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Synchromodal transport re-planning: an agent-based simulation approach

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Abstract

In the rapidly evolving global marketplace, the logistics sector faces a multitude of challenges that demand implementation of more resilient solutions to respond to any future disturbance. Synchromodal transport, which is viewed as an extension of multimodal transport, is known as a key answer to this issue, as it provides more flexible and sustainable freight transport and also focuses on collaboration between different logistics players. We consider synchromodal transport as a collection of agents that not only have their own characteristics and behaviors, but also interact with each other, which impacts the entire system. In this paper, we study the system using an Agent-Based Modeling approach. The network represents the combination of long-haul and drayage transport, where pre-haulage and end-haulage are done only by truck, and the rest can be done by trucks, trains, or barges. A numerical experiment is conducted to evaluate cost savings and emissions reduction under different logistics service providers' relation and re-routing scenarios. Our findings show that synchromodal scenarios are more economically and environmentally efficient, and that they lead to higher flexibility and reliability compared to business-as-usual scenarios. Additionally, our model verifies that the cost saving is considerable when logistics service providers collaborate with each other. The results of sensitivity analyses show consistent overall trends when comparing the different scenarios. Therefore, the conclusions drawn from the original experiment appear to be applicable, not only for that specific instance, but have broader relevance and applicability.

Keywords Synchromodal transport, Multimodal transport, Agent-based modelling, Simulation

1 Introduction

The freight transport demand is predicted to increase 2.6 times by 2050 [23], and it is expected that the existing policies will not be able to meet the goal of climate neutrality in 2050. Indeed, CO_2 emissions produced by the transport sector will increase by 16% by 2050, even if the current obligations to decarbonize transport are fully implemented [24]. For long, the modal shift has been put forward as a key solution to environmental and congestion problems associated with freight transport. Accordingly, different novel concepts have been introduced in the literature, such as intermodality, multimodality, and more recently, synchromodality.

Synchromodal Transport (ST) is one of the extensions of multimodal transport. It focuses on the cooperation of shippers and logistic service providers to make real-time mode switching, as well as *mode-free* transport bookings, and enabling more flexible and sustainable freight transport [25]. ST allows shifting freely between different modes at particular times/nodes while the shipload is in transit [10]. In ST, a shipper usually signs an '*a-modal*' or '*modal-free*' contract and agrees with a Logistics Service Provider (LSP) on the delivery of goods at the specified service level, costs, duration, and sustainability, but gives the LSP the freedom to decide on how to plan the transportation [13].

Although many scholars have done research on modal shift for over 50 years, and despite the politicians and

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policymakers' efforts to make more effective policies in line with increasing sustainability, most companies still rely on road transport, while modal shifts to railways and inland waterways have remained modest in the best case [10]. The share of road transport within EU-28 has even risen around 9.5% over the period 1995–2017, while the share of rail transport has decreased approximately 18%, and the inland waterways share remained relatively stable (EEA, 2020). Moreover, in the period of 2017–2021, the total road freight transport in the EU also registered an average annual growth rate of 2.1% [11]. Many scholars argue why the modal shift is still more of a theoretical concept rather than an operational one. Several authors believe that the key stakeholders have not adequately taken into account the overall impact of multimodal transport in supply chains [3]. Dong et al. [10] discuss that this could be due to companies' failures to internalize environmental costs, variations in regulations and pricing regimes of different modes of transport, as well as greater planning complexity in multi-modal transport. Additionally, the real-time routing of flows, which is central to synchromodality, entails uncertainties (e.g., regarding the availability of different capacities).

In order to implement synchromodal transport, a transparent and financially feasible mechanism is required; this mechanism should also describe the current and forthcoming state of the system and allow the decision-makers to plan ahead (accounting for uncertainties involved) while staying flexible in their decisions. Kurapati et al. [17] discuss that collaboration between actors is one of the crucial elements in complex transport systems, and this is inevitable in a synchromodal transport system. Behdani et al. [4] propose that stakeholders' collaboration, and integration of resources leads to better resource utilization and, consequently, higher service levels. On the other hand, some authors believe that the adaptation of synchromodal transport would not completely take place unless players go further than information sharing; they believe that the key is communicating dynamically and in an integrated way [1]. Dong et al. [10] claim that synchromodal transport is not only the synchronization of different modes of transport, it is the synchronization of transport operations with the rest of supply chain activities, such as supply and demand planning, fleet management, inventory management, and production planning. Besides, in an ST setting, not only can different actors act independently, but they can also interact with other players in the network. The interactions and relations between actors make decision-making in the associated system more complex. Our primary focus in this paper is to study the dynamic interactions between different actors and their impacts on the entire system, both cost-wise and pollution-wise.

Synchromodal transport has been studied by many scholars using mathematical modeling (see Sect. 2). However, at almost every step of a mathematical modeling process, simplifying assumptions and estimations need to be made. Thus, the current mathematical models are often not accurate enough to represent the real system. To have a better estimation of relations between agents and the system itself, and to avoid those simplifying assumptions, we develop an agent-based simulation of the synchromodal transport network.

In short, there is still a notable research gap in terms of the integration of logistics network activities, as well as dynamic collaborations between logistics actors. Moreover, previous studies have been mostly limited to using mathematical modeling, which does not thoroughly represent the real system. This paper is to fill these gaps by developing an agent-based simulation model. The model provides a virtual environment and allows us to test different systems' layouts, like higher speeds, higher frequency of the vehicles, travel time uncertainty, etc. This study contributes in several ways to our understanding of how much ST contributes to freight modal shift by making a difference in economic and environmental costs, flexibility, reliability, and capacity utilization when comparing it with traditional multi-modal transport planning. Moreover, this paper provides important insights on whether horizontal collaboration between actors (in addition to vertical collaboration) can improve the functioning of the ST system.

The remainder of this paper is structured as follows: We provide the relevant literature on simulation and optimization in the context of synchromodal transport in Sect. 2. Then, we discuss the problem description and the model details in Sect. 3. Subsequently, in Sect. 4, we present the details of the experiment we conducted, discuss the findings, and then conduct two sensitivity analyses. Finally, in Sect. 5, we provide our main conclusion and insights for further research.

2 State of the art

This section discusses the state of the art of optimization and simulation in the context of synchromodal transport with regard to the decision level and solution methods. We restrict our focus to quantitative studies in the synchromodal transport context. We refer the readers to Delbart et al. [8] and Rentschler et al. [25] for detailed discussions regarding qualitative and quantitative techniques in ST.

2.1 Optimization of synchromodal transport

Mathematical modeling and optimization techniques are widely used in many works focused on synchromodal transport. These studies can be categorized into three decision levels: strategic, tactical, and operational. However, most of these studies done in this context correspond to the operational level.

Strategic level problems mainly address investment decisions in infrastructure and designing physical networks, i.e., hub locating problems. Crainic et al. [7] and Giusti et al. [12] discuss the hub locating problem for transshipment facilities in synchromodal transport networks. Crainic et al. [7] applied a mixed integer linear programming formulation (MILP) in the context of synchromodal logistics. Then, they solve the problem by an exact method using a commercial solver. Giusti et al. [12] implement a two-stage stochastic programming formulation to deal with the problem. To solve the problem, they propose three Progressive Hedging-based heuristic algorithms.

Decisions on the tactical level mainly imply resource allocation on existing networks, such as service network designs and planning. Van Riessen et al. [28] and Van Riessen et al. [27] propose novel pricing strategies considering "a-modal" booking, which is centered to synchromodality. In their work, Van Riessen et al. [28] formulate a mixed integer programming model for a revenue management problem in order to find the optimal fare class set for intermodal hinterland transportation of maritime containers in an ST setting. To solve the problem, they propose an exact algorithm. Van Riessen et al. [27] apply a Markov chain for the same problem as Van Riessen et al. [28], then, they use a greedy search algorithm to solve the problem. Kalicharan et al. [16] study an integral multi-commodity network design problem in an interactive synchromodal network. They develop an integer linear programming model, and then apply an exact method to solve it.

