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Collaborative planning for intermodal transport with eco-label preferences

Yimeng Zhang [a,*], Arne Heinold [b], Frank Meisel [b], Rudy R. Negenborn [a], Bilge Atasoy [a]

[a] Department of Maritime and Transport Technology, Delft University of Technology, 2628 CD Delft, The Netherlands
[b] School of Economics and Business, Kiel University, Kiel, Germany

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ABSTRACT

Sustainability is a common concern in intermodal transport. Collaboration among carriers may help in reducing emissions. In this context, this work establishes a collaborative planning model for intermodal transport and uses eco-labels (a series of different levels of emission ranges) to reflect shippers' sustainability preferences. A mathematical model and an Adaptive Large Neighborhood Search heuristic are proposed for intermodal transport planning of carriers and fuzzy set theory is used to model the preferences towards eco-labels. For multiple carriers, centralized, auction-based collaborative, and non-collaborative planning approaches are proposed and compared. Real data from barge, train and truck carriers in the European Rhine-Alpine corridor is used for extensive experiments where both unimodal carrier collaboration and intermodal carrier collaboration are analyzed. Compared with non-collaborative planning without eco-labels, the number of served requests increases and emissions decrease significantly in the collaborative planning with eco-labels as transport capacity is better utilized.

1. Introduction

In intermodal transport, containers are routed from their origins to their destinations by using multiple transport modes like trucks, trains, or barges (SteadieSeifi et al., 2014). While intermodal routings are often triggered by potential cost reductions, they are also considered as a means for more sustainable transport solutions. For example, Heinold and Meisel (2018) show in a comprehensive simulation study for Europe that 90% of the shipments have a lower environmental impact if they are routed in an intermodal rail–road connection instead of using a road-only connection. For shippers, such considerations play an increasing role as transportation contributes to "almost a quarter of Europe's greenhouse gas emissions and is the main cause of air pollution in cities" (European Commission, 2020). To achieve sustainable freight transportation, the European Commission proposes to cut carbon emissions in transport by 60% by 2050 and shift 50% of freight from road to rail and to waterborne transport (European Commission, 2011). China has announced its "Carbon Peak and Carbon Neutrality" policy, which aims at achieving a peak in carbon emissions by 2030 and carbon neutrality by 2060, for which the volume of rail–ship container transportation should increase by 15% each year between 2021 and 2025 (State Council of China, 2021a,b). According to surveys and expert interviews conducted in Zhang et al. (2022c), reducing emissions is important for carriers and shippers when the government releases policies or sets emission reduction goals. Shippers and transport companies will need to comply with regulations and they will become motivated to keep track of their footprint. Moreover, with the raising awareness of global warming, more and more carriers and shippers will want to contribute to sustainable transportation. Therefore, several approaches and policies have been proposed to reduce

* Corresponding author.
E-mail addresses: Yimeng.Zhang@tudelft.nl (Y. Zhang), arne.heinold@bwl.uni-kiel.de (A. Heinold), meisel@bwl.uni-kiel.de (F. Meisel), R.R.Negenborn@tudelft.nl (R.R. Negenborn), B.Atasoy@tudelft.nl (B. Atasoy).

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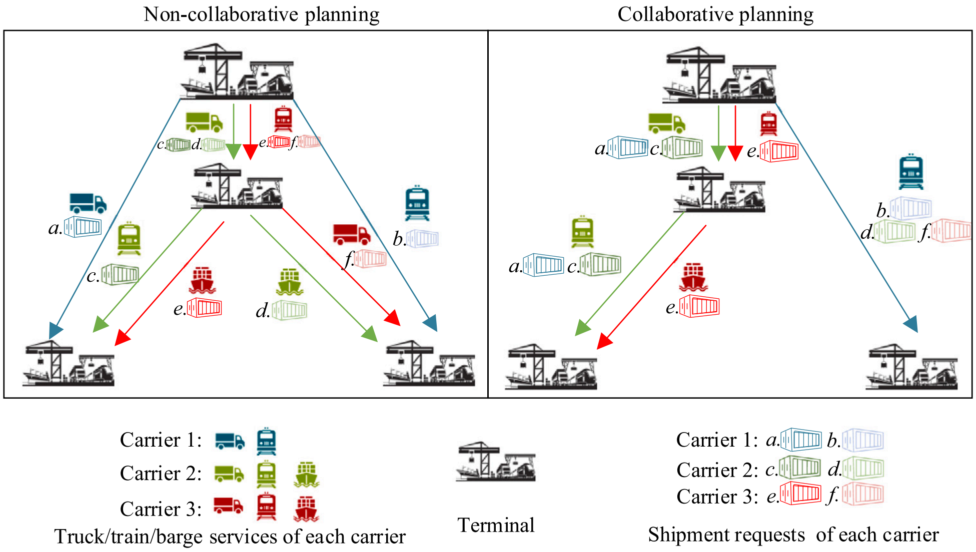


Fig. 1. Example of non-collaborative and collaborative planning.

the environmental impact of logistics, such as low-emission zones for heavy vehicles (Fensterer et al., 2014), emission reduction targets (Chen and Wang, 2016), or emission trading systems (Demailly and Quirion, 2008). Recently, the concept of eco-labels has been proposed to achieve a more sustainable freight transportation (Heinold and Meisel, 2020; Kirschstein et al., 2022). Thereby, eco-labels use a traffic light-colored preset scheme to indicate a shipment's relative environmental impact. For example, an eco-label "A" indicates that emissions caused in a transport process are very low whereas somewhat higher emissions lead to eco-label "B", and so on. Eco-labels can then be used as an indicator for a shipper's environmental preference, e.g., by requesting for a shipment that it is transported in accordance to a certain label.

The services of each transport carrier (operators of transport modes) are limited and may not be sufficient to achieve sustainable transport, especially when emission reduction requirements are high. Collaborative planning may then help in reducing emissions. Collaborative planning is becoming more and more prevalent due to the intensive competition in the transport market (Li et al., 2015b). There are different types of collaborative planning and collaboration partners can be shippers, receivers, or carriers (Pan et al., 2019). This study focuses on collaborative planning among carriers by exchanging shipment requests from shippers. Fig. 1 shows an example of non-collaborative and collaborative planning. In this example, there are three intermodal transport carriers and each carrier has two requests with high requirements on sustainability. When carriers do not collaborate, requests are served by their own services and the environmental requirements of some requests are not reached. For example, request a is served by carrier 1's truck service, and request f is served by carrier 3's train and truck services with transshipment. In collaborative planning, carriers decide which requests they are willing to share or serve. After collaboration, carrier 1's request a is shared with carrier 2 and carrier 2/3's requests d/f are shared with carrier 1. Thus, the capacity of low-cost and low-emission vehicles is better utilized and all carriers improve service levels and avoid unnecessary trips.

In its essence, collaboration enables the aggregated consideration of each carrier's demand, which is placed by shippers who own or supply shipments that can then be transported in a more efficient and sustainable way through a larger and more diverse logistics network. Large vehicles in intermodal transport, such as trains or barges, benefit from economies of scale by increasing capacity which reduces costs and emissions per container. Therefore, they are more profitable and sustainable if there is sufficient demand, which can be achieved through collaboration among carriers (e.g., Groothedde et al., 2005). Collaborating carriers can make better use of their vehicles' capacity and avoid empty trips, which then leads to cost and emission reductions, service improvements, and market share increases (e.g., Krajewska and Kopfer, 2006; Cruijssen et al., 2007; Schmoltzi and Wallenburg, 2011).

To achieve a more sustainable intermodal transport, we present a collaborative planning model with eco-labels. The considered carriers each operate networks on their own that differ in structure. For example, the predominant mode might be trains in one network and barges in another network. We consider shippers with different expectations regarding a shipment request's eco-label. However, integrating environmental preferences through eco-labels for each request imposes additional challenges to the underlying transport planning problem as well as to the collaborative planning model. The transport planning needs to handle vague preferences on eco-labels, such as "around eco-label B is fine". Appropriate collaborative planning approaches also need to be proposed to reach the required eco-label at the lowest cost by using different modes of service of carriers. To address these challenges, we provide a mathematical model and an Adaptive Large Neighborhood Search (ALNS) heuristic for intermodal transport planning considering vague preferences on eco-labels. We do not view eco-labels exclusively as either "fulfilled" or "not fulfilled" but calculate the degree of how much a request's routing complies with its requested eco-label using fuzzy set theory. Regarding the collaboration, we consider centralized, collaborative, and non-collaborative approaches. An auction-based mechanism is adopted for exchanging requests among carriers in the collaborative planning. We apply our model to a realistic case study in which we consider collaboration among unimodal or intermodal carriers along the European Rhine-Alpine corridor. Based on obtained results, we provide insights on situations in which collaboration is beneficial out of reasons of sustainability.

To the best of our knowledge, our paper is the first to propose and analyze the collaborative planning for carriers in intermodal transport considering shippers' (vague) sustainability preferences. Our main contributions to the existing literature are as follows. First, an optimization model with eco-label preferences is developed considering characteristics of intermodal transport and vagueness of preferences. Second, we provide a conceptual framework for horizontal collaborative planning in the context of sustainability. Finally, we perform an experimental study that investigates settings in which collaboration leads to more sustainable solutions.

The rest of this paper is structured as follows. Section 2 presents a review of the relevant literature. Section 3 describes the studied problem. Section 4 provides the approach for handling vague preferences, the mathematical model and heuristic algorithm for transport planning of each carrier, and the collaborative planning approach for multiple carriers. Section 5 describes the experimental settings and the results from the case study. Section 6 concludes the paper.

2. Literature review

This paper considers horizontal collaboration between intermodal transport carriers that principally offer the same service, namely, transporting a freight shipment from its origin to its destination. Accordingly, this literature review comprises two fields: (i) collaborative planning in unimodal freight transportation and (ii) collaborative planning in intermodal transportation. A brief review of relevant literature in these fields is provided in Sections 2.1 and 2.2, respectively. Note that the first field is very general but, in the context of our paper, comprises those papers on collaboration that do not belong to intermodal transport but are considered as relevant for our study. A summary of the reviewed literature is provided in Section 2.3.

2.1. Collaborative planning in freight transport

This section provides a review on collaborative planning in freight transportation. It starts with a general overview of how collaborations can be classified and continues with a review on collaboration in networks in which only a single mode of transportation is used. The latter review is included as it introduces general concepts of collaborative planning in freight transport. These concepts are used in Section 2.3 to highlight the distinct characteristics of our paper.

Gansterer and Hartl (2018) identify three major streams of research for collaborative vehicle routing: centralized collaborative planning, decentralized planning without auctions, and auction-based decentralized planning. If a central coordinator has full power on carriers, it is called centralized planning, otherwise called decentralized planning. Further divided by the means of exchanging requests, decentralized planning can be non-auction or auction-based.

Assuming a powerful central coordinator is not necessarily practical because carriers may not be willing to give full information to such a party. Moreover, the optimization problems in centralized collaborative planning are usually hard to solve because the overall transport network is of a large scale. Decentralized approaches without auctions typically involve various steps such as partner selection, request selection, and request exchange (Gansterer and Hartl, 2018). Compared to non-auction-based systems, the auction-based approaches are more complex due to the bidding procedure. However, it is in the nature of auctions to address the reassignment of transport requests and the allocation of the profit gained by carrier collaboration simultaneously (Berger and Bierwirth, 2010).

The research on collaborative freight transportation for unimodal transport often focuses on road freight transport be it for Full Truckload (FTL, size of shipment equal to vehicle capacity) or Less Than Truckload (LTL, size of shipment less than vehicle capacity) services. Collaborative planning of FTL mainly benefits from avoiding empty trips (Liu et al., 2010) and collaborative planning of LTL mainly benefits from making better use of vehicle capacity (Dai and Chen, 2012; Wang and Kopfer, 2014). Berger and Bierwirth (2010) propose two solution approaches for the LTL request reassignment problem involving decentralized control and auction-based selection and exchange of requests. Dai and Chen (2011) propose a multi-agent and auction-based framework for carrier collaboration in LTL transport. Lai et al. (2017) propose an iterative auction approach in FTL transport, which enables carriers to collaborate by exchanging their shipping requests iteratively. Wang et al. (2014) extend the pickup and delivery problem with time windows to collaborative transport planning, where both subcontracting and collaborative request exchange are taken into account. There is also some research on collaborative planning in maritime transport and inter-terminal transport. For example, Agarwal and Ergun (2010) study collaboration among carriers in liner shipping. Both tactical problems such as the design of large-scale networks and operational problems such as the allocation of limited capacity on a transport network among the carriers are discussed. Vojdani et al. (2013) focus on collaborative approaches in the empty container management. They demonstrate the potential for cost savings through the use of container pooling in comparison to non-cooperative solutions. For inter-terminal transports, Kopfer et al. (2016) evaluate by experiment scenarios for isolated planning, central planning, and collaborative planning. Their results show there are discrepancies in the collaboration profits of individual carriers.

Table 1
Summary of the literature review.

Literature	Domain	CA	T	FT	OTN	S
Liu et al. (2010)	FTL	DP				
Li et al. (2015b)	FTL	ADP				
Lai et al. (2017)	FTL	ADP				
Dai and Chen (2011)	LTL	ADP				
Dai and Chen (2012)	LTL	CP				
Wang and Kopfer (2014)	LTL	ADP				
Berger and Bierwirth (2010)	RFT	ADP			✓	
Wang et al. (2014)	RFT	ADP				
Özener (2014)	RFT	–				Carrier
Agarwal and Ergun (2010)	MFT	DP	✓	✓		
Vojdani et al. (2013)	MFT	DP			✓	
Kopfer et al. (2016)	ITT	ADP	✓			
Zhang et al. (2020)	IWT	–	✓			
Puettmann and Stadtler (2010)	IFT	ADP	✓	✓		
Xu et al. (2015)	IFT	ADP				
Di Febbraro et al. (2016)	IFT	DP	✓	✓		
Li et al. (2017)	IFT	DP	✓	✓		
Sun et al. (2019)	IFT	ADP				
Liotta et al. (2014)	IFT	CP				Carrier
Zhang et al. (2022a)	IFT	–	✓	✓		Carrier
This research	IFT	ADP	✓	✓	✓	Shipper

2.2. Collaborative planning in intermodal transport

Compared to the literature on collaboration in single-mode networks, there is a lack of research on collaborative planning for intermodal transport (Pan, 2017; Gumuskaya et al., 2020). In the last decade, some scholars researched the cooperation in intermodal transport at a strategical level from a business model perspective (Lin et al., 2017; Saeed, 2013). Nevertheless, very few research effort has been spent on the collaborative planning of independent players in an intermodal transport chain at the tactical and operational level, see the survey of Gansterer and Hartl (2018). The recent study of Gumuskaya et al. (2020) presents a framework for such collaboration but no decision support model. An example of a more decision-oriented study is Puettmann and Stadtler (2010), who investigate the coordination of a long-haul carrier and a drayage carrier in an intermodal transport chain. The carriers are allowed to keep their private planning information and critical data. The focus of the paper is on analyzing the impact of stochastic demand. Di Febbraro et al. (2016) propose a multi-actor system for cooperation in intermodal freight transport. They decompose the optimization problem into a set of sub-problems, each of them representing the operations of one actor. Through a Lagrangian-based Network Communication Coordinator, each actor receives information from its preceding and successive actor, and then optimizes its local operations. The dynamics of intermodal transport are studied by developing a discrete event model based on the concept of a rolling horizon. Li et al. (2017) investigate cooperative planning among multiple carriers that connect deep-sea ports and inland terminals where the transport networks of these carriers are interconnected with each other. Li et al. (2017) investigate service networks that are non-overlapping and the cooperative planning is done at the tactical flow level by all operators.

