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Demand rerouting mechanisms with revenue management for intermodal barge transportation networks

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ABSTRACT

Inland waterway transportation plays a crucial role in Europe's transportation network and economy. It is an efficient and sustainable mode of transportation, with lower emissions and energy consumption than other modes of transportation, such as road and air. However, the services provided by inland waterway transport can be significantly impacted by adverse weather conditions such as heavy rain, strong winds, and flooding. These disruptions can cause delays, cancellations, or even damage to vessels or infrastructure. To improve the system reliability, we propose a set of revenue management based (demand itinerary) rerouting mechanisms for intermodal barge transportation optimisation. Revenue Management policies including several customer categories and fare differentiation are applied. Sequential accept/reject decisions are made based on a probabilistic mixed integer programming model maximising the expected revenue of a carrier. A booking framework is defined over a rolling horizon and capacity allocation/reallocation decisions are made for a set of demands including the current and relevant past and potential future transportation requests. Several (demand) rerouting mechanisms are defined and implemented on different service network configurations. The service network status is regularly updated, in particular with respect to barge capacity variations due to changing water levels. An extensive set of experiments is performed and numerical results are analysed. The study results emphasise the added value but also the need for data availability and information sharing between the different stakeholders of Inland Waterway Transportation systems.

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1. Introduction

Inland waterway transportation (IWT) is a vital component of Europe's transportation network and economy. Its efficiency, sustainability, and economic benefits make it an essential mode of transport, and as Europe continues to pursue its climate change goals, IWT will become increasingly important as stressed in European Commission (2011, 2021). The goal of the European IWT for the years to come is to further increase its economic and ecologic performances. The European Union has thus set several targets for IWT, as part of its overall transport policy (European Commission 2021; Kinga et al. 2022; Muench et al. 2022). The core objectives are to shift more cargo over Europe's rivers and canals, and facilitate the transition to zero-emission barges by 2050. This is in line with the European Green Deal[1] and the Sustainable and Smart Mobility Strategy,[2] which set the goal of increasing transport by inland waterways and short sea shipping up to 25% by 2030, and up to 50% by 2050.

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However, IWT can be unreliable due to several factors, including weather conditions, water levels, infrastructure limitations, and lack of investment in the sector (Christodoulou, Christidis, and Bisselink 2020; Maciulyte-Sniukiene and Butkus 2022).

- Weather conditions: IWT can be affected by weather conditions such as storms, heavy rainfalls and flooding, which can cause delays, damages to vessels and infrastructure, and even accidents.
- Water levels: the depth of water in rivers and canals is also a significant factor that affects the reliability of IWT. Low water levels can make navigation difficult or even impossible for vessels, while high water levels can cause flooding and disrupt traffic (Prandtstetter et al. 2022).
- Infrastructure limitations: the reliability of IWT is also influenced by the infrastructure available to support it, such as the quality and capacity of locks, dams, bridges and ports. Inadequate or poorly maintained infrastructure can cause delays and increase the risk of accidents.
- Lack of investment: in many countries, IWT is an underdeveloped sector, and there has been limited investment in improving the infrastructure and services. This lack of investment can lead to outdated or insufficient equipment, low levels of safety and security, and inadequate management of human resources.

However, it is worth noting that the reliability of IWT varies depending on the region, country, and even the specific waterway. In some cases, IWT may be reliable and offer significant benefits over other modes of transport such as in The Netherlands, Belgium, or Germany.

To answer the needs for innovation and increased attractiveness within IWT, as described in European Commission (2021), more reliable transportation systems are to be developed. In an attempt to contribute in this direction, our research focuses on proposing a revenue management (RM) based online booking framework, defining and implementing demand rerouting mechanisms for IWT networks, designed to improve the system's efficiency following two main perspectives:

- Increase economic performance: RM-based optimisation with demand rerouting may help IWT operators to improve operational decisions and profitability through optimal vessel capacity utilisation, thus better managing their inventory of assets; this can lead to a more efficient and profitable business, benefiting both operators and their customers (Bilegan, Gabriel Crainic, and Wang 2022);
- Maintain service reliability: demand itinerary re-planning allows operators to identify alternative routes that can help minimising delays and disruptions; by using advanced decision-making tools, operators can make more informed decisions resulting into more efficient transportation systems (Liu, Cats, and Gkiotsalitis 2021; Sharma and Kumar Awasthi 2022).

Revenue management (RM) can play an important role in IWT by fostering market segmentation, demand forecasting, and optimal dynamic capacity allocation techniques to maximise revenue and profitability. RM involves analysing demand patterns and market conditions to determine differentiated fares and optimal allocation of vehicle capacities. In IWT, RM can help operators balance supply and demand by adjusting the allocation of offered services to reflect changes in network status conditions. RM can also help operators improve capacity utilisation by filling residual empty space on vessels or barges. Based on demand forecasts and capacity availability, operators can ensure that their vessels are optimally utilised, maximising revenue and profitability. These techniques are very often used when planning transportation activities on the short-term (on a daily basis), at the so called operational decision level. Additionally, RM can help IWT operators to better manage their inventory of vessels, barges, and other assets, this type of decisions being often recognised as tactical network planning (Elbert, Philipp Müller and Rentschler 2020; Taherkhani et al. 2022), where the transport services designed are usually fixed for a relatively long scheduling period (several months, a season) (Caris, Macharis, and Janssens 2008, 2013). By analysing demand patterns and adjusting offered services and capacity utilisation accordingly, operators can make informed decisions about when to invest in new assets, retire old ones, or modify existing ones.

At the operational decision level, unforeseen data fluctuations stemming from disruptions or other incidents often lead to congestion, delays, and financial loss. Rerouting is recognised in the literature (Ke 2022; Liu, Cats, and Gkiotsalitis 2021; Sharma and Kumar Awasthi 2022) as crucial for ensuring safety, improving efficiency, reducing environmental impact, and achieving economic benefits in any transportation system. However, demand itinerary rerouting in IWT, particularly in the context of facing synchromodal transport challenges (ALICE 2017; Ambra, Caris, and Macharis 2019), is a critical aspect for improving the efficiency, sustainability, and reliability of the entire logistics and supply chain network. The concept of synchromodal transportation was introduced in 2010 by Tavasszy et al. (2010). It represents an expansion of intermodal transportation, incorporating the dynamic rerouting of cargo units in response to disruptions and to meet operational or customer requirements (Verweij 2011). The synchromodal concept holds the potential to outperform intermodal transportation in terms of flexibility, reliability, and various modal choice criteria. This process involves altering the pre-planned transportation routes or modes to adapt to changing circumstances, such as congestion, weather events, infrastructure maintenance, or shifts in demand in a short scheduling period (one or several days), in order to conduct a real-time and dynamic itinerary re-planning and asset management (Ghiani et al. 2003; Giusti et al. 2019; Li, Negenborn, and Schutter 2015; SteadieSeifi et al. 2014).

