D92451B3D13E6904C72D7F8A.

[16] E. Ostrom. *Understanding Institutional Diversity.* Princeton University Press, Nov. 2009. ISBN: 9781400831739. DOI: 10.2307/J.CTT7S7WM. URL: http://www.jstor.org/stable/10.2307/j.ctt7s7wm.

[17] European Commission. *Strategic Transport Research and Innovation Agenda (STRIA) - Roadmap on Network and Traffic Management Systems.* Tech. rep. European Commission Directorate-General for Research and Innovation, 2016.

URL: https://trimis.ec.europa.eu/system/files/2021-04/stria_roadmap_-_network_and_traffic_management_systems_0.pdf.

[18] I. Harris, Y. Wang, and H. Wang. "ICT in multimodal transport and technological trends: Unleashing potential for the future". In: *International Journal of Production Economics* 159 (Sept. 2014), pp. 88–163. DOI: 10.1016/j.ijpe.2014.09.005.

[19] M. K. Natvig, E. Stav, T. M. Stene, W. Qu, I. Parmaksizoglou, A. Sharpanskykh, L. Truaisch, J. Huber, E. Skuggevik, P. Rosland, and T. Hovland. *Intermediate PMA for Multimodal Traffic Management*. Tech. rep. D3.2. ORCHESTRA Project, Dec. 2022. URL: https://www.orchestra-project.eu.

[20] E. Stav, M. K. Natvig, and T. M. Stene. "Using a board game to explain a concept model: Experience from multimodal traffic management". In: *Journal of Transport & Health* 38 (2024), p. 101880. ISSN: 2214-1405. DOI: https://doi.org/10.1016/j.jth.2024.101880. URL: https://www.sciencedirect.com/science/article/pii/S2214140524001269.

[21] T. Stene and E. Skuggevik. "Multimodal Traffic Management (MTM) – Future Training emphasizing Collaboration and Coordination." In: *European Conference on Knowledge Management* 25 (Sept. 2024), pp. 799–808. DOI: 10.34190/eckm.25.1.2741.

[22] M. Acciaro, H. Ghiara, and M. Cusano. "Energy management in seaports: A new role for port authorities". In: *Energy Policy* 71 (Aug. 2014), pp. 4–12. DOI: 10.1016/j.enpol.2014.04.013.

[23] T. E. Notteboom and J.-P. Rodrigue. "Port regionalization: towards a new phase in port development". In: *Maritime Policy & Management* 32.3 (July 2005), pp. 297–313. ISSN: 0308-8839. DOI: 10.1080/03088830500139885. URL: https://doi.org/10.1080/03088830500139885.

[24] J. Monios. "Polycentric port governance". In: *Transport Policy* 83 (Aug. 2019), pp. 26–36. DOI: 10.1016/j.tranpol.2019.08.005.

[25] A. Al Sabouni, A. Freiberger, B. Grobe, A.-K. Hübers, S. Kamenz, and S. Kaser. "Drivers for multimodal traffic management". In: *Transportation Research Procedia*. Vol. 72. 2023, pp. 2347–2354. DOI: 10.1016/j.trpro.2023.11.726. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85182931957&doi=10.1016%2fj.trpro.2023.11.726&partnerID=40&md5=129018bf6a708d101cffc79542c9d06a.

[26] M. Mesbah, M. Sarvi, I. Ouveysi, and G. Currie. "Optimization of transit priority in the transportation network using a decomposition methodology". In: *Transportation Research Part C: Emerging Technologies* 19.2 (2011), pp. 363–373. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2010.05.020. URL: https://www.sciencedirect.com/science/article/pii/S0968090X1000104X.

6

[27] B. Yu, L. Kong, Y. Sun, B. Yao, and Z. Gao. “A bi-level programming for bus lane network design”. In: *Transportation Research Part C: Emerging Technologies* 55 (2015), pp. 310–327. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2015.02.014. URL: https://www.sciencedirect.com/science/article/pii/S0968090X15000698.

[28] N. Zheng and N. Geroliminis. “On the distribution of urban road space for multimodal congested networks”. In: *Transportation Research Part B: Methodological* 57 (2013), pp. 326–341. ISSN: 0191-2615. DOI: https://doi.org/10.1016/j.trb.2013.06.003. URL: https://www.sciencedirect.com/science/article/pii/S0191261513001021.

[29] D. Tsitsokas, A. Kouvelas, and N. Geroliminis. “Modeling and optimization of dedicated bus lanes space allocation in large networks with dynamic congestion”. In: *Transportation Research Part C: Emerging Technologies* 127 (2021), p. 103082. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2021.103082. URL: https://www.sciencedirect.com/science/article/pii/S0968090X21001042.

[30] S. Melo, R. Gomes, R. Abbasi, and A. Arantes. “Demand-Responsive Transport for Urban Mobility: Integrating Mobile Data Analytics to Enhance Public Transportation Systems”. In: *Sustainability* 16.11 (2024). ISSN: 2071-1050. DOI: 10.3390/su16114367. URL: https://www.mdpi.com/2071-1050/16/11/4367.

[31] P. Vansteenwegen, L. Melis, D. Aktaş, B. D. G. Montenegro, F. Sartori Vieira, and K. Sörensen. “A survey on demand-responsive public bus systems”. In: *Transportation Research Part C: Emerging Technologies* 137 (2022), p. 103573. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2022.103573. URL: https://www.sciencedirect.com/science/article/pii/S0968090X22000195.

[32] L. Buics, A. Prayogo, and B. E. Balassa. “The Role of Demand-Responsive Transport Systems in Sustainable Urban Mobility: A Systematic Literature Review and Stakeholder Analysis”. In: *Engineering Proceedings* 79.1 (2024). ISSN: 2673-4591. DOI: 10.3390/engproc2024079040. URL: https://www.mdpi.com/2673-4591/79/1/40.

[33] G. Parkhurst. “Park and ride: Could it lead to an increase in car traffic?” In: *Transport Policy* 2 (Jan. 1995), pp. 15–23. DOI: 10.1016/0967-070X(95)93242-Q.

[34] M. Kuby, A. Barranda, and C. Upchurch. “Factors influencing light-rail station boardings in the United States”. In: *Transportation Research Part A: Policy and Practice* 38.3 (2004), pp. 223–247. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2003.10.006. URL: https://www.sciencedirect.com/science/article/pii/S0965856403001046.

[35] H. Liu, Y. Li, J. Li, B. Hou, and S. Zhao. "Optimizing the Location of Park-and-Ride Facilities in Suburban and Urban Areas Considering the Characteristics of Coverage Requirements". In: *Sustainability* 14.3 (2022). ISSN: 2071-1050. DOI: 10.3390/su14031502. URL: https://www.mdpi.com/2071-1050/14/3/1502.

[36] S. Moslem, J. Ortega, J. Ortega, M. Padilla, D. Ouelhadj, and D. Esztergár-Kiss. "Optimizing park and ride location selection using the novel parsimonious full consistency method: Insights from Cuenca, Ecuador". In: *Research in Transportation Business & Management* 56 (2024), p. 101171. ISSN: 2210-5395. DOI: https://doi.org/10.1016/j.rtbm.2024.101171. URL: https://www.sciencedirect.com/science/article/pii/S2210539524000737.