Only few papers have studied the auctioning of requests in intermodal transport collaboration. Xu et al. (2015) study intermodal transport auctions for B2B (Business to Business) e-commerce logistics with transaction costs. Sun et al. (2019) focus on intermodal transport service procurement problem in the context of the "Belt and Road Initiative", where a shipper contains a bundle of requests in different lanes (origin–destination pairs) and each carrier may cover either one or multiple lanes. The results indicate that the auctioneer should decrease transaction costs, increase the numbers of shippers/carriers, control the types of shipper demand, and induce true biding prices of bidders.

2.3. Summary

Table 1 provides a summary of the reviewed papers. We also added our previous work (Zhang et al., 2020, 2022a), which studied routing optimization in inland waterways and intermodal transport but without considering collaborative planning or eco-label requirements of shippers. All papers are divided by their research domains, i.e., FTL road transport, LTL road transport, Road Freight Transport (RFT) without specifying FTL/LTL, Maritime Freight Transport (MFT), Inter Terminal Transport (ITT), Inland Waterway Transport (IWT), and Intermodal Freight Transport (IFT). The collaboration approaches (CA) are divided by the categories proposed by Gansterer and Hartl (2018), i.e., Centralized Planning (CP), Non-auction-based Decentralized Planning (DP), Auction-based Decentralized Planning (ADP). The table furthermore reports if papers consider features such as transshipments (T), fixed timetables (FT), overlapping transport networks (OTN), or sustainability preferences (S).

As shown in Table 1, there are many studies on collaborative vehicle routing in unimodal road freight transportation (including RFT, LTL and FTL). However, there are significant differences between unimodal and intermodal settings. For example, in many studies on road freight transport, the carrier has only one type of vehicles (homogeneous fleet). In intermodal transport, the carrier

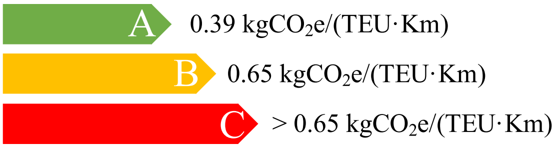


Fig. 2. Eco-labeling scheme.

potentially owns vehicles of multiple modes and different characteristics. In particular, vehicles can be very large, which has various implications such as that the emissions of barges and trains are highly influenced by their actual load. Furthermore, the requests in intermodal transport can be segmented and transported by multiple vehicles, while requests in the road mode usually just comprise one vehicle. When a request is segmented, it will be transferred between vehicles at transshipment terminals. Therefore, synchronization at transshipment terminals needs to be considered in intermodal transport. Furthermore, intermodal carriers often have specific terminals and operating areas where trains and ships typically follow fixed timetables and predefined routes, which is hardly the case in traditional road freight transportation.

The research in RFT/LTL/FTL, MFT, and ITT only considers one transport mode, either trucks or ships. Some research has been done in IFT, however, the carriers in these papers are hardly modeled realistically. For instance, the carriers assumed by Puettmann and Stadtler (2010) and Li et al. (2017) can control different transport networks whereas in reality a transport network may be occupied by multiple carriers. When considering carriers that serve the same or at least overlapping parts of a transport network, horizontal collaboration approaches become relevant (Cleophas et al., 2019). Moreover, most papers ignore the individual sustainability preferences of carriers or shippers. Some papers regard reducing emissions as an objective from the perspective of carriers (Özener, 2014; Liotta et al., 2014; Zhang et al., 2022a). However, they do not study how carriers take shippers' sustainability preferences into account and Zhang et al. (2022a) do not even consider collaborative planning.

3. Problem description

We consider a problem in which multiple intermodal transport carriers are willing to achieve increased sustainability through collaboration. Eco-labels are used to evaluate the relative environmental impact of transporting a shipper's order from its origin to its destination. We measure this impact by subsuming relevant greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4) or nitrous oxide (N_2O), resulting from transportation under the term 'emissions' and evaluate their impact on global warming relative to CO_2, the most important greenhouse gas (United States Environmental Protection Agency, 2022). With this, we use the single measure CO_2e to state the amount of CO_2-equivalents resulting from transportation, and use those emissions (kgCO_2e) per container and per kilometer (km) as a sustainability measure and refer to it as emission rate (kgCO_2e/(TEU km)). Thereby, we assume that each container corresponds to one twenty-foot equivalent unit (TEU) of 13 tons. The eco-labeling scheme is derived from a large-scale simulation study in Europe's intermodal rail/road network (Heinold and Meisel, 2018) and consists of three classes A, B, and C with emission rate limits as shown in Fig. 2.

Fig. 3 shows a conceptional sketch of the considered problem. In this figure, there are two requests in the request pool and three carriers. Each carrier needs to solve an Intermodal Transport Planning Problem with Sustainability Preferences (ITPP-SP) to match its offered services with the placed requests. In these services, combinations of modes and routes can be used to serve requests while distinct combinations result in distinct emissions. If the carrier cannot match the services with the preferred eco-label of request r, r will be shared with other carriers. In this case, the Collaborative Planning Problem in Intermodal Transport with Sustainability Preferences needs to be solved to find a suitable carrier.

The notations used for modeling the ITPP-SP are provided in Table 2. Each carrier $c \in C$ owns a set of heterogeneous vehicles K^c of capacity u_k and speed v_k, and receives a set of requests R^c with preferred eco-labels from shippers. The pickup and delivery terminals of request $r \in R^c$ are designated by $p(r)$ and $d(r)$. Request $r \in R^c$ must be picked up in time window $[a_{p(r)}, b_{p(r)}]$ and needs to be delivered in time window $[a_{d(r)}, b_{d(r)}]$, but the delivery time can exceed $b_{d(r)}$ with a delay penalty. Further, we use el_r (A, B, or C) to express the *eco-label* of request r, where emission rates per eco-label level el_r can be found in Fig. 2.

The transport network of a carrier $c \in C$ is defined as a directed graph $G = (N^c, A^c)$. $N^c = P^c \cup D^c \cup O^c \cup T^c$ represents the set of all vertices, where P^c, D^c, O^c, and T^c are pickup terminals, delivery terminals, depots of vehicles, and transshipment terminals, respectively. $A^c \subseteq (i,j)|i,j \in N^c, i \neq j$ represents the set of arcs. The transport networks of different carriers may overlap with each other. The nonnegative travel time τ_{ij}^k equals distance between i and j divided by speed of vehicle k. Note that distances are different for different modes because they use different infrastructure between i and j. A vehicle k is allowed to wait at terminal i and a request r is allowed to be stored temporarily at terminal i.

To provide more sustainable transport and better services, carriers collaborate by exchanging requests, i.e., horizontal collaboration. Carriers only share requests when they cannot match requirements by themselves because they want to satisfy shippers and gain additional profits. The shared requests can be served by any other carrier as long as the required eco-label is respected.

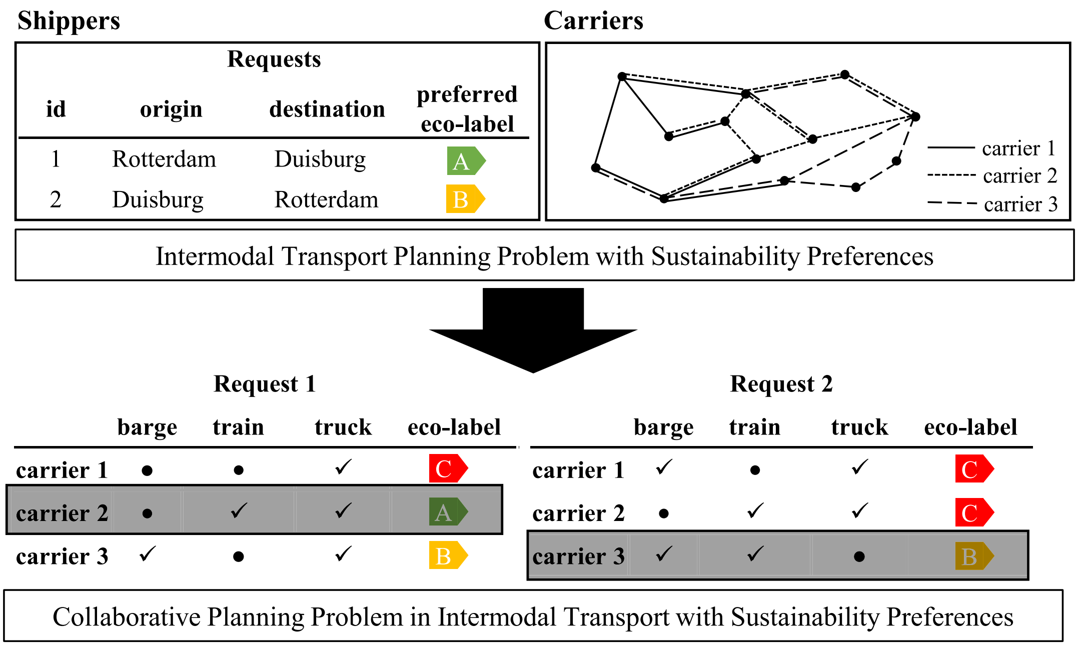


Fig. 3. Conceptional sketch of the considered problem.

4. Modeling and solution approach

This section presents the modeling and heuristic algorithm to solve the ITPP-SP together with a framework for the collaborative planning approach. Firstly, we introduce how emissions are calculated and how to handle vague sustainability preferences by fuzzy logic theory in Section 4.1. Then, the mathematical model for the ITPP-SP of an individual carrier is presented in Section 4.2 and an ALNS heuristic is illustrated in Section 4.3. Finally, the collaborative planning framework is described in Section 4.4.

4.1. Emissions calculation and vague preferences

To analyze whether or not a request is shipped in accordance to its eco-label we have to measure the emissions that are emitted while shipping the request from its origin to destination. For this, two kind of transport-related emissions need to be considered for a request r: first, emissions from the vehicles that are transporting requests on the arcs (e_r^{arcs}), and, second, emissions from transshipment operations at the nodes that are required in an intermodal transport setting (e_r^{nodes}).

Regarding emissions from the vehicles, several emission estimation models have been proposed in the literature. We refer to Demir et al. (2011) and Heinold (2020) for studies comparing models for trucks and trains, respectively. Generally, the models differ in the level of detail of the required input data, with microscopic models requiring granular data inputs (e.g., speed profiles) and macroscopic models requiring only a few rough data inputs (e.g., average speed). For our purpose, we use a macroscopic methodology proposed by the EcoTransIT World Initiative (2020), the so-called ETW model. The model provides calculation procedures for all of our considered transport modes: trucks, trains, and barges. The model is further in accordance with the European norm EN 16258 (European Committee for Standardization, 2012) on the calculation of freight transport related greenhouse gas emissions. Generally, the ETW method uses empirically-based functions that take the vehicle's load q_{ij}^k (in TEU) and traveled distance d_{ij}^k (in km) between terminals i and j as the main input to estimate emissions. Thereby, various sources are used to come up with realistic functions like the average annual energy consumption of rail freight transport companies or surveys among transport companies. With this, the model considers emissions from the driving of vehicles as well as from the idling of vehicles (e.g., Rahman et al., 2013). In our problem, we consider emissions that relate to a regular 40-ton truck (Euro VI norm), a typical diesel train with "sgis" cars, and a standard European barge. We refer to EcoTransIT World Initiative (2020) for details on the model's methodology and data of the parameters that are used for these vehicle types. Further emission estimation model parameters are set as follows: the empty trip factor is set to 0.2, the slope profile is set to 1, and the well-to-wheel emission factor is set to 3.90 ($kgCO_2e/kg$) for regular diesel and to 3.92 ($kgCO_2e/kg$) for marine diesel (see European Committee for Standardization (2012)). With this, the condensed formulas to calculate emissions e_w^{kij} (in $kgCO_2e$) of vehicle k traveling between terminals i and j in one of the three modes $w \in \{\text{truck, train, barge}\}$ are shown in Eqs. (1) to (3), respectively.

$$e_{truck}^{kij} = 0.7233 \cdot d_{ij}^k + 0.1872 \cdot d_{ij}^k \cdot q_{ij}^k \tag{1}$$

$$e_{train}^{kij} = 22.6278 \cdot d_{ij}^k \cdot q_{ij}^k \cdot (123 + 13 \cdot q_{ij}^k + 23 \cdot \lceil q_{ij}^k \cdot 13/40 \rceil)^{-0.62} \tag{2}$$

Table 2
Notations used in the paper.

