Global synchromodal transport with dynamic and stochastic shipment matching

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\section{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). With the increasing volume of global trade, container transportation becomes more and more important in improving the efficiency of global supply chains. As the fastest-growing cargo segment, global containerized trade reached 152 million twenty-foot equivalent units (TEUs) in 2018 (UNCTAD, 2019). Traditionally, global container transportation is organized by multiple operators. For example, an inland operator in Asia transports containers from Chongqing Terminal to Shanghai Port; a shipping liner company manages the container transport from Shanghai Port to Rotterdam Port; an inland operator in Europe further transports containers from Rotterdam Port to Duisburg Terminal.

In the past decade, horizontal collaboration between shipping lines has been very popular by forming an alliance to improve the utilization of resources and increase service frequency and capacity (Lee and Song, 2017). Recently, port operators and shipping lines appear to be focusing more attention on vertical integration by expanding service networks to inland terminals, such as Maersk and...
COSCO shipping Lines (UNCTAD, 2019). The vertical and horizontal collaboration among players in global container transport brings new challenges to global operators because of integrated planning in larger and more complex networks, as in Fig. 1. In such a global network, we define the global operator as the integrator that collaborates with inland carriers, ocean carriers, and terminal operators.

Apart from integrated transportation, amodal booking and differentiated fare classes have also been introduced in container transportation (van Riessen et al., 2015). Amodal booking implies that shippers do not select modes and routes for their shipments and leave the choices to a global operator. This increases the flexibility of the global operator to optimize the available capacities and to react effectively to disruptions by dynamically updating transport plans (Giusti et al., 2019). Differentiated fare classes have been proposed as incentives to promote the concept of amodal booking (van Riessen et al., 2017). For each origin–destination (OD) pair, the global operator offers multiple fare classes to shippers. A fare class is characterized by a specific price, lead time, and delay cost. Once a booking request associated with a fare class is accepted by the global operator, the transport plan that assigns specific transport services to accepted requests needs to be created.

Furthermore, digitalization and online booking platforms enabled by advanced information technologies are being increasingly used by the container industry. For example, Maersk launched an online booking platform called Maersk Spot in 2018 that allows customers to check the real-time freight rates, book ship slots online, and track their bookings (Meng et al., 2019). With Maersk Spot, the shipping company can instantly confirm whether to accept or reject a booking request and react dynamically to disturbances (e.g., service delays) by adjusting the transport plan.

The combined trend towards vertical and horizontal collaboration, amodal booking, differentiated fare classes, and digitalization gives rise to the concept of synchromodality in the container industry (van Riessen et al., 2015). Synchromodality aims to reduce transport costs, delays, and carbon emissions while improving the utilization of resources based on real-time information (Giusti et al., 2019). However, implementing synchromodality in practice is still challenging from several aspects, including pricing strategies and collaboration contracts at the strategical level, integrated service network design at the tactic level, and the allocation of resources to demands under a dynamic and stochastic environment at the operational level (Giusti et al., 2019).

In this paper, we investigate a dynamic and stochastic global shipment matching problem (DSGSM) under synchromodality. We consider a platform owned by a global operator that receives contractual and spot shipment requests from shippers and receives multimodal services from carriers. While the contractual requests are received before the planning horizon, the spot requests appear in the platform dynamically. The platform creates online decisions for shipment requests including acceptance and matching decisions in a global synchromodal network, as shown in Fig. 2. A match between a shipment and a service represents that the shipment will be transported by the service from the service’s origin to the service’s destination. The platform combines the matched services into shipments’ itineraries. Due to spot request uncertainty and service capacity limitations, the decisions made for current requests might become suboptimal upon receiving new requests. Due to travel time uncertainty and the utilization of multimodal services, the matches made for accepted requests might become infeasible at transshipment terminals. The objective of the platform is to maximize the total profits over a given planning horizon taking into account transport costs, delays, and carbon emissions.

Thanks to the development in data analytics, probability distributions of uncertainties are often available to online platforms. While dynamic and stochastic approaches that incorporate stochastic information of random variables in online decision-making processes have been well investigated in vehicle routing problems (e.g., Ritzinger et al., 2015), resource allocation problems (e.g., Wang et al., 2017), and hinterland synchromodal transport planning problems (e.g., Guo et al., 2020a), the dynamic and stochastic approach that handles shipment request and travel time uncertainties simultaneously in global synchromodal transportation is still missing in the literature.

Fig. 1. Map of the integrated global network representing our vision.
This paper contributes to the literature in the following ways:

- We introduce the DSGSM problem for global synchromodal transport networks that integrates online acceptance and matching decisions, and considers stochastic spot requests and travel times simultaneously.
- To solve the problem, we develop a rolling horizon framework to handle dynamic events and a hybrid stochastic approach to address uncertainties. The hybrid stochastic approach consists of a sample average approximation method addressing spot request uncertainty and a chance-constrained programming method addressing travel time uncertainty. Besides, we design a preprocessing-based heuristic algorithm to generate timely solutions at each decision epoch. The methodological framework for the DSGSM problem is shown in Fig. 3.
- We evaluate the performance of the hybrid stochastic approach in comparison to the approaches that do not consider any uncertainty or only consider one type of uncertainties under a comprehensive set of experiments. The experimental results highlight the benefits of incorporating stochastic information in dynamic shipment matching processes in terms of total profits, the number of infeasible transshipments, and delay in deliveries.

![Fig. 2. Illustration of a global synchromodal matching platform.](image)

![Fig. 3. Proposed methodological framework for the DSGSM problem.](image)
| Articles | Formulation characteristics | Time windows | Time schedules | Transshipment | Synchronization | Objectives | Dynamic events | Uncertainties | Methodologies |
|----------|-----------------------------|--------------|----------------|---------------|-----------------|-----------|----------------|---------------|---------------|
| Lee et al. (2009) | Maritime (single leg) | Acceptance of bookings | - | - | - | Maximize revenues | Booking request | Container volume | FCFS | BL | HA |
| Wang (2017) | Single leg | Acceptance of bookings | - | - | - | Maximize profits | Booking request | Container volume, service capacity | FCFS | BL | HA |
| Zurheide and Fischer (2012) | Maritime | Acceptance of bookings | - | Y | - | Maximize profits | - | Container volume | - | BL | MILP solver |
| Zurheide and Fischer (2014) | Maritime | Acceptance of bookings | - | Y | - | Maximize profits | - | Container volume | - | BP | MILP solver |
| Wang (2016) | General network | Acceptance of bookings | - | Y | - | Maximize profits | - | Container volume, service capacity | - | SAA, PAA | IP solver |
| van Riessen et al. (2017) | Inland | Acceptance of bookings | - | Y | - | Maximize revenues | - | Container volume | - | BL | MIP solver |
| Bilegan et al. (2014) | Railway | Acceptance of bookings Hard and container routing | Fixed | Y | Y | Maximize revenues | Booking request | Container volume | FCFS | SPR | MIP solver |
| Wang et al. (2016) | Waterway | Acceptance of bookings Hard and container routing | Fixed | Y | Y | Maximize revenues | Booking request | Container volume | FCFS | SPR | MIP solver |
| Wang et al. (2017) | Inland | Acceptance of bookings | - | Y | - | Maximize revenues | Booking request | Container volume | BC | VFA | MIP solver |
| Dynamic and stochastic container routing models | Maritime | Service capacity Hard planning and shipment routing | Fixed | Y | Y | Minimize costs | - | Container volume | - | SAA, PHA, APHA | MILP solver |

(continued on next page)
| Articles                      | Formulation characteristics | Methodologies                                                                 |
|------------------------------|-----------------------------|------------------------------------------------------------------------------|
|                              | Network                     | Decisions | Time windows | Time schedules | Transshipment | Synchronization | Objectives | Dynamic events | Uncertainties | Dynamic approach | Stochastic approach | Optimization algorithm |
| **Dynamic and stochastic container booking models** |                            |           |              |                |               |                 |            |                |               |                  |                   |                        |
| Demir et al. (2016)          | Inland                      | Service schedule and shipment routing | Soft       | Flexible      | Y             | Y              | Minimize costs | -            | Container volume, travel time | - | SAA | MILP solver |
| Li et al. (2015)             | Inland                      | Container flow control | -          | Fixed, flexible | Y             | Y              | Minimize costs | Container flow, travel time | RHF | - | HA |
| Qu et al. (2019)             | Inland                      | Service schedule, shipment routing | Soft       | Flexible      | Y             | Y              | Minimize costs | Release time, container volume, travel time | RPP | - | MILP solver |
| Guo et al. (2020b)           | Inland                      | Shipment matching | Soft       | Fixed, flexible | Y             | Y              | Minimize costs | Shipment request | RHF | - | HA |
| van Riessen et al. (2016)    | Inland                      | Container routing | Soft       | Fixed, flexible | -             | Y              | Minimize costs | Container request, Container volume | FCFS | DT | MILP solver |
| Rivera and Mes (2017)        | Inland                      | Assignment of freights to modes and vehicle routing | Hard       | -             | -             | Y              | Minimize costs | Shipment request, Shipment request | RP | VFA | MILP solver |
| Guo et al. (2020a)           | Inland                      | Shipment matching | Soft       | Fixed, flexible | Y             | Y              | Minimize costs | Shipment request, Shipment request | RHF | SAA | HA |
| Guo et al. (2020c)           | Global                      | Acceptance of bookings and shipment matching | Soft       | Fixed, flexible | Y             | Y              | Maximize profits | Travel time, Travel time | RHF | CCP | MILP solver |
| **This paper**               | Global                      | Acceptance of bookings and shipment matching | Soft       | Fixed, flexible | Y             | Y              | Maximize profits | Shipment request, Shipment request, travel time | RHF | HSP | HA |

1. FCFS: First-come-first-serve strategy; BC: Booking control strategy; RHF: Rolling horizon framework; RPP: Re-planning procedure; RP: Rollout procedures.
2. BL: Booking limit strategy; BP: Bid-price strategy; SAA: Sample average approximation method; PAA: Progressive augmentation algorithm; SPR: Stochastic programming model with recourse; VFA: Value function approximation; PHA: Progressive hedging algorithm; APHA: Adapted progressive hedging algorithm; DT: Decision trees; CCP: Chance-constrained programming; HSA: Hybrid stochastic approach.
3. HA: Heuristic algorithm; MILP: Mixed integer linear programming; MIP: Mixed integer programming; MINLP: Mixed integer non-linear programming.
• Although we focus on the application in global synchronomodal transportation, the developed methodologies can also be applied to the more specific fields of inland and maritime transportation.

