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DOI
10.1016/j.tre.2024.103535

Publication date
2024

Document Version
Final published version

Published in
Transportation Research Part E: Logistics and Transportation Review

Citation (APA)
Guo, W., Zhang, Y., Li, W., Negenborn, R. R., & Atasoy, B. (2024). Augmented Lagrangian relaxation-based coordinated approach for global synchromodal transport planning with multiple operators. *Transportation Research Part E: Logistics and Transportation Review*, *185*, Article 103535. https://doi.org/10.1016/j.tre.2024.103535

Transportation Research Part E 185 (2024) 103535

Contents lists available at ScienceDirect

Transportation Research Part E

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

Augmented Lagrangian relaxation-based coordinated approach for global synchromodal transport planning with multiple operators[☆]

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ARTICLE INFO

Keywords:
Global synchromodal transport systems
Multiple operators
Coordinated mechanism
Augmented Lagrangian relaxation approach
Heuristic algorithm

ABSTRACT

Global synchromodal transportation is a promising strategy for providing efficient, reliable, flexible, and sustainable container shipping services across continents. It involves integrating multiple modes and routes owned by various operators to create a comprehensive transport plan. However, these operators often have their own local networks and are hesitant to cede control to a centralized platform. Instead, they prefer to share limited information in a coordinated manner to achieve a common goal without sacrificing their own benefits. This paper proposes a coordinated mechanism for global synchromodal transport planning, in which a global operator proposes incentives to local operators to select the most efficient modes and routes for shipping containers from one continent to another. An augmented Lagrangian relaxation approach is developed for the global operator to generate incentives, and a heuristic algorithm is designed to address the computational complexity of the optimization problems faced by local operators. We incorporate the proposed approaches with a rolling horizon framework to handle dynamic shipment requests received from spot markets and with a buffer strategy to address travel time uncertainties. The coordinated mechanism is tested on a real network between Asia and Europe, and results show that it can significantly increase total profits, reduce request rejections, and reduce infeasible transshipments compared to decentralized global transportation plans currently in use, particularly under scenarios with higher degrees of dynamism and uncertainty.

1. Introduction

Global container transportation is the movement of containers between inland terminals located in different continents by using ships, barges, trains, trucks, or any combination of them (Yang et al., 2018). World container port throughput increased about 50% over a decade between 2010 (542 million TEUs) and 2020 (799 million TEUs) (UNCTAD, 2022). Over the next decade, the containerization trend is expected to increase steadily as well (Rodrigue and Notteboom, 2015). With the growth of global container

☆ This research is supported by the National Natural Science Foundation of China (Grants 72301203 and 62173263), the Fundamental Research Funds for the Central Universities (Grant 233102002), and the China Scholarship Council (Grant 201906950085).

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https://doi.org/10.1016/j.tre.2024.103535
Received 7 September 2023; Received in revised form 6 March 2024; Accepted 10 April 2024
Available online 19 April 2024

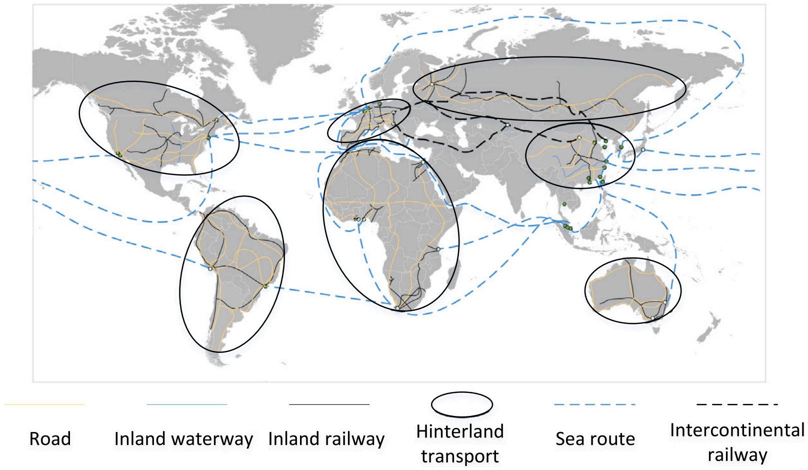

Fig. 1. Map of the global network consisting of hinterland and intercontinental transport.

traffic, current infrastructure capacity is under pressure, resulting in congestion issues, safety concerns, environmental concerns and reduced service reliability (Ambra et al., 2018).

Global synchromodal transportation is a promising strategy to provide efficient, reliable, flexible, and sustainable services through mode-free booking, differentiated fare classes, vertical and horizontal collaboration, and integrated planning (Archetti et al., 2022). Mode-free booking means that shippers leave mode and route choices to service operators (Tavasszy et al., 2017). This increases the flexibility to optimize service capacities and to react effectively to disruptions by dynamically updating transport plans (Giusti et al., 2023). Differentiated fare classes ensure that shippers have multiple choices of fare classes (Riessen et al., 2020). A fare class is characterized by a specific price, lead time, and delay cost. Vertical and horizontal collaboration assumes that all the stakeholders either in different levels of supply chains or the same level form an alliance to improve the utilization of resources and increase service frequency (Lee and Song, 2017). This gives rise to integrated planning in which a centralized platform controls the movement of container shipments over a global network (Guo et al., 2021). However, in practice, the operators of a global transport system are often geographically distributed, which makes it very difficult to apply a central controller to manage the whole system (Febbraro et al., 2016). As shown in Fig. 1, each continent has its hinterland transport network and these continents are connected by sea-going ships or intercontinental railways. For example, the hinterland transportation from Chongqing terminal to Shanghai Port is managed by China Railway Container Transport, the maritime transportation from Shanghai port to Rotterdam port is organized by COSCO Shipping Lines, and the hinterland transportation from Rotterdam port to Duisburg terminal is controlled by European Gateway Services. The objective and constraints of one local operator may be in conflict with those of the other operators and the global objective. Coordination among these local operators to select the local routes that meet time and spatial compatibility at interconnecting terminals is a key challenge for achieving synchromodality in global transportation.

In this paper, we introduce a coordinated mechanism for global synchromodal transport planning in which a platform owned by a global operator that receives real-time shipment requests from shippers and sends incentives to local operators to select the modes and routes that can achieve global optimum, as shown in Fig. 2. The global synchromodal transport network consists of both interconnected networks (e.g., China–Europe transport network and Europe's hinterland transport network) and overlapping networks (e.g., transport networks of different European transport operators). This coordinated mechanism allows for both vertical coordination among operators with interconnected networks and horizontal collaboration among operators with overlapping networks. Thanks to the development of information and communication technologies and intelligent transport systems, operators can not only make online decisions but also exchange information in real-time (Giusti et al., 2019). Under the coordinated mechanism, the global operator acts as an intermediary between shippers and local operators, to connect transport demand and supply without having direct control over these entities. Specifically, the global operator sends transport requests and incentives to local operators and leaves the routing decisions to local operators. In this way, local operators have independent planning authority in their service networks and cooperate to achieve a common goal, such as increasing total profits, reducing request rejections, reducing the number of infeasible transshipments at interconnecting terminals, and reducing delays in deliveries at destinations. In vertical coordination, the global operator adjusts incentives to align the routing decisions of local operators. In horizontal collaboration, the global operator selects the best local routes in each area, and combines the selected local routes into global itineraries to provide an integrated transport plan for each shipment request. The global operator will keep adjusting incentives based on the local routing decisions until achieving consistency among local operators.

To design the incentives that stimulate local operators choosing the 'optimal' decisions that benefit the common goal, coordinated approaches that handle interconnecting constraints at transshipment terminals are required. Although coordinated approaches have been applied in many fields, such as power distribution networks (Negenborn, 2007), railway traffic management (Luan et al., 2020), vehicle platoons (Zheng et al., 2017), intermodal freight transport chains (Febbraro et al., 2016), and hinterland synchromodal

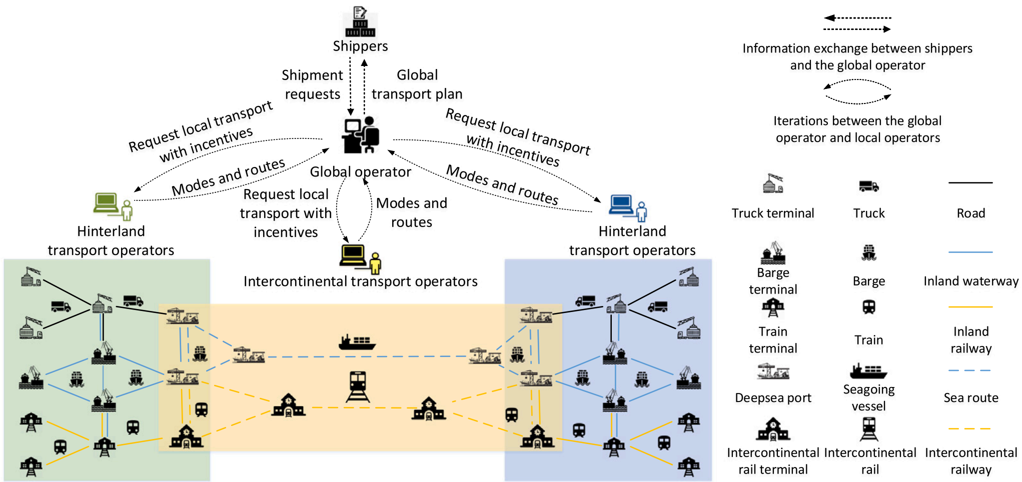

Fig. 2. A coordinated mechanism for global synchromodal transport planning with multiple operators.

container flow control (Li et al., 2017), it is still challenging for global synchromodal transport planning which has different network topology, coordinated mechanism, and time and spatial interconnecting constraints from above studies. In this paper, we develop an augmented Lagrangian relaxation (ALR) approach to handle the couplings. The main idea of ALR is to relax interconnecting constraints using Lagrangian multipliers that play as incentives. To speed up the convergence of ALR, departure time lower bounds at transfer terminals are designed when infeasible transshipments achieve a certain number. Due to the computational complexity of the optimization models of local operators, a heuristic algorithm is designed to generate timely solutions for each operator at each iteration.

In addition to the distributed nature of global transport systems, another challenge is that shipment requests are received not only from contractual markets but also from spot markets in the container industry (Bilegan et al., 2022). While contractual requests are often fixed and received in advance based on contracts from large shippers, spot requests arrive in real-time and require receiving transport solutions as soon as possible (Taherkhani et al., 2022). In this paper, we develop a rolling horizon framework to adapt the global synchromodal transport system to dynamic contexts in which decisions are made at fixed time points and requests are re-routed when infeasible transshipments happen. Furthermore, travel time uncertainty is quite common in global transportation resulting from weather conditions and traffic congestion (Demir et al., 2016). As discussed in Guo et al. (2022a), ignoring travel time uncertainty in global synchromodal transport planning might result in suboptimal or even infeasible solutions. This paper designs a buffer strategy to guarantee a certain level of feasible transshipments at transshipment terminals.

The relationships between the proposed approaches under the coordinated mechanism are illustrated in Fig. 3. The global operator utilizes the rolling horizon framework to adapt to dynamic contexts when receiving new requests and actual travel times, and the augmented Lagrangian relaxation approach to update Lagrangian multipliers and departure time lower bounds based on received local routing decisions. Meanwhile, local operators apply the buffer strategy to generate buffer times for each transport service to prevent infeasible transshipments, and the heuristic algorithm to generate efficient local routing decisions.

The remainder of this paper is organized as follows: Section 2 presents a brief literature review. Section 3 describes the global synchromodal transport planning problem with multiple operators. Section 4 compares the coordinated mechanism with a centralized and a decentralized mechanism. Section 5 introduces optimization models and algorithms used by different mechanisms. The experimental settings and results are provided in Section 6. Section 7 concludes and gives future research directions.

2. Literature review

In this section, the studies related to the coordinated synchromodal transport planning problem with dynamic requests and stochastic travel times have been divided into two categories: collaborative transport planning and dynamic and stochastic synchromodal transportation.

2.1. Collaborative transport planning

To use vehicles more efficiently and to avoid idle capacities, transport operators are tending to share their vehicles by collaboration (Gansterer et al., 2022). The studies in collaborative transport planning can be divided into two groups: horizontal coordination and vertical collaboration. While horizontal collaboration refers to the collaborative activities (e.g., request exchange and capacity sharing) among stakeholders acting at the same levels of transport chains (Los et al., 2022), vertical coordination is often organized by carriers that serve distinct tiers to achieve the synchronization of shipment flow at interconnecting areas (Cleophas et al., 2019).

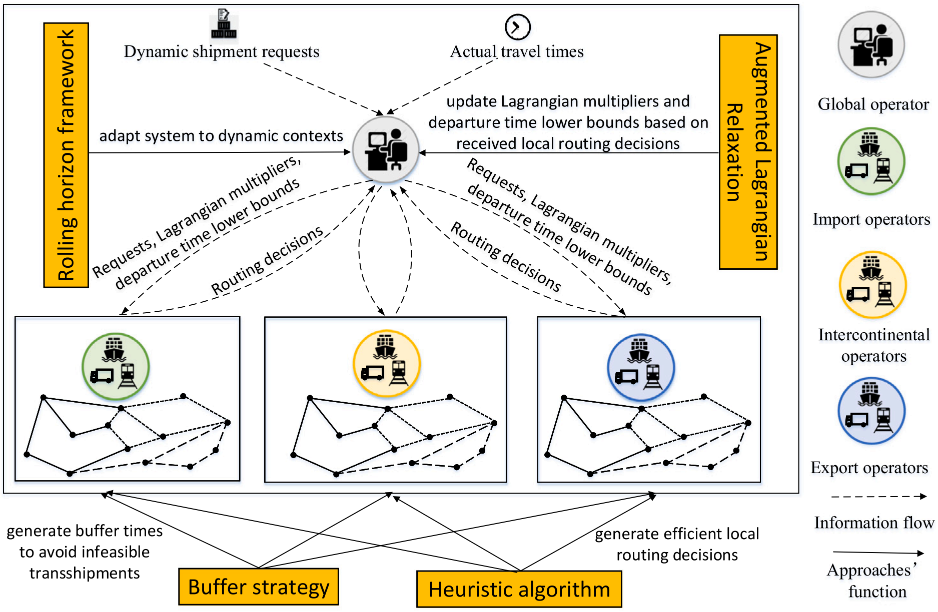

Fig. 3. Relationships between proposed approaches under the coordinated mechanism.

2.1.1. Horizontal collaboration

Current research in freight transport planning mainly focuses on horizontal collaboration among carriers in road transportation, including transportation with Full Truckload (FTL) or Less Than Truckload (LTL) (Zhang et al., 2022b). FTL collaboration mainly benefits from avoiding empty trips (Liu et al., 2010) and LTL collaboration mainly benefits from making better use of capacities (Dai and Chen, 2012; Wang and Kopfer, 2014). The methods used to achieve horizontal collaboration can be divided into three groups: centralized collaborative planning, decentralized planning without auctions, and auction-based decentralized planning (Gansterer and Hartl, 2018). If the central coordinator has full power on carriers, it is called centralized planning, otherwise called decentralized planning. Further divided by request exchanging types, decentralized planning can be non-auction or auction-based. Studies on horizontal collaboration in freight transportation are briefly reviewed below.