[37] G. Scozzaro, C. Buire, D. Delahaye, and A. Marzuoli. "Optimizing air-rail travel connections: A data-driven delay management strategy for seamless passenger journeys". In: *SESAR Innovation Days*. Vol. 2023-November. 2023. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85185530798&partnerID=40&md5=1d367a6eea9e42d5dd1faef236a8813b.

[38] G. Scozzaro, C. Mancel, D. Delahaye, and E. Feron. "An ILP approach for tactical flight rescheduling during airport access mode disruptions". In: *International Transactions in Operational Research* 31.3 (May 2024), pp. 1426–1457. ISSN: 0969-6016. DOI: https://doi.org/10.1111/itor.13396. URL: https://doi.org/10.1111/itor.13396.

[39] J. Bueno-González, J. Burrieza-Galán, O. G. Cantú-Ros, C. Livingston, S. Penazzi, C. Buire, A. Marzuoli, and D. Delahaye. "Air-rail timetable synchronisation for seamless multimodal passenger travel: a case study for Valencia-Lanzarote door-to-door journeys". In: *Transportation Research Procedia* 71 (2023), pp. 85–92. ISSN: 2352-1465. DOI: https://doi.org/10.1016/j.trpro.2023.11.061. URL: https://www.sciencedirect.com/science/article/pii/S2352146523003423.

[40] M. Weiszer, L. Delgado, and G. Gurtner. "Evaluation of Passenger Connections in Air-rail Multimodal Operations". In: *Proceedings of the 2024 SESAR Innovation Days (SID)*. Centre for Air Traffic Management Research, University of Westminster. London, UK, 2024, pp. 1–9. URL: https://www.sesarju.eu/sites/default/files/documents/sid/2024/papers/SIDs_2024_paper_050%20final.pdf.

[41] S. A. Alumur, J. F. Campbell, I. Contreras, B. Y. Kara, V. Marianov, and M. E. O'Kelly. "Perspectives on modeling hub location problems". In: *European Journal of Operational Research* 291.1 (2021), pp. 1–17. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2020.09.039. URL: https://www.sciencedirect.com/science/article/pii/S0377221720308432.

[42] E. Kurtuluş. "Optimizing Inland Container Logistics and Dry Port Location-Allocation from an Environmental Perspective". In: *Research in Transportation Business and Management* (May 2022). DOI: 10.1016/j.rtbm.2022.100839.

6

[43] A. Alibeyg, I. Contreras, and E. Fernández. "Hub network design problems with profits". In: *Transportation Research Part E: Logistics and Transportation Review* 96 (2016), pp. 40–59. ISSN: 1366-5545. DOI: https://doi.org/10.1016/j.tre.2016.09.008. URL: https://www.sciencedirect.com/science/article/pii/S136655451630271X.

[44] W. Qu, J. Rezaei, Y. Maknoon, and L. Tavasszy. "Hinterland freight transportation replanning model under the framework of synchromodality". In: *Transportation Research Part E: Logistics and Transportation Review* 131 (2019), pp. 308–328. ISSN: 1366-5545. DOI: https://doi.org/10.1016/j.tre.2019.09.014. URL: https://www.sciencedirect.com/science/article/pii/S1366554519301917.

[45] N. Huynh, D. Smith, and F. Harder. "Truck Appointment Systems: Where We Are and Where to Go from Here". In: *Transportation Research Record* 2548.1 (Jan. 2016), pp. 1–9. ISSN: 0361-1981. DOI: 10.3141/2548-01. URL: https://doi.org/10.3141/2548-01.

[46] G. Giuliano and T. O'Brien. "Reducing port-related truck emissions: The terminal gate appointment system at the Ports of Los Angeles and Long Beach". In: *Transportation Research Part D: Transport and Environment* 12.7 (Oct. 2007), pp. 460–473. ISSN: 1361-9209. DOI: 10.1016/J.TRD.2007.06.004.

[47] F. Schulte, E. Lalla-Ruiz, R. G. González-Ramírez, and S. Voß. "Reducing port-related empty truck emissions: A mathematical approach for truck appointments with collaboration". In: *Transportation Research Part E: Logistics and Transportation Review* 105 (Sept. 2017), pp. 195–212. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2017.03.008.

[48] A. Azab, A. Karam, and A. Eltawil. "A simulation-based optimization approach for external trucks appointment scheduling in container terminals". In: *International Journal of Modelling and Simulation* 40.5 (Sept. 2020), pp. 321–338. ISSN: 19257082. DOI: 10.1080/02286203.2019.1615261. URL: https://www.tandfonline.com/action/journalInformation?journalCode=tjms20.

[49] E. Zehendner and D. Feillet. "Benefits of a truck appointment system on the service quality of inland transport modes at a multimodal container terminal". In: *European Journal of Operational Research* 235.2 (2014), pp. 461–469. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2013.07.005. URL: https://www.sciencedirect.com/science/article/pii/S0377221713005675.

[50] G. Chen and L. Jiang. "Managing customer arrivals with time windows: a case of truck arrivals at a congested container terminal". In: *Annals of Operations Research* 244.2 (2016), pp. 349–365. DOI: 10.1007/s10479-016-2150-3. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84960095081&doi=10.1007%2fs10479-016-2150-3&partnerID=40&md5=31011499f2e582f32ac27fa7643b71f9.

6

[51] C. Zhou, H. Li, B. K. Lee, and Z. Qiu. “A simulation-based vessel-truck coordination strategy for lighterage terminals”. In: *Transportation Research Part C: Emerging Technologies* 95 (2018), pp. 149–164. DOI: 10.1016/j.trc.2018.07.015. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85050344515&doi=10.1016%2fj.trc.2018.07.015&partnerID=40&md5=7ba97f57b59837ae6a6ca13495a0c860.

[52] G. Scozzaro, M. M. Mota, D. Delahaye, and C. Mancel. “Simulation-Optimisation-based decision support system for managing airport security resources”. In: *EUROSIM 2023*. Amsterdam, France, July 2023. URL: https://enac.hal.science/hal-04202616.

[53] W. Rattanakijsuntorn, B. Suwannarat, N. Samittivate, and C. Nithikitti-wat. “Success Factors and Partnership Evaluation of Air–Rail Integration Development: A Case of a High-Speed Rail Project Linking Three Airports in Thailand”. In: *Infrastructures* 9.7 (2024). ISSN: 2412-3811. DOI: 10.3390/infrastructures9070115. URL: https://www.mdpi.com/2412-3811/9/7/115.

[54] N. Huynh. “Methodologies for Reducing Truck Turn Time at Marine Container Terminals”. PhD thesis. Austin: University of Texas, 2005.

[55] E. Ahmed, M. S. El-Abbasy, T. Zayed, G. Alfalah, and S. Alkass. “Synchronized scheduling model for container terminals using simulated double-cycling strategy”. In: *Computers and Industrial Engineering* 154 (2021). DOI: 10.1016/j.cie.2021.107118. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85100153975&doi=10.1016%2fj.cie.2021.107118&partnerID=40&md5=e0417053cf7b67cdd3b295b26b9cf7a8.

