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A Global Intermodal Shipment Matching Problem Under Travel Time Uncertainty

Wenjing Guo(✉), Bilge Atasoy, Wouter Beelaerts van Blokland, and Rudy R. Negenborn

Department of Maritime and Transport Technology, Delft University of Technology, Delft, The Netherlands
{W.Guo-2,B.Atasoy,W.W.A.BeelaertsvanBlokland,R.R.Negenborn}@tudelft.nl

Abstract. Global intermodal transportation involves the movement of shipments between inland terminals located in different continents by using ships, barges, trains, trucks, or any combination among them through integrated planning at a network level. One of the challenges faced by global operators is the matching of shipment requests with transport services in an integrated global network. The characteristics of the global intermodal shipment matching problem include acceptance and matching decisions, soft time windows, capacitated services, and transshipments between multimodal services. The objective of the problem is to maximize the total profits which consist of revenues, travel costs, transfer costs, storage costs, delay costs, and carbon tax. Travel time uncertainty has significant effects on the feasibility and profitability of matching plans. However, travel time uncertainty has not been considered in global intermodal transport yet leading to significant delays and infeasible transshipments. To fill in this gap, this paper proposes a chance-constrained programming model in which travel times are assumed stochastic. We conduct numerical experiments to validate the performance of the stochastic model in comparison to a deterministic model and a robust model. The experiment results show that the stochastic model outperforms the benchmarks in total profits.

Keywords: Global intermodal transportation · Shipment matching problem · Travel time uncertainty · Chance-constrained programming

1 Introduction

With the increasing volumes of global trade and the trend towards time-sensitive shipments, efficient global transportation becomes increasingly important in global supply chains [18]. Intermodal transportation is the provision of efficient, effective, and sustainable transport services thanks to the horizontal and vertical collaboration among players [15]. However, implementing intermodality in global transport is still challenging from several aspects, including: the design of collaboration contracts and pricing strategies that ensure fairness and attractiveness among players at the strategic level [8]; integrated service network design

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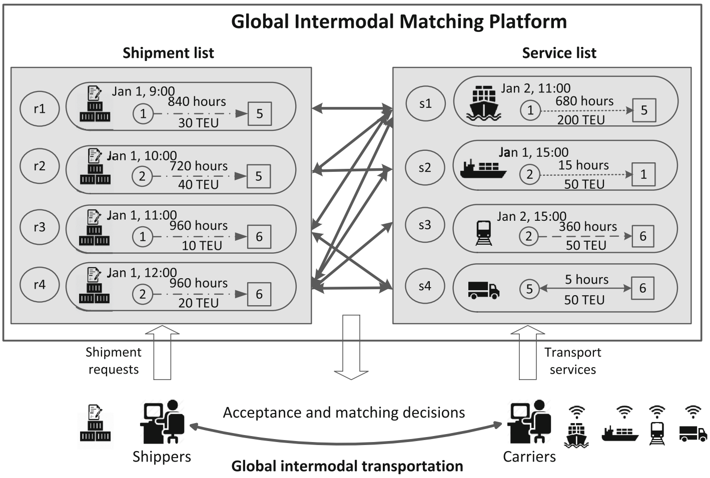

Fig. 1. A global intermodal matching platform.

that determines service frequencies and time schedules at the tactical level [12]; and integrated transport plan that assigns specific shipments with transport services under a dynamic or stochastic environment at the operational level [15]. This paper investigates a global intermodal shipment matching (GISM) problem under travel time uncertainty at the operational level.

With the development of digitization in the logistics industry, increasing matching/booking platforms have appeared in freight transportation [13], such as Uber Freight and Quicargo. We consider a platform owned by a global operator that receives shipment requests from shippers and receives transport services from carriers, as shown in Fig. 1. The global operator could be a logistics service provider or an alliance formed by multiple carriers, such as Maersk and COSCO Shipping lines. A shipment request is defined as a batch of containers that must be transported from its origin to its destination within a specific time window. For example, shipment r1 consists of 30 containers which require to be transported from origin terminal 1 to destination terminal 5 with a release time of Jan 1, 9:00, and a lead time of 840 h. A transport service is characterized by its mode, origin, destination, time schedule, and free capacity. For example, ship service s1 with capacity 200 TEU (twenty-foot equivalent unit) will depart from terminal 1 on Jan 2, 11:00, and arrive to terminal 5 with an estimated travel time of 680 h. The platform aims to provide optimal acceptance and matching decisions in a global intermodal network. A match between a shipment request and a transport 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 itineraries to provide integrated transport for global shipments. For instance, shipment r2 will be transported by barge service s2 from origin terminal 2 to transshipment terminal 1 and by ship service s1 from transshipment terminal 1 to destination terminal 5. The objective of the platform is to maximize the total profits which consists of revenues and costs.

Due to travel time uncertainty and the utilization of multimodal services, the matches made for accepted requests might become suboptimal or even infeasible at transshipment terminals. Thanks to the development in data analytics, probability distributions of uncertainties are often available to transport systems [3]. However, while stochastic approaches that incorporate stochastic information of travel times in decision-making processes have been well investigated in vehicle routing problems [2,9] and inland intermodal transport planning [1,6], the stochastic approach for the GISM problem under travel time uncertainty is still missing. This paper contributes to the literature by developing a chance-constrained programming model to set confidence levels of chance constraints regarding infeasible transshipments in a global intermodal network.

In the literature, most similar to our work are the work of Demir et al. [1] and Guo et al. [4]. Demir et al. [1] investigated an inland intermodal service network design problem with travel time uncertainty. In comparison to [1], this paper considers fixed time schedules of multimodal services in a global network, and develops a model that integrates acceptance and matching decisions. Guo et al. [4] studied an inland intermodal shipment matching problem with request uncertainty. In comparison to [4], this paper considers travel time uncertainty in a global intermodal network.