Berger and Bierwirth (2010) consider both decentralized and auction-based approaches for a collaborative traveling salesman problem. Dai and Chen (2011) propose an auction-based framework for a carrier collaboration problem in LTL transportation with pickup and delivery requests. Wang et al. (2014) study a collaborative pickup and delivery problem with time windows, taking into account both subcontracting and collaborative request exchanges, while Lai et al. (2017) propose an iterative auction mechanism with request exchanges to reduce empty miles. Karels et al. (2020) use limited and combinatorial reassignment auctions to facilitate horizontal collaborative planning in order to reach targeted efficiency levels. Los et al. (2020) solve a dynamic collaborative pickup and delivery problem using combinatorial auctions and evaluate nine different information sharing policies. Zhang et al. (2022c) investigate a multi-depot collaborative vehicle routing problem to select transfer points for product transshipment between vehicles from different depots, utilizing transshipment at customer locations and depots for collaboration. Zhang et al. (2022b) use the auction-based approach for horizontal collaborative planning in intermodal transport, considering collaboration among both unimodal and intermodal operators and comparing centralized, collaborative, and non-collaborative approaches using three large transport networks in the Rhine-Alpine corridor in Europe.

The coordinated mechanism proposed in this paper differs from above mechanisms in the way it handles horizontal collaboration. At each iteration, the global operator sends requests with Lagrangian multipliers to local operators either in the same level or different tiers of global transportation. These local operators then propose local routing decisions based on their own service schedules. For local operators serving the same level of global transportation, the global operator selects the most cost-effective local routes and combines them into global itineraries. This process continues until interconnecting constraints are consistently met.

2.1.2. Vertical coordination

Similar to horizontal collaboration, centralized or decentralized mechanisms could be adopted in vertical coordinated transport planning. Centralized mechanisms assume that full information is shared with a central coordinator (e.g., Arslan et al., 2019; Guo et al., 2021). Generally, these studies assume that there is a centralized platform that controls the plan of the whole transport system. In contrast, decentralized mechanisms relax that assumption and consider a coordinator that allows local operators to share limited information and keep their planning authority (e.g., Puettmann and Stadtler, 2010). Although not all information is shared, the coordinator can contribute to a solution by iteratively updating incentives (e.g., Dai et al., 2014; Li et al., 2017; Huang et al., 2021). Hence, the coordinator supports the collaboration but has no full control.

Compared to the literature in freight transport, there is a lack of research on coordinated planning for synchromodal transport (Gumuskaya et al., 2020). In the last decade, some scholars researched partner selection at the strategic level and cooperative game theory for profit/cost allocation at the tactical level (Lin et al., 2017; Saeed, 2013). Nevertheless, very few research efforts have been spent on coordinated planning among service operators in synchromodal transport at the operational level, and these studies are listed below.

Puettmann and Stadtler (2010) coordinate an intermodal operator and two carriers by iterative exchange of proposals. One carrier is responsible for the drayage in the shipper's region and the other in the region of the receiver. The proposals state the transshipment periods per request at terminals. The stochastic demand on the coordinated plans is also analyzed.

Febbraro et al. (2016) model the cooperation between actors in intermodal transport by a Lagrangian-based Network Communication Coordinator and consider the dynamics by using a Discrete Event System. The major differences between Febbraro et al. (2016) and our paper include: (a) our paper considers a global synchromodal transport network and coordinates the global operator with local operators of different networks in terms of time and space compatibility at interconnecting terminals, while Febbraro et al. (2016) investigate the cooperation between carriers and terminal operators in determining the departure times at terminals in an intermodal transport chain; (b) our paper uses the ALR-based heuristic approach to solve the optimization problem in a distributed way; (c) (Febbraro et al., 2016) neither consider travel time uncertainties nor re-optimize requests when infeasible transshipments happen.

Li et al. (2017) and Zhou et al. (2022) investigate a distributed model predictive container flow control problem among multiple hinterland operators in different but interconnected service areas. These operators coordinate to reach an agreement on the volumes of container flows that each operator will hand over to other operators. Different from the work of Li et al. (2017) and Zhou et al. (2022), our study investigates a global network that includes not only interconnected networks that have interconnected service areas but also overlapping networks that have overlaps in service areas, which makes the coordination mechanism more complicated. Besides, we focus on shipment requests that have specific time windows instead of container flows. Therefore, the interconnecting constraints include not only spatial compatibility but also time compatibility at transshipment terminals.

Larsen et al. (2020) propose a departure learning method to achieve the co-planning between barge and truck operators. In their study, a barge operator learns what departure times perform better based on indications from the truck operator. However, they assume only one barge and one truck company in a transport network with three terminals, making their model unable to fit more complex networks.

2.2. Dynamic and stochastic synchromodal transportation

The other group related to our research comprises studies that consider dynamic events and uncertainties in synchromodal transportation. The existence of dynamic events requires transport systems have the ability to adapt to dynamic contexts (Ferrucci and Bock, 2014). Transport uncertainties can increase risk and vulnerability (Gendreau et al., 2016). The ability to respond to dynamics and uncertainties has emerged as a vital capability in synchromodal transportation.

The recent developments in information technologies and data analytics have facilitated the utilization of dynamic and stochastic information in decision-making processes (Ritzinger et al., 2015). In the literature, the most considered dynamic event is the arrival of new shipment requests (Pillac et al., 2013; SteadieSeifi et al., 2014; Zhang et al., 2022a). Rolling horizon framework, as a periodic reoptimization approach, has been well applied in vehicle routing problems (Arslan et al., 2019; Yıldız, 2021) and synchromodal transport planning (Li et al., 2015; Guo et al., 2020). In practice, travel time uncertainties are quite common resulted from many situations, such as congestion on roads and disruptions at transshipment terminals (Meng et al., 2014; Febbraro et al., 2016). In synchromodal transportation, travel time uncertainties might cause delays (high frequency, low impact) and disruptions (low frequency, high impact) on the transport network. The planned routes by deterministic models may not be feasible anymore when disturbances happen. Moreover, infeasible solutions obtained by deterministic models may be feasible when travel times are considered stochastic (Long et al., 2018). This implies that the deterministic model may also miss effective solutions. In the literature, different methods have been developed to handle travel time uncertainties in synchromodal transportation. Qu et al. (2019) propose a mixed integer programming model to re-plan shipment routes and service schedules when uncertainties cause deviations from the original plan. Giusti et al. (2021a) propose a two-stage stochastic programming formulation with recourse for a transshipment location–allocation problem to consider uncertainties on facility capacity and handling operations utility. Giusti et al. (2021b) focus on dynamic speed adjustment procedures and use smart steaming to improve the sustainability of synchromodal transport. Akyüz et al. (2023) formulate a path-based multi-commodity network flow model to re-plan shipment flows caused by delays and cancellations of scheduled services. Demir et al. (2016) develop a sample average approximation method to generate robust transport plans and define a delay cost for late delivery in the objective function without the consideration of reoptimization after disturbances. Guo et al. (2021) develop a chance-constrained programming (CCP) model to ensure a certain level of feasible transshipments at terminals, and shipments are rerouted under a rolling horizon framework when disturbances happen. Guo et al. (2022a) develop a reinforcement learning approach to learn the value of matching a shipment with a service through simulations. Shipment routes are updated instantly when infeasible transshipments happen based on evaluated value functions.

Our work is most similar to that of Guo et al. (2021) in the literature. However, the approaches proposed by Guo et al. (2021) are limited to centralized settings that are hard to be implemented in practice because transport operators in global networks are distributed geographically and do not want to relinquish control to a central operator. This paper extends the work of Guo et al. (2021) by adapting dynamic and stochastic approaches to a coordinated planning setting, with multiple operators making mode and route decisions within their own local networks rather than a single decision-maker determining the acceptance and routing

Table 1
The formulation characteristics and methodologies in related literature.

Articles	Formulation characteristics						Methodologies			
	Network	Decisions	Objectives	Decentralized decision making[a]	Dynamic events	Uncertainties	Dynamic approach[b]	Stochastic approach[c]	Coordinated approach[d]	Optimization algorithm[e]
Horizontal collaboration in freight transportation										
Berger and Bierwirth (2010)	Road	Vehicle routing	Maximize profits	HC	–	–	–	–	ABA	HA
Dai and Chen (2011)	Road	Vehicle routing	Maximize profits	HC	Shipment request	–	ETS	–	ABA	HA
Wang et al. (2014)	Road	Vehicle routing	Minimizing costs	HC	–	–	–	–	EPI	HA
Lai et al. (2017)	Road	Vehicle routing	Maximize profits	HC	–	–	–	–	ABA	HA
Karels et al. (2020)	Road	Vehicle routing	Minimize costs	HC	–	–	–	–	ABA	HA
Los et al. (2020)	Road	Vehicle routing	Maximizing profits	HC	Shipment request	–	DF	–	ABA	HA
Zhang et al. (2022c)	Road	Vehicle routing	Minimize costs	HC	–	–	–	–	BBC	HA
Zhang et al. (2022b)	Inland	Vehicle routing	Minimize costs	HC	–	–	–	–	ABA	HA
Vertical coordination in synchromodal transportation										
Puettmann and Stadtler (2010)	Inland	Container flow	Minimize costs	VC	–	Container volume	–	ST	EPI	HA
Febbraro et al. (2016)	Inland	Shipments' departure time	Minimize costs	VC	Delivery time	–	RHF	–	LR	MILP solver
Li et al. (2017)	Inland	Container flow	Minimize costs	VC	Container flow, travel time	–	MPC	–	ALR, ADMM	–
Larsen et al. (2020)	Inland	Container flow	Minimize costs	VC	Container flow	–	MPC	–	DL	MILP solver
Zhou et al. (2022)	Inland	Container flow	Minimize costs	VC	Container flow	–	MPC	-	ADMM	–
Dynamic and stochastic synchromodal transport planning										
Qu et al. (2019)	Inland	Service schedule, shipment routing	Minimize costs	–	Release time, container volume, travel time	–	RPP	–	–	MILP solver
Guo et al. (2020)	Inland	Shipment routing	Minimize costs	–	Shipment request	–	RHF	–	–	HA
Akyüz et al. (2023)	Inland	Shipment flow	Minimize costs	–	Service delays and cancellations	–	RPP	–	–	CG
Demir et al. (2016)	Inland	Service schedule and shipment routing	Minimize costs	–	–	Container volume, travel time	–	SAA	–	MILP solver
Giusti et al. (2021a)	General	Hub location, freight flow	Maximize net transportation utility	–	–	General uncertainties	–	SAA	–	PHA
van Riessen et al. (2016)	Inland	Container routing	Minimize costs	–	Container flow	Container volume	FCFS	DT	–	MILP solver
Rivera and Mes (2017)	Inland	Assignment of freights to modes	Minimize costs	–	Shipment request	Shipment request	RP	VFA	–	MILP solver
Guo et al. (2021)	Global	Acceptance of bookings and shipment routing	Maximize profits	–	Shipment request, travel time	Shipment request, travel time	RHF	SAA, CCP	–	HA
Guo et al. (2022a)	Global	Acceptance of bookings and shipment routing	Maximize profits	–	travel time	Travel time	RHF	RL	–	–
This paper	Global	Acceptance of bookings and shipment routing	Maximize profits	HC, VC	Shipment request, travel time	Travel time	RHF	BS	ALR	HA

[a] HC: Horizontal collaboration; VC: Vertical collaboration.

[b] ETS: Event-triggered system; DF: Dynamic framework; RHF: Rolling horizon framework; MPC: Mode predictive control; RPP: Re-planning procedure; FCFS: First-come-first-serve; RP: Rollout procedures.

[c] ST: Scenario tree; SAA: Sample average approximation method; DT: Decision trees; VFA: Value function approximation; CCP: Chance-constrained programming; RL: Reinforcement Learning; BS: Buffer Strategy.

[d] ABA: Auction-based approach; EPI: Exchanging proposals iteratively; BBC: Benders-based branch-and-cut framework; LR: Lagrangian relaxation; ALR: augmented Lagrangian relaxation; ADMM: alternating direction method of multipliers; DL: Departure time learning.

[e] HA: Heuristic algorithm; MILP: Mixed integer linear programming; CG: Column generation; PHA: Progressive hedging-based heuristic algorithm.

for all shipments. A coordinated mechanism and an augmented Lagrangian relaxation-based heuristic approach are designed to support coordinated planning. Moreover, we design a rolling horizon framework to update system states and re-plan requests facing infeasible transshipments, and a buffer strategy to address travel time uncertainty. The advantage of the buffer strategy is that it can be applied to coordinated settings without requiring travel time information from other operators. Additionally, the buffer strategy can be applied to any probability distribution, while the CCP model proposed in Guo et al. (2021) is only applicable to normal distributions.

2.3. Summary

Table 1 summarizes the formulation characteristics and methodologies in related literature. All the coordinated studies are conducted under road or inland networks, and none of these studies consider dynamic requests and stochastic travel times simultaneously, except for the work of Guo et al. (2021). In studies on collaborative vehicle problems, they usually only consider horizontal collaboration and do not take uncertainties into account. Most of the sychromodality studies take either dynamic events or/and uncertainties into account but under a centralized environment. While most of the studies investigate shipment routing from an operations management perspective, this paper takes into account the acceptance of shipment requests and designs the objective to maximize total profits that consist of revenues received from shippers, transport costs paid to local operators, and delay costs paid to shippers.

The contributions of this paper are summarized as follows: (i) we introduce a coordinated mechanism for global synchromodal transport planning with multiple operators; (ii) we develop an augmented Lagrangian relaxation-based heuristic approach considering characteristics of global synchromodal transport to support efficient coordination among local operators under the coordinated

Table 2
Notation.

