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Evaluating the sustainability and resilience of an intermodal transport network leveraging consolidation strategies

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ABSTRACT

Intermodal freight transport plays a pivotal role in addressing the challenges posed by global warming. The incorporation of consolidation strategies within intermodal transport networks introduces specific challenges that can exacerbate vulnerability to disruptions. This paper presents a two-stage stochastic optimization model that aims to enhance the sustainability and resilience of intermodal transport networks in the face of unexpected disruptions, while also harnessing the potential benefits of consolidation strategies. The proposed model incorporates various environmental and social sustainability metrics, including greenhouse gas emissions, noise pollution, and traffic congestion. An efficient solution methodology grounded in Lagrangian relaxation and valid inequalities is developed to deal with the inherent complexities of the proposed model. Real data from the UK's transportation system is employed to validate the effectiveness of the proposed approach. The case study exemplifies the application of the proposed model in generating practical insights for transport managers and policymakers to help them identify where to prioritize investments across the transport network. Most notably, we find that allocating a mere 0.4% of the total cost to preparedness and recovery initiatives can yield a substantial reduction of approximately 4.7% in total costs. Likewise, we find that even a modest investment in consolidation initiatives can result in remarkable cost savings of up to 34 times of the initial investment.

1. Introduction

The rapid growth of freight transport industry has sparked significant concerns about its environmental footprint and climate change consequences largely due to its reliance on fossil fuels (Čižiūnienė et al., 2022). Statistically, the transportation sector is the second largest producer of CO_2 emissions, accounting for more than 20 % of global energy-related emissions in 2023 (Statista, 2023). Despite the outbreak of COVID-19 resulting in a 5.8 % drop in global transportation emissions in 2020, sector emissions rebounded in 2021, growing by 8 % as pandemic restrictions were lifted. By 2022, these emissions had nearly returned to their 2019 levels (IEA, 2023). The GHG emissions from this sector grew at an annual average rate of 1.7 % from 1990 to 2022 (IEA, 2023).

Emissions volumes from freight versus passenger transportation can vary across regions. According to the International Transport

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Forum (2021), freight transport is responsible for more than 40 % of all transport-related emissions, standing for approximately 8–10 % of GHG emissions globally. On the other hand, road transport (including freight and passenger), which accounts for three-quarters of transport emissions (IEA, 2023), contributes to 15 % of total GHG emissions. This explains the global shift towards adopting more environmentally sustainable modes of transportation, such as railways and waterways, instead of road transport (European Commission, 2019). Environmental studies on freight transport have shown that road-rail systems exhibits better environmental performance compared to all-road transport (Aminzadegan et al., 2022). While inland and overseas waterways transport boast the highest energy efficiency, their implementation is often hindered by geographical limitations. On the other hand, road transport provides a flexible solution for inland direct links (Jakara & Brnjac, 2023).

A promising solution for reducing environmental impacts is multimodal transport which involves transshipping freight from its origin to the destination using at least two different transportation modes (Nocera et al., 2024). One specific type of multimodal transport is *intermodal* transport, involving a sequence of transportation modes and transfer between different modes, with separate contracts for each segment (Rodrigue, 2020). The *transfer* operation occurs when a shipment is transferred from one mode to another at an intermodal terminal (Wei et al., 2024). Intermodal transport is also defined as a specific type of multimodal transport, in which the same loading unit (e.g., container) is preserved throughout the journey (Karam et al., 2023). Our interpretation of intermodal transport aligns with the definitions provided by researchers such as Gronalt et al. (2019), Archetti et al. (2022), and Karam et al. (2023), emphasizing the continuity of loading units throughout the journey.

To achieve even higher efficiency, intermodal transportation is integrated with consolidation strategies. By definition, inland freight consolidation occurs when a shipper combines multiple Less than Truck-Load (LTL) shipments from different origin points, destined for the same region, into a single vehicle (Sarder, 2020). Several practical examples have shown that substantial cost savings can be achieved through consolidation. Companies such as Colgate-Palmolive, GlaxoSmithKline, Kellogg's, Kimberly-Clark, Mars, Nestlé, Procter & Gamble, and Unilever have reported enhanced load factors and reduced empty miles, resulting in less fuel consumption, operating costs, and carbon emissions (CSCMP et al., 2014). In another example, a cost saving of around \$35-\$40 million per year has been estimated for Kellogg Company through implementation of consolidation (Rijal et al., 2023).

Intermodal transportation coupled with consolidation strategy presents promising sustainability benefits. Decisive actions such as load consolidation, standardization, and collaboration can lead to a substantial 72 % reduction in CO_2 emissions from freight transport by 2050 compared to 2015 levels (International Transport Forum, 2021). However, the inherent complexity of consolidating multiple transport modes can make it more vulnerable to disruptions, primarily due to the need for synchronization between shipments, as delays can expose the system to greater risks. While consolidation strategies offer several benefits, they can also introduce supply chain risk as they require different types of operations and resources, as well as the addition of new links to the supply chain (Hasani Goodarzi et al., 2020). Resilience to disruptions plays a crucial role in freight transport services (Jabbarzadeh et al., 2018) with logistics managers increasingly prioritizing attributes such as safety and resilience over cost (Durugbo & Al-Balushi, 2022). Recent examples have highlighted the vulnerability of transportation networks to disruptions, which can lead to reduced efficiency, cancellations, or the need for freight distribution replanning (Hrušovský et al., 2021). Examples are abundant. The COVID-19 pandemic disrupted the supply chains of 94 % of Fortune 1000 companies in the USA (Accenture report, 2021). A three-week rail blockade in Montreal resulted in a 0.3 % shrinkage of Canada's GDP growth in the first quarter of 2020 (Ke, 2020). A six-day blockage of the Suez Canal in 2021 prevented approximately US\$9.6 billion in trade (BBC News, 2021; The Guardian, 2021). Designing a *resilient intermodal network* is an important step towards mitigating disruptions in the freight transport industry (Hasani Goodarzi et al., 2020). While intermodal networks may be more exposed to disruptions than unimodal networks, they provide greater opportunities for recovery after disasters due to the opportunity to switch between transport modes (Rodríguez-Espíndola et al., 2023).

With this background, this study aims to address the following research question. How can intermodal transport networks utilize consolidation strategies to concurrently enhance sustainability performance and bolster resilience against unexpected disruptions? To address this question, we present a novel scenario-based two-stage stochastic model designed to facilitate advanced planning and decision-making across different disruption scenarios. Our research contributes to the literature in several ways. Firstly, unlike existing literature on intermodal transportation, which often overlooks the joint incorporation of sustainability and resilience in planning, this paper integrates sustainability and resilience measures into the planning model, leveraging a consolidation strategy. Our approach allowing for advanced network planning and decision-making by accounting for random disruptions and carbon emissions, while consolidation is possible. The proposed approach determines optimal proactive and reactive actions to enhance the system's resilience and explores their impact on sustainability performance and cost-benefit assessments of implementing consolidation. Secondly, compared to prior studies, the proposed approach provides a more comprehensive and precise sustainability assessment for intermodal transport. In addition to economic measures, the proposed model accommodates various environmental and social negative externalities, including carbon emissions, noise pollution, congestion, and road accidents. By incorporating these factors, a more holistic evaluation of economic, social, and environmental aspects can be achieved. Furthermore, the proposed model incorporates diverse resilience metrics, including the percentage of satisfied demand and delays, which allows for the generation of optimal choices for both proactive and reactive approaches when tackling disruptions within the transportation system. This flexibility enables companies with budgetary constraints to decide between a set of resilience initiatives.

Given the complexity of the proposed model, we develop an efficient solution approach grounded in Lagrangian relaxation and valid inequalities. This approach effectively solves the model within a reasonable CPU time and with an acceptable gap. The approach is validated using real-world data from a case study of the UK's transportation system. Examining the UK transportation network as a case study, our investigation explores how the proposed approach supports transport companies in decision-making, leading to managerial insights and implications. Our aim is to minimize total cost, environmental and social impacts, address disruption risks, and achieve desired service levels.

The theory of externalities studies the environmental impacts of transportation, categorizing them into negative (e.g., noise, emissions, congestion, and accidents) and positive (e.g., enhanced economic performance and trade facilitation) (Riha et al., (2022). The term "externalities", as defined by Mesa-Arango and Ukkusuri (2013), Demir et al. (2015), Riha et al. (2022), and Gandhi et al. (2024), encompass various negative impacts produced by freight transportation, including air and water pollution, GHGs emissions, noise pollution, congestion, accidents, and land use. In this paper, we focus specifically on GHGs, noise pollution, congestion, and accidents as primary transport externalities.

The remainder of this paper is structured as follows. Section 2 presents a review of the related literature. Section 3 introduces the problem characteristics and the mathematical models. The Lagrangian relaxation method is presented in Section 4, followed by a case study, computational experiments, and analysis of the obtained results in Section 5. Discussion and managerial implications are provided in Section 6 and the last section, Section 7, offers concluding remarks and outlines potential directions for future research.

2. Literature review

Several papers have reviewed the literature that focuses on planning of multimodal freight transportation, including SteadieSeifi et al. (2014), Archetti et al. (2022) and Gbako et al. (2024). In this section, we briefly review the literature that focuses on resilience, sustainability, and consolidation within the context of intermodal networks. Our primary emphasis is on reviewing studies that develop mathematical models, complemented by relevant papers that utilize other operations research (OR) tools. In the first subsection, we examine various facets of multimodal/intermodal transport, beginning with an exploration of how these systems handle disruptions and stay resilient. The next subsection discusses *sustainability in* multimodal/intermodal transport, focusing on the studies considering emission as an environmental indicator, and those that consider social sustainability, particularly traffic congestion. In the third subsection, we discuss consolidation strategies resulting in identifying research gaps which justify our contributions to this literature.

2.1. Disruption in multimodal/intermodal freight transport

Seminal studies such as Huang et al. (2011), Chen and Miller-Hooks (2012), and Miller-Hooks et al. (2012) addressed *resilience* in multimodal transportation systems by introducing recovery plans to handle disruptions. Huang et al. (2011) evaluated the resilience of the network based on the duration of a disruptive event. They employed a decision tree to forecast the duration of a disruption and to determine whether rearrangement is necessary. They proposed rerouting as a recovery plan. Chen and Miller-Hooks (2012) defined network resilience indicator as the expected fraction of demand that can be satisfied after a disaster. Miller-Hooks et al. (2012) extended the study of Chen and Miller-Hooks (2012) by including preparedness activities to cope with disruptions. Later, Uddin and Huynh (2016) and Uddin and Huynh (2019) extended the works of Chen and Miller-Hooks (2012) and Miller-Hooks et al. (2012) to examine reliable routing plans in road-rail intermodal networks. The aforementioned works focused on the ratio of the demand that can be satisfied during disruptions and did not account for delays in disruption scenarios. Ishfaq (2017) investigated the flexibility of a road/rail multimodal system in the face of disruptions. They developed an integer linear programming model to address alternate routings assuming that the entire shipment of an order, not partially, can be transferred to a new mode.