Operational level planning mainly entails real-time planning, i.e., real-time switching, flexible re-scheduling, and resource management. Behdani et al. [4] formulate a mathematical model for operational resource scheduling as well as designing service schedules in an ST network, their focus is on the network resource integration and optimization of the rail and barge operations. They develop an integer programming formulation; then, they solve the model by applying an exact method using a commercial solver. Guo et al. [14] study a dynamic shipment matching problem in which orders should be allocated to the existing transport services. They developed a mixed integer programming and a binary integer programming model to optimize the problem. They propose a heuristic algorithm as well as a rolling horizon approach to support the decision-making process. Rivera and Mes [26] address the container scheduling problem in an ST setting. They formulate this problem as a Markov decision process and designed a heuristic algorithm to solve it. Yee et al. [29] investigate a synchromodal transport planning problem. They use the Markov decision process to model the problem, then solve it using backtracking to determine the optimal modal choice for the shipments. Zahid et al. [30] study the cargo allocation problem. They develop a mixed integer nonlinear programming model to minimize the total travel time and cost in the One Belt One Road (OBOR) project. They use an integer solver to perform the tests. Dong et al. [10] investigate synchromodality from a shipper perspective. They developed an integer programming model to formulate the optimal freight allocation in a ST network while considering inventory-related decisions. Larsen et al. [18, 19] study the interdependency of the containers and vehicle routes, and they propose a predictive model controller as well as a benchmark. They solve their model using an optimization solver. Then, they conduct a simulation experiment to assess the possible benefits of simultaneous routing of containers and trucks. Larsen et al. [18, 19] propose a real-time co-planning approach for a synchromodal transport setting that facilitate barge and truck operators to synchronize their schedule without sharing their sensitive information. Their method is called *secure departure learning* and is developed in a model development framework. Finally, they conduct several experiments on a realistic transport network to evaluate their proposed method.

In short, mathematical modeling has been widely applied in the ST context for optimizing decisions. By developing mathematical models, we are able to enhance efficiency and sustainability. However, simulation has emerged as a complementary tool to overcome some limitations of mathematical models. In the following section, we explore the applications of simulation in ST.

2.2 Simulation of synchromodal transport

Simulation modeling is an important decision-making tool used by different scholars in the logistics and supply chain context. Especially in complex networks, where it is necessary to act quickly and effectively in response to circumstances, simulation modeling plays an important role as it helps decision-makers to study individuals and their interactions in detail, and it provides a strong tool for them to make sure that the operation of their systems is flexible and efficient [6].

In general, there are three main methods in simulation modeling: agent-based, system dynamics, and discrete events [5]. Although system dynamics simulation techniques provide a broad representation of complex systems, aiming at exploring the dynamic interconnections within the system as time progresses, they can get highly complicated when actual real-life situations with lots of variables are modelled. Additionally, the discrete-event simulation techniques are not capable enough to capture the interconnectivity of the components of complex systems. Agent-based simulation techniques, on the other hand, focus on the individual active components of a system and provide the flexibility and adaptability to design heterogeneous actors that interact with each other, as well as with the environment [6]. As a result, the agent-based simulation approach is used in this paper to model the ST network.

In the following, we review the works which applied simulation modeling in synchromodal transport settings. However, it is worth noting that only a limited number of studies have employed simulation in the synchromodal transport context.

Mes and Iacob [22] consider a multi-objective k-shortest path intermodal problem at the operational level. Then, they propose a synchromodal planning algorithm for the problem, which is implemented at a Fourth Party Logistics (4PL). Ultimately, they use simulation to represent their model and their proposed (heuristic) synchromodal algorithm. Li et al. [21] also conduct a simulation-based work. Using simulation, they study cooperative synchromodal hinterland transport among several transport operators at a tactical level. First, they proposed different distributed predictive control approaches for different transport operators to evaluate their respective container flows in the interconnected intermodal networks. Then, they conduct a simulation to compare their proposed methods in terms of computational time. Dobrkovic et al. [9] propose an automatic identification system (AIS) for a synchromodal logistics network in order to identify maritime patterns. They discuss how to use the real-time data (operational level) to make strategic-level decisions (long-term prediction of vessel arrival time and maritime patterns). First, they use a genetic algorithm to cluster vessel position data. Then, using simulation, they illustrate how to improve the process to allow fast computation of incremental real-time data coming from the sensors. Lemmens et al. [20] propose a policy on environmental and logistics costs in an ST network. In their work, they consider real-time stock levels as well as the service requirements of the shipper. They conduct a simulation experiment to assess the performance of their proposed policy. Ambra et al. [2] investigate synchromodal resilience using an agent-based simulation from a decentralized perspective. Their model assesses different stochastic parallel processes for each modality and simulates decentralized delivery for each order at an operational level.

The work of Ambra et al. [2] is the most related to our work. However, the model we discussed in this work is also capable of evaluating centralized logistics operations. Furthermore, our work is more detailed, especially concerning synchromodal transport rather than intermodal transport (i.e., such as the interaction between different actors). This allows for a more specific assessment of the performance of the logistic network in the tested scenarios (see Sects. 3 and 4).

In summary, research concerning analysis on the dynamic interactions of different players in ST networks is still lacking. Moreover, there is insufficient analysis of ST networks using simulation techniques. Consequently, this study aims to study the interaction between actors in a synchromodal transport setting at the operational level using simulation modeling.

3 Problem description and the simulation model

In this section, we formulate a synchromodal transport problem using an agent-based simulation technique. First, we provide a detailed description of the problem and the assumptions we make. Next, we present the details regarding the formulation of the simulation model itself.

The main question we try to answer is how much synchromodality affects cost and emission reductions. Our problem implies a logistics network in which several actors play their roles to meet the system's ultimate goal: transporting orders from their respective origins to their destinations, within a given time window, and with minimum costs and emissions.

3.1 Model's assumptions

In this research, we take the LSPs' perspective; in other words, our focus is mainly on the synchromodality as a *logistics* concept rather than the entire supply chain. In this case, LSPs tend only to consider how synchromodality affects their own operations.

As noted, our work addresses the synchromodal transport problem at the operational planning level, as it entails routing decisions as well as scheduling based on real-time information, such as new order arrivals or disruptions. Based on Delbart et al. [8], operational-level planning can be divided into two sub-categories: (1) real-time planning or re-planning and (2) resource management. This work can be categorized and also be considered as the former one.

The model comprises a set of nodes (origins, destinations, multimodal terminals, depot). There are two types of nodes in the model: (intermodal) terminals and customer locations. Intermodal terminals can also be considered as transshipment or storage nodes and can be visited by trains and barges and if needed, by trucks. However, the customer locations, i.e., origins, destinations, and depots, can only be visited by trucks; depots here refer to the places where trucks are kept when they are waiting to be assigned to an order. The model represents drayage and long-haul transport. First and last haul operations, starting and ending customer nodes, respectively, are all executed by truck in our model. Long-haul operations, however, can be done by train, trucks, or barges.

We consider the operation of several LSPs, which provide services such as transshipment, transportation, warehousing, etc. LSPs can either collaborate or compete with each other. In case of collaboration, they can use each other's assets and capacities (evidently, at a higher price). Three modes of transport are considered in the network: inland waterways (barges), railways (trains), and roads (trucks). Trains and barges are only allowed to move according to predefined timetables. Generally, LSPs have contracts with different carriers, meaning that they usually book slots on trains and barge services in advance. Thus, in the short term, typically, there are different amounts of available capacity for different LSPs. Trucks, on the other hand, are more flexible in terms of scheduling. Each LSP has a limited availability of trucks (fleets of trucks), which need to be managed by them. The fleets of trucks are available in the predefined depots assigned to each LSP. Moreover, at any point during the operations, if the LSPs face a shortage of trucks, we assume that there are always external trucks available that can be used (at a higher price).

3.2 Simulation process

In this subsection, we explore the logic that the simulation model follows to proceed. Figure 1 shows how orders are handled in the model.

The arrival of orders is stochastic, and is defined by an origin, destination, and a time window. Once an order is placed, first, LSPs evaluate whether it is feasible for them to satisfy the requested order or not; they make this decision based on the current list of tasks that need to be served, as well as the current state of their fleets of trucks, availability of truck drivers (considering their maximum working hours and the minimum rest times between their tasks), and their available capacities on train and barge services. Then, if it is practical for the LSPs to respond to the order, they make price offers to transport it from its origin to the destinations. The offers are made by LSPs based on available capacities they have normally booked beforehand on different carriers' vessels as well as their available fleets of trucks. Here, we assume the shipper chooses the LSP that has the cheapest offer. Then, that LSP takes responsibility for the order to transport it to its corresponding destination, based on the travel plan assigned to that order and LSP. In the initial travel plan, the departure and arrival times, route, and mode of transport are determined.