Sets and indices:	
C	Set of carriers indexed by c.
W^c	Set of modes owned by carrier c indexed by w.
R^c	Set of requests of carrier c indexed by r.
N^c	Set of terminals in carrier c's transport network indexed by i and j. $P^c/D^c/T^c \subseteq N^c$, set of pickup/delivery/transshipment terminals. $O^c/\overline{O^c} \subseteq N^c$, set of depots/virtual depots.
A^c	Set of arcs in carrier c's transport network. For $i, j \in N^c$, the arc from i to j is denoted by $(i,j) \in A^c$. $A^c_p/A^c_d \subseteq A^c$ represents the set of pickup/delivery arcs. For $(i,j) \in A^c_p$, $i \in P^c$. For $(i,j) \in A^c_d$, $j \in D^c$. $A^c_w \subseteq A^c$ represents the set of arcs belonging to a specific mode w. $A^k_{\text{fix}} \subseteq A^c$ represents the set of arcs for a fixed-route vehicle $k \in K^c_{\text{fix}}$.
K^c	Set of vehicles owned by carrier c indexed by k and l. $K^c_{\text{b\&t}} \subseteq K^c$, set of barges and trains. $K^c_{\text{truck}} \subseteq K^c$, set of trucks. $K^c_w \subseteq K^c$, set of vehicles belonging to a specific mode w. $K^c_{\text{fix}} \subseteq K^c$, set of fixed-route vehicles. $K^c_r \subseteq K^c$, set of vehicles that can serve request r.
Parameters:	
u_k	Capacity (TEU) of vehicle k.
q_r	Payload quantity (TEU) of request r.
τ^k_{ij}	The travel time (in hours) on arc (i,j) for vehicle k.
$[a_{p(r)}, b_{p(r)}]$	The pickup time window for request r.
$[a_{d(r)}, b_{d(r)}]$	The delivery time window for request r.
el_r	The requested *eco-label* of request r.
$[a^k_i, b^k_i]$	The opening time window for fixed vehicle k at terminal i.
t''^k_i	The loading/unloading time (in hours) for vehicle k at terminal i.
v_k	Speed (km/h) of vehicle k.
d^k_{ij}	Distance (km) between terminals i and j by vehicle k.
e^{kl}	The CO_2e emissions (kg/TEU) of vehicle k during the transshipment between vehicles k and l.
c^n_k	$c^1_k/c^{1'}_k$ is unit cost (euro per TEU) of transportation per hour/km using vehicle $k \in K^c$. c^2_k is the loading/unloading cost per container. c^3_k is the storage cost per container per hour. c^4_k is the carbon tax coefficient per ton. c^5_k is the cost per hour of waiting time.
c^{delay}_r	The delay penalty per container per hour of request r.
$\overline{S}$	Satisfaction benchmark.
M	A large enough positive number.
Variables:	
x^k_{ij}	Binary variable; 1 if vehicle k uses arc (i,j), 0 otherwise.
y^{kr}_{ij}	Binary variable; 1 if request r transported by vehicle k uses arc (i,j), 0 otherwise.
z^k_{ij}	Binary variable; 1 if terminal i precedes (not necessarily immediately) terminal j in the route of vehicle k, 0 otherwise.
s^{kl}_{ir}	Binary variable; 1 if request r is transferred from vehicle k to vehicle $l \neq k$ at terminal i, 0 otherwise.
$t^{kr}_i/t'^{kr}_i/\bar{t}^{kr}_i$	The arrival time/service start time/service finish time of request r served by vehicle k at terminal i.
$t^k_i/t'^k_i/\bar{t}^k_i$	The arrival time/last service start time/departure time of vehicle k at terminal i.
t^{wait}_{ki}	The waiting time of vehicle k at terminal i.
t^{delay}_r	The delay time of request r at delivery terminal.
q^k_{ij}	The load of vehicle k between terminals i and j.
e^{kij}_r	The CO_2e emissions (kg) of request r transported by vehicle k between terminals i and j.
e^k_r	The CO_2e emissions (kg) of request r transported by vehicle k.
e^{kl}_r	The CO_2e emissions (kg) of request r during the transshipment between vehicles k and l.
e'_r	The unit CO_2e emissions (kg) of request r per TEU per km.
S_r	Satisfaction value of request r.

$$e^{kij}_{barge} = 35.9525 \cdot d^k_{ij} + 0.0819 \cdot d^k_{ij} \cdot q^k_{ij} \tag{3}$$

These emissions are then allocated among the requests based on each request's contribution to a service's overall load between terminals i and j:

$$e^{kij}_r = e^{kij}_w \cdot q_r / q^k_{ij} \tag{4}$$

The emissions of request r using vehicle k is the sum of emissions of all trips served by k:

$$e^k_r = \sum_{(i,j)\in A^c} y^{kr}_{ij} e^{kij}_r \tag{5}$$

The total emissions on arcs of request r is:

$$e^{\text{arcs}}_r = \sum_{k\in K^c_r} e^k_r \tag{6}$$

Regarding emissions from transshipment processes at ports (i.e., transshipments involving barge l), the values of e^{kl} are 6.3, 19.6, and 11.2 $kgCO_2e$/TEU when vehicle k is a truck, a train, and a barge, respectively, as reported in an analysis of two container terminals in the Port of Rotterdam (Geerlings and van Duin, 2011). For all other transshipment operations (e.g., from truck to train and vice versa), we assume the value of e^{kl} is 2.6 $kgCO_2e$/TEU. This value is based on the energy consumption of such processes as reported for the European intermodal rail/road network by Kim and van Wee (2009). The emissions of request r during transshipment between vehicles k and l can be obtained by the following equation:

$$e_r^{kl} = q_r(e^{kl} + e^{lk}) \tag{7}$$

The total emissions at nodes of request r are:

$$e_r^{\text{nodes}} = \sum_{k,l \in K^c, k \neq l} \sum_{i \in T^c} s_{ir}^{kl} e_r^{kl} \tag{8}$$

The total emissions of request r are:

$$e_r = e_r^{\text{arcs}} + e_r^{\text{nodes}} \tag{9}$$

The unit emissions of request r are:

$$e'_r = e_r / (q_r \sum_{k \in K} \sum_{(i,j) \in A} d_{ij}^k y_{ij}^{kr}) \tag{10}$$

Shippers' sustainability preferences are usually vague, such as "around eco-label B is fine" or "eco-label C is enough", i.e., a shipper's satisfaction is still relatively high when the emission value does not perfectly match the required eco-label but is very close to it. Therefore, simple rules like only accepting services with lower emissions than the eco-label are not necessarily appropriate for the evaluation of shippers' satisfaction. Instead, we use the fuzzy set theory to capture such vague preferences. Fuzzy set theory is a methodology that does not express the "truthiness" in a discrete manner as either true or false but instead also allows for partially true or partially false. Accordingly, whether an emission value belongs to a particular eco-label or not is also expressed as (partially) true or false in our study. For this, emissions can be represented by a fuzzy variable, which has a predefined value range and eco-labels are used to describe it. The value in the value range is called crisp value, which is how we think of the variable using normal mathematics, e.g., 0.4 $kgCO_2e$/(TEU km). Each eco-label has a membership function that defines the degree of truth of a crisp value that belongs to the eco-label on a scale of 0 to 1. For example, 0.4 $kgCO_2e$/(TEU km)'s membership to eco-label A and eco-label B could be 0.8 and 0.2, respectively.

Based on request r's actually caused unit emissions e'_r and the emission boundary el_r of the requested eco-label, the satisfaction value S_r will be obtained by fuzzy set theory:

$$S_r = Fuzzy(e'_r, el_r) \tag{11}$$

where $Fuzzy()$ represents the fuzzy set theory approach used in this study as is described next.

The membership function of emissions e'_r and satisfaction S_r are shown in Fig. 4. The trapezoidal and triangle fuzzy numbers are used in the membership function, where the triangular membership function is a special trapezoidal membership function. The trapezoidal membership function is given in Eq. (12) for the trapezoidal fuzzy number of e'_r involving scalar parameters a, b, c, d, whereby $a \leq b \leq c \leq d$ and $b = c$ for the triangular membership function. For the fuzzy number of S_r, we use the same type of function.

$$\mu(e'_r) = \begin{cases} 0, & e'_r < a \\ \dfrac{(e'_r - a)}{(b - a)}, & a \leq e'_r \leq b \\ 1, & b \leq e'_r \leq c \\ \dfrac{(d - e'_r)}{(d - c)}, & c \leq e'_r \leq d \\ 0, & e'_r > d \end{cases} \tag{12}$$

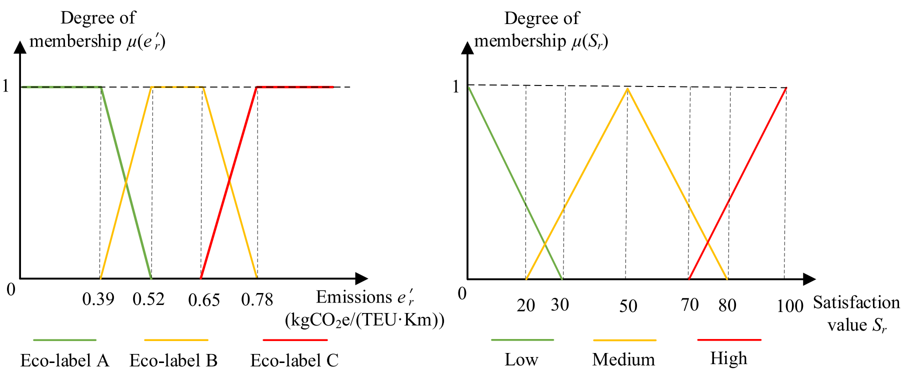
Fuzzy variables for the emissions and satisfaction can be linked using a set of rules, which are IF-THEN statements that describe how one variable relates to another. The used fuzzy rules are as follows:

1. When the shipper prefers eco-label A, IF the obtained eco-label *equals/is worse than* A, THEN the satisfaction will be *high/low*.

2. When the shipper prefers eco-label B, IF the obtained eco-label *is better than/equals/is worse than* B, THEN the satisfaction will be *high/medium/low*.

3. When the shipper prefers eco-label C, IF the obtained eco-label *is better than/equals* C, THEN the satisfaction will be *high/medium*.

After defining fuzzy variables and fuzzy rules, the satisfaction value S_r can be obtained using a defuzzification method, such as Center of Gravity used in van Leekwijck and Kerre (1999). The same emissions may lead to different satisfaction because preferred eco-labels are different for different shippers. For example, if shipper 1 prefers eco-label B and shipper 2 prefers eco-label C, shipper 2 will be more satisfied than shipper 1 when the actual eco-label is B.



(a) The membership function for emissions e'_r (b) The membership function for satisfaction S_r

Fig. 4. Membership functions for emissions and satisfaction.

4.2. Mathematical model for ITPP-SP

This section presents the mathematical model for one carrier c. In this model, we try to ensure shippers' satisfaction while minimizing the carrier's costs. There are two levels of objectives. The upper-level objective (F_1) is to maximize the number of served requests of the considered carrier c. The lower-level objective (F_2) is minimizing the carrier's cost, which consists of transport cost, transfer cost, storage cost, carbon tax, waiting cost, and delay penalty. For the lower-level objective (F_2), we refer to Guo et al. (2020). In practice, it is important to serve as many requests as possible for long-term trust. Shippers will not opt for a less costly service when it is not reliable. Therefore, the model will choose the solution with the highest objective value of F_1. If several solutions have the same optimal value for F_1, the solution with a lower objective value of F_2 among these is selected. There are also other ways to model the objective function, e.g., the objective (13) can be weighted by a penalty and added to objective function (14). The results of this alternative approach are compared in Section 5.3.

The binary variables x_{ij}^k and y_{ij}^{kr} decide whether vehicle k uses arc (i,j) or not and whether vehicle k carries request r on arc (i,j) or not, respectively. The binary variable z_{ij}^k is used for subtour elimination. We also have the binary variable s_{ir}^{kl}, which decides whether request r is transferred from vehicle k to vehicle l at terminal i or not. Other variables related to time, emissions, load, and satisfaction are shown in Table 2. For barge and train services, constraints for both vehicle flow (constraints related to variables x_{ij}^k) and request flow (constraints related to variables y_{ij}^{kr}) are considered. Some constraints for vehicle flows do not apply to truck services, because truck services in this study are truck fleets and trucks in a truck fleet may serve different requests with different schedules.

Objective:

$$\max \ F_1 = \sum_{r\in R^c}\sum_{k\in K^c}\sum_{j\in N^c} y_{p(r)j}^{kr} \tag{13}$$

$$\begin{aligned}
\min \ F_2 = & \sum_{k\in K^c}\sum_{(i,j)\in A^c}\sum_{r\in R^c}\left(c_k^1\tau_{ij}^k + c_k^{1'} d_{ij}^k\right)q_r y_{ij}^{kr} + \sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c}\left(c_k^2+c_l^2\right)q_r s_{ir}^{kl} \\
& + \sum_{k\in K^c}\sum_{(i,j)\in A_p^c}\sum_{r\in R^c} c_k^2 q_r y_{ij}^{kr} + \sum_{k\in K^c}\sum_{(i,j)\in A_d^c}\sum_{r\in R^c} c_k^2 q_r y_{ij}^{kr} + \sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c} c_k^3 q_r s_{ir}^{kl}\left(t_i^{\prime lr} - \bar{t}_i^{kr}\right) \\
& + \sum_{k\in K^c}\sum_{(i,j)\in A_p^c}\sum_{r\in R^c} c_k^3 q_r y_{ij}^{kr}\left(t_i^{\prime kr} - a_{p(r)}\right) + \sum_{k\in K^c}\sum_{r\in R^c} c_k^4 e_r^k \\
& + \sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c} q_r s_{ir}^{kl}\left(c_k^4 e^{kl} + c_l^4 e^{lk}\right) + \sum_{k\in K_{\text{b\&t}}^c}\sum_{i\in N^c} c_k^5 t_{ki}^{\text{wait}} + \sum_{r\in R^c} c_r^{\text{delay}} q_r t_r^{\text{delay}}
\end{aligned} \tag{14}$$

Constraints (15)–(33) are the routing constraints. Constraints (15) and (16) ensure that a vehicle begins and ends at its starting/ending depot, respectively. Some depots may be the same terminals as pickup/delivery terminals, which makes some constraints of pickup/delivery terminals, such as time window constraints, also work on these depots when the related vehicle does not serve the request. For this purpose, virtual depots $\overline{o}(k)/\overline{o'}(k) \in \overline{O^c}$ are introduced as additional nodes that have the same location of starting/ending depot $o(k)/o'(k) \in O^c$ but a distinct naming. Constraints (17) and (18) ensure that each request must be picked and delivered at its pickup and delivery terminal, respectively.

$$\sum_{j\in N^c} x_{\overline{o}(k)j}^k \leqslant 1 \quad \forall k \in K_{\text{b\&t}}^c \tag{15}$$

$$\sum_{j\in N^c} x_{\overline{o}(k)j}^k = \sum_{j\in N^c} x_{j\overline{o'}(k)}^k \quad \forall k \in K_{\text{b\&t}}^c \tag{16}$$

$$\sum_{k\in K^c}\sum_{j\in N^c} y_{p(r)j}^{kr} \leqslant 1 \quad \forall r \in R^c \tag{17}$$

$$\sum_{k\in K^c}\sum_{j\in N^c} y^{kr}_{jd(r)} \leqslant 1 \quad \forall r \in R^c \tag{18}$$

Constraints (19) represent flow conservation for vehicle flow and (20)–(23) represent flow conservation for request flow. Constraints (20) are for regular terminals and Constraints (21) are for transshipment terminals. Constraints (22) and (23) ensure the flow conservation of requests when request r is not transferred at terminal $i \in T^c$ but vehicle k passes terminal i due to operations for other requests. Constraints (24) link y^{kr}_{ij} and x^k_{ij} variables in order to guarantee that for a request to be transported by a vehicle, that vehicle needs to traverse the associated arc.