The remainder of this paper is structured as follows. In Sect. 2, we provide a detailed problem description, followed by a mathematical formulation in Sect. 3. In Sect. 4, we develop the Chance-constrained programming model. In Sect. 5, we present the experimental results. Finally, in Sect. 6, we provide concluding remarks and directions for future research.

2 Problem Description

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

Let R be the set of shipment requests. Each request $r \in R$ is characterized by its container type CT_r (i.e., dry or reefer), origin terminal o_r, destination terminal d_r, container volume u_r, release time $\mathbb{T}_r^{\text{release}}$ (i.e., the time when the shipment is available for transport process), lead time LD_r, freight rate p_r, and delay cost c_r^{delay}. The due time of request r is $\mathbb{T}_r^{\text{due}} = \mathbb{T}_r^{\text{release}} + LD_r$.

Let S be the set of services. Each service $s \in S$ is characterized by its mode $MT_s \in M$, origin terminal o_s, destination terminal d_s, total free capacity U_s, free capacity U_s^k in terms of container type $k \in K = \{\text{dry, reefer}\}$, estimated travel time t_s, travel cost c_s, and generation of carbon emissions e_s^k for container type k. We consider ship, barge and train services as time scheduled services with scheduled departure time TD_s and scheduled arrival time TA_s for $s \in S^{\text{ship}} \cup S^{\text{barge}} \cup S^{\text{train}}$. Each truck service consists of a fleet of trucks that have flexible departure times. We define TD_{rs} as a variable that indicates the departure time of service $s \in S^{\text{truck}}$ with shipment $r \in R$. 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 l_{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.

In practice, travel time uncertainties are quite common resulting from weather conditions and traffic congestion [1]. In this paper, we use common assumption that the travel times $\left[\tilde{t}_s\right]_{\forall s \in S}$ are continuous random variables following normal distributions, and are statistically independent [2]. Let $\tilde{t}_s \sim N(\mu_s, \sigma_s^2)$, in which μ_s is the mean travel time between terminal o_s and terminal d_s, and σ_s is the corresponding standard deviation. Due to the 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 $v \in V$, we define the itinerary of vehicle v as the sequence of services that the vehicle operated, and define I_v^n as the n^{th} service of vehicle v. Therefore, the departure time of service $s = I_v^n$ follows normal distribution given by:

$$\tilde{T}D_s \sim N(TD_{I_v^1} + \sum_{j \in \{1 \dots n-1\}} \mu_{I_v^j} + \sum_{j \in \{1 \dots n-1\}} 2lt_{d_{I_v^j}}^{MT_v}, \sum_{j \in \{1 \dots n-1\}} \sigma_{I_v^j}^2),$$

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

$$\tilde{T}A_s \sim N(TD_{I_v^1} + \sum_{j \in \{1 \dots n\}} \mu_{I_v^j} + \sum_{j \in \{1 \dots n-1\}} 2lt_{d_{I_v^j}}^{MT_v}, \sum_{j \in \{1 \dots n\}} \sigma_{I_v^j}^2).$$

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

Travel time uncertainty of services in a global intermodal network may lead to infeasible transshipments in addition to the commonly studied outcome of late or early delivery at destinations [9,14]. An illustrative example is shown in Fig. 2. 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 intermodal 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 re-planning from port B to destination terminal.

The objective of the platform is to maximize the total profits by optimizing acceptance and matching decisions over a given planning horizon T. The total profits consist of revenues received from shippers, travel costs paid to carriers, transfer costs and storage costs paid to terminal operators, delay costs paid to shippers, and carbon tax charged by institutional authorities.

The notation used in this paper is shown in Table 1.

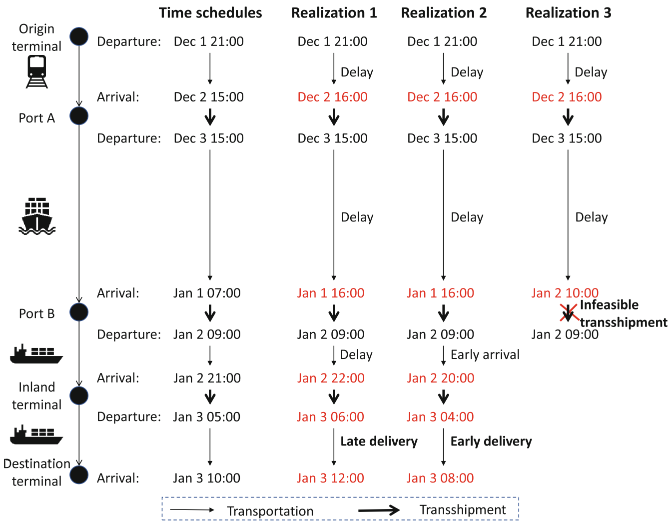

Fig. 2. Possible outcomes of travel time uncertainty in global transport.

Table 1. Notation.

Sets:	
N	Terminals N
K	Container types, $K = \{\text{dry}, \text{ reefer}\}$
R	Shipment requests
R^k	Requests with container type $k \in K$
M	Modes, $M = \{\text{ship}, \text{ barge}, \text{ train}, \text{ truck}\}$
V	Set of vehicles $V = V^{\text{ship}} \cup V^{\text{barge}} \cup V^{\text{train}} \cup V^{\text{truck}}$
S	Services, $S = S^{\text{ship}} \cup S^{\text{barge}} \cup S^{\text{train}} \cup S^{\text{truck}}$
S_i^+	Services departing at terminal i, $S_i^+ = S_i^{+\text{ship}} \cup S_i^{+\text{barge}} \cup S_i^{+\text{train}} \cup S_i^{+\text{truck}}$
S_i^-	Services arriving at terminal i, $S_i^- = S_i^{-\text{ship}} \cup S_i^{-\text{barge}} \cup S_i^{-\text{train}} \cup S_i^{-\text{truck}}$
Deterministic parameters	
T	Length of the planning horizon
α	Confidence level
CT_r	Container type of request $r \in R, CT_r \in K$
o_r	Origin terminal of request $r \in R$, $o_r \in N$
d_r	Destination terminal of request $r \in R, d_r \in N$
u_r	Container volume of request $r \in R$
$\mathbb{T}_r^{\text{release}}$	Release time of request $r \in R$
$\mathbb{T}_r^{\text{due}}$	Due time of request $r \in R$
p_r	Freight rate of request $r \in R$
LD_r	Lead time of request $r \in R$, $LD_r = \mathbb{T}_r^{\text{due}} - \mathbb{T}_r^{\text{release}}$
c_r^{delay}	Delay cost of request $r \in R$ per container per hour overdue
MT_s	Mode of service $s \in S, MT_s \in M$
o_s	Origin terminal of service $s \in S, o_s \in N$