[56] M. Öberg, K. L. Nilsson, and C. Johansson. “Governance of Major Transport Corridors Involving Stakeholders”. In: *Transportation Research Procedia* 14 (2016), pp. 860–868. ISSN: 2352-1465. DOI: https://doi.org/10.1016/j.trpro.2016.05.034. URL: https://www.sciencedirect.com/science/article/pii/S2352146516300345.

[57] T. A. Arentze and E. J. E. Molin. “Travelers’ preferences in multimodal networks: Design and results of a comprehensive series of choice experiments”. In: *Transportation Research Part A: Policy and Practice* 58 (2013), pp. 15–28. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2013.10.005. URL: https://www.sciencedirect.com/science/article/pii/S0965856413001857.

[58] D. Teodorovic´. “Transport modeling by multi-agent systems: a swarm intelligence approach”. In: *Transportation Planning and Technology* 26.4 (2003), pp. 289–312. DOI: 10.1080/0308106032000154593. URL: https://doi.org/10.1080/0308106032000154593.

[59] M. Zargayouna. “Multi-Agent Approaches for Dynamic Transportation Problems”. PhD thesis. Université Paris Dauphine, Jan. 2019. URL: https://hal.science/tel-02465720.

6

[60] A. L. C. Bazzan and F. Klügl. "A review on agent-based technology for traffic and transportation". In: *The Knowledge Engineering Review* 29.3 (2014), pp. 375–403. ISSN: 0269-8889. DOI: DOI:10.1017/S0269888913000118. URL: https://www.cambridge.org/core/product/00947E41817CA7336E0A130CBF353D16.

[61] M. Kramarz, L. Knop, E. Przybylska, and K. Dohn. "Stakeholders of the Multimodal Freight Transport Ecosystem in Polish–Czech–Slovak Cross-Border Area". In: *Energies* 14.8 (2021). ISSN: 1996-1073. DOI: 10.3390/en14082242. URL: https://www.mdpi.com/1996-1073/14/8/2242.

[62] D. K. Kwesiga, S. C. Vishnoi, A. Guin, and M. Hunter. *Integrating Transit Signal Priority into Multi-Agent Reinforcement Learning based Traffic Signal Control*. 2024. URL: https://arxiv.org/abs/2411.19359.

[63] G. Weiss. *Multiagent Systems*. 2nd ed. Cambridge, MA: MIT Press, 2013.

[64] R. P. McAfee and J. McMillan. "Auctions and Bidding". In: *Journal of Economic Literature* 25.2 (June 1987), pp. 699–738. URL: https://ideas.repec.org/a/aea/jeclit/v25y1987i2p699-738.html.

[65] M. O. Ball, A. S. Estes, M. Hansen, and Y. Liu. "Quantity-Contingent Auctions and Allocation of Airport Slots". In: *https://doi.org/10.1287/trsc.2020.0995* 54.4 (June 2020), pp. 858–881. ISSN: 15265447. DOI: 10.1287/TRSC.2020.0995. URL: https://pubsonline.informs.org/doi/abs/10.1287/trsc.2020.0995.

[66] Y. Hara and E. Hato. "A car sharing auction with temporal-spatial OD connection conditions". In: *Transportation Research Part B: Methodological* 117 (Nov. 2018), pp. 723–739. ISSN: 0191-2615. DOI: 10.1016/J.TRB.2017.08.025.

[67] D. K. Giampouranis, M. Golias, S. Theofanis, and M. Boile. "Berth Allocation at Passenger Terminals Using Auctions". In: *Journal of Marine Science and Engineering* 10.8 (Aug. 2022). ISSN: 20771312. DOI: 10.3390/JMSE10081010.

[68] S. Bouarfa, R. Aydoğan, and A. Sharpanskykh. "Formal modelling and verification of a multi-agent negotiation approach for airline operations control". In: *Journal of Reliable Intelligent Environments* 7.4 (2021), pp. 279–298. ISSN: 2199-4676. DOI: 10.1007/s40860-020-00123-0. URL: https://doi.org/10.1007/s40860-020-00123-0.

[69] X. Mao, A. Mors, N. Roos, and C. Witteveen. *Coordinating Competitive Agents in Dynamic Airport Resource Scheduling*. Sept. 2007, pp. 133–144. ISBN: 978-3-540-74948-6. DOI: https://doi.org/10.1007/978-3-540-74949-3{_}12.

[70] A. Torreño, E. Onaindia, A. Komenda, and M. Štolba. "Cooperative Multi-Agent Planning: A Survey". In: *ACM Computing Surveys* 50.6 (Nov. 2017), pp. 1–32. ISSN: 1557-7341. DOI: 10.1145/3128584. URL: http://dx.doi.org/10.1145/3128584.

6

[71] T. Wang, M. Li, and H. Hu. "Berth allocation and quay crane-yard truck assignment considering carbon emissions in port area". In: *International Journal of Shipping and Transport Logistics* 11.2-3 (2019), pp. 216–242. DOI: 10.1504/IJSTL.2019.099275. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85065071746&doi=10.1504%2fIJSTL.2019.099275&partnerID=40&md5=f69b84b709e0ef00b1bb4176333beab0.

[72] F. Fioretto, E. Pontelli, and W. Yeoh. "Distributed constraint optimization problems and applications: a survey". In: *J. Artif. Int. Res.* 61.1 (Jan. 2018), pp. 623–698. ISSN: 1076-9757.

[73] S. Zhang, J. Li, T. Huang, S. Koenig, and B. Dilkina. "Learning a Priority Ordering for Prioritized Planning in Multi-Agent Path Finding". In: *Proceedings of the Symposium on Combinatorial Search (SoCS)*. 2022, pp. 208–216.

[74] W. Vickrey. "Counterspeculation, Auctions, and Competitive Sealed Tenders". In: *The Journal of Finance* 16.1 (Mar. 1961), p. 8. ISSN: 00221082. DOI: 10.2307/2977633.

[75] G. Chen, K. Govindan, and Z. Yang. "Managing truck arrivals with time windows to alleviate gate congestion at container terminals". In: *International Journal of Production Economics* 141.1 (2013), pp. 179–188. ISSN: 0925-5273. DOI: https://doi.org/10.1016/j.ijpe.2012.03.033. URL: https://www.sciencedirect.com/science/article/pii/S0925527312001417.

[76] Q. Xu, J. Li, S. Koenig, and H. Ma. "Multi-Goal Multi-Agent Pickup and Delivery". In: *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 2022, pp. 9964–9971. DOI: 10.1109/IROS47612.2022.9981785.

[77] G. Scozzaro, J. Ma, D. Delahaye, E. Feron, and C. Mancel. "Flight Rescheduling to Improve Passenger Journey during Airport Access Mode Disruptions". In: *International Conference on Research in Air Transportation (ICRAT 2022)*. Tampa, United States, June 2022. URL: https://enac.hal.science/hal-03701665.