Ke and Verma (2021) focused on recovery plans from disruptions at intermodal terminals, within a rail-truck network. They presented two mixed-integer programming (MIP) models for normal and post-disruption operations, applied them to a case study in the USA, and proposed mitigation and recovery strategies. He et al. (2021) employed a robust approach to tackle infrastructure disruptions and capacity degradation in a rail-road-inland waterway network. Their assessment of network robustness was based on increase in total travel time resulting from disturbances. Hrušovský et al. (2021) introduced a novel real-time decision support system that combines simulation and optimization techniques. When disruptions occur, the system identifies affected services and orders, applying effective re-planning policies to mitigate their impact. In a practical application, Pudasaini (2021) investigated uncertain downstream petroleum supply chain planning aiming to minimize transportation costs and product loss costs incurred during transportation between supply chain notes. Akyüz et al. (2023) proposed a replanning decision tool for managing disruptions. Although their model does not explicitly address CO_2 emissions, they argued that reducing road transportation can minimize GHG emissions by minimizing total transportation costs, which serves as an indicator of carbon emissions. Zanjirani Farahani et al. (2023) developed a MIP model for optimizing path selection in synchro-modality for a case study in the US. The proposed model minimizes total transportation costs, transshipment costs, and tardiness penalties for delays at intermodal terminals. Despite the interesting insights offered by these studies, their scope does not cover the examination of sustainability performance within multi-modal transportation networks.

2.2. Sustainability in multimodal/intermodal freight transport

In the realm of *sustainable* freight transport planning, most studies have primarily focused on minimizing carbon emissions (Demir et al., 2016; Fahimnia et al., 2015; Lu et al., 2019; Maiyar and Thakkar, 2019b; Mostert et al., 2017; Qu et al., 2014; Sun et al., 2018; Yang et al., 2021; Zakeri et al., 2015) and the associated costs (Fahimnia et al., 2013; Hrušovský et al., 2016; Balaman et al., 2018; Demir et al., 2019; Maiyar & Thakkar, 2019b, 2019c, Maiyar and Thakkar, 2019a; Okyere et al., 2019) overlooking other significant environmental and social sustainability factors. Qu et al. (2014), for example, incorporated sustainability in a road-rail-seaway intermodal network and proposed a model to determine routes, transport modes, and flow distribution. Mostert et al. (2017) developed a bi-objective location formulation for the road-rail-inland waterway intermodal network in Belgium, considering environmental effects in terms of CO_2e. Demir et al. (2019) combined economic and environmental criteria at the tactical and operational levels for a service network design problem.

To address traffic congestion, Resat and Turkay (2015) developed a bi-objective optimization model that included transportation cost and delivery time objectives for a rail-road-sea transportation network in the Marmara region. The study of Resat and Turkay (2015) focused on enhancing transport safety and sustainability by decreasing traffic congestion. To model travel congestion and to predict delays, they considered time-dependent traffic congestion constraints using the speed-flow equation of the BPR (Bureau of Public Roads, 1964). In their approach, transport duration on each modal-link is calculated using distance, speed limit on this link and a modification factor using BPR equation as a function of link usage and volume/capacity ratios of links. Sun et al. (2018) investigated road traffic congestion in a green multimodal routing problem with rail service capacity uncertainty. They incorporated both emission charging methods and bi-objective optimization to minimize CO_2 emissions as an independent objective in the routing problem. To explore the dynamics of competition between conventional road systems and intermodal road-rail configurations, Tamannaei et al. (2021) utilized a game-theoretic approach to investigate the effectiveness of government interventions. Despite these research efforts, the incorporation of the social dimension of sustainability remains largely underexamined.

2.3. Order consolidation in multimodal/intermodal transport

When it comes to *consolidation* strategies, several studies have examined different aspects of consolidation benefits and challenges. Lu et al. (2019) studied a location-routing problem with consolidation in a sustainable rail-road network. They developed a two-layer mixed-integer linear programming model that emphasized the integration of highways and railways in a multimodal transport network to optimize flow routes. Lv et al. (2019) defined transit consolidation as the simultaneous loading/unloading of cargo to/from containers, assuming that the size of cargo batches at all pickup and delivery nodes is less than a container. Exploring sustainable avenues for supply chain enhancement, Lin (2019) examines the feasibility of upstream buyer consolidation coupled with downstream rail-based intermodal transportation. The study revealed that upstream buyer consolidation has the potential to synergize rail and road transport leading to CO_2 emissions reduction. Anoop and Panicker (2020) focused on freight consolidation in a multimodal rail-road network with a volume discount on rail freight rates, allowing the consolidation of the demand of two destinations at most in their model. Huang et al. (2020) provided a model for routing and consolidation decisions in an air-land intermodal system, where shipments are transported to gateway airports by air and then delivered to final destinations by trucks. Similarly, Li et al. (2021) studied order consolidation in a capacitated multimodal network to determine the delivery paths of orders and the transportation modes on these paths. Jakara and Brnjac (2023) provided a survey paper offering an overview of previous research in the field of hybrid transport systems, known as foliated transport networks. The aim of these networks is to improve transport system efficiency by combining direct connections with a hub and spoke design. Despite these commendable research endeavors, none of these studies comprehensively encompass the intricacies of disruptions within a transport planning framework with consolidation options.

2.4. Comparative analysis and contributions

While the significance of logistics sustainability and effective disruption management is increasingly recognized (e.g., Fahimnia et al., 2018; Kabadurmus & Erdogan, 2020), relatively limited attention has been placed on the intersection of sustainability and resilience in multimodal transportation networks. To the best of our knowledge, only two studies (Maiyar & Thakkar, 2019b, 2019c) have investigated the simultaneous examination of sustainability and disruption management aspects using mathematical models. Both of these studies mainly focused on the strategic aspects of multimodal hub and spoke problems under hub disruptions, overlooking the tactical decisions, while the transportation cost function in these studies simply considers a consolidation factor for intermodal transfers. In Hrušovský et al. (2021), the decision support system is simulation-based. Furthermore, our review of this literature reveals the absence of studies that simultaneously address sustainability and resilience of intermodal transportation networks when consolidation options are available at the tactical level.

Our aim in this paper is to address the gaps in the existing literature. On this basis, the main contributions of this study are as follows:

- We present a new optimization model that carefully features sustainability, resilience, and consolidation aspects in an intermodal freight transport system, allowing for advanced network planning and decision-making. Despite the considerable number of publications on multimodal transportation in recent years, the joint area of these streams remains under-explored.
- The proposed model accounts for various environmental and social factors, including GHG emissions, noise pollution, traffic congestion, and road transportation accidents, allowing for a more comprehensive sustainability assessment.
- The model incorporates multiple performance measures for cost-efficiency (measured by total transportation cost, and cost of preparedness and recovery initiatives), resilience level (measured by delay cost and percentage of satisfied demand) and carbon emission. This holistic approach aims to achieve a realistic trade-off among these factors. In the realm of intermodal/multimodal freight route planning, existing models mostly focus on either economic performance or system resilience and reliability. By including metrics such as percentage of satisfied demand and delays, our model allows for generating optimal decisions for both proactive and reactive approaches when confronted with disruptions.
- Given the complexity of the proposed model, an efficient solution method based on Lagrangian relaxation and valid inequalities is developed. The proposed solution approach is able to reduce the model complexity, and outperform CPLEX and Gurobi solvers, in terms of both model run time and MIP/convergence gap. The proposed method is capable of handling large sized problems.

- The proposed model and solution approach are validated using real-world data obtained from a case study of the UK's transportation system, yielding interesting and important managerial insights. A contribution of this study is the development of disruption scenarios based on historical data and the specific geographical and social conditions of this network. Due to limited data availability in existing literature, disruption scenarios are determined based on a thorough investigation of historical data and records to identify the most frequent disruptive events, including both human-made and natural disasters.

3. Problem statement and model formulation

3.1. Problem description

The problem focuses on sustainable and resilient planning of an intermodal transport network with the consolidation option. The proposed network comprises road, rail, and water transportation modes, as illustrated in Fig. 1. Although the proposed model can incorporate all transport modes, we exclude air transport and drone operations in our setting to avoid the unnecessary assumptions or constraints pertaining to these transport modes. Node E is an island, only accessible by waterways; and the node F is an inland terminal, only accessible by rail and road.

Orders are defined based on origin–destination (OD) pairs, represented by k ($k \in K$), where K is the set of all origin–destination pairs. r^k represents the demand of order k, which is the number of containers transported between its origin node, O(k), and destination, D(k) (Nocera et al., 2024).

The network is exposed to random disruptions which can impact the network's transport capacity as well as the transit time. To mitigate the impact of disruptions, proactive preparedness actions and reactive recovery activities can be implemented (Miller-Hooks et al., 2012). The planning objective is to minimize the overall expected cost including transportation cost, resilience cost, environmental sustainability cost, and social sustainability cost. Transportation cost comprises the costs of shipping freight, consolidation, delays, and lost sales. Resilience cost encompasses the expenses incurred in implementing preparedness and recovery activities. The environmental and social sustainability costs and measures are as follows:

- *GHG emissions* are typically measured using total CO_2e emissions converted into monetary values to calculate their cost based on the degree of the environmental impact per container and container-mile, as will be specified in section 3.2 (United States Environmental Protection Agency, 2023).
- *Noise pollution* from transportation activities has adverse effects on both physical and mental health, particularly for individuals in close proximity to the sources, so it can be transferred into indirect cost associated with transportation (Wang et al., 2022). Various equations have been developed in the literature, to estimate and predict traffic noise levels, considering several parameters such as vehicle speed, calculation time, traffic flow, road surfaces and vehicle type (Ranaiefar & Amelia, 2011; Wang et al., 2022). These equations express noise levels in decibels (dB) and typically demonstrate a logarithmic relationship with traffic volume. For instance, the formulation provided by Demir et al. (2015) shows a 3 % increase in noise power in high octave bands between speeds of 60 km/h to 80 km/h. Additionally, the Victoria Transport Policy Institute (2022) reported that increasing a truck speed by 10 mph can raise its noise level by about 2 %. The output of these equations calculates the noise pollution generated by every vehicle passing a unit of distance, such as mile or kilometer. To estimate the average or marginal cost of noise pollution produced by different truck types, several methods have been developed, including those based on the reduction of property values caused by vehicle noise emissions and the willingness to pay for a quieter environment. This amount is then multiplied by the number of people exposed to the noise (Ranaiefar & Amelia, 2011).

  Studies have provided statistics on noise pollution costs, such as the European Network of the Heads of Environment Protection Agencies, which estimated that traffic noise costs 25 Euros annually per dB per household in 2003. Another research estimates noise pollution costs for large intercity trucks per ton-mile of freight shipped (Victoria Transport Policy Institute, 2022).

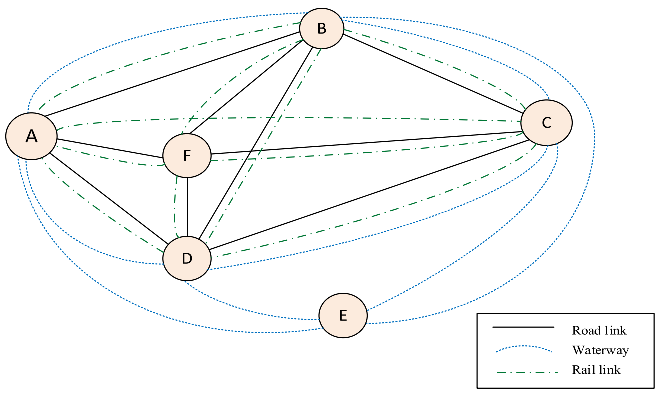

Fig. 1. The intermodal freight transport network under study.