Sets:	
K	set of local operators indexed by k
$K^{\exp}/K^{\text{int}}/K^{\text{imp}}$	set of operators in the export hinterland/intercontinental/import hinterland area
N	set of terminals indexed by i, $N = N^1 \cup \cdots \cup N^k \cup \cdots \cup N^K$
N^k	set of terminals of operator $k \in K$, $N^k \subset N$
$N^{\exp}/N^{\text{imp}}$	set of export /import terminals, $N^{\exp} \subset N$, $N^{\text{imp}} \subset N$, $N^{\exp} \cap N^{\text{imp}} = \emptyset$
S	services indexed by s, $S = S^{\text{ship}} \cup S^{\text{barge}} \cup S^{\text{train}} \cup S^{\text{truck}}$
S^k	services offered by operator $k \in K$
S_i^{k-}/S_i^{k+}	the set of services of operator k arriving at/departing from terminal i
R	shipment requests indexed by r, $R = R^0 \cup R^1 ... \cup R^T$
R^t	requests received during time interval $(t-1,t], t > 0$
$\bar{R}^t$	accepted requests that require reoptimization at decision epoch t due to infeasible transshipments, $t > 0$
P	set of feasible paths indexed by p
P^k	set of feasible paths in local network of operator $k \in K$
Φ_r^k	set of feasible paths within network $k \in K$ for request r
Parameters:	
T	length of the planning horizon
o_s	origin terminal of service $s \in S, o_s \in N$
d_s	destination terminal of service $s \in S, d_s \in N$
U_s^t	free capacity of service $s \in S$ at time $t \in \{0, 1, \dots, T\}$
D_s	Scheduled departure time of service $s \in S \backslash S^{\text{truck}}$ before loading operation
A_s	Scheduled arrival time of service $s \in S \backslash S^{\text{truck}}$ after unloading operation
t_s	scheduled travel time of service $s \in S$
μ_s	mean of the travel time of service $s \in S$
σ_s	standard deviation of the travel time of service $s \in S$
c_s	travel cost of service $s \in S$ per container
o_r	origin terminal of request $r \in R$, $o_r \in N$
d_r	destination terminal of request $r \in R, d_r \in N$
u_r	container volume of request $r \in R$
$\mathbb{T}_r^{\text{announce}}$	announce time of request $r \in R$
$\mathbb{T}_r^{\text{release}}$	release time of request $r \in R$
$\mathbb{T}_r^{\text{due}}$	due time of request $r \in R$
LD_r	lead time of request $r \in R$, $LD_r = \mathbb{T}_r^{\text{due}} - \mathbb{T}_r^{\text{release}}$
p_r	freight rate of request $r \in R$
c_r^{delay}	delay cost of request $r \in R$ per container per hour overdue
α	confidence level
θ	buffer parameter
M	a large number used for binary constraints
$N^{\text{iteration}}$	maximum number of iteration and the iteration is indexed by n
λ	Lagrangian multiplier
ρ	step size
b	a parameter control the changes of departure/arrival times at different iterations
$\zeta 1, \zeta 2$	parameters control step size iteration
lb_{ri}^+	departure time lower bound at terminal i for request r
N_{ri}^{Inf}	the number of infeasible transshipments at terminal $i \in N^{\exp} \cup N^{\text{imp}} \backslash \{o_r, d_r\}$
c_{rp}^k	the objective value of path $p \in \phi_r^k$ with network k for request r
Variables:	
y_r^t	binary variable; 1 if request $r \in R^t$ is accepted at decision epoch t
x_{rs}^t	binary variable; 1 if request $r \in R^t \cup \bar{R}^t$ is matched with service $s \in S$ at decision epoch t, 0 otherwise
z_{rp}^t	binary variable; 1 if request $r \in R^t \cup \bar{R}^t$ is matched with path $p \in P$, 0 otherwise
$\mathbb{T}_r^k$	delay of request r at its destination terminal d_r served by operator k
D_{rs}	departure time of truck service $s \in S^{\text{truck}}$ with request $r \in R^t \cup \bar{R}^t$
t_{ri}^{--}	arrival time of request r at export or import terminal $i \in N^{\exp} \cup N^{\text{imp}} \backslash \{o_r, d_r\}$
t_{ri}^+	departure time of request r at export or import terminal $i \in N^{\exp} \cup N^{\text{imp}} \backslash \{o_r, d_r\}$

mechanism; (iii) we design a rolling horizon framework and a buffer strategy to address dynamic shipment requests and stochastic travel times in a coordinated context, respectively; (iv) we evaluate the performance of the proposed approaches under a real network between Asia and Europe; (v) we demonstrate that with the proposed approaches, global container transportation can be more efficient, reliable, and flexible under distributed, dynamic, and stochastic scenarios.

3. Problem description

In this paper, we introduce a coordinated global synchromodal transport planning problem with multiple operators in which container shipments need to be transported from inland terminals of one continent to inland terminals of another continent, such as from Wuhan (in Asia) to Duisburg (in Europe). Each container will be transported from its origin terminal to an export terminal (i.e., export hinterland transportation), then from the export terminal to an import terminal (i.e., intercontinental transportation),

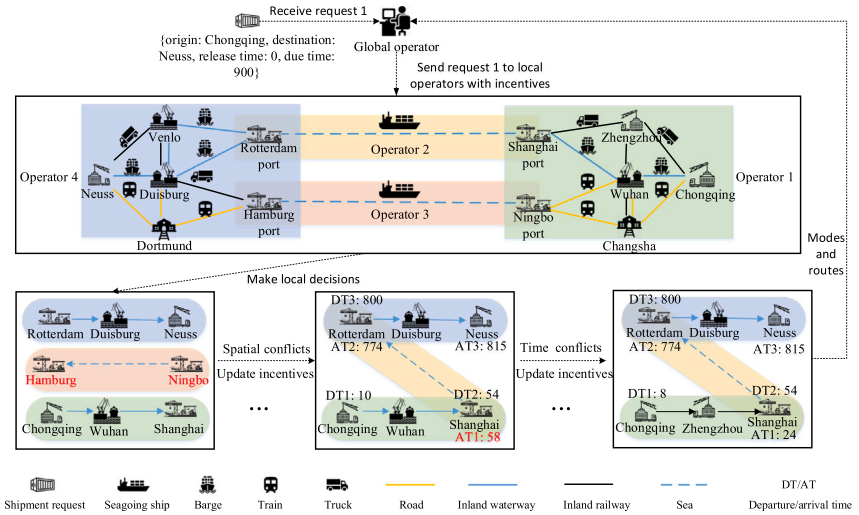

Fig. 4. An illustrative example of coordinated global synchromodal transport planning.

and finally from the import terminal to the destination terminal (i.e., import hinterland transportation). Let $K = K^{\text{exp}} \cup K^{\text{int}} \cup K^{\text{imp}}$ be the set of local operators, K^{exp} represents the set of operators in the export hinterland area, K^{int} represents the operators in the intercontinental area, and K^{imp} represents the operators in the import hinterland area. Let N be the set of terminals, and let N^k be the set of terminals of operator $k \in K$; let N^{exp} be the set of export terminals in the export continent; let N^{imp} be the set of import terminals in the import hinterland. We make a common assumption that the loading/unloading and storage capacity at terminals are unlimited (Demir et al., 2016). The notations used in this study are provided in Table 2.

Let S be the set of transport services, S^k is the set of services offered by operator $k \in K$. Each service $s \in S^k$ is characterized by its origin terminal o_s, destination terminal d_s, free capacity U_s^t at time t, scheduled departure time D_s, scheduled arrival time A_s, estimated travel time t_s, and travel cost c_s. Let $\tilde{t}_s$, $\tilde{D}_s$ and $\tilde{A}_s$ be the actual travel, departure and arrival time of service s which are unknown before their realization. We consider each truck service as a fleet of trucks that have flexible departure times. We define D_{rs} as the variable that indicates the departure time of service $s \in S^{\text{truck}}$ with shipment $r \in R$. Thanks to the collection of historical data, the probability distributions of uncertain travel times are assumed available. We use μ_s and σ_s to denote the mean and standard deviation of travel times $\left[\tilde{t}_s\right]_{\forall s \in S}$.

Let R be the set of shipment requests. Each request $r \in R$ is characterized by its origin terminal $o_r \in N$, destination terminal $d_r \in N$, container volume u_r, announce time $\mathbb{T}_r^{\text{announce}}$ (i.e., the time when global operator receives the request), release time $\mathbb{T}_r^{\text{release}}$ (i.e., the time when the shipment is available for transport process), and fare class including freight rate p_r, lead time LD_r, and delay cost c_r^{delay}. The due time of request r is represented as $\mathbb{T}_r^{\text{due}} = \mathbb{T}_r^{\text{release}} + LD_r$. Shipment requests arrive dynamically in the system, and the information about these requests is unknown until they are announced. When a request is announced, it is important for the global operator to respond quickly. Let $R^t = \{r \in R | t-1 < \mathbb{T}_r^{\text{announce}} \le t\}$ be the set of new requests received during time period $(t-1, t]$; let $\bar{R}^t$ be the set of accepted requests that need reoptimization at decision epoch t due to infeasible transshipments caused by travel time variations.

While the objective of the global operator is to maximize revenues by accepting requests at each decision epoch, the objectives of local operators are to minimize local costs for transporting shipments. The coordinated common goal is to maximize the total profits that include revenues and costs. Fig. 4 shows an illustrative example of coordinated global synchromodal transport planning. The system consists of four local operators, including one in each continent and two in the intercontinental area. The global operator receives request 1 that needs to be transported from Chongqing after time 0 to Neuss before time 900, and sends the request to local operators with initial incentives. Local operators make local decisions under local service networks. Since barge transportation is the cheapest, operators 1 and 4 select barges for hinterland transportation. Sea route from Ningbo to Hamburg is selected in the intercontinental area which is designed cheaper than from Shanghai to Rotterdam. To handle spatial conflicts at transshipment terminals, incentives need to be updated until finding a solution that follows spatial compatibility. Besides, the arrival time of the previous service must be earlier than the departure time of the succeeding service at transshipment terminals. When time conflicts happen, the global operator needs to further update incentives until finding a feasible solution. However, a feasible solution might not be the best solution. The main challenge of the problem is how to design incentives to coordinate local operators to select the modes and routes on local networks that can achieve a global optimum.

Once a coordinated transport plan is created, it is implemented in a dynamic and stochastic environment. An example of this process is illustrated in Fig. 5, which shows a system with four operators: a global operator responsible for deciding which shipments to accept, and three local operators responsible for making mode and route choices within their local areas. At t_0, the system receives shipment request 1, and plans to transport it using a truck in hinterland area 1, a seagoing ship 1 in the intercontinental area, and a barge in hinterland area 2. However, at t_1, the transshipment from the truck to ship 1 at the export port becomes infeasible due to

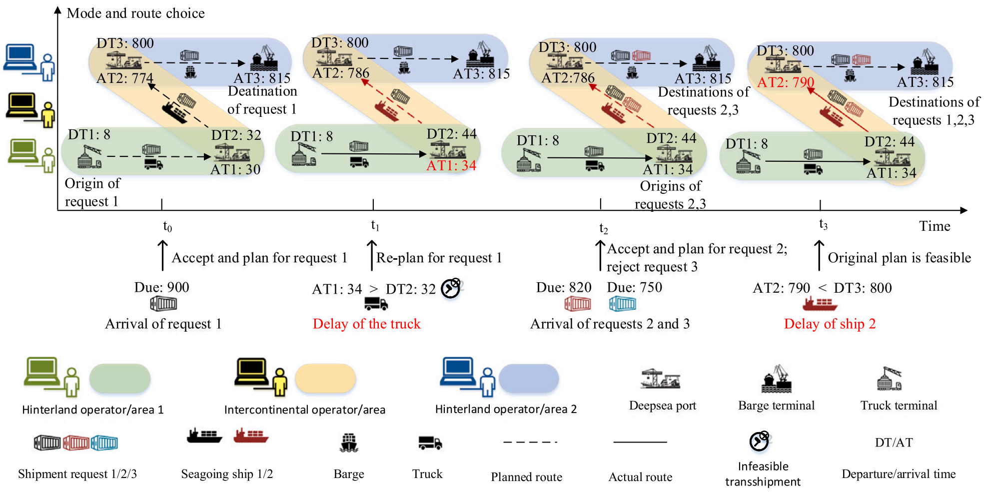

Fig. 5. Coordinated global synchromodal transport planning with dynamic requests and travel time uncertainties.

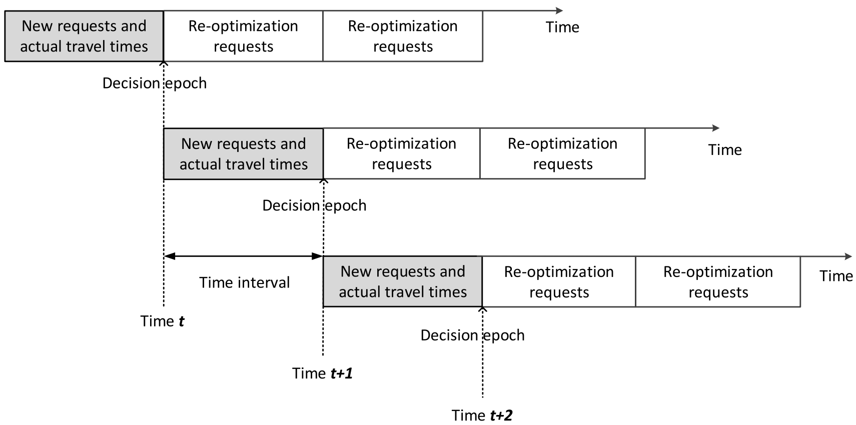

Fig. 6. Rolling horizon framework for global synchromodal transport planning.

the delay of the truck transportation in area 1. As a result, ship 2 is planned to replace ship 1 for the remainder of the journey. At t_2, two new shipment requests (2 and 3) are received. Requests 2 and 3 can be transported together with request 1 using ship 2 and a barge from the export port to the destination terminal. However, request 3 needs to be delivered before time 750, and accepting it would result in a high delay penalty. Therefore, the global operator decides to reject request 3, as it is not profitable. Even though ship 2 arrives slightly later at transshipment terminal at time 790 due to travel time uncertainty, the transshipment to the barge is still feasible, and the global operator decides to maintain the original plan. This gives rise to another challenge of the problem which is how to design dynamic and stochastic approaches that can reduce request rejections, infeasible transshipments, and delay in deliveries in a coordinated manner.

In this paper, we employ a rolling horizon framework to handle dynamic events in global synchromodal transportation, including the arrival of new shipment requests and the actual travel times of transport services, as shown in Fig. 6. Decisions are made at a given set of time points $\{0, 1, \ldots, T\}$, T is the length of the planning horizon. At any time t, the global operator updates the set of new requests received during time period $(t-1, t]$. Due to travel time uncertainty, the global operator also needs to update the set of requests to be re-optimized caused by infeasible transshipments at transshipment terminals. The pseudocode of the rolling horizon framework is presented in Appendix.

Chance constrained programming model (CCP) is a commonly used method to address travel time uncertainties (Guo et al., 2021). However, in this paper, we cannot use the CCP to deal with travel time uncertainties. Under CCP, each stochastic constraint will hold at least with probability α, which is the confidence level regarding the probability of feasible transshipments. However, in decentralized settings, stochastic constraints that link different operators cannot be solved integrally. Inspired by Guo et al. (2021), we design a buffer parameter θ to deal with travel time uncertainties, which uses the scheduled arrival time of a service plus a buffer time ($\theta\sigma_s$) to represent the estimated arrival time. Compared with CCP which is restricted to normal distributions, the buffer strategy can be applied to any distribution.

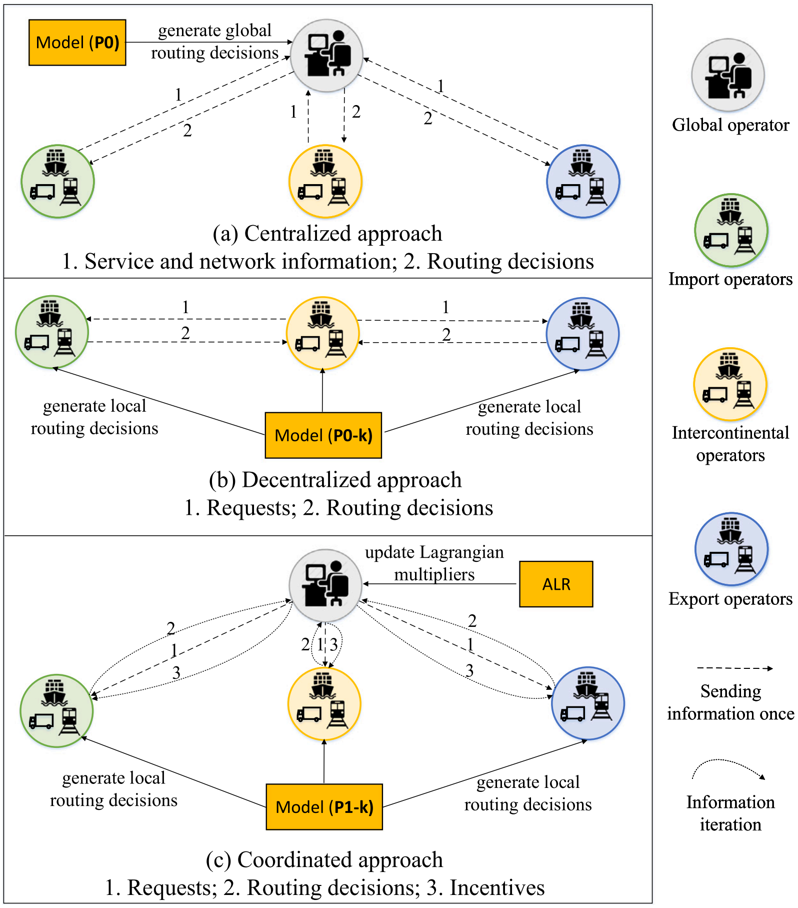

Fig. 7. Comparison among centralized, decentralized, and coordinated mechanisms.

