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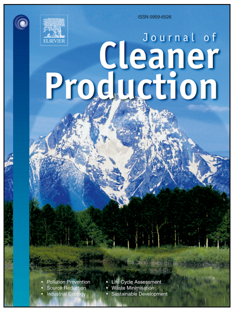


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# Real-time disruption management approach for intermodal freight transportation

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**Abstract**

The share of intermodal transportation, which is often considered as a sustainable transportation alternative, is rather low compared to road transportation. There are several reasons for this situation, including the increased need for coordination of scheduled transport services and the reduced reliability of intermodal transport chains in case of disruptions. In this regard, developing an advanced algorithmic approach can help to handle real-time data during the execution of transportation and react adequately to detected unexpected events. In this way the reliability of intermodal transport can be increased, which might help to increase its usage and to minimize the negative externalities of freight transportation. This paper proposes a novel real-time decision support system based on a hybrid simulation-optimization approach for intermodal transportation which combines offline planning with online re-planning based on real-time data about unexpected events in the transportation network. For each detected disruption, the affected services and orders are identified and the best re-planning policy is applied. The proposed decision support system is successfully tested on real-life scenarios and is capable of delivering fast and reasonably good solutions in an online environment. This research might be of particular benefit to the transport industry for using advanced solution methodologies and give advice to transportation planners about the optimal policies that can be used in case of disruptions.

*Keywords:* Real-time planning, intermodal freight transportation, disruption management, simulation-optimization

## 1. Introduction

With the increasing internationalization of trade, the tasks of transportation planners are becoming more complex (Bontekoning et al., 2004). Whereas the efficiency in the past meant the minimization of transportation costs (Agamez-Arias and Moyano-Fuentes, 2017), the discussions about negative influence of transportation operations on environment and society have put more focus to sustainability in recent years (Hoen et al., 2014). In this respect, especially the consideration of greenhouse gas emissions (GHGs) in road transportation planning in form of $CO_2$ or $CO_2$-equivalent ($CO_2e$) emissions is an evolving field (see, e.g., Demir et al., 2019b; Moghdani et al., 2020).

Even though transportation plans can be optimized by available Transport Management System (TMS) software, the exact execution of these plans in real life cannot be guaranteed. Since the infrastructure capacity is limited, small disturbances in traffic flow (e.g., accidents, congestion, road maintenance) can cause delays and infeasibility of any transportation plan. Besides that, the occurrence of unexpected events can also lead to disruptions lasting for several hours or even days (e.g., due to severe weather)

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(Xia et al., 2013), which should be dealt with within disruption management. However, disruption management is often not seen as an important point by the managers since they have to focus on other problems within their responsibility area (Ludvigsen and Klaeboe, 2014).

Reactions to disruptions are relatively easy in case of road transportation, which is the mostly used transportation mode in freight transportation in Europe (Eurostat, 2018a). Various approaches have been applied to mitigate the influence of disruptions on short-haul transportation. However, extensive use of long-distance road transportation might not be suitable for reducing the negative externalities of transportation, especially the increasing amount of $CO_2e$ emissions (Eurostat, 2017; Van Fan et al., 2018).

One of the alternatives is intermodal transportation, combining multiple transportation modes and using standardized loading units in order to facilitate the transshipment of goods between different modes (Crainic and Kim, 2005). In this setting, more environmentally friendly transportation modes such as rail or inland waterway can be used to transport goods for longer distances, which reduces the overall negative environmental impacts of transport. Although this option offers numerous advantages, the usage of intermodal transportation within the European Union (EU) is still relatively low (Eurostat, 2018b). There are multiple reasons for this situation, including the current situation on the European railway market, which is still dominated by big state-owned companies (De Langen et al., 2017), or geographical reasons, where often the goods are transported over relatively short distances where it is not competitive to use the intermodal transport (Frémont and Franc, 2010). Moreover, most of the ports, which are used for import and export of goods, are located in the Western Europe, therefore the density of the intermodal network is much higher there than in the Eastern Europe (UIC, 2019). However, in addition to these strategic reasons, there are also operational issues in intermodal transport planning, since it requires higher effort to coordinate all involved actors and to ensure reliability and flexibility of transportation (Grue and Ludvigsen, 2006). Therefore this paper focuses mainly on the operational level of planning, where it proposes a novel planning approach that should support the planners by including disruption management techniques and in this way help to increase the usage of intermodal transport.

To be able to respond to potential transportation disruptions, it is necessary to identify unexpected events as potential sources of disruptions and to analyze their influence on transportation. Moreover, an appropriate re-planning strategy should be proposed to minimize the impact of such events by offering a fast and effective alternative solution. For this purpose it is necessary to integrate planning with transportation execution and monitoring in order to achieve the desired results (Fazi et al., 2015). As a response to this problem, we propose a decision support system (DSS) based on a hybrid simulation-optimization to integrate different phases of the transportation process at the operational level.