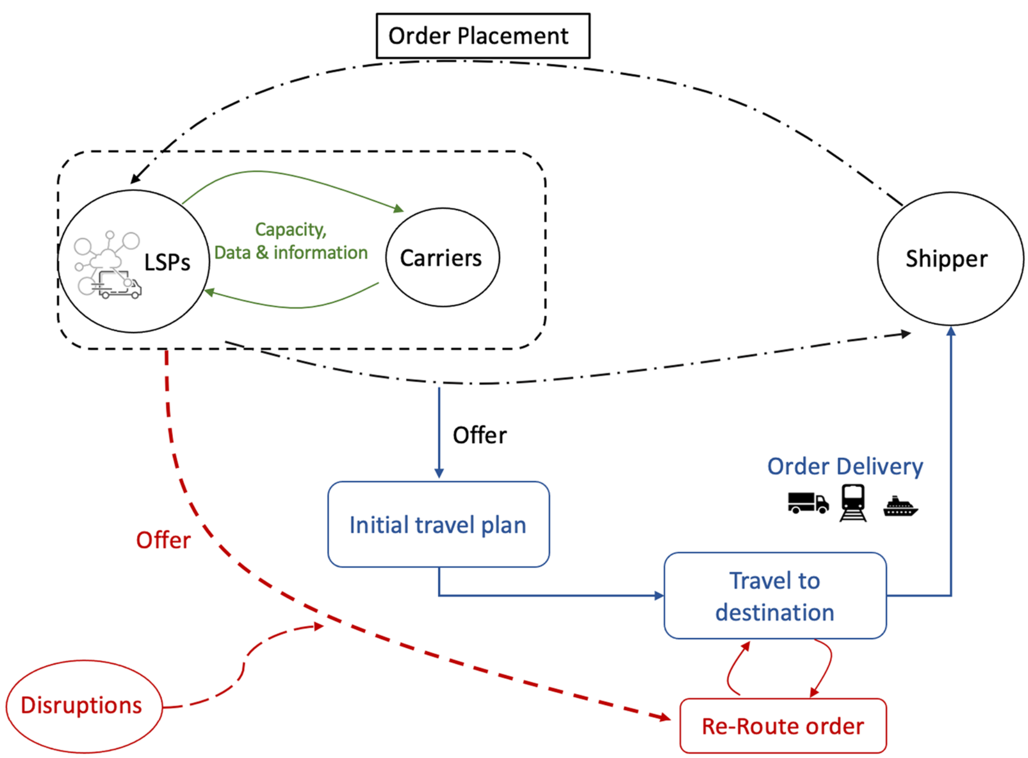

Fig. 1 Process chart of an order

The selection of the initial route is determined by considering several factors, such as expected pick-up and delivery time, availability of modes, distance, and emissions. To identify the best route, alternative multimodal options are thoroughly examined, considering all potential transfer points and verifying their compatibility within specified time windows. A heuristic approach inspired by Dijkstra's algorithm is applied to assess these routes and determine the shortest path. The algorithm explores all possible paths and evaluates their feasibility based on time constraints and available modes; it starts with creating a primarily truck path from the origin to the destination. Then it modifies the path by adding trains or barge connections between terminals; travel time between terminals is determined by scheduled barge and train services. The algorithm evaluates the feasibility of different paths based on the earliest arrival and the latest departure time, taking into account the availability of barge and train services. Finally, the algorithm adjusts the last mile of each path by truck. It is worth mentioning that the algorithm permits a direct truck route from the origin to the destination.

To ensure efficient route selection, the algorithm also considers specific constraints; the algorithm avoids revisiting the same terminals during the route planning process. This constraint helps optimize the overall path by eliminating unnecessary detours. The algorithm also permits transfers between (train or/ and barge) services, enabling seamless transitions between different routes. This allows for more flexible and efficient route options. While trucks can be used for the initial and final legs of the route, the algorithm tries to avoid their usage between intermodal terminals. This limitation encourages the utilization of more sustainable modes of transport, for the intermediate segments.

After generating all possible paths, the path with the lowest total cost is selected as the best route. Each path can consist of one or more legs, and each can be done by different modes. The cost of each route is determined by a summation of the costs associated with its legs. Here, the route with the least (total) cost has precedence over the other routes.

The cost of each leg/route consists of two components: CO_2 emission costs and operational costs. The operational cost function takes into account the cost of transport, transshipments, and the cost of late deliveries. Emissions costs refer to climate change impact (CO_2 emissions) costs, which are determined by calculating the monetary value of the total damages from emitting CO_2 equivalent per TEU (twenty-foot equivalent unit). This is obtained by multiplying the distance traveled by each mode of transport by an appropriate factor, depending on each mode of transport. A weighted objective function is used to incorporate the relative importance of each objective component. Equation (1) represents the weighted sum function, where $f_i(x)$ corresponds to the operational costs and emissions costs (as previously described), while w_i are weight coefficients, which represent the importance of the corresponding objective functions.

$$Min \sum_{i=1}^{k} w_i f_i(x) w_i \geq 0, \sum_{i=1}^{k} w_i = 1 \tag{1}$$

The coefficients w_i can be adjusted according to the preferences and requirements of individual customers or other requirements and priorities of the system. This flexibility allows for customization and optimization of the route selection process based on specific factors and priorities. It is worth highlighting that this formula is not only utilized in prioritizing and selecting routes, but also, it has been used in calculating total costs.

Afterwards, the order takes the selected route and mode of transport to its destination. It is worth mentioning that each order corresponds to one container in the model, and all the orders are assumed to be served.

In the following, we provide the associated pseudocode to the routing algorithm.

Algorithm 1 Pseudocode for the initial route selection

```
Define collection of incompletePaths
Define collection of completePaths

//Generate path by truck only
Create the initial path (path0) by truck from the Origin to Destination
completePaths.add (path0)

//Generate multimodal paths
for each terminal T1
        path1 ← new empty path
        path1.add(T1)     //add a leg from T1 to Destination by Truck
        Check the feasibility of path1 (based on the time constraints and truck travel times)
        if feasible: incompletePaths.add (path1)
end for


//Extend the multimodal paths backward:
while size of incompletePaths > 0
        get path1 from incompletePaths
       T1 ← first terminal visited in path1
       for each terminal T2
                for each train/barge service between T2 and T1
                        path2 ← a copy of path1
                        path2.add(T2)      //add a connection between T2 and T1 considering…
                                         //… specific train/barge service
                       Check the feasibility of path2
                       if feasible: incompletePaths.add (path2)
                end for
        end for

        completePaths.add (path1)       //Considering truck connection from Origin to T1
        incompletePaths.remove(path1)
end while

//Select the cheapest path
for each path in completePaths
        calculate the totalCost
end for

Return the path with minimum totalCost
```

It is also possible that disruptions happen in the network; in this case, all the decisions will be updated depending on the current state of the network. The disruptions refer to the train and barge service cancellations and/or service delays. We assume two responsive reactions when a train/barge service delay occurs. Orders (containers) have three options for re-routing: (1) continue with the same service, i.e., wait until the disruption is over; (2) take an alternative service on the same mode; or (3) switch to another mode of transport. We consider different scenarios depending on the option taken by LSPs (see Sect. 4.1.2). Besides switching mode or service, disruptions can lead to the re-routing of trucks that are on the road at the moment, either due to a change in the destination of the container that is currently carrying, or to pick up a new order if it was empty. For instance, if a truck returning to the depot is closer to an order's pick-up location (after the disruption happened), it may be more efficient to send that truck instead of dispatching a different truck from a farther location. By allowing for re-routing, such adjustments and the overall efficiency will improve. The re-routing algorithm is a heuristic algorithm that shares similarities with the routing algorithm explained earlier, except that the re-routing algorithm continuously evaluates the network's state and makes adaptive decisions in real-time. The algorithm begins by checking if re-routing is necessary due to missed train or barge connections, caused by delays or cancelation. If re-routing is required, the model determines the new departure (re-routing) point, and it updates the pick-up and delivery times for each leg accordingly. The times are adjusted based on the load and unload times associated with the respective modes of transport. The model then performs the re-routing action by modifying the existing path. It removes any remaining legs from the old path and updates the load in the remaining legs. If needed,

Table 1 General parameters used in the experiment

Parameters	Unit	Value
Order arrival rate	event/day	500
Order's time window	h	48
Late delivery costs	€/h	10
Truck speed	Km/h	60
Truck min rest time between shipments	h	0.75
Max work time for drivers	h/day	10
Storage costs	€/h	0.01

a final leg by truck directly to the destination is added. Depending on the current state of the order, different re-routing methods, which re-route the orders based on the new departure time and departure point, are called to handle the order appropriately (e.g., re-routing from a terminal, re-routing from a moving train, re-routing from an unloading train, etc.). For instance, if the order is within a terminal at the time of disruption, it will be instantly handled in the same terminal. If the order is on a moving truck, it can be re-routed and proceed toward a new destination, with adjustments made to the tasks assigned to the truck. However, in the case of a moving train or barge, the order continues its journey until the next scheduled stop, before considering any alterations. It is important to note that when re-routing is involved, additional considerations come into play depending on the circumstances (e.g., avoiding the initial transfer time if the new plan continues on the same vehicle). After the re-routing is completed, the delivery time of the order is updated based on the new path. In the following, we provide the pseudocode associated with the re-routing algorithm in the event of disruption.