Throughout this paper, *'Demand routing/rerouting'* typically refers to the process of dynamically directing or rerouting demand for goods or containers in response to changing conditions or constraints. In transportation and logistics contexts, demand routeing involves adjusting the flow of goods or passengers to optimise efficiency, minimise costs, or accommodate disruptions such as changes in capacity, weather conditions, or other factors affecting transportation routes or modes. However, it is important to emphasise that the vast majority of transportation rerouting discussions in the literature primarily focus on vehicles (Dua and Sinha 2019; Hrušovskỳ et al. 2021; Kumar and Anbanandam 2019) rather than the demand itself, especially in vehicle routeing problems (Ghiani et al. 2003; Heggen et al. 2019; Tan and Yeh 2021). For example, in the context of applications involving inland barge transportation, Gumuskaya et al. (2020) and Gumuskaya et al. (2021) introduced a dynamic barge planning system, taking into account stochastic container arrivals and addressing the impact of an uncertain and dynamic environment. Real data from an inland terminal was utilised, and the problem was solved through an approach that combines optimisation techniques with machine learning to enhance capacitated barge planning. Additionally, Aghalari, Nur, and Marufuzzaman (2021) addressed an inland waterway port management problem, incorporating the selection of barges, based on scenarios considering stochastic commodity supply and water level fluctuations. This problem was tackled using a tailored parallelised hybrid decomposition algorithm, as discussed in the corresponding publication. Another study, conducted by Larsen, Negenborn, and Atasoy (2023), introduced a real-time co-planning approach, named 'departure learning', using model predictive control. In this method, a barge operator takes into account the joint cost involving both its own operations and those of a truck operator when making decisions regarding barge departures within a synchromodal transportation system. However, transportation demand, which refers to the number of trips and the volume of people or goods being transported (Fenyk 2002), plays a significant role in shaping transportation systems (Black and Schreffler 2010). It is often overshadowed by discussions on infrastructure development, technology advancements, and mode-specific strategies (Hrušovskỳ et al. 2021). This oversight can lead to incomplete and ineffective solutions that fail to address the root causes of congestion, pollution, and other transportation-related challenges. By neglecting the demand side of transportation, we miss out on opportunities for comprehensive and sustainable solutions. Understanding and managing transportation demand are crucial for achieving long-term success in creating efficient, environmentally friendly, and equitable transportation systems (Wachsmuth and Duscha 2019). Strategies such as promoting alternative travel modes, encouraging carpooling and ride-sharing, implementing congestion pricing, improving public transportation services, and fostering smart urban planning all contribute to effectively managing transportation demand (Zijm and Klumpp 2017). To ensure that transportation systems are truly optimised and resilient, it is imperative to shift the focus from purely vehicle-centric approaches to a more holistic perspective that encompasses both vehicle planning and demand management. For example, in Bock (2010), the author presents a real-time-focussed control strategy for the effective consolidation, transshipment, and adaptive management of disruptions, such as vehicle breakdowns and accidents. In this study, the simulation generates a forthcoming temporary optimisation problem. The solutions to this problem are used to determine the subsequent transportation routes for each demand and vehicle at the end of the current time interval. In Goel (2010), the author explores the advantages of incorporating radio frequency identifiers (RFID) technology and shipment visibility in a multimodal transportation system encompassing both road and fixed-scheduled rail modes, where transit times can vary. This transportation network involves two key decision-makers: a transportation manager tasked with shipment planning and a terminal operator responsible for addressing unforeseen disruptions. If the manager fails to promptly detect and adapt to these disruptions, the terminal operator must step in to make decisions regarding shipment flows. In Goel (2010) study, four levels of visibility are examined: no visibility, daily snapshots, departure/arrival tracking, and checkpoint monitoring and it concludes that on-time delivery performance can be significantly improved by increasing the level of visibility. With the advancements in RFID technology and the emergence of the Physical Internet (PI) concept, the advantages of demand rerouting have become more evident, as demonstrated by the research of Pan and Ballot (2015). Their work illustrates the benefits of tracking asset positions through a framework designed to optimise the repositioning of open containers using RFID. Readers seeking a comprehensive review of PI and its integration into synchromodal transport may refer to Ambra, Caris, and Macharis (2019).

As information technologies and digitalisation advance in the container industry, there is a growing focus among researchers and industries on dynamic models. These models offer a suitable representation of the time dimension within decision-making processes like, for instance, online transportation requests booking. For example, Wang et al. (2016) developed a probabilistic mixed integer programming optimisation model for demand acceptance decisions, aiming to maximise the expected revenue of a barge carrier within a specified planning horizon, based on future demand forecasts. Guo et al. (2021) explored a dynamic and stochastic shipment matching problem, where a platform seeks to make online decisions regarding the acceptance or rejection of newly received shipment requests and the matching of shipments to services in global synchromodal transportation. The problem is regarded as stochastic due to the uncertainty associated with transport demands and barge travel times. To address this problem, a rolling horizon framework is implemented to manage dynamic events, a hybrid stochastic approach is employed to tackle uncertainties, and a preprocessing-based heuristic algorithm is used to generate timely solutions at each decision epoch. However, to the best of our knowledge, demand rerouting methodologies have not been reported in the literature related to barge transportation systems and IWT so far.

IWT is subject to various environmental and operational factors that can affect the initial planning of demand itineraries, such as weather conditions, water levels, and lock operations. These factors can cause delays or disruptions in vessel schedules and impact the efficiency and effectiveness of transportation operations. In intermodal barge transportation, demand rerouting involves changing the planned itinerary of a demand to take into account factors such as changing weather patterns, port congestion, or unexpected delays. In this article, we follow the footpath of the work initiated in Wang et al. (2016), by focussing on the development of a new demand rerouting framework to be applied at the operational level of decision-making in particular with respect to barge capacity variations due to changing water levels. To be more precise, a demand booking framework is established, running over a rolling horizon. Decisions on capacity allocation and reallocation are assessed and executed, for a range of demands encompassing current, pertinent past, and potential future transportation requests. Several rerouting mechanisms are formulated and applied to different service network configurations. The status of the service network is consistently updated, when new information becomes available, especially concerning changes in barge capacities, as a result of fluctuating water levels. A comprehensive set of experiments is conducted, and numerical results are thoroughly analysed.

The remainder of the paper is organised as follows. We describe the dynamic demand rerouting problem and the online RM-based booking framework in Section 2 and its mathematical formulation in Section 3. The experimental settings and numerical results are discussed and analysed in Section 4. We conclude in Section 5.

2. Problem characterisation

In this section, we briefly present the general problem of Dynamic Capacity Allocation (DCA) for barge transportation. The mechanisms of the booking system are then discussed, together with the proposed RM and reroute strategies.

Dynamic Capacity Allocation (DCA) for barge transportation is a strategy used to optimise the allocation of transportation capacity on barges dynamically based on demand fluctuations and operational considerations. Traditionally, transport booking requests are answered on a first-come first-served (FCFS) basis. A transport request is generally accepted provided the network currently has the capability to satisfy both the volume and the due date specified by the customer. Nevertheless, this may result into unwanted consequences, since requests coming at a latter time during the booking horizon might get rejected due lack of available transport capacity, even though they present the potential to generate higher revenues. This loss in additional revenue for the carrier could be avoided if rerouting of already accepted requests is allowed in the booking mechanism, such that part of the network resources may be reallocated and used in a more efficient way. This type of booking is meant to contribute to increasing global request acceptance rates and resource utilisation. Moreover, the rerouting mechanisms once in place, this could also yield better performances when the inland waterway and the network capacities are affected by weather conditions and variations in water levels predicted on a short or very short term.

RM based rerouting booking systems operate according to principles and techniques allowing to overcome the above shortcomings of a basic FCFS booking strategy. The booking mechanisms proposed in this paper manage the network transport capacity and the time constraints specified by the customers, yielding an optimal decision to accept or reject the current transport demand. This is performed by integrating in the decision-making process all relevant potential future demands as well as some of the already accepted demands that might be rerouted. The transportation demands are characterised by different fare classes, different origin-destination pairs, different volumes and different time constraints. The final decision to accept or reject an incoming demand is based on the maximisation of the expected total revenue generated by past (not yet transported to destination), current and potential future demands. On the one hand, in a RM based booking process setting, a current transport request may be rejected if it appears less profitable compared with the estimated revenue of future demands competing for the same transport capacities, within the same time window. In the case of rejection, the resource is saved for the expected future high-contribution demands, instead of allocating the capacity corresponding to the volume of the current demand. On the other hand, the use of rerouting mechanisms in the booking process may generate better capacity allocation plans and offer good quality alternative solutions when facing network status changes, without necessarily taking future demands into consideration. It appears then very interesting to combine these two different booking policies into a single dynamic capacity allocation mechanism with revenue management and rerouting capabilities, and thus solving a so called dynamic capacity allocation problem with reroute and revenue management (DCA-RRM).

In this study, each barge within the inland barge transportation system is regarded as a distinct service. We assume these services to be fixed in terms of barge type and operating periodically along the inland waterway. We do not account for the rescheduling/rerouting of a service under any circumstances. Rerouting of a demand entails redistributing demand across various services to ensure timely delivery to destinations. This operational adjustment accounts for complex and realistic factors like service disruptions and fluctuations in water levels.