4. Coordination mechanisms

In this paper, we evaluate the performance of the proposed coordinated mechanism (CoM) in comparison to the centralized mechanism (CeM) proposed in Guo et al. (2021) and a decentralized mechanism (DeM) used in current practice. While CoM and DeM are implemented in a decentralized environment, CeM can only be implemented in a centralized environment in which one decision-maker gets access to all information and decision authority. Therefore, CeM represents an ideal benchmark that is not feasible in practice. Fig. 7 shows the comparison of these mechanisms in global synchromodal transportation. The characteristics of each mechanism are illustrated below.

1. In CeM, a global operator collects services and transport network information from local operators and makes routing decisions integrally by solving the integrated model **P0** presented in Section 5.1. Local operators are assumed to give full authority to a global operator.
2. In DeM, first, the intercontinental operators decide intercontinental routes for each request received from shippers based on model **P0-k**, $k \in K^{\text{int}}$ presented in Section 5.2. Then, the intercontinental operators send requests to the export and import hinterland operators with selected export and import terminals. Hinterland operators send local routing decisions back to the intercontinental operator by solving model **P0-k**, $k \in K^{\text{exp}} \cup K^{\text{imp}}$.
3. In CoM, the local operators collaborate with the global operator by sharing routing information but making decisions by themselves via model **P1-k** presented in Section 5.3. The global operator plays a role in aligning the schedules of local operators by iteratively sending them incentives generated by the ALR approach presented in Section 5.3.

5. Optimization models and algorithms

In this section, we first present the optimization models used under the centralized and decentralized mechanisms. Then, we present the optimization models and algorithms for the coordinated mechanism.

5.1. Centralized optimization model

Let y_r^t be the binary variable which equals to 1 if new request $r \in R^t$ is accepted at decision epoch t, 0 otherwise. Let x_{rs}^t be the binary variable which is 1 if request $r \in R^t \cup \bar{R}^t$ is assigned to service $s \in S$. Let $\mathbb{T}_r^k$ be the delay of request r at its destination terminal d_r served by operator k. With this setting, delay for delivery of shipments is allowed but with a penalty. Let t_{ri}^-/t_{ri}^+ be the arrival/departure time of request r at terminal $i \in N^{\exp} \cup N^{\mathrm{imp}} \backslash \{o_r, d_r\}$. We denote S_i^{k-}/S_i^{k+} as the set of services of operator k arriving at/departing from terminal i. The coordinated common goal is to maximize total profits which consist of revenues received from shippers, transport costs paid to carriers, and delay costs paid to shippers. The formulation of centralized global synchromodal transport planning at decision epoch t is presented as follows:

$$(\mathbf{P0})\quad Z0 = \max_{y^t, x^t} \sum_{r \in R^t} p_r u_r y_r^t - \sum_{k \in K} \left(\sum_{r \in R^t \cup \bar{R}^t} \sum_{s \in S^k} c_s x_{rs}^t u_r + \sum_{r \in R^t \cup \bar{R}^t} c_r^{\mathrm{delay}} \mathbb{T}_r^k u_r \right) \tag{1}$$

subject to

Local constraints of operator k.

$$\sum_{s \in S_i^{k-}} x_{rs}^t \le 1, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \backslash \{o_r\}, \tag{2}$$

$$\sum_{s \in S_i^{k+}} x_{rs}^t \le 1, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \backslash \{d_r\}, \tag{3}$$

$$\sum_{s \in S_{o_r}^{k-}} x_{rs}^t \le 0, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, \tag{4}$$

$$\sum_{s \in S_{d_r}^{k+}} x_{rs}^t \le 0, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, \tag{5}$$

$$\sum_{s \in S_i^{k+}} x_{rs}^t = \sum_{s \in S_i^{k-}} x_{rs}^t, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \backslash \{\{o_r\}, \{d_r\}, N^{\exp}, N^{\mathrm{imp}}\}, \tag{6}$$

$$\sum_{r \in R^t \cup \bar{R}^t} x_{rs}^t u_r \le U_s^t, \quad \forall k \in K, s \in S^k, \tag{7}$$

$$\mathbb{T}_r^{\mathrm{release}} \le D_s + \mathbf{M}(1 - x_{rs}^t),\ \forall r \in R^t \cup \bar{R}^t, k \in K, s \in S_{o_r}^{k+} \backslash S_{o_r}^{k+\mathrm{truck}}, \tag{8}$$

$$\mathbb{T}_r^{\mathrm{release}} \le D_{rs} + \mathbf{M}(1 - x_{rs}^t), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, s \in S_{o_r}^{k+\mathrm{truck}}, \tag{9}$$

$$A_s + \theta\sigma_s \le D_q + \mathbf{M}(1 - x_{rs}^t) + \mathbf{M}(1 - x_{rq}^t), \quad \forall r \in R^t \cup \bar{R}^t, i \in N^k \backslash \{o_r, d_r\}, \\ s \in S_i^{k-} \backslash S_i^{k-\mathrm{truck}}, q \in S_i^{k+} \backslash S_i^{k+\mathrm{truck}}, \tag{10}$$

$$D_{rs} + t_s + \theta\sigma_s \le D_q + \mathbf{M}(1 - x_{rs}^t) + \mathbf{M}(1 - x_{rq}^t), \quad \forall r \in R^t \cup \bar{R}^t, \\ i \in N^k \backslash \{o_r, d_r\}, s \in S_i^{k-\mathrm{truck}}, q \in S_i^{k+} \backslash S_i^{k+\mathrm{truck}}, \tag{11}$$

$$A_s + \theta\sigma_s \le D_{rq} + \mathbf{M}(1 - x_{rs}^t) + \mathbf{M}(1 - x_{rq}^t), \quad \forall r \in R^t \cup \bar{R}^t, i \in N^k \backslash \{o_r, d_r\}, \\ s \in S_i^{k-} \backslash S_i^{k-\mathrm{truck}}, q \in S_i^{k+\mathrm{truck}}, \tag{12}$$

$$D_{rs} + t_s + \theta\sigma_s \le D_{rq} + \mathbf{M}(1 - x_{rs}^t) + \mathbf{M}(1 - x_{rq}^t), \quad \forall r \in R^t \cup \bar{R}^t, \\ i \in N^k \backslash \{o_r, d_r\}, s \in S_i^{k-\mathrm{truck}}, q \in S_i^{k+\mathrm{truck}}, \tag{13}$$

$$\mathbb{T}_r^k \ge A_s + \theta\sigma_s - \mathbb{T}_r^{\mathrm{due}} + \mathbf{M}(x_{rs}^t - 1), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, s \in S_{d_r}^{k-} \backslash S_{d_r}^{k-\mathrm{truck}}, \tag{14}$$

$$\mathbb{T}_r^k \ge D_{rs} + t_s + \theta\sigma_s - \mathbb{T}_r^{\mathrm{due}} + \mathbf{M}(x_{rs}^t - 1), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, s \in S_{d_r}^{k-\mathrm{truck}}, \tag{15}$$

$$t_{ri}^- \ge A_s + \theta\sigma_s + \mathbf{M}(x_{rs}^t - 1), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \cap \{N^{\exp} \cup N^{\mathrm{imp}}\} \backslash \{o_r, d_r\}, \\ s \in S_i^{k-} \backslash S_i^{k-\mathrm{truck}}, \tag{16}$$

$$t_{ri}^- \ge D_{rs} + t_s + \theta\sigma_s + \mathbf{M}(x_{rs}^t - 1), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \cap \{N^{\exp} \cup N^{\mathrm{imp}}\} \backslash \{o_r, d_r\}, \\ s \in S_i^{k-\mathrm{truck}}, \tag{17}$$

$$t_{ri}^+ \le D_q + \mathbf{M}(1 - x_{rq}^t),\ \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \cap \{N^{\exp} \cup N^{\mathrm{imp}}\} \backslash \{o_r, d_r\}, q \in S_i^{k+} \backslash S_i^{k+\mathrm{truck}}, \tag{18}$$

$$t_{ti}^+ \le D_{rq} + \mathbf{M}(1 - x_{rq}^t), \quad \forall r \in R^t \cup \bar{R}^t, k \in K, i \in N^k \cap \{N^{\exp} \cup N^{\mathrm{imp}}\} \backslash \{o_r, d_r\}, q \in S_i^{k+\mathrm{truck}}, \tag{19}$$

$$y_r^t, x_{rs}^t \in \{0, 1\}, \quad \forall r \in R^t \cup \bar{R}^t, k \in K, s \in S^k. \tag{20}$$

Constraints (2)–(5) eliminate subtours. Constraints (6) ensure flow conservation at transshipment terminals under local networks. Constraints (7) represent capacity limitations of transport services. Constraints (8)–(9) ensure that the release time of request r will be earlier than the departure time of service s if it is selected to transport request r departing from its origin. Constraints (10)–(13)

ensure that the scheduled arrival time of service s plus buffer time should be earlier than the scheduled departure time of service q if shipment r is transferred between s and q at terminal i. Constraints (14)–(15) calculate the estimated delay in deliveries of request r at its destination terminal. Constraints (16)–(17) calculate the estimated arrival time of request r at transshipment terminals. Constraints (18)–(19) calculate the departure time of request r at transshipment terminals. Constraints (20) indicate binary variables.

Interconnecting constraints among operators.

$$y_r^t \le \sum_{k\in K} \sum_{s\in S_{o_r}^{k+}} x_{rs}^t, \quad \forall r \in R^t, \tag{21}$$

$$y_r^t \le \sum_{k\in K} \sum_{s\in S_{d_r}^{k-}} x_{rs}^t, \quad \forall r \in R^t, \tag{22}$$

$$\sum_{k\in K} \sum_{s\in S_{o_r}^{k+}} x_{rs}^t \le 1, \quad \forall r \in R^t, \tag{23}$$

$$\sum_{k\in K} \sum_{s\in S_{d_r}^{k-}} x_{rs}^t \le 1, \quad \forall r \in R^t, \tag{24}$$

$$\sum_{k\in K} \sum_{s\in S_{o_r}^{k+}} x_{rs}^t = 1, \quad \forall r \in \bar{R}^t, \tag{25}$$

$$\sum_{k\in K} \sum_{s\in S_{d_r}^{k-}} x_{rs}^t = 1, \quad \forall r \in \bar{R}^t, \tag{26}$$

$$\sum_{k\in K^{\text{exp}}} \sum_{s\in S_i^{k-}} x_{rs}^t = \sum_{k\in K^{\text{int}}} \sum_{s\in S_i^{k+}} x_{rs}^t, \quad \forall r \in R^t \cup \bar{R}^t, i \in N^{\text{exp}} \backslash \{o_r, d_r\}, \tag{27}$$

$$\sum_{k\in K^{\text{int}}} \sum_{s\in S_i^{k-}} x_{rs}^t = \sum_{k\in K^{\text{imp}}} \sum_{s\in S_i^{k+}} x_{rs}^t, \quad \forall r \in R^t \cup \bar{R}^t, i \in N^{\text{imp}} \backslash \{o_r, d_r\}, \tag{28}$$

$$t_{ri}^- \le t_{ri}^+, \quad \forall r \in R^t \cup \bar{R}^t, i \in N^{\text{exp}} \cup N^{\text{imp}} \backslash \{o_r, d_r\}. \tag{29}$$

Constraints (21)–(22) link the acceptance decisions of the global operator with the routing decisions of local operators, to ensure that new request $r \in R^t$ will be transported by services departing from its origin terminal o_r and arriving to its destination terminal d_r if the request is accepted. Constraints (23)–(29) connect the routing decisions of local operators. Constraints (23)–(24) ensure that at most one service transports new request $r \in R^t$ departing from its origin or arriving to its destination. Constraints (25)–(26) ensure that requests to be re-optimized $r \in \bar{R}^t$ will be transported by one service departing from its current position o_r and by one service arriving to its destination d_r. Constraints (27) ensure flow conservation at export terminals N^{exp} for request $r \in R^t \cup \bar{R}^t$. Constraints (28) ensure flow conservation at import terminals N^{imp} for request $r \in R^t \cup \bar{R}^t$. Constraints (29) connect the time decisions of local operators to ensure the arrival time at export and import terminals will be earlier than the departure time for each request $r \in R^t \cup \bar{R}^t$.

5.2. Decentralized optimization model

In decentralized settings, shipment routing decisions are made by local operators independently with local information, model **P0** thus cannot be solved directly. Local operators make local routing decisions based on the decentralized optimization model shown in the following:

$$(\mathbf{P0-k}) \quad \min_{x^t} \sum_{r\in R^t\cup\bar{R}^t} \sum_{s\in S^k} c_s x_{rs}^t u_r + \sum_{r\in R^t\cup\bar{R}^t} c_r^{\text{delay}} \mathbb{T}_r^k u_r \tag{30}$$

subject to constraints (2)–(20) for operator $k \in K$.

Due to the computational complexity, the centralized and decentralized optimization models under dynamic and stochastic scenarios are solved via the heuristic algorithm published in Guo et al. (2021).

5.3. Coordinated optimization model

In this section, we develop an ALR-based heuristic approach to solve the optimization problem in a coordinated way. The main idea of the ALR is to relax interconnecting constraints by bringing them into the objective function $Z0$ with associated *Lagrangian multipliers* (Guo, 2020), as shown in Fig. 8. In this way, the original problem can be decomposed into subproblems that relate to each operator. At each iteration, the global operator creates acceptance decisions based on the relaxed model and receives routing decisions from the local operators. If the interconnecting constraints cannot be met, the Lagrangian multipliers will be updated. The process will be repeated until a consistency on interconnecting constraints is reached. We employ Lagrangian multipliers as the primary mechanism for setting incentives. By manipulating these multipliers, we effectively incentivize local operators to adapt their routing and scheduling operations in a manner that aligns with the overall global objective. This approach fosters collaboration among all local operators, contributing to the achievement of the desired synchromodal transport planning outcomes.