(*continued*)

Table 1. (*continued*)

Deterministic parameters	
d_s	Destination terminal of service $s \in S, d_s \in N$
U_s	Free capacity of service $s \in S$
U_s^k	Free capacity of service $s \in S$ regarding container type $k \in K$
c_s	Travel cost of service $s \in S$ per container
e_s^k	Carbon emissions of service $s \in S$ per container with type $k \in K$
MT_v	Mode of vehicle $v \in V$
I_v^n	The n^{th} service of vehicle $v \in V \backslash V^{\text{truck}}, I_v^n \in S \backslash S^{\text{truck}}$
TD_s	Scheduled departure time of service $s \in S \backslash S^{\text{truck}}$
TA_s	Scheduled arrival time of service $s \in S \backslash S^{\text{truck}}$
t_s	Estimated travel time of service $s \in S$
l_{sq}	Binary variable; 0 if services s and q are operated by the same vehicle, and Service s is the preceding service of service q, 1 otherwise
lc_i^m	Loading/unloading cost per container at terminal $i \in N$ with mode $m \in M$
lt_i^m	Loading/unloading time at terminal $i \in N$ with mode $m \in M$
c_i^{storage}	Storage cost at terminal i per container per hour
c^{emission}	Activity-based carbon tax charged by institutional authorities
$\mathbf{M}$	A large number used for binary constraints
Random variables	
$\tilde{t}_s$	Travel time of service $s \in S$, $\tilde{t}_s \sim N(\mu_s, \sigma_s^2)$
$\tilde{T}D_s$	Departure time of service $s \in S \backslash S^{\text{truck}}$, $\tilde{T}D_s \sim N(\mu_s^+, {\sigma_s^+}^2)$
$\tilde{T}A_s$	Arrival time of service $s \in S \backslash S^{\text{truck}}$, $\tilde{T}A_s \sim N(\mu_s^-, {\sigma_s^-}^2)$
Variables	
y_r	Binary variable; 1 if request $r \in R$ is accepted
x_{rs}	Binary variable; 1 if request $r \in R$ is matched with service $s \in S$, 0 otherwise
z_{rsq}	Binary variable; 1 if request $r \in R$ is matched with service $s \in S$, $x_{rs} = 1$ And service $q \in S$, $x_{rq} = 1$, 0 otherwise
TD_{rs}	Departure time of truck service $s \in S^{\text{truck}}$ with request $r \in R$
f_{ri}	Transshipment cost of request $r \in R$ at terminal $i \in N$ per container
$\tilde{w}_{ri}$	Storage time of request $r \in R$ at terminal $i \in N$
$\tilde{\mathbb{T}}_r^{\text{delay}}$	Delay of request $r \in R$ at destination terminal $d_r \in N$

3 Mathematical Formulation

Let y_r be the binary variable which is 1 if request $r \in R$ is accepted, otherwise 0. We use the binary variable x_{rs} to represent the match between request $r \in R$ and service $s \in S$. A match between request r and service s means shipment r will be transported by service s from terminal o_s to terminal d_s. Due to the travel time uncertainty, the transport plan might become infeasible and requires re-planning. Therefore, the costs generated by accepted requests are uncertain and hard to estimate. We use $\tilde{\mathbf{C}}_r(\mathbf{x})$ to denote the random cost generated for request $r \in R$ which consists of travel costs, transfer costs, storage costs, delay costs, and carbon tax. The mathematical formulation of the GISM problem is:

$$\mathbf{P0} \quad \max_{\mathbf{y},\mathbf{x}} \sum_{r \in R} p_r u_r y_r - \sum_{r \in R} \tilde{\mathbf{C}}_r(\mathbf{x}) \tag{1}$$

subject to

$$y_r \le \sum_{s \in S_{o_r}^{+}} x_{rs}, \quad \forall r \in R, \tag{2}$$

$$y_r \le \sum_{s \in S_{d_r}^{-}} x_{rs}, \quad \forall r \in R, \tag{3}$$

$$\sum_{s \in S_i^{+}} x_{rs} \le 1, \quad \forall r \in R, i \in N \backslash \{d_r\}, \tag{4}$$

$$\sum_{s \in S_i^{-}} x_{rs} \le 1, \quad \forall r \in R, i \in N \backslash \{o_r\}, \tag{5}$$

$$\sum_{s \in S_{o_r}^{-}} x_{rs} \le 0, \quad \forall r \in R, \tag{6}$$

$$\sum_{s \in S_{d_r}^{+}} x_{rs} \le 0, \quad \forall r \in R, \tag{7}$$

$$\sum_{s \in S_i^{+}} x_{rs} = \sum_{s \in S_i^{-}} x_{rs}, \quad \forall r \in R, i \in N \backslash \{o_r, d_r\}, \tag{8}$$

$$\sum_{r \in R} x_{rs} u_r \le U_s, \quad \forall s \in S, \tag{9}$$

$$\sum_{r \in R^k} x_{rs} u_r \le U_s^k, \quad \forall s \in S, k = \text{reefer}, \tag{10}$$