[78] UNCTAD. *Review of Maritime Transport 2022*. Tech. rep. New York: United Nations Conference on Trade and Development, 2022. URL: https://unctad.org/publication/review-maritime-transport-2022.

[79] E. A. Lezhnina and Y. E. Balykina. "Cooperation between Sea Ports and Carriers in the Logistics Chain". In: *Journal of Marine Science and Engineering* 9.7 (July 2021), p. 774. ISSN: 2077-1312. DOI: 10.3390/JMSE9070774. URL: https://www.mdpi.com/2077-1312/9/7/774/htm%20https://www.mdpi.com/2077-1312/9/7/774.

[80] M. Svanberg, H. Holm, and K. Cullinane. "Assessing the Impact of Disruptive Events on Port Performance and Choice: The Case of Gothenburg". In: *Journal of Marine Science and Engineering* 9.2 (Jan. 2021), p. 145. ISSN: 2077-1312. DOI: 10.3390/JMSE9020145. URL: https://www.mdpi.com/2077-1312/9/2/145/htm%20https://www.mdpi.com/2077-1312/9/2/145.

[81] S. Shiri and N. Huynh. "Optimization of drayage operations with time-window constraints". In: *International Journal of Production Economics* 176 (June 2016), pp. 7–20. ISSN: 0925-5273. DOI: 10.1016/J.IJPE.2016.03.005.

[82] M. Gansterer and R. F. Hartl. "Collaborative vehicle routing: A survey". In: *European Journal of Operational Research* 268.1 (July 2018), pp. 1–12. ISSN: 03772217. DOI: 10.1016/j.ejor.2017.10.023.

[83] A. Bombelli and S. Fazi. "The ground handler dock capacitated pickup and delivery problem with time windows: A collaborative framework for air cargo operations". In: *Transportation Research Part E: Logistics and Transportation Review* 159 (Mar. 2022). ISSN: 13665545. DOI: 10.1016/j.tre.2022.102603.

[84] X. Zhang, Q. Zeng, and Z. Yang. "Optimization of truck appointments in container terminals". In: *Maritime Economics and Logistics* 21.1 (Mar. 2019), pp. 125–145. ISSN: 1479294X. DOI: 10.1057/S41278-018-0105-0/FIGURES/13. URL: https://link.springer.com/article/10.1057/s41278-018-0105-0.

[85] A. Azab and H. Morita. "Coordinating truck appointments with container relocations and retrievals in container terminals under partial appointments information". In: *Transportation Research Part E: Logistics and Transportation Review* 160 (Apr. 2022), p. 102673. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2022.102673.

[86] M. Torkjazi, N. Huynh, and S. Shiri. "Truck appointment systems considering impact to drayage truck tours". In: *Transportation Research Part E: Logistics and Transportation Review* 116 (Aug. 2018), pp. 208–228. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2018.06.003.

[87] C. Caballini, M. D. Gracia, J. Mar-Ortiz, and S. Sacone. "A combined data mining – optimization approach to manage trucks operations in container terminals with the use of a TAS: Application to an Italian and a Mexican port". In: *Transportation Research Part E: Logistics and Transportation Review* 142 (Oct. 2020), p. 102054. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2020.102054.

[88] H. Im, J. Yu, and C. Lee. "Truck Appointment System for Cooperation between the Transport Companies and the Terminal Operator at Container Terminals". In: *Applied Sciences* 11.1 (Dec. 2021), p. 168. ISSN: 2076-3417. DOI: 10.3390/APP11010168. URL: https://www.mdpi.com/2076-3417/11/1/168/htm%20https://www.mdpi.com/2076-3417/11/1/168.

[89] M. H. Phan and K. H. Kim. "Negotiating truck arrival times among trucking companies and a container terminal". In: *Transportation Research Part E: Logistics and Transportation Review* 75 (Mar. 2015), pp. 132–144. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2015.01.004.

[90] M. H. Phan and K. H. Kim. "Collaborative truck scheduling and appointments for trucking companies and container terminals". In: *Transportation Research Part B: Methodological* 86 (Apr. 2016), pp. 37–50. ISSN: 0191-2615. DOI: 10.1016/J.TRB.2016.01.006.

6

[91] X. Chen, X. Zhou, and G. F. List. "Using time-varying tolls to optimize truck arrivals at ports". In: *Transportation Research Part E: Logistics and Transportation Review* 47.6 (Nov. 2011), pp. 965–982. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2011.04.001.

[92] D. Li, J. X. Dong, D. P. Song, C. Hicks, and S. P. Singh. "Optimal contract design for the exchange of tradable truck permits at multiterminal ports". In: *International Journal of Production Economics* 230 (Dec. 2020), p. 107815. ISSN: 0925-5273. DOI: 10.1016/J.IJPE.2020.107815.

[93] S. Rassenti, V. Smith, and R. Bulfin. "A Combinatorial Auction Mechanism for Airport Time Slot Allocation". In: *Bell Journal of Economics* 13.2 (1982), pp. 402–417. URL: https://ideas.repec.org/a/rje/bellje/v13y1982iautumnp402-417.html%20https://ideas.repec.org//a/rje/bellje/v13y1982iautumnp402-417.html.

[94] L. Le, G. Donohue, and C. H. Chen. "Auction-based slot allocation for traffic demand management at hartsfield Atlanta International Airport: A case study". In: *Transportation Research Record* 1.1888 (2004), pp. 50–58. ISSN: 03611981. DOI: 10.3141/1888-07.

[95] R. Herranz, D. Toribio, M. Ramírez, F. Villafáñez, J. A. Araúzo, D. Poza, N. Alsina, L. Garrigó, L. Castelli, and T. Bolic. "Price-Setting Auctions for Airport Slot Allocation: a Multi-Airport Case Study An Agent-Based Computational Economics Approach to Strategic Slot Allocation". In: *SESAR Innovation Days, Bologna, Italy* (2015). URL: www.access-sesar.eu.

[96] D. Sheng, Z. C. Li, Y. b. Xiao, and X. Fu. "Slot auction in an airport network with demand uncertainty". In: *Transportation Research Part E: Logistics and Transportation Review* 82 (Oct. 2015), pp. 79–100. ISSN: 1366-5545. DOI: 10.1016/J.TRE.2015.07.010.

[97] F. Lu, H. Bi, W. Feng, Y. Hu, S. Wang, and X. Zhang. "A Two-Stage Auction Mechanism for 3PL Supplier Selection under Risk Aversion". In: *Sustainability* 13.17 (2021). ISSN: 2071-1050. DOI: 10.3390/su13179745. URL: https://www.mdpi.com/2071-1050/13/17/9745.

[98] S. Pettersen Strandenes and E. Wolfstetter. "Efficient (re-)scheduling: An auction approach". In: *Economics Letters* 89.2 (2005), pp. 187–192. URL: https://ideas.repec.org/a/eee/ecolet/v89y2005i2p187-192.html%20https://ideas.repec.org//a/eee/ecolet/v89y2005i2p187-192.html.