The remainder of this paper is structured as follows. We briefly review the relevant literature in Section 2. In Section 3, we provide a detailed problem description, followed by the methodology in Section 4. In Section 5, we present the experimental results. Finally, in Section 6, we provide concluding remarks and directions for future research.

2. Literature review

Global transportation consists of intercontinental transportation and inland transportation (Yang et al., 2018). In intercontinental transportation, containers are transported from export terminals to import terminals. In inland transportation, export containers are transported from inland origins to export terminals; import containers are transported from import terminals to inland destinations. While extensive studies investigated maritime transportation (Meng et al., 2014) and inland transportation (SteadieSeifi et al., 2014) in the literature, only a few studies investigated global transportation (Lee and Song, 2017). Furthermore, most of the existing global transport planning models (e.g., Meng et al., 2012; Liu et al., 2014; Tran et al., 2017; Yang et al., 2018; Wei and Dong, 2019) assumed that all the input information is static and deterministic. However, in reality, multiple dynamic events and uncertainties exist in global synchronomodal transportation which highly affect the feasibility and profitability of transport plans.

In container transportation, the dynamic and stochastic models related to the DSGSM problem mainly include container booking and container routing problems. While the former considers the acceptance of booking requests to maximize revenue, the latter emphasizes the decisions on routing containers to minimize costs (Meng et al., 2014). The formulation characteristics and methodologies of dynamic and stochastic container booking and routing models are summarized in Table 1.

2.1. Dynamic and stochastic container booking models

Container booking control, also called slot allocation and capacity control, is one of the primary research topics in revenue management and is widely adopted by the airline industry (Meng et al., 2019). Container booking control aims to maximize revenue in a stochastic environment by effectively deciding on the acceptance of booking requests. According to the network structure, studies on container booking control can be divided into two groups: single-leg level and network level. While the single-leg level models (e.g., Lee et al., 2009; Wang, 2017) consider services operating on a single corridor, the network level models study services that operate on a network with the possibility of transshipments (Meng et al., 2019).

Most network container booking control models study static environments with the main strategies of booking limits and bid-price. A booking limit represents the maximum number of containers that should be allocated to a service. For example, Zurheide and Fischer (2012) proposed a slot allocation model for a liner shipping network to determine the booking limits for different booking classes (e.g. OD pair, container type, and service segment). van Riessen et al. (2017) investigated a cargo fare class mix problem in an intermodal network to maximize revenue by determining the booking limits on each fare class. Under a bid-price strategy, the decision of whether to accept or reject a booking is made based on the lowest acceptable profit value or the marginal costs for the next unit of capacity. Zurheide and Fischer (2014) developed a slot allocation model for a liner shipping company to decide the opportunity cost of a container slot as the bid-price and proved that the bid-price strategy outperforms the booking limit strategy due to the better utilization of capacity for profitable requests.

With the development of information technologies and digitalization in the container industry, researchers and industries have increasingly shifted their attention to dynamic models (Meng et al., 2019). These models can better reflect the online container booking processes and therefore better manage resource capacity. Bilegan et al. (2014) designed a load acceptance management system for rail container transport planning to dynamically accept or reject requests to favor the decisions of future requests with potentially higher profit. Wang et al. (2016) developed a probabilistic mixed integer programming optimization model to make acceptance decisions with the objective to maximize the expected revenue of a barge carrier over a given planning horizon. Wang et al. (2017) investigated a dynamic resource allocation problem, in which an intermodal operator attempts to determine the policy that characterizes the optimal quantities of each service product allowed to be sold during each time interval within a finite selling horizon.

In comparison to the DSGSM problem proposed in this paper, the above-mentioned container booking models focus on the acceptance decisions of requests before the transport process by setting booking limits or bid-price to maximize revenue. However, we take into account the synchronization of shipments with specific time windows and services with specific time schedules during the transport process. Besides, our work considers the dynamic and stochastic information of shipment requests and travel times in a global synchronomodal network, and re-optimizes the transport plan when disturbances (i.e., infeasible transshipments) happen.

2.2. Dynamic and stochastic container routing models

In the literature, container routing models have been well investigated at the strategic and tactical levels under a static context (Meng et al., 2014). Most of the studies integrate the container routing decision with other decisions such as empty container repositioning (e.g., Song and Dong, 2012) and service network design (e.g., Dong et al., 2015; Demir et al., 2016). Recently, with the increasing interest towards synchronomodality, several dynamic container routing models in synchronomodal transportation have been proposed. Li et al. (2015) proposed a rolling horizon approach to control and reassign container flows in an inland synchronomodal freight transport network with dynamic transport demand and traffic conditions. Qu et al. (2019) proposed a mixed-integer
Table 2  
Notation.

| Sets | Description |
|------|-------------|
| \(N\) | Terminals \(N\) |
| \(K\) | Container types, \(K = \{\text{dry, reefer}\}\) |
| \(R\) | Shipment requests, \(R = R^0 \cup R^1 \cup \ldots \cup R^T\) |
| \(R^0\) | Contractual requests received before the planning horizon |
| \(R^k\) | Contractual requests received before the planning horizon with container type \(k \in K\) |
| \(R^t\) | Spot requests received during time interval \([t-\delta,t)\), \(\delta > 0\) |
| \(R^k_t\) | Spot requests received during time interval \([t-\delta,t)\), \(\delta > 0\) with container type \(k \in K\) |
| \(\mathcal{R}\) | Accepted requests that require reoptimization at decision epoch \(t\) due to infeasible transshipments, \(t > 0\) |
| \(\mathcal{R}^k_t\) | Accepted requests that require reoptimization at decision epoch \(t\) due to infeasible transshipments, \(t > 0\) with container type \(k \in K\) |
| \(\omega^{kh}\) | Sampled requests under scenario \(\gamma \in \{1, \ldots, \Gamma\}\) at stage \(h \in H\) |
| \(\mathcal{H}\) | Prediction stages after decision epoch \(t\), \(H = \{t+1, \ldots, \max\{t+H,T\}\}\) |
| \(M\) | Modes, \(M = \{\text{ship, barge, train, truck}\}\) |
| \(V\) | Set of vehicles \(V = V^{\text{ship}} \cup V^{\text{barge}} \cup V^{\text{train}} \cup V^{\text{truck}}\) |
| \(\mathcal{V}\) | Vehicles with mode \(m \in M\) |
| \(S\) | Services, \(S = S^{\text{ship}} \cup S^{\text{barge}} \cup S^{\text{train}} \cup S^{\text{truck}}\) |
| \(\mathcal{S}\) | Services with mode \(m \in M\) |
| \(S_i\) | Services departing at terminal \(i \in N\), \(S_i = S^{\text{ship}}_i \cup S^{\text{barge}}_i \cup S^{\text{train}}_i \cup S^{\text{truck}}_i\) |
| \(S_i^m\) | Services departing at terminal \(i \in N\) with mode \(m \in M\) |
| \(S'_i\) | Services arriving at terminal \(i \in N\), \(S'_i = S^{\text{ship}}_i \cup S^{\text{barge}}_i \cup S^{\text{train}}_i \cup S^{\text{truck}}_i\) |
| \(S^m_i\) | Services arriving at terminal \(i \in N\) with mode \(m \in M\) |
| \(S^{\text{e}}-\) | Services departing at origin terminals during time interval \([t-\delta,t]\) |
| \(S^{\text{d}}-\) | Services arriving at destination terminals during time interval \([t-\delta,t]\) |

Deterministic parameters

| Parameter | Description |
|-----------|-------------|
| \(T\) | Length of the planning horizon |
| \(\sigma\) | Confidence level |
| \(H\) | Length of the prediction horizon |
| \(\Gamma\) | Number of scenarios |
| \(k_r\) | Container type of request \(r \in R, k_r \in K\) |
| \(\alpha_r\) | Origin terminal of request \(r \in R, \alpha_r \in N\) |
| \(d_r\) | Destination terminal of request \(r \in R, d_r \in N\) |
| \(u_r\) | Container volume of request \(r \in R\) |
| \(\alpha_t\) | Announce time of request \(r \in R\) |
| \(\varepsilon_t\) | Release time of request \(r \in R\) |
| \(\beta_t\) | Due time of request \(r \in R\) |
| \(p_t\) | Freight rate of request \(r \in R\) |
| \(l_t^r\) | Lead time of request \(r \in R, l_t^r = \delta_t - \varepsilon_t\) |
| \(c_{l_t^r}^{m}\) | Delay cost of request \(r \in R\) per container per hour overdue |
| \(m_s\) | Mode of service \(s \in S, m_s \in M\) |
| \(\alpha_s\) | Origin terminal of service \(s \in S, \alpha_s \in N\) |
| \(d_s\) | Destination terminal of service \(s \in S, d_s \in N\) |
| \(U^s_t\) | Free capacity of service \(s \in S\) at decision epoch \(t\) |
| \(U^k_s\) | Free capacity of service \(s \in S\) at decision epoch \(t\) for container type \(k \in K\) |
| \(c_t\) | Carbon emissions of service \(s \in S\) per container |
| \(c_t^k\) | Carbon emissions of service \(s \in S\) per container with type \(k \in K\) |
| \(m_{v_t}\) | Mode of vehicle \(v \in V\) |
| \(I_v\) | Itinerary of vehicle \(v \in V\) |
| \(I^t_v\) | The \(n^t\)th service of vehicle \(v \in V\), \(I^t_v \in S^{\text{truck}}\) |
| \(D_s\) | Scheduled departure time of service \(s \in S, D_s \in S^{\text{truck}}\) |
| \(A_s\) | Scheduled arrival time of service \(s \in S, A_s \in S^{\text{truck}}\) |
| \(T_s\) | Actual departure time of service \(s \in S, T_s \in S^{\text{truck}}\) |
| \(A_s\) | Actual arrival time of service \(s \in S, A_s \in S^{\text{truck}}\) |
| \(t_s\) | Estimated travel time of service \(s \in S\) |
| \(t_s\) | Actual travel time of service \(s \in S\) |
| \(q_{s-1}\) | A binary variable equal to 0 if service \(s\) is the preceding service of service \(q_s\), otherwise 1 |
| \(c_{l_t^r}^{m}\) | Loading/unloading cost per container at terminal \(i \in N\) with mode \(m \in M\) |