2.1. Transport network representation and notations

In the current study, and in line with the previous work, the dynamic capacity allocation problem is formulated using a time-space network representation. Typically, the time horizon is represented by a discrete time interval composed of T time periods $(1, \ldots, T)$. The time-space network is cast as the directed graph $G = (N_{IT}, A)$ where I and T are respectively the sets of terminals and time intervals. A node $n(i, t) \in N_{IT}$ specifies the physical terminal i at the time period t. The set of arcs A is made up of the sets A_L and A_H representing the transport and holding arcs, respectively. The set A_L is composed of all the transportation arcs, representing the legs of all the services planned to operate over the network, while the set A_H contains all holding arcs defined on the time-space network. Each holding arc is linking two nodes representing the same terminal at two consecutive time periods. Holding arcs thus represent the possibility for demand flows to wait at their respective origins or at intermediate terminals during their journey, to be picked up by services passing by at later periods.

A set of services S, each with a given schedule, route and capacity, provides transportation among the nodes in N_{IT}. The nominal capacities of scheduled services are fixed since vehicles are already assigned to services and no extra-vehicles are considered to be available upon request. However, the actual capacities of the scheduled services may vary due to the environmental status changes, as, for instance, weather conditions, and consequently water level changes along the waterway.

2.2. RM based rerouting strategies

RM in IWT sector involves a range of different price levels (fares), customer categories and demand types, jointly used with dynamic capacity allocation techniques to maximise expected revenues for transportation companies operating on the waterway network. The utilisation of these concepts implies understanding customer demand patterns to accurately forecast potential future demands. Then, the purpose is to identify the most profitable match between the residual capacity on the network and current and future customer demands. The key objective of RM is to ensure that the available capacity is utilised effectively to accommodate different fare-products belonging to different customer categories in order to optimise the total revenue generated by operating the planned services over the network.

Customers are classified into three categories according to the business relationship: regular customers (R), who sign long-term contracts with the carrier or whom the carrier trusts and engages to transport all their demands with no exception; partially-spot customers (P), who contact the carrier infrequently and do accept their demand volumes to be partially accepted; fully-spot customers (F), who also require service irregularly but whom demand volumes must be accepted either entirely or completely rejected.

Let $\widetilde{k}$ be the current booking request. Let $D(\widetilde{k})$ be the set of demands already accepted before the arrival of $\widetilde{k}$, and $K(\widetilde{k})$ the set of potential future demands with direct possible interactions in time with $\widetilde{k}$. A transport demand $k \in D(\widetilde{k}) \cup \widetilde{k} \cup K(\widetilde{k})$ is defined by a set of attributes, as listed in Table 1.

Table 1. Transport demand attributes.

Attributes	Definition
vol (k)	Volume (TEU[3])
$o(k)$	Origin terminal
$d(k)$	Destination terminal
t_{res} (k)	Reservation/booking time
t_{avl} (k)	Time of availability at its origin
t_{due} (k)	Due time at destination
cat (k)	Customer category (R, P, F)
$f(k)$	Unit tariff (per TEU) according to the fare class

We assume and denote as VMAX (k) the maximum volume a demand request may take. Regarding the set of potential future demands ($K(\widetilde{k})$), we assume that for any $k \in K(\widetilde{k})$ there is a discrete probability distribution function, denoted $P_k(x)$, associated to the volume (x) of a demand, where x stands for a discrete random variable such as $0 \le x \le$ VMAX (k).

The proposed RM based rerouting mechanism is intended to deal with each new incoming transport request, $\widetilde{k}$, and compute the optimal decision of acceptance/rejection based on the following elements: feasibility of the demand, profitability of the demand, the current status of the network, the set of potential future demands, and eventually the possibility to reroute already accepted demands. The feasibility criterion stands for the existence of sufficient capacity on the time-space network to satisfy the current demand $\widetilde{k}$ when considering updated residual capacities on each leg. The profitability criterion indicates that the expected total revenue computed in case of acceptance of $\widetilde{k}$ is higher than the one corresponding to rejection, while taking into account all relevant potential future demands and rerouting some of the already accepted ones.

In the DCA-RRM model proposed in the current study, the routeing plan of any incoming demand $\widetilde{k}$ is decided and fixed at reservation time $t_{\text{res}}(\widetilde{k})$. Regarding the already accepted transport requests $k \in D(\widetilde{k})$ existing in the booking system and not delivered yet, their itineraries are already fixed as well, such that at time $t_{\text{res}}(\widetilde{k})$ the set of past demands $D(\widetilde{k})$ is known and fixed.

However, rerouting an already accepted demand $k \in D(\widetilde{k})$ means the itinerary of that demand can be modified after its reservation time $t_{\text{res}}(k)$. On the one hand, better revenues can be obtained by taking more information under consideration: at $t_{\text{res}}(\widetilde{k})$ there is more information in the system than at $t_{\text{res}}(k)$; thus, re-optimising the resources already allocated may generate better solutions. On the other hand, the rerouting process may contribute to recover from network service failure when incidents occur, by locally determining recourse routeing solutions and eventually suggesting alternative transportation modes.

3. Mathematical formulation

The proposed rerouting mechanisms are all based on the general RM booking model formalised below. The decision consists in accepting or rejecting the current customer demand $\widetilde{k}$, given the current status of residual capacities on the network, and, depending on the chosen routeing type, the past – already accepted – demands and/or the potential future demands (Table 2). Q1

Both already accepted requests and potential future requests play an important role when making the final decision. Indeed, regarding already accepted requests, $k \in D(\widetilde{k})$, the decision value $\xi(k)$ is not supposed to change, since this demand is already accepted (a contractual agreement with the customer has already been concluded). Nevertheless, when using rerouting, the updated available

Table 2. Decision variables.

Current request $\widetilde{k}$:	
$\xi(\widetilde{k})$	Acceptance value for $\widetilde{k}$, where $\xi(\widetilde{k})$:
	– Fixed to 1 when $cat(\widetilde{k}) = R$
	– Continuous value [0, 1] when cat $(\widetilde{k}) = P$
	– Binary value 0 or 1 when $cat(\widetilde{k}) = F$
$v(\widetilde{k}, a)$	Volume of current demand $\widetilde{k}$ to be transported on arc a
Future requests $k \in K(\widetilde{k})$:	
$maxvol(k)$	Maximum volume that future demand k could book on the Network (at decision time of $\widetilde{k}$)
y_{kj}	Binary variable used to identify the maximum volume j that Future demand k could book on the network
$v(k, a)$	Volume of future demand k to be transported on arc a
Already accepted requests $k \in D(\widetilde{k})$:	
$\xi(k)$	Acceptance value for demand k, already computed, fixed
$v(k, a)$	Volume of already accepted demand k to be transported on arc a

resources on the network are to be reallocated and the already accepted demands are all treated as regular (R) customer type demands, regardless of their initial customer category.

For the RM based Reroute DCA model, we assume the customer agrees to change the routeing plan of a demand as long as the transport request has not yet reached its final destination on the network. To this purpose, for each transport request k, an additional characteristic is stored for rerouting purposes only, namely $t_{\mathrm{arr}}(k)$, which indicates the latest allowed arrival time of any fragment of k.

When the booking decision for the current transport request $\widetilde{k}$ is computed, if some fragments of k have not yet reached their destination terminal, these particular fragments of k will have to be rerouted and so the corresponding values of $v(k,a)$ variables have to be calculated again.