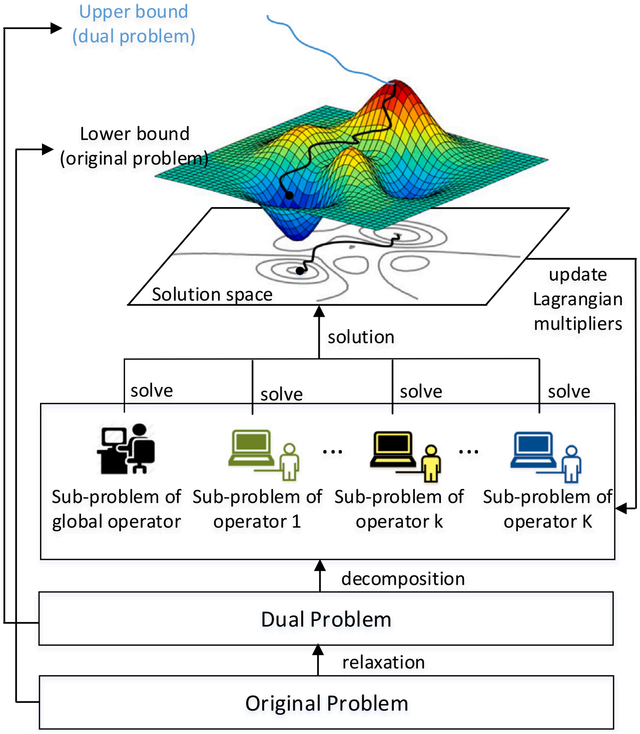

Fig. 8. ALR for coordinated global synchromodal transport planning.

5.3.1. Augmented Lagrangian relaxation

In this section, we develop the ALR approach to deal with interconnecting constraints (21)–(29). The ALR approach relaxes the interconnecting constraints by adding a linear penalty term to the objective function $Z0$ using a Lagrange multiplier. Specifically, we introduce Lagrangian multipliers $\lambda 1_r$, $\lambda 2_r$, $\lambda 3_r$, $\lambda 4_r$, $\lambda 5_{ri}$, $\lambda 6_{ri}$, $\lambda 7_{ri}$ to dualize interconnecting constraints (21), (22), ((23) and (25)), ((24) and (26)), (27), (28), (29), respectively. The global operator guides local operators to make 'right' decisions by sending Lagrangian multipliers, and updates their values based on routing decisions received from local operators. Since t^-_{ri} and t^+_{ri} are continuous variables, time constraints (29) are harder to converge than spatial constraints (21)–(28) which consist of binary variables. To improve the solution quality, an additional quadratic term to mimic a Lagrangian multiplier is added for time constraints (29). The formulation of the relaxed model is presented as follows:

$$
\begin{aligned}
(\mathbf{P1})\ Z1 = \max_{y^t,x^t} & \sum_{r\in R^t} p_r u_r y^t_r - \sum_{k\in K}\left(\sum_{r\in R^t\cup\bar{R}^t}\sum_{s\in S^k} c_s x^t_{rs} u_r + \sum_{r\in R^t\cup\bar{R}^t} c^{\text{delay}}_r \mathbb{T}^k_r u_r\right) \\
& + \sum_{r\in R^t} \lambda 1_r \Big(\sum_{k\in K}\sum_{s\in S^{k+}_{o_r}} x^t_{rs} - y^t_r\Big) + \sum_{r\in R^t} \lambda 2_r \Big(\sum_{k\in K}\sum_{s\in S^{k-}_{d_r}} x^t_{rs} - y^t_r\Big) \\
& + \sum_{r\in R^t\cup\bar{R}^t} \lambda 3_r \Big(\sum_{k\in K}\sum_{s\in S^{k+}_{o_r}} x^t_{rs} - 1\Big) + \sum_{r\in R^t\cup\bar{R}^t} \lambda 4_r \Big(\sum_{k\in K}\sum_{s\in S^{k-}_{d_r}} x^t_{rs} - 1\Big) \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in N^{\exp}\backslash\{o_r,d_r\}} \lambda 5_{ri} \left(\sum_{k\in K^{\text{int}}}\sum_{s\in S^{k+}_i} x^t_{rs} - \sum_{k\in K^{\exp}}\sum_{s\in S^{k-}_i} x^t_{rs}\right) \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in N^{\text{imp}}\backslash\{o_r,d_r\}} \lambda 6_{ri} \left(\sum_{k\in K^{\text{imp}}}\sum_{s\in S^{k+}_i} x^t_{rs} - \sum_{k\in K^{\text{int}}}\sum_{s\in S^{k-}_i} x^t_{rs}\right) \\
& - \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in N^{\exp}\cup N^{\text{imp}}\backslash\{o_r,d_r\}} \lambda 7_{ri}\Delta t_{ri} - \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in N^{\exp}\cup N^{\text{imp}}\backslash\{o_r,d_r\}} \frac{\rho 7_{ri}}{2}\Delta t^2_{ri}
\end{aligned}
\tag{31}
$$

where $\Delta t_{ri} = \max\{0, t^-_{ri} - t^+_{ri}\}$, $\rho 7$ is a penalty parameter, the objective function Z1 is subjected to constraints (2)–(20).

The quadratic term in the new formulation is non-separable with respect to the set of operators which prevents us from decomposing the dual problem to local operator-related subproblems. Inspired by Negenborn et al. (2008), we introduce a parallel scheme to approximate it. The parallel scheme applies the auxiliary problem principle to decouple the quadratic terms (Li et al., 2017; Luan et al., 2020), as shown in model **P1 − 0** and **P1 − k**.

At iteration n, each operator k optimizes its local and coupling variables while the variables of other operators are fixed with the value generated from the previous iteration. Note that the quadratic term could also be approximated by a serial scheme (i.e., the alternating direction method of multipliers, ADMM) in which subproblems are optimized in a given sequence by using information from both the current iteration and the previous iteration. Detailed analysis for the comparison of different schemes in coordinated global synchromodal transport planning could be found in the thesis of Guo (2020), which shows that the parallel scheme performs better than the serial scheme in both solution quality and computation time.

- Optimization model for global operator:

$$(\mathbf{P1-0})\quad \max_{y^t} \sum_{r\in R^t} p_r u_r y_r^t - \sum_{r\in R^t} \lambda 1_r y_r^t - \sum_{r\in R^t} \lambda 2_r y_r^t \tag{32}$$

- Optimization model for local operator $k \in K$:

$$\begin{aligned}(\mathbf{P1-k})\quad \min_{x^t} & \sum_{r\in R^t\cup\bar{R}^t}\sum_{s\in S^k} c_s x_{rs}^t u_r + \sum_{r\in R^t\cup\bar{R}^t} c_r^{\text{delay}} \mathbb{T}_r^k u_r - \sum_{r\in R^t}\lambda 1_r \sum_{s\in S_{o_r}^{k+}} x_{rs}^t - \sum_{r\in R^t}\lambda 2_r \sum_{s\in S_{d_r}^{k-}} x_{rs}^t \\
& - \sum_{r\in R^t\cup\bar{R}^t}\lambda 3_r \sum_{s\in S_{o_r}^{k+}} x_{rs}^t - \sum_{r\in R^t\cup\bar{R}^t}\lambda 4_r \sum_{s\in S_{d_r}^{k-}} x_{rs}^t \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap N^{\text{exp}}\}\setminus\{o_r,d_r\}} \lambda 5_{ri} \sum_{s\in S_i^{k-}} x_{rs}^t \\
& - \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap N^{\text{int}}\}\setminus\{o_r,d_r\}} \lambda 5_{ri} \sum_{s\in S_i^{k+}} x_{rs}^t + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap N^{\text{int}}\}\setminus\{o_r,d_r\}} \lambda 6_{ri} \sum_{s\in S_i^{k+}} x_{rs}^t \\
& - \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap N^{\text{imp}}\}\setminus\{o_r,d_r\}} \lambda 6_{ri} \sum_{s\in S_i^{k-}} x_{rs}^t \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\}\setminus\{o_r,d_r\}} \lambda 7_{ri}\Delta t1_{ri} + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\setminus\{o_r,d_r\}} \frac{\rho 7_{ri}}{2}\Delta t1_{ri}^2 \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\}\setminus\{o_r,d_r\}} \frac{b7_{ri}-\rho 7_{ri}}{2}\left(t_{ri}^{k+} - t_{ri}^{+(n-1)}\right)^2 \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\}\setminus\{o_r,d_r\}} \lambda 7_{ri}\Delta t2_{ri} + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\}\setminus\{o_r,d_r\}} \frac{\rho 7_{ri}}{2}\Delta t2_{ri}^2 \\
& + \sum_{r\in R^t\cup\bar{R}^t}\ \sum_{i\in\{N^k\cap\{N^{\text{exp}}\cup N^{\text{imp}}\}\}\setminus\{o_r,d_r\}} \frac{b7_{ri}-\rho 7_{ri}}{2}\left(t_{ri}^{k-} - t_{ri}^{-(n-1)}\right)^2
\end{aligned} \tag{33}$$

subject to constraints (2)–(20) for operator $k \in K$, where $\Delta t1_{ri} = \max\{0, t_{ri}^{-(n-1)} - t_{ri}^{k+}\}$, $\Delta t2_{ri} = \max\{0, t_{ri}^{k-} - t_{ri}^{+(n-1)}\}$. Note that the parameters indexed with $(n-1)$ are the known values obtained from the previous iteration.

Let (y^{t*}, x^{t*}) be the optimal solution of the original problem **P0**, (y^{t**}, x^{t**}) the optimal solution of dual problem **P1**. However, the optimal solution of the dual problem might be infeasible to the original problem. Therefore, we transform the infeasible solution to a feasible solution by setting $y_r^t = 0, [x_{rs}^t] = [0]$ for request r if its transport plan is infeasible, and define (y^t, x^t) as the transformed feasible solution of the original problem. Based on the properties of Lagrangian relaxation (Negenborn, 2007), we can get $Z0(y^t, x^t) \le Z0(y^{t*}, x^{t*}) \le Z1(y^{t*}, x^{t*}) \le Z1(y^{t**}, x^{t**})$. We define $LB = Z0(y^t, x^t)$ as the lower bound of the original problem, and define $UB = Z1(y^{t**}, x^{t**})$ as the upper bound of the original problem. When $UB = LB$, the best feasible solution is found under the ALR approach. Therefore, the objective of the ALR is to find the optimum Lagrangian multipliers and penalty parameters that satisfy $UB = LB$.

In the following, a standard subgradient method is used to update the Lagrangian multipliers:

$$\lambda 1_r^{n+1} = \max\{0, \lambda 1_r^n + \rho 1_r^n (y_r^t - \sum_{k\in K}\sum_{s\in S_{o_r}^{k+}} x_{rs}^t)\}, \quad \forall r \in R^t, \tag{34}$$

$$\lambda 2_r^{n+1} = \max\{0, \lambda 2_r^n + \rho 2_r^n (y_r^t - \sum_{k\in K}\sum_{s\in S_{d_r}^{k-}} x_{rs}^t)\}, \quad \forall r \in R^t, \tag{35}$$

$$\lambda 3_r^{n+1} = \lambda 3_r^n + \rho 3_r^n (1 - \sum_{k\in K}\sum_{s\in S_{o_r}^{k+}} x_{rs}^t), \quad \forall r \in R^t \cup \bar{R}^t, \tag{36}$$

$$\lambda 4_r^{n+1} = \lambda 4_r^n + \rho 4_r^n (1 - \sum_{k\in K}\sum_{s\in S_{d_r}^{k-}} x_{rs}^t), \quad \forall r \in R^t \cup \bar{R}^t, \tag{37}$$

$$\lambda 5_{ri}^{n+1} = \lambda 5_{ri}^n + \rho 5_{ri}^n \left(\sum_{k\in K^{\text{exp}}}\sum_{s\in S_i^{k-}} x_{rs}^t - \sum_{k\in K^{\text{int}}}\sum_{s\in S_i^{k+}} x_{rs}^t \right), \quad \forall r \in R^t \cup \bar{R}^t, i \in N^{\text{exp}}\setminus\{o_r, d_r\}, \tag{38}$$

$$\lambda 6_{ri}^{n+1} = \lambda 6_{ri}^{n} + \rho 6_{ri}^{n} \left(\sum_{k \in K^{\text{int}}} \sum_{s \in S_i^{k-}} x_{rs}^{t} - \sum_{k \in K^{\text{imp}}} \sum_{s \in S_i^{k+}} x_{rs}^{t} \right), \quad \forall r \in R^{t} \cup \bar{R}^{t}, i \in N^{\text{imp}} \backslash \{o_r, d_r\}, \tag{39}$$

$$\lambda 7_{ri}^{n+1} = \lambda 7_{ri}^{n} + \rho 7_{ri}^{n} \Delta t_{ri}, \quad \forall r \in R^{t} \cup \bar{R}^{t}, i \in N^{\text{exp}} \cup N^{\text{imp}} \backslash \{o_r, d_r\}, \Delta t_{ri} = \max\{0, t_{ri}^{-} - t_{ri}^{+}\}. \tag{40}$$

Here, the superscript n is the iteration index used in the dual updating process; ρ^n is the step size at iteration n. To mitigate the issues of slow convergence, early stopping, and possible traps in local optimality, the step size parameters are updated according to the following strategy: $\rho^{n+1} = \zeta 1 * \rho^n$ if $\lambda^{n+1} > \lambda^n$; $\rho^{n+1} = \zeta 2 * \rho^n$ if $\lambda^{n+1} < \lambda^n$; $\zeta 1 > 1$, $0 < \zeta 2 < 1$. To speed up the convergence rate of ALR, we design departure time lower bounds at export and import terminals. Let N_{ri}^{Inf} denote the number of infeasible transshipments at terminal $i \in N^{\text{exp}} \cup N^{\text{imp}} \backslash \{o_r, d_r\}$. When $N_{ri}^{\text{Inf}} > a$, set the departure time lower bound at terminal i for request r to be the arrival time at current iteration: $lb_{ri}^{+} = t_{ri}^{-n}$. In this way, time variables can avoid the following situations: when the Lagrangian multiplier is positive, the minimum value is always chosen as departure times; when the Lagrangian multiplier is negative, the maximum value is always chosen.

5.3.2. Heuristic algorithm

Due to the computational complexity of the optimization models discussed above, we present a heuristic algorithm to generate timely solutions for each operator under the ALR context. The algorithm is adapted from the work of Guo et al. (2021) which is proven to be an efficient algorithm for global multimodal networks. Different from Guo et al. (2021), the heuristic designed in this paper aims to find the set of feasible paths within each local network. It mainly consists of four steps: generation of feasible paths; generation of feasible matches; binary integer programming (BIP) model; generation of global paths.

Generation of feasible paths. We define a path p as a combination of one or more services in sequence. A path p is feasible if the services inside a combination satisfy time-spatial compatibility. Specifically, for two consecutive services s_i, s_{i+1} within path p, the destination of service s_i must be the same as the origin of service s_{i+1}; the arrival time of service s_i plus buffer time must be earlier than the departure time of service s_{i+1} minus loading and unloading time at transshipment terminal d_{s_i}. Let P denote the collection of feasible paths, and P^k denote the set of feasible paths in the local network of operator $k \in K$.

Generation of feasible matches. A match $\langle r, p \rangle$ means shipment r will be transported through path p from the path's origin to destination. A match between request $r \in R$ and path $p = [s_1, \ldots, s_l] \in P$ is feasible if it satisfies time compatibility: the release time of request r should be earlier than the departure time of service s_1 minus loading time at origin terminal o_{s_1}. We set the departure time of truck services D_{rs} for $r \in R, s \in S_{o_r}^{+\text{truck}}$: $D_{rs} = \mathbb{T}_r^{\text{release}}$; for $r \in R, i \in N^{\text{imp}} \backslash \{o_r, d_r\}, s \in S_i^{+\text{truck}}$, $D_{rs} = lb_{ri}^{+}$; for $r \in R, i \in N^{\text{exp}} \cup N^{\text{imp}} \backslash \{o_r, d_r\}$, select the lowest feasible value for t_{ri}^{+} and the largest feasible value for t_{ri}^{-}. Let Φ_r^k be the set of feasible paths within network k for request r, and let c_{rp}^k denote the objective value of path p with network k for request r which is calculated based on the objective function of model $\mathbf{P1-k}$.