$$\mathbb{T}_r^{\text{release}} + lt_{o_r}^{MT_s} \le TD_{rs} + \mathbf{M}(1 - x_{rs}), \quad \forall r \in R, s \in S_{o_r}^{+\text{truck}}, \tag{11}$$

$$\mathbb{T}_r^{\text{release}} + lt_{o_r}^{MT_s} \le \tilde{T}D_s + \mathbf{M}(1 - x_{rs}), \quad \forall r \in R, s \in S_{o_r}^{+} \backslash S_{o_r}^{+\text{truck}}, \tag{12}$$

$$\begin{aligned} \tilde{T}A_s + lt_i^{MT_s} + lt_i^{MT_q} \le \tilde{T}D_q + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}), \quad \forall r \in R, \\ i \in N \backslash \{o_r, d_r\}, s \in S_i^{-} \backslash S_i^{-\text{truck}}, q \in S_i^{+} \backslash S_i^{+\text{truck}}, l_{sq} = 1, \end{aligned} \tag{13}$$

$$\begin{aligned} TD_{rs} + \tilde{t}_s + lt_i^{MT_s} + lt_i^{MT_q} \le \tilde{T}D_q + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}), \quad \forall r \in R, \\ i \in N \backslash \{o_r, d_r\}, s \in S_i^{-\text{truck}}, q \in S_i^{+} \backslash S_i^{+\text{truck}}, \end{aligned} \tag{14}$$

$$\tilde{T}A_s + lt_i^{MT_s} + lt_i^{MT_q} \leq TD_{rq} + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}), \quad \forall r \in R, \\ i \in N \backslash \{o_r, d_r\}, s \in S_i^- \backslash S_i^{-\text{truck}}, q \in S_i^{+\text{truck}}, \tag{15}$$

$$TD_{rs} + \tilde{t}_s + lt_i^{MT_s} + lt_i^{MT_q} \leq TD_{rq} + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}), \quad \forall r \in R, \\ i \in N \backslash \{o_r, d_r\}, s \in S_i^{-\text{truck}}, q \in S_i^{+\text{truck}}. \tag{16}$$

Constraints (2–3) ensure that request $r \in R$ will not be accepted by the platform if there is no matching possibilities. Constraints (4–5) ensure that at most one service transports request r departing from or arriving to a terminal. Constraints (6–7) are designed to eliminate subtours. Subtours might be formed since in one OD pair, there exist services in both directions. Constraints (8) ensure flow conservation. Constraints (9) ensure that the total container volumes of requests matched with service s do not exceed its total free capacity. Constraints (10) ensure that the total volumes of reefer containers matched with service s cannot exceed its free capacity on reefer slots. Constraints (11–12) 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, $\mathbf{M}$ is a large enough number which ensures the time compatibility between shipment r and service s when binary variable x_{rs} equals to 1, but leaves the constraints "open" if x_{rs} is 0. Constraints (13–16) ensure that the arrival time of service $s \in S_i^-$ plus loading and unloading time must be earlier than the departure time of service $q \in S_i^+$ if request r will be transported by service s entering terminal i and by service q leaving terminal i.

4 Chance-Constrained Programming Model

In the literature, different techniques have been developed to deal with travel time uncertainty: deterministic, stochastic, and robust programming [14]. While deterministic programming considers average travel times and robust programming considers minimum and maximum travel times, stochastic programming considers the probability distributions of travel times. Chance-constrained programming (CCP) is one of the major stochastic approaches to solve optimization problems under travel time uncertainty [9]. In this section, we develop a CCP model to approximate stochastic constraints (12–16) and random cost $\tilde{\mathbf{C}}_r(\mathbf{x})$ for request r in model **P0**. The CCP model does not take into account the correction costs caused by the re-planning of requests.

Under the CCP, each stochastic constraint will hold at least with probability α, where α is referred to as the confidence level provided by the platform. A high α means the matches have a low probability causing infeasible transshipments. When $\alpha = 0.5$, the CCP model becomes a deterministic model; when $\alpha = 1$, the CCP model becomes a robust model. The objective is to maximize expected total profits while ensuring that the probability of infeasible transshipments does not exceed α. The formulation of the CCP model is:

$$\begin{aligned}\mathbf{P1} \quad & \max_{\mathbf{y},\mathbf{x}} \sum_{r\in R} p_r u_r y_r - \Bigg(\sum_{r\in R}\sum_{s\in S} c_s x_{rs} u_r + \sum_{r\in R}\sum_{i\in N} f_{ri} u_r \\ & + \sum_{r\in R}\sum_{i\in N} c_i^{\text{storage}} \mathbb{E}(\tilde{w}_{ri}) u_r + \sum_{r\in R} c_r^{\text{delay}} \mathbb{E}(\tilde{\mathbb{T}}_r^{\text{delay}}) u_r \\ & + \sum_{k\in K}\sum_{r\in R^k}\sum_{s\in S} c^{\text{emission}} e_s^k x_{rs} u_r \Bigg)\end{aligned} \tag{17}$$

subject to constraints (2–11),

$$\mathrm{P}\{\mathbb{T}_r^{\text{release}} + lt_{o_r}^{MT_s} \leq \tilde{T}D_s + \mathbf{M}(1-x_{rs})\} \geq \alpha, \quad \forall r\in R, s\in S_{o_r}^{+}\backslash S_{o_r}^{+\text{truck}}, \tag{18}$$

$$\begin{aligned}&\mathrm{P}\{\tilde{T}A_s + lt_i^{MT_s} + lt_i^{MT_q} \leq \tilde{T}D_q + \mathbf{M}(1-x_{rs}) + \mathbf{M}(1-x_{rq})\} \geq \alpha, \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-}\backslash S_i^{-\text{truck}}, q\in S_i^{+}\backslash S_i^{+\text{truck}}, l_{sq}=1,\end{aligned} \tag{19}$$