The formulation of the RM based dynamic capacity allocation with reroute (DCA-RRM) model is:

$$\begin{aligned}\max \quad & f(\tilde{k}) \cdot \xi(\tilde{k}) \cdot \mathrm{vol}\,(\tilde{k}) \\ & + \sum_{k \in K(\tilde{k})} f(k) \sum_{1 \le j \le \mathrm{VMAX}\,(k)} y_{kj} \sum_{x=0}^{j} (xP_k(x)) \\ & - \sum_{k \in D(\tilde{k}) \cup \tilde{k}} \mathrm{pen}\,(k) \cdot \mathrm{vol}(k) \end{aligned} \tag{1}$$

Subject to:

Capacity restrictions constraints for each service leg, $\forall\, a \in A_L$:

$$\sum_{k \in D(\tilde{k}) \cup \tilde{k} \cup K(\tilde{k})} v(k,a) \le \mathrm{cap\_avl}\,(a) \tag{2}$$

Flow conservation constraints for each terminal node, $\forall\, n(i,t) \in N_{IT}$:

$$\sum_{a \in A^{+}(n(i,t))} v(\tilde{k},a) - \sum_{a \in A^{-}(n(i,t))} v(\tilde{k},a) = \begin{cases} \xi(\tilde{k})\mathrm{vol}\,(\tilde{k}) & \text{if } (i,t) = o(\tilde{k}) \\ -\xi(\tilde{k})\mathrm{vol}\,(\tilde{k}) & \text{if } (i,t) = d(\tilde{k}) \\ 0 & \text{else} \end{cases} \tag{3}$$

$$\forall\, k \in K(\tilde{k}): \sum_{a \in A^{+}(n(i,t))} v(k,a) - \sum_{a \in A^{-}(n(i,t))} v(k,a) = \begin{cases} \mathrm{maxvol}\,(k) & \text{if } (i,t) = o(k) \\ -\mathrm{maxvol}\,(k) & \text{if } (i,t) = d(k) \\ 0 & \text{else} \end{cases} \tag{4}$$

$$\forall\, k \in D(\tilde{k}): \sum_{a \in A^{+}(n(i,t))} v(k,a) - \sum_{a \in A^{-}(n(i,t))} v(k,a) = \begin{cases} \xi(k)\ \mathrm{vol}\,(k) & \text{if } (i,t) = o(k) \\ -\xi(k)\ \mathrm{vol}\,(k) & \text{if } (i,t) = d(k) \\ 0 & \text{else} \end{cases} \tag{5}$$

$$\mathrm{maxvol}\,(k) = \sum_{1 \le j \le \mathrm{VMAX}\,(k)} j y_{kj}, \quad \forall\, k \in K(\tilde{k}) \tag{6}$$

$$\sum_{1 \le j \le \mathrm{VMAX}\,(k)} y_{kj} \le 1, \quad \forall\, k \in K(\tilde{k}) \tag{7}$$

where $A^{+}(n(i,t))$ and $A^{-}(n(i,t))$ stand for the sets of outgoing and incoming arcs of node $n(i,t) \in N_{IT}$.

Range and type of the decision variables:

$$v(k,a) \geq 0, \quad \forall\, k \in D(\tilde{k}) \cup \tilde{k} \cup K(\tilde{k}), \quad \forall\, a \in A \tag{8}$$

$$y_{kj} \in \{0,1\}, \quad \forall\, k \in K(\tilde{k}), \quad \forall\, j \in \{0,\ldots,\mathrm{VMAX}\,(k)\} \tag{9}$$

$$\xi(\tilde{k}) = \begin{cases} 1, & \text{if cat}\,(\tilde{k}) = R \\ [0,1], & \text{if cat}\,(\tilde{k}) = P \\ \{0,1\}, & \text{if cat}\,(\tilde{k}) = F \end{cases} \tag{10}$$

The objective function (1) is the sum of the revenue obtained from the current demand, if accepted, and the total revenue expected from future potential demands; it also includes the penalty costs incurred in case of shifting demand volumes from barge to trucks when using rerouting mechanisms.

4. Experimental setting, numerical results and analysis

A basic Dynamic Capacity Allocation (DCA) algorithm is derived from the DCA-RM model by not taking into account any future potential demand (in the model, $K(\tilde{k})$ is assumed to be the empty set). The numerical results provided by this mechanism will be used as reference values in all our experiments.

To validate the proposed RM based Reroute DCA model, we use computer simulation. We simulate the sequential arrival of current demands as an iterative process. For each randomly generated demand, we run and solve the optimisation problem and use the optimal decision to accept/reject the demand based on the current network conditions, and update accordingly the status of the network in terms of remaining available capacity. Then, a new iteration is performed. The demand forecasts are considered to be given at the beginning of the simulation process. The two rerouting perspectives highlighted in the Introduction (Section 1) will be examined and discussed within the following subsections using two different simulation scenarios where different fares are introduced, corresponding to different classes of anticipation of booking and delivery delays required by the customers. To define the two simulation scenarios, here we recall a barge *service status* within the inland barge transportation system refers to the current operational condition or situation of a barge within the transportation system. It typically includes information such as whether the barge is in operation, undergoing maintenance, experiencing delays, or encountering disruptions. The status of a barge service provides stakeholders with crucial information about its availability and readiness to fulfil transportation requirements. This information is essential for planning and decision-making in logistics and supply chain management, helping to optimise the allocation of resources and ensure efficient cargo movement. The description of the two simulation scenarios is as follows:

- *Reroute without service status change:* In this scenario, we assume no service failures occur in the network. In other words, the maximum service capacity remains fixed with the service status remaining stable, and the remaining capacity within a service can only be adjusted by incoming or outgoing demand. Under this problem assumption, we analyse how different booking mechanisms used in barge transportation system can impact the global total revenue (see Table 3);
- *Reroute with service status change:* In this scenario, the service status within the network is periodically modified with new forecasts for water levels. In this problem setting, we analyse how demand rerouting responds to changing conditions and optimises carriers' operations to achieve a reliable and efficient transportation system.

All models and solution methods utilising different booking and rerouting policies have been implemented in Python 3.8 on a desktop equipped with an Intel Core i7 3.6 GHz processor and 64.0 GB RAM. The optimisation solver utilised throughout the solution process was CPLEX Optimizer version 22.1.1, running on the same equipment.

Table 3. Booking policies used in barge transportation system.

DCA Dynamic Capacity Allocation The model is solved for each new demand $\tilde{k}$ The future demands are not known, i.e. $K(\tilde{k}) = \emptyset$
DCA-RM RM based Dynamic Capacity Allocation The model is solved for each new demand $\tilde{k}$ The potential future demands follow a probability distribution function
DCA-Reroute Dynamic Capacity Allocation with Reroute The model is solved for each new demand $\tilde{k}$ and for all demands k already accepted, i.e. with $k \in D(\tilde{k})$ and $t_{\text{res}}(\tilde{k}) < t_{\text{arr}}(k)$ The future demands are not known, i.e. $K(\tilde{k}) = \emptyset$
DCA-RRM RM based Dynamic Capacity Allocation with Reroute The model is solved for each new demand $\tilde{k}$ and for all demands k already accepted, i.e. with $k \in D(\tilde{k})$ and $t_{res}(\tilde{k}) < t_{arr}(k)$ The potential future demands follow a probability distribution function

4.1. Experimental setting

The experiments are cast with respect to different customer categories, different service densities, different levels of transportation capacity on the network, as well as different booking policies.

For all the scenarios, a physical network with five consecutive terminals, i.e. A, B, C, D and E, is considered. The number of nodes used in our experiments is representative to a large extent of the river and canal networks in Europe (Danube or the Northern France and Belgium). Without loss of generality, the terminals are assumed to be located along the inland waterway such that the travel times for barges between any two consecutive terminals to be the same.

The experimental time unit is half a day, and the barge services are predefined on a weekly basis. In other words, these services will repeat every week, which corresponds to every 14 time units. It's worth noting that all the attributes of a service mentioned in Section 2.1 remain consistent throughout each week. While the maximum capacity of services remains consistent within a particular set of experiments, it is subject to variation across different scenarios. The remaining capacities of service segments are systematically adjusted based on the accepted demands and their optimal routeing. Note that holding arcs for containers at terminals are assumed unlimited in capacity.

We recall that any demand k is characterised by its $\text{vol}\,(k)$, $o(k)$, $d(k)$, $t_{\text{res}}(k)$, $t_{\text{avl}}(k)$, $t_{\text{due}}(k)$, $\text{cat}\,(k)$, and $f(k)$ as in Table 1. Then the volume $\text{vol}\,(k)$, is represented by a realisation of a random discrete value ranging from 0 to VMAX (assuming a unique maximum volume for all demands), and following a specific probability distribution. The origin-destination (OD) pair, specifically the values of $o(k)$ and $d(k)$, are uniformly generated from the set of possible OD pairs corresponding to a given scenario. The anticipation $\Theta(k)$ and delivery time $\Delta(k)$ are randomly chosen from a predefined pool of possible values, and these selections follow a uniform distribution. The generation of these values is associated with the distance between the origin $o(k)$ and destination $d(k)$ of the demand. Subsequently, $t_{\text{avl}}\,(k)$ and $t_{\text{due}}\,(k)$ are computed based on these values. Anticipation and delivery time thresholds are predefined to classify demands into categories of early/late reservation and standard/express delivery, respectively. For a specific OD distance, a basic fare p is predetermined. The unit transportation price, $f(k)$, per container (per TEU), is then defined as $f(k) = p \times r_{\Theta}(k) \times r_{\Delta}(k)$, where $r_{\Theta}(k)$ and $r_{\Delta}(k)$ represent the anticipation price rate and delivery price rate, respectively. In this context, the price rates for early reservation and standard delivery are set to 1, while the other values are strictly greater than one, reflecting higher fares charged for high contribution demands that request higher quality-of-service transportation. Lastly, the category $\text{cat}\,(k)$ is randomly assigned from the options R, P, and F, following a uniform distribution. In our experimental setup, the demand instances are characterised by a density of 10. This density indicates the frequency of demand occurrences within each time unit. In simpler terms, a demand density of 10 implies that for every half-day, 10 demand requests will enter the system, and their acceptance will be determined based on various booking policies.