[99] H. C. Lau, S. F. Cheng, T. Y. Leong, J. H. Park, and Z. Zhao. "Multi-period combinatorial auction mechanism for distributed resource allocation and scheduling". In: *Proceedings of the 2007 IEEE/WIC/ACM International Conference on Intelligent Agent Technology, Silicon Valley, CA, USA, November 2-5* (2007), pp. 407–411. DOI: 10.1109/IAT.2007.41.

[100] R. Li, M. Nie, and X. Liu. "Auction-Based Permit Allocation and Sharing System (A-Pass) for Travel Demand Management". In: *Transportation Science* 56.2 (Jan. 2020), pp. 322–337. DOI: 10.2139/SSRN.3529527. URL: https://papers.ssrn.com/abstract=3529527.

6

[101] H. Xiao, M. Xu, and Z. Gao. “Shared parking problem: A novel truthful double auction mechanism approach”. In: *Transportation Research Part B: Methodological* 109 (Mar. 2018), pp. 40–69. ISSN: 01912615. DOI: 10.1016/J.TRB.2018.01.008.

[102] J. L. Cohon. *Multiobjective programming and planning*. 1st ed. Vol. 140. Academic Press, 1978. ISBN: 9780080956497.

[103] K. H. Chung, C. S. Ko, J. Y. Shin, H. Hwang, and K. H. Kim. “Development of mathematical models for the container road transportation in Korean trucking industries”. In: *Computers & Industrial Engineering* 53.2 (2007), pp. 252–262. ISSN: 0360-8352. URL: https://www.academia.edu/7491157/Development_of_mathematical_models_for_the_container_road_transportation_in_Korean_trucking_industries.

[104] R. Zhang, W. Y. Yun, and H. Kopfer. “Heuristic-based truck scheduling for inland container transportation”. In: *OR Spectrum* 32.3 (July 2010), pp. 787–808. ISSN: 01716468. DOI: 10.1007/S00291-010-0193-4/METRICS. URL: https://link.springer.com/article/10.1007/s00291-010-0193-4.

[105] G. Chen, K. Govindan, Z. Z. Yang, T. M. Choi, and L. Jiang. “Terminal appointment system design by non-stationary M(t)/Ek/c(t) queueing model and genetic algorithm”. In: *International Journal of Production Economics* 146.2 (Dec. 2013), pp. 694–703. ISSN: 0925-5273. DOI: 10.1016/J.IJPE.2013.09.001.

[106] RWG. *Surcharge on time slots during peak hours*. 2023. URL: https://metrans.eu/time-slot-surcharge-at-the-rwg-terminal-in-rotterdam/.

[107] Gurobi Optimization LLC. *Gurobi Optimizer Reference Manual*. 2023. URL: https://www.gurobi.com.

[108] Y. Akakura. “Analysis of offshore waiting at world container terminals and estimation of CO2 emissions from waiting ships”. In: *Asian Transport Studies* 9 (2023), p. 100111. ISSN: 2185-5560. DOI: https://doi.org/10.1016/j.eastsj.2023.100111. URL: https://www.sciencedirect.com/science/article/pii/S2185556023000160.

[109] W. Li, Z. Wu, P. Yang, and L. Cai. “Collaborative Scheduling Optimization of Equipment in Multimodal Transport Harbor Considering Hybrid Operation Mode of "train-yard-vessel" and "train-vessel"”. In: *2022 IEEE 18th International Conference on Automation Science and Engineering (CASE)*. 2022, pp. 86–91. DOI: 10.1109/CASE49997.2022.9926622.

[110] N. N. Huynh and C. M. Walton. *Methodologies for reducing truck turn time at marine container terminals*. Tech. rep. University of Texas at Austin. Center for Transportation Research, May 2005. URL: https://rosap.ntl.bts.gov/view/dot/29635.

6

[111] I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. “A Novel Auction-Based Truck Appointment System for Marine Terminals”. In: *Logistics* 8.2 (2024). ISSN: 2305-6290. DOI: 10.3390/logistics8020040. URL: https://www.mdpi.com/2305-6290/8/2/40.

[112] M. Ma, H. Fan, X. Jiang, and Z. Guo. “Truck Arrivals Scheduling with Vessel Dependent Time Windows to Reduce Carbon Emissions”. In: *Sustainability* 11.22 (2019). ISSN: 2071-1050. DOI: 10.3390/su11226410. URL: https://www.mdpi.com/2071-1050/11/22/6410.

[113] C. Bierwirth and F. Meisel. “A follow-up survey of berth allocation and quay crane scheduling problems in container terminals”. In: *European Journal of Operational Research* 244.3 (2015), pp. 675–689. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2014.12.030. URL: https://www.sciencedirect.com/science/article/pii/S0377221714010480.

[114] F. Rodrigues and A. Agra. “Berth allocation and quay crane assignment/scheduling problem under uncertainty: A survey”. In: *European Journal of Operational Research* 303.2 (2022), pp. 501–524. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2021.12.040. URL: https://www.sciencedirect.com/science/article/pii/S0377221721010961.

[115] L. Zhen. “Tactical berth allocation under uncertainty”. In: *European Journal of Operational Research* 247.3 (2015), pp. 928–944. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2015.05.079. URL: https://www.sciencedirect.com/science/article/pii/S0377221715004919.

[116] M. Ma, W. Zhao, H. Fan, and Y. Gong. “Collaborative Optimization of Yard Crane Deployment and Inbound Truck Arrivals with Vessel-Dependent Time Windows”. In: *Journal of Marine Science and Engineering* 10.11 (2022). ISSN: 2077-1312. DOI: 10.3390/jmse10111650. URL: https://www.mdpi.com/2077-1312/10/11/1650.

[117] X. F. Yin, L. P. Khoo, and C.-H. Chen. “A distributed agent system for port planning and scheduling”. In: *Advanced Engineering Informatics* 25.3 (2011), pp. 403–412. ISSN: 1474-0346. DOI: https://doi.org/10.1016/j.aei.2010.10.004. URL: https://www.sciencedirect.com/science/article/pii/S1474034610001023.

[118] Z. Sun, L. H. Lee, E. P. Chew, and K. C. Tan. “MicroPort: A general simulation platform for seaport container terminals”. In: *Advanced Engineering Informatics* 26.1 (2012), pp. 80–89. ISSN: 1474-0346. DOI: https://doi.org/10.1016/j.aei.2011.08.010. URL: https://www.sciencedirect.com/science/article/pii/S1474034611000796.

[119] F. Feng, Y. Pang, and G. Lodewijks. “Integrate multi-agent planning in hinterland transport: Design, implementation and evaluation”. In: *Advanced Engineering Informatics* 29.4 (2015), pp. 1055–1071. ISSN: 1474-0346. DOI: https://doi.org/10.1016/j.aei.2015.08.001. URL: https://www.sciencedirect.com/science/article/pii/S1474034615000762.

[120] Z. Chen, J. Alonso-Mora, X. Bai, D. D. Harabor, and P. J. Stuckey. "Integrated Task Assignment and Path Planning for Capacitated Multi-Agent Pickup and Delivery". In: *IEEE Robotics and Automation Letters* 6.3 (2021), pp. 5816–5823. DOI: 10.1109/LRA.2021.3074883.