Using these marginal/average cost estimations, a social cost conversion factor ($C_{n\phi}$) is developed to convert noise pollution into a monetary unit per vehicle-distance or consignment weight-distance. Researchers have proposed different values for this conversion factor of noise pollution in road travel, either in terms of monetary unit per vehicle-distance (Nash, 2003; Maiyar & Thakkar, 2019b; Wang et al., 2022; Nayak et al., 2024) or monetary unit per consignment weight-distance (Hofbauer & Putz, 2020). By considering the number of trucks and the distance they travel, noise pollution on roads can then be quantified by multiplying the resulting product by the social cost conversion factor ($C_{n\phi}$), allowing for a monetary evaluation of this negative externality.

- *Traffic congestion* results in unpredictability in travel times, elevated fuel consumption, and air pollution on account of reduced speeds, and results in added costs tied to travel time delays (Maiyar & Thakkar, 2019b). Moreover, in the face of congestion, potentially substantial costs may be incurred in a transport network. These cost pertain to the increased risk of disruption, as delays are more likely to affect other services on a congested route (Ricci & Black, 2005).

  To quantify congestion costs, various methods have been developed in the literature, such as estimations based on direct costs, including fuel consumption and pollution costs (Samaras et al., 2019), as well as congestion delay costs (Fattah et al., 2022). The U. S. Department of Transportation (2009) also developed a model to consider reliability costs in addition to direct costs, calculating the total travel time variability caused by congestion per vehicle mile traveled.

  Using congestion cost estimations from the literature, a social cost conversion factor ($C_{c\phi}$) can be applied to convert traffic congestion into a monetary unit per vehicle-distance. Researchers have proposed various values for this conversion factor of congestion in road travel, expressed in monetary unit per vehicle-distance or per container-distance (Bickel & Friedrich, 2005; Janic, 2007; U.S. Department of Transportation, 2009; Maiyar & Thakkar, 2019b; Hofbauer & Putz, 2020; Nayak et al., 2024). By considering the number of trucks and the distance they travel, traffic congestion on roads can be quantified by multiplying the resulting product by the social cost conversion factor ($C_{c\phi}$), enabling a monetary evaluation of congestion in road travel.
- *Accidents* can be quantified using the cost of emergency services, traffic congestion delays, and the emotional toll on the victims' families. Each accident incurs both monetary and non-monetary costs. Monetary costs, such as automobile insurance and medical expenses, are borne by affected road users, so these are viewed as internal costs, while non-monetary costs include increased travel time, emissions, and the long-term pain from injuries (Ranaiefar & Amelia, 2011). Estimating even the monetary value of the costs caused by freight trucks requires access to accident records detailing the role of trucks in these accidents.

Ranaiefar and Amelia (2011) suggested viewing accident costs as the amount of money individuals would pay to mitigate accident risks, while Lindberg (2005) categorized accident costs into direct and indirect parts. The direct cost pertains to tangible expenses in the present or future, whereas the indirect cost reflects the lost production capacity resulting from the loss of a member of society (also known as external cost). He estimated the indirect cost as a percentage of the Value of a Statistical Life (VSL) for fatal (8 % of VSL) and injury accidents (20 % of VSL), along with an additional external cost for the affected person's relatives and friends (40 % of VSL).

Delucchi and McCubbin (2011) provided estimates for the external cost of accidents per ton-mile using US data. Various researchers have quantified or reported road accident costs based on consignment weight-distance or vehicle-distance, including Ranaiefar and Amelia (2011), Maiyar and Thakkar (2019b), Hofbauer and Putz (2020), Nayak et al. (2024). However, Lindberg (2005) highlighted the correlation between vehicle weight and accident rates and noted that the road accident rate (number of accidents per 1000 vehicles) significantly increases with an increase in vehicle weight. Demir et al. (2015) also emphasized measuring accidents as a social sustainability cost of road transportation in terms of cost per container-mile. In our study, given the importance of shipment weight, we calculate the number of containers multiplied by the distance traveled rather than the number of vehicles. This metric is then converted into a social sustainability cost using $C_{a\phi}$ (social cost conversion factor for accidents in road travel).

The overall social impacts of rail and water transport can be quantified on a per container-mile basis by measuring and aggregating the negative externalities of these modes of transportation (such as air pollution, noise disturbances and irreversible harm to the environment), applying an approach in line with Maiyar and Thakkar (2019b). To do so, the costs of negative externalities for these modes, including costs related to air pollution, climate change, noise, and accidents per container-mile, are combined.

We make the following assumptions to better define the problem boundaries and scope.

- The intermodal network can be represented by a directed graph, including nodes and links.
- For each mode of transport, the transportation cost is comprised of fixed costs (e.g., vehicle rental, insurance, operator salaries) and variable costs (e.g., fuel, crew, overhead, administration).
- Shipments can be transferred between different transport modes at intermodal terminals, incurring transfer costs and potential delays.
- The multimodal system allows for a consolidation process. Consolidation refers to the process of combining multiple smaller shipments into a single vehicle (Li et al., 2021). In this operation, LTL shipments are combined in the same vehicle in order to achieve economies of scale (similar to the concept of public transport used by passengers with different origins and destinations). In freight transport, consolidation is defined as sharing the containerized transportation vehicle for containers coming from different origins, or heading to different destinations (Mesa-Arango & Ukkusuri, 2013).
- It is possible to consolidate containers from different orders in the same vehicle, when they pass through the same modal link, as part of their journeys. Consolidation operations are carried out in intermodal terminals, where the change of transport mode takes place simultaneously (Jakara & Brnjac, 2023).

- The model determines "the number of consolidation operations" carried out in each modal link, indicating how many times shipments are combined within the same modal link. Consolidation operations can take place in all transport modes and across all links.
- Vehicles in each mode of transport have the same capacity.
- The implementation of consolidation operations incurs costs and carbon emissions.
- Each modal link has a capacity in terms of the number of containers transported. Disruptions can impact the capacity of each link. Proactive preparedness actions can be undertaken to improve the capacity impact following disruptions. Examples of preparedness actions include equipment prepositioning, alternative route consideration, and special training of staff along certain routes to improve the recovery speed (Miller-Hooks et al., 2012).
- In normal conditions, the total transit time for a shipment is calculated as the sum of transit times over links and transfer times. In the face of disruptions, transit times may increase. Reactive recovery activities can be implemented to reduce this impact. Examples of reactive recovery activities include rerouting shipments, rescheduling transportation plans, switching between/among alternative modes, repairing the impacted infrastructure, and employing additional resources (Chen & Miller-Hooks, 2012).
- Delay costs may be incurred if delivery times (due dates) are violated. Note that we use the terms "delivery time" and "due date" interchangeably.

The programming model incorporates capacity constraints on modal-links to ensure that the total number of containers passing through each modal-link does not exceed its capacity. This constraint accounts for the impact of disruption scenarios and the implementation of pre-disaster activities or recovery actions. By using this constraint, we can determine the required number of vehicles in different disruption scenarios, enabling the transportation company to estimate the maximum fleet size needed to cover all possible disruptions. Additionally, we include delivery time constraints to estimate delays or lost sales in different disruption scenarios. A resilience budget is allocated for implementing preparedness and recovery actions, with a maximum of one recovery action allowed for each modal-link in each scenario. Similarly, a threshold of one is set for preparedness activities for each modal-link, as different preparedness or recovery activities may interfere with each other.

We do not restrict the maximum number of transferred containers at intermodal terminals. The allocation of resources for transfer operations within intermodal terminals is not within the scope of this study. Similarly, the aggregation of different products in containers is excluded from our analysis as we assume that all orders are containerized. We assume a port-to-port delivery where operations such as transporting containers from suppliers to ports, as well as from ports to the final destination (end customer), are beyond the scope of this study. While it is possible for two suppliers to incorporate their products in the same container, according to the Maritime Transport Safety Act, all full containers entering a terminal must be sealed, a procedure that falls outside the scope of this study. Thus, we assume that the origin and destination nodes are ports.

The proposed tactical planning model aims to allocate transportation modes to orders, and determine the routes and distribution strategies. The following set of decisions are determined by the model:

a. The number of vehicles for each transportation mode.
b. The proactive preparedness actions to be undertaken before disruptions occur.
c. The reactive recovery activities to implement in the face of disruptions.
d. The flow of shipments within the network.
e. The number of containers transshipped at the intermodal terminals.
f. The number of consolidation operations.

A two-stage stochastic MIP model is developed (for an in-depth review of stochastic programming, readers are referred to Birge and Louveaux (2011)), in which the first stage involves decisions that remain consistent across disruption scenarios (i.e., decision sets a and b), and the second stage considers disruption-specific decisions (i.e., decision sets c-f).

3.2. Notations

The following notations are used to formulate the problem in the Section 3.3.

Sets and indices:	
N	Set of all nodes indexed by i, j, l
K	Set of all origin–destination (OD) city-pairs (order) indexed by k
M	Set of all modes including road, rail, and waterways indexed by m
S	Set of disruption scenarios indexed by s
W	Set of candidate recovery activities indexed by w
P	Set of available preparedness actions indexed by p
$O(k)$	Set of origin of orders indexed by $o(k)$
$D(k)$	Set of destination of orders indexed by $d(k)$
Parameters:	
c_{ij}^m	Variable cost of shipping on link (i, j) using mode m
d_{ij}^m	Distance between node i and j using mode m

(continued on next page)

(*continued*)