Table 2 Assumed parameters in the experiment based on different transport modes

Mode type	Cost (€/TEU)	Emission (kg CO2-eq/TEU)	(Un) Loading time (hour)	Service cancelation rate (events/day)	Service delay rate (events/day)
Road	1/km	0.84/km	0.25	–	–
Rail	0.65/km	0.21/km	0.5	1	4
IWW	0.25/km	0.356/km	1.25	1	4
Transshipment	25	2.74	2	–	–

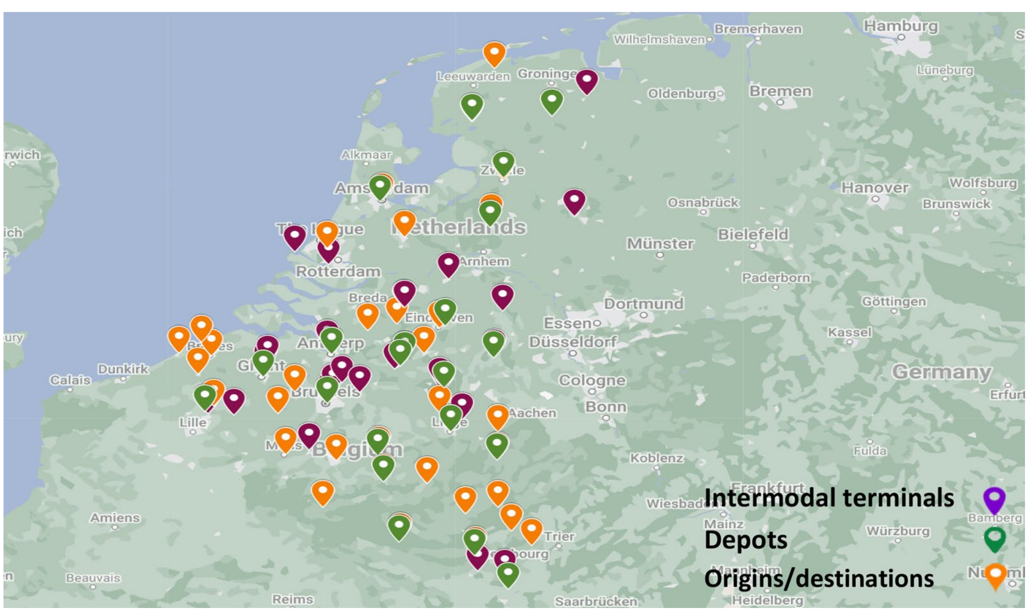

Fig. 2 the GIS view of the studied network

Algorithm 2 Pseudocode for re-routing

```
path0 ← Current travel plan

//Call the corresponding re-routing function depending on the LSPs' strategy and the order's state

Determine Origin1, depending on the current state of the order

Adjust the order's new departure time, and time-window

path1 ← New path from Origin1 to the Destination (using Algorithm 1), given the time constraints

if path1 !== path0
       Remove all remaining legs of path0 after the re-routing point (Origin1)
       Update path0 considering path1

Return path0
```

As mentioned, an agent-based simulation technique is applied in this paper to mimic the system's operation and study the behavior of different components. Commonly, in an ST setting, different players are involved, which are considered as agents. The main agent types in our model are nodes (origins, destinations, terminals, depots), vehicles (trains, trucks, barges), services (trains services, barge services), orders, and LSPs. The overall dynamics of the system then emerge from the interactions of these agents' behaviors. It is notable that within the model, agents are equipped with optimizations and decision-making algorithms that, for example, allow the LSPs to choose the best synchromodal route in response to disruptions or pulsations in demand.

4 Case study

This section provides the details of the numerical experiment we conducted to validate our model. We also discuss the results and analyze the findings. Finally, two sensitivity analyses are conducted, and the results are discussed, along with the discussion of the model's scalability.

4.1 Experiment design

Within this section, we begin by addressing the inputs to the model, followed by an in-depth exploration of the different scenarios that are considered.

4.1.1 Model's inputs

We consider a regional-level logistics network in a short-term decision horizon. The case study is performed on the Benelux (Belgium, Netherlands, Luxembourg) region, with the real roads, rails, and inland waterways network and synthetic data. A total of 62 nodes consisting of origins, destinations, terminals, and depots are considered.

Figure 2 shows the map view of the locations studied in the experiment. The instance consists of 27 intermodal terminals. We assume the terminals have no capacity limitations and are operating 24/7. There are also 35 origin/destinations (customer nodes) scattered throughout the entire region. Moreover, there are 21 truck depots (customer nodes) in the network. A total of 96 train services and 80 barge services are considered in the network over the period of five days. It is also assumed that three logistics service providers are operating in the network. Each of them has a certain number of trucks and also a number of slots in trains and barges services, which they have booked from the carriers beforehand. In addition to the capacity booked by the LSPs, there might be additional available spaces on trains and barges to book in the short term, although it is assumed that most of the capacity in these services is already taken by exogenous demand, and, therefore is not available for the transportation requests of this study.

As stated in the previous section, the objective is to minimize operational costs and emission costs. As mentioned, the operational cost function consists of the cost of transport, delays, and transshipment. The emissions costs function also refers to the CO_2 emissions cost. The assumed emission parameters for different types of logistics activities are provided in Table 2. Moreover, as mentioned in the previous chapter, we use a weighted sum method for calculating the total cost function when making decisions for the best routes and modes of transport. We assign a weight of 0.7 to the operational costs, and 0.3 to the emission costs.

In the experiment, it is assumed that orders arrive following a Poisson distribution with a mean of 500. It means that the system receives 500 orders per day on average. Each order consists of an origin, a destination, and a time window. The total duration of the time window is considered to be the same for all orders, which is 48 h, starting from the moment in which the request is made. In Table 1 and 2, the other assumed parameters used in the model are provided. The values for the maximum working hours for truck drivers, and their minimum resting time are taken from the European Commission (2006). The parameter values for costs and emissions in Table 2, are also taken from Yee et al. [29].

4.1.2 Scenario design

As noted earlier, different scenarios are examined to evaluate different problem settings. Three scenarios are explored concerning LSPs' relations, and two scenarios are established to evaluate (re)routing strategies in the event of disruptions.

LSPs' relation: Three scenarios are defined to evaluate different LSPs collaboration approaches: competitive, collaborative, and centralized. In the competitive scheme, LSPs tend to operate independently and only use their own assets (i.e., fleets of trucks and/or booked capacities on the carriers' vessels) to fulfill customers' orders. Each LSP tends to optimize its own operation and maintain a competitive advantage. This approach often leads to a more efficient utilization of individual resources but may result in limited flexibility and higher costs in the system due to the lack of resource sharing and collaboration.

On the other hand, in the collaborative approach, LSPs have the possibility of making use of each other's assets and capacities, in case of a shortage of their own capacities; this helps them to enhance their service offering. However, this collaboration incurs additional costs, since LSPs have to pay more to utilize the other LSPs' assets, but yet this collaboration enables them access to a broader range of facilities which may not be readily available within their own organization. The option of using other LSPs' available resources will come into play in several points within the (re) routing process; when LSPs consider offering truck services to cover specific trip legs within the orders' specified time window, they can make these offers, taking into account their own availabilities as well as other LSPs'. Initially, they evaluate their own fleets, and if they encounter a shortage of trucks, they may approach other LSPs, even if it incurs higher costs. Ultimately, they opt for the most cost-effective option among the available fleets. Moreover, there comes a point where it becomes necessary to identify the specific transport service (or even vehicle) to be employed, thus taking capacity from the corresponding LSP. LSPs take this option into account when determining if there is enough available capacity on train or barge services between the nodes. First, they check their own capacities, and if they find that their reserved capacities are insufficient, they have the option to ask other LSPs, and use their booked capacities, evidently with higher costs. Normally, they choose the cheapest option if there are multiple options available. These communications and negotiations are assumed to be done within a platform resembling the synchromodal or Physical Internet (PI) platform. Within the platform, the LSP, which is primarily assigned to the order, does the planning for the requested order between two nodes, within a specified time window via a specific mode of transport. Subsequently, each of the other LSPs make their own offers based on their availabilities for transporting the same order. In this case, the pricing is determined

Table 3 Characteristics of the simulated scenarios

Scenario	(Re)routing strategy	LSPs relation
S1	Conventional	Competitive
S2	Conventional	Collaborative
S3	Conventional	Centralized
S4	Flexible	Competitive
S5	Flexible	Collaborative
S6	Flexible	Centralized