[121] X. Wu, Y. Liu, X. Tang, W. Cai, F. Bai, G. Khonstantine, and G. Zhao. "Multi-Agent Pickup and Delivery with Task Deadlines". In: *IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*. WI-IAT '21. New York, NY, USA: Association for Computing Machinery, 2022, pp. 360–367. ISBN: 9781450391153. DOI: 10.1145/3486622.3493915. URL: https://doi.org/10.1145/3486622.3493915.

[122] E. Ahmadi, M. Zandieh, M. Farrokh, and S. M. Emami. "A multi objective optimization approach for flexible job shop scheduling problem under random machine breakdown by evolutionary algorithms". In: *Computers & Operations Research* 73 (2016), pp. 56–66. ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2016.03.009. URL: https://www.sciencedirect.com/science/article/pii/S0305054816300600.

[123] Y. Wu, H. Yang, J. Tang, and Y. Yu. "Multi-objective re-synchronizing of bus timetable: Model, complexity and solution". In: *Transportation Research Part C: Emerging Technologies* 67 (2016), pp. 149–168. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2016.02.007. URL: https://www.sciencedirect.com/science/article/pii/S0968090X16000607.

[124] S. Bandyopadhyay and R. Bhattacharya. "Solving multi-objective parallel machine scheduling problem by a modified NSGA-II". In: *Applied Mathematical Modelling* 37.10 (2013), pp. 6718–6729. ISSN: 0307-904X. DOI: https://doi.org/10.1016/j.apm.2013.01.050. URL: https://www.sciencedirect.com/science/article/pii/S0307904X13001200.

[125] A. Amini and R. Tavakkoli-Moghaddam. "A bi-objective truck scheduling problem in a cross-docking center with probability of breakdown for trucks". In: *Computers & Industrial Engineering* 96 (2016), pp. 180–191. ISSN: 0360-8352. DOI: https://doi.org/10.1016/j.cie.2016.03.023. URL: https://www.sciencedirect.com/science/article/pii/S0360835216300961.

[126] X. Wen, Q. Chen, Y.-Q. Yin, Y.-y. Lau, and M. A. Dulebenets. "Multi-Objective Optimization for Ship Scheduling with Port Congestion and Environmental Considerations". In: *Journal of Marine Science and Engineering* 12.1 (2024). ISSN: 2077-1312. DOI: 10.3390/jmse12010114. URL: https://www.mdpi.com/2077-1312/12/1/114.

[127] B. Niu, Q. Liu, Z. Wang, L. Tan, and L. Li. "Multi-objective bacterial colony optimization algorithm for integrated container terminal scheduling problem". In: *Natural Computing* 20.1 (2021), pp. 89–104. ISSN: 1572-9796. DOI: 10.1007/s11047-019-09781-3. URL: https://doi.org/10.1007/s11047-019-09781-3.

6

[128] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. “A fast and elitist multiobjective genetic algorithm: NSGA-II”. In: *IEEE Transactions on Evolutionary Computation* 6.2 (2002), pp. 182–197. DOI: 10.1109/4235.996017.

[129] E. Zitzler, M. Laumanns, and L. Thiele. “SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization”. In: *Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems. Proceedings of the EUROGEN'2001*. Athens, Sept. 2001, pp. 19–21.

[130] C. C. Minh and N. V. Noi. “Optimising truck arrival management and number of service gates at container terminals”. In: *Maritime Business Review* 8.1 (Jan. 2023), pp. 18–31. ISSN: 2397-3757. DOI: 10.1108/MABR-08-2021-0060. URL: https://doi.org/10.1108/MABR-08-2021-0060.

[131] C. C. Minh and N. Huynh. “Planning-Level Tool for Assessing and Optimizing Gate Layout for Marine Container Terminals”. In: *Transportation Research Record* 2409.1 (Jan. 2014), pp. 31–39. ISSN: 0361-1981. DOI: 10.3141/2409-05. URL: https://doi.org/10.3141/2409-05.

[132] R. Stolletz. “Analysis of passenger queues at airport terminals”. In: *Research in Transportation Business & Management* 1.1 (Aug. 2011), pp. 144–149. ISSN: 2210-5395. DOI: 10.1016/J.RTBM.2011.06.012.

[133] X. Zhang, Q. Zeng, and W. Chen. “Optimization Model for Truck Appointment in Container Terminals”. In: *Procedia - Social and Behavioral Sciences* 96 (2013), pp. 1938–1947. ISSN: 1877-0428. DOI: https://doi.org/10.1016/j.sbspro.2013.08.219. URL: https://www.sciencedirect.com/science/article/pii/S1877042813023458.

[134] The World Bank. *The Container Port Performance Index 2023: A Comparable Assessment of Performance Based on Vessel Time in Port*. Tech. rep. Washington, DC: The World Bank, Transport Global Practice, 2024.

[135] J. Blank and K. Deb. “Pymoo: Multi-Objective Optimization in Python”. In: *IEEE Access* 8 (2020), pp. 89497–89509. DOI: 10.1109/ACCESS.2020.2990567.

[136] G. P. Cosmetatos. “Approximate Equilibrium Results for the Multi-Server Queue (GI/M/r)”. In: *Operational Research Quarterly* 25.4 (1974), pp. 625–634. ISSN: 00303623. DOI: 10.2307/3008094. URL: http://www.jstor.org.tudelft.idm.oclc.org/stable/3008094.

[137] G. Bolch, S. Greiner, H. De Meer, and K. S. Trivedi. *Queueing networks and Markov chains: modeling and performance evaluation with computer science applications*. John Wiley & Sons, 2006.

[138] European Commission. *Flightpath 2050 – Europe's vision for aviation – Maintaining global leadership and serving society's needs*. Tech. rep. Directorate-General for Mobility and Transportr, 2011. DOI: doi/10.2777/50266.

6

[139] A. Colovic, S. G. Pilone, K. Kukić, M. Kalić, S. Dožić, D. Babić, and M. Ottomanelli. "Airport Access Mode Choice: Analysis of Passengers' Behavior in European Countries". In: *Sustainability* 14.15 (2022). ISSN: 2071-1050. DOI: 10.3390/su14159267. URL: https://www.mdpi.com/2071-1050/14/15/9267.

[140] Lufthansa. *Rail&Fly*. 2019. URL: https://www.lufthansa.com/at/de/rail-and-fly.

[141] D. Babic, A. Colovic, S. Dožic, M. Kalic, T. K. Simic, K. Kukic, M. Ottomanelli, and S. G. Pilone. "Towards seamless door-to-door travelling within Europe: Transport operators' and pabengers' perspectives". In: *Transportation Research Procedia*. Vol. 72. 2023, pp. 1589–1596. DOI: 10.1016/j.trpro.2023.11.628. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85182924268&doi=10.1016%2fj.trpro.2023.11.628&partnerID=40&md5=39469f12da993eaad72cf1676e788071.

[142] I. Laplace, A. Marzuoli, and E. Féron. "META-CDM : Multimodal, Efficient Transportation in Airports and Collaborative Decision Making". In: *AUN 2014, Airports in Urban Networks*. Paris, France, Apr. 2014. URL: https://enac.hal.science/hal-01016793.