Binary integer programming model. We denote z_{rp}^k as a binary variable which is 1 if request $r \in R$ is assigned to path $p \in P^k$, and 0 otherwise. For operator k, model $\mathbf{P1-k}$ changes to:

$$(\mathbf{P2-k}) \quad \min \sum_{r \in R} \sum_{p \in \phi_r^k} c_{rp}^k z_{rp}^k \tag{41}$$

subject to

$$\sum_{r \in R} \sum_{p \in \Phi_r^k} z_{rp}^k \le 1, \quad \forall s \in S^k, \tag{42}$$

$$\sum_{r \in R} \sum_{p \in \Phi_r^k : s \in p} u_r z_{rp}^k \le U_s^t, \quad \forall s \in S^k, \tag{43}$$

$$z_{rp}^k \in \{0, 1\}, \quad \forall r \in R, p \in \Phi_r^k. \tag{44}$$

Constraints (42) ensure that for request $r \in R$, at most one path is selected within local network $k \in K$. Constraints (43) guarantee the capacity limitations.

Generation of global paths. In each area (including export hinterland, inter-continent, and import hinterland), multiple operators might exist. Let p_r^{k*} denote the best path of operator k for request r decided via model $\mathbf{P2-k}$, let c_r^k denote the best objective value in operator k for request r. The global operator selects the best local path in each area: $p_r^{\text{exp}} = \arg\min_{p_r^{k*}, k \in K^{\text{exp}}} c_r^k$, $p_r^{\text{int}} = \arg\min_{p_r^{k*}, k \in K^{\text{int}}} c_r^k$, $p_r^{\text{imp}} = \arg\min_{p_r^{k*}, k \in K^{\text{imp}}} c_r^k$. The global operator combines the best local paths into a global path for each request.

The solution framework of the ALR-based heuristic approach is presented in Algorithm 1. The pseudocode of the proposed approach is presented in Appendix.

6. Numerical experiments

In this section, we evaluate the performance of the coordinated mechanism (CoM) in comparison to the centralized mechanism (CeM) and the decentralized mechanism (DeM). All approaches are implemented in MATLAB, and all experiments are executed on 3.70 GHz Intel Xeon processors with 32 GB of RAM. The optimization problems are solved with CPLEX 12.6.3.

Algorithm 1 Solution framework of the ALR-based heuristic approach.

1: **Generation of feasible paths**. Generate feasible paths within each local network.
2: **Initialization**. Set iteration number $n = 1$; maximum iteration number $N^{\text{iteration}}$; Lagrangian multipliers $\lambda^n = [0]$; positive parameters ρ^0 and b^0; assign small positive numbers to $\zeta 1$, $\zeta 2$, ξ, a; lower bound of departure time of request r at transshipment terminals $[lb^+_{ri}] = [0]$; number of infeasible transshipment $[N^{\text{Inf}}] = [0]$;
3: **Generation of feasible matches**. Generate feasible paths for each request in each local network; generate time schedules for each request matched with each path.
4: **BIP model**. Solve the BIP model for each operator.
5: **Generation of global paths**. Merge local paths to a global path for each request, and transit to solutions y^t_r, $[x^t_{rs}]$, $[\mathbb{T}_r]$, $[t^+_{ri}]$, and $[t^-_{ri}]$ for the nth iteration.
6: **Modification**. Update Lagrangian multipliers λ^{n+1} based on equations (34)-(40); update parameters $\rho^{n+1} \leftarrow \zeta_1 * \rho^n$ if $\lambda^{n+1} > \lambda^n$, $\rho^{n+1} = \zeta 2 * \rho^n$ if $\lambda^{n+1} < \lambda^n$; for $r \in R^t \cup \bar{R}^t, i \in N^{\text{imp}} \backslash \{o_r, d_r\}$, if $t^{+n}_{ri} < t^{-n}_{ri}$, $N^{\text{Inf}}_{ri} = N^{\text{Inf}}_{ri} + 1$; if $N^{\text{Inf}}_{ri} > a$, update lower bounds of request departure time at import terminal i: $lb^+_{ri} = t^{-n}_{ri}$.
7: **Calculation**. Calculate objective lower bound LB based on $Z0$: for $r \in R^t \cup \bar{R}^t$, if y^t_r, $[x^t_{rs}]$ are infeasible solutions, reject request r, $y^t_r \leftarrow 0$, $[x^t_{rs}] \leftarrow [0]$. calculate objective upper bound UB based on $Z1$: the Lagrangian objective function.
8: **Termination**. Terminate if either of the following criteria is satisfied:
   - $UB - LB \leq \xi$;
   - $n > N^{\text{iteration}}$.
9: $n \leftarrow n + 1$, and go to step (3).

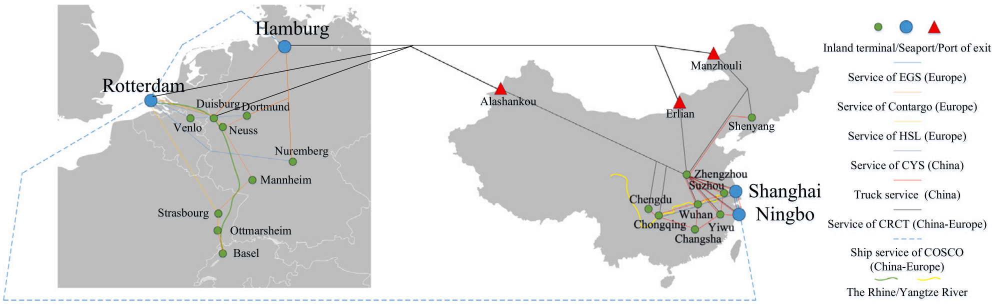

Fig. 9. Topology of the global synchromodal network.

We use a global network that includes two operators in China (China Yangtze Shipping (CYS) with 4 terminals, and a truck operator with 10 terminals), two intercontinental operators (COSCO shipping lines with 4 seaports and China Railway Container Transport (CRCT) with 10 terminals), and three operators in Europe (European Gateway Services (EGS) with 5 terminals, Contargo with 10 terminals, and Haeger & Schmidt Logistics (HSL) with 6 terminals), as depicted in Fig. 9. The intercontinental network connects China and Europe by two routes: Eurasia Land Bridge and Suez Canal Route. At each terminal, the loading/unloading times (unit: hours) are set as 12, 4, 2, 1 for ships, barges, trains and trucks respectively. We design 12 barge services for the CYS network, 29 truck services for the China-truck network, 14 ship services for the COSCO shipping network, 22 train services for the CRCT network, 103 multimodal services for the Contargo network, 47 multimodal services for the EGS network, and 27 multimodal services for the HSL network. We generate requests' origin, destination, volume, announce time, release time, due time, and expiry date according to a series of probability distributions, as reported in Guo et al. (2022b). All instances are available at a research data website.[1] We use I-Kn_1-Nn_2-Sn_3-Rn_4 to represent an instance with n_1 operators, n_2 terminals, n_3 services, and n_4 requests in the given distributed global network.

6.1. Parameter tuning

To analyze the sensitivity of algorithm parameters under the ALR approach, we vary the values of $\rho 1$, $\rho 2$, $\rho 3$, $\rho 4$, $\rho 5$, $\rho 6$, $\rho 7$, $b7$, $\zeta 1$, and $\zeta 2$ for a given instance, the results are shown in Table 3. It is noted that the performance of ALR is quite sensitive to the parameter settings. For penalty parameters $\rho 1 - \rho 6$ that control the modification of Lagrangian multipliers with spatial conflicts, their values need to be set large enough to impact shipments' flow in and flow out at certain nodes; for parameters $\rho 7$ that controls time conflicts at transshipment terminals and $b7$ that controls the difference between departure/arrival times at different iterations, their values need to be set quite small. We also find that the proper settings of step size updating control parameters $\zeta 1$ and $\zeta 2$ are 2 and 0.5, respectively. It shows that when $\lambda^{n+1} > \lambda^n$, the value of ρ should be doubled; when $\lambda^{n+1} < \lambda^n$, the

[1] https://figshare.com/s/01a6c8d6d7d8b9071683

Table 3
Parameter tuning in ALR.

	$\rho 1$	$\rho 2$	$\rho 3$	$\rho 4$	$\rho 5$	$\rho 6$	$\rho 7$	$b7$	$\zeta 1$	$\zeta 2$	Iteration	Total profits	CPU (seconds)
1	**2500**	**2500**	**2500**	**2500**	**2500**	**2500**	**0.0010**	**0.005**	**2.0**	**0.5**	78	**84 437**	**2**
2	1500	1500	1500	1500	1500	1500	0.0010	0.005	2.0	0.5	258	80 811	12
3	4000	4000	4000	4000	4000	4000	0.0010	0.005	2.0	0.5	223	80 811	10
4	2500	2500	2500	2500	2500	2500	0.0001	0.005	2.0	0.5	86	80 781	4
5	2500	2500	2500	2500	2500	2500	0.0050	0.005	2.0	0.5	391	80 811	17
6	2500	2500	2500	2500	2500	2500	0.0010	0.001	2.0	0.5	141	80 811	6
7	2500	2500	2500	2500	2500	2500	0.0010	0.020	2.0	0.5	34	81 095	2
8	2500	2500	2500	2500	2500	2500	0.0010	0.005	0.5	0.5	81	77 268	4
9	2500	2500	2500	2500	2500	2500	0.0010	0.005	1.0	0.5	176	75 943	8
10	2500	2500	2500	2500	2500	2500	0.0010	0.005	2.0	0.1	246	80 811	11
11	2500	2500	2500	2500	2500	2500	0.0010	0.005	2.0	0.9	78	75 943	4

value of ρ should be halved. The coordination parameters that perform the best are used in the following experiments, as follows: $[\rho 1] = [\rho 2] = [\rho 3] = [\rho 4] = [\rho 5] = [\rho 6] = [2500]$, $[\rho 7] = [0.001]$, $[b7] = [0.005]$, $\zeta 1 = 2$, $\zeta 2 = 0.5$, $\xi = 0.003$, $a = 10$, $N^{\text{iteration}} = 1000$.

6.2. Comparison among centralized, decentralized, and coordinated mechanisms

In this section, the performance of centralized, decentralized, and coordinated mechanisms are analyzed. To ensure a range of realistic instances, we design 25 instances with varying numbers of operators, terminals, services, and requests. We consider large-scale instances with up to 7 transport operators, 21 terminals, and 254 services. These instances are considerably larger than those commonly found in the literature, as reported by Demir et al. (2016) and Zhang et al. (2022b). By using these large instances, we are able to provide a more comprehensive evaluation of the performance of the different mechanisms in handling complex real-world scenarios. We range the number of requests from 5 to 50 which is the largest instance that can be solved by CPLEX under CeM within 24 h. For each request, we randomly assign origins among terminals in the export hinterland and destinations among terminals in the import hinterland. The container volume is uniformly distributed in the range of 1 to 20 TEUs. The earliest pickup time for each request is uniformly distributed in the range of 1 to 120. The fare class including lead time (unit: hours), fare (unit: €), and delay cost coefficient (unit: €) is randomly selected from $\{\langle 768, 4000, 20\rangle, \langle 816, 3500, 17.5\rangle, \langle 864, 3000, 15\rangle, \langle 912, 2500, 12.5\rangle, \langle 960, 2000, 10\rangle\}$.

We consider two performance indicators: total profits (unit: €) and computation time (CPU, unit: seconds). While the CPU of the CeM is the time of solving the centralized model, the CPU of the DeM is the summation of the CPU generated by local operators, and the CPU of the CoM is the summation of the maximum CPU generated by local operators at each iteration. We calculate the gaps between the profits of the CeM and the CoM by

$$\text{gap} = \frac{\text{profits(CeM)} - \text{profits(CoM)}}{\text{profits(CeM)}} * 100\%,$$

and calculate the improvements between the profits generated by the CoM and the DeM by

$$\text{improvements} = \frac{\text{profits(CoM)} - \text{profits(DeM)}}{\text{profits(CoM)}} * 100\%.$$

Table 4 shows that the CoM outperforms the DeM in all the instances. For example, in instances I-K3-N8-S106-R5 and I-K3-N8-S106-R10, the improvements can be as high as 95.13% and 92.68%, respectively, indicating that the problem is unsuitable to be solved by DeM. The DeM leads to a loss of profits because information is not effectively transmitted between decision-makers. The CoM reduces the gap and brings the profit back to the level of the CeM with communication through incentives in a distributed environment except for a few cases where there are small percentage differences. The CPU time required to solve the problems also increases with the increase in the number of operators, terminals, services, and requests. In general, the CoM and the DeM require less CPU time than the CeM. Moreover, with the heuristics we have developed, CoM is able to find those high-quality solutions in seconds even for instances with a larger number of requests. The gaps between the optimal solutions and the solutions found by CoM are generally small (less than 2.5% in most cases). The CeM may potentially generate higher profits than the CoM because all decisions are made by a global operator who has a comprehensive view of the transport system. However, the CoM allows local operators to make their own decisions and contribute to the transport system by sharing limited information, and the obtained results can be more responsive to local conditions. The number of iterations required by the CoM increases for larger instances. In instances with a small number of services and requests, such as I-K3-N5-S18-R5 and I-K3-N5-S18-R10, the algorithm can find the optimal solution within a small number of iterations (15 and 74, respectively), while in instances with a large number of services and requests, such as I-K3-N8-S106-R30 and I-K5-N15-S103-R50, the algorithm needs a much larger number of iterations (320 and 474, respectively) to converge to a near-optimal solution.

To show how incentives are distributed along the coordination process and how the ARL-heu converges, we use request $r8 = \{o_r$: Suzhou; d_r : Neuss; u_r : 12; $\mathbb{T}_r^{\text{release}}$: 106; $\mathbb{T}_r^{\text{due}}$: 970; p_r : 3000; c_r^{delay} : 15$\}$ from instance I-K7-N21-S254-R10. The services associated with this request are presented in Table 5, and the coordination process are shown in Table 6. The service IDs are used to represent the chosen routes in Table 6. The selection of a particular service depends on the service area of the

Table 4
Comparison results for different mechanisms.