$$\sum_{j\in N^c} x^k_{ij} - \sum_{j\in N^c} x^k_{ji} = 0 \quad \forall k \in K^c_{\text{b\&t}},\ \forall i \in N^c \setminus \overline{o}(k), \overline{o'}(k) \tag{19}$$

$$\sum_{j\in N^c} y^{kr}_{ij} - \sum_{j\in N^c} y^{kr}_{ji} = 0 \quad \forall k \in K^c,\ \forall r \in R^c,\ \forall i \in N^c \setminus T^c, p(r), d(r) \tag{20}$$

$$\sum_{k\in K^c}\sum_{j\in N^c} y^{kr}_{ij} - \sum_{k\in K^c}\sum_{j\in N^c} y^{kr}_{ji} = 0 \quad \forall r \in R^c,\ \forall i \in T^c \setminus p(r), d(r) \tag{21}$$

$$\sum_{j\in N^c} y^{kr}_{ij} - \sum_{j\in N^c} y^{kr}_{ji} \leqslant \sum_{l\in K^c} s^{lk}_{ir} \quad \forall k \in K^c,\ \forall r \in R^c,\ \forall i \in T^c \setminus p(r), d(r) \tag{22}$$

$$\sum_{j\in N^c} y^{kr}_{ji} - \sum_{j\in N^c} y^{kr}_{ij} \leqslant \sum_{l\in K^c} s^{kl}_{ir} \quad \forall k \in K^c,\ \forall r \in R^c,\ \forall i \in T^c \setminus p(r), d(r) \tag{23}$$

$$y^{kr}_{ij} \leqslant x^k_{ij} \quad \forall (i,j) \in A^c,\ \forall k \in K^c,\ \forall r \in R^c \tag{24}$$

Constraints (25) and (26) facilitate transshipment. Constraints (25) ensure that the transshipment occurs only once per transshipment terminal. Constraints (26) forbid transshipment between the same vehicle k.

$$\sum_{j\in N^c} y^{kr}_{ji} + \sum_{j\in N^c} y^{lr}_{ij} \leqslant s^{kl}_{ir} + 1 \quad \forall r \in R^c,\ \forall i \in T^c,\ \forall k, l \in K^c \tag{25}$$

$$s^{kk}_{ir} = 0 \quad \forall r \in R^c,\ \forall i \in T^c,\ \forall k \in K^c \tag{26}$$

Constraints (27)–(29) are the subtour elimination constraints (Öncan et al., 2009). Constraints (30) are the capacity constraints.

$$x^k_{ij} \leqslant z^k_{ij} \quad \forall i, j \in N^c,\ \forall k \in K^c_{\text{b\&t}} \tag{27}$$

$$z^k_{ij} + z^k_{ji} = 1 \quad \forall i, j \in N^c,\ \forall k \in K^c_{\text{b\&t}} \tag{28}$$

$$z^k_{ij} + z^k_{jp} + z^k_{pi} \leqslant 2 \quad \forall i, j, p \in N^c,\ \forall k \in K^c_{\text{b\&t}} \tag{29}$$

$$\sum_{r\in R^c} q_r y^{kr}_{ij} \leqslant u_k x^k_{ij} \quad \forall (i,j) \in A^c,\ \forall k \in K^c \tag{30}$$

The characteristics of intermodal transport are considered in (31)–(33). Constraints (31) avoid vehicles running on unsuitable routes, for example, trucks cannot run on inland waterways. Constraints (32) take care of predefined routes for certain vehicles, for example, trains have fixed routes and terminals. Constraints (33) ensure the transshipment occurs in the right terminal because some transshipment terminals ($T^{w_2}_{w_1}$) only allow the transshipment between two specific modes (w_1 and w_2).

$$x^k_{ij} = 0 \quad \forall k \in K^c_w,\ \forall (i,j) \in A^c \setminus A^c_w,\ \forall w \in W^c \tag{31}$$

$$x^k_{ij} = 0 \quad \forall k \in K^c_{\text{fix}},\ \forall (i,j) \in A^c \setminus A^k_{\text{fix}} \tag{32}$$

$$s^{kl}_{ir} = 0 \quad \forall k \in K_{w_1},\ \forall l \in K_{w_2},\ \forall i \in T^c \setminus T^{w_2}_{w_1},\ \forall r \in R^c,\ \forall w_1, w_2 \in W^c \tag{33}$$

Constraints (34)–(47) are temporal constraints. Constraints (34)–(38) are time constraints on services. Constraints (34) guarantee that the service starts after the arrival of a request. Constraints (35) ensure that the service finishes after the service start time plus the service time. Constraints (36) maintain that the departures of barges and trains happen only after all services are completed. Constraints (37) ensure that the request's arrival time cannot be earlier than the vehicle's arrival time. Constraints (38) define the vehicle's last service start time.

$$t^{kr}_i \leqslant t'^{kr}_i \quad \forall i \in N^c,\ \forall k \in K^c,\ \forall r \in R^c \tag{34}$$

$$t'^{kr}_i + t''^{kr}_i \sum_{j\in N^c} y^{kr}_{ij} \leqslant \bar{t}^{kr}_i \quad \forall i \in N^c,\ \forall k \in K^c_{\text{b\&t}},\ \forall r \in R^c \tag{35}$$

$$\bar{t}^{k}_i \geqslant \bar{t}^{kr}_i \quad \forall i \in N^c,\ \forall k \in K^c_{\text{b\&t}},\ \forall r \in R^c \tag{36}$$

$$t^{k}_i \leqslant t^{kr}_i \quad \forall i \in N^c,\ \forall k \in K^c_{\text{b\&t}},\ \forall r \in R^c \tag{37}$$

$$t'^{k}_i \geqslant t'^{kr}_i \quad \forall i \in N^c,\ \forall k \in K^c_{\text{b\&t}},\ \forall r \in R^c \tag{38}$$

Constraints (39) and (40) ensure that the time on route of barges and trains is consistent with the distance traveled and speed, and Constraints (41) and (42) ensure the time on route of trucks. Constraints (43) and (44) take care of the time windows for pickup terminals and fixed terminals, respectively.

$$\bar{t}^{k}_i + \tau^k_{ij} - t^k_j \leqslant M(1 - x^k_{ij}) \quad \forall (i,j) \in A^c,\ \forall k \in K^c_{\text{b\&t}} \tag{39}$$

$$\bar{t}_i^k + \tau_{ij}^k - t_j^k \geqslant -M(1 - x_{ij}^k) \quad \forall (i,j) \in A^c, \ \forall k \in K_{\text{b\&t}}^c \tag{40}$$

$$\bar{t}_i^{kr} + \tau_{ij}^k - t_j^{kr} \leqslant M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A^c, \ \forall k \in K_{\text{truck}}^c \tag{41}$$

$$\bar{t}_i^{kr} + \tau_{ij}^k - t_j^{kr} \geqslant -M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A^c, \ \forall k \in K_{\text{truck}}^c \tag{42}$$

$$t'^{kr}_{p(r)} \geqslant a_{p(r)} y_{ij}^{kr}, \ \bar{t}_{p(r)}^{kr} \leqslant b_{p(r)} + M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A^c, \forall r \in R^c, \ \forall k \in K^c \tag{43}$$

$$t_i^{kr} \geqslant a_i^k y_{ij}^{kr}, \ \bar{t}_i^{kr} \leqslant b_i^k + M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A^c, \ \forall r \in R^c, \ \forall k \in K_{\text{fix}}^c \tag{44}$$

Constraints (45) are time constraints for transshipment. If there is a transshipment from vehicle k to vehicle l, but vehicle l arrives before vehicle k departs, vehicle l can wait until vehicle k completes its unloading. Constraints (46) and (47) calculate waiting time and delay time, respectively.

$$\bar{t}_i^{kr} - t'^{lr}_i \leqslant M(1 - s_{ir}^{kl}) \quad \forall r \in R^c, \ \forall i \in T^c, \ \forall k,l \in K^c, \ k \neq l \tag{45}$$

$$t_{ki}^{\text{wait}} \geqslant t'^k_i - t_i^k \quad \forall i \in N^c, \ \forall k \in K_{\text{b\&t}}^c \tag{46}$$

$$t_r^{\text{delay}} \geqslant (\bar{t}_{d(r)}^{kr} - b_{d(r)}) \sum_{i \in N^c} y_{id(r)}^{kr} \quad \forall r \in R^c, \ \forall k \in K^c \tag{47}$$

Constraints (48) and (49) define the binary variables.

$$x_{ij}^k \in \{0,1\} \quad \forall (i,j) \in A^c, \ \forall k \in K^c \tag{48}$$

$$y_{ij}^{kr} \in \{0,1\} \quad \forall (i,j) \in A^c, \ \forall k \in K^c, \ \forall r \in R^c \tag{49}$$

Constraints (50) ensure that preferences are respected. $\overline{S}$ is a preset satisfaction benchmark. It is set as 50 in our experiments, which means "medium satisfaction". Only when the satisfaction value S_r reaches satisfaction benchmark $\overline{S}$, the solution for request r is considered acceptable.

$$S_r \geqslant \overline{S} \quad \forall r \in R^c \tag{50}$$

4.3. ALNS for ITPP-SP

ALNS is a powerful and well-suited algorithm for Vehicle Routing Problems and has been further developed since its introduction by Ropke and Pisinger (2006). Using the insertion and removal operators iteratively, ALNS achieves the exploration and exploitation in the search space and finds (near) optimal solutions. Different types of ALNS operators, such as greedy, random, and regret operators, can be customized according to the characteristics of the problem. ALNS adapts to different problem instances because it selects operators according to their historical performance during the search. ALNS has been applied to similar problems successfully, such as the pickup and delivery problem with transshipment (Qu and Bard, 2012; Masson et al., 2013) and synchromodal transport planning problems (Zhang et al., 2022b,c). As verified in Zhang et al. (2022c), solving a similar problem to optimality using an exact approach (Gurobi) is more computationally expensive than ALNS and the exact approach is unable to provide the optimal solution for large instances due to the complexity. Zhang et al. (2022b) verify that ALNS produces high-quality solutions with low computation time and performs well on large-scale instances in intermodal transport. Therefore, we use ALNS to solve the ITPP-SP in this study. The pseudocode of the developed ALNS is shown in Appendix A. The operators and adaptive mechanism of ALNS are illustrated in detail in the literature (Ropke and Pisinger, 2006) and our previous papers (Zhang et al., 2022a,b). As these papers did not involve eco-labels, we briefly sketch here how this feature is incorporated into the ALNS.

The emissions in this study are load-dependent, which means the load of barges/trains will influence the emissions allocated to a transported request. Therefore, it is difficult for ALNS to "predict" which vehicle is more suitable to reduce the emissions because the final load of the vehicle is not yet known while constructing a solution. For example, when ALNS inserts a new request to a route of an empty barge, it will obtain a very high emission. But later in the solution process, this barge may serve many requests with a high load factor, and the emissions allocated to a single request are then much lower. To alleviate the impact of the load-dependent emissions, we expect large capacity vehicles will be utilized at the end and set the load factors of trains and barges as 60% during each iteration of ALNS when computing emissions. By doing so, requests may be added to these large-capacity vehicles already when these vehicles are quite empty. After each iteration, the preference Constraints (50) are then rechecked using the actual load, and requests will be removed when Constraints (50) cannot be satisfied due to a too low load factor.

4.4. Collaborative planning approach

In the following, we consider three approaches of a (non-)collaboration of the carriers in set C, namely: (a) a centralized approach, (b) an auction-based collaborative approach, and (c) a non-collaborative approach. Since carriers do not want to reveal private information (such as costs) to their competitors, we assume there is a neutral coordinator in approaches (a) and (b). In reality, the coordinator could be a collaborative planning platform in intermodal transport. In approach (a), the coordinator conducts the routing and scheduling for carriers. In approach (b), carriers make decisions by themselves and the coordinator only plays a role in connecting carriers and providing request and bid pools.

More precisely, in the approach (a), shippers send requests, including lanes (origin–destination pairs), time windows, amounts of containers, and requested eco-labels, to carriers which then forward this information to the coordinator. Furthermore, carriers send

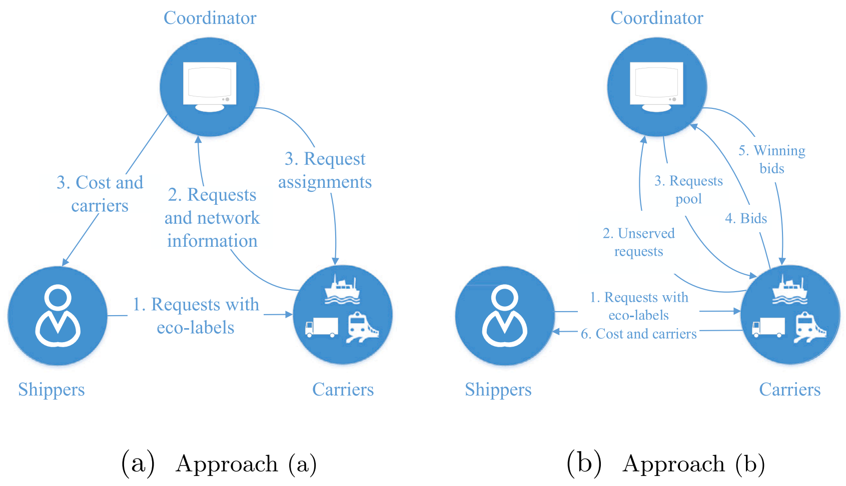


Fig. 5. Collaboration approaches (a) and (b), which are centralized approach and auction-based collaborative approach, respectively.

their transport network information including terminals, vehicle fleets, and associated parameters to the coordinator, as shown in Fig. 5(a). The coordinator solves a single holistic ITPP-SP and optimizes the overall intermodal network based on this information, then assigns requests to carriers and reports costs to shippers either directly or via the carriers.

In approach (b), when a carrier has unserved requests, they will be exchanged with others via the coordinator as shown in Fig. 5(b). This is done through an auction as is explained later in this section. In approach (c), carriers receive requests from shippers and do not share them with others. Each carrier solves an ITPP-SP and optimizes schedules only using their own services, and some requests might be rejected when their requirements cannot be met by the carrier who received these requests.

In approaches (a) and (c), solutions are obtained by the ALNS directly where approach (a) optimizes schedules based on requests and resources of all carriers C, i.e., $X^C_{\text{best}}, R^C_{\text{pool}} = ALNS(K^C, R^C, N^C, A^C, X^C_{\text{best}})$ and approach (c) optimizes the operations individually for each carrier $c \in C$. For approach (b), a request exchanging mechanism is needed and an auction-based approach is adopted in this study because auctions can respect the preferences of participants by bidding (Li et al., 2015b; Gansterer and Hartl, 2018). For example, consider two carriers A and B that bid for requests in an auction pool. The bidding of carrier A is based on costs and the bidding of carrier B is based on both costs and emissions. The auction will then reveal the carriers' preferences as they only place a bid if it is reasonable to add a request to the current routing with respect to their individual criteria. Specifically, we use a sealed-bid first-price iterative auction, where bidders submit sealed bids and the bidder submitting the lowest cost wins the request and charges this cost to the shipper. In an iterative auction, there are multiple rounds until a stopping criterion is reached and bidders can adapt their bids during the iterative process. The flowchart of the iterative auction procedure in collaborative planning is shown in Fig. 6.