(continued on next page)
anticipatory optimization approach to create online matches between shipment requests and transport services in an inland synchromodal network. Guo et al. (2020a) proposed an approximate dynamic programming algorithm to assign the newly arrived shipment requests to a barge or trucks incorporating the solution structure of an optimization model on historical data of transport demand. Rivera and Mes (2017) proposed an adaptive dynamic events cause deviations from original plans. Guo et al. (2020b) investigated a dynamic shipment matching problem in which a global operator as the coordinator that receives ship, barge, train, and truck services from carriers, as shown in Fig. 2. We define the global operator as the coordinator that

Table 2 (continued)

| $f^m_i$ | Loading/unloading time at terminal $i \in N$ with mode $m \in M$ |
| $c^t_i$ | Storage cost at terminal $i$ per container per hour |
| $c^c$ | Activity-based carbon tax charged by institutional authorities |
| $B$ | A large number used for binary constraints |

Random variables

| $\tilde{t}_i$ | Travel time of service $s \in S \tilde{t}_i \sim N(\mu^t_i, \sigma^t_i)$ |
| $\tilde{D}_i$ | Departure time of service $s \in S', \tilde{D}_i \sim N(\mu^d_i, \sigma^d_i)$ |
| $\tilde{A}_i$ | Arrival time of service $s \in S' \backslash \tilde{A}_i \sim N(\mu^a_i, \sigma^a_i)$ |
| $\tilde{R}_i$ | Future requests received at decision epoch $t$. The probability distributions $\{x^t_0, x^t_1, x^t_2, x^t_3, x^t_4, x^t_5, x^t_6\}$ are assumed known. |

Variables

| $y^t_r$ | Binary variable; 1 if request $r \in R'$ is accepted at decision epoch $t$ |
| $\gamma^t_r$ | Binary variable; 1 if request $r \in R'$ is matched with service $s \in S$ at decision epoch $t$, 0 otherwise |
| $\gamma^t_{\mu}$ | Binary variable; 1 if sample request $r \in w^\mu$ is accepted at decision epoch $t$ |
| $\gamma^t_{\sigma}$ | Binary variable; 1 if sample request $r \in w^\sigma$ is matched with service $s \in S$ at decision epoch $t$, 0 otherwise |
| $\gamma^t_{\rho}$ | Binary variable; 1 if request $r \in R' \cup \tilde{R}$ is matched with service $s \in S$, $x_a = 1$ and service $q \in S$, $x_q = 1$, 0 otherwise |
| $\gamma^t_{\rho'}$ | Itinerary of request $r \in R' \cup \tilde{R}$ consists of matched services |
| $D_{rs}$ | Departure time of truck service $s \in S' \setminus \tilde{A}$ with request $r \in R' \cup \tilde{R}$ |
| $c^t_{rs}$ | Transshipment cost of request $r \in R' \cup \tilde{R}$ at terminal $i \in N$ per container |
| $\hat{w}_{si}$ | Storage time of request $r \in R' \cup \tilde{R}$ at terminal $i \in N$ |
| $\tilde{I}^t_{c}$ | Delay of request $r \in R' \cup \tilde{R}$ at destination terminal $d_r \in N$ |

programming model to reschedule services and reroute shipment flows under the framework of synchronomodality when unexpected dynamic events cause deviations from original plans. Guo et al. (2020b) investigated a dynamic shipment matching problem in which a platform provides online matches between shipment requests and transport services in an inland synchronomodal network.

The recent developments in information technologies and data analytics have facilitated the utilization of stochastic information in online decision-making processes (Ritzinger et al., 2015). With regards to dynamic and stochastic container routing problems, van Riessen et al. (2016) proposed a decision tree to instantaneously allocate incoming containers to inland services by analyzing the solution structure of an optimization model on historical data of transport demand. Rivera and Mes (2017) proposed an adaptive approximate dynamic programming algorithm to assign the newly arrived shipment requests to a barge or trucks incorporating the probability distributions of future requests, to achieve cost minimization over a multi-period horizon. Guo et al. (2020a) proposed an anticipatory optimization approach to create online matches between shipment requests and transport services in an inland synchronomodal network by incorporating the probability distributions of future requests. Guo et al. (2020c) developed a chance-constrained programming model to address travel time uncertainty in a global synchronomodal shipment matching problem.

Compared with the DSGSM problem proposed in this paper, the majority of the dynamic and stochastic container routing models focus on the routing/matching decisions for booking requests in inland networks to minimize total costs without the consideration of acceptance decisions. Furthermore, none of them consider the dynamic and stochastic shipment requests and travel times simultaneously in global synchronomodal transportation.

2.3. Summary

According to the above literature review, the majority of the dynamic and stochastic container booking and routing studies focus on inland networks. In this paper, we investigate global networks that integrate inland and intercontinental transportation. Besides, most of the above-mentioned studies only consider container volume uncertainty. This paper considers that all the attributes of a shipment request are uncertain, including shippers’ origin, destination, container volume, time window, and fare class. Although Rivera and Mes (2017) considered shipment request uncertainty, their model neither considers the time schedules of transport services nor the transshipment operations between different modalities. To the best of our knowledge, most related to our work are the papers of Guo et al. (2020a) that addressed shipment request uncertainty and Guo et al. (2020c) that addressed travel time uncertainty in synchronomodal transportation with the consideration of re-optimization procedures when disturbances happen. However, none of them consider stochastic shipment requests and travel times simultaneously. This paper develops a hybrid stochastic approach to address shipment request and travel time uncertainties integrally in online decision-making processes under the field of global synchronomodal transportation.

3. Problem description

We consider a platform owned by a global operator that receives contractual and spot shipment requests from shippers, and receives ship, barge, train, and truck services from carriers, as shown in Fig. 2. We define the global operator as the coordinator that
collaborates with shippers, carriers and terminal operators to provide integrated transport planning in a global synchronomodal network. The global operator does not typically own any of the transport services used to move a shipment from its origin to its destination or any of the terminals used for transshipments. Instead, the global operator enters into contracts for transport services with carriers and for loading/unloading and storage operations with terminal operators. The contract with carriers specifies the services that are available to the global operator with specific modalities, OD pairs, time schedules, available capacities, and costs. The global operators combine these services into itineraries to provide integrated transport for shipments. The global operator publishes the fare classes for each OD pair with specified freight rates, lead times, and delay costs. Shippers choose the fare classes for their shipments based on the value and urgency of commodities. After that, they initiate requests to the platform with specific OD pairs, container volumes, time windows, and fare classes, and leaves the choices of services to the platform. The notation used in this paper is shown in Table 2.

3.1. Terminals

Let \( N \) be the set of terminals. Each terminal \( i \in N \) is characterized by its loading/unloading cost \( c_i^m \), loading/unloading time \( f_i^m \) with mode \( m \in M = \{ \text{ship, barge, train, truck} \} \), and storage cost per container per hour \( c_i^t \). We assume terminal operators provide unlimited loading/unloading and storage capacity to the global operator.

3.2. Shipments requests

Let \( R \) be the set of requests. Each request \( r \in R \) is characterized by its container type \( k_i \) (i.e., dry or reefer), origin terminal \( o_i \), destination terminal \( d_i \), container volume \( u_i \), announce time \( a_i \) (i.e., the time when the platform receives the request), release time \( e_i \) (i.e., the time when the shipment is available for transport process), and fare class including freight rate \( p_i \), lead time \( L_i \), and delay cost \( c_i^d \). The due time of request \( r \) is represented as, \( L_i = e_i + L_i \). Requests \( R \) consist of two groups: contractual requests \( R^c \) and spot requests \( R^s \). For a contractual request \( r \in R^c \), the global operator has long-term contracts with shippers. Therefore, the announce time of contractual request \( r \) is \( a_i = 0 \). All the information \( \{ k_i, o_i, d_i, u_i, e_i, L_i, p_i, c_i^d \} \) is known in advance. On the contrary, for a spot request \( r \in R^s \), the platform receives the request from spot markets during time interval \( [t-1, t] \). The information of the spot request \( \{ k_i, o_i, d_i, u_i, e_i, L_i, p_i, c_i^d \} \) is unknown before its announce time \( a_i \). However, the probability distributions of spot requests \( \{ \pi_k, \pi_o, \pi_d, \pi_u, \pi_e, \pi_L, \pi_p, \pi_c^d \} \) are assumed to be available to the platform. In addition, shippers require their shipments to be transported as a whole, and ask to receive the transport plan as soon as possible. As a result, we do not consider cancellation of requests from shippers. The requests accepted by the platform will not be rejected in the future.

3.3. Transport services

Let \( S \) be the set of services. Each ship, barge or train service \( s \in S^{\text{ship}} \cup S^{\text{barge}} \cup S^{\text{train}} \) is characterized by its mode \( m_s \in M \), origin terminal \( o_s \), destination terminal \( d_s \), free capacity \( U^s_k \) in terms of container type \( k \in K = \{ \text{dry, reefer} \} \) at decision epoch \( t \), total free capacity \( U^t_s \), scheduled departure time \( D_s \), scheduled arrival time \( A_s \), estimated travel time \( t_s \), travel cost \( c_s \), and generation of carbon emissions \( e_s^t \) for container type \( k \). Let \( \bar{t}_s, \bar{D}_s \) and \( \bar{A}_s \) be the actual travel, departure and arrival time of service \( s \) which are unknown before their realization. Moreover, different services with the same mode might be operated by the same vehicle. For two successive services operated by the same vehicle, transshipment is unnecessary at the intermediate terminal. Let \( \xi_{sq} \) be equal to 0 if services \( s \) and \( q \) are operated by the same vehicle, and service \( s \) is the preceding service of service \( q \), 1 otherwise. Each truck service \( s \in S^{\text{truck}} \) is characterized by its origin terminal \( o_s \), destination terminal \( d_s \), free capacity \( U^s_k \) in terms of container type \( k \in K \) at decision epoch \( t \), total free capacity \( U^t_s \), estimated travel time \( t_s \), travel cost \( c_s \), and generation of carbon emissions \( e_s^t \) for container type \( k \). Let \( \bar{t}_s, \bar{D}_s \) and \( \bar{A}_s \) be the actual travel time of service \( s \) which is unknown before its realization. Each truck service consists of a fleet of trucks that have flexible departure times. We define \( D_s \) as a variable that indicates the departure time of service \( s \in S^{\text{truck}} \) with shipment \( r \in R \). We assume the platform receives real-time information once a service \( s \in S \) departs from or arrives to a terminal.