6

[143] L. Wang, J. G. Jin, L. Sun, and D.-H. Lee. "Urban rail transit disruption management: Research progress and future directions". In: *Frontiers of Engineering Management* 11.1 (2024), pp. 79–91. ISSN: 2096-0255. DOI: 10.1007/s42524-023-0291-z. URL: https://doi.org/10.1007/s42524-023-0291-z.

[144] L. Calvet. "Towards Environmentally Sustainable Aviation: A Review on Operational Optimization". In: *Future Transportation* 4.2 (2024), pp. 518–547. ISSN: 2673-7590. DOI: 10.3390/futuretransp4020025. URL: https://www.mdpi.com/2673-7590/4/2/25.

[145] B. F. Santos, M. M. E. C. Wormer, T. A. O. Achola, and R. Curran. "Airline delay management problem with airport capacity constraints and priority decisions". In: *Journal of Air Transport Management* 63 (2017), pp. 34–44. ISSN: 0969-6997. DOI: https://doi.org/10.1016/j.jairtraman.2017.05.003. URL: https://www.sciencedirect.com/science/article/pii/S0969699716302514.

[146] D. Esztergár-Kiss, A. Ansariyar, and G. Katona. "Developing a Heuristic Route Planning Method to Support Seamless Mobility Solutions". In: *Lecture Notes in Intelligent Transportation and Infrastructure* Part F1378 (2023), pp. 266–275. DOI: 10.1007/978-3-031-23721-8{_}23. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85171341887&doi=10.1007%2f978-3-031-23721-8_23&partnerID=40&md5=0502dc073c92f3e38eaf1b86f6732670.

[147] T. S. L. Prashanth, A. K. Tamilselvan, and S. Chandrodaya. "Multimodal transport model: Enhancing collaboration among mobility sharing schemes by identifying an optimal transit station". In: *2016 International Conference on Internet of Things and Applications, IOTA 2016*. 2016, pp. 286–291.

DOI: 10.1109/IOTA.2016.7562739. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84988958281&doi=10.1109%2fIOTA.2016.7562739&partnerID=40&md5=b39b4b94e25bcce86534652b74aa2df1.

[148] I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. "Design of a Demand Responsive Transport service using Distributed Constraint Optimization for airport access". In: *2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. 2023, pp. 1–6. DOI: 10.1109/MT-ITS56129.2023.10241535.

[149] M. Cebecauer, W. Burghout, E. Jenelius, T. Babicheva, and D. Leffler. "Integrating Demand Responsive Services Into Public Transport Disruption Management". In: *IEEE Open Journal of Intelligent Transportation Systems* 2 (2021), pp. 24–36. DOI: 10.1109/OJITS.2021.3057221.

[150] L. Reis, A. P. Rocha, and A. J. M. Castro. "An Agent-based Electronic Market to Help Airlines to Recover from Delays". In: *Proceedings of the 10th International Conference on Agents and Artificial Intelligence - Volume 2: ICAART*. SciTePress, 2018, pp. 176–183. ISBN: 978-989-758-275-2. DOI: 10.5220/0006582401760183.

[151] ORCHESTRA. *D5.4 Final Living Labs*. Tech. rep. ORCHESTRA Project, 2021. URL: https://orchestra2020.eu/wp-content/uploads/2021/07/D5.4-Final-Living-Labs.pdf.

[152] Transit.Land. *Comune di Milano GTFS Feed*. 2025. URL: https://www.transit.land/feeds/f-u0nd-comunedimilano.

[153] Flightera. *Flightera: Flight Tracking and Statistics*. 2025. URL: https://www.flightera.net/.

[154] L.-M. Brause, A. Popa, T. Koch, A. Deutschmann, and M. Hellmann. "Optimization of resource demand for passenger services at airports during system failures such as blackouts". In: *European Transport Research Review* 12.1 (2020), p. 54. ISSN: 1866-8887. DOI: 10.1186/s12544-020-00446-2. URL: https://doi.org/10.1186/s12544-020-00446-2.

[155] A. Cook, G. Tanner, and A. Lawes. "The Hidden Cost of Airline Unpunctuality". In: *Journal of Transport Economics and Policy* 46.2 (2012), pp. 157–173. ISSN: 00225258. URL: http://www.jstor.org/stable/24396360.

[156] A. J. Cook, G. Tanner, and T. Bolic. *D3.2 Industry Briefing on Updates to the European Cost of Delay*. Tech. rep. BEACON Consortium, 2021. URL: https://www.beacon-sesar.eu/wp-content/uploads/2022/10/893100-BEACON-D3.2-Industry-briefing-on-updates-to-the-European-cost-of-delay-V.01.01.00-1.pdf.

[157] L. S. Shapley. "A Value for n-Person Games". In: *Contributions to the Theory of Games II*. Ed. by H. W. Kuhn and A. W. Tucker. Princeton: Princeton University Press, 1953, pp. 307–317.

6

[158] E. Hoeven, J. Kwakkel, V. Hess, T. Pike, B. Wang, rht, and J. Kazil. "Mesa 3: Agent-based modeling with Python in 2025". In: *Journal of Open Source Software* 10 (Apr. 2025), p. 7668. DOI: 10.21105/joss.07668.

[159] S. Gupta, P. Vovsha, and R. Donnelly. "Air passenger preferences for choice of airport and ground access mode in the New York city metropolitan region". In: *Transportation Research Record* 2042 (2008), pp. 3–11. DOI: 10.3141/2042-01.

[160] M. L. Tam, W. H. K. Lam, and H. P. Lo. "Modeling air passenger travel behavior on airport ground access mode choices". In: *Transportmetrica* 4.2 (2008), pp. 135–153. DOI: 10.1080/18128600808685685.

[161] R.-C. Jou, D. A. Hensher, and T.-L. Hsu. "Airport ground access mode choice behavior after the introduction of a new mode: A case study of Taoyuan International Airport in Taiwan". In: *Transportation Research Part E: Logistics and Transportation Review* 47.3 (2011), pp. 371–381. DOI: 10.1016/j.tre.2010.11.008.

[162] H. Chebli and H. Mahmassani. "Air Travelers' Stated Preferences Towards New Airport Landside Access Mode Services". In: (Apr. 2002).

[163] R. Hernández-Martín and H. Padrón-ávila. "The carbon footprint of airport ground access as part of an outbound holiday trip". In: *Sustainability (Switzerland)* 13.16 (2021). DOI: 10.3390/su13169085.

6

[164] "Topical Report: Airport Accessibility in Europe". In: *Topical Report : Airport Accessibility in Europe* (2010).

[165] C. W. JENK, C. F. JENCKS, and D. S. SCHWAGER. "Guidebook for measuring, assessing, and improving performance of demand-response transportation (Report No. 124)". In: *TCRP Report 124: Guidebook for Measuring, Assessing, and Improving Performance of Demand-Response Transportation* (2008).

[166] Y. Liu and Y. Ouyang. "Mobility service design via joint optimization of transit networks and demand-responsive services". In: *Transportation Research Part B: Methodological* 151 (2021), pp. 22–41. DOI: 10.1016/j.trb.2021.06.005.