In conclusion, the general characteristics of the experimental setting are:

- five consecutive terminals (A, B, C, D and E), located along a corridor network structure, with equal travel times between any two consecutive terminals;
- a simulated rolling-time horizon of a duration of 400/800 time instants (nearly 28/57 weeks);
- two sets of services, defined with different service frequency, the first with two services (Service no.1), defined in both directions, repeating every 14 time units (one week), and the second (Service no. 2) with four services, defined in both directions, repeating every 14 time units;
- different capacities of services: 10, 15, 20, 30, 40 (TEU);
- different reductions in water levels: 1, 0.9, 0.8, 0.7, where 1 stands for the standard water level, and 0.9, 0.8, 0.7 represent 10%, 20% and 30% reduction in water levels, respectively. A lower water level will result into lower capacity of a service vessel;
- different routeing mechanisms: DCA, DCA-Reroute, DCA-RM, DCA-RRM.

4.2. Numerical results and analysis

In this subsection, we examine the outcomes based on the two scenarios introduced earlier in this section. First, in the scenario labelled as 'Reroute without service status change', we assume no service failures occur in the network. Here, we delve into the analysis of how various booking mechanisms employed in the barge transportation system can influence the overall revenue on a global scale.

Second, in the scenario termed as 'Reroute with service status change', the service status, namely capacity, within the network is periodically modified with new forecasts for water levels. In this scenario, we investigate how demand rerouting adapts to these changing conditions and optimises carriers' operations to establish a reliable and efficient transportation system. Variants of Revenue Management (RM) mechanisms involving future expected demands do not have a direct impact on the performances of rerouting when the network status is subject to changes. This is particularly true when less than nominal capacity is available on the network and the entire set of already accepted demands, regardless of their category, needs to be rerouted and transported to destination, eventually by truck. Therefore, RM policies based on future demand forecasts are not integrated in the experiments deployed for the second scenario.

4.2.1. Reroute without service status change

Within this section, we make the assumption that external factors will not affect the capacities of the services. However, we acknowledge that the residual capacities of the services will be updated at each time instant following the booking and allocation of resources. In the experiments, when the rerouting procedure is executed for each new demand entering the system, it is referred to as *Full-Reroute*. Conversely, if the rerouting procedure is performed at predetermined intervals (e.g. every half-day, daily, weekly, etc.), it is referred to as *Partial-Reroute*. In this subsection, the Full-Reroute technique is assumed to be applied without allowing any volume of demand to be shifted to an alternative transport mode, even if it has the potential to generate higher revenue.

The computational results obtained when running the experiments are illustrated in Table 4. The term *improvement ratio* (IR) refers to the improved ratio between the total revenue (or volume) generated by using the DCA-RM, DCA-Reroute, or DCA-RRM mechanisms, and the total revenue (or volume) generated by using the base DCA procedure alone. The results are calculated for various service sets with different service capacities. The Total Revenue IR indicates the revenue increase rate achieved with the same level of transportation network capacities; the same applies for the Total Volume IR, which stands for an indicator of resource utilisation improvement, i.e. more demand volumes transported, using the same level of transportation network capacities. Additionally, these improvement ratios provide insights into the enhancements in demand acceptance and consolidation and the opportunities for optimising transportation network capacity organisation and utilisation.

Table 4. Revenue and volume improvement ratio (IR) without service status change.

			Total revenue IR (%)			Total volume IR (%)		
Service no.	Service capacity	Booking policy	Avg.	Min.	Max.	Avg.	Min.	Max.
1	10	DCA	0	0	0	0	0	0
		DCA-RM	15	0	42	1	0	7
		DCA-Reroute	23	7	55	8	7	14
		DCA-RRM	24	4	66	10	7	14
	15	DCA	0	0	0	0	0	0
		DCA-RM	7	3	15	1	0	5
		DCA-Reroute	8	3	12	6	4	10
		DCA-RRM	9	3	19	5	0	10
	20	DCA	0	0	0	0	0	0
		DCA-RM	6	3	8	2	0	4
		DCA-Reroute	10	6	13	5	4	8
		DCA-RRM	10	6	14	5	4	8
2	10	DCA	0	0	0	0	0	0
		DCA-RM	8	3	13	3	0	4
		DCA-Reroute	16	9	22	9	3	14
		DCA-RRM	18	10	28	11	3	19
	15	DCA	0	0	0	0	0	0
		DCA-RM	9	4	15	3	0	7
		DCA-Reroute	15	10	23	10	7	15
		DCA-RRM	15	10	24	10	7	15
	20	DCA	0	0	0	0	0	0
		DCA-RM	11	8	12	5	4	8
		DCA-Reroute	15	11	17	10	8	12
		DCA-RRM	15	10	18	9	8	12

The results indicate that in our experiments of 120 problem instances (with five demand sets, four routeing mechanisms, three values for service capacities, and two families of services), the DCA-RM, DCA-Reroute, and DCA-RRM consistently outperformed the basic DCA booking policy. Moreover, when comparing the average outcomes of DCA-RM, DCA-Reroute, and DCA-RRM, the DCA-RRM rerouting mechanism proves to be superior to both DCA-Reroute and DCA-RM policies across all cases (highlighted in red in the table).

We may also observe that the DCA-RM policy outperforms DCA in all tested situations. Our results suggest that the performance of RM is highly dependent on the demand structure, service capacity, and the accuracy of demand forecasting. As an intuition, better outcomes from RM based booking policies would require inextricably intertwined interactions between the current and future demands, as well as more limited service capacity resources. This is indeed the case in our experiment setting corresponding to the Service Family No. 1 with a very low level of capacity (10 TEUs).

When keeping the same set of demands for different experiment settings, with a higher level of capacity with respect to the level of total demand volumes (like in the case of Service Family No. 1 and No. 2, for capacities 15 and 20) the Total Revenue IR when using DCA-RM increases with Service Family No.2. This is due to the fact that within this Service Family, service frequency is twice higher than in the first one, thus more demands can be accommodated on the network.

The implementation of RM policies allows the acceptance of an increased rate of high-valued demands. This leads to an overall improvement in yield, defined as Total Revenue IR/Total Volume IR (Improvement Ratio), through better consolidation of all accepted demands (high-valued and low-valued ones). Even in cases where there is no improvement in Total Volume IR, better revenues are often found, indicating the effectiveness of the RM policy. The implementation of rerouting mechanisms aims at a better utilisation of the network capacities and transporting more demand volume on the IWT network, leading to an improvement in accepted demand volumes. It is important to note that both approaches have resulted in high-quality solutions, as the Total Revenue IR is consistently higher than the Total Volume IR.