In practice, travel time uncertainties are quite common resulting from weather conditions and traffic congestions (Demir et al., 2016). The probability distributions of travel times are assumed to be available to the platform through the analysis of historical data and external factors. In the literature, different distributions have been used to characterize travel times, such as normal distributions (e.g., Li et al., 2010; Ehmke et al., 2015; Shi et al., 2018) and Gamma distributions (e.g., Tas¸ et al., 2014b; Long et al., 2018). Researches on fitting continuous distributions to travel time variations tend to present inconclusive and inconsistent results due to different traffic conditions and different service areas (Rahman et al., 2018). The main objective of this paper is not to find the best fit distributions of travel times but rather to investigate the benefits of incorporating travel time uncertainty in online decision-making processes under the field of global synchronomodal transportation. Thanks to the properties of normal distributions, the sum and difference between two independent normal random variables are still normal distributed. These properties are critical for checking the feasible transshipments between different services. Therefore, we assume the travel times \( [t_i]_{r \in R^c} \) are continuous random variables following normal distributions, and are statistically independent. Let \( t_i \sim N(\mu_i, \sigma_i^2) \), in which \( \mu_i \) is the mean travel time between terminal \( o_i \) and terminal \( d_i \), and \( \sigma_i \) is the corresponding standard deviation. To avoid the generation of too small or too large values, we set fixed lower and upper bounds for the realization of travel times in experimental tests.

Due to travel time uncertainties, the actual departure and arrival time of service \( s \in S \) are also uncertain. The distribution of the departure time of service \( s \) is based on the distribution of the arrival time of its preceding service; the distribution of the arrival time of
service $s$ is based on the distributions of the departure and travel time of service $s$. For vehicle $v \in V \setminus V^{truck}$, we define the itinerary of vehicle $v$ as the sequence of services that the vehicle operated, and define $I^n_v$ as the $n^{th}$ service of vehicle $v$. Therefore, the departure time of service $s = I^n_v$ follows normal distribution given by:

$$
\tilde{D_s} \sim N(D_{I^n_v} + \sum_{j \in [1, n-1]} \mu_{I^n_v} + \sum_{j \in [1, n-1]} 2\mu_{I^n_v} \sum_{j \in [1, n-1]} \sigma_{I^n_v}^2),
$$

where $m_v$ is the mode of vehicle $v$. We denote $\tilde{D_s} \sim N(\mu_s^+, \sigma_s^2)$. Similarly, the arrival time of service $s = I^n_v$ follows normal distribution given by:

$$
\tilde{A_s} \sim N(D_{I^n_v} + \sum_{j \in [1, n-1]} \mu_{I^n_v} + \sum_{j \in [1, n-1]} 2\mu_{I^n_v} \sum_{j \in [1, n-1]} \sigma_{I^n_v}^2).
$$

We denote $\tilde{A_s} \sim N(\mu_s^+, \sigma_s^2)$.

### 3.4 Objectives and infeasible transshipments

The objective of the platform is to maximize total profits over the planning horizon $T$ by dynamically optimizing acceptance and matching decisions over a global synchromodal network. In practice, the first-come-first-served (FCFS) strategy has been widely adopted in the container industry (Meng et al., 2019). Under such a strategy, decisions are made based on deterministic information only. An illustrative example of online matching processes under the FCFS strategy is shown in Fig. 4. At decision epoch $t = 8$, the platform accepts request $r_1$, and matches $r_1$ with ship service $s_1$ and barge service $s_2$ which are the cheapest services. At decision epoch $t = 9$, the platform accepts request $r_2$, and matches $r_2$ with rail service $s_3$ and truck service $s_4$. At decision epoch $t = 10$, the platform receives reefer request $r_3$ which is very profitable. However, the platform has to reject request $r_3$ since no capacity is available. To make better decisions over the planning horizon, the platform needs to consider the stochastic information of future requests.

On the other hand, travel time uncertainty of services in a global synchromodal network may lead to infeasible transshipments in addition to the commonly studied outcome of late or early delivery at destinations (e.g., Li et al., 2010; Taş et al., 2014a; Rodrigues et al., 2019). An illustrative example is shown in Fig. 5. A shipment is planned to be transported by a train service from its origin terminal to port A, by a ship service from port A to port B, and by two barge services from port B to its destination terminal according to fixed time schedules. The outcomes of travel time uncertainty in global synchromodal transportation include late delivery at destination terminal under realization 1 which causes delayed costs, early delivery at destination terminal under realization 2 which causes storage costs, and infeasible transshipment at port B under realization 3 which requires reoptimization.

### 4. Methodology

Methodologies for dynamic and stochastic problems can be divided into two categories: methods based on preprocessed decisions which determine the values and policies of decision making before the execution of the transport plan, such as approximate dynamic programming, and methods that make decisions dynamically during the execution of the transport plan.
programming; and methods based on online decisions which focus on the computation when a dynamic event occurs with respect to the current system state and the available stochastic information, such as rolling horizon approaches (Ritzinger et al., 2015). The methodology proposed for the DSGSM problem belongs to the class of online decision methods. The methodology consists of a rolling horizon framework (RHF) that handles dynamic events, a hybrid stochastic approach (HSA) that addresses two types of uncertainties integrally, and a preprocessing-based heuristic algorithm (P-HA) that generates timely solutions at each optimization run, as shown in Fig. 3. Specially, we use the RHF to adapt the matching platform to new states upon receiving new requests or real-time travel times; we use a chance-constrained programming method (CCP) to generate chance constraints regarding infeasible transshipments caused by travel time uncertainty; we use a sample average approximation method (SAA) to sample requests appearing in the near future. Due to the computational complexity, we adopt the P-HA to solve the optimization problem at each decision epoch.

4.1. Rolling horizon framework

RHF is known as an efficient periodic reoptimization approach that has been applied in many fields, such as routing problems (Arslan et al., 2019) and scheduling problems (Silvente et al., 2015). Compared with the FCFS strategy, the RHF can handle multiple dynamic events that appear in a system simultaneously, which is quite common in global synchronomodal transport, as illustrated in

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**Fig. 5.** Possible outcomes of travel time uncertainty in global transport.

![Possible outcomes of travel time uncertainty in global transport](image)

**Fig. 6.** Illustration of the rolling horizon framework.

![Illustration of the rolling horizon framework](image)
Algorithm 1. Rolling horizon framework.

Input: Terminals $N$; contractual requests $R^2$; services $S$; free capacity $\{U^k_r\}_{r \in S,k \in K}$; length of planning horizon $T$; probability distributions of spot requests and travel times; confidence level $\alpha_r$; length of prediction horizon $H$, and number of scenarios $\Gamma$.

Output: Acceptance decision $\{y^r_t\}_{t \in \mathbb{N}; r \in [0, \ldots, T]}$; matching decision $\{x^r_t\}_{t \in \mathbb{N}; r \in S_0; \Gamma}$; itinerary $\{t^r_k\}_{r \in \mathbb{N}; k \in \mathbb{K}}$; number of infeasible transshipments $N^\text{infeasible}$; actual profits $\{\Delta P^r_t\}_{t \in [0, \ldots, T]}$.

Initialize: Let $R' \leftarrow \emptyset$, $R \leftarrow \emptyset$, $U'_t \leftarrow \emptyset$, $N^\text{infeasible} \leftarrow 0$, $\Delta P^r \leftarrow 0$.

1: for decision epoch $t \in [0, 1, \ldots, T]$ do
2:    receive requests $R'$, actual departure time $\bar{D}_s$ of service $s \in S^{T} \setminus S^{\text{max}}$, actual arrival time $\bar{A}_s$ of service $s \in S^{T} \setminus S^{\text{max}}$, actual departure time $\bar{D}_o$ of service $s \in S^{T} \cap S^{\text{max}}$, and actual arrival time $\bar{A}_o$ of service $s \in S^{T} \cap S^{\text{max}}$.
3:    if request $r \in R'' \cup \ldots \cup R'^{-1}$ do
4:        if $R_t = \emptyset$ then
5:            go to $r = r + 1$;
6:        else
7:            for terminal $i \in N$ do
8:                if request $r$ just arrived terminal $i$, service $s \in \{S^{t+1} \cup \ldots \cup S^{T} | o_i = i\}$ has already departed; or request $r$ has already arrived terminal $i$, service $s \in \{S^t | o_i = i\}$ just departed, but the time for transshipment operations is not enough then
9:                    update reoptimization requests $R'' \leftarrow R'' \cup \{r\}$
10:                   update number of infeasible transshipments $N^\text{infeasible} \leftarrow N^\text{infeasible} + 1$
11:                   update free capacity $U'_r \leftarrow U'_r + u_r$ for $s \in \{t^r_k | \exists o_i > t\}$
12:                   if $k_s = \text{reefer}$ then
13:                        update free capacity $U'_s \leftarrow U'_s + u_s$ for $s \in \{t^r_k | \exists o_i > t\}$, $k = \text{reefer}$
14:                   get optimization model $\rightarrow$ HSA
15:                   obtain acceptance and matching decision $\{y^r_t, x^r_t\} \rightarrow$ P-HA
16:                   update free capacity $U'_r \leftarrow U'_r - \sum_{s \in S} x^r_t$ for $s \in S$
17:                   update free capacity $U'_s \leftarrow U'_s - \sum_{s \in S} x^r_t$ for $s \in S$.
18:                   update itinerary $\{t^r_k\}$ for $r \in R$
19:                   calculate total actual profits $\Delta P^r$ generated at decision epoch $t$
20:                   calculate the total profits over the planning horizon $T$

We define $t$ as the points in time at which decisions are made under the RHF, referred to as the decision epoch. The planning horizon is divided into $T$ consecutive time intervals. At decision epoch $t \in \{0, \ldots, T\}$, the RHF updates the new information received during time interval $[t - 1, t]$, including new requests $R' = \{r | r \in \mathbb{N}; r \leq t\}$, actual departure times $\bar{D}_s$ of ship, barge, and train services, and actual departure times $\bar{D}_o$ of truck services, where $S^{T} = \{s \in S | 0 < \bar{A}_s - \bar{D}_o \leq \bar{A}_s - \bar{D}_o \leq t\}$ is the set of services departing their origin terminals during time interval $[t - 1, t]$; $S^{T} = \{s \in S | 0 < \bar{A}_s - \bar{D}_o \leq \bar{A}_s - \bar{D}_o \leq t\}$ is the set of services arriving at their destination terminals during time interval $[t - 1, t]$.