Sets and indices:	
f_{ij}^{m}	Fixed cost of shipping on link *(i, j)* using mode *m*
TC_j	Unit transfer cost in terminal *j*
r^k	Quantity of order *k* to be shipped from *o(k)* to *d(k)*
q_{ij}^{m}	Capacity of link *(i, j)* in normal condition (in containers) for mode *m*
Δq_{ij}^{mw}	Change in capacity of link *(i, j)* for mode *m*, if recovery activity *w* is implemented
$\Delta q_{ij}^{'mp}$	Change in capacity of link *(i, j)* for mode *m*, if preparedness action *p* is undertaken
v^m	Capacity of vehicles in mode *m* (in containers)
T_k	Due date of order *k*
τ_j	Time delay at terminal *j* for transferring a shipment from one mode to another
t_{ij}^{m}	Transit time of a shipment between *i* and *j* using mode *m* in normal condition
$t_{ij}^{'mw}$	Transit time of a shipment between *i* and *j* using mode *m* after implementing recovery activity *w*
o_{ij}^{mw}	Time needed to implement recovery activity *w* on link (*i, j*) using mode *m*
g_{ijs}^{m}	Percentage capacity of link (*i, j*) for mode *m* disrupted under scenario *s*
δ_{ijs}^{m}	Percentage increase in transit time of a shipment between *i* and *j* using mode *m* due to disruption in scenario *s*
u_k	Unit cost of lost sales for order *k* (£/container)
a_{ij}^{mw}	Cost of implementing recovery activity *w* on link (*i, j*) for mode *m*
$\widetilde{a}_{ij}^{mpw}$	Cost of implementing recovery activity *w* on link (*i, j*) for mode *m*, if preparedness action *p* is undertaken
h_{ij}^{mp}	Cost of implementing preparedness action *p* on link (*i, j*) for mode *m*
A	Resilience budget (i.e., maximum budget for recovery and preparedness activities)
π_s	Likelihood of occurrence of scenario *s*
η	Matrix of preparedness-recovery activity relationship in which each element η_{pw} is set to 1 if recovery activity *w* is affected by preparedness action *p*, and 0, otherwise
$f_{ij}^{'m}$	Unit cost of consolidation operation in link (*i, j*) using mode *m*
e_j	Emissions in kg per container transshipment in terminal *j* (in kg of CO_2e/ container)
e_m	Emissions in kg per container transportation using mode *m* (in kg of CO_2e/ container-mile)
ec_m	Emissions in kg for a consolidation operation for mode *m* (in kg of CO_2e/ container)
C_{so}	Social cost conversion factor for emissions generation (£/kg)
$C_{n\phi}$	Social cost conversion factor for noise pollution in road travel (£/vehicle-mile)
$C_{c\phi}$	Social cost conversion factor for congestion in road travel (£/vehicle-mile)
$C_{a\phi}$	Social cost conversion factor for accidents in road travel (£/container-mile)
$C_{e\psi}$	Combined social cost conversion factor for negative externalities of rail travel (£/container-mile)
$C_{e\varphi}$	Combined social cost conversion factor for negative externalities of waterway travel (£/container-mile)
$u_k^{'}$	Unit delay cost for each time unit violated from due date, for order *k* (£/container)
Decision variables:	
X_{ijs}^{km}	Flow of order *k* on link (*i, j*) using mode *m* in scenario *s* (in container)
n_{js}^{k}	Number of containers of order *k* transferred at terminal *j* in scenario *s*
Z_{ijs}^{km}	Binary variable, equal to 1 if a shipment for order *k* passes through (*i, j*) using mode m in scenario *s*; 0, otherwise
U_s^k	Number of shipments that cannot be satisfied for order *k* in scenario *s*
γ_{ijs}^{mw}	Binary variable, equal to 1 if recovery activity *w* is undertaken on link (*i, j*) for mode *m* in scenario *s*; 0, otherwise
β_{ij}^{mp}	Binary variable, equal to 1 if preparedness activity *p* is undertaken on link (*i, j*) for mode *m*; 0, otherwise
con_{ijs}^{m}	Number of consolidation operations implemented on link (*i, j*) for mode *m* in scenario *s*
$\overline{Y}_{ijs}^{mk}$	Number of vehicles of mode *m* assigned to order *k* on link (*i, j*) in scenario *s* when consolidation is not used
$Y_{ijs}^{'m}$	Number of vehicles of mode *m* on link (*i, j*) in scenario *s* when consolidation is used
Y_{ij}^{m}	Total number of vehicles of mode *m* for link (*i, j*) (i.e., fleet size for mode *m*)
DL_{ks}	Transportation delay of order *k* in scenario *s*
Ari_{ks}	Arrival time of order *k* at destination in scenario *s*

3.3. The Model

The proposed two-stage stochastic programming model (hereafter referred to as MIP) is formulated in this section aiming to design and plan a resilient and sustainable intermodal transport system.

(MIP):

$$\min \sum_m \sum_i \sum_j f_{ij}^m Y_{ij}^m + \sum_i \sum_j \sum_m \sum_p h_{ij}^{mp} \beta_{ij}^{mp} + \sum_s \pi_s \left(\sum_k \sum_m \sum_i \sum_j c_{ij}^m X_{ijs}^{km} + \sum_k \sum_j TC_j n_{js}^k + \sum_m \sum_i \sum_j f_{ij}^{\prime m} con_{ijs}^m \right.$$
$$\left. + \sum_i \sum_j \sum_m \sum_w a_{ij}^{mw} \gamma_{ijs}^{mw} + \sum_k u_k U_s^k + \sum_k u_k^{\prime} DL_{ks} \right) + C_{so} \left[\sum_s \pi_s \left(\sum_m \sum_i \sum_j ec_m con_{ijs}^m + \sum_k \sum_m \sum_i \sum_j d_{ij}^m X_{ijs}^{km} e_m + \sum_k \sum_j e_j n_{js}^k \right) \right]$$
$$+ \left(C_{n\phi} + C_{c\phi} \right) \left[\sum_{m=1} \sum_i \sum_j d_{ij}^m Y_{ij}^m \right] + C_{a\phi} \left[\sum_s \pi_s \sum_{m=1} \sum_i \sum_j \sum_k d_{ij}^m X_{ijs}^{km} \right] + C_{e\psi} \left[\sum_s \pi_s \sum_{m=2} \sum_i \sum_j \sum_k d_{ij}^m X_{ijs}^{km} \right]$$
$$+ C_{e\varphi} \left[\sum_s \pi_s \sum_{m=3} \sum_i \sum_j \sum_k d_{ij}^m X_{ijs}^{km} \right] \tag{1}$$

Subject to

$$\sum_j \sum_m X_{ijs}^{km} - \sum_l \sum_m X_{lis}^{km} = \begin{cases} r^k - U_s^k; if\ i = O(k), \forall k \in K, \forall s \in S \\ -r^k + U_s^k; if\ i = D(k), \forall k \in K, \forall s \in S \\ 0;\ otherwise \end{cases} \tag{2}$$

$$\sum_k X_{ijs}^{km} \leq \left(1 - g_{ijs}^m\right) q_{ij}^m + \sum_w \gamma_{ijs}^{mw} \Delta q_{ij}^{mw} + \sum_p \beta_{ij}^{mp} \Delta q_{ij}^{\prime mp}; \quad \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{3}$$

$$\sum_k X_{ijs}^{km} \leq v^m Y_{ijs}^{\prime m}; \quad \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{4}$$

$$X_{ijs}^{km} \leq v^m \overline{Y}_{ijs}^{mk}; \quad \forall k \in K,\ \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{5}$$

$$con_{ijs}^m = \left(\sum_k \overline{Y}_{ijs}^{mk} \right) - Y_{ijs}^{\prime m};\ \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{6}$$

$$Y_{ijs}^{\prime m} \leq Y_{ij}^m;\ \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{7}$$

$$\sum_i \sum_j \sum_m Z_{ijs}^{km} \left(t_{ij}^m \right) \left(1 + \delta_{ijs}^m \right) + \sum_i \sum_j \sum_m \sum_w Z_{ijs}^{km} \gamma_{ijs}^{mw} \left(t_{ij}^{\prime mw} - t_{ij}^m \left(1 + \delta_{ijs}^m \right) \right) + \sum_i \sum_j \sum_m \sum_w \gamma_{ijs}^{mw} o_{ij}^{mw} + \sum_j \tau_j n_{js}^k \leq Ari_{ks};\ \forall k \in K,\ \forall s \in S \tag{8}$$

$$\sum_i X_{ijs}^{km} - \sum_l X_{jls}^{km} \leq n_{js}^k; \quad \forall k \in K,\ j \in N \backslash D(k),\ \forall m \in M,\ \forall s \in S \tag{9}$$

$$Z_{ijs}^{km} \leq X_{ijs}^{km}; \quad \forall (i,j) \in N,\ \forall k \in K,\ \forall m \in M,\ \forall s \in S \tag{10}$$

$$X_{ijs}^{km} \leq r^k Z_{ijs}^{km};\ \forall (i,j) \in N,\ \forall k \in K,\ \forall m \in M,\ \forall s \in S \tag{11}$$

$$\sum_i \sum_j \sum_m \sum_p h_{ij}^{mp} \beta_{ij}^{mp} + \sum_i \sum_j \sum_m \sum_w a_{ij}^{mw} \gamma_{ijs}^{mw} + \sum_i \sum_j \sum_m \sum_p \sum_w \left(\widetilde{a}_{ij}^{mpw} - a_{ij}^{mw} \right) \eta_{pw} \beta_{ij}^{mp} \gamma_{ijs}^{mw} \leq A; \quad \forall s \in S \tag{12}$$

$$\sum_w \gamma_{ijs}^{mw} \leq 1;\ \forall (i,j) \in N,\ \forall m \in M,\ \forall s \in S \tag{13}$$

$$\sum_p \beta_{ij}^{mp} \leq 1;\ \forall (i,j) \in N,\ \forall m \in M \tag{14}$$

$$\gamma_{ijs=1}^{mw} = 0\ \ \forall (i,j) \in N,\ \forall m \in M, \forall w \in W \tag{15}$$

$$Ari_{ks} - T_k DL_{ks} \leq DL_{ks};\ \forall k \in K,\ \forall s \in S \tag{16}$$

$$DL_{ks} \geq 0;\ \forall k \in K,\ \forall s \in S \tag{17}$$

$$n_{js}^{k},\ Y'^{m}_{ijs},\ \overline{Y}^{mk}_{ijs},\ Y_{ij}^{m} \in \{0, 1, 2, \cdots\} \quad \forall(i,j)\in N,\ \forall m\in M,\ \forall k\in K,\ \forall s\in S \tag{18}$$

$$X_{ijs}^{km} \geq 0;\ U_{s}^{k} \geq 0;\ \forall(i,j)\in N, \quad \forall m\in M,\ \forall k\in K,\ \forall s\in S \tag{19}$$

$$Z_{ijs}^{km},\ \gamma_{ijs}^{mw},\ \beta_{ij}^{mp} \in \{0, 1\} \quad \forall(i,j)\in N,\ \forall m\in M,\ \forall k\in K,\ \forall w\in W,\ \forall s\in S \tag{20}$$

The objective function (1) aims to minimize the expected total cost of the network, comprised of the expected total transportation costs, resilience costs, and social and environmental sustainability impacts including costs of noise pollution, accidents, congestion, and carbon emissions. Constraint (2) encompasses a set of flow conservation constraints that express demand requirements for orders and the quantities of lost sales for each.

Constraint (3) formulates the capacity constraint for each link after a disruption occurs, accounting for preparedness and recovery activities. This constraint ensures that the total flow in link *(i, j)* using mode *m* remains below the maximum capacity of the modal link across different scenarios. Constraint (4) determines the optimal number of vehicles required for mode *m* after consolidation in each scenario. Constraint (5) determines the required number of vehicles for each order before consolidation, while Constraint (6) counts the number of consolidation operations.

Constraint (7) determines the required number of vehicles for each mode, accounting for potential variations in different scenarios, with the upper bound representing the optimal fleet size. Constraint (8) calculates the total shipment time for the orders, considering transfer time during mode changes and variations in shipment time resulting from disruptive events and recovery actions. Constraint (9) determines whether a transfer operation is conducted at terminal, and calculates the number of transferred containers. Constraints (10) and (11) are used to define the binary variable Z_{ijs}^{km} based on the value of X_{ijs}^{km} in a way that: when $X_{ijs}^{km} > 0$, then $Z_{ijs}^{km} = 1$. Constraint (12) ensures that the total cost of the chosen preparedness and recovery actions remains within a given budget. Constraint (13) stipulates that only one recovery action from a set of options can be chosen for each link. Constraint (14) is identical to Constraint (13) but pertaining to preparedness activities. Constraint (15) prohibits the execution of recovery actions under normal conditions. Constraints (16) and (17) determine the potential delay for each order. The domains of the decision variables are defined in Constraints (18) to (20).