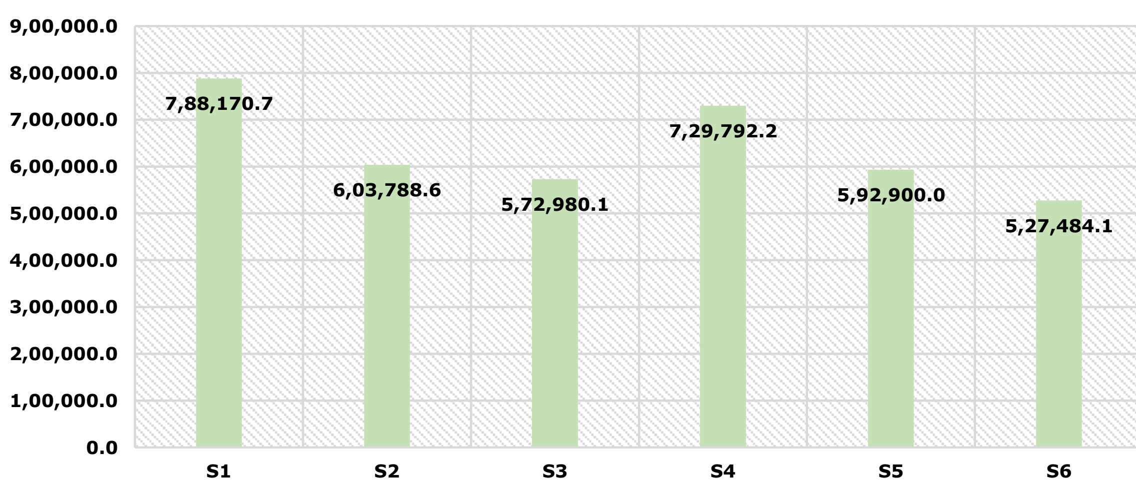

Fig. 3 Total cost (€) per each scenario

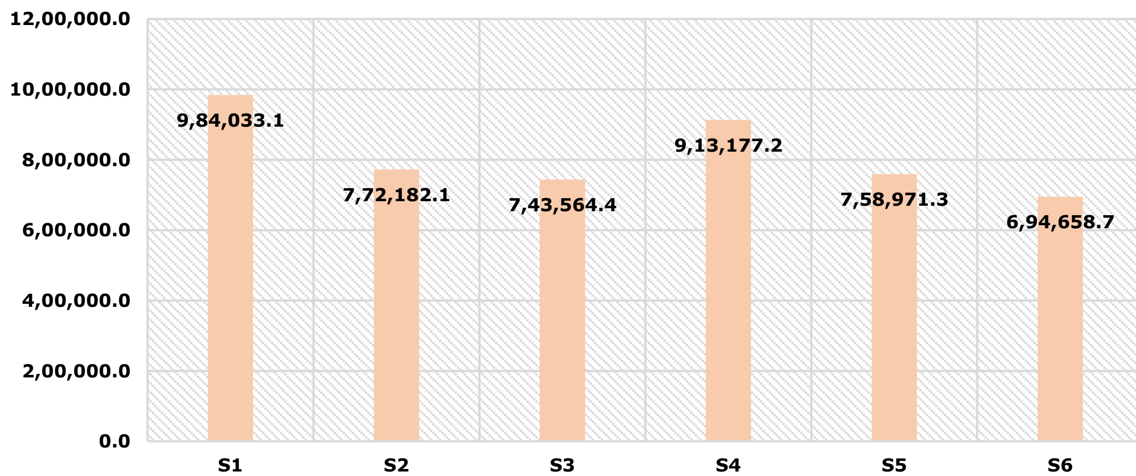

Fig. 4 Operational cost (€) per each scenario

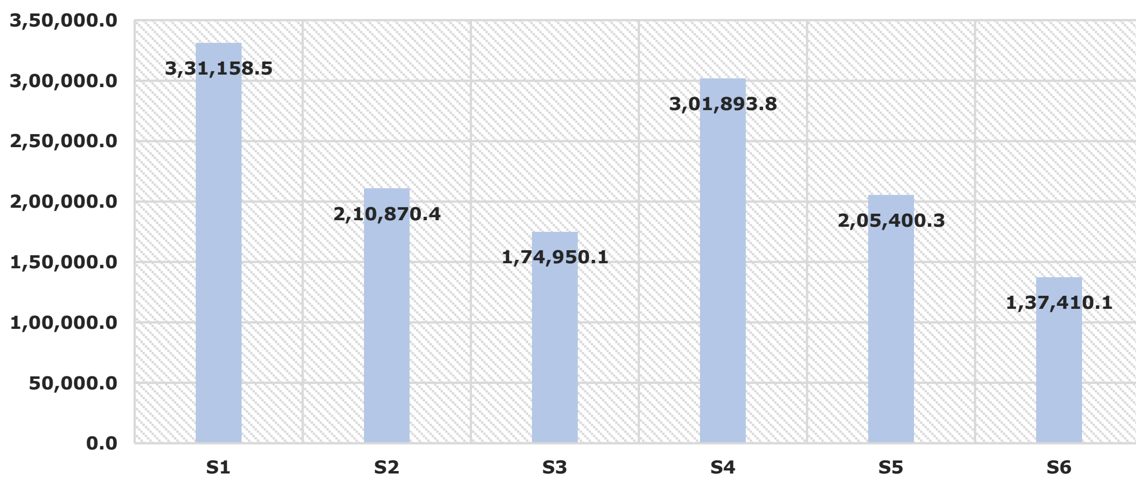

Fig. 5 Emissions cost (€) per each scenario

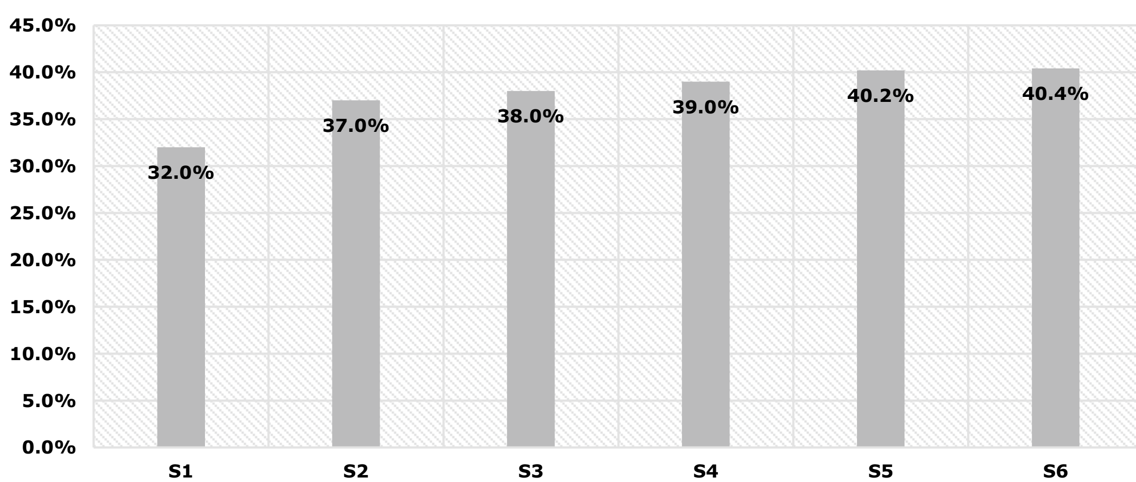

Fig. 6 Share of orders, that transported multimodal per scenario

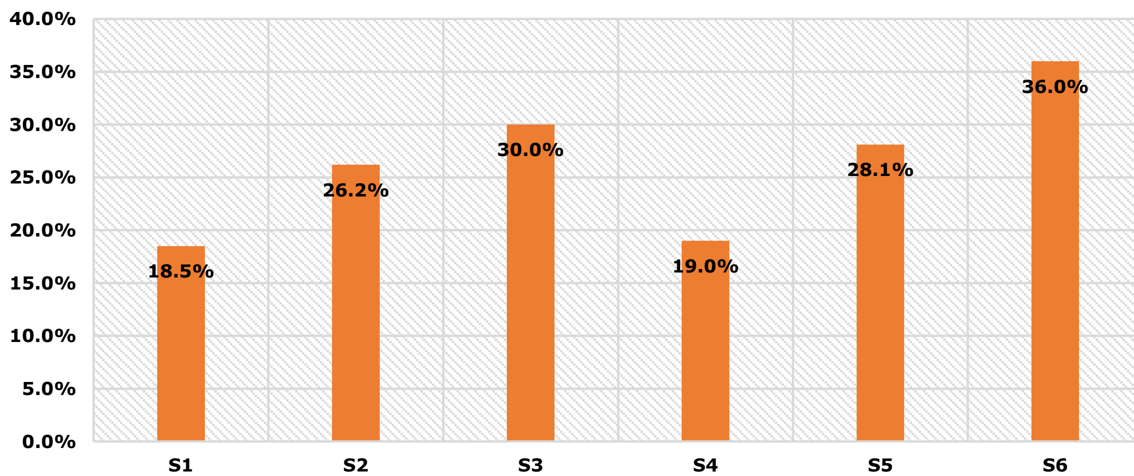

Fig. 7 Trains and barges capacity utilization per scenario

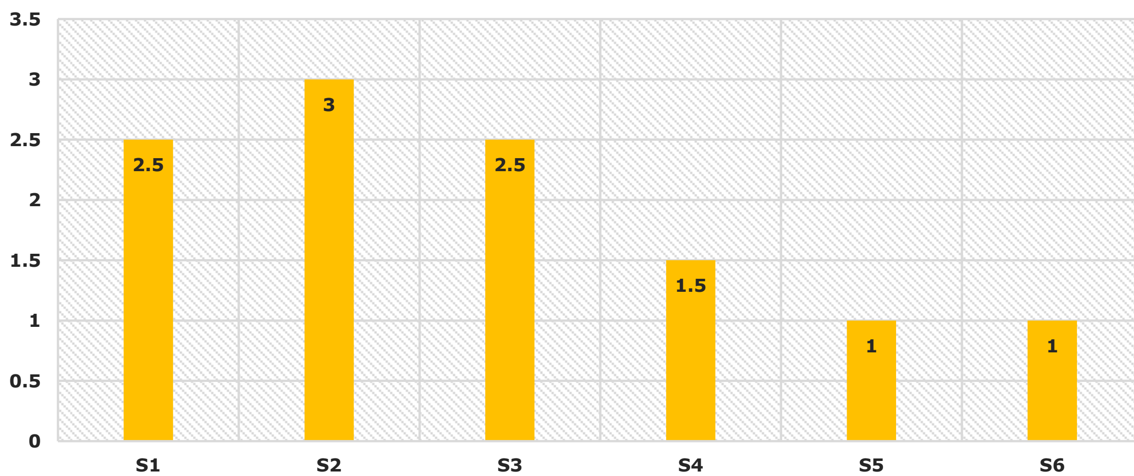

Fig. 8 Number of late deliveries per scenario

by adding a fixed margin to the additional transportation costs incurred by the second LSP. However, the specific workings of this platform fall outside the scope of our discussion, and we simply assume its existence.

Finally, in the centralized approach, there is one central operator who manages all the assets and capacities. Here, all the assets and services associated with different LSPs, are assumed to be a large resource pool. The central operator is responsible for managing the entire system, including resource allocation, order management, and coordination among different entities [15]. In this case, LSPs are mostly responsible for offering different services or functions, as well as ensuring the quality of the services they provide to the network users. On the other hand, the central operator facilitates collaboration and coordination among LSPs and ensures transparency. In short, this centralized approach aims to ensure efficient resource utilization and more smooth operations, resulting in increased efficiency. It is worth noting that the distribution of revenues between LSPs in the centralized scenario is out of the scope of this paper. Here, we are only exploring the impact on the global operations and the costs for the system as a whole.

Re-routing strategies: Two scenarios are considered for evaluating (re)routing strategies in the event of disruptions: conventional and flexible. In the conventional approach, in case of delays, LSPs try to keep the initial plan, even if it results in delays and higher costs, and in case of cancelation, orders will be transported by trucks directly to their destinations. On the other hand, in the flexible scenario, the orders can be re-routed to a better service (barge or trains). In this case, the search for a new travel plan is done similarly to the initial plan (explained in Sect. 3.2), only that in this case, the LSP in charge of the order is already assigned, so, other LSPs do not offer alternative plans. Table 3 shows the combination of these scenarios.

4.2 Simulation results

In this section, we evaluate and compare the performance of the simulation model under different LSPs relations and re-routing scenarios. The model is integrated with the GIS environment and is developed in Anylogic software. All the experiments are conducted on Mac OS, on Intel® Core™ i7 2.6 GHz machine with 16.00 GB RAM. For each scenario, multiple replications are performed using random seeds in order to mediate the impact of stochasticity of demand and disruptions events. The number of