We define $y^r_t$ as the binary variable which is 1 if request $r \in R'$ is accepted, 0 otherwise. Let $x^r_t$ be the binary variable which is 1 if request $r \in R'' \cup R'$ is matched with service $s \in S$, 0 otherwise. Here, $R''$ is the set of accepted requests that require reoptimization at decision epoch $t$ due to infeasible transshipments. Based on the actual arrival and departure times of matched services $\{s \in S \neq y^r_t = 1\}$ of accepted request $r \in \{R' \cup \ldots \cup R'^{-1} | y^r_t = 1\}$, the RHF checks which requests need reoptimization due to infeasible transshipments. An infeasible transshipment happens in two situations: first, the accepted shipment $r$ has just arrived terminal $i$, the matched service $s \in \{S^{t+1} \cup \ldots \cup S^{T} | x^r_s = 1, o_i = i\}$ has already departed; second, the accepted shipment $r$ has already arrived terminal $i$, the matched service $s \in \{S^{t+1} | x^r_s = 1, o_i = i\}$ has just departed from terminal $i$, but the remaining time is not enough for transhipments. The platform thus cancels the capacity bookings on the matched services which depart after decision epoch $t$ for reoptimization request $r \in R''$. The RHF then updates the free capacity regarding dry and reefer slots of these services.

The optimization model used at each decision epoch is developed based on the HSA (presented in Section 4.2). The RHF uses the P-HA (presented in Section 4.3) to generate acceptance and matching decisions based on the input parameters and the optimization model. The platform thus books capacities on the matched services based on the matching decisions. After that, the RHF updates free capacities of services and itineraries of requests, and calculates the actual profits $\Delta P^r$ generated at each decision epoch. At the end of the planning horizon, the RHF calculates the total actual profit generated over planning horizon $T$.

4.2. Hybrid stochastic approach

In this section, we develop the HSA to address uncertainties, which consists of the CCP that handles travel time uncertainty and the SAA that handles shipment request uncertainty.

4.2.1. Chance-constrained programming model

In the literature, different stochastic programming models have been developed to handle travel time uncertainty (Gendreau et al., 2016). In general, stochastic programming can be either formulated as a CCP model or a stochastic programming model with recourse
(SPR) (Li et al., 2010). While CCP models ensure the feasibility of stochastic constraints, SPR models define recourse actions to induce an expected penalty cost on objective functions. Typically, SPR models define a delay cost for late delivery, a storage cost for early delivery, and a large penalty cost for infeasible transshipments without the consideration of reoptimization after disturbances. Since the extra costs caused by reoptimization procedures at later stages are hard to estimate, we develop a CCP model to address travel time uncertainty. The CCP model does not take into account the correction costs caused by the reoptimization of requests.

Under CCP, each stochastic constraint will hold at least with probability \( \alpha \), where \( \alpha \) is referred to as the confidence level provided by the platform. A high \( \alpha \) means the matches have a low probability causing infeasible transshipments. The confidence level \( \alpha \) also controls the problems’ tightness and computational complexity. The objective is to maximize the total profits which consist of the planned profits at decision epoch \( t \) including freight rates, travel costs, transfer costs, storage costs, delay costs and carbon tax. The optimization model under the CCP at decision epoch \( t \) is:

\[
P_1 \max_{y, s} \sum_{r \in R} p_r u_r, y_r = - \left( \sum_{s \in S} c_s y_s u_s + \sum_{s \in S} \sum_{r \in R} c_s y_s u_s + \sum_{s \in S} E(\bar{w}_s) u_s + \sum_{s \in S} c_s\left( \frac{\partial P_s}{\partial y_s} \right) u_s + \sum_{s \in S} \sum_{k \in K} \sum_{s \in S} c_s\left( \frac{\partial P_s}{\partial y_s} \right) u_s \right)
\]

subject to

\[
y_r \leq \sum_{s \in S} y_s, \quad \forall r \in R,
\]

\[
y_r \leq \sum_{s \in S} y_s, \quad \forall r \in R,
\]

\[
\sum_{s \in S} y_s \leq 1, \quad \forall r \in R,
\]

\[
\sum_{s \in S} y_s \leq 1, \quad \forall r \in R,
\]

\[
\sum_{s \in S} y_s = 1, \quad \forall r \in R,
\]

\[
\sum_{s \in S} y_s = 1, \quad \forall r \in R,
\]

\[
\sum_{s \in S} y_s \leq 0, \quad \forall r \in R \cup \bar{R},
\]

\[
\sum_{s \in S} y_s \leq 0, \quad \forall r \in R \cup \bar{R},
\]

\[
\sum_{s \in S} y_s \leq 0, \quad \forall r \in R \cup \bar{R},
\]

\[
\sum_{s \in S} y_s \leq 0, \quad \forall r \in R \cup \bar{R},
\]

\[
\sum_{s \in S} y_s \leq 0, \quad \forall r \in R \cup \bar{R},
\]

\[
\sum_{s \in S} y_s = \sum_{s \in S} y_s, \quad \forall r \in R \cup \bar{R}, i \in N \setminus \{o, d\},
\]

\[
\sum_{s \in S} y_s = \sum_{s \in S} y_s, \quad \forall r \in R \cup \bar{R}, i \in N \setminus \{o, d\},
\]

\[
\sum_{r \in R \cap S} y_s u_s \leq U_r, \quad \forall s \in S,
\]

\[
\sum_{r \in R \cap S} y_s u_s \leq U_r, \quad \forall s \in S, k = reefer,
\]

\[
e_r + f_m r \leq \bar{D}_r + B(1 - y_n), \quad \forall r \in R \cup \bar{R}, s \in S_{i,m}^\text{track},
\]

\[
P\{e_r + f_m r \leq \bar{D}_r + B(1 - y_n)\} \geq \alpha, \quad \forall r \in R \cup \bar{R}, s \in S_{i,m}^\text{track},
\]

\[
P\{e_r + f_m r \leq \bar{D}_r + B(1 - y_n)\} \geq \alpha, \forall r \in R \cup \bar{R}, i \in N \setminus \{o, d\}, s \in S_i \setminus S_{i,m}^\text{track}, q \in S_i \setminus S_{i,m}^\text{track}, z_{ij} = 1,
\]
services that depart from or arrive at a transshipment terminal are selected. Constraints (12) ensure flow conservation at transshipment
where
\[ z_{rs}^t \] equals to 1 if request
\[ r \] is
\[ \forall t \in T \] and
\[ t \in T \]
\[ s \in S \] and
\[ q \in S \]
\[ z_{rs}^t \] is the estimated delay in delivery of request
\[ r \] at
\[ t \] and
\[ s \] and
\[ q \] and
\[ \alpha \] and
\[ \forall r \in R \cup \overline{R}, i \in N \backslash \{ o_i, d_i \}, s \in S_i \backslash S_i^\text{track}, q \in S_i^\text{track}, \]
\[ \alpha \]
\[ \forall r \in R \cup \overline{R}, i \in N \backslash \{ o_i, d_i \}, s \in S_i \backslash S_i^\text{track}, q \in S_i^\text{track}, \]
\[ \alpha \]
\[ \forall r \in R \cup \overline{R}, i \in N \backslash \{ o_i, d_i \}, s \in S_i \backslash S_i^\text{track}, q \in S_i^\text{track}, \]
Constraints (14) ensure that the total volumes of reefer containers matched with service
\[ r \] do not exceed its free capacity at
\[ t \]. Constraints (14) ensure that the total volumes of reefer containers matched with service
\[ r \] cannot exceed its free capacity on reefer slots. In practice, dry containers can use reefer slots, but reefer containers cannot use dry slots (Meng et al., 2019).
Constraints (15) ensure that the departure time of service \( s \) minus loading time must be earlier than the release time of request \( r \), if request \( r \) will be transported by service \( s \) depart its origin terminal. Here, \( B \) is a large enough number which ensures the time compatibility between shipment \( r \) and service \( s \) when binary variable \( x_{rs}^t \) equals 1, but leaves the constraints “open” if \( x_{rs}^t \) is 0. Constraints (16)–(20) ensure that the possibility of feasible transshipment at terminals will be higher than the confidence level \( \alpha \). Constraints (21)–(23) calculate the loading costs at origin terminals, the unloading costs at destination terminals, and the loading and unloading costs at transshipment terminals. Constraints (24)–(26) ensure that binary variable \( x_{rs}^t \) equals 1 if \( x_{rs}^t = 1 \) and \( x_{rs}^t = 1 \), 0 otherwise. Constraints (27)–(34) calculate the storage time at origin, transshipment, and destination terminals. Constraints (35),(36) calculate delay in deliveries at destination terminals.

To solve the CCP model, the traditional methods is to convert the chance constraints into their corresponding deterministic equations. Based on the properties of normal distributions, constraints (16)–(20) can be linearized as:

\[
\frac{e_r + f_{o_r}^m + B(x_{rs}^t - 1) - \mu_r^+}{\sigma_r} \leq \Phi^{-1}(1 - \alpha), \quad \forall r \in R' \cup \overline{R}, s \in S_{\alpha}^+ \backslash S_{\text{track}}^t, \tag{37}
\]

\[
\frac{f_{r_s}^m + f_{r_s}^m + B(x_{rs}^t - 1) + B(x_{rs}^t - 1) - (\mu_r^+ - \mu_s^+)}{(\sigma_r^2 + (\sigma_s^2))^2} \leq \Phi^{-1}(1 - \alpha), \quad \forall r \in R' \cup \overline{R}, s \in S_{\alpha}^+ \backslash S_{\text{track}}^t, \tag{38}
\]

\[
D_{\alpha} + f_{r_s}^m + f_{r_s}^m + B(x_{rs}^t - 1) + B(x_{rs}^t - 1) - (\mu_r^+ - \mu_s^+), \quad \forall r \in R' \cup \overline{R}, i \in N \backslash \{o_i, d_i\}, s \in S_{\alpha}^+ \backslash S_{\text{track}}^t, q \in S_{\alpha}^+ \backslash S_{\text{track}}^t, \tag{39}
\]

\[
D_{\alpha} - f_{r_s}^m - f_{r_s}^m + B(1 - x_{rs}^t) + B(1 - x_{rs}^t) - \mu_r^+ \geq \Phi^{-1}(\alpha), \quad \forall r \in R' \cup \overline{R}, i \in N \backslash \{o_i, d_i\}, s \in S_{\alpha}^+ \backslash S_{\text{track}}^t, q \in S_{\text{track}}^t, \tag{40}
\]

\[
D_{\alpha} - D_{\alpha} - f_{r_s}^m - f_{r_s}^m + B(1 - x_{rs}^t) + B(1 - x_{rs}^t) - \mu_r^+ \geq \Phi^{-1}(\alpha), \quad \forall r \in R' \cup \overline{R}, i \in N \backslash \{o_i, d_i\}, s \in S_{\text{track}}^t, q \in S_{\text{track}}^t, \tag{41}
\]

where \( \Phi^{-1}(\alpha) \) is the inverse function of standardized normal distributions.