[167] T.-Y. Ma. "On-demand dynamic Bi-/multi-modal ride-sharing using optimal passenger-vehicle assignments". In: *Conference Proceedings - 2017 17th IEEE International Conference on Environment and Electrical Engineering and 2017 1st IEEE Industrial and Commercial Power Systems Europe, EEEIC / I and CPS Europe 2017*. 2017. DOI: 10.1109/EEEIC.2017.7977646.

[168] J. Wen, Y. X. Chen, N. Nassir, and J. Zhao. "Transit-oriented autonomous vehicle operation with integrated demand-supply interaction". In: *Transportation Research Part C: Emerging Technologies* 97 (2018), pp. 216–234. DOI: 10.1016/j.trc.2018.10.018.

[169] Y. Shen, H. Zhang, and J. Zhao. "Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore". In: *Transportation Research Part A: Policy and Practice* 113 (2018), pp. 125–136. DOI: 10.1016/j.tra.2018.04.004.

[170] K. Kinoshita, K. Iizuka, and Y. Iizuka. “Effective disaster evacuation by solving the distributed constraint optimization problem”. In: *Proceedings - 2nd IIAI International Conference on Advanced Applied Informatics, IIAI-AAI 2013*. 2013, pp. 399–400. DOI: 10.1109/IIAI-AAI.2013.40.

[171] P. Dalapati, A. J. Singh, A. Dutta, and S. Bhattacharya. “Multi agent based railway scheduling and optimization”. In: *IEEE Region 10 Annual International Conference, Proceedings/TENCON*. Vol. 2015-January. 2015. DOI: 10.1109/TENCON.2014.7022389.

[172] S. Li, R. R. Negenborn, and G. Lodewijks. “Distributed constraint optimization for addressing vessel rotation planning problems”. In: *Engineering Applications of Artificial Intelligence* 48 (2016), pp. 159–172. ISSN: 0952-1976. DOI: https://doi.org/10.1016/j.engappai.2015.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0952197615002481.

[173] R. Junges and A. L. C. Bazzan. “Evaluating the performance of DCOP algorithms in a real world, dynamic problem”. In: *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS*. Vol. 1. 2008, pp. 590–597.

[174] P. Toth and D. Vigo. “The vehicle routing problem”. In: *The Vehicle Routing Problem* (2002).

[175] T. R. P. Ramos, M. I. Gomes, and A. P. B. Póvoa. “Multi-depot vehicle routing problem: a comparative study of alternative formulations”. In: *International Journal of Logistics Research and Applications* 23.2 (2020), pp. 103–120. DOI: 10.1080/13675567.2019.1630374.

[176] HERE Developer. *HERE Developer Portal*. https://developer.here.com/. Oct. 2022.

[177] A. Bernini, A. L. Toure, and R. Casagrandi. “The time varying network of urban space uses in Milan”. In: *Applied Network Science* 4.1 (2019). DOI: 10.1007/s41109-019-0245-x.

[178] Comune di Milano. *Proiezioni della popolazione per quartiere - Anni 2021–2040 (base 2020) - Open Data - Comune di Milano*. https://dati.comune.milano.it/dataset/ds25-popolazione-proiezione-popolazione-quartiere. Oct. 2022.

[179] OpenStreetMap contributors. *Planet dump retrieved from https://planet.osm.org*. https://planet.osm.org. 2025.

[180] T. Léauté, B. Ottens, and R. Szymanek. “FRODO 2.0: An open-source framework for distributed constraint optimization”. In: *Proceedings of the IJCAI’09 Distributed Constraint Reasoning Workshop (DCR’09)* (2009), pp. 160–164.

[181] A. Petcu and B. Faltings. “A scalable method for multiagent constraint optimization”. In: *IJCAI International Joint Conference on Artificial Intelligence*. 2005, pp. 266–271.

6

[182] C. Y. Cheong, K. C. Tan, D. K. Liu, and C. J. Lin. "Multi-objective and prioritized berth allocation in container ports". In: *Annals of Operations Research* 180.1 (2010), pp. 63–103. ISSN: 1572-9338. DOI: 10.1007/s10479-008-0493-0. URL: https://doi.org/10.1007/s10479-008-0493-0.

[183] I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. "A Multi-Agent Optimization Approach for Multimodal Collaboration in Marine Terminals". In: *Logistics* 9.3 (2025). ISSN: 2305-6290. DOI: 10.3390/logistics9030110. URL: https://www.mdpi.com/2305-6290/9/3/110.

[184] I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. "Agent-based simulation of passenger-centric disruption management for multimodal airport access". In: *Transportation Research Procedia* - (2025), pp. -. DOI: -. URL: -.

Curriculum Vitæ

Ilias Alexandros Parmaksizoglou was born on October 7, 1995, in Athens, Greece. In 2014, he began his studies in Civil Engineering at the National Technical University of Athens, where he specialized in Transport Engineering. During his studies, he developed a strong interest in transport systems and operations, which led him to focus on transport modelling and planning for his coursework and thesis. Alongside his academic work, he was an active volunteer in the Board of European Students of Technology (BEST), a student organization dedicated to engineering and STEM students. He contributed to the organization of engineering competitions, academic courses, and events focused on the future of engineering education. He also served as president of the local BEST group in Athens, where he led and coordinated engineering events at both national and international levels.

In 2020, he enrolled in the MSc program in Operational Research with Data Science at the University of Edinburgh, United Kingdom. There, he deepened his knowledge of optimization, simulation, and machine learning, and actively applied these techniques to real-world problems in logistics and transportation. He completed the program in 2021 with merit. That same year, he began his PhD at the Air Transport and Operations group of the Aerospace Engineering faculty at Delft University of Technology in the Netherlands. His research was part of the EU HORIZON 2020 ORCHESTRA project and focused on polycentric coordination in multimodal transport. His work centered on developing optimization-based decision-support tools to promote collaboration among stakeholders in various transport systems.

In his free time, he enjoys long-distance running, trying new recipes in the kitchen, traveling, and mostly playing board games.

List of Publications

4. I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. “Design of a Demand Responsive Transport service using Distributed Constraint Optimization for airport access”. In: *2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. 2023, pp. 1–6. DOI: 10.1109/MT-ITS56129.2023.10241535

3. I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. “A Novel Auction-Based Truck Appointment System for Marine Terminals”. In: *Logistics* 8.2 (2024). ISSN: 2305-6290. DOI: 10.3390/logistics8020040. URL: https://www.mdpi.com/2305-6290/8/2/40

2. I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. “A Multi-Agent Optimization Approach for Multimodal Collaboration in Marine Terminals”. In: *Logistics* 9.3 (2025). ISSN: 2305-6290. DOI: 10.3390/logistics9030110. URL: https://www.mdpi.com/2305-6290/9/3/110

1. I. A. Parmaksizoglou, A. Bombelli, and A. Sharpanskykh. “Agent-based simulation of passenger-centric disruption management for multimodal airport access”. In: *Transportation Research Procedia* - (2025), pp. -. DOI: -. URL: -