4. Solution method

We develop a solution method based on Lagrangian relaxation approach and valid inequalities. Lagrangian relaxation has proven to

Initialise Lagrange multipliers

($\lambda^{0}, \mu^{0}, \theta_{0}, MaxIter, Maxtime, Optimality\_gap = \varepsilon, non\_imp\_counter = 0$

$non\_imp\_limit, Z_{UB} = +\infty, Z_{LB} = 0, Z_{lp}$)

While (Termination condition not met) Do

{

Increment iteration counter

Compute the lower bound

(a) Solve Sub-1 → *output*= $\hat{X}_{ijs}^{kmt}$, *objective function*= $Z_{\mathrm{Sub1}}(\lambda^{t}, \mu^{t})$

(b) Solve Re-Sub2, input=$\hat{X}_{ijs}^{kmt}$ → *output*=$\hat{Y}_{ij}^{mt}, \hat{Y}'^{mt}_{ijs}, \hat{\overline{Y}}_{ijs}^{mkt}$, *objective function*= $Z_{\mathrm{Re-Sub2}}(\lambda^{t}, \mu^{t})$

(c) Set $Z_{LR}(\lambda^{t}, \mu^{t}) = Z_{\mathrm{Sub1}}(\lambda^{t}, \mu^{t}) + Z_{\mathrm{Re-Sub2}}(\lambda^{t}, \mu^{t})$

If $Z_{LR}(\lambda^{t}, \mu^{t}) \leq Z_{LB}$; *set* $non\_imp\_counter = non\_imp\_counter + 1$

Otherwise set $non_{imp_{counter}} = 0$

(d) Set $Z_{LB} = \max\{Z_{LR}(\lambda^{t}, \mu^{t}), Z_{LB}\}$ *as the best lower bound*

Compute the upper bound

(a) Solve FUB model, input=$\hat{Y}_{ij}^{mt}, \hat{Y}'^{mt}_{ijs}, \hat{\overline{Y}}_{ijs}^{mkt}$ → *output*= $\hat{X}_{ijs}^{kmt}$, *objective function* = $Z_{\mathrm{FUB}}(\lambda^{t}, \mu^{t})$

(b) Set $Z_{UB} = \min\{Z_{FUB}(\lambda^{t}, \mu^{t}), Z_{UB}\}$ *as the best upper bound*

Check termination condition

$$If\ t \leq MaxIter\ and\ CPU\ time \leq Maxtime\ and\ \frac{Z_{UBD} - Z_{LBD}}{Z_{UBD}} > \varepsilon\ and\ stepsize^{t} > 10^{-8};$$

then update Lagrange multipliers; otherwise stop.

Update Lagrange multipliers using Eqs (28-31)

If $non\_imp\_counter \geq non\_imp\_limit$, *set* $\theta_{t+1} = \frac{\theta_{t}}{2}$ *and* $non\_imp\_counter = 0$

Otherwise set $\theta_{t+1} = \theta_{t}$

}

Fig. 2. The steps of the proposed solution method.

be a highly effective solution approach that has successfully addressed various supply chain and logistics problems (e.g., Mohammad Nezhad et al., 2013; Jabbarzadeh et al., 2016). Essentially, Lagrangian relaxation offers both upper and lower bounds for the optimal objective value, enabling decision-makers to gauge the proximity of the best feasible solution to optimality (Mohammad Nezhad et al., 2013). The method operates in three key steps: (1) driving a lower bound for optimal solutions, (2) driving an upper bound for optimal solutions, and (3) iteratively updating the upper and lower bounds. These steps are iteratively performed until the lower and upper bounds reach a predefined level of proximity. Fig. 2 outlines the pseudocode of the proposed algorithm. The following subsections delve into these steps in detail, focusing on their application to solve the model introduced in Section 3.

4.1. Driving a lower bound

In the first step, specific constraints are relaxed to create Lagrangian Dual problems. By solving these modified problems, a lower bound for the original optimization problem can be obtained (Gaudioso, 2020). For this purpose, Constraints (4) and (5) are relaxed with Lagrangian multipliers λ_{ijsm} and μ_{ijmsk} to arrive at the following Lagrangian dual problem:

(LR):

$$\begin{aligned} min \sum_m\sum_i\sum_j f_{ij}^m Y_{ij}^m + \sum_i\sum_j\sum_m\sum_p h_{ij}^{mp}\beta_{ij}^{mp} + \sum_s \pi_s \Bigg(\sum_k\sum_m\sum_i\sum_j c_{ij}^m X_{ijs}^{km} + \sum_k\sum_j TC_j n_{js}^k + \sum_m\sum_i\sum_j f_{ij}^{'m} con_{ijs}^m \\ + \sum_i\sum_j\sum_m\sum_w a_{ij}^{mw}\gamma_{ijs}^{mw} + \sum_k u_k U_s^k + \sum_k u_k^{'} DL_{ks} \Bigg) + C_{so}\left[\sum_s \pi_s \left(\sum_m\sum_i\sum_j ec_m con_{ijs}^m + \sum_k\sum_m\sum_i\sum_j X_{ijs}^{km} d_{ij}^m e_m + \sum_k\sum_j e_j n_{js}^k \right)\right] \\ + (C_{n\phi} + C_{c\phi})\left[\sum_{m=1}\sum_i\sum_j Y_{ij}^m d_{ij}^m\right] + C_{a\phi}\left[\sum_s \pi_s \sum_{m=1}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] + C_{e\psi}\left[\sum_s \pi_s \sum_{m=2}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] \\ + C_{e\varphi}\left[\sum_s \pi_s \sum_{m=3}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] + \sum_s\sum_i\sum_j\sum_m \lambda_{ijsm}\left[\left(\sum_k X_{ijs}^{km}\right) - Y_{ijs}^{'m} v^m\right] + \sum_s\sum_i\sum_j\sum_m\sum_k \mu_{ijmsk}\left[X_{ijs}^{km} - \overline{Y}_{ijs}^{mk} v^m\right] \end{aligned} \tag{21}$$

Subject to

(2–3)

(6–20).

This formulation can be decomposed into two separate subproblems: Sub1 (x-related sub-model) and Sub2 (y-related sub-model) which are both easier to solve compared to the original problem. The first sub-problem (Sub1), which exclusively involves x variables, can be defined as follows.

(Sub1):

$$\begin{aligned} min \sum_i\sum_j\sum_m\sum_p h_{ij}^{mp}\beta_{ij}^{mp} + \sum_s \pi_s \left(\sum_k\sum_m\sum_i\sum_j c_{ij}^m X_{ijs}^{km} + \sum_k\sum_j TC_j n_{js}^k + \sum_i\sum_j\sum_m\sum_w a_{ij}^{mw}\gamma_{ijs}^{mw} + \sum_k u_k U_s^k + \sum_k u_k^{'} DL_{ks} \right) \\ + C_{so}\left[\sum_s \pi_s \left(\sum_k\sum_m\sum_i\sum_j X_{ijs}^{km} d_{ij}^m e_m + \sum_k\sum_j e_j n_{js}^k \right)\right] + C_{a\phi}\left[\sum_s \pi_s \sum_{m=1}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] + C_{e\psi}\left[\sum_s \pi_s \sum_{m=2}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] \\ + C_{e\varphi}\left[\sum_s \pi_s \sum_{m=3}\sum_i\sum_j\sum_k X_{ijs}^{km} d_{ij}^m\right] + \sum_s\sum_m\sum_i\sum_j \lambda_{ijms} \sum_k X_{ijs}^{km} + \sum_s\sum_k\sum_m\sum_j\sum_i \mu_{ijmsk} X_{ijs}^{km} \end{aligned} \tag{22}$$

Subject to.

(2–3)

(8–20).

The second sub-problem (Sub2) is exclusively formulated in terms of y-related variables.

(Sub 2):

$$\begin{aligned} min \sum_m\sum_i\sum_j f_{ij}^m Y_{ij}^m + \sum_s \pi_s \left(\sum_m\sum_i\sum_j f_{ij}^{'m} con_{ijs}^m \right) + C_{so}\left[\sum_s \pi_s \left(\sum_m\sum_i\sum_j ec_m con_{ijs}^m \right)\right] + (C_{n\phi} + C_{c\phi})\left[\sum_{m=1}\sum_i\sum_j Y_{ij}^m d_{ij}^m\right] \\ - \sum_s\sum_m\sum_i\sum_j \lambda_{ijms} Y_{ijs}^{'m} v^m - \sum_s\sum_k\sum_m\sum_j\sum_i \mu_{ijmsk} \overline{Y}_{ijs}^{mk} v^m \end{aligned} \tag{23}$$

Subject to

(6–7)

(18).

Upon solving the second sub-problem, the model would yield an objective function value of 0, as all decision variables are set to 0.

To rectify this issue, Constraint (24) is incorporated to Sub2.

$$\sum_{k} \widehat{X}_{ijs}^{km} \leq v^m Y_{ij}^m; \quad \forall (i,j) \in N, \ \forall m \in M, \ \forall s \in S \tag{24}$$

Where $\widehat{X}_{ijs}^{km}$ is optimal value of variable X_{ijs}^{km}, invoked from Sub1.

Proposition 1: Constraint (24) is a valid inequality.

Proof: By considering Constraints (4) and (7), the following inequalities can be observed:

$$\sum_{k} X_{ijs}^{km} \leq v^m Y'^m_{ijs}; \quad \forall (i,j) \in N, \ \forall m \in M, \ \forall s \in S \tag{4}$$

$$Y'^m_{ijs} \leq Y_{ij}^m; \quad \forall (i,j) \in N, \ \forall m \in M, \ \forall s \in S \text{ then } v^m Y'^m_{ijs} \leq v^m Y_{ij}^m; \ \forall (i,j) \in N, \ \forall m \in M, \ \forall s \in S \tag{7}$$

By substituting the right hand side of Constraint (7) into the right hand side of Constraint (4) and replacing X_{ijs}^{km} with $\widehat{X}_{ijs}^{km}$, we obtain inequality (24).

Adding Constraint (24) to Sub2 cuts away the solutions of Sub2, leading to the revised sub-problem 2 (Re-Sub2).

(Re-Sub2):

min Objective (23)

Subject to

(6–7)

(18)

(24).

To establish a lower bound for the original problem (MIP), we solve Sub1 and Re-Sub2 models. Let $Z_{\text{Sub-1}}$ and $Z_{\text{Re-Sub2}}$ indicate their respective optimal values. Then, $Z_{\text{Sub-1}} + Z_{\text{Re-Sub2}}$ serves as a lower bound for MIP.

4.2. Driving an upper bound

To establish an upper bound, the following procedure is employed to generate feasible solutions for the MIP model. First, the results of the Re-Sub2 model are utilized, which entails the inclusion of all y-related variables. The obtained values are then inserted into the original MIP model while maintaining the relaxed constraint sets and in the presence of x-related variables. Subsequently, the following model, hereafter referred to as FUB, determines the values for the x-related variables.