$$\begin{aligned}&\mathrm{P}\{TD_{rs} + \tilde{t}_s + lt_i^{MT_s} + lt_i^{MT_q} \leq \tilde{T}D_q + \mathbf{M}(1-x_{rs}) + \mathbf{M}(1-x_{rq})\} \geq \alpha, \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-\text{truck}}, q\in S_i^{+}\backslash S_i^{+\text{truck}},\end{aligned} \tag{20}$$

$$\begin{aligned}&\mathrm{P}\{\tilde{T}A_s + lt_i^{MT_s} + lt_i^{MT_q} \leq TD_{rq} + \mathbf{M}(1-x_{rs}) + \mathbf{M}(1-x_{rq})\} \geq \alpha, \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-}\backslash S_i^{-\text{truck}}, q\in S_i^{+\text{truck}},\end{aligned} \tag{21}$$

$$\begin{aligned}&\mathrm{P}\{TD_{rs} + \tilde{t}_s + lt_i^{MT_s} + lt_i^{MT_q} \leq TD_{rq} + \mathbf{M}(1-x_{rs}) + \mathbf{M}(1-x_{rq})\} \geq \alpha, \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-\text{truck}}, q\in S_i^{+\text{truck}},\end{aligned} \tag{22}$$

$$f_{ri} = \sum_{s\in S_i^{+}} x_{rs} lc_i^{MT_s}, \quad \forall r\in R, i=o_r, \tag{23}$$

$$f_{ri} = \sum_{s\in S_i^{-}} x_{rs} lc_i^{MT_s}, \quad \forall r\in R, i=d_r, \tag{24}$$

$$f_{ri} = \sum_{s\in S_i^{+}}\sum_{q\in S_i^{-}} \left(lc_i^{MT_s} + lc_i^{MT_q}\right) z_{rsq} l_{sq}, \quad \forall r\in R, i\in N\backslash\{o_r,d_r\}, \tag{25}$$

$$z_{rsq} \leq x_{rs}, \qquad \forall r\in R, s\in S, q\in S, \tag{26}$$

$$z_{rsq} \leq x_{rq}, \qquad \forall r\in R, s\in S, q\in S, \tag{27}$$

$$z_{rsq} \geq x_{rs} + x_{rq} - 1, \qquad \forall r\in R, s\in S, q\in S, \tag{28}$$

$$\mathbb{E}(\tilde{w}_{ro_r}) \geq \mathbb{E}(\tilde{T}D_s) - lt_{o_r}^{MT_s} - \mathbb{T}_r^{\text{release}} + \mathbf{M}(x_{rs}-1), \; \forall r\in R, s\in S_{o_r}^{+}\backslash S_{o_r}^{+\text{truck}}, \tag{29}$$

$$\mathbb{E}(\tilde{w}_{ro_r}) \geq TD_{rs} - lt_{o_r}^{MT_s} - \mathbb{T}_r^{\text{release}} + \mathbf{M}(x_{rs}-1), \; \forall r\in R, s\in S_{o_r}^{+\text{truck}}, \tag{30}$$

$$\begin{aligned}&\mathbb{E}(\tilde{w}_{ri}) \geq \mathbb{E}(\tilde{T}D_q) - \mathbb{E}(\tilde{T}A_s) - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(x_{rs}-1) + \mathbf{M}(x_{rq}-1), \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-}\backslash S_i^{-\text{truck}}, q\in S_i^{+}\backslash S_i^{+\text{truck}},\end{aligned} \tag{31}$$

$$\begin{aligned}&\mathbb{E}(\tilde{w}_{ri}) \geq \mathbb{E}(\tilde{T}D_q) - TD_{rs} - \mathbb{E}(\tilde{t}_s) - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(x_{rs}-1) + \mathbf{M}(x_{rq}-1), \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-\text{truck}}, q\in S_i^{+}\backslash S_i^{+\text{truck}},\end{aligned} \tag{32}$$

$$\begin{aligned}&\mathbb{E}(\tilde{w}_{ri}) \geq TD_{rq} - \mathbb{E}(\tilde{T}A_s) - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(x_{rs}-1) + \mathbf{M}(x_{rq}-1), \\ &\qquad \forall r\in R, i\in N\backslash\{o_r,d_r\}, s\in S_i^{-}\backslash S_i^{-\text{truck}}, q\in S_i^{+\text{truck}},\end{aligned} \tag{33}$$

$$\mathbb{E}(\tilde{w}_{ri}) \geq TD_{rq} - TD_{rs} - \mathbb{E}(\tilde{t}_s) - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(x_{rs} - 1) + \mathbf{M}(x_{rq} - 1),$$
$$\forall r \in R, i \in N \backslash \{o_r, d_r\}, s \in S_i^{-\text{truck}}, q \in S_i^{+\text{truck}}, \quad (34)$$

$$\mathbb{E}(\tilde{w}_{rd_r}) \geq \mathbb{T}_r^{\text{due}} - \mathbb{E}(\tilde{T}A_s) - lt_{d_r}^{MT_s} + \mathbf{M}(x_{rs} - 1), \quad \forall r \in R, s \in S_{d_r}^- \backslash S_{d_r}^{-\text{truck}}, \quad (35)$$

$$\mathbb{E}(\tilde{w}_{rd_r}) \geq \mathbb{T}_r^{\text{due}} - TD_{rs} - \mathbb{E}(\tilde{t}_s) - lt_{d_r}^{MT_s} + \mathbf{M}(x_{rs} - 1), \quad \forall r \in R, s \in S_{d_r}^{-\text{truck}}, \quad (36)$$

$$\mathbb{E}(\tilde{\mathbb{T}}_r^{\text{delay}}) \geq \mathbb{E}(\tilde{T}A_s) + lt_{d_r}^{MT_s} - \mathbb{T}_r^{\text{due}} + \mathbf{M}(x_{rs} - 1), \quad \forall r \in R, s \in S_{d_r}^- \backslash S_{d_r}^{-\text{truck}}, \quad (37)$$