4.2.2. Sample average approximation method

Based on model P1, in this section, we present the SAA that samples requests which appear in the near future. At decision epoch \( t \), a sample \( \{a^0, a^1, \ldots, a^t, \ldots, a^T\} \) of \( \Gamma \) scenarios is generated according to the probability distributions \( \{\pi_1, \pi_2, \ldots, \pi_{\Gamma}\} \) of shipment requests. Each scenario includes a prediction of spot requests arrived between stage \( t + 1 \) and stage \( t + H \), \( a^t = \{a^{t+1}, a^{t+2}, \ldots, a^{t+H}\} \). Here, \( H \) is the prediction horizon that is just long enough to obtain good decisions at decision epoch \( t \). The expected cost in the future is approximated by the sample average function \( \Gamma^{-1} \sum_{r=1}^{\Gamma} \tilde{c}_r^T \). Let \( \tilde{y}_r^T \) be the binary variable which equals 1 if sample request \( r \in \omega^h \) is accepted, and \( \hat{z}_{rs}^{\gamma} \) be the binary variable which equals 1 if sample request \( r \in \omega^h \) is matched with service \( s \) under scenario \( \gamma \in \{1, \ldots, \Gamma\} \) at stage \( h \in H = \{t + 1, \ldots, \max\{T, t + H\}\} \). We define \( \tilde{c}_r^T \) as the transfer cost and \( \tilde{E}(\tilde{w}_r) \) as the waiting time of sample request \( r \in \omega^h \) at terminal \( \tilde{E}(\tilde{w}_r) \) as the delay in delivery of sample request \( r \). The optimization model of the DSGSM problem at decision epoch \( t \) changes to:

\[
\text{subject to constraints (2)–(12), (15), (21)–(41) for } r \in R' \cup \overline{R} \cup \omega^h, \gamma \in \{1, \ldots, \Gamma\}, h \in H,
\]

\[
P2 \quad \max_{\gamma \neq h \neq t, \gamma \in H} \sum_{r \in R' \cup \overline{R}} p_r^h x_{rs} \left( \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i \tilde{E}(\tilde{w}_r) u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i \tilde{E}(\tilde{w}_r) u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i \tilde{E}(\tilde{w}_r) u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i \tilde{E}(\tilde{w}_r) u_{ir} + \sum_{r \in R' \cup \overline{R}} \sum_{i \in N} c_{rs}^i \tilde{E}(\tilde{w}_r) u_{ir} \right) \tag{42}
\]
Constraints (43,44) ensure that the total container volumes of new requests, reoptimization requests, and sample requests matched with service \( s \) do not exceed its free capacity at decision epoch \( t \) under each scenario.

### 4.3. Preprocessing-based heuristic algorithm

Due to the computational complexity, we design the P-HA to solve model \( P2 \) at each decision epoch. The P-HA is adapted from the heuristic algorithm designed by Guo et al. (2020b) in which travel times are considered deterministic. The P-HA consists of three steps: preprocessing of feasible paths, preprocessing of feasible matches, and binary integer linear programming.

#### 4.3.1. Preprocessing of feasible paths

We define a path \( p \) as a combination of services in sequence. A path \( p \) is feasible only 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 unloading time must be earlier than the departure time of service \( s_{i+1} \) minus loading time at transshipment terminal \( d_i \) with confidence level \( \alpha \). We define \( N_{\text{path}} \) as the largest number of services in a path. Let \( P \) denote the set of feasible paths, and \( P_{lj} \) represent the set of feasible paths with \( l \) services that depart from terminal \( i \) and arrive to terminal \( j \).

The pseudocode of preprocessing of feasible paths is shown in Algorithm 2. The algorithm starts with determining the feasible paths for each OD pair with just one service, and subsequently combines these paths with a single service to create feasible paths with two services, three services, and so on. To examine whether a new path \( [s_1, \ldots, s_{l-1}, s] \in P_{lj} \) consisting of feasible path \( p = [s_1, \ldots, s_{l-1}] \in P_{lj}^{l-1} \) and service \( s \in S_j \) is feasible, we check the transshipment feasibility between service \( s_{l-1} \) and service \( s \) by using constraints (38)–(41) with \( x_{rs_{l-1}} = 1, x_{rs} = 1 \). After that, we check whether feasible path \( p \in P \) has subtours, and remove paths with subtours.

![Fig. 7. The topology of global synchromodal network G1.](image-url)
Sensitivity analysis of different policies.

Table 5
Sensitivity analysis of different policies.

| Cases   | Subsidies | Ice-breaking fee | IMO regulations | Itineraries | Request 1 | Request 2 | Request 3 | Request 4 | Request 5 | Request 6 |
|---------|-----------|------------------|-----------------|-------------|-----------|-----------|-----------|-----------|-----------|-----------|
| Benchmark | 0         | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 1       | 10%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 2       | 20%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 3       | 30%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 4       | 40%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 5       | 50%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 6       | 60%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 7       | 70%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 8       | 80%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 9       | 90%       | with             | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 10      | 100%      | without          | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,16]    | []         | [1,2,16,9]|
| 11      | 0         | without          | with            | [3,4,17,10]  | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|
| 12      | 0         | without          | with            | 16           | 16        | [4,17,14] | [2,15]    | []         | [1,2,15,9]|

Algorithm 2. Feasible path generation algorithm.

Input: Terminals $N$, services $S$, the largest number of services in a path $N_{\text{max}}$, index $l \in \{1, 2, \ldots, N_{\text{max}}\}$.

Output: Feasible paths $\{P^l_i\}_{l=1}^{N_{\text{max}}}$.

Initialize: Let $P \leftarrow \emptyset$, $l \leftarrow 1$.

1: for terminal $i \in N$, terminal $j \in N$ do
2:     for service $s \in S$ do
3:         if origin $o_i = i$ and destination $d_i = j$ then
4:             $P^l_j \leftarrow P^l_j \cup \{s\}$
5:         $l \leftarrow l + 1$
6:     while $l \leq N_{\text{max}}$ do
7:         for terminal $i \in N$, terminal $j \in N$ do
8:             for service $s \in S$ do
9:                 if origin $o_i \neq i$ and destination $d_i = j$ then
10:                for feasible path $p = \{s_1, \ldots, s_l\} \in P^l_i$ do
11:                   if $P(\text{feasible transshipment between service } s_{l-1} \text{ and } s) \geq \alpha$ then
12:                      $P^l_j \leftarrow P^l_j \cup \{s_1, \ldots, s_{l-1}, s\}$
13:                 $l \leftarrow l + 1$
14:         for path $p \in P^l_i$ do
15:             for service $s \in p$ do
16:                 if $d_s = i$ or $o_s = j$ then
17:                     $P^l_j \leftarrow P^l_j \setminus \{p\}$
18:             for service $s \in p$, $q \in p$ do
19:                 if $o_s = o_q$ then
20:                     $P^l_j \leftarrow P^l_j \setminus \{p\}$

4.3.2. Preprocessing of feasible matches

A match between request $r \in R$ and path $p = \{s_1, \ldots, s_l\} \in P$ is feasible if it satisfies time-spatial compatibility. Specifically, the origin terminal of shipment request $r$ should be the same as the origin of service $s_1$, the destination of request $r$ should be the same as the destination of service $s_l$. The release time of request $r$ should be earlier than the departure time of service $s_l$ minus loading time at origin terminal $o_r$ with confidence level $\alpha$. We denote $N_{\text{match}}$ as the maximum number of feasible matches. Let $\Phi_r$ be the set of feasible paths for request $r$, and $c_{\Phi_r}$ be the total costs of matching request $r$ with path $p$ including travel costs, transfer costs, storage costs, delay costs.
costs, and carbon tax.

The pseudocode of preprocessing of feasible matches is shown in Algorithm 3. For request \( r \) and path \( p = [s_1, \ldots, s_l] \in P_{\text{most}} \), the transshipment feasibility between \( r \) and \( p \) is checked by using constraints (15) and (37) with \( x_{rs_1} = 1 \). For each request \( r \), if the number of feasible matches in \( \Phi_r \) exceeds \( N_{\text{match}} \), \( \Phi_r \) will be replaced by the set of \( N_{\text{match}} \) cheapest matches.

**Algorithm 3.** Feasible match generation algorithm.

Input: Feasible paths \( P \), requests \( R = R_t \cup R_t \cup \{ \omega \gamma h \} \), the largest number of services in a path \( N_{\text{path}} \), maximum matches \( N_{\text{match}} \), objective function (42).

Output: Feasible matches \( \{ \Phi_r \} \forall r \in R \), total costs \( \{ c_{rp} \} \forall r \in R \).

Initialize: Let \( \Phi \leftarrow \emptyset \), \( l \leftarrow 1 \).

1: for request \( r \in R \) do
2: \hspace{1em} for \( l \in \{1, 2, \ldots, N_{\text{path}}\} \) do
3: \hspace{2em} for feasible path \( p = [s_1, \ldots, s_l] \in P_{\text{most}} \) do
4: \hspace{3em} if \( \text{P{feasible transshipment at origin terminal}} \geq \alpha \) then
5: \hspace{4em} \( \Phi_r \leftarrow \Phi_r \cup \{ p \} \)
6: \hspace{4em} \( c_{rp} \leftarrow \text{Calculate the objective function} \)
7: \hspace{2em} if the number of feasible matches in \( \Phi_r > N_{\text{match}} \) then
8: \hspace{3em} \( \Phi_r \leftarrow \text{the } N_{\text{match}} \text{ cheapest matches in } \Phi_r \)

### 4.3.3. Binary integer programming model

Based on the above preprocessing procedures, the objective function is updated to maximize the total profits for the matching of requests with feasible paths. Let \( z_{rp} \) be a binary variable equal to 1 if request \( r \in R_t \cup R_t \cup \{ \omega \gamma h \} \) is matched with path \( p \in P \), and 0 otherwise. Let \( \hat{z}_{rp} \) be the binary variable equal to 1 if request \( r \in \omega \gamma h, \gamma \in \{1, \ldots, \Gamma\} \) is matched with path \( p \in P \), and 0 otherwise. Model P2 will be translated into a binary integer programming (BIP) model:

\[
\begin{align*}
\max & \quad \sum_{r \in R} \sum_{p \in \Phi_r} c_{rp} z_{rp} + \frac{1}{\Gamma} \sum_{h \in H} \left( \sum_{r \in \omega \gamma h} \sum_{p \in \Phi_r} c_{rp} \hat{z}_{rp} - \sum_{r \in \omega \gamma h} \sum_{p \in \Phi_r} c_{rp} \hat{z}_{rp} \right) \\
\text{subject to} & \quad \sum_{p \in \Phi_r} z_{rp} = 1, \quad \forall r \in R_t, \\
& \quad \sum_{p \in \Phi_r} \hat{z}_{rp} = 1, \quad \forall r \in R_t, \\
& \quad \sum_{p \in \Phi_r} z_{rp} = 1, \quad \forall r \in R_t.
\end{align*}
\]

Fig. 8. The topology of global synchromodal network G2.
Performance of the preprocessing-based heuristic algorithm.