(FUB):

$$\begin{aligned} min & \sum_{m}\sum_{i}\sum_{j} f_{ij}^m \widehat{Y}_{ij}^m + \sum_{i}\sum_{j}\sum_{m}\sum_{p} h_{ij}^{mp}\beta_{ij}^{mp} + \sum_{s}\pi_s \left(\sum_{k}\sum_{m}\sum_{i}\sum_{j} c_{ij}^m X_{ijs}^{km} + \sum_{k}\sum_{j} TC_j n_{js}^k + \sum_{m}\sum_{i}\sum_{j} f'^m_{ij} \widehat{con}_{ijs}^m \right. \\ & \left. + \sum_{i}\sum_{j}\sum_{m}\sum_{w} a_{ij}^{mw}\gamma_{ijs}^{mw} + \sum_{k} u_k U_s^k + \sum_{k} u'_k DL_{ks} \right) + C_{so}\left[\sum_{s}\pi_s \left(\sum_{m}\sum_{i}\sum_{j} ec_m \widehat{con}_{ijs}^m + \sum_{k}\sum_{m}\sum_{i}\sum_{j} X_{ijs}^{km} d_{ij}^m e_m + \sum_{k}\sum_{j} e_j n_{js}^k \right) \right] \\ & + \left(C_{n\phi} + C_{c\phi}\right)\left[\sum_{m=1}\sum_{i}\sum_{j} \widehat{Y}_{ij}^m d_{ij}^m \right] + C_{a\phi}\left[\sum_{s}\pi_s \sum_{m=1}\sum_{i}\sum_{j}\sum_{k} X_{ijs}^{km} d_{ij}^m \right] + C_{e\psi}\left[\sum_{s}\pi_s \sum_{m=2}\sum_{i}\sum_{j}\sum_{k} X_{ijs}^{km} d_{ij}^m \right] \\ & + C_{e\varphi}\left[\sum_{s}\pi_s \sum_{m=3}\sum_{i}\sum_{j}\sum_{k} X_{ijs}^{km} d_{ij}^m \right] \end{aligned} \tag{25}$$

Subject to.

(2–3)

(8–20)

$$\sum_{k} X_{ijs}^{km} \leq v^m \widehat{Y}'^m_{ijs}; \forall (i,j) \in N, \forall m \in M, \forall s \in S \tag{26}$$

$$X_{ijs}^{km} \leq v^m \widehat{\overline{Y}}_{ijs}^{mk}; \forall k \in K, \forall (i,j) \in N, \forall m \in M, \forall s \in S \tag{27}$$

where $\widehat{Y}_{ij}^m$, $\widehat{Y}'^m_{ijs}$, $\widehat{\overline{Y}}_{ijs}^{mk}$ and $\widehat{con}_{ijs}^m$ stand for the optimal solution of Re-Sub2.

4.3. Iteratively updating the upper and lower bounds

In each iteration, the subgradient direction method is used to update the Lagrangian multipliers. This method is commonly employed by Tautenhain et al. (2021) and Mohammad Nezhad et al. (2013) and can be seen as an adapted version of the gradient technique. It involves obtaining the subgradient direction by minimizing the dual function. The validation and theoretical convergence properties of this method can be found in Held et al. (1974).

By applying the subgradient direction method, the Lagrange multipliers λ^t_{ijsm} and μ^t_{ijmsk} are updated using Eqs. (28) and (29):

$$\lambda^{t+1}_{ijsm} = Max\left\{0,\ \lambda^t_{ijsm} + stepsize^t \times Penalty\_I^t_{ijsm}\right\} \tag{28}$$

$$\mu^{t+1}_{ijmsk} = Max\left\{0,\ \mu^t_{ijmsk} + stepsize^t \times Penalty\_II^t_{ijskm}\right\} \tag{29}$$

Note that the penalty terms for the constraint sets (i.e., Constraint sets (4) and (5)) are obtained as follows:

$$Penalty\_I^t_{ijsm} = \sum_k X^{kmt}_{ijs} - Y'^{mt}_{ijs}v^m;\quad \forall (i,j)\in N,\ \forall m\in M,\ \forall s\in S \tag{30}$$

$$Penalty\_II^t_{ijskm} = X^{kmt}_{ijs} - \overline{Y}^{mkt}_{ijs}v^m;\quad \forall k\in K,\ \forall (i,j)\in N,\ \forall m\in M,\ \forall s\in S \tag{31}$$

Additionally, the step size in iteration t, is calculated as:

$$stepsize^t = \frac{\theta_t(Z_{UBD} - Z_{LBD})}{\|Penalty\_I^t_{ijsm}\|^2 + \|Penalty\_II^t_{ijskm}\|^2} \tag{32}$$

Here, Z_{UBD} and Z_{LBD} represent the best upper and lower bounds for the original model (MIP), respectively. Also, θ_t is a control parameter that falls within the range $0 \le \theta_t \le 2$. When the algorithm fails to improve the lower bound for a predefined number of consecutive iterations (*non_imp_limit*) (i.e., *non_imp_counter* $\ge$ *non_imp_limit*), θ_t is halved. If θ_t is less than a preset value, the heuristic is stoppled. Another stopping criterion is based on the convergence gap, which is calculated using the following formula and compared to a small value ε.

$$Convergence\ gap = \frac{Z_{UBD} - Z_{LBD}}{Z_{UBD}} \le \varepsilon \tag{33}$$

5. Case study and computational results

We investigate the application of the proposed model and solution method in a realistic case study. In the following sections, we describe the characteristics of the case study followed by the presentation and discussion of the computational results. The problem is coded in Jupyter Notebook in Anaconda as a Python (version 3.10), and all experiments are conducted on a PC with an i7 processor, 16 GB RAM, and 512 GB SSD.

5.1. Case description

We consider an intermodal transportation freight network in the UK, where nodes are connected by highways, railways, and waterways. The proposed network consists of 292 links, as described by Qu et al. (2014). We validate the proposed model using data from the UK transport network for several reasons. Firstly, the transportation infrastructure in the UK provides a diverse and comprehensive dataset for our analysis, incorporating highways, railways, and seaways for freight transport. Additionally, the availability and acceptable quality of transportation data in the UK, relative to other regions, enabled a more robust validation process. Given the attention this network has received from prior researchers (e.g., Qu et al., 2014), it gave us the opportunity to compare our findings with existing literature. **Figure A in the online appendix** illustrates the geographical distribution of the nodes within the network.

For network disruption scenarios, the absence of available data from existing research compelled us to assess all potential natural and man-made disasters within the region to create our own disruption scenarios. Beyond incidents like bombing and terrorist attacks, occurrences of natural disruptions such as floods are relatively significant in the UK. We identified vulnerable locations for each type of disaster and estimated the frequency and likelihood of each event in these areas. We utilized the approach used by Jabbarzadeh et al. (2020) to calculate the occurrence probability of disruption scenarios in the transportation network.

Table A in the online appendix presents the order information within the transport network, including the origin and destination nodes, demand in terms of TEU containers, and the due date for each order. **Table B in the online appendix** provides the essential data on the capacity, variable cost, transfer cost, and CO_2 emissions factor associated with each mode of transport. To estimate emissions in kilograms per transfer of a container at terminal j (e_j), we employed the approach proposed by Budiyanto et al. (2019) in which each TEU container produces 11.27 kg of CO_2e emissions at a terminal. The delay cost for each time unit violation from the due date is set at £5,000, and the unit cost of a lost sale is £30,000. Additionally, the fixed cost of vehicles for the truck, train, and barge modes is respectively set to £1,000, £1,000, and £3,000. As assumed by Venkatadri et al. (2016), unit cost of consolidation operation in each modal-link is 0.05 of the fixed cost of vehicles from the same model; that is, each consolidation operation costs £50, £50, and £150 for truck, rail, and barge, respectively. The sustainability measures and cost conversion factors are provided in **Table C of the online appendix**. The characteristics of the disruption scenarios are detailed in **Table D of the online appendix**.

Table 1
Performance comparison of the proposed solution method.

Number of scenarios	Resilience Budget	**The proposed solution method**				**Gurobi**			**CPLEX**		
		Lower bound (£)	Upper bound (£)	Convergence gap	CPU time (S)	Obj (£)	MIP gap	CPU time (S)	Obj (£)	MIP gap	CPU time (S)
4	30,000	951,168	960,080	0.9 %	58.6	955,011	0.0003 %	76.5	959,383	0.87 %	291.5
26	30,000	1,077,936	1,110,078	2.9 %	587.0	1,089,709	0.15 %	950	1,080,597	1 %	10486.8
40	0	1,307,517	1,352,903	3.4 %	1397	1,324,254	0.92 %	956	NA	NA	NA
40	5000	1,262,021	1,294,090	2.5 %	5070.6	6,377,486	81.49 %	6000	NA	NA	NA
40	10,000	1,251,172	1,283,963	2.6 %	4719.3	1,290,871	2.21 %	6000	NA	NA	NA
40	15,000	1,251,363	1,306,296	4.2 %	5330.4	6,376,650	81.48 %	6000	NA	NA	NA
40	20,000	1,238,144	1,275,277	2.9 %	3218.6	1,279,811	1.73 %	6000	NA	NA	NA
40	25,000	1,235,213	1,277,101	3.3 %	3096.2	1,285,323	3.43 %	6000	NA	NA	NA
40	30,000	1,236,549	1,277,869	3.2 %	2966.7	1,279,436	1.76 %	6000	NA	NA	NA
40	35,000	1,232,574	1,275,894	3.4 %	2923.6	1,270,931	1.19 %	6000	NA	NA	NA
40	40,000	1,242,647	1,281,418	3.0 %	5034.6	1,284,645	2.58 %	6000	NA	NA	NA
40	45,000	1,232,915	1,270,350	2.9 %	4407.9	1,276,059	1.46 %	6000	NA	NA	NA
40	50,000	1,234,654	1,268,312	2.7 %	5788.6	1,285,989	2.59 %	6000	NA	NA	NA
Average				*2.9 %*			*13.92 %*				

NA: not available.

5.2. Performance evaluation of the proposed solution method

Before running the numerical experiments, we first assessed the performance of the method presented in Section 4. We solved various problem sizes using two well-known solvers – Gurobi and CPLEX – and compared the results with those of the proposed solution method. The problems were categorized into small, medium, and large sizes. For the experiments with S = 26 scenarios, a time limit of 950 s was imposed on all solution methods. Gurobi terminated upon reaching this time limit, reporting an MIP gap of 0.15 %. Our algorithm achieved a lower bound solution and a feasible upper bound solution within the time limit, with a convergence gap of 2.9 %. CPLEX also was unable to find a solution within 950 s. Consequently, we extended the time limit to 20,000 s for CPLEX and set the MIP gap of 1 % as the termination criterion. At 10,487 s, CPLEX eventually obtained a solution with a 1 % MIP gap. For the large problems (S = 40), we were unable to obtain results from CPLEX due to memory limitations. For Gurobi, we used two termination conditions: a time limit of 6,000 s and an MIP gap of 1 %, whichever occurred first. For the proposed solution method, the termination criteria were a time limit of 6,000 s, 30 iterations, a step size of 10^{-8}, or a convergence gap (ε) of 9×10^{-3}, whichever happened first. The results are summarized in Table 1.