$$\mathbb{E}(\tilde{\mathbb{T}}_r^{\text{delay}}) \geq TD_{rs} + \mathbb{E}(\tilde{t}_s) + lt_{d_r}^{MT_s} - \mathbb{T}_r^{\text{due}} + \mathbf{M}(x_{rs} - 1), \quad \forall r \in R, s \in S_{d_r}^{-\text{truck}}, \quad (38)$$

where f_{ri} is the planned loading and unloading cost of request r at terminal i; $\mathbb{E}(\tilde{w}_{ri})$ is the expected storage time of request r at terminal i; $\mathbb{E}(\tilde{\mathbb{T}}_r^{\text{delay}})$ is the expected delay in delivery of request r at destination terminal d_r; P is the probability measure; z_{rsq} is a binary variable which equals to 1 if request r has to transfer between service s and q, 0 otherwise; $\mathbb{E}(\tilde{T}D_s) = \mu_s^+$, $\mathbb{E}(\tilde{T}A_s) = \mu_s^-$, $\mathbb{E}(\tilde{t}_s) = \mu_s$.

The objective function **P1** is to maximize the expected total profits which consist of total revenues, travel costs, transfer costs, storage costs, delay costs and carbon tax. Constraints (18–22) ensure that the possibility of feasible transshipment at terminals will be higher than the confidence level α. Constraints (23–25) calculate the loading costs at origin terminals, the unloading costs at destination terminals, and the loading and unloading costs at transshipment terminals. Constraints (26–28) ensure that binary variable z_{rsq} equals to 1 if $x_{rs} = 1$ and $x_{rq} = 1$, 0 otherwise. Constraints (29–36) calculate the storage time at origin, transshipment, and destination terminals. Constraints (37–38) calculate delayed time at destination terminals.

To solve the CCP model, the traditional method is to convert the chance constraints into their corresponding deterministic equations. Based on the properties of normal distributions, chance constraints (18–22) can be linearized as:

$$\frac{\mathbb{T}_r^{\text{release}} + lt_{o_r}^{MT_s} + \mathbf{M}(x_{rs} - 1) - \mu_s^+}{\sigma_s^+} \leq \phi^{-1}(1 - \alpha), \forall r \in R, s \in S_{o_r}^+ \backslash S_{o_r}^{+\text{truck}}, \quad (39)$$

$$\frac{lt_i^{MT_s} + lt_i^{MT_q} + \mathbf{M}(x_{rs} - 1) + \mathbf{M}(x_{rq} - 1) - (\mu_q^+ - \mu_s^-)}{\sqrt{(\sigma_q^+)^2 + (\sigma_s^-)^2}} \leq \phi^{-1}(1 - \alpha), \quad (40)$$
$$\forall r \in R, i \in N \backslash \{o_r, d_r\}, s \in S_i^- \backslash S_i^{-\text{truck}}, q \in S_i^+ \backslash S_i^{+\text{truck}}, l_{sq} = 1,$$

$$\frac{TD_{rs} + lt_i^{MT_s} + lt_i^{MT_q} + \mathbf{M}(x_{rs} - 1) + \mathbf{M}(x_{rq} - 1) - (\mu_q^+ - \mu_s)}{\sqrt{(\sigma_q^+)^2 + (\sigma_s)^2}} \leq \phi^{-1}(1 - \alpha), \quad (41)$$
$$\forall r \in R, i \in N \backslash \{o_r, d_r\}, s \in S_i^{-\text{truck}}, q \in S_i^+ \backslash S_i^{+\text{truck}},$$

$$\frac{TD_{rq} - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}) - \mu_s^-}{\sigma_s^-} \geq \phi^{-1}(\alpha), \quad (42)$$
$$\forall r \in R, i \in N \backslash \{o_r, d_r\}, s \in S_i^- \backslash S_i^{-\text{truck}}, q \in S_i^{+\text{truck}},$$

$$\frac{TD_{rq} - TD_{rs} - lt_i^{MT_s} - lt_i^{MT_q} + \mathbf{M}(1 - x_{rs}) + \mathbf{M}(1 - x_{rq}) - \mu_s}{\sigma_s} \geq \phi^{-1}(\alpha), \quad (43)$$
$$\forall r \in R, i \in N \backslash \{o_r, d_r\}, s \in S_i^{-\text{truck}}, q \in S_i^{+\text{truck}},$$

where ϕ^{-1} is the inverse function of standardized normal distribution.

5 Numerical Experiments

We evaluate the performance of the CCP on the GISM problem in comparison to a deterministic approach (DA) which uses average travel times (i.e., $\alpha = 0.5$) and a robust approach (RA) which considers the maximum and minimum travel times (i.e., $\alpha = 1$). Compared with the CCP, the DA is a risk neutral approach in which decision makers are indifferent to uncertainties, and the RA is a risk averse approach that seeks guarantee. 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: loading cost (unit: €/TEU) $lc_i^{\text{ship}} = 18$, $lc_i^{\text{barge}} = 18$, $lc_i^{\text{train}} = 12$, $lc_i^{\text{truck}} = 12$ for $i \in N$; loading time (unit: hours) $lt_i^{\text{ship}} = 12$, $lt_i^{\text{barge}} = 4$, $lt_i^{\text{train}} = 2$, $lt_i^{\text{truck}} = 1$ for $i \in N$; storage cost (unit: €/TEU-h) $c_i^{\text{storage}} = 1$ for $i \in N$; carbon tax (unit: €/kg) $c^{\text{emission}} = 0.07$.