Table 7

| Instances | Exact approach | P-HA (3, 100) | P-HA (5, 200) | P-HA (N⁴∅=7, N⁴∅=unlimited) |
|-----------|----------------|---------------|---------------|-------------------------------|
|           | N.var | N.con | Obj   | CPU | gaps (%) | CPU | gaps (%) | CPU | gaps (%) | CPU |
| G0-5-0    | 2268  | 6540  | 13107 | 40.44 | 2.06    | 0.16 | 0.00   | 0.24 | 76     | 46   |
| G0-10-0   | 3780  | 10840 | 26114 | 181.36 | 2.74    | 0.17 | 0.00   | 0.24 | 121    | 52   |
| G1-1-0    | 11466 | 35994 | 23127 | 7417.06 | 0.00   | 1.23 | 0.00   | 13.03 | 297    | 53   |
| G1-10-0   | 11466 | 362164| 23127 | 7417.06 | 6.90   | 1.30 | 0.00   | 15.81 | 34613  | 192  |
| G1-100-0  | 11466 | 361248| 23127 | 7417.06 | 8.14    | 4.29 | 0.00   | 56.69 | 368430 | 391  |
| G1-200-0  | 2293200| 7224988| 19216 | 145.96  | 5.67   | 7.81 | 0.00   | 97.58 | 716098 | 592  |
| G1-300-0  | 3439800| 1084652| 19216 | 145.96  | 4.69   | 16.33 | 0.00 | 146.96 | 1075646| 792  |
| G1-400-0  | 4586400| 14439116| 19216 | 145.96  | 2.60   | 26.27 | 0.00 | 212.37 | 1431162| 991  |

Table 6

Probability distributions of spot requests.

| Parameters       | Value               | Probability   |
|------------------|---------------------|---------------|
| Container type   | (dry,reefer)        | (0.9,0.1)     |
| Origin           | (Shanghai,Zhengzhou,Wuhan,Chongqing) | Uniform distribution |
| Destination      | (Rotterdam,Duisburg,Neuss,Dortmund) | Uniform distribution |
| Container volume | (1,2,…,9)           | Uniform distribution |
| ΔT1              | (0,1,2,…)           | Poisson distribution with mean 24 min |
| Announce time    | a_{i,t-1} = a_{r,t} + ΔT1 | (0.15,0.15,0.2,0.2,0.15,0.15) |
| ΔT2              | (1,2,…,24)          | Uniform distribution |

5. Numerical experiments

In this section, we evaluate the performance of the HSA on the DSGSM problem in comparison to a deterministic approach (DA) which does not consider spot request and travel time uncertainties, a stochastic approach (SA1) which only considers travel time uncertainty, and a stochastic approach (SA2) which only considers spot request uncertainty. While the DA is similar to the approach presented in Guo et al. (2020b), the SA1 is similar to the approach presented in Guo et al. (2020c) and the SA2 is similar to the approach of Guo et al. (2020a). All of the above approaches are implemented under the RHF and supported by the P-HA that generates timely solutions at each decision epoch. The methodological differences among these approaches are summarized in Table 3. The 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.

Unless otherwise stated, the benchmark values of coefficients are set as follows: planning horizon (unit: hours) T = 1400; the length of time intervals is one hour; loading cost (unit: €/TEU) c_{i}^{hip} = 18, c_{i}^{barge} = 18, c_{i}^{train} = 12, c_{i}^{truck} = 12 for i ∈ N; loading time (unit: hours) f_{i}^{hip} = 12, f_{i}^{barge} = 4, f_{i}^{train} = 2, f_{i}^{truck} = 1 for i ∈ N; storage cost (unit: €/TEU-h) c_{i} = 1 for i ∈ N; carbon tax (unit: €/kg) c_{i} = 0.07;
Table 8
Impact of different confidence levels on instances with different DODs.

| Instances       | Degree of dynamism | Confidence level | Total profits (€) | Infeasible transshipments | Rejections | CPU (seconds) | Gaps (%) |
|-----------------|--------------------|------------------|-------------------|---------------------------|------------|---------------|----------|
| G2-225-75       | 25%                | 0.50             | 1443321           | 75                        | 4          | 0.22          | 0.00     |
|                 |                    | 0.70             | 1469731           | 45                        | 9          | 0.18          | 1.83     |
|                 |                    | 0.75             | 1434690           | 16                        | 15         | 0.17          | −0.60    |
|                 |                    | 0.90             | 1334829           | 9                         | 25         | 0.13          | −7.52    |
|                 |                    | 0.95             | 1271550           | 9                         | 31         | 0.14          | −11.90   |
| G2-150-150      | 50%                | 0.50             | 1334025           | 72                        | 6          | 0.43          | 0.00     |
|                 |                    | 0.70             | 1413988           | 44                        | 11         | 0.39          | 5.99     |
|                 |                    | 0.75             | 1362974           | 17                        | 19         | 0.36          | 2.17     |
|                 |                    | 0.90             | 1253208           | 8                         | 28         | 0.32          | −6.96    |
|                 |                    | 0.95             | 1215809           | 8                         | 35         | 0.31          | −8.86    |
| G2-75-225       | 75%                | 0.50             | 1328131           | 77                        | 6          | 0.69          | 0.00     |
|                 |                    | 0.70             | 1364769           | 50                        | 12         | 0.62          | 2.76     |
|                 |                    | 0.75             | 1333812           | 18                        | 22         | 0.57          | 0.43     |
|                 |                    | 0.90             | 1247088           | 8                         | 31         | 0.50          | −6.10    |
|                 |                    | 0.95             | 1214627           | 9                         | 36         | 0.50          | −8.35    |
| G2-0-300        | 100%               | 0.50             | 1256014           | 75                        | 20         | 0.96          | 0.00     |
|                 |                    | 0.70             | 1276508           | 52                        | 25         | 0.86          | 1.63     |
|                 |                    | 0.75             | 1275004           | 19                        | 28         | 0.86          | 1.51     |
|                 |                    | 0.90             | 1263179           | 10                        | 33         | 0.75          | 0.57     |
|                 |                    | 0.95             | 1205402           | 10                        | 41         | 0.73          | −4.03    |

Table 9
Impact of different standard deviations.

| Instances       | Standard deviation coefficients (*benchmark value) | Total profits (€) | Infeasible transshipments | Rejections | Delay (TEU-h) | Gaps (%) |
|-----------------|--------------------------------------------------|-------------------|---------------------------|------------|---------------|----------|
| G2-225-75       | 1.0                                              | 1469731           | 45                        | 9          | 14013         | 1.83     |
|                 | 1.5                                              | 1348739           | 25                        | 19         | 13834         | 17.80    |
|                 | 2.0                                              | 895563            | 39                        | 26         | 30751         | 26.96    |
| G2-150-150      | 1.0                                              | 1413988           | 44                        | 11         | 13834         | 17.80    |
|                 | 1.5                                              | 1262171           | 25                        | 21         | 16735         | 19.89    |
|                 | 2.0                                              | 866506            | 35                        | 28         | 31336         | 42.04    |
| G2-75-225       | 1.0                                              | 1364769           | 50                        | 12         | 16247         | 2.76     |
|                 | 1.5                                              | 1253172           | 27                        | 25         | 16953         | 26.65    |
|                 | 2.0                                              | 866958            | 35                        | 33         | 30925         | 67.85    |
| G2-0-300        | 1.0                                              | 1276508           | 52                        | 25         | 15388         | 1.63     |
|                 | 1.5                                              | 1220973           | 27                        | 30         | 17437         | 28.61    |
|                 | 2.0                                              | 852891            | 34                        | 37         | 31538         | 60.61    |
delay cost (unit: €/TEU-h) $c^d = 0.005 \times p_r$ for $r \in R$; mean of travel times $t_s = t_s$ for $s \in S$; standard deviation of travel times $\sigma_s = 0.1 \times t_s$ for $s \in S \setminus S_{\text{truck}}, \sigma_s = 0.5 \times t_s$ for $s \in S_{\text{truck}}$. Regarding the P-HA, the default settings are as follows: the largest number of services in a path $N_{\text{path}} = 7$, the maximum number of feasible matches for each request $N_{\text{match}} = 300$.

### 5.1. A small network

To test the impact of different policies in global synchromodal transport, we first consider a small network $G_1$ presented by Guo et al. (2020c), as shown in Fig. 7. It consists of two terminals in Europe and three terminals in Asia that are connected by Suez Canal (SCR), Northern Sea Route (NSR), and Eurasia Land Bridge (ELB). Compared with the SCR, the NSR has a shorter travel time but a higher travel cost caused by ice-breaking fees (Lin and Chang, 2018). With the implementation of IMO 2020 regulations, shipping liner companies are required to use low-sulfur fuels on the sea, which in turn increases about 60% of travel costs in the SCR and the NSR (Lian et al., 2020). As an alternative, the ELB becomes more and more competitive thanks to its shortest travel time. However, without subsidies from governments, the ELB is still the most expensive route.

We use the same service data designed by Guo et al. (2020b) which consists of 18 services: 8 in Asia, 6 in Europe and 4 connecting Asia and Europe. We consider 6 contractual requests received by the system before the planning horizon. The detailed request data is shown in Table 4. Compared with reefer shipments (requests 1, 3, 5), dry shipments (requests 2, 4, 6) have longer lead times, lower freight rates, and lower delay costs.