Hybrid simulation-optimization is a viable option for dealing with such complex networks. For the distribution network design of third party logistics (3PL) service providers, Ko et al. (2006) proposed a hybrid simulation-optimization model using genetic algorithm for optimization and capturing uncertainties in several performance measurements in simulation. Another application of hybrid simulation-optimization model is studied by Zeng and Yang (2009) for loading operations in container terminals. In another study, De Keizer et al. (2015) studied a cost-optimal network design problem under product quality requirements using mixed-integer linear programming combined with simulation. Hrušovský et al. (2018) used hybrid simulation-optimization approach for offline intermodal transportation planning problem in a stochastic environment. The contributions of this research are listed as follows.

- The proposed DSS focuses on intermodal freight transportation and analyzes the effect of unexpected events on individual transportation orders, in contrast to the available literature where the focus is put on passenger transportation and global impact of unexpected events (see, e.g., Cacchiani et al., 2014; Mattson and Jenelius, 2015).

- The hybrid simulation-optimization model integrates various phases of transportation planning and execution process. It starts with the optimization of transportation plans and continues with real-time transportation monitoring where unexpected events can be detected and their impact can be analyzed. Afterwards a re-planning approach is applied to obtain alternative plans for transportation orders which are disrupted by an unexpected event.

- Within the online planning, several basic policies are defined to obtain alternative plans within a short time. The applicability of these policies is then analyzed based on scenarios with different event durations. As a result, important insights could be gained with regards to the situations in which the policies can be used.

- The proposed DSS is applied to a real-world case study covering several European countries, which is based on realistic schedules and integrates three transportation modes, i.e. road, rail and inland waterway. In this extensive case study, important managerial insights could be derived regarding the disruption management based on the characteristics of the unexpected events.

The rest of the paper is structured as follows. Section 2 gives a short overview about possible disruptions and methods used in disruption management literature. Section 3 defines the problem and discusses factors which need to be considered in defining the DSS. In Section 4 the proposed DSS is described. Section 5 focuses on the application of the proposed methodology to a case study based on real-life European intermodal transportation network. Conclusions are provided in Section 6.

## 2. Literature review

Intermodal transportation planning needs to address a number of interrelated and important planning problems covering strategic, tactical and operational level decisions as discussed by Macharis and Bontekoning (2004). As shown in the review of Mathisen and Hanssen (2014), numerous optimization models have been developed to solve such complex problems. However, the operational level of planning, especially disruption management in this context, is still not sufficiently covered (SteadieSeifi et al., 2014). This section provides a brief literature review on synchromodality and disruption management in transportation and highlights the differences between the available literature and this paper.

Synchromodality is a promising concept to promote modal shift by motivating logistics service providers (LSPs) to move from a single mode to multimodal (intermodal) transportation. In this concept, transportation of goods is carried through the most reliable transportation mode. It also helps to reduce transportation costs, improve utilization and offer environmentally-friendly transportation. This topic is studied in the literature by several researchers but it is still limited. Lin et al. (2016) proposed a decision-making system for perishable good LSPs to reduce loss of freshness using synchromodal transportation. Extensive simulation experiments illustrated how the proposed approach can improve the quality and reduce the operation time during the transportation processes. In another study, Resat and Turkay (2019) presented a multi-objective mixed-integer programming problem for integrating various characteristics of synchromodal transportation. The authors investigated three different objective functions including total transportation cost, travel time and GHGs emissions. The authors solved the proposed linear model by using a customized implementation of the epsilon constraint method. In related study, Qu et al. (2019) provided a mixed-integer programming model to replan hinterland freight transportation, based on the framework of synchromodality. The authors showed that the replanning can benefit from a high operational flexibility and coordination via a split of shipment and aligning the departure time of service flows with the shipment flows. Interested readers are referred to the survey on real-life developments on synchromodality by Giusti et al. (2019).

Transportation operations are negatively influenced by unexpected events that cause vulnerability and reduced serviceability of transportation networks (Mattson and Jenelius, 2015; Pizzol, 2019; Hong et al., 2019). The impact of the event depends on its type and duration, since different events pose different risks to the network. As an example, a small accident on a local road usually has a smaller impact than a tree blocking an important railway corridor. Therefore the events should be distinguished based on their frequency and impact.

Risk sources for unexpected events can be classified into different categories. Treitl et al. (2013) differentiate between human failures, exogenous factors, endogenous factors and other events. Out of these, exogenous factors cannot be influenced by the responsible managers/planners, so that reaction to these events is only possible after their occurrence. These events include mainly natural disasters and adverse weather conditions that can range from low-impact events up to blockages of multiple days (see, e.g., Brazil et al., 2017; Ludvigsen and Klaeboe, 2014). Another important category is the endogenous factors which include transportation mode-specific disruptions. In this context, Amrouss et al. (2017) studied the influence of disruptions on road transports in forestry, Azad et al. (2016) and Gedik et al. (2014) dealt with rail disruptions and potential disruptions in inland waterway transportation (IWT) were analyzed by Eberdorfer and Wolfinger (2010).