In an auction round, there are three steps for each carrier c:

1. Obtain an initial solution: Based on the K^c, N^c, A^c, and the carrier's own requests R^c, each carrier solves an ITPP-SP and the routes are optimized by the ALNS. Then, the carrier sends unserved requests R^c_{pool} to the coordinator.

2. Try and bid: The carrier obtains requests $CPR^{C\backslash c}_{\text{pool}}$ shared by other carriers from the coordinator and sets $CPR^{C\backslash c}_{\text{pool}}$ as R^c_{pool}. Then the carrier tries to insert these requests into its routes by Algorithm 1. If the carrier can serve requests $R^c_{\text{try}} = CPR^{C\backslash c}_{\text{pool}} \setminus R^c_{\text{pool}}$ and finds a better solution than before, the carrier submits bids Bid^c to the coordinator with costs of these requests R^c_{try}.

3. Insert new requests: For those bids $Bid^c_{\text{win}} \subseteq Bid^c$ that carrier c won through the auction, requests in Bid^c_{win} are set as R^c_{pool} and the carrier inserts these requests into its routes by Algorithm 1. It is worth noting that maybe a request r that can be served in Step 2 cannot be served in Step 3, because it can only be served in combination with some other requests in the failed bids. In this case, r will be added to R^c_{pool} and considered in the next round of the auction. Finally, the carrier sends the information of served new requests R_{new} to the coordinator.

Algorithm 1: Re-planning with shared requests.

Input: K^c, R^c_{pool}, N^c, A^c, X^c_{best}; **Output**: X^c_{best};
Obtain served requests R^c_{serve} in X^c_{best};
Combine R^c_{pool} and R^c_{serve} as a set of requests R^c;
$R^c_{\text{pool}}, X^c_{\text{best}} = ALNS(K^c, R^c, N^c, A^c, X^c_{\text{best}})$
return R^c_{pool}, X^c_{best};

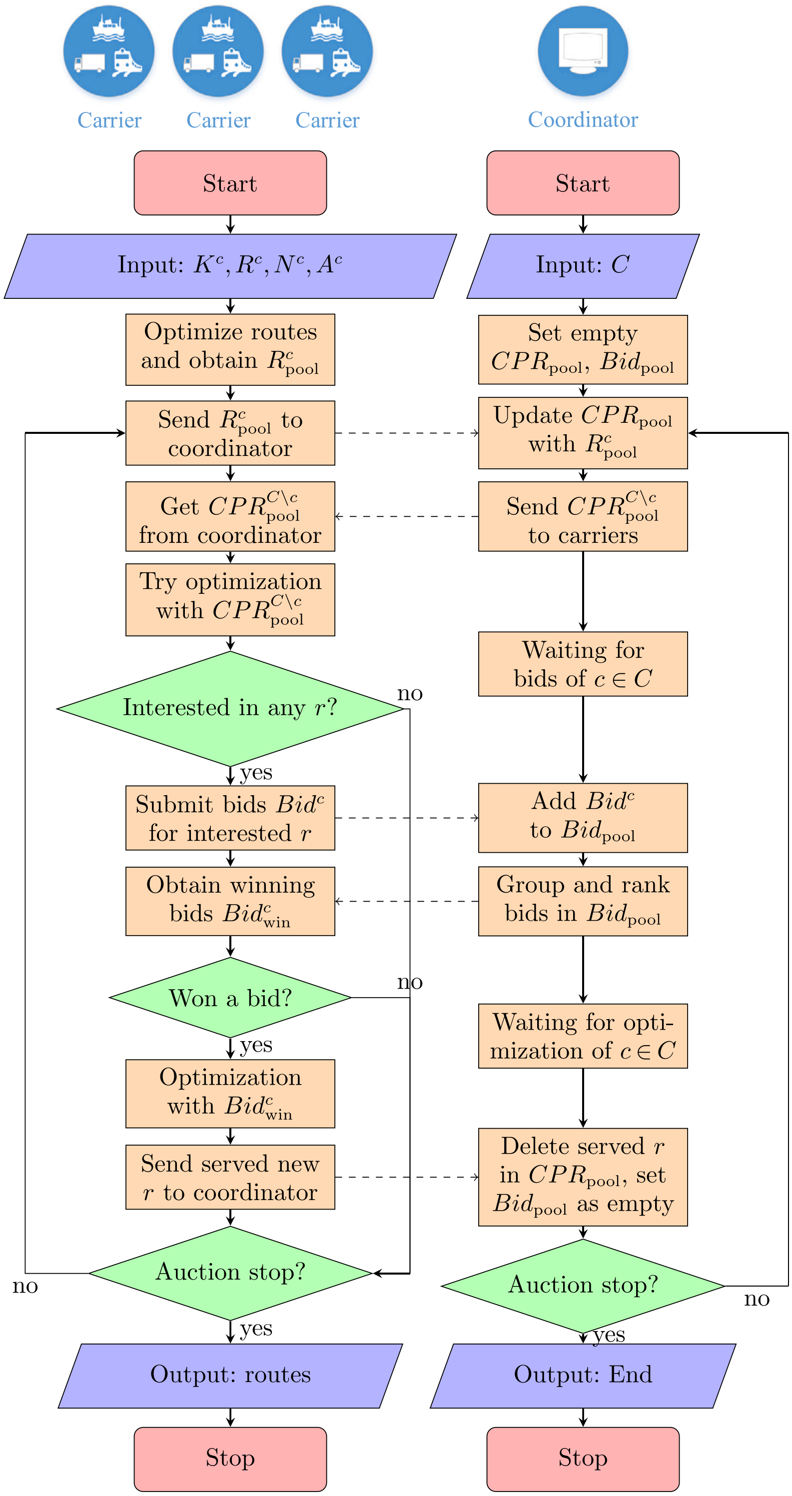


Fig. 6. Flowchart of the iterative auction procedure in the collaborative planning. Dashed arrows represent exchange of information between carriers and the coordinator.

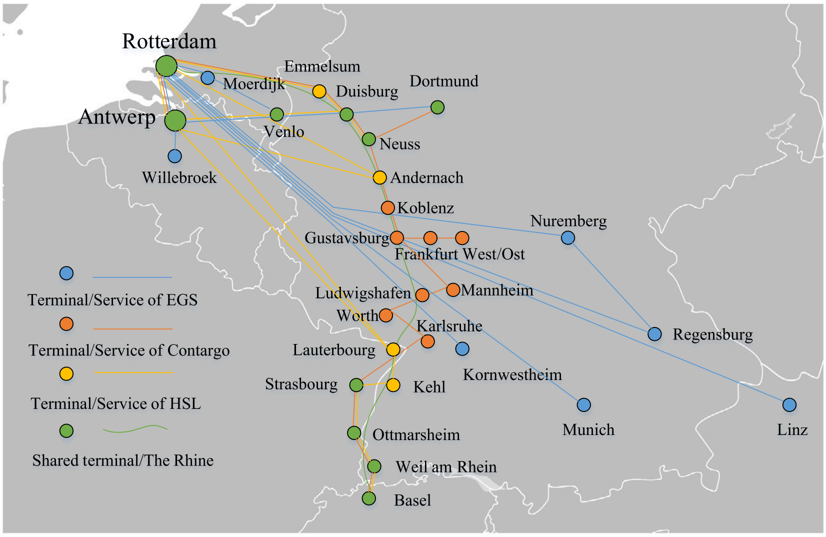


Fig. 7. Transport networks of EGS, Contargo, and HSL.

From the perspective of the coordinator, the procedure is as follows: The coordinator operates two pools, i.e., a collaborative planning request pool (CPR_{pool}) and a bids pool (Bid_{pool}). The coordinator adds or deletes requests in CPR_{pool} when receiving related information from carriers. Before an auction starts, the coordinator sets these two pools as empty and then receives unserved requests R^c_{pool} of each carrier $c \in C$. Request $r \in R^c_{\text{pool}}$ will be added in CPR_{pool} if $r \notin CPR_{\text{pool}}$. After receiving all carriers' R^c_{pool} and updating CPR_{pool}, the coordinator sends unserved requests of other carriers $CPR^{C\backslash c}_{\text{pool}}$ to each carrier c and waits for bids. After receiving bids from carriers, the coordinator groups bids according to requests and ranks them depending on the cost. Then, the coordinator sends winning bids to carriers and waits for the final optimization of carriers. Finally, the served requests are removed from CPR_{pool} and Bid_{pool} is set empty to prepare for the next round of the auction.

The auction will stop either when no carrier wants to exchange further requests or a predefined number of rounds is reached. This mechanism aims to provide carriers enough chances to share requests.

5. Case study

A network with three carriers along the European Rhine-Alpine corridor is considered as a real-world case to test the proposed model. The Rhine-Alpine corridor constitutes one of the busiest freight routes in Europe. Around 138 billion tonne-kilometers of freight is transported along this corridor annually, accounting for 19% of total GDP of the EU. The three carriers are European Gateway Services (EGS), Contargo, as well as Haeger & Schmidt Logistics (HSL) which are all intermodal transport carriers that provide barge, train, and truck services from sea ports (Rotterdam and Antwerp) to inland terminals. Fig. 7 presents the transport networks of these carriers. In this case study, EGS, Contargo, and HSL provide services among 10, 20, and 15 terminals/ports, respectively. A total of 11 terminals are shared by two or three carriers (there are multiple terminals in the sea port). The three carriers can share their requests in the overlapping transport network. Services' information is obtained from schedules on their websites (EGS, 2021; Contargo, 2021; HSL, 2021), and EGS, Contargo, and HSL operate 49/33/34, 38/23/95, and 41/8/70 barge/train/truck services, respectively, according to this data. For the distances between terminals of different modes, we use the same data sources as in Shobayo et al. (2021).

The origins and destinations of requests are distributed randomly among deep-sea terminals and inland terminals, respectively. The container volumes of requests are drawn independently from a uniform distribution with range [10, 30] (unit: TEU). According to services of EGS/Contargo/HSL, the earliest pickup time $a_{p(r)}$ of requests is drawn independently from a uniform distribution with range [1, 120]/[1, 140]/[1, 140]; the latest delivery time $b_{d(r)} = a_{p(r)} + LD_r$, where LD_r is the lead time and it is independently and identically distributed among 24, 48, 72 (unit: hours) with probabilities 0.15, 0.6, 0.25. Moreover, to define pickup and delivery time windows, we set $b_{p(r)}$ and $a_{d(r)}$ equal to $b_{d(r)}$ and $a_{p(r)}$, respectively. Parameters for vehicles are taken from the literature and shown in Table 3. In the objective function (13), the transport cost is a linear function of the travel time τ^k_{ij} and distance d^k_{ij}. We use different unit costs c^1_k and $c^{1'}_k$ for τ^k_{ij} and d^k_{ij}, which makes it possible to handle differences in the speed of vehicles. For trucks and trains, as reported in Li et al. (2015a), we set $c^1_{\text{truck}}/c^{1'}_{\text{truck}}$ as 30.98 euros/(TEU h)/0.2758 euro/(TEU km) and 7.54 euros/(TEU h)/0.0635 euro/(TEU km). According to the used type of barges and the database of an inland shipping community (Association of the inland shipping, 2010), the parameters of the Large Rhine Vessel (Va class) are used. Considering the labor, capital, maintenance,

Table 3
Vehicle parameters used in the paper.

Parameter	Value	Parameter	Value	Parameter	Value
c^1_{truck}	30.98	c^1_{train}	7.54	c^1_{barge}	0.6122
$c^{1'}_{\text{truck}}$	0.2758	$c^{1'}_{\text{train}}$	0.0635	$c^{1'}_{\text{barge}}$	0.0213
c^2_{truck}	3	c^2_{train}	18	c^2_{barge}	18
c^3_k	1	c^4_k	8	c^5_k	1

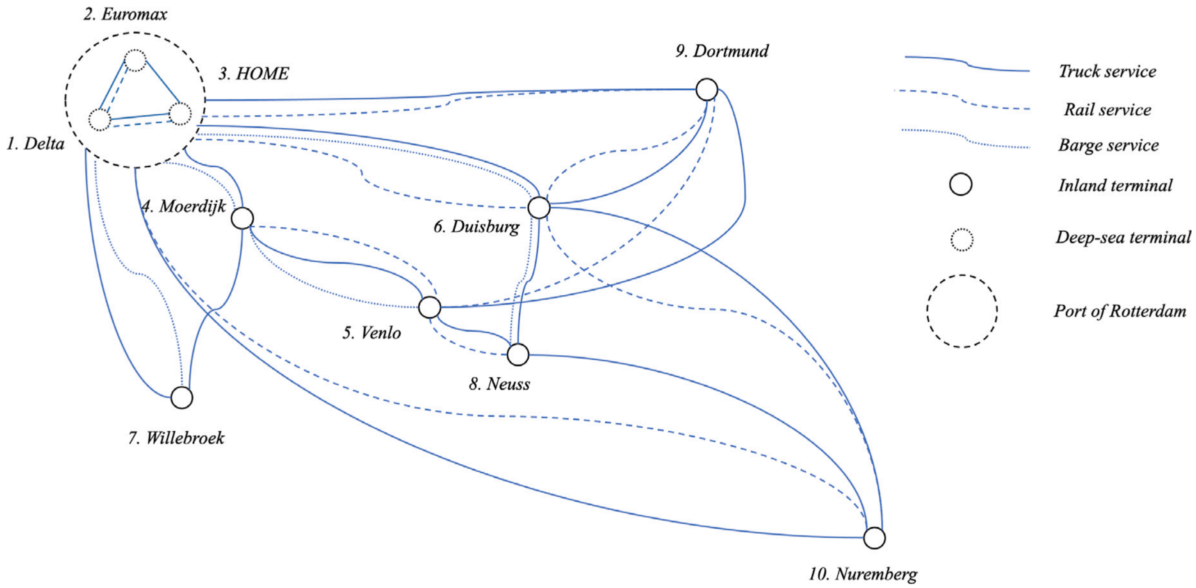


Fig. 8. Transport network of EGS.

total sailing hours in a year, and occupancy rate, the time-related cost for barges c^1_{barge} is set as 0.6122 euro/(TEU h). Based on the fuel consumption, the distance related cost unit $c^{1'}_{\text{barge}}$ is set as 0.0213 euro/(TEU km). According to Sun and Lang (2015), the loading/unloading costs c^2_k for trucks, trains, and barges are set as 3, 18, and 18 euros/(TEU h). The CO_2e is converted into carbon tax using a price c^4_k of 8 euros per ton, based on the price of the EU emission allowance (Riessen et al., 2015). As reported in Guo et al. (2020) and Zhang et al. (2022b), the vehicle can wait for containers with a waiting fee, and containers can be stored in the terminal with a storage fee. We use the same storage and waiting unit costs c^3_k and c^5_k of 1 euro/(TEU h).