replications is decided by Anylogic by setting the minimum confidence level in the software. The calculations are done by Anylogic are based on a normal distribution. The experiment will always run the minimum number of replications for a solution, then it determines if more replications are needed. The experiment stops running next replications when one of the following occurs; (1) the confidence interval is small enough to fit in the given percentage of expression value; (2) the current expression value is not inside the mean confidence interval; (3) the maximum number of replications is run. Here, we considered that the minimum and maximum numbers of replications are 2 and 20, and the minimum confidence level is assumed to be 85% for the *total cost* expression with a 0.005 error. In our experiment, Anylogic stopped after six replications. The total computational time for the conducted experiment (for the six scenarios and six replications in each case) is 6 h and 40 min.

A detailed comparison of the average output values between different scenarios is presented in Figs. 3, 4, 5, 6, 7, 8. The comparison of different scenarios shows a great improvement in the costs due to the added collaboration and flexibility. The total cost in scenario S1, which is the most similar to the traditional transport planning, is approximately 15% higher than the total cost in scenario S6, which is the most related to the ideal synchromodal transport (Fig. 3); this verifies the cost efficiency of synchromodal transport compared to the traditional planning.

Besides, by comparing the flexible with conventional re-routing scenarios (S4, S5, S6, and S1, S2, S3, respectively) in Figs. 3 and 4, we observe that the flexible scenarios result in slightly lower costs than the corresponding scenarios with the conventional approach. A similar pattern can also be observed in Fig. 5, which represents emission costs. However, in emission costs, we notice even a greater decrease when comparing conventional to flexible scenarios; this can be inferred that flexible re-routing, which is core to synchromodality, does not only provide economic efficiency, but it is also environmentally efficient since it shifts toward greener modes of transport (Fig. 6). The results also indicate that LSPs bear significant amount of costs if they opt for a competitive approach and do not collaborate with other LSPs.

According to Fig. 4, the operational costs of LSPs in the competitive scenarios (S1 and S4) are considerably higher (between 16 to 24%) than in the other scenarios. The higher costs in the competitive scenarios can interpret why LSPs should collaborate with each other rather than compete. However, we observe that the collaborative scenarios offer a greater operational cost improvement compared to the centralized scenarios, which is also more feasible to implement than having a central operator manage all the capacities. However, in the emission costs,

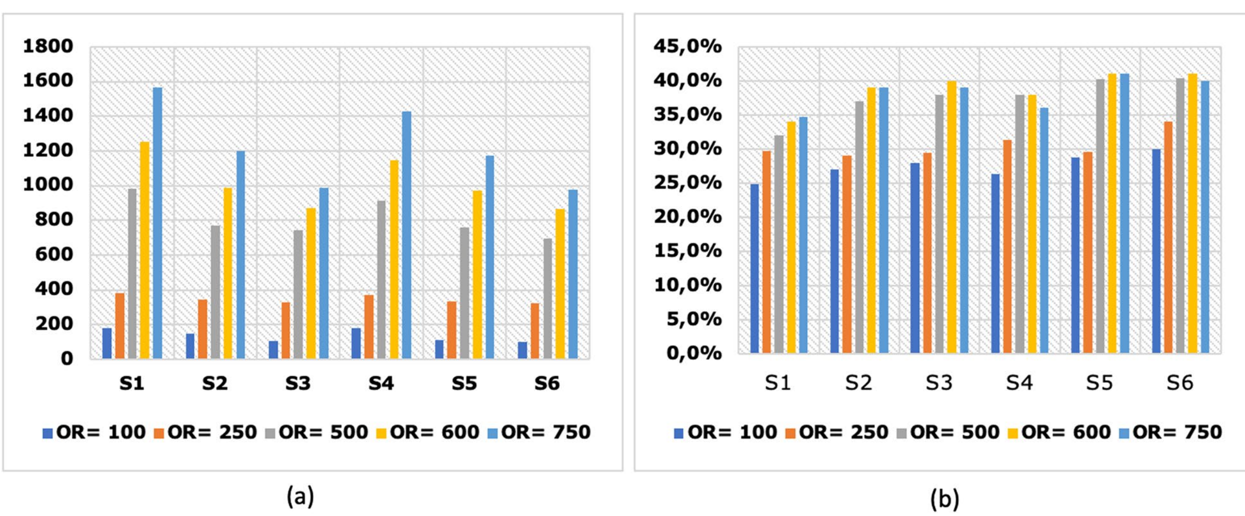

Fig. 9 Impact of Order Rates (ORs) on **a** operational costs (k€) and **b** multimodally-transported orders (%)