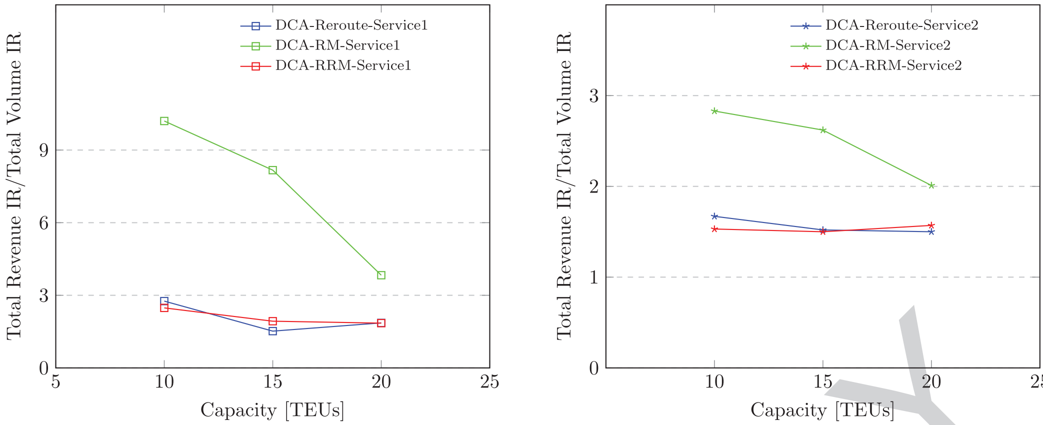

Figure 1. IR trend in demand quality with respect to different capacities.

Colour online, B/W in print

When we enhance the service capabilities (increased service capacities) of the two different service families, the average Total Revenue IR and Total Volume IR indicators for DCA-Reroute, DCA-RM and DCA-RRM policies decrease. The same decreasing trend is observed for the accepted demand quality or yield, see Figure 1. This implies that the policies we propose are more effective when the resources are scarce.

Although the results show that, on an average, the DCA-Reroute mechanism outperforms the DCA-RM one, it is important to note that the aim of the study is not to compare the revenue results obtained with these two policies, as they are both designed to improve the system efficiency using different approaches. Our focus, instead, is on evaluating the performance of each policy in improving revenue outcomes, and identifying the factors that influence their effectiveness. By comparing the performances of these policies in different experimental settings, we aim at providing insights that can help IWT network service providers optimise their resource allocation strategies. Overall, our analysis suggests that both the DCA-Reroute and DCA-RM policies can offer significant benefits in terms of improving system efficiency and generating higher revenues. This is particularly true when they are jointly used, as it is the case for the DCA-RRM booking mechanism.

4.2.2. Reroute with service status change

To address changes in service status, namely capacities of different transportation legs on the network, we assume that variations on nominal vessel capacities are computed based on regularly updated forecasts of weather conditions and, consequently, water levels. These updates are integrated in the system via two parameters:

- *updates frequency:* the forecast updates frequency determines how often new forecasts are aggregated and provided to the system; this may range from daily, weekly, to monthly intervals.
- *forecast reliability:* the forecast reliability provides information about the accuracy of the predicted data; for instance, when it comes to inland waterways, one can consider a two-day period for predicting highly accurate water level estimates.

For the experiments in this paper, we make the following assumptions:

- Water level forecasts are updated every n days;
- Water level accuracy holds over m days;
- rerouting is performed at every new forecast update;
- changes in water levels induce proportionally modified vessel capacities.

The process thus involves using updated forecasts on the network conditions every n days, having an impact on all transportation leg capacities assumed highly reliable over the next m days. Using the updated transportation capacities of vessels, the rerouting procedure is executed to find a new optimal routeing solution for demand itineraries.

Different values for n and m lead to different scenarios. When n is smaller than m, it indicates more accurate information available for the decision-maker, since forecasts are more frequently updated and new values are used; this would naturally result into better solutions. When n is larger than m, the information would become outdated before a new rerouting procedure execution takes place, leading to planning periods where less accurate information might be used. However, the analysis of these different scenarios will not be discussed in this paper.

Our objective is to demonstrate that the rerouting techniques proposed are able to effectively handle incidents that may occur during execution of planned transportation activities within the system. We aim at addressing these problems promptly while maintaining a high level of resource utilisation. Thus, in this subsection, we assume that $n = m = 2$ days (*i.e.* four time-periods of half-a-day), allowing us to make new planning and rerouting decisions before the previous forecasts become obsolete.

To guarantee that a feasible solution is consistently maintained, it is crucial to execute the rerouting procedure at least once after each new forecast update. To that purpose, alternative transport modes, such as trucks, are assumed to be available as an ad-hoc solution to accommodate fragments of the demand volumes that eventually cannot be transported by barge when facing very low water levels. A penalty is assumed to be payed by the carrier in such cases.

The rerouting procedure may be repeated multiple times between two forecast updates. To evaluate the proposed mechanisms, we run experiments on a range of decreasing water levels, resulting into a series of decreasing capacities for services. We compared the utilisation rates of the services (measured by the fill rates of the barges), total revenue, and total volume of demand moved to trucks due to lower water levels.

Q2 We performed the experiments based on various simulation settings, using two different families services, four types of vessels (and thus four levels of nominal capacities), four water levels, and a set of 800 demands, with origin-destinations evenly distributed over the five-terminal waterway network. The numerical results obtained are displayed in Tables 5 and 6. A set of service performance indicators (see Table 7) are used to evaluate the proposed rerouting mechanisms.

As already mentioned, trucks are assumed to be available as an alternative transport mode to integrate the intermodal transportation system. We conduct comparisons using three approaches: Dynamic Capacity Allocation (DCA), DCA with Partial-Reroute (PR), and DCA with Full-Reroute (FR). These comparisons are performed assuming standard water level conditions, with no variation. As a result, the actual average fill rate (AFR) is identical to the nominal average fill rate (NFR). Additionally, we introduce the solving time (ST) as a measure to evaluate their computational time. It is important to note that, on one hand, the Partial-Reroute (PR) approach calls the rerouting procedure at each forecast update (every two days, *i.e.* four time periods, in our experimental setting); during four time periods, 40 demand requests are assumed to occur. On the other hand, the Full-Reroute (FR) approach triggers the rerouting procedure at each new incoming demand. The results indicate that rerouting outperforms the base DCA mechanism in all aspects. Indeed, the Full-Reroute approach provides not only higher fill rates of the barges (AFR), but also improved demand acceptance for both original barge transportation (VOB) and overall acceptance (VOA). Additionally, it significantly increases the total revenue (TR). Moreover, with the advantage of having access to an alternative transportation mode (trucks), even if penalty costs are incurred for shifting some demand volumes to truck, the solution will still guarantee a favourable revenue outcome. Nevertheless, Full-Reroute (FR) mechanisms require more time to solve the problem. However, the main focus of this subsection is to emphasise how rerouting mechanisms can be applied to address variations in water levels or other incidents that would decrease the capacities of barges within the system. With lower computational times, Partial-Reroute (PR) mechanisms also yield competitive results when compared to the base DCA approach.

Table 5. Different service indicators for three methods.

Service no.	Service capacity	Booking policy	AFR(%)	VTR(%)	VFB(%)	VOB(%)	VOA(%)	TR	ST (s)
1	10	DCA	100	–	35	35	42	716	18
		PR	98	2	35	37	44	746	40
		FR	100	37	25	62	53	1735	788
	20	DCA	97	–	57	57	53	2184	18
		PR	96	3	56	59	56	2320	64
		FR	98	35	43	78	66	3681	1380
	30	DCA	90	–	70	70	62	3570	19
		PR	90	1	70	71	63	3659	84
		FR	97	25	59	83	73	5191	1975
	40	DCA	83	–	77	77	69	4667	19
		PR	855	1	78	79	71	4875	89
		FR	92	13	73	86	78	6112	2555
2	10	DCA	99	–	56	56	53	2054	20
		PR	98	9	52	61	56	2572	78
		FR	100	46	38	84	72	4211	2240
	20	DCA	93	–	81	81	72	5034	22
		PR	93	6	76	83	75	5492	128
		FR	98	29	65	94	86	7716	4007
	30	DCA	82	–	92	92	83	7641	23
		PR	84	2	91	93	85	7986	160
		FR	90	17	82	98	93	9502	5057
	40	DCA	71	–	97	97	91	9292	22
		PR	75	1	97	98	92	9363	175
		FR	78	6	93	99	96	10115	4122

Therefore, Partial-Reroute is implemented for each tested problem instance and the corresponding results computed and displayed (Table 6). The numerical values presented in Table 6 show that when the network status changes, specifically when there are fluctuations in water levels over time, it becomes essential to carry out necessary network operations in order to sustain the network service system. Our observations revealed that, for each problem instance, a large volume of demand initially intended for transportation by barge should be shifted to trucks due to decreasing water levels. Thanks to the demand rerouting mechanisms, it is possible to devise a new plan with changed demand itineraries, but keep most of the already accepted demands on barge.