On average, the convergence gap of our method was 2.9 %, compared to Gurobi's average MIP gap of 13.92 %. Additionally, in 9 out of 13 problem instances, our algorithm found a feasible solution with a lower objective function value. Moreover, our proposed method required less CPU time to reach a solution across all problems. The effectiveness of the proposed method will be further analyzed in the subsequent sections when the method is utilised to deal with a real-life problem.

5.3. Identifying critical and semi critical links

Identifying the vulnerable links in transportation networks is essential for mitigating the impact of disruptions. We conducted an analysis across a range of budgets (i.e., A) and due dates (i.e., T_k). The resilience budget varies from £0 to £50,000. Critical links are those selected by the model for preparedness activities with a resilience budget of £10,000 or less, while semi-critical links are chosen with budgets ranging from £15,000 to £50,000. For due dates, the range is from 0.5 T to 1.4 T, with a resilience budget of £30,000.

We observed that regardless of the budget and due date, a set of links are consistently selected for preparedness actions. These are as

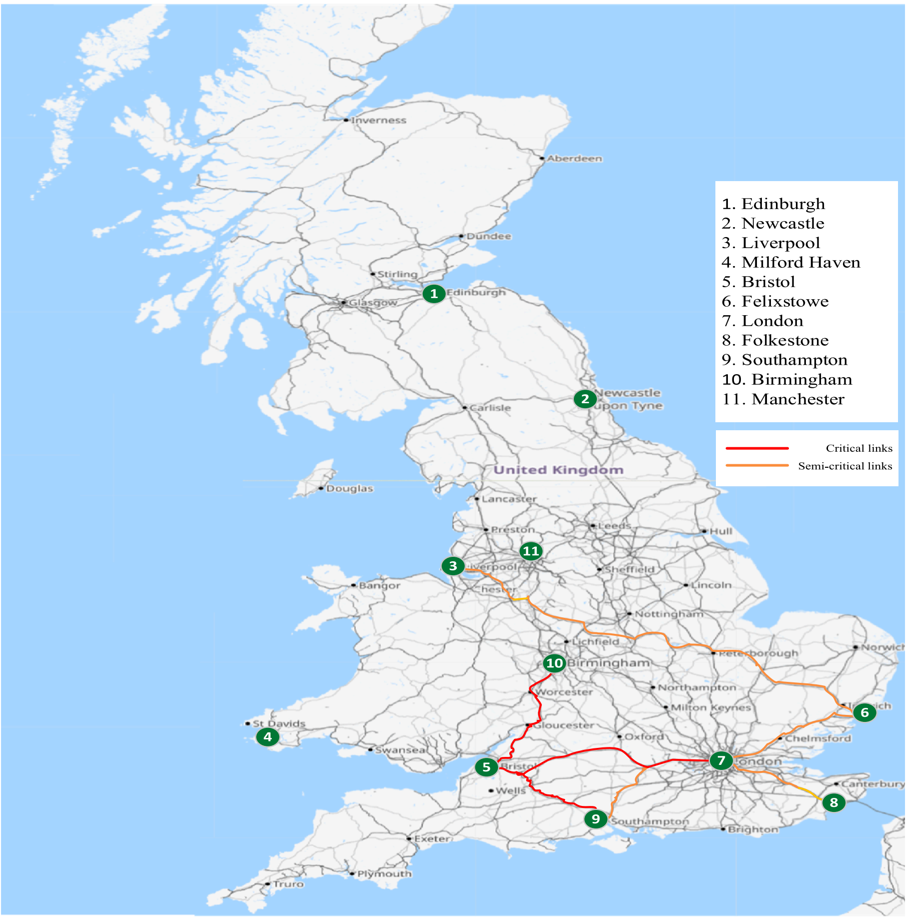

Fig. 3. Critical and semi-critical links for pre-disaster retrofitting.

critical links of the network that require more attention. On the other hand, there are links that are selected for preparedness actions only under certain budget constraints and/or due date tightness. These are the *semi-critical links*. For instance, the link between London and Felixstowe is a semi-critical one as it is only selected for preparedness actions when the budget exceeds £10,000. Besides, solving the model reveals that for due dates ranging from 0.8 T (equivalent to a 20 % reduction in time) to 1.4 T (equivalent to a 40 % increase in time), the candidate links for fortification remain consistent. However, when the due dates are set tighter than 0.7 T, the model identifies an additional semi-critical link. Fig. 3 illustrates the critical and semi-critical links based on variations in resilience budget and due dates. Another finding from this analysis is that all identified critical and semi-critical links are railways. The preparedness decisions prioritize investing in the links Bristol-Birmingham, Bristol-London, and Bristol-Southampton. At a higher budget allocation, the model recommends investing in additional railway links, including Liverpool-Felixstowe, London-Felixstowe, London-Folkestone, and London-Southampton. Among the semi-critical links, the London-Felixstowe link holds a particular importance because this link is selected for preparedness actions when either the budget is tight OR the due date is tight (the other semi-critical links are selected only when the budget is tight).

5.4. Allocating recovery budget to disruption categories

We now complete another analysis to determine the optimal budget allocation for recovery activities across different disruption categories considering due date variations. These results are derived from the experiments of Section 5.3 to identify critical and semi-critical links by altering the due dates within a resilience budget of £30,000. All disruption scenarios are included. The findings are presented in Fig. 4. The due dates vary between 50 % (0.5 T) and 140 % (1.4 T) of the nominal values. We observe that in all the test problems the largest portion of the budget is dedicated to recovering from the floods. As the due date becomes 60 % tighter (0.6 T), there is a significant relative increase in the allocated recovery budget for bombing disruptions (i.e., from £130 to £3,310) compared to other types of disruptions.

5.5. The impact of varying due dates

Fig. 5 illustrates the impact of changes in the due dates on various cost elements, including (i) transportation cost, (ii) resilience cost (i.e., the cost of preparedness and recovery activities), (iii) environmental sustainability cost, (iv) social sustainability cost as well as the expected total cost. It also presents the proportion of different cost elements and their behavior in response to changes in due dates.

From Fig. 5, we observe that the model can accommodate the changes in the due date within the range of 0.7 T to 1.4 T, indicating its tolerance towards tighter due dates with time reductions of less than 30 %. When the time reduction exceeds 30 %, changing due dates increases the total system cost. For instance, when due dates are tightened to 50 % of normal conditions (i.e., 0.5 T), the expected total cost increases by approximately 10 %, from £1,205,570 to £1,324,310.

To compensate for tight due dates, the model adjusts by assigning more trains instead of barges, resulting in a decrease of about 6 % in the average flow of containers in waterways (from 43 % to 37 %). The share of highways remains unchanged.

5.6. The benefits of recovery and preparedness activities

To examine the benefits of preparedness and recovery activities, we investigate four resilience building settings and compare their total costs. In the first setting, both recovery and preparedness activities are undertaken, while the second setting assumes no budget allocated for resilience activities. The third and fourth settings focus, respectively, on preparedness activities and recovery activities in isolation. Fig. 6 presents the results, illustrating how factoring in recovery and preparedness initiatives can alter the expected total cost.

From Fig. 6, a mere allocation of 0.3 % of the total cost towards preparedness and recovery activities (0.3 % was derived from the ratio of the resilience budget to the expected total cost after solving the model) can lead to a 3 % reduction in the overall expected costs – a good resilience investment strategy. In the absence of recovery actions, a substantial budget must be invested in preparedness activities to achieve a comparable level of total cost reduction. However, comparing settings 3 (i.e., only preparedness initiatives are available) and 4 (i.e., only recovery initiatives are available) reveals that implementing preparedness activities results in a lower

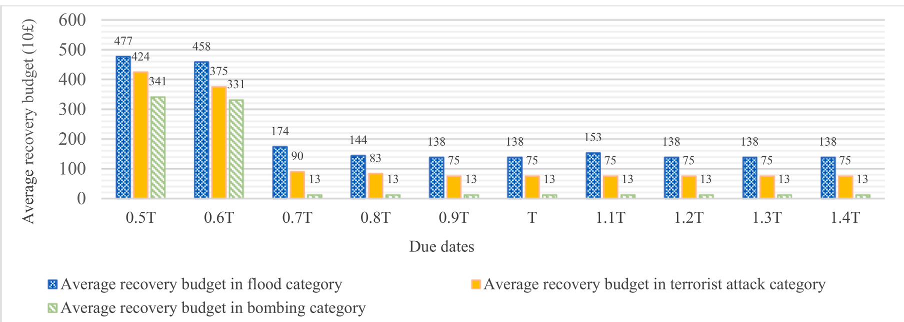

Fig. 4. Allocation of recovery budget to various disruption categories at various due dates.

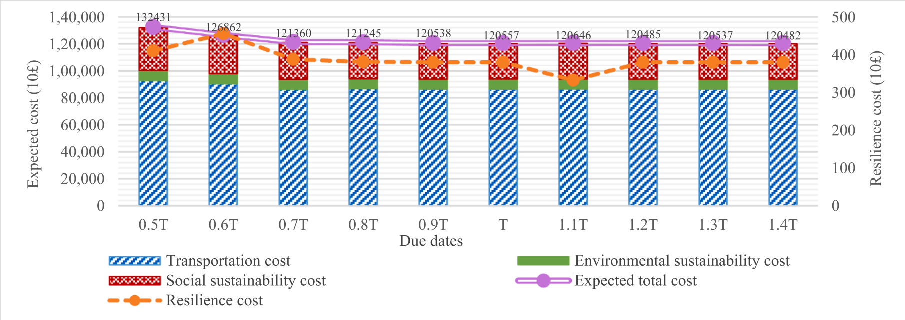

Fig. 5. The impact of varying due dates on cost elements.

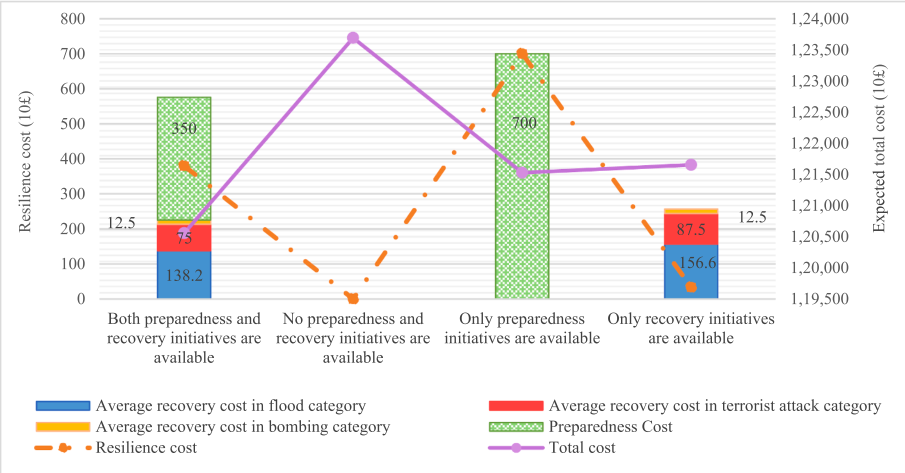

Fig. 6. The effects of preparedness and recovery initiatives on total cost.

expected total cost (about 1 %). This result calls for investment in preparation instead of relying on recovery initiatives.