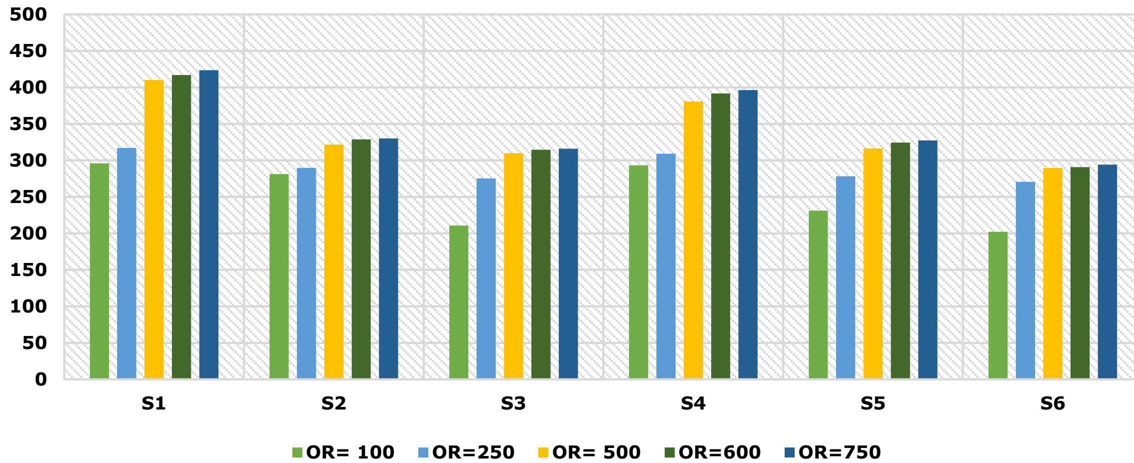

Fig. 10 Operational costs (K€) per scenario, for different Order Rates (ORs)

this is different; the greater cost improvement is due to the centralized operation.

Moreover, Fig. 6 shows that between 32 to 40% of the orders are transported at least in one leg by railways or inland waterways, in addition to road transport, which is used for the first and last haul. In the flexible scenarios this number tends to be higher, indicating that ST is environmentally efficient as it uses greener modes of transport.

Moreover, as shown in Fig. 7, in all the scenarios, between 18.5% to 36% of the capacity of the trains and barges are used. However, the highest share of capacity utilization is associated with the cases that a central operator manages all the capacities (S6, S3). Thus, a centralized approach not only closes the gap between carriers and LSPs, and contributes to the costs, it improves efficiency by increasing capacity utilization. After the centralized scenarios, the highest share of capacity utilization is related to the collaborative scenarios, where LSPs opt for collaboration with each other, as collaborative scenarios allow LSPs to use each other's capacities. Indeed, it was expected that the utilization rate would be higher compared to competitive scenarios.

It is notable that, although in all cases, the number of orders delivered late is small (below 1%), in the scenarios without flexibility after disruptions, the number of late deliveries is larger (S3, S1, S2) (Fig. 8). In other words, in the cases more related to synchromodality (S4, S5, S6), the probability of delivering orders on time, and therefore reliability, is higher.

To summarize the experiment's findings, using ST for transport planning is more cost and environmentally efficient than conventional methods. It also increases the flexibility and reliability of the system. Additionally, implementing a centralized approach, as well as assuming collaborations between LSPs leads to greater cost savings and higher capacity utilization.

4.3 Sensitivity analysis and scalability

In this section, we conduct two sensitivity analyses to explore the model's responsiveness. By systematically varying the key parameters, we aim to understand their individual impact on the overall system's behavior and outcomes. Finally, at the end of this section, we discuss the scalability of the model.

4.3.1 Sensitivity analysis on different values for order arrival rate

First, we study the impact of the different demand (order) levels on total cost and share of orders transported multimodal. The experiments are conducted with the same parameters used in the previous Sect. 4.1, changing only the orders rate, in order to observe the impact of different orders' arrival rate on the entire system. The number of replications here is likewise decided by Anylogic considering the 85% confidence level of the operational costs' expression with 0.005 error. The results are provided in Fig. 9. It is worth highlighting that the observed trend between different scenarios here, remained consistent, similar to the original experiment discussed in the previous section, across all the parameters when the demand was changed.

Figure 9a clearly illustrates that an increase in the number of orders directly affects operational costs. As the Order Rate (indicated as OR in the chart) rises, the operational cost also rises accordingly. This behavior becomes evident when examining average costs per order (Fig. 10), which also demonstrates an upward trend alongside the increase in the order rate. Additionally, another

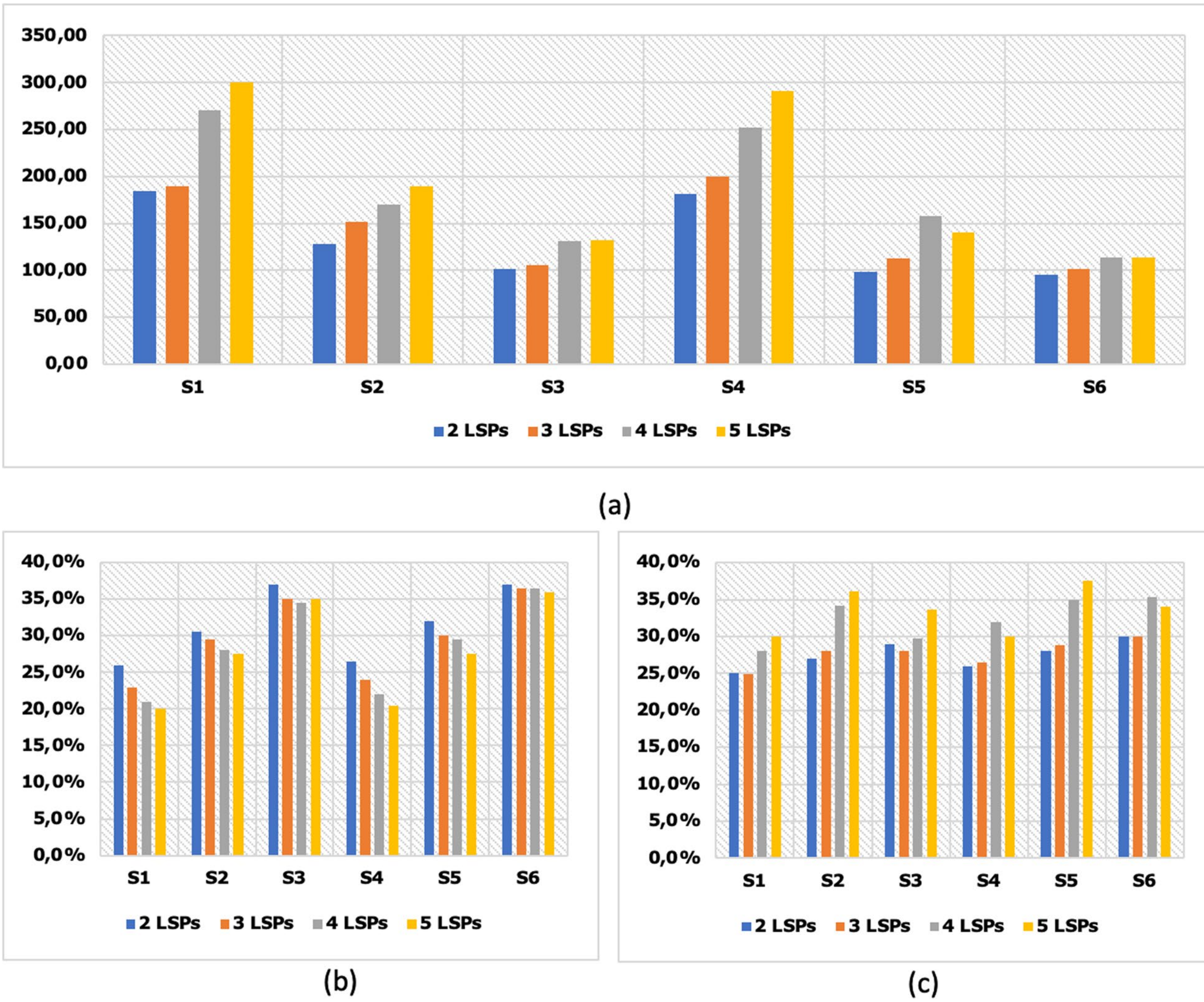

Fig. 11 Impact of numbers of LSPs on **a** Operational-costs (k€), **b** Capacity-utilization (%), **c** Multimodally-transported-orders (%)

potential reason for the increase in operational cost could be attributed to the fact that, as the number of orders increases, the capacity of certain services may become fully occupied during specific time periods. In that case, there is a need to utilize more trucks, including external trucks, which further increases the costs involved. This can explain the jump in the costs when the order rate increases from 250 to 500.