In all the tested scenarios, the demand rerouting mechanisms result into optimised utilisation of service network resources, as demonstrated by the consistently high actual average fill rate (AFR). Despite the need to shift some demand volume to trucks when water levels decrease, the IWT network utilisation remains remarkably high, with the majority of AFR surpassing 90%. When the vessel capacities are limited (e.g. in Service No. 1 with capacities of 10 and 20, and Service No. 2 with a capacity of 10), the AFR remains close to or at 100% across all tested water levels. This indicates the necessity of redirecting demand volumes to trucks at certain terminals, while still striving for an optimal allocation of resources across all IWT services. Conversely, when the barge capacities are sufficient (such as in Service No. 2 with a capacity of 40), there is guarantee that most of the originally accepted demand volumes for transportation by barge (VOB) may still be accommodated without the need for redirection to trucks (VFB), if water levels decrease.

In conclusion, when comparing the results of different mechanisms, we demonstrate that full rerouting consistently outperforms partial rerouting. Although full rerouting may require more computational time, it proves to be superior in terms of various aspects. On the contrary, the base DCA policy performs poorly in multiple aspects, including lower revenue, sub-optimal resource utilisation, reduced flexibility, and difficulties in adapting to system status changes. This is particularly true when incidents occur with barges, requiring rapid identification of alternative demand routeing plans.

Table 6. Different service indicators with service status change.

Service no.	Service capacity	Water level	AFR (%)	NFR (%)	VT (%)	VFB (%)	VOB (%)
1	10	1	98	98	2	35	37
		0.9	99	89	7	31	37
		0.8	100	80	11	26	37
		0.7	99	69	16	22	38
	20	1	96	96	3	56	59
		0.9	97	87	9	49	59
		0.8	98	79	16	43	59
		0.7	98	69	22	37	59
	30	1	90	90	1	70	71
		0.9	94	84	7	62	69
		0.8	96	76	15	54	69
		0.7	96	67	22	47	69
	40	1	85	85	1	78	79
		0.9	89	8	7	71	78
		0.8	93	75	13	64	77
		0.7	95	67	22	54	77
2	10	1	98	98	9	52	61
		0.9	99	90	10	48	58
		0.8	100	80	15	42	57
		0.7	99	69	20	38	58
	20	1	93	93	6	76	83
		0.9	96	87	9	72	81
		0.8	99	79	14	64	79
		0.7	99	69	24	55	79
	30	1	84	84	2	91	93
		0.9	91	82	5	87	92
		0.8	94	75	13	78	91
		0.7	97	68	20	70	90
	40	1	75	75	1	97	98
		0.9	82	73	2	95	97
		0.8	87	70	7	89	96
		0.7	92	65	16	79	95

Table 7. Service performance indicators.

Performance indicator	Definition
1. AFR	Actual Fill Rate of the services in average
2. NFR	Nominal Fill Rate of the services in average
3. VTR	Volume rate of demand on Truck due to Reroute
4. VFB	Volume rate of demand Finally allocated on Barge
5. VOB	Volume rate of demand Originally accepted on Barge
6. VOA	Volume rate of demand Originally Accepted
7. TR	Total Revenue
8. ST	Solving Time

5. Conclusions

Based on the analysis presented in this paper, it can be concluded that the implementation of RM-based rerouting mechanisms in intermodal barge transportation networks can significantly improve the overall efficiency and profitability of the system. These mechanisms can effectively manage and allocate resources, and improve reliability by dynamically rerouting demands in response to changing waterway network operating conditions and levels of available capacities.

As expected, the rerouting mechanisms consistently generate better revenues than a basic dynamic capacity allocation (DCA), as it allows demand itineraries to be modified in real-time to respond to new, more accurate information available in the system. Therefore, the proposed rerouting policies may help inland waterway carriers to improve their service network by optimising vessels' capacity utilisation and reallocating demands on the network services. By being more flexible and responsive to changes in demand and capacity constraints, this approach can help achieve better revenue and offer better quality-of-service to the market, ultimately driving growth and profitability.

The study highlights the importance of considering both operational and economic factors when designing and implementing such mechanisms, as well as the need for effective communication and collaboration between different stakeholders in the transportation network. The findings of this paper provide valuable insights into the potential benefits of online RM-based rerouting mechanisms in IWT networks, and suggest that further research in this area could lead to significant improvements in the efficiency and sustainability of intermodal and synchromodal barge transportation.

Notes

1. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en.
2. https://transport.ec.europa.eu/transport-themes/mobility-strategy_en.
3. The twenty-foot equivalent unit (abbreviated TEU or teu) is an inexact unit of cargo capacity, often used for container ships and container ports.

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References Q4

Aghalari, Amin, Farjana Nur, and Mohammad Marufuzzaman. 2021. "Solving a Stochastic Inland Waterway Port Management Problem Using a Parallelized Hybrid Decomposition Algorithm." *Omega* 102:102316. https://doi.org/10.1016/j.omega.2020.102316.

ALICE. 2017. "Alliance for Logistics Innovation Through Collaboration in Europe. Corridors, Hubs and Synchromodality Research and Innovation Roadmap." https://www.etp-logistics.eu/wp-content/uploads/2015/08/W26mayo-kopie.pdf.

Ambra, Tomas, An Caris, and Cathy Macharis. 2019. "Towards Freight Transport System Unification: Reviewing and Combining the Advancements in the Physical Internet and Synchromodal Transport Research." *International Journal of Production Research* 57 (6): 1606–1623. https://doi.org/10.1080/00207543.2018.1494392.

Bilegan, Ioana C., Teodor Gabriel Crainic, and Yunfei Wang. 2022. "Scheduled Service Network Design with Revenue Management Considerations and an Intermodal Barge Transportation Illustration." *European Journal of Operational Research* 300 (1): 164–177. https://doi.org/10.1016/j.ejor.2021.07.032.

Black, Colin S., and Eric N. Schreffler. 2010. "Understanding Transport Demand Management and Its Role in Delivery of Sustainable Urban Transport." *Transportation Research Record* 2163 (1): 81–88. https://doi.org/10.3141/2163-09.

Bock, Stefan. 2010. "Real-Time Control of Freight Forwarder Transportation Networks by Integrating Multimodal Transport Chains." *European Journal of Operational Research* 200 (3): 733–746. https://doi.org/10.1016/j.ejor.2009.01.046.

Caris, An, Cathy Macharis, and Gerrit K. Janssens. 2008. "Planning Problems in Intermodal Freight Transport: Accomplishments and Prospects." *Transportation Planning and Technology* 31 (3): 277–302. https://doi.org/10.1080/03081060802086397.

Caris, An, Cathy Macharis, and Gerrit K. Janssens. 2013. "Decision Support in Intermodal Transport: A New Research Agenda." *Computers in Industry* 64 (2): 105–112. https://doi.org/10.1016/j.compind.2012.12.001.

Christodoulou, Aris, Panayotis Christidis, and Berny Bisselink. 2020. "Forecasting the Impacts of Climate Change on Inland Waterways." *Transportation Research Part D: Transport and Environment* 82:102159. https://doi.org/10.1016/j.trd.2019.10.012.

Dua, Aman, and Deepankar Sinha. 2019. "Quality of Multimodal Freight Transportation: A Systematic Literature Review." *World Review of Intermodal Transportation Research* 8 (2): 167–194. https://doi.org/10.1504/WRITR.2019.099136.

Elbert, Ralf, Jan Philipp Müller, and Johannes Rentschler. 2019. "Tactical Network Planning and Design in Multimodal Transportation – A Systematic Literature Review." *Research in Transportation Business & Management* 35:100462. https://doi.org/10.1016/j.rtbm.2020.100462.

European Commission. 2011. *White Paper on Transport: Roadmap to a Single European Transport Area: Towards a Competitive and Resource-Efficient Transport System*. Directorate-General for Mobility and Transport. Publications Office of the European Union. https://www.eea.europa.eu/policy-documents/roadmap-to-a-single-european.

European Commission. 2021. *NAIADES III. Boosting Future Proof Europe an Inland Navigation*. Directorate-General for Mobility and Transport. https://transport.ec.europa.eu/transport-modes/inland-waterways/promotion-inland-waterway-transport/naiades-iii-action-plan_en.