Instances	CeM		DeM		CoM			Gaps	Improvements
	Total profits	CPU	Total profits	CPU	Iterations	Total profits	CPU		
I-K3-N5-S18-R5	37 126	0.08	18 410	0.09	15	37 126	0.36	0.00%	50.41%
I-K3-N5-S18-R10	54 666	0.12	48 786	0.04	74	54 666	1.71	0.00%	10.76%
I-K3-N8-S106-R5	46 293	31	2254	0.07	31	46 293	1	0.00%	95.13%
I-K3-N8-S106-R10	84 437	103	6181	0.05	78	84 437	2	0.00%	92.68%
I-K3-N8-S106-R20	165 583	2943	92 129	0.05	62	161 854	3	2.25%	43.08%
I-K3-N8-S106-R30	247 182	4575	96 144	0.07	320	241 209	17	2.42%	60.14%
I-K3-N9-S63-R10	19 228	4	8514	0.05	45	19 228	1	0.00%	55.72%
I-K3-N9-S63-R20	48 864	46	32 603	0.06	94	48 864	3	0.00%	33.28%
I-K3-N9-S63-R30	60 865	606	41 225	0.08	106	60 730	4	0.22%	32.12%
I-K3-N9-S63-R32	90 615	2972	48 011	0.07	106	90 480	4	0.15%	46.94%
I-K3-N9-S63-R35	96 430	293 813	53 826	0.07	106	96 295	4	0.14%	44.10%
I-K4-N10-S68-R10	46 276	8	20 346	0.04	143	46 276	4	0.00%	56.03%
I-K4-N10-S68-R20	80 274	83	34 539	0.06	330	80 274	12	0.00%	56.97%
I-K4-N10-S68-R30	121 882	289	50 985	0.06	330	121 882	14	0.00%	58.17%
I-K4-N10-S68-R40	192 780	576	119 355	0.08	330	191 467	19	0.68%	37.66%
I-K4-N10-S68-R50	251 853	1274	164 642	0.08	330	250 540	50	0.52%	34.29%
I-K5-N15-S103-R10	18 356	43	11 191	0.04	35	18 356	1	0.00%	39.03%
I-K5-N15-S103-R20	25 166	288	18 001	0.06	49	24 331	2	3.32%	26.01%
I-K5-N15-S103-R30	45 548	928	38 095	0.07	49	44 713	2	1.83%	14.80%
I-K5-N15-S103-R40	76 252	2753	59 864	0.08	49	73 889	3	3.10%	18.98%
I-K5-N15-S103-R50	129 946	4319	97 580	0.09	474	127 056	76	2.22%	23.20%
I-K6-N21-S227-R5	30 908	255	15 275	0.06	35	30 908	4	0.00%	50.58%
I-K6-N21-S227-R10	58 266	2165	17 671	0.07	70	58 266	16	0.00%	69.67%
I-K7-N21-S254-R5	17 467	555	0	0.06	29	17 467	5	0.00%	100.00%
I-K7-N21-S254-R10	46 494	6389	11 858	0.09	756	43 645	245	6.13%	72.83%
Average								**1.00%**	**50.50%**

Table 5
Services used in the coordination analysis.

Operator	Service ID	Mode	Origin	Destination	Transit time	Distance	Departure time	Arrival time	Capacity	Transport cost
China-truck	27	Truck	Suzhou	Shanghai	1	111			1000	216
	28	Truck	Suzhou	Ningbo	3	224			1000	333
	29	Truck	Suzhou	Zhengzhou	11	858			1000	993
	30	Truck	Suzhou	Wuhan	10	742			1000	872
Contargo	43	Barge	Duisburg	Neuss	3	38	923	925	200	41
	49	Barge	Duisburg	Neuss	3	38	930	932	200	41
	76	Train	Rotterdam	Duisburg	6	270	908	914	90	69
	88	Train	Hamburg	Duisburg	7	330	443	450	90	78
HSL	193	Barge	Duisburg	Neuss	3	38	936	938	200	41
	198	Train	Rotterdam	Duisburg	6	270	910	916	90	69
COSCO	226	Ship	Shanghai	Rotterdam	741	22 222	132	873	1000	1732
	231	Ship	Ningbo	Rotterdam	738	22 126	208	946	1000	1724

Table 6
Coordination processes for an illustrative example.

Iterations	Incentives proposed by the global operator					Routing decisions decided by local operators				Merged global itinerary
	$\lambda 1_8$	$\lambda 2_8$	$\lambda 5_{8,1}$	$\lambda 6_{8,11}$	$\lambda 7_{8,11}$	CN: truck	EU: Contargo	EU: HSL	CN-EU: COSCO	
1	0	0	0	0	0	[]	[]	[]	[]	[]
2	2500	2500	0	0	0	[]	[]	193	[]	193
3	5000	2500	0	0	0	27	[76,49]	[198,193]	[]	[27,198,193]
4	5000	2500	2500	−2500	0	28	[]	[]	[]	28
5	5000	5000	2500	−2500	0	[]	[88,49]	193	[]	[88,49]
...										
21	15 000	12 500	12 500	−10000	0	28	[76,43]	[198,193]	226	[28,226,198,193]
22	15 000	12 500	11 250	−10000	0	27	[76,43]	[198,193]	231	[27,231,198,193]
23	15 000	12 500	11 875	−10000	0.05	28	[76,49]	[198,193]	226	[28,226,198,193]
24	15 000	12 500	11 250	−10000	0.05	27	[76,43]	[198,193]	231	[27,231,198,193]
25	15 000	12 500	11 563	−10000	0.15	28	[76,49]	[198,193]	226	[28,226,198,193]
26	15 000	12 500	11 250	−10000	0.15	27	[76,43]	[198,193]	226	[27,226,198,193]

involved operators and the availability of services within that area. At iteration 1, all the Lagrangian multipliers are set to 0, so local operators do not arrange any services to transport the request. At iteration 2, the global operator increases the value of $\lambda 1_8$ and

Table 7
Sensitivity analysis of the buffer parameter.

DOD	Buffer parameter	Planned profits	Actual profits	Rejection/ Acceptance	Inf	Delay	CPU
25%	0	1 875 293	1 674 542	60/240	27	5462	10
	0.530	1 678 736	1 571 433	80/220	18	3303	11
	0.674	1 598 911	1 476 257	89/211	10	3173	11
	1.290	1 489 710	1 402 580	97/203	3	3190	10
	3.719	1 201 142	1 116 293	125/175	1	3124	11
50%	0	2 002 916	1 776 948	45/255	39	6635	15
	0.530	1 880 998	1 779 845	53/247	25	4270	16
	0.674	1 866 351	1 801 584	55/245	12	3750	11
	1.290	1 756 861	1 673 247	65/235	4	4116	9
	3.719	1 308 564	1 221 987	111/189	2	3350	9
75%	0	2 081 806	1 843 619	40/260	43	7563	15
	0.530	1 956 186	1 835 534	44/256	28	5466	15
	0.674	1 950 500	1 866 161	49/251	15	4553	27
	1.290	1 847 305	1 747 697	59/241	9	4449	25
	3.719	1 254 534	1 234 626	109/191	4	3061	17
100%	0	2 053 228	1 835 628	42/258	42	7177	12
	0.530	1 968 135	1 846 296	45/255	34	5458	27
	0.674	1 931 342	1 863 937	49/251	20	4460	26
	1.290	1 824 334	1 772 727	61/239	7	3702	25
	3.719	1 264 306	1 234 570	110/190	1	2625	16

$\lambda 2_8$ to 2500. With this incentive, operator HSL arranges service 193 to transport the request to its destination terminal. At iteration 3, the global operator increases the value of $\lambda 1_8$ to 5000. With this incentive, operator China-truck arranges service 27 to transport the request from Suzhou to Shanghai; two import operators propose import routes for the request, and the global operator selects the import route (Rotterdam–Duisburg–Neuss) of HSL which is cheaper in the current iteration, and merges the local routes into global itineraries $[27, 198, 193]$. Since no services are selected to transport the request flow out of Shanghai port (terminal 1) and flow into Rotterdam port (terminal 11), the global operator increases the value of $\lambda 5_{8,1}$ to push flow out of export terminal 1 and decreases the value of $\lambda 6_{8,11}$ to push flow into import terminal 11 at iteration 4. This process continues until iteration 26 where spatial and time compatibility is achieved. The final global route selected for request $r8$ is $[27, 226, 198, 193]$ which means $r8$ will be first transported by truck service 27 from Suzhou to Shanghai, then transported by ship service 226 from Shanghai to Rotterdam, and finally transported by inland services 198 and 193 from Rotterdam to Neuss.

6.3. Dynamic and stochastic scenarios

In this section, we further test the performance of CeM, DeM, and CoM under dynamic and stochastic scenarios. We set the mean of travel times $\mu_s = t_s$ for $s \in S$; standard deviation of travel times $\sigma_s = 0.1 * t_s$ for $s \in S \backslash S^{\text{truck}}$, $\sigma_s = 0.5 * t_s$ for $s \in S^{\text{truck}}$. We set the planning horizon (unit: hours) $T = 1400$. Due to travel time variations, the planned profits might be different from the actual profits for each instance.

To analyze the impact of the buffer parameter under the CoM, we use instance I-K3-N8-S106-R300 with different degrees of dynamism (DOD = number of spot requests/number of total requests). For each case, we replicate the travel time realizations 10 times and report the average value. We use "Inf" to represent the number of infeasible transshipments. Table 7 shows that the CoM has the best performance in actual profits when $\theta = 0.674$ for instances with a higher DOD. When $\theta = 0.674$, the stochasticity is considered and the taken actions are not too conservative, therefore the proposed approach performs the best. For each case, the planned profits decrease with the increase of the buffer parameter. The reason is that with a higher buffer parameter, the system will choose 'suboptimal' decisions that have a lower possibility of infeasible transshipments. We also notice that the higher the buffer parameter, the larger the number of rejections. The number of infeasible transshipments shows the opposite trend. Besides, we observe that under the same buffer parameter, in general, the larger the DOD, the lower the number of rejections and the higher the number of infeasible transshipments. The computation time per time step also typically rises with the increase of DOD.

Dynamic requests are quite common in global synchromodal transport, as shippers may need to adjust their logistics plans at short notice due to changes in demand or other factors. To compare the performance of CoM in comparison to CeM and DeM in dynamic scenarios, we use the same instance with different DODs. For each case, we replicate the travel time realizations 5 times and report the average value. Table 8 shows that the larger the DOD, the smaller the gaps between CeM and CoM and the larger the improvements between CoM and DeM. For the case with 100% DOD, the gap between CeM and CoM is less than 4% and the improvement between CoM and DeM is above 60%. It means that communication becomes more important in scenarios with a higher DOD. It is noteworthy that as DOD increases, the number of rejections under CeM and DeM also increases, while the opposite trend is observed under CoM. The CeM utilizes a significant portion of its resources to handle requests at earlier times, which can lead to poorer performance for later requests. Therefore, the CeM may reject more requests as DOD increases, compared to the CoM which is more able to adapt to changes in demand. Besides, we notice that increasing the DOD, the modal share of trucks in export

Table 8
Impact of the degree of dynamism.

DOD	Mechanism	Total profits	Rejection/ acceptance	Inf	Delay (TEU-h)	Export hinterland			Inter-continent		Import hinterland			Gaps	Improvements
						Barge	Train	Truck	Ship	Train	Barge	Train	Truck		
25%	CeM	2 273 831	12/288	53	8326	4.71%	86.86%	8.43%	50.05%	49.95%	21.20%	32.82%	45.98%		
	DeM	1 322 551	96/204	63	7613	0.00%	70.38%	29.62%	67.70%	32.30%	25.38%	28.97%	45.65%		
	CoM	1 606 240	66/234	22	11 913	0.00%	97.73%	2.27%	44.14%	55.86%	29.92%	36.91%	33.17%	29.36%	17.66%
50%	CeM	2 227 002	12/288	58	8795	5.65%	82.78%	11.57%	50.31%	49.69%	20.28%	31.68%	48.04%		
	DeM	1 164 282	127/173	62	6064	0.00%	73.25%	26.75%	74.97%	25.03%	27.10%	30.15%	42.75%		
	CoM	1 912 997	44/256	27	11 052	0.96%	96.85%	2.20%	46.54%	53.46%	31.08%	34.33%	34.59%	14.10%	39.14%
75%	CeM	2 200 422	12/288	64	8992	5.31%	80.43%	14.26%	51.49%	48.51%	19.53%	31.34%	49.13%		
	DeM	971 529	156/144	62	5117	0.00%	69.02%	30.98%	89.90%	10.10%	33.24%	28.88%	37.88%		
	CoM	2 009 857	41/259	30	10 436	0.00%	98.41%	1.59%	48.16%	51.84%	31.70%	33.89%	34.41%	8.66%	51.66%
100%	CeM	2 091 484	21/279	67	9768	9.65%	77.81%	12.54%	54.29%	45.71%	9.13%	27.96%	54.09%		
	DeM	756 430	182/118	53	6047	0.00%	58.94%	41.06%	100.00%	0.00%	37.57%	28.71%	33.73%		
	CoM	2 013 902	41/259	33	10 397	0.00%	98.48%	1.52%	50.79%	49.21%	32.59%	31.57%	35.84%	3.71%	62.44%

Table 9
Impact of the degree of uncertainty.

DOU	Mechanism	Total profits	Rejection/ acceptance	Inf	Delay (TEU-h)	Export hinterland			Inter-continent		Import hinterland			Gaps	Improvements
						Barge	Train	Truck	Ship	Train	Barge	Train	Truck		
$0.05{*}t_s$	CeM	2 252 541	21/279	14	5576	9.66%	78.58%	11.76%	54.17%	45.83%	27.01%	32.53%	40.46%		
	DeM	831 476	182/118	16	3602	0.00%	59.57%	40.43%	100.00%	0.00%	51.34%	22.86%	25.80%		
	CoM	2 105 492	41/259	9	6859	0.00%	98.48%	1.52%	50.79%	49.21%	38.41%	31.80%	29.79%	6.53%	60.51%
$0.1{*}t_s$	CeM	2 102 786	21/279	45	9892	9.63%	77.08%	13.29%	54.29%	45.71%	23.23%	28.31%	48.45%		
	DeM	783 519	182/118	34	5303	0.00%	58.80%	41.20%	100.00%	0.00%	46.28%	25.73%	27.99%		
	CoM	2 020 318	41/259	21	10 251	0.00%	98.49%	1.51%	50.62%	49.38%	37.29%	29.82%	32.89%	3.92%	61.22%
$0.125{*}t_s$	CeM	2 001 509	21/279	45	15 457	9.64%	77.80%	12.55%	54.26%	45.74%	24.19%	26.63%	49.19%		
	DeM	702 151	182/118	40	9054	0.00%	59.24%	40.76%	100.00%	0.00%	44.22%	23.59%	32.19%		
	CoM	1 955 090	41/259	23	13 665	0.00%	98.49%	1.51%	50.62%	49.38%	38.50%	28.57%	32.93%	2.32%	64.09%

and import hinterland decreases under the CoM and increases under the CeM. In import and export areas, trucks are generally more expensive but faster than barges and trains. The intercontinental transportation distance is the longest, and ship services are slower but cheaper than train services. Under the CoM, which is a coordinated approach that allows local operators to make their own decisions and potentially choose transportation modes that are more cost-effective, the local operators in the export area use more barges and trains in order to minimize costs. The CoM considers the costs of local operators in the import and export areas and may therefore use more train services in the intercontinental area. By using more faster trains, the import operator has more alternative options available to transfer shipments from trains if they are delayed, resulting in a more robust and reliable transport system that takes into account the needs and interests of all local operators. The local operators in the import hinterland need to consider delays, so they use more trucks than in the export hinterland. In contrast, the CeM considers the overall global transportation as a whole to avoid delay penalties and maximize profits. As a result, it uses ships in the intercontinental area and uses more trucks in both the export and import hinterlands.

Handling travel time uncertainty is also important in global synchromodal transport, as it can be difficult to predict and manage changes in travel times that can affect the performance of logistics networks. To analyze the impact of the degree of uncertainty, we vary the travel time variations from $0.05 * t_s$ to $0.125 * t_s$. For each case, we replicate the travel time realizations 5 times and report the average value.