We generate six instances for each carrier with 5, 10, 20, 30, 50, and 100 requests, respectively. Each instance contains three sub-instances with homogeneous preferences, i.e., all shippers prefer the same eco-label (A, B, or C), and one sub-instance with heterogeneous preferences (labeled as H), i.e., shippers have different preferred eco-labels. Under heterogeneous preferences, the eco-label for each request is obtained randomly from a uniform distribution over eco-labels A, B, and C.

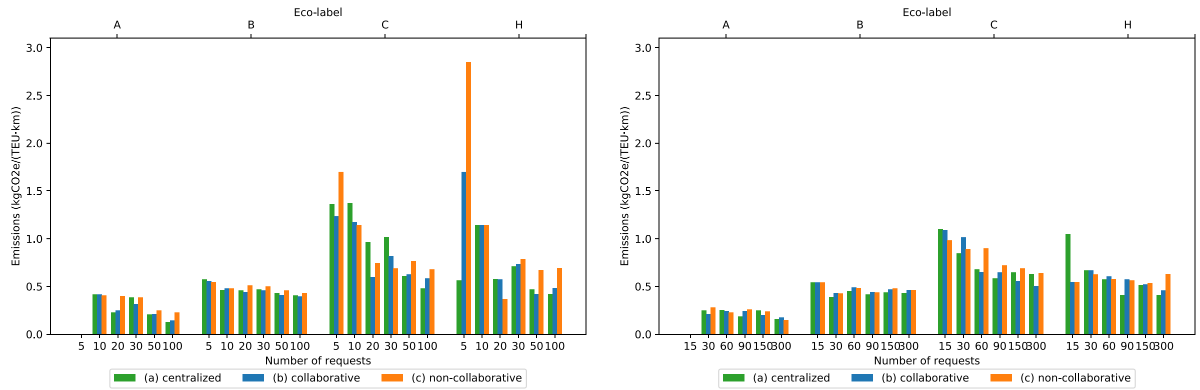
We consider two scenarios of collaborative planning. Scenario 1 is the collaboration among unimodal transport carriers and each carrier operates one of three modes (inland waterway, railway, and road). Scenario 2 is the collaboration among intermodal transport carriers and each carrier offers services in all three modes. In scenario 1, services of unimodal transport carriers are based on the transport network of EGS, as shown in Fig. 8 with varying total number of requests [5, 10, 20, 30, 50, 100] across instances. In scenario 2, the intermodal transport carriers are EGS, Contargo, and HSL and the total number of requests are [15, 30, 60, 90, 150, 300]. To ensure the accuracy of experimental results, all experiments are repeated five times and the results are averaged. The detailed results are presented in Appendix B.

5.1. Results analysis

Table 4 shows the average computation time of instances with different numbers of requests under centralized, collaborative, and non-collaborative approaches with preferences (a, b, c) and without (a∗, b∗, c∗) preferences. The computation time in scenario 2 is shorter than the computation time in scenario 1, because scenario 2 has more requests, more vehicles, and a larger transport network. Due to the communication time used in collaboration, approach (b)/(b∗) needs more computation time than approach (a)/(a∗) in most cases. On some exceptionally large instances, such as the instance with 300 requests in scenario 2, approach (b)/(b∗) uses less computation time than approach (a)/(a∗), because the collaborative approach (b)/(b∗) saves computation time by parallel computation which compensates the communication time. The computation time with preferences is usually larger since

Table 4
Computation time (s).

Approach	Scenario 1						Scenario 2					
	5	10	20	30	50	100	15	30	60	90	150	300
a	2.3	13.6	52.4	135.5	434.8	3041.1	36.0	534.1	1824.8	3976.5	6145.3	34 646.2
a*	0.7	3.3	12.3	14.3	92.2	604.1	17.7	119.8	2299.0	4247.0	7065.0	22 697.7
b	284.4	399.7	906.6	1767.5	2467.2	7667.3	801.5	1192.3	3129.9	4467.0	12 309.3	13 282.7
b*	178.4	172.8	324.4	513.3	711.5	1544.7	182.4	184.6	276.6	495.3	603.3	2225.8
c	0.3	0.9	1.9	3.1	27.7	92.2	4.5	55.2	162.4	505.7	1897.0	5385.4
c*	0.2	0.6	1.4	1.7	31.9	68.2	3.4	3.4	23.4	364.9	1004.7	3188.4



(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (intermodal carriers)

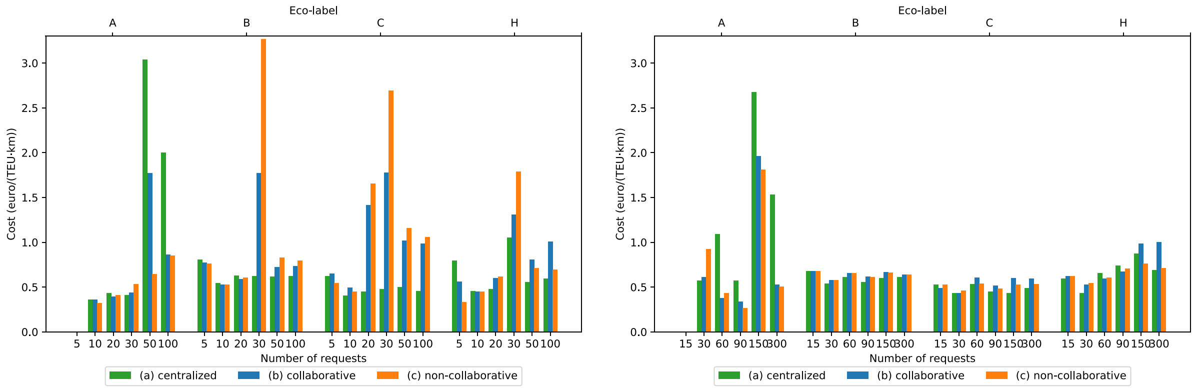
Fig. 9. Emissions comparison across approaches and eco-labels.

it is harder to find feasible solutions when preferences are incorporated. In most cases, the computation time is less than 2 h even on large instances.

Fig. 9 shows the resulting emissions across different approaches, scenarios and eco-label settings. Under eco-label A, no requests are served in the instances with 5/15 requests because the sustainability requirement is high and load factors of sustainable vehicles are still too low to reach the requirement. For the instances with more requests, the average unit emissions for eco-label A, B, C, and H under scenario 1/2 are 0.29/0.24, 0.47/0.47, 0.92/0.84, 0.86/0.62 $kgCO_2e/(TEU\ km)$, respectively. The corresponding solutions meet the requested eco-labels and it is observed that higher requirements on eco-labels indeed lead to lower average emissions. The emissions under eco-label A are reduced around 70% compared with eco-label C. Under eco-label C, more requests lead to lower emissions due to the high load factor of vehicles, but they still cannot reach the same level as of eco-labels B and A. Scenario 2 has a better performance compared with scenario 1 under the same eco-label due to the additional services.

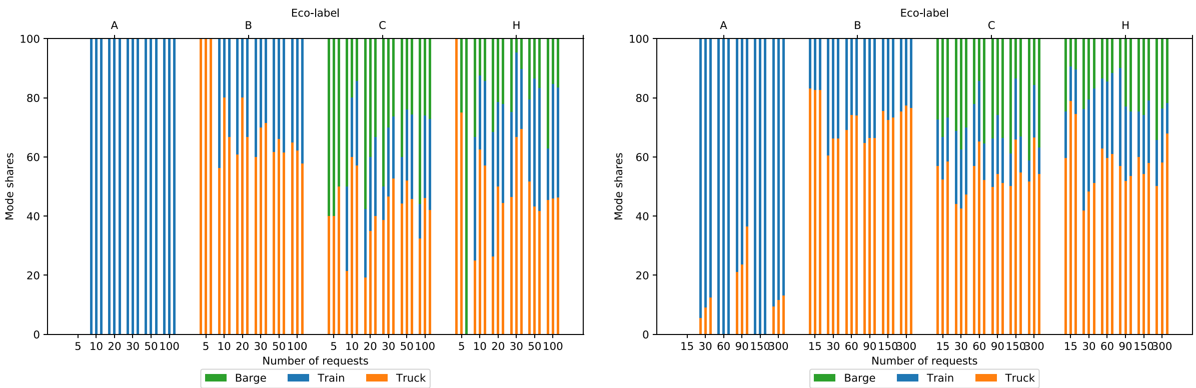
Fig. 10 shows a cost comparison across approaches and eco-labels. We compare solutions based on cost per TEU km rather than total cost as the number of served requests may differ in the solutions, which means that their total cost cannot be compared suitably with each other. In scenario 1, the average unit costs under eco-labels A, B, C, and H (heterogeneous preferences) are 0.85, 0.88, 0.93, and 0.74 euro/(TEU km), respectively. In scenario 2, these average unit costs are 0.95, 0.62, 0.51, and 0.69 euro/(TEU km), respectively. From eco-labels A to C, the emissions restriction decreases, while costs under scenario 1 increase. Scenario 2 shows the opposite trend. The truck carrier will keep requests when sustainability requirements are low, and requests will only be shared with train and barge unimodal carriers under high sustainability requirements. Therefore, for unimodal carriers under scenario 1, higher eco-labels could decrease costs because more low-cost vehicles are used due to emissions constraints. However, for intermodal carriers with all three modes, costs will be minimized and barges will be used as much as possible when they do not consider sustainability preferences, therefore cost under eco-label C is the lowest. When sustainability requirements are high, more requests will be served by trains, which is more expensive than barges, hence costs increase. In some cases, the cost under the centralized approach is higher than the collaborative approach because the served requests are different under these two approaches, and the transshipment and storage costs vary for different requests. In some other cases, the collaborative approach has higher costs which happen more in scenario 1. The reason behind is that truck carriers in scenario 1 serve requests by themselves with a high cost when the eco-label requirement is not high, such as the instance with 30 requests under eco-label B and instances with 20, 30, 50, and 100 requests under eco-label C. Therefore, unimodal carriers, especially truck carriers, need to share more requests in collaborative planning to reduce the overall cost and achieve a similar performance as centralized planning.

Fig. 11 shows the share of transport modes under both scenarios. Under eco-label A, trains dominate, especially in scenario 1, because using unimodal truck transport cannot reach the requirement of eco-label A and barges are sustainable only when the load factor is high. Under eco-label B, trucks serve more requests than trains and the reason behind is different for scenarios 1 and 2.



(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (intermodal carriers)

Fig. 10. Costs comparison across approaches and eco-labels.



(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (intermodal carriers)

Fig. 11. Mode share comparison across approaches and eco-labels. There are three bars (left, middle, and right) for each instance, which represents mode shares under approaches (a), (b) and (c), respectively.

In scenario 1, emissions of trucks with full truckload reach the requirement of eco-label B, hence part of the requests are served by trucks from which the load factors of trains become low. Then, trains are used less due to higher emissions than trucks. In scenario 2, trucks can not only transport containers by unimodal transport but also be combined with trains in intermodal transports to reach a lower cost. Therefore, the share of trucks is also higher than trains in scenario 2 under eco-label B. Under eco-labels C and H, more barges are used to serve requests because barges are sustainable and have a lower cost when the load factor is high. Furthermore, Fig. 12 shows the proportions of served requests by carriers in scenario 2. Compared with HSL, EGS and Contargo serve more requests under eco-label A, because they operate more trains than HSL. Under eco-labels B, C, and H, the proportions are similar.

Fig. 13 shows proportions of served requests, requests that satisfy fuzzy constraints, and requests that satisfy hard constraints under approaches with environmental preferences (a, b, c) and without preferences (a∗, b∗, c∗). For the results without preferences, the eco-labels are ignored, i.e., Constraints (50) are not considered. The higher the sustainability requirement is, the less the proportion of served requests is. Almost all requests can be served when sustainability preferences are not considered. The proportion of requests that satisfy fuzzy or hard constraints is in most cases higher when considering preferences compared to the approaches that ignore preferences. In some others, e.g., in scenario 2 under eco-label A, more requests satisfy fuzzy or hard constraints when preferences are not considered because more requests are served and load factors of sustainable vehicles are high. However, this relies on the sacrifice of requests that have high emissions. Using fuzzy constraints, the number of served requests is increased by an average of 10% compared with using hard constraints since the fuzzy constraints give the model flexibility to find a more suitable solution. For unimodal carriers (scenario 1), centralized and collaborative approaches increase the number of served requests significantly compared with non-collaboration, because unimodal carriers need the services of others to satisfy emission preferences, especially under high sustainability requirements. Compared with the non-collaborative approach, the proportion in the collaborative

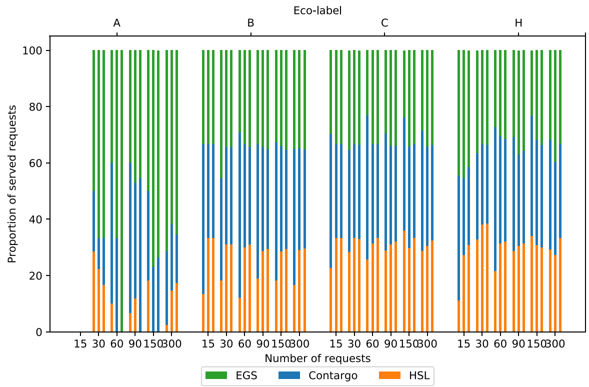
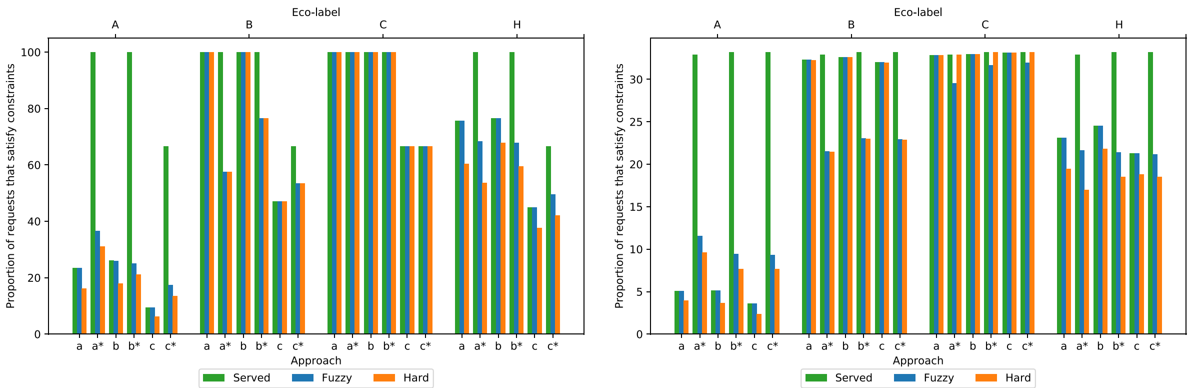


Fig. 12. Proportions of served requests by carriers in scenario 2. There are three bars (left, middle, and right) for each instance, which represents mode shares under approaches (a), (b), and (c), respectively.