Fenyk, Heather M. 2002. "Intelligent Transportation Primer." *American Planning Association. Journal of the American Planning Association* 68 (2): 226.

Ghiani, Gianpaolo, Francesca Guerriero, Gilbert Laporte, and Roberto Musmanno. 2003. "Real-Time Vehicle Routing: Solution Concepts, Algorithms and Parallel Computing Strategies." *European Journal of Operational Research* 151 (1): 1–11. https://doi.org/10.1016/S0377-2217(02)00915-3.

Giusti, Riccardo, Daniele Manerba, Giorgio Bruno, and Roberto Tadei. 2019. "Synchromodal Logistics: An Overview of Critical Success Factors, Enabling Technologies, and Open Research Issues." *Transportation Research Part E: Logistics and Transportation Review* 129:92–110. https://www.sciencedirect.com/science/article/pii/S1366554519303928. https://doi.org/10.1016/j.tre.2019.07.009.

Goel, Asvin. 2010. "The Value of In-Transit Visibility for Supply Chains with Multiple Modes of Transport." *International Journal of Logistics: Research and Applications* 13 (6): 475–492. https://doi.org/10.1080/13675567.2010.482522.

Gumuskaya, Volkan, Willem van Jaarsveld, Remco Dijkman, Paul Grefen, and Albert Veenstra. 2020. "Dynamic Barge Planning with Stochastic Container Arrivals." *Transportation Research Part E: Logistics and Transportation Review* 144:102161. https://doi.org/10.1016/j.tre.2020.102161.

Gumuskaya, Volkan, Willem van Jaarsveld, Remco Dijkman, Paul Grefen, and Albert Veenstra. 2021. "Integrating Stochastic Programs and Decision Trees in Capacitated Barge Planning with Uncertain Container Arrivals." *Transportation Research Part C: Emerging Technologies* 132:103383. https://doi.org/10.1016/j.trc.2021.103383.

Guo, Wenjing, Bilge Atasoy, Wouter Beelaerts van Blokland, and Rudy R. Negenborn. 2021. "Global Synchromodal Transport with Dynamic and Stochastic Shipment Matching." *Transportation Research Part E: Logistics and Transportation Review* 152:102404. https://doi.org/10.1016/j.tre.2021.102404.

Heggen, Hilde, Yves Molenbruch, An Caris, and Kris Braekers. 2019. "Intermodal Container Routing: Integrating Long-Haul Routing and Local Drayage Decisions." *Sustainability* 11 (6): 1634. https://doi.org/10.3390/su11061634.

Hrušovskỳ, Martin, Emrah Demir, Werner Jammernegg, and Tom Van Woensel. 2021. "Real-Time Disruption Management Approach for Intermodal Freight Transportation." *Journal of Cleaner Production* 280:124826. https://doi.org/10.1016/j.jclepro.2020.124826.

Ke, Ginger Y. 2022. "Managing Rail-Truck Intermodal Transportation for Hazardous Materials with Random Yard Disruptions." *Annals of Operations Research* 309 (2): 457–483. https://doi.org/10.1007/s10479-020-03699-1.

Kinga, Hat, Helene Gorny, Mailin Guapp-Berghausen, Bernd Schuh, Sergio Barroso, Markus Hametner, Patricia Urban, Katharina Umpfenbach, and Deyana Spasova. 2022. *Research for REGI Committee: EU Regions in the Transformation Towards a Climate-Neutral Future*. EPRS: European Parliamentary Research Service. https://policycommons.net/artifacts/2389515/research-for-regi-committee/3410723/ Q5

Kumar, Aalok, and Ramesh Anbanandam. 2019. "Multimodal Freight Transportation Strategic Network Design for Sustainable Supply Chain: An Or Prospective Literature Review." *International Journal of System Dynamics Applications (IJSDA)* 8 (2): 19–35. https://doi.org/10.4018/IJSDA.2019040102.

Larsen, Rie B., Rudy R. Negenborn, and Bilge Atasoy. 2023. "A Learning-Based Co-Planning Method with Truck and Container Routing for Improved Barge Departure Times." *Annals of Operations Research* 1–31. https://doi.org/10.1007/s10479-023-05706-7. Q6

Li, Le, Rudy R. Negenborn, and Bart De Schutter. 2015. "Intermodal Freight Transport Planning–A Receding Horizon Control Approach." *Transportation Research Part C: Emerging Technologies* 60:77–95. https://doi.org/10.1016/j.trc.2015.08.002.

Liu, Tao, Oded Cats, and Konstantinos Gkiotsalitis. 2021. "A Review of Public Transport Transfer Coordination at the Tactical Planning Phase." *Transportation Research Part C: Emerging Technologies* 133:103450. https://doi.org/10.1016/j.trc.2021.103450.

Maciulyte-Sniukiene, Alma, and Mindaugas Butkus. 2022. "Does Infrastructure Development Contribute to EU Countries' Economic Growth?" *Sustainability* 14 (9): 5610. https://doi.org/10.3390/su14095610.

Muench, S., E. Stoermer, K. Jensen, T. Asikainen, M. Salvi, and F. Scapolo. 2022. "Towards a Green and Digital Future: Key Requirements for Successful Twin Transitions in the European Union." *Publications Office of the European Union*. https://doi.org/10.2760/977331. Q7

Pan, Shenle, and Eric Ballot. 2015. "Open Tracing Container Repositioning Simulation Optimization: A Case Study of FMCG Supply Chain." *Service Orientation in Holonic and Multi-Agent Manufacturing*281–291. https://doi.org/10.1007/978-3-319-15159-5_26. Q8

Prandtstetter, Matthias, Peter Widhalm, Herfried Leitner, and Immanuel Czege. 2022. *A Novel Visualisation Tool for Reliable Inland Navigation*, 1–8. Netherlands: Elsevier.

Sharma, Shivani, and Sateesh Kumar Awasthi. 2022. "Introduction to Intelligent Transportation System: Overview, Classification Based on Physical Architecture, and Challenges." *International Journal of Sensor Networks* 38 (4): 215–240. https://doi.org/10.1504/IJSNET.2022.122593.

SteadieSeifi, Maryam, Nico P. Dellaert, Wim Nuijten, Tom Van Woensel, and Rasa Raoufi. 2014. "Multimodal Freight Transportation Planning: A Literature Review." *European Journal of Operational Research* 233 (1): 1–15. https://doi.org/10.1016/j.ejor.2013.06.055.

Taherkhani, Gita, Ioana C. Bilegan, Teodor Gabriel Crainic, Michel Gendreau, and Walter Rei. 2022. "Tactical Capacity Planning in an Integrated Multi-Stakeholder Freight Transportation System." *Omega* 110:102628. https://doi.org/10.1016/j.omega.2022.102628.

Tan, Shi-Yi, and Wei-Chang Yeh. 2021. "The Vehicle Routing Problem: State-Of-the-Art Classification and Review." *Applied Sciences* 11 (21): 10295. https://doi.org/10.3390/app112110295.

Tavasszy, L, R. Janssen, L. Van der Lugt, and L. Hagdorn. 2010. *Verkenning Synchromodaal Transportsysteem*. Delft, The Netherlands.

Verweij, Kees. 2011. "Synchronic Modalities–Critical Success Factors." *Logistics Yearbook Edition*75–88. Q9

Wachsmuth, Jakob, and Vicki Duscha. 2019. "Achievability of the Paris Targets in the EU–the Role of Demand-Side-Driven Mitigation in Different Types of Scenarios." *Energy Efficiency* 12 (2): 403–421. https://doi.org/10.1007/s12053-018-9670-4.

Wang, Yunfei, Ioana C. Bilegan, Teodor Gabriel Crainic, and Abdelhakim Artiba. 2016. "A Revenue Management Approach for Network Capacity Allocation of an Intermodal Barge Transportation System." In *Computational Logistics. ICCL 2016. LNCS, 9855*, edited by A. Paias, M. Ruthmair, and S. Voß, 243–257. Springer. Q10

Zijm, Henk, and Matthias Klumpp2017. "Future Logistics: What to Expect, How to Adapt." In *Dynamics in Logistics: Proceedings of the 5th International Conference LDIC, 2016 Bremen, Germany*, 365–379. Springer. Q11