Table 9 shows that the larger the DOU, the better the performance of CoM. Increasing the DOU, the delay in deliveries increases under all the mechanisms, same as the number of infeasible transshipments. As the DOU in a synchromodal transport system increases, the coordinated mechanism is better to handle uncertainties due to its ability to coordinate and communicate among different transport operators. With the coordinated approach, different transport operators can respond to changes in real-time and take local actions to adapt to the changing environment under the coordination of a global transport operator, which can help to minimize the risk of delays or disruptions, and improve the reliability of logistics operations, which can avoid high delay penalty and have a positive impact on customer satisfaction.

To analyze the impact of the delay cost coefficient, we vary its value from $0.25\% * p_r$ to $1\% * p_r$. Table 10 shows that the larger the delay cost coefficient, the larger the gaps between CeM and CoM, the larger the improvements between CoM and DeM. The delay in deliveries decreases dramatically with the increasing of delay cost coefficient. Increasing the delay cost leads to more requests switching from the slower but cheaper ship services on the Suez Canal Route to the faster but more expensive train services on the Eurasia Land Bridge in intercontinental transportation. This is because the higher delay penalties of ship services may outweigh the higher cost of train services, making the faster train services a more attractive option in terms of cost and efficiency.

In summary, the proposed coordinated mechanism can consider the objectives of all operators and improve the flexibility and adaptability of synchromodal transport systems in decentralized settings.

7. Conclusions

This paper investigated a dynamic, stochastic, and coordinated global synchromodal transport planning problem. A rolling horizon framework was developed to handle dynamic shipment requests; a buffer strategy was designed to address travel time

Table 10
Impact of the delay cost coefficient.

Delay cost	Mechanism	Total profits	Rejection/ acceptance	Inf	Delay (TEU-h)	Export hinterland			Inter-continent		Import hinterland			Gaps	Improvements
						Barge	Train	Truck	Ship	Train	Barge	Train	Truck		
0.25%*p_r	CeM	2 244 994	11/289	70	23 791	12.09%	78.87%	9.04%	57.00%	43.00%	17.72%	28.16%	54.12%		
	DeM	821 582	167/133	58	30 119	0.00%	66.03%	33.97%	100.00%	0.00%	36.44%	32.27%	31.29%		
	CoM	2 173 991	29/271	41	21 372	0.00%	98.54%	1.46%	52.19%	47.81%	31.66%	31.81%	36.53%	3.16%	62.21%
0.5%*p_r	CeM	2 091 484	21/279	67	9768	9.65%	77.81%	12.54%	54.29%	45.71%	17.95%	27.96%	54.09%		
	DeM	756 430	182/118	53	6047	0.00%	58.94%	41.06%	100.00%	0.00%	37.57%	28.71%	33.73%		
	CoM	2 013 902	41/259	33	10 397	0.00%	98.48%	1.52%	50.79%	49.21%	32.59%	31.57%	35.84%	3.71%	62.44%
1%*p_r	CeM	1 964 000	27/273	66	5202	8.54%	78.97%	12.49%	52.43%	47.57%	17.97%	27.86%	54.17%		
	DeM	611 505	188/112	52	3600	0.00%	52.02%	47.98%	100.00%	0.00%	40.06%	27.03%	32.91%		
	CoM	1 856 295	44/256	33	5222	0.00%	98.67%	1.33%	48.45%	51.55%	37.11%	31.33%	31.56%	5.48%	67.06%

uncertainties; an augmented Lagrangian relaxation-based heuristic approach was developed to stimulate efficient coordination between a global operator and multiple local operators under a coordinated mechanism (CoM). Both vertical and horizontal collaboration were considered in the coordination. We used 25 instances with real transport networks to compare the performance of the CoM in comparison to a centralized mechanism (CeM) and a decentralized mechanism (DeM) in total profits and computation time. The experiment results showed that on average, the gaps between the CoM and the CeM are no more than 1% while the improvements between the CoM and the DeM are above 50%. With the proposed CoM, all the instances can be solved within 5 min in a distributed way. Furthermore, we investigated the performance of the coordinated mechanism combined with a rolling horizon framework and a buffer strategy in dynamic and stochastic scenarios. The following managerial insights are obtained from the analysis of the results:

1. The larger the degrees of dynamism and uncertainty, the better the performance of the CoM.
2. CoM and CeM with information sharing generate better solutions compared to the DeM. Information sharing becomes more important in scenarios with a higher degree of dynamism. This suggests that transport operators should prioritize effective communication channels and strategies when dealing with dynamic requests.
3. Although CeM may potentially generate higher profits than CoM since CeM makes all decisions centrally, the CeM is infeasible in practice because local transport operators are geographically distributed and have their specific goals. Therefore, CeM rather represents an ideal unattainable benchmark for us to evaluate the performance. The CoM keeps the decision authority of local transport operators and leads to a robust and reliable transport system that takes into account the needs and interests of all transport operators.
4. The CoM results in a smaller modal share of trucks in export and import areas compared to the CeM, while the CeM uses more trains in the intercontinental area. This suggests that the CoM may be more cost-effective in export and import areas, while the CeM minimizes the cost in the intercontinental area to obtain a global maximum profit, potentially at the expense of the interests of hinterland transport operators.
5. Transport operators should carefully consider the impact of delay costs when making transportation decisions because the higher delay cost coefficient can make the train services a more attractive option in terms of cost and efficiency compared to ship services.

The proposed coordinated mechanism can help to improve the efficiency, effectiveness, and sustainability of synchromodal transport systems and optimize the performance of logistics networks in a decentralized context. Coordination is important in global synchromodal transport because it helps to ensure that goods are transported smoothly and efficiently from their point of origin in one continent to their final destination in another continent. By providing coordination, local operators can optimize the use of resources and improve cost efficiency independently in global synchromodal transport. Some potential benefits of this mechanism include:

1. Improved efficiency: by coordination, transport operators can optimize the use of resources and minimize bottlenecks in the transport system. This can lead to more efficient and cost-effective operations.
2. Enhanced coordination: the proposed mechanism can help to improve coordination among different transport operators in the transport system, leading to a more seamless and integrated transport system.
3. Increased reliability: by synchronizing the flow of shipments across different tiers of the supply chain, the proposed mechanism can help to improve the reliability and predictability of the transport system, enabling better planning and forecasting.
4. Improved sustainability: by optimizing the use of resources and reducing truck utilization, the proposed mechanism can help to reduce the environmental impact of the transport system and contribute to greater sustainability.

The designed coordinated mechanism is able to identify global synchromodal transport plans which improve the efficiency of the whole system. However, local operators may not be willing to participate in the global collaboration because there is no guarantee that each party is better than before. It is possible that some operators might sacrifice for reducing the cost of other operators in order to achieve the coordinated common goal. Therefore, proper profit distribution approaches that compensate for the sacrifice made by some operators have to be designed in future research.

CRediT authorship contribution statement

Wenjing Guo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yimeng Zhang:** Writing – review & editing, Writing – original draft. **Wenfeng Li:** Supervision, Writing – review & editing. **Rudy R. Negenborn:** Supervision, Writing – review & editing. **Bilge Atasoy:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Pseudocodes

Algorithms 2, 3, and 4 provide pseudocodes of the rolling horizon framework, augmented Lagrangian relaxation-based heuristic approach, and heuristic algorithm, respectively.

Algorithm 2 Rolling horizon framework.

Input: Terminals N; contractual requests R^0; spot requests R^t; length of the planning horizon T.
Output: Itinerary $\{I_r\}_{r\in R}$; number of infeasible transshipments $N^{\text{infeasible}}$; actual profits $\left[\mathbf{AP}^t\right]_{t\in\{0,\ldots,T\}}$.
Initialize: Let $R^t \leftarrow \emptyset$, $\bar{R}^t \leftarrow \emptyset$, $I_r \leftarrow \emptyset$, $N^{\text{infeasible}} \leftarrow 0$, $\mathbf{AP}^t \leftarrow 0$.

for decision epoch $t \in \{0, 1, \ldots, T\}$ **do**
  receive new requests $R^t = \{r \in R | t-1 < \mathbb{T}_r^{\text{announce}} <= t\}$
  check accepted requests that need reoptimization caused by infeasible transshipments:
  for requests received before time $t-1$: $r \in R^0 \cup \ldots \cup R^{t-1}$ **do**
    if it was accepted: $y_r = 1$ **then**
      for terminal $i \in N$ **do**
        if request r just arrived at terminal i, service $s \in \{I_r | o_s = i\}$ has already departed or the time for transshipment operations is not enough **then**
          update reoptimization requests $\bar{R}^t \leftarrow \bar{R}^t \cup \{r\}$
          update number of infeasible transshipments $N^{\text{infeasible}} \leftarrow N^{\text{infeasible}} + 1$
  obtain acceptance and matching decisions $\left[y^t, x^t\right] \leftarrow$ **Augmented Lagrangian relaxation-based heuristic approach**
  update itinerary $\{I_r\}$ for $r \in R^t \cup \bar{R}^t$
  calculate total actual profits $\mathbf{AP}^t$ generated at decision epoch t including revenues received from new requests accepted at t and transport costs by services arrived at destinations at time t
calculate the total profits over the planning horizon T

Algorithm 3 Augmented Lagrangian relaxation-based heuristic approach.

Input: New requests R^t; reoptimization requests $\bar{R}^t$; simulation length $N^{\text{simulation}}$, stopping criteria ξ.
Output: Acceptance decision $\left[y_r^t\right]_{\forall r\in R^t, t\in\{1,\ldots,T\}}$; matching decision $\left[x_{rs}^t\right]_{\forall r\in R^t\cup\bar{R}^t, s\in S}$.
Initialize: Let $n \leftarrow 1$, $\lambda \leftarrow [0]$, $N^{\text{Inf}} \leftarrow [0]$, $lb^+ \leftarrow [0]$.

while iteration $n \leq N^{\text{simulation}}$ **do**
  for new request $r \in R^t$ **do**
    if $\lambda 1_r^n + \lambda 2_r^n \leq u_r * p_r$ **then**
      accept request r at current iteration: $y_r^n \leftarrow 1$
  obtain matching decisions for new and reoptimization requests $[x^n] \leftarrow$ **Heuristic algorithm**
  for request $r \in R^t \cup \bar{R}^t$ **do**
    if $\left[y_r^n, x_r^n\right]$ is infeasible **then**
      set $y_r^n \leftarrow 0$, $x_r^n \leftarrow 0$
  update Lagrangian multipliers based on Constraints (31-37)
  for request $r \in R^t \cup \bar{R}^t$ **do**
    for import terminal $i \in N^{\text{imp}}$ **do**
      if infeasible transshipment $t_{ri}^{+n} \leq t_{ri}^{-n}$ **then**
        $N_{ri}^{\text{Inf}} \leftarrow N_{ri}^{\text{Inf}} + 1$
        if $N_{ri}^{\text{Inf}} > a$ **then**
          update departure time lower bound $lb_{ri}^+ \leftarrow t_{ri}^{-n}$
  calculate objective lower bound LB based on the objective function Z0
  calculate objective upper bound UB based on the objective function Z1
  if $UB - LB \leq \xi$ **then**
    return
  else
    $n \leftarrow n + 1$

Algorithm 4 Heuristic algorithm.

Input: New requests R^t; reoptimization requests $\bar{R}^t$; services $S = S^1 \cup ...S^k ... \cup S^K$; terminals $N = N^1 \cup ...N^k ... \cup N^K$; buffer parameter θ.
Output: Matching decisions $\left[x_{rs}\right]_{\forall r \in R^t \cup \bar{R}^t, s \in S}$.
Initialize: Let $P^k \leftarrow \emptyset$, $\Phi^k \leftarrow \emptyset$.

generate feasible paths:
for operator $k \in \{1, ..., K\}$ **do**
  for terminal $i \in N^k$, terminal $j \in N^k$ **do**
    for service $s \in S^k$ **do**
      if origin $o_s = i$ and destination $d_s = j$ **then**
        $P^k_{ij} \leftarrow P^k_{ij} \cup [s]$
  for terminal $i \in N^k$, terminal $j \in N^k$ **do**
    for service $s \in S^k$ **do**
      if origin $o_s \neq i$ and destination $d_s = j$ **then**
        for feasible path $p = [q] \in P^k_{io_s}$ **do**
          if arrival time of service q plus buffer time $\theta * \sigma_q$ is earlier than the departure time of service s **then**
            $P^k_{ij} \leftarrow P^k_{ij} \cup [q, s]$
  for terminal $i \in N^k$, terminal $j \in N^k$ **do**
    for service $s \in S^k$ **do**
      if origin $o_s \neq i$ and destination $d_s = j$ **then**
        for feasible path $p = \left[s_1, s_2\right] \in P^k_{io_s}$ **do**
          if arrival time of service s_2 plus buffer time $\theta * \sigma_{s_2}$ is earlier than the departure time of service s **then**
            $P^k_{ij} \leftarrow P^k_{ij} \cup \left[s_1, s_2, s\right]$
generate feasible matches:
for export hinterland operator $k \in K^{\text{exp}}$ **do**
  for request $r \in R^t \cup \bar{R}^t$ **do**
    for export terminal $i \in N^{\text{exp}}$ **do**
      for feasible path $p \in P^k_{o_r i}$ **do**
        if the release time of request r plus loading time is earlier than the departure time of path p **then**
          $\Phi^k_r \leftarrow \Phi^k_r \cup \{p\}$
          $c^k_{rp} \leftarrow$ Calculate the path cost based on the objective function of model **P1-k**
for import hinterland operator $k \in K^{\text{imp}}$ **do**
  for request $r \in R^t \cup \bar{R}^t$ **do**
    for import terminal $i \in N^{\text{imp}}$ **do**
      for feasible path $p \in P^k_{id_r}$ **do**
        if the departure time lower bound $lb^+_{ri} \leq$ the departure time of path p **then**
          $\Phi^k_r \leftarrow \Phi^k_r \cup \{p\}$
          $c^k_{rp} \leftarrow$ Calculate the path cost based on the objective function of model **P1-k**
for intercontinental operator $k \in K^{\text{int}}$ **do**
  for request $r \in R^t \cup \bar{R}^t$ **do**
    for export terminal $i \in N^{\text{exp}}$ **do**
      for import terminal $j \in N^{\text{imp}}$ **do**
        for feasible path $p \in P^k_{ij}$ **do**
          if the release time of request r plus loading time is earlier than the departure time of path p **then**
            $\Phi^k_r \leftarrow \Phi^k_r \cup \{p\}$
            $c^k_{rp} \leftarrow$ Calculate the path cost based on the objective function of model **P1-k**
solve the BIP model P2-k for each operator via CPLEX solver
generate global paths:
for request $r \in R^t \cup \bar{R}^t$ **do**
  for export hinterland operator $k \in K^{\text{exp}}$ **do**
    best path in the export hinterland area: $p^{\text{exp}}_r = \arg\min_{k \in K^{\text{exp}}} c^k_r$
  for import hinterland operator $k \in K^{\text{imp}}$ **do**
    best path in the export hinterland area: $p^{\text{imp}}_r = \arg\min_{k \in K^{\text{imp}}} c^k_r$
  for export hinterland operator $k \in K^{\text{int}}$ **do**
    best path in the export hinterland area: $p^{\text{int}}_r = \arg\min_{k \in K^{\text{int}}} c^k_r$
  global path $p_r \leftarrow \left[p^{\text{exp}}_r, p^{\text{int}}_r, p^{\text{imp}}_r\right]$
  for $s \in p_r$ **do**
    $x_{rs} \leftarrow 1$

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