This figure also illustrates the allocation of recovery costs and preparedness costs for different disruption scenarios, and their impacts on the expected total cost. The distribution of the resilience budget between preparedness and recovery initiatives in different categories of disruption scenarios shows that a larger portion of the recovery budget is allocated to the flood category, while the bombing category receives the smaller portion. Fig. 6 also provides helpful insights into estimating the category-based recovery costs in the face of disruptions. For instance, when both preparedness and recovery initiatives are undertaken, the combined cost of preparedness and recovery amounts to £3,800, from which £3,500 are specifically allocated to preparedness activities. In the flood category, an average of £1,382 is assigned to recovery efforts. For the terrorist attack category, £750 are allocated to recovery activities. The bombing category also receives an average of £125 for recovery efforts. When recovery is not possible following a disruption (i.e., setting 3), a higher investment in preparedness initiatives (almost twice the preparedness costs of setting 1) is required to compensate for the lack of recovery capabilities. On the other hand, even with a small allocation of recovery costs in setting 4,

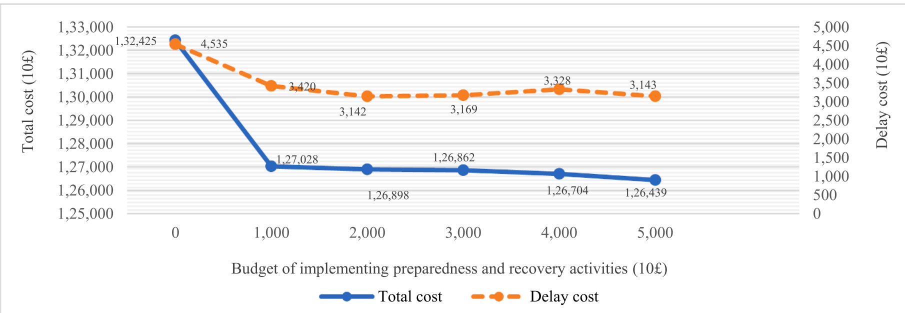

Fig. 7. The impact of resilience budget on total cost and delay cost.

comparable performance to setting 3, in terms of the objective function cost, can be achieved. This reveals the significant effectiveness of the recovery strategy.

To provide further clarity, in two situations where only preparedness initiatives (setting 3) and only recovery initiatives (setting 4) are allowed, the overall costs are almost the same. However, in setting 3, the expected cost is approximately 1 % lower than that of setting 4. Looking at the resilience-building budget in Fig. 6, we observe that, instead of allocating £7,000 to preparedness initiatives in setting 3, we could invest a smaller budget in recovery initiatives. We are also interested in understanding the impact of increasing the recovery and preparedness budget on the total cost of the system. To examine this, we increase the budget from 0 to £50,000 while recording the total cost and the delay cost. The results are plotted in Fig. 7, assuming that both recovery and preparedness initiatives are allowed.

Fig. 7 provides important insights for managers and policymakers seeking to decide about the appropriate budget allocation for resilience building in transport networks. The sharp steepness of the curve on the left indicates that increasing the budget from 0 to £10,000 is remarkably cost-effective. As the investment budget increases beyond £10,000, the resulting cost benefits start to fade away. Beyond £30,000, the cost savings start be become more pronounced. Fig. 7 also illustrates the effect of resilience building budget on the expected delay cost. The delay cost initially exhibits a decreasing trend with an increase in the resilience building budget. This information can aid in making informed budget allocation decisions when trade-offs are needed between costs and due dates.

By varying the available preparedness and recovery budget, the average flow of containers assigned to railways, waterways, and highways is as follows: 54 %, 40 %, and 6 %, respectively. This means that with different resilience budget, the model allocates a significant flow of containers to the rail mode in order to minimize the overall negative externalities which constitute a significant portion of total transportation costs, as demonstrated in the experiments of Fig. 5. Interestingly, when the resilience budget is set to zero and no recovery or preparedness activities are implemented, to avoid lost sales or delay costs, railways handle even more containers (approximately 59 %), followed by barges at 34 %, while the share of roadways remains consistent. This underscores the reliability of railways compared to other modes.

5.7. *The benefits of consolidation*

We now want to examine the advantages of implementing a consolidation strategy with respect to different resilience building budgets. We compare the total costs in two settings: (1) when consolidation is offered, and (2) when consolidation is not offered. Fig. 8 presents the potential cost savings that can be achieved through consolidation. On average, an investment of approximately £696 in consolidation initiatives results in a total cost saving of £23,620. This result reveals a substantial return on investment given that the savings generated from consolidation are approximately 34 times greater than the initial investment.

To further investigate the relationship between consolidation strategy and resilience initiatives, we examine the impact of four resilience building settings on consolidation costs and the resulting savings. These settings are: (i) when both preparedness and recovery initiatives are undertaken, (ii) when no preparedness or recovery initiatives are undertaken, (iii) when only preparedness initiatives are undertaken, and (iv) when only recovery initiatives are undertaken. Fig. 9 displays the results.

We find that the cost savings from consolidation are maximized when both preparedness and recovery activities are undertaken (i. e., the resilience building budget is invested on both preparedness and recovery initiatives). When preparedness and recovery initiatives are undertaken, a £710- investment in consolidation strategy can yield an estimated cost saving of approximately £23,000. Conversely, no resilience building investment is made, the cost saving achieved through consolidation is capped at only £9,000. These results provide additional support for the significance of combined investment in preparedness and recovery initiatives to (a) maximize the potential cost savings in business-as-usual and business-not-as-usual situations, and (b) enhance the potential return on investment in consolidation strategies.

6. Conclusion

The paramount importance of intermodal transportation in addressing global warming challenges through the seamless integration

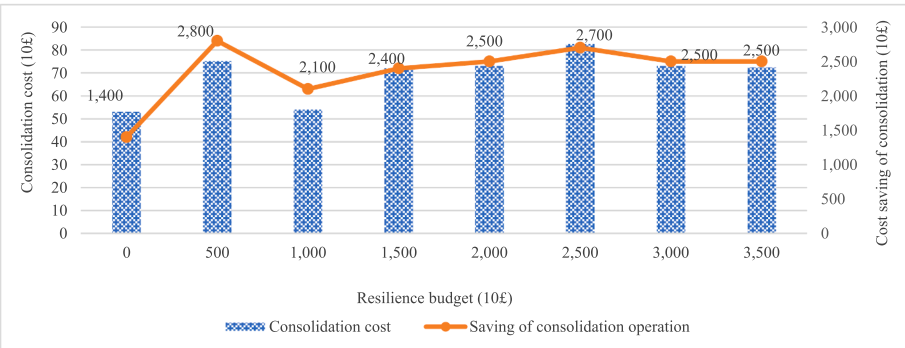

Fig. 8. Consolidation cost and cost savings achieved at different resilience budgets.

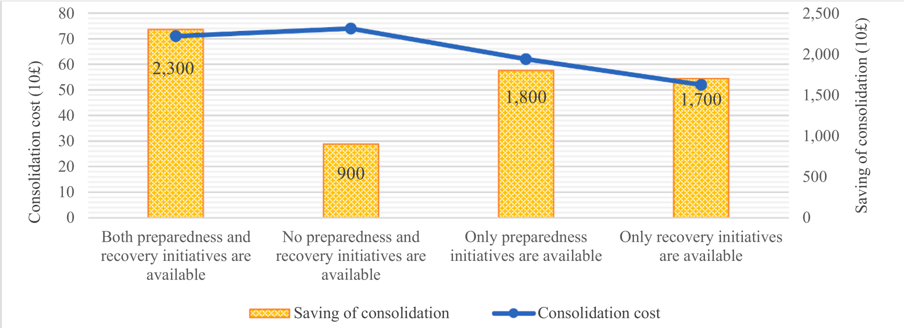

Fig. 9. The impact of preparedness and recovery initiatives on consolidation costs and potential savings.

of road, rail, and waterway systems cannot be overstated. However, the incorporation of consolidation strategies within intermodal transport networks introduces new challenges and complexities that can negatively impact the network's vulnerability to disruptions. This study introduced a modeling approach for evaluating the sustainability and resilience of intermodal transport networks, while leveraging the potential benefits of consolidation strategies. A two-stage stochastic optimization model was developed featuring various sustainability measures (i.e., greenhouse gas emissions, noise pollution, and traffic congestion), proactive and reactive resilience strategies (i.e., preparedness and recovery initiatives), and consolidation opportunities.

Real data from the UK's transportation system was utilized to validate the effectiveness of our solution approach. We demonstrated the superiority of our model and solution method over established solvers CPLEX and Gurobi. In our case study, we exemplified the application of the proposed approach in identifying the critical and semi-critical transport links. The findings of such analysis prove valuable in helping transport managers and policymakers to determine where investments should be prioritized across the transport network (e.g., emergency response plans, redundancy assessment, infrastructure maintenance, technology advancements, personnel training, and collaborative partnerships) and to make more informed budget allocation decisions when trade-offs are needed. For example, in our case study, we found that allocating a mere 0.4 % of the total transport cost to preparedness and recovery initiatives can yield a substantial reduction of approximately 4.7 % in overall costs and 24.6 % in expected delay cost in the face of unpredictable disruptions.

Our case study results also highlight the critical role of railways in mitigating negative externalities and ensuring the reliability of freight transportation networks. Regardless of budget variations, we observed that a substantial portion of container flow was consistently assigned to railways (about 54 %). When deciding about preparedness initiatives, across all our experiments, railways consistently emerged as the primary focus for implementing preparedness activities, demonstrating its importance in mitigating disruptions and ensuring the continuity of freight operations. By prioritizing investments in railway preparedness, managers can improve the overall resilience of the transportation network and reduce the potential for delays and disruptions, ultimately enhancing operational efficiency and customer satisfaction. Furthermore, we found that a modest investment in consolidation initiatives can result in remarkable cost savings of up to 34 times of the initial investment.

Some operations are beyond the scope of this study. This includes the aggregation of demand from multiple customers into the same container. Additionally, this study focuses exclusively on port-to-port delivery, omitting operations involved in transferring cargoes to and from ports. It is important to note that all containers entering an intermodal terminal must be sealed. Also, several types of trucks may be used in consolidation centres (e.g., semi-trailers and rigid trucks), each with distinct cost structures and environmental/social impacts. In our study, to maintain focus on primary objectives, we consider identical trucks with the same capacity, acknowledging this as a practical limitation of our model.

We recognize promising avenues for future research in this domain. In light of the above-mentioned research limitation, we recommend considering a consolidation system in which vehicles in each mode of transport do not necessarily have the same capacity. One area that deserves further research attention is container scheduling for optimized consolidation operations, with the aim to minimize waiting times and delays. Although consolidation strategies offer several benefits, they may introduce supply chain risks as they require different types of operations and resources, and they add new links to the supply chains. Examining these potential risks against the numerous benefits discussed in this paper presents another opportunity for further research. We also encourage future research on examining the role of government policies in encouraging the implementation of sustainability and resilience initiatives within intermodal transport networks through the introduction of new subsidies and toll mechanisms. While the approach proposed in this study can serve as the basis for such analysis, game theoretic methods can offer a valuable lens to further investigate the policy dynamics. The incorporation of innovative solution methods such as decomposition algorithms and heuristics can further improve the practicality and effectiveness of these methods.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tre.2024.103616.

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