(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (intermodal carriers)

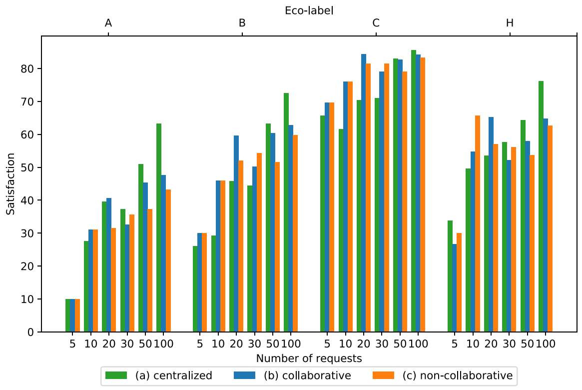
Fig. 13. Proportions of served requests, requests that satisfy fuzzy constraints, and requests that satisfy hard constraints.

approach is increased by an average of 65%, 53%, 33%, and 41% under eco-labels A, B, C, and H, respectively. For intermodal carriers (scenario 2), such an increase is not significant under eco-labels B, C, and H, because carriers own enough services. However, the increase is still significant under eco-label A (29%). In both scenarios, the proportions of served requests of centralized and collaborative approaches are similar.

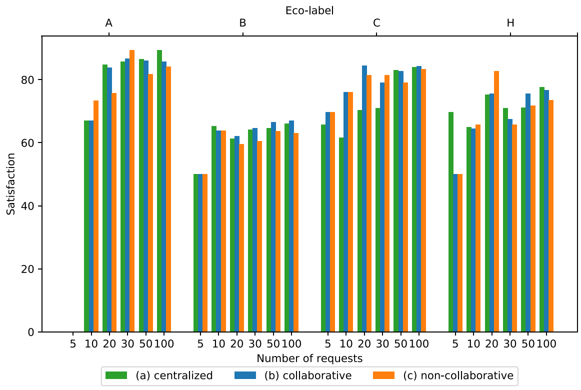
Fig. 14 shows satisfaction values S_r across approaches with and without respecting preferences, i.e. with and without Constraint (50) for the satisfaction benchmark. As expected, considering preferences in the planning improves the satisfaction significantly, especially under eco-label A. However, under eco-label C, satisfaction is slightly better when preferences are ignored since more requests can be served, which increases the load factors and in turn reduces the emissions. In Figs. 14(b) and (d), the satisfaction under eco-label B is lower than under eco-label A because more trucks are used due to reasons mentioned in the analyses of Fig. 11.

5.2. Sensitivity analysis and convergence of the ALNS

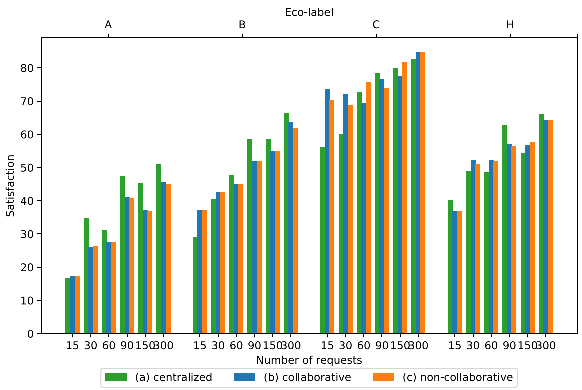
Due to the different infrastructure in terminals and types of vehicles, the costs may be different. Advances in technology may also change the structure of the costs across different modes. Therefore, a sensitivity analysis is needed for the parameters presented in Table 3 to evaluate the influence of potential changes on the benefit of our proposed approach. We varied the values of all parameters in Table 3 under the instance with 20 requests (EGS carrier) and the consistency of the results under varying parameters are presented in Appendix C. We also conduct sensitivity analysis comparing centralized, collaborative, and non-collaborative approaches to check whether the obtained insights still hold when the parameter values vary. The costs per km may be different for vehicles with different loads and types and the carbon tax may differ in different countries/regions, therefore distance cost $c^{1'}_{\text{barge}}$ and carbon tax c^4_k are interesting parameters to conduct the sensitivity analysis. The worst case of $c^{1'}_{\text{barge}}$ relates to the possibility of having higher cost than the truck distance cost with very low load on the barge. When it comes to c^4_k, according to Yan et al. (2021), carbon tax will increase



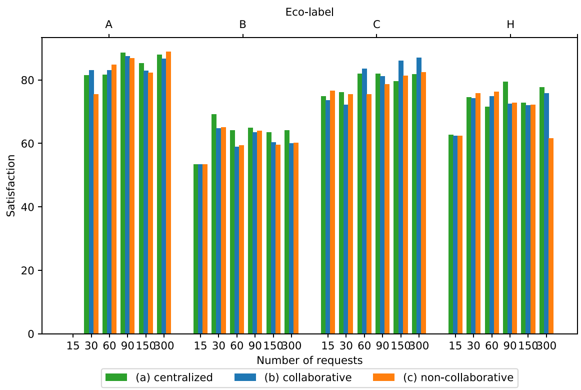
(a) Scenario 1 (unimodal carriers) without preferences



(b) Scenario 1 (unimodal carriers) with preferences



(c) Scenario 2 (intermodal carriers) without preferences



(d) Scenario 2 (intermodal carriers) with preferences

Fig. 14. Satisfaction S_r comparison across approaches with and without preferences.

to 80 euros per ton by 2030 and this could be higher to reach net zero emissions by 2050. Considering the best- and worst-case scenarios, we vary $c^{1'}_{\text{barge}}$ and c^4_k in [0, 0.32] and [0, 128], respectively. The results are displayed in Fig. 15 and as expected, when $c^{1'}_{\text{barge}}$ or c^4_k increases, the costs under all approaches rise. However, the cost gaps between different approaches stay similar due to the nature of approaches. The centralized approach obtains the lowest cost and the collaborative approach has better cost than the non-collaborative approach. The emission gaps of these approaches are similar in most cases, while they change in extreme cases, e.g., the carbon tax is 128 euros per ton, where all approaches have to reduce emissions as much as possible to minimize the total cost. The number of served requests does not change for all approaches. The centralized and collaborative approaches can serve all requests, while one quarter of requests cannot be served in the non-collaborative approach. Therefore, the proposed model is robust and the obtained insights still hold under reasonable changes in parameters.

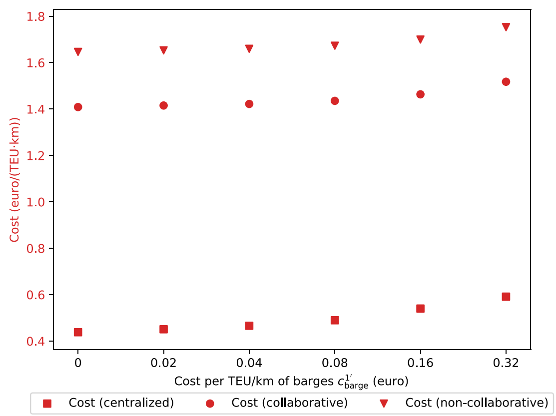
We use instances with different numbers of requests to illustrate the convergence of the ALNS heuristic. Fig. 16 shows the costs and emissions of the best solution over 200 iterations. The cost could increase when there are more served requests and the cost is minimized when the number of served requests is stable. Fig. 16 shows that ALNS clearly converges before terminating it on all instances. For small instances (R = 5, 10, and 20), ALNS converges rapidly in early iterations. For large instances (R = 30, 50, and 100), no better solutions are found in the final 90 iterations.

5.3. Results under different objectives and preferences

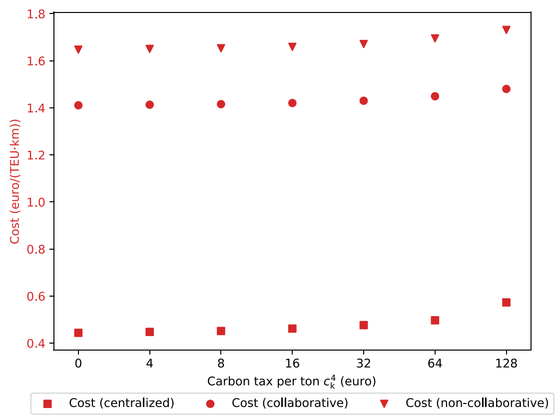
In practice, the transportation cost and time are important for shippers, and there are two methods to consider preferences on cost and time, i.e., (a) incorporate them as part of the objective function together with the number of served requests, (b) consider these preferences in a similar way as eco-labels.

In method (a), we minimize F_3, which is the sum of the costs F_2 and the penalty for unserved requests:

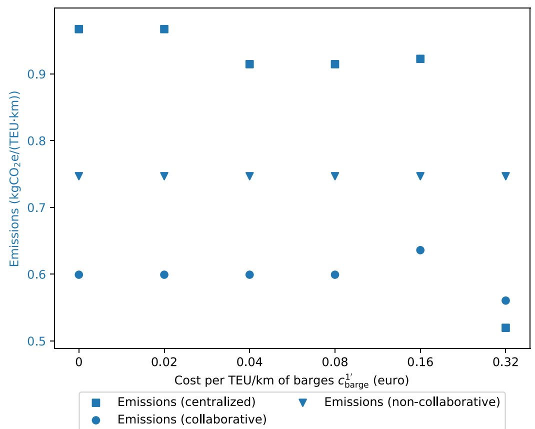
$$\min \ F_3 = F_2 + \sum_{r \in R^c} (1 - g_r)\lambda_r F^r_{\text{truck}}, \tag{51}$$



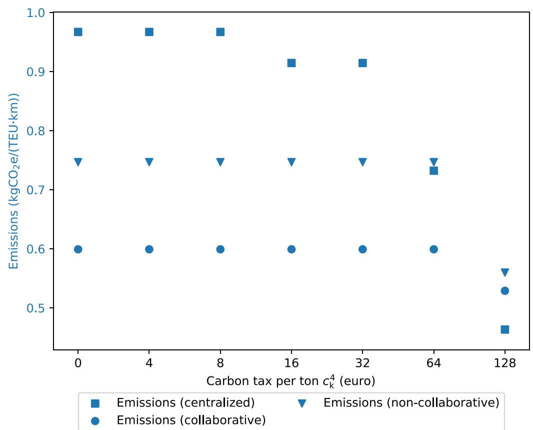
(a) Cost under varying $c^{1'}_{\text{barge}}$



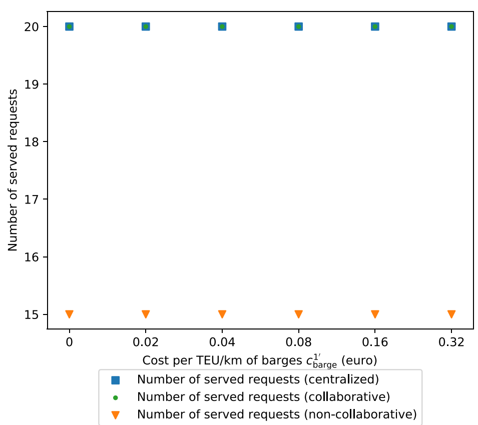
(b) Cost under varying c^4_k



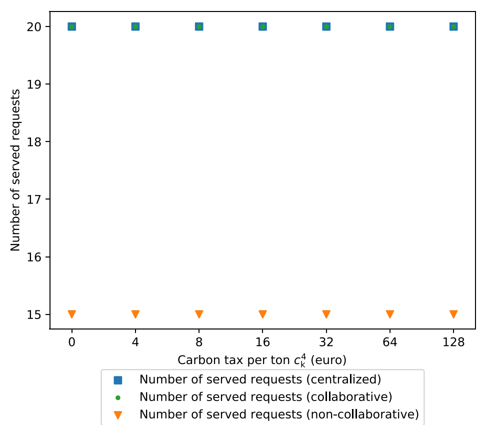
(c) Emissions under varying $c^{1'}_{\text{barge}}$



(d) Emissions under varying c^4_k



(e) Number of served requests under varying $c^{1'}_{\text{barge}}$



(f) Number of served requests under varying c^4_k

Fig. 15. Sensitivity analysis on distance cost $c^{1'}_{\text{barge}}$ and carbon tax c^4_k under different approaches.

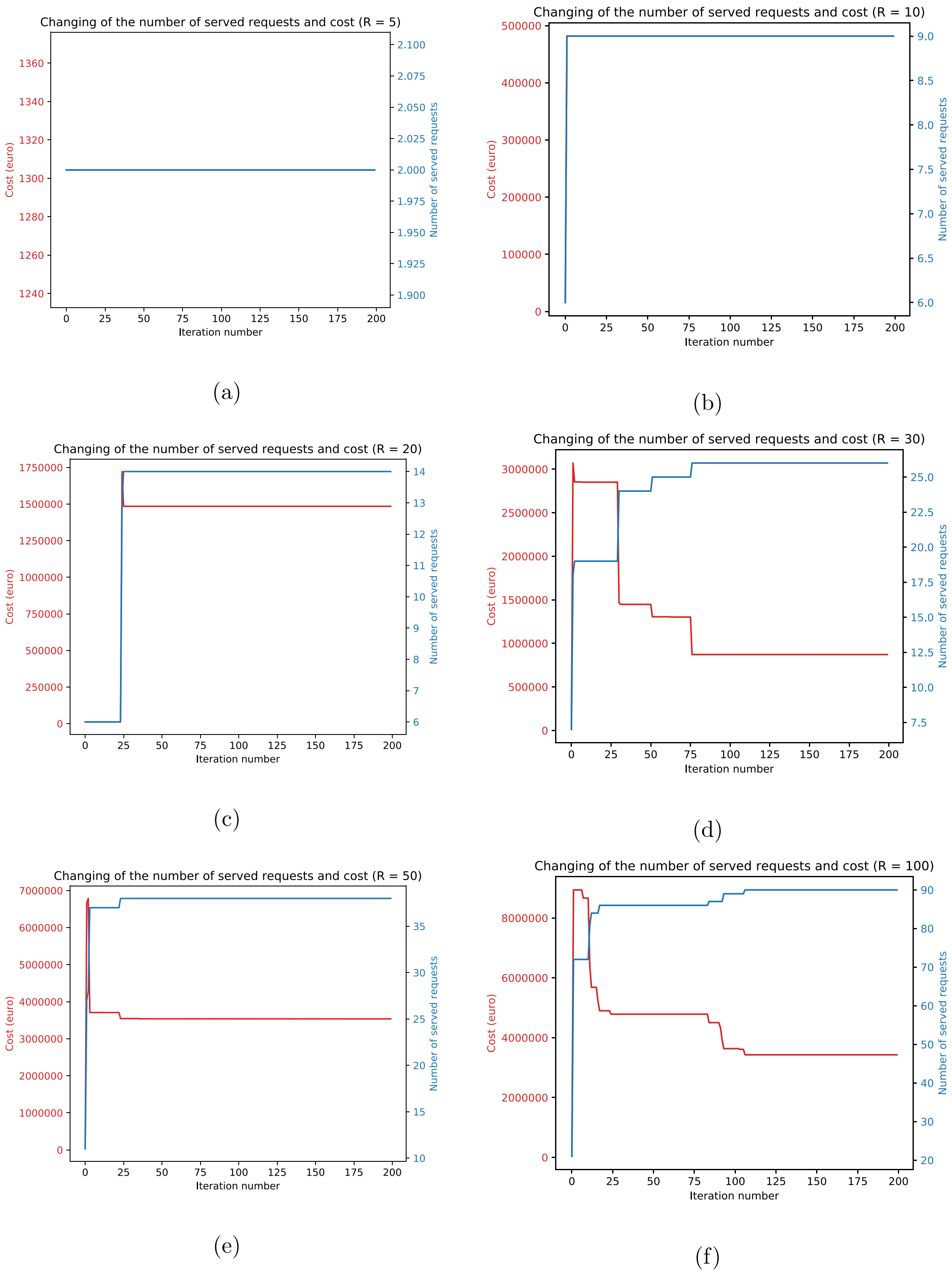


Fig. 16. Convergence of ALNS on instances with preferences.