We consider a global intermodal network that consists of two terminals in Europe and three terminals in Asia that are connected by Suez Canal Route (SCR), Northern Sea Route (NSR), and Eurasia Land Bridge (ELB), as shown in Fig. 3. Compared with the SCR, the NSR has a shorter travel time but a higher travel cost caused by ice-breaking fees [11]. With the implementation of IMO 2020 regulations, shipping liner companies are required to use low-sulfur fuels on the sea, which in turn increases travel costs in the SCR and the NSR [10]. 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 consider 18 services operating on the network: 8 in Asia, 6 in Europe, and 4 connecting Asia and Europe as presented in Table 2. The hinterland-related data is adapted from the work of [5]; the intercontinental-related data is adapted from the works of [7,16,17]. We consider 6 shipment requests received by the platform at time 0. The detailed request data is shown in Table 3. Compared

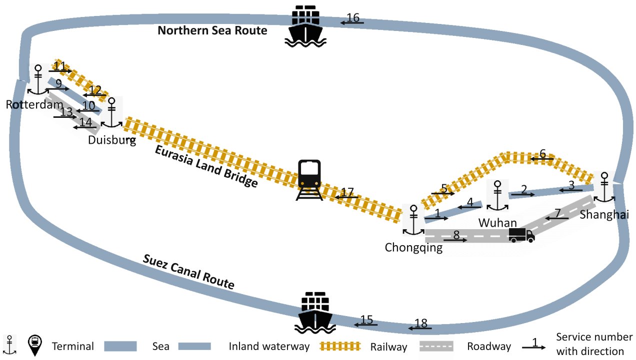

Fig. 3. The topology of a global intermodal network.

Table 2. Service data.

Service. ID	Mode	Origin	Destination	Total capacity (TEU)	Reefer slots (TEU)	Departure time	Arrival time	Travel time (h)	Travel cost (€)	Carbon emissions-dry (kg)	Carbon emissions-reefer (kg)	Preceding service	Succeeding service
1	barge	Chongqing	Wuhan	160	50	144	235	91	192	313	940		2
2	barge	Wuhan	Shanghai	160	50	243	328	85	178	291	874	1	
3	barge	Shanghai	Wuhan	160	50	144	229	85	178	291	874		4
4	barge	Wuhan	Chongqing	160	50	237	328	91	192	313	940	3	
5	train	Chongqing	Shanghai	90	30	144	181	37	269	526	1578		
6	train	Shanghai	Chongqing	90	30	144	181	37	269	526	1578		
7	truck	Shanghai	Chongqing	200	60			22	1823	1489	4466		
8	truck	Chongqing	Shanghai	200	60			22	1823	1489	4466		
9	barge	Rotterdam	Duisburg	160	30	1010	1027	17	35	57	170		
10	barge	Duisburg	Rotterdam	160	30	750	767	17	35	57	170		
11	train	Rotterdam	Duisburg	90	30	910	917	7	48	92	276		
12	train	Duisburg	Rotterdam	90	30	750	757	7	48	92	276		
13	truck	Rotterdam	Duisburg	200	60			3	334	219	658		
14	truck	Duisburg	Rotterdam	200	60			3	334	219	658		
15	ship	Shanghai	Rotterdam	200	50	350	988	638	1441	2161	6483		
16	ship	Shanghai	Rotterdam	200	50	350	900	550	2240	1631	4894		
17	train	Chongqing	Duisburg	90	30	350	723	373	2007	3517	10551		
18	ship	Shanghai	Rotterdam	200	50	518	1156	638	1441	2161	6483		

with reefer shipments (requests 1, 3, 5), dry shipments (requests 2, 4, 6) have longer lead times, lower freight rates, and lower delay costs.

5.1 Impact of Different Objective Functions

The effects of objective functions are tested under a deterministic environment without travel time uncertainties, i.e., mean of travel times $\mu_s = t_s$, standard deviation $\sigma_s = 0$, $\forall s \in S$. We set the confidence level $\alpha = 0.5$ for the CCP model, and therefore $\phi^{-1}(\alpha) = \phi^{-1}(1 - \alpha) = 0$.

Table 3. Request data.

Requests	Container type	Origin	Destination	Container volume (TEU)	Release time	Lead time (h)	Freight rate (€/TEU)	Delay cost (€/TEU-h)
1	Reefer	Shanghai	Rotterdam	5	100	720	4000	20
2	Dry	Shanghai	Rotterdam	5	100	840	3500	17.5
3	Reefer	Wuhan	Rotterdam	5	100	600	4500	22.5
4	Dry	Wuhan	Rotterdam	5	100	960	3000	15
5	Reefer	Chongqing	Duisburg	5	100	480	5000	25
6	Dry	Chongqing	Duisburg	5	100	1080	2500	12.5

The results generated under different objective functions are shown in Table 4. Under cases 1 to 6, all the requests are accepted. Comparing case 6 with cases 1 to 5, the total profit is the highest. It means that considering the trade-off among logistics costs, delays, and emissions is very important. While cases 1 to 6 are designed to minimize different costs, case 7 aims to maximize the total profit that consists of revenue and total costs. Compared with cases 1 to 6, the total profit is significantly higher under case 7. Comparing case 6 and case 7 shows that it may be necessary to reject the requests that are not profitable.

Table 4. Impact of different objective functions.

Cases	Objective function	Total profits	Revenue	Travel costs	Transfer costs	Storage costs	Delay costs	Carbon tax	Rejections	Delay (TEU-h)	Emission (kg)
1	Travel costs	−67978	112500	**48061**	2040	6914	113163	10300	0	4945	147146
2	Transfer costs	−34695	112500	50677	**1320**	8890	74925	11383	0	3416	162611
3	Storage costs	−47333	112500	59413	2400	**4814**	81063	12144	0	3482	173483
4	Delay costs	1590	112500	63648	1560	9317	**21439**	14947	0	**873**	213529
5	Carbon tax	−67375	112500	72030	2040	8367	89363	**8076**	0	3773	**115366**
6	Total costs	4946	112500	63282	2100	5983	21439	14750	**0**	873	210711
7	Total profits	**13107**	87500	53249	1980	4743	3364	11057	**1**	150	157957

5.2 Comparing Deterministic, Stochastic, and Robust Approaches

To investigate the differences between solutions generated by the CCP, DA, and RA under travel time uncertainty, we set the mean of travel times $\mu_s = t_s$ for $s \in S$, standard deviation of travel times $\sigma_s = 0.1t_s$ for $s \in S \backslash S^{\text{truck}}$, $\sigma_s = 0.5t_s$ for $s \in S^{\text{truck}}$. Besides, we let $0.9t_s$ be the fixed lower bound for travel times of service $s \in S$. Under the realization of travel times as shown in Table 5, barge service 2 is delayed, the transfers between barge service 2 and ship service 15 and 16 are therefore becoming infeasible. Regarding the CCP, we set the confidence level $\alpha = 0.7$, and therefore $\phi^{-1}(\alpha) = 0.524$, $\phi^{-1}(1-\alpha) = -0.524$.