The effects of policies are tested under instance $G_1$-6-0 without spot request and travel time uncertainties, i.e., $\mu_s = t_s, \sigma_s = 0$. Therefore, we set $a = 0.5, H = 0, \Gamma = 0$. Under the benchmark case, the travel costs are designed under the consideration of ice-breaking fees in the NSR, IMO 2020 regulations in the SCR and the NSR, and without subsidies from governments. Table 5 shows that the itineraries of dry shipments (i.e., requests 2, 4, 6) are more sensitive to different policies than reefer shipments (i.e., requests 1, 3, 5). Under the same policy, it is obvious that reefer shipments are more likely to be assigned on the ELB.
compared to dry shipments due to the time sensitivity of reefer cargoes. When government subsidies cover above 50% of ELB transport costs, all dry shipments will be switched from maritime to railway transportation. With the government subsidies and the IMO 2020 regulations, the ELB becomes more competitive in the global transport market than the SCR and the NSR. Liner shipping companies need to take actions to meet these challenges, such as adjusting sailing routes and adopting low sulfur fuel. Besides, due to the existence of the ice-breaking fee, the SCR is still more competitive than the NSR. To attract more demands on the NSR, liner shipping companies can adopt smart navigation methodologies to avoid the ice-breaking fee.

5.2. A realistic network

In this section, we test the behavior of the methodologies under a realistic network G2 with 8 terminals and 106 services. The hinterland-related data is adapted from Guo et al. (2020b); the intercontinental-related data is adapted from Guo et al. (2020c). The topology of network G2 is shown in Fig. 8. We generate several instances to represent different characteristics of requests under network G2. The probability distributions of spot requests are shown in Table 6. To ensure demand and supply balance, the total number of shipment requests is set to 300. We use $G2 - n_1 - n_2$ to represent an instance under network G2 with $n_1$ contractual requests and $n_2$ spot requests.

5.2.1. Performance of the P-HA

The P-HA is tested under 8 instances without dynamic events and uncertainties. The P-HA is based on pre-processing procedures which may lead to suboptimal solutions. However, when $N^{\text{auth}}$ is large enough and $N^{\text{match}}$ is unlimited, the P-HA generates optimal solutions. We use $N^{\text{auth}} = 7$ and $N^{\text{match}} = \text{unlimited}$ as the benchmark and vary $N^{\text{auth}}$ from 3 to 7 and $N^{\text{match}}$ from 100 to unlimited. We also report the results generated by an exact approach in which optimization model $P2$ is solved by CPLEX directly. We denote ‘N.var’ as the number of variables, ‘N.con’ as the number of constraints, ‘Obj’ as the total profits, and ‘CPU’ as the computation time in seconds. We use ‘gaps’ to represent the gaps in total profits between the P-HA with different settings, i.e.,

$$\text{gaps} = \frac{\text{Total profits}(N_{\text{auth}}, N_{\text{match}}) - \text{Total profits}(7, \text{unlimited})}{\text{Total profits}(7, \text{unlimited})}.$$  

Table 7 shows that the exact approach can only solve the first three small instances within 24 h. Increasing the largest number of services in a path to 5 and the maximum number of feasible matches to 200, the P-HA can get optimal solutions for these instances within 13.03 s. Under the same setting, the P-HA can generate ‘very good’ solutions within 4 min for large instances in which the largest gap is just $-0.01\%$. By using the P-HA, the system has the flexibility to choose proper $N^{\text{auth}}$ and $N^{\text{match}}$ values to achieve the trade-off between computational complexity and solution quality.

5.2.2. Performance of the SA1 for travel time uncertainties

In this section, we aim to investigate the performance of the SA1 in addressing travel time uncertainties under the impact of different confidence levels, degrees of dynamism, and travel time deviations.

To test the impact of different confidence levels, we use instance $G2-150-150$ under 20 realizations of travel times. The realizations of travel times are generated based on Monte Carlo Simulation by sampling their probability distributions with a fixed lower bound of 0.9 + $\frac{t_s}{S}$ for $s \in S$. Fig. 9 shows that with the same confidence level, different solutions are generated under different realizations of travel times. From Fig. 9(a), we can see that on average, the SA1 has the best performance in total profits when $\alpha = 0.7$. Fig. 9(b) shows that in general, the higher the confidence level, the lower the delays in deliveries. Fig. 9(c) indicates that with a higher confidence level, the platform will choose ‘suboptimal’ decisions that have lower probability of infeasible transshipments. Fig. 9(d) shows that the higher the confidence level, the higher the number of rejections. Although we use profit maximization as the objective function, infeasible transshipments, delays, and rejections are also important performance indicators which reflect the platform’s service level. By playing with the confidence level, decision makers can decide on how risk-averse they are and manage the trade-off between operational efficiency and service level.

To test the impact of different standard deviations of travel times, we set $\alpha = 0.7$ for the SA1 and use average results generated based on 20 realizations of actual travel times. Let ‘gaps’ be the gaps in total profits between the SA1 and the DA. Table 9 shows that travel time deviations have a large impact on the performance of the SA1 in increasing total profits. The larger the standard deviation, the better the performance of the SA1 in comparison to the DA. This is reasonable since with higher standard deviations, the variability in travel times is very high and the estimations are not as accurate. In comparison, instance $G2-75-225$ has the best performance in improving the total profits that achieves 67.85% with standard deviations $\sigma_s = 0.2 + \frac{t_s}{S^\text{track}}$ for $s \in S^\text{track}$ and $\sigma_s = t_s$ for $s \in S^\text{track}$. Companies that have the main source of uncertainty as travel time with larger variations may benefit more from the stochastic approach SA1.
5.2.3. Performance of the SA2 for spot request uncertainties

In this section, we aim to investigate the performance of the SA2 in addressing spot request uncertainties under the impact of different numbers of scenarios ($\Gamma$) and lengths of the prediction horizon ($H$). We use $\Gamma = 0, H = 0$ as the benchmark. Let ‘gaps in total profits’ = \frac{\text{Total profit} (\Gamma, H) - \text{Total profit} (0, 0)}{\text{Total profit} (0, 0)}. Here, the total profits are the average total profits generated under 20 realizations of travel times. In case of sample requests instability, we replicate the optimization process 10 times for all instances. Fig. 10(a) shows that under instance G2-150-150, the performance of the SA2 in total profits increases as the number of scenarios and the length of the prediction horizon grow up. We set $\Gamma = 10, H = 12$ for the SA2 and use the DA as the benchmark. Fig. 10(b) shows that the SA2 outperforms the DA in all the instances, and the gap between the SA2 and the DA grows with the increasing DOD. Companies running on a larger percentage of spot requests are expected to benefit more from the stochastic approach SA2.

5.2.4. Performance of the HSA for travel time and spot request uncertainties

To investigate the benefits of incorporating the stochastic information of both travel times and spot requests, we compare the performance of the HSA with the DA, the SA1, and the SA2 under default settings. We use the DA as the benchmark and report the average results under 20 realizations of travel times and 10 samples of spot requests. We use ‘gaps’ to represent the gaps in total profits between different approaches, which is given by (objective value-benchmark value)/benchmark value. Table 10 shows that the HSA has better performance in total profits than the DA in all the instances and than the SA1 and SA2 in highly dynamic instances, namely above 50% DODs. On average, while the SA1 has 3.05% improvements and the SA2 has 5.01% improvements in comparison to the DA, the HSA has the largest improvements, namely 7.03%. In addition, for all the instances, the HSA generates lower infeasible transshipments and delays than other approaches. Furthermore, we notice that the number of rejections increases with the increasing DOD and achieves the highest under instance G2-0-300 which has no contractual requests. This is reasonable since the system cannot reject contractual requests. Moreover, we observe that the HSA has the best performance in instance G2-0-300 as stochastic information pays off when it is highly dynamic. Besides, it is obvious that increasing the confidence level, the computational complexity will decrease thanks to the chance constraints. However, increasing the number of scenarios and the length of the prediction horizon, the computational complexity will increase dramatically caused by the increasing size of sample requests.

5.2.5. Managerial insights

In this section, we summarize the key managerial insights derived from the above experimental results.

- Thanks to the horizontal and vertical collaboration among carriers, global operators have more flexibility to choose different routes for shipments which is critical when disturbances happen (e.g., Suez Canal blockage in March 2021). However, the increased integration in global transportation gives rise to large instances which generally cannot be solved by commercial software. Heuristic algorithms that can generate timely and high-quality solutions, like the one designed in this paper, are essential to global operators.
- Travel time uncertainty, as the main source of uncertainties in global transportation, not only affects operational efficiency but also the feasibility of transport plans. Stochastic approaches that address travel time uncertainties are critical for global operators to improve the robustness of transport plans and ensure the on-time delivery of shipments under traffic disruptions.
- Due to future request uncertainty and service capacity limitations, the capacity assigned to current requests will be unavailable for future requests which might be more profitable. Stochastic approaches that evaluate the impact of current decisions on the future state and behavior of the system play a key role in increasing the total profits of global companies over a given planning horizon.
- In practice, travel time uncertainty and shipment request uncertainty always happen simultaneously. Stochastic approaches that consider these two types of uncertainties integrally can help global companies achieve better performance in profits, feasible transshipments, and on-time deliveries in transport planning.

6. Conclusions and future research

In this paper, we investigated a dynamic and stochastic shipment matching problem in global synchronomodal transportation. We considered a platform that aims to provide online acceptance and matching decisions for contractual and spot shipment requests in a global synchronomodal transport network. The platform receives requests and travel times dynamically, but the probability distributions of dynamic events are available. To solve the problem, we developed a rolling horizon framework to handle dynamic events, a hybrid stochastic approach (HSA) to address shipment request and travel time uncertainties, and a preprocessing-based heuristic algorithm to generate solutions at each decision epoch.

We conducted extensive experiments to validate the performance of the HSA in comparison to the approaches that do not consider any uncertainty or only consider one type of uncertainties. The experimental results indicate that the HSA is highly effective in increasing total profits, reducing infeasible transshipments and delays on instances with a large degree of dynamism. Thanks to the flexibility of the HSA, global companies are able to adapt the transport system to their business characteristics by tuning the parameters accordingly. This way they can manage the trade-off between computational complexity and solution quality, and the trade-off between operations efficiency and service level.

This research can be extended in several directions. First, in this paper, we considered a centralized platform that provides integrated decisions for global shipments. To ensure the fairness among players, profit-sharing mechanism design is a promising research direction. Second, in practice, a large number of entities are involved in global container transport and they may not all be willing to
give authority to a centralized platform. The coordination mechanism among them and incentives to stimulate cooperation are part of future research. Third, we assumed that the platform publishes fixed fare classes for container bookings. Future research can consider dynamic pricing strategies for online platforms to realize the balance between supply and demand. Fourth, in this paper, we assumed travel times follow normal distributions, future research will be conducted to relax this restriction.

CRediT authorship contribution statement

Wenjing Guo: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. Bilge Atasoy: Conceptualization, Writing - review & editing, Supervision. Wouter Beelaerts van Blokland: Conceptualization, Supervision. Rudy R. Negenborn: Conceptualization, Supervision.

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