Table 5
Results under different preferences.

Objective	N	Cost	Time	Emissions	Barge	Train	Truck	S	T
Low-cost transport (cost-label A)									
F_1, F_2	16	0.48	1.18	0.43	28.57	38.10	33.33	77	70
Fast transport (time-label A)									
F_1, F_2	28	0.83	0.53	0.78	0.00	21.62	78.38	80	126
Sustainable transport (eco-label A)									
F_1, F_2	18	0.52	1.33	0.44	20.00	44.00	36.00	78	85

N: number of served requests; Cost: average cost of shipping one TEU one km; Time: average time ratio; Emissions: average emissions per TEU per km; Barge/Train/Truck: mode share of used barges/trains/trucks; S: average satisfaction value; T: Times of using objective function F_2 in total 200 iterations.

where g_r is a binary variable indicating whether request r is served or not and λ_r is a parameter that controls the size of the penalty for each unserved request r. The variable g_r respects the following constraints:

$$g_r \geqslant \sum_{(i,j)\in A^c} y_{ij}^{kr} \quad \forall k \in K^c,\ \forall r \in R^c, \tag{52}$$

$$g_r \in \{0,1\} \quad \forall r \in R^c. \tag{53}$$

When a request cannot be served by available vehicles, spot-market trucks can usually be used. Therefore, the penalty is calculated by F^r_{truck}, which is the cost of transporting request r using trucks:

$$F^r_{\text{truck}} = (c^1_{\text{truck}}\tau^{\text{truck}}_{p(r)d(r)} + c^{1'}_{\text{truck}}d^{\text{truck}}_{p(r)d(r)})q_r + 2c^2_{\text{truck}}q_r + c^4_{\text{truck}}e^{\text{truck}}_r. \tag{54}$$

Fig. 17 shows results for the instance with 30 requests. Similar insights are obtained from results of other instances, as shown in Appendix D. The size of the penalty needs to be set according to the importance of requests. We vary it from 0 to 100 to evaluate the performance of method (a) in different scenarios. In the extreme case of $\lambda_r = 0$, serving requests is not important and the carrier only cares about minimizing cost F_2. The number of served requests is then significantly less than in other cases. Compared to using objectives F_1 and F_2 hierarchically as proposed in this paper, minimizing F_3 could obtain solutions with lower unit cost or emissions by not serving requests with high cost/emissions in some scenarios, such as results when $\lambda_r = 0.5$, $\lambda_r = 1$, and $\lambda_r = 2$ in Fig. 17(b). Nevertheless, in order to reach those results, one needs to tune the penalty term thoroughly for each instance with different number of requests, problem parameters, etc. When the penalty λ_r is large, i.e., $\lambda_r = 5$, $\lambda_r = 10$, and $\lambda_r = 100$, the number of served requests is the same as the proposed approach with similar costs and emissions. Except for the scenario in which $\lambda_r = 0$, these two ways of modeling the objective function have similar performance when eco-label preferences are ignored, because all requests can be served and the objective is essentially translated into the minimization of costs (F_2).

For method (b), the proposed model can be extended easily to consider cost-label and time-label. For the cost-label, the unit cost of shipping one TEU for request r is calculated by:

$$c'_r = F_2^r / (q_r \sum_{k\in K}\sum_{(i,j)\in A} d^k_{ij} y^{kr}_{ij}) \tag{55}$$

where F_2^r is the overall cost of request r and the calculation of F_2^r is similar to objective (14).

For the time-label, we use the ratio of actual time to expected time to evaluate how fast the transportation is, calculated by:

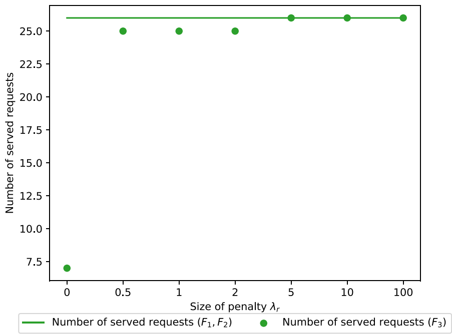
$$t'_r = t_r / (d^{\text{average}}_{p(r)d(r)} / v_{\text{average}}), \tag{56}$$

where $d^{\text{average}}_{p(r)d(r)} / v_{\text{average}}$ is the average travel distance/speed of all vehicles and t_r is the actual travel time:

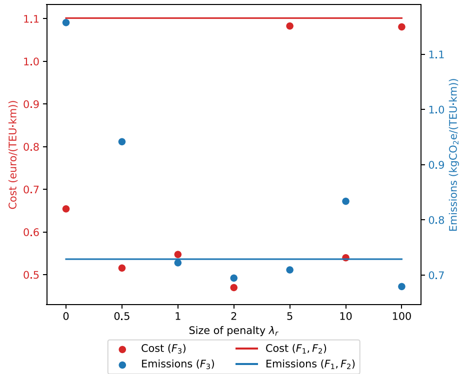
$$t_r = \max\{\bar{t}^{kr}_i y^{kr}_{ij} \ :\ \forall (i,j) \in A,\ \ \forall k \in K\} - \min\{t'^{kr}_i y^{kr}_{ij} \ :\ \forall (i,j) \in A,\ \forall k \in K\}. \tag{57}$$

The rates of cost-label/time-label A, B, and C are set as 0.6/0.8, 0.9/1.1, and 1.2/1.4, respectively. Then, we can adopt a similar method as in Section 4.1 to obtain the satisfaction value S_r and set constraints for S_r to ensure that the solutions are in line with cost or time preferences of shippers.

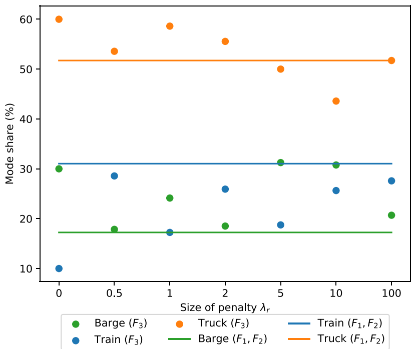
Table 5 shows the results under different preferences on the instance with 30 requests, where the related cost, time, or emission of the obtained solution is reduced according to the required labels. For example, when shippers prefer low-cost transport, the cost is the lowest and the mode shares of low-cost modes (barges and trains) are the largest compared with other solutions. Column T shows the frequency of using objective function F_2, and it is used on average in 47% iterations out of 200 iterations when both objective functions F_1 and F_2 are considered. Therefore, F_2 plays an important role in the optimization and the model finds solutions with the same number of served requests frequently.



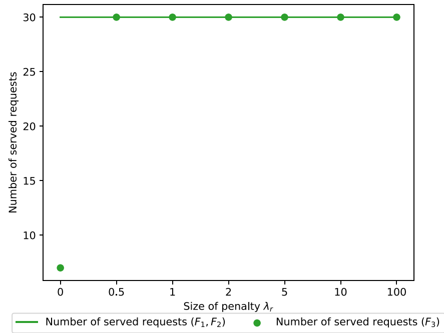
(a) Number of served requests under varying sizes of penalty (R = 30, considering preferences)



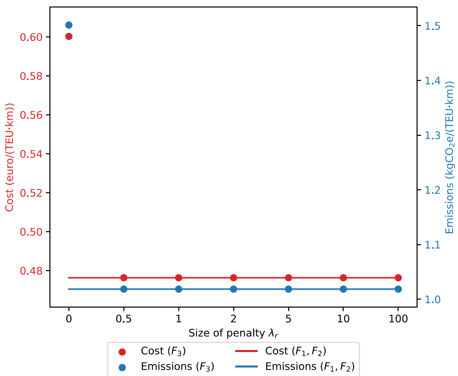
(b) Cost and emissions under varying sizes of penalty (R = 30, considering preferences)



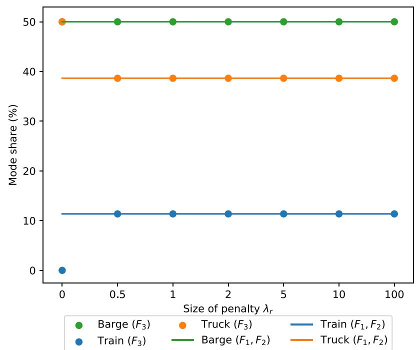
(c) Mode shares under varying sizes of penalty (R = 30, considering preferences)



(d) Number of served requests under varying sizes of penalty (R = 30, ignoring preferences)



(e) Cost and emissions under varying sizes of penalty (R = 30, ignoring preferences)



(f) Mode shares under varying sizes of penalty (R = 30, ignoring preferences)

Fig. 17. Comparison of results with different objectives (R = 30).

6. Conclusions

In this paper, we have proposed a collaborative planning model for carriers in intermodal transport. It opens up a way to route more shipments in accordance to their requested eco-label and, ultimately, to achieve a more sustainable overall transport solution. The eco-labels requested by shippers are considered in the optimization of carriers, and carriers exchange requests that cannot be served by themselves. An auction mechanism is proposed for collaborative planning. Three approaches are compared using realistic transport networks and schedules. The experimental results show that collaboration can lead to 48%/11% increases of proportions of served requests for unimodal/intermodal carriers, and the highest/mixed eco-labels reduce 70%/15% emissions compared with ignoring preferences. Based on the experimental results, the following managerial insights are obtained: (a) Considering eco-label preferences reduces emissions significantly. (b) Compared with the scheme without eco-label preferences, considering eco-labels reduces the emissions at the expense of decreasing the number of served requests. (c) For collaboration among unimodal carriers, high eco-labels reduce more costs than schemes with low eco-labels or ignoring eco-labels because requests of the truck carrier will be served by train and barge carriers, who can provide both low-emissions and low-cost services. For collaboration among intermodal carriers, satisfying high eco-labels requires more trains, and ignoring eco-labels increases barge use. Therefore, higher eco-labels cause more costs as using trains is more expensive than barges. (d) When minimizing the sum of costs and penalty of unserved requests, high-cost/-emissions requests cannot be served with a low penalty. Whereas, the solutions under high penalty are similar to those obtained with the proposed approach. (e) Compared with non-collaborative planning, collaborative planning supports both intermodal and unimodal carriers to provide more sustainable services and serve more requests, especially under high eco-label requirements. (f) Compared with intermodal carriers, unimodal carriers can benefit more from collaborative planning and need a higher degree of collaboration (i.e., sharing more requests) to reduce both emissions and costs. (g) Using fuzzy set theory gives carriers more room to find a more suitable solution and the number of served requests is increased compared with using hard constraints. Therefore, from the policy-making perspective to develop intermodal transport, the policy makers can set incentives for collaborative planning and use eco-labels to achieve sustainable intermodal transport. The proposed model provides a basis for further research analysis in policy making implications. Using the proposed model with transport networks to be analyzed, the policy maker can simulate scenarios with different carriers, different degrees of collaboration, and different levels of eco-labels to determine the degree of collaboration for each carrier and the needed eco-label to achieve emission reduction goals.

In practice, carriers in intermodal transport can use the proposed model to improve their service quality and competitiveness by providing more sustainable solutions. Our study used greenhouse gases as sustainability measure, but it might also be interesting to expand this focus on other negative impacts from transportation like the air pollution from particulate matter. In a transportation planning model, the proposed model can be integrated with a Geographic Information System (GIS) that provides real data about characteristics of the roads, railways, inland waterways, and terminals in the transport network. The GIS can greatly improve the realistic representation of the intermodal transportation network as well as the visualization of results, and further enhance the role of the proposed model as a decision support tool in transportation planning. The proposed model can also be used to solve similar optimization problems, such as pickup and delivery problems with transshipment and sustainability preferences, by simplifying the objectives and constraints related to multiple modes and fixed services.

The proposed model has some limitations. To gain more profits, carriers may compete in the auction and have strategic behaviors in the bidding. The proposed model only assumes that carriers share unserved requests; it does not consider further competition among carriers. The methodology proposed in this study relies on eco-label preferences provided by each shipper. The preferences might not be easy to obtain in real life and even so shipper's stated preferences may differ from actual preferences. Therefore, the behavior of shippers needs to be observed and preferences can be learned from their behavior. The uncertainty is a common issue in intermodal transportation, which may result from congestion on the roads, waterways, railways, or at the terminals. To tackle dynamic transportation planning under uncertainty, the proposed model can be extended in different manners, in a predictive way or in a reactive way. Stochastic programming is an example of incorporating uncertainties upfront when optimizing the decisions and therefore has a predictive nature. On the reactive side, re-planning actions can be taken when unexpected events occur in the transport network. Moreover, predictive and reactive strategies can be combined and machine learning techniques could be incorporated to learn from historical experiences.

This work has concentrated on collaborative planning among carriers that exchange requests, while collaboration among carriers that serve the same requests in different sections of the transport chain is not considered. The later type of collaboration is an interesting future direction. The consideration of a more detailed estimation of emissions in stochastic settings is also a promising research direction. For example, the load-dependent emissions make it difficult to anticipate the actual emissions of a vehicle if the carrier has no full knowledge about all future requests. Moreover, profit sharing could be worth studying. The profit margins resulting from collaboration need to be fairly shared among carriers. Determining a fair allocation mechanism will attract more carriers to join such a collaboration.

CRediT authorship contribution statement

Yimeng Zhang: Conceptualization, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Arne Heinold:** Software, Validation, Writing – review & editing. **Frank Meisel:** Conceptualization, Writing – review & editing. **Rudy R. Negenborn:** Writing – review & editing, Supervision. **Bilge Atasoy:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision.

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Appendix. ALNS algorithm and detailed results

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