Table 5. The realization of travel times.

Service. ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Actual travel time	98	99	89	101	40	36	23	21	18	15	7	7	3	4	631	537	384	657
Actual departure time	144	250	144	241	144	144			1010	750	910	750			350	350	350	518
Actual arrival time	242	349	233	342	184	180			1028	765	917	757			981	887	734	1175

Due to travel time uncertainty, the planned profits are different from the actual profits. Table 6 shows the results received before the realization of travel times. We note that the DA generates the highest planned profits with the lowest number of rejections and the highest delay in deliveries. In comparison, the CCP takes into account the trade-off between feasibility and profitability. It rejects requests 3 to 6 which might be non-profitable under travel time uncertainties and chooses rail service 6 instead of barge services 3 and 4 for request 2. The RA is the most conservative approach which has the lowest planned profits and the highest number of rejections. Regarding the results received after the realization of travel times, Table 7 shows that the DA generates the lowest actual profits due to infeasible transshipments at Shanghai Port for requests 4 and 6.

Table 6. Results received before the realization of travel times.

Approaches	Planned profits	Rejection	Delay (TEU-h)	Planned itinerary of requests					
				1	2	3	4	5	6
DA	13107	1	150	3,4,17,10	16	4,17,14	2,15		1,2,15,9
CCP	6553	4	0	6,17,10	16				
RA	4217	5	0		16				

Table 7. Results received after the realization of travel times.

Approaches	Actual Profits	Infeasible Transshipments	Rejection	Delay (TEU-h)	Actual itinerary of requests					
					1	2	3	4	5	6
DA	−438	2	1	911	3,4,17,10	16	4,17,14	2,18		1,2,18,13
CCP	6533	0	4	0	6,17,10	16				
RA	4151	0	5	0		16				

In comparison, the CCP has the highest actual profits thanks to the rejection of non-profitable requests 4 and 6. Compared with the DA and the CCP, the RA is the safest approach which avoids the possibility of infeasible transshipments but loses the opportunity to get higher profits.

The difference among the deterministic, stochastic, and robust solutions is graphically represented in Fig. 4. Under the DA, request 5 is rejected; requests 1 and 3 with reefer shipments are assigned to the ELB; requests 2, 4, 6 with dry shipments are assigned to the SCR and NSR. Due to travel time variations, requests 4 and 6 switch from service 15 to 18 at Shanghai Port. Under the CCP, request 1 arrives Chongqing terminal by using rail service 6 which is

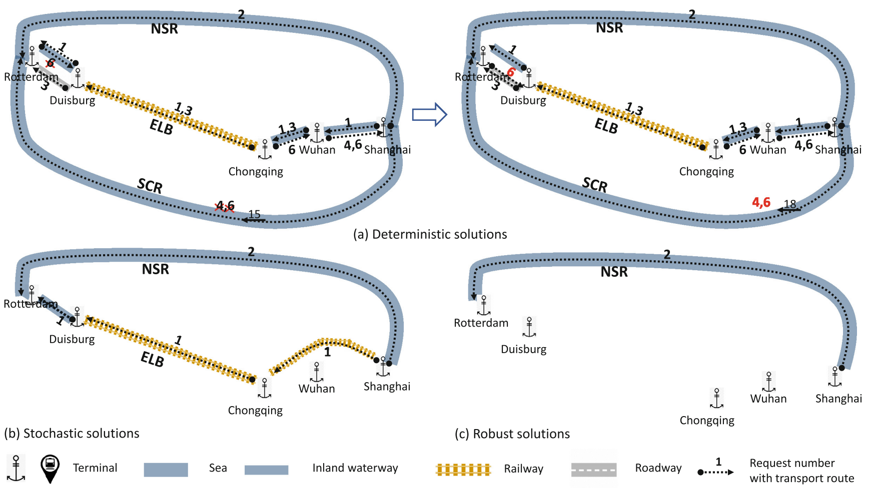

Fig. 4. Comparison of deterministic, stochastic and robust solutions.

faster than barges services 3 and 4. Under the RA, all the requests that require transshipments at terminals are rejected.

6 Conclusions and Future Research

In this paper, we investigated a stochastic shipment matching problem in global intermodal transport. The problem is stochastic since the uncertainties in travel times are incorporated. We developed a chance-constrained programming (CCP) model to address travel time uncertainties. We conducted experiments to validate the performance of the CCP in comparison to a deterministic approach (DA) in which decisions are made based on estimated travel times and a robust approach (RA) in which decisions are made based on maximum and minimum travel times. The experimental results indicate that the CCP increases total profits by 1591.55% in comparison to the DA and by 57.38% in comparison to the RA under the designed case.

This research can be extended in several promising directions. First, due to the computational complexity, we only conducted small experiments in this paper, future research can be extended to large-scale instances by designing efficient algorithms that benefit from parallelization and distributed structure. Second, this paper used fixed settings of parameters, conducting sensitivity analysis of parameters is a promising future research direction. Third, due to the fluctuation of freight rates in spot markets, future requests are quite uncertain. Combining travel time uncertainty with spot request uncertainty in global intermodal transport planning deserves further research.

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