According to Fig. 9b, as the number of orders increases, the percentage of orders delivered by multimodal transport also increases. In other words, it is more likely that orders being transported by barges and/or trains in addition to trucks. However, as it is depicted in the figure, this upward trend does not always continue, as the availability of capacity does not follow a predictable behavior; for instance, certain services may experience full capacity utilization during specific time periods. In that case, LSPs need to use alternative modes such as trucks. So, we expect the relationship between the number of orders and the share of orders delivered through multimodal transport may deviate from a linear pattern over time. This can be studied further by conducting additional experiments, with a higher number of orders rates. However, due to the considerable computational time required, we do not conduct more experiments.

4.3.2 Sensitivity analysis on different numbers of LSPs

In this subsection, we evaluate the impact of different number of LSPs on the system. Initially, we assumed 3 LSPs were operating within the system. However, to examine the system's sensitivity to the number of LSPs, and given the size of the network, we further considered layouts with 2, 4, and 5 LSPs. The other parameters have remained the same as the experiment conducted in Sect. 4.1. The number of replications here is likewise decided by Anylogic considering the 85% confidence level of the operational costs' expression with 0.005 error. While evaluating settings involving varying numbers of LSPs, it is assumed that the total available capacities (on trains and barge services) remain fixed; it means that the available capacities are divided (randomly) among the LSPs. In other words, with an increase in the number of LSPs, the (potential) share of available capacity per each LSP decreases. On the other hand, the total number of trucks is correlated with the number of LSPs, since a constant number of trucks is assigned to each LSP. It is also remarkable that in the case of only one LSP, the collaborative and centralized scenarios lose their significance and impact. Therefore, it is not relevant to be studied.

It should be pointed out that, the experiments in this section are conducted with the fixed order rate of 100 orders per day. This choice is made to ensure faster experimentation, considering the consistent behavior observed across different scenarios for different order rates discussed in Sect. 4.3.1. Therefore, by maintaining a constant order rate, the experiments are expected to be conducted efficiently, ensuring the accuracy of the results remains uncompromised.

Figure 11a presents a comparison of operational costs across various scenarios for different LSP quantities. The results indicate that increasing the number of LSPs in the system correlates with higher costs across almost all scenarios. This is expected since a larger number of LSPs leads to a greater degree of vehicle shifting, and consequently higher costs. In collaborative scenarios (S2, S5), where LSPs can utilize each other's assets, the frequency of shifting to other LSPs' resources increases. On the other hand, in competitive scenarios (S1, S4), LSPs face challenges due to their inability to utilize other LSPs' assets and therefore, they face additional challenges in optimizing their own asset. However, the situation differs in centralized scenarios, as LSPs lack autonomy in managing their assets. Instead, a centralized operator takes this responsibility, resulting in more cost efficiency.

Another variable that is studied in relation to different numbers of LSPs is capacity utilization. Similar to the previous section, capacity utilization refers to the extent to which the booked capacities on trains or barges have been utilized (in percentages). As shown in Fig. 11b, with an increase in the number of LSPs, we observe a decrease in the utilization of available capacities. This can be explained by the fact that, the total available capacities are distributed between a larger number of LSPs. Thus, each LSP has access to a smaller portion of the overall capacity, leading to a lower capacity utilization rate. However, this downward trend is not observed in centralized scenarios (S3, S6), where the allocation of capacities is done by the central operator, which leads to a more efficient utilization of capacities.

The percentage of orders that are transported using multimodal transport is also investigated in relation to different numbers of LSPs. According to Fig. 11c, with an increase in the number of LSPs, we observe a higher share of multimodal transport in collaborative scenarios (S2, S5). This is also expected, since in this case, there is greater flexibility in utilizing the other LSPs' assets, so, they have more freedom to manage the available assets based on their own priorities. This enhanced flexibility allows for more efficient utilization of multimodal transport options, leading to a higher percentage of orders being transported using a multimodal approach. However, in other scenarios, there appears to be no detectable connection between the number of (LSPs) and the variable's behavior. Thus, conducting a comprehensive analysis may be challenging.

In short, looking at all the experiments conducted, it can be concluded that the model can effectively handle various situations and problem layouts. While the results provide important insights on the behavior of different parameters under different orders arrival rates and different numbers of LSPs operating in the network, it is crucial to highlight that the overall trends in the results when comparing the different scenarios remain consistent. Therefore, the conclusions of the original experiment appear to be applicable, not only for that specific instance but have broader applicability.

4.3.3 Scalability

In terms of scalability, the model exhibits a high degree of flexibility, allowing for different analyses to be performed. This flexibility allows testing the impact of different parameters and events on a wide range of variables. The model is also quite adaptable and can be customized to suit different case studies and geographic regions. This can be achieved by adjusting the nodes' coordinates and incorporating networks of streets, railways, inland waterways, and other parameters. The ability to incorporate new assumptions can help to improve the accuracy and reliability of the model. Additionally, various parameters such as costs, loading and unloading durations, speed of trucks, weights of objective function's components, etc., can be modified based on different problem settings. This allows the model to be adapted to different scenarios and can help to study the transport flows and processes based on specific requirements.

As mentioned before, there are also several logics and (heuristic) algorithms applied in different steps of the model (e.g., algorithms related to routing, mode selections, re-routing algorithms, etc.). Each of these algorithms could be modified and adapted based on the different decision-makers preferences to test different ideas and scenarios. The model is also capable of evaluating bigger and smaller instances. It is notable that an increase in the number of nodes will lead to a substantial increase in computational time, and vice versa for smaller networks. For instance, for the experiments conducted in Sect. 4.3.1, the computational time for order rates of 100, 250, 500, 600, and 750 (considering all the replications conducted for each scenario) were approximately 1, 2.5, 6.5, 8, and 10.5 h respectively. However, there is a possibility to speed up the model by making the matrix generating and routing algorithms more efficient (which the authors are currently working on it).

5 Conclusion and future research venues

This paper proposes an agent-based simulation model for a regional-level synchromodal transport network at the operational decision term and from LSPs' point of view. Our model evaluates both centralized and decentralized logistics operations and analyzes which one has more benefits for the system as a whole. The studies show that although intermodal companies are aware of the benefits of synchromodal transport, they are still not implementing it because of the high level of uncertainty and planning complexities in ST. This agent-based model is developed to provide a planning tool considering real-life constraints (i.e., stochastic orders, disruptions accordance) and to offer a virtual tool for all the actors to test different systems' layouts and algorithms. It also provides an excellent tool for them to assess different collaboration scenarios with other actors. By developing the model, we study how much ST contributes to cost reduction and sustainability improvement.

Through conducting an experiment and evaluating different LSPs relations and re-routing scenarios, we compare ST with business-as-usual transport planning to assess the flexibility and reliability in the two cases. The results show that, for the tested instance, synchromodal transport provides more flexibility and reliability compared to traditional transport planning approaches, as it results in less operational costs, fewer emissions, and there are almost no late deliveries of the orders. Moreover, it is shown that horizontal collaboration, in addition to vertical collaboration, plays an important role in cost savings and better functionality of the whole system in synchromodal transport networks. Also, the results indicate that adopting a centralized approach yields several advantages, including increased efficiency and capacity utilization, as well as cost reduction. The results of sensitivity analyses show consistent overall trends when comparing the different scenarios. Therefore, the conclusions drawn from the original experiment appear to be applicable, not only for that specific instance but have broader relevance and applicability.

However, this work is based on certain assumptions, which could be addressed and further explored in future works. For example, in our work, it is assumed that the terminals are continuously operating, and there is no maximum available capacity in terminals for accepting and operating vehicles. Future research on ST should include limited operating hours and capacity for terminal handling operations. Moreover, in this work, orders are specifically considered in the form of containers. In future research, the inclusion of other forms of freights could be explored to broaden the scope and applicability of the findings. Another future research venue could be to consider order consolidations; in our case, we considered single shipments. i.e., each (set of) order(s) is (are) assigned to a vehicle; however, in reality, the orders usually consolidate before being shipped.

Abbreviations

Benelux	Belgium, Netherlands, Luxembourg
ST	Synchromodal transport
LSP	Logistics service provider
OBOR	One belt one road
OR	Order rate
4PL	Fourth-party logistics provider
AIS	Automatic identification system

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Author contributions
Shafagh Alaei was responsible for the design of the study, the implementation of the agent-based simulation model, validation, analysis of the results, and writing the first draft. Javier Durán-Micco developed the framework of the agent-based simulation model and contributed to the conceptualization of the study and provided constructive feedback that greatly contributed to the final outcome. Cathy Macharis supervised the work and provided valuable feedback on the manuscript. All authors have read and approved the final manuscript.

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Availability of data and material
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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