Despite the high variety of unexpected events, their impact can be summarized to three categories: demand changes due to changing order quantities (see, e.g., Lium et al., 2009), capacity restrictions due to vehicle problems (see, e.g., Wang, 2016; Soltani-Sobh et al., 2016) or changed travel times due to delays (see, e.g., Kalinina et al., 2013). Whereas the first two categories have been extensively investigated in the literature, consideration of travel time uncertainties is still an emerging field.

Possible travel time uncertainties can already be considered in the planning phase where historical data or statistical travel time distribution help to create more reliable plans. This has been applied by Colicchia et al. (2010) for various stages in a global supply chain and Kalinina et al. (2013) analyzed the impact of uncertain delivery times in an intermodal network. In addition to that, Demir et al. (2016) integrated travel time uncertainty into the service network design approach for creating reliable intermodal transportation plans and Hrušovský et al. (2018) extended the model by developing an integrated simulation-optimization approach. The results and differences between the last two models were then compared in Demir et al. (2017). However, these models are only able to cover smaller disturbances since including long delays would lead to extensive buffer times in transportation chains resulting in high costs. Consequently, approaches dealing with long delays by adjusting infeasible plans according to the actual traffic situation in real-time need to be developed.

The topic of re-planning and dynamic adjustments of plans to unexpected changes in freight transportation was mainly discussed in vehicle routing problems (see, e.g., Ichoua et al., 2000; Pillac et al., 2013; Ferrucci and Bock, 2014). In contrast to that, the publications in intermodal freight transportation context are rather limited and focusing more on overall network reliability than on the specific solutions for individual transportation orders (Rosyida et al., 2018; Fikar et al., 2016). However, disruption management has been extensively studied in the area of passenger transportation, which can be also helpful for freight transportation.

In passenger transportation context, the models are generally classified according to the severity of unexpected events (i.e., disturbances and disruptions) and the level of details (i.e., microscopic and macroscopic models). As described by Cacchiani et al. (2014), disturbances can be defined as small delays with minor impact on transportation operations, whereas disruptions are events with major impact where re-planning is necessary. Louwerse and Huisman (2014) state that the available literature is rather concentrated on disturbances and studies on dealing with disruptions are scarce. In case of microscopic models, all infrastructure details, including factors such as number of tracks, signaling equipment, etc., are considered (Corman et al., 2017; D'Ariano et al., 2007). Infrastructure modeling in macroscopic approaches is more abstract and therefore usually used for disruptions, where detours and changes on multiple links within the network might be necessary (Zhan et al., 2016; Binder et al., 2017).

The definition of disruptions and their duration is highly dependent on the analyzed case. Whereas Khosravi et al. (2012) find delays between 15 and 30 minutes as sufficient for disrupting passenger railway services, Fischetti and Monaci (2017) consider disruptions lasting for 15–60 minutes. Binder et al. (2017) found out that average disruption duration for Dutch railways was 1.7 hours and Zhan et al. (2016) analyzed the impact of disruptions lasting for two hours. However, such short delays might not have high impact on intermodal services, where the frequencies of services are much lower and transshipment times in terminals are longer. Therefore, in intermodal context, Burgholzer et al.

(2013) studied disruptions lasting between two and 24 hours, Ludvigsen and Klaeboe (2014) identified 12 hours as critical for dividing services into different priority categories and Fikar et al. (2016) dealt with disruptions of 24 and 72 hours.

When developing a re-planning model that reacts to network disruptions, the speed of obtaining a solution is more important than the efficiency of the plans, since the involved actors have to be informed as fast as possible (Cacchiani et al., 2014). According to Fischetti and Monaci (2017), solutions should be obtained within two to 10 seconds whereas Sato and Fukumura (2012) give an overview of available models that are able to deliver a solution within 120 seconds. In order to achieve such short solution times, pre-defined policies are usually used as a solution approach, with a pre-defined simple rule used in case of a disruption. These policies usually include waiting, rerouting, changing transportation modes, canceling some of the affected services or using emergency services which should help to solve the problem (Louwerse and Huisman, 2014; Zhan et al., 2016; Binder et al., 2017).

Since the literature review shows that the topic of disruption management is not sufficiently covered in intermodal context, this paper aims to analyze the best possibilities to react to disruptions in real-time and to create alternative plans in a fast way. The focus is put on individual transportation orders and services which have to be re-routed in the available transportation network, therefore the macroscopic approach is suitable for this research. In order to be able to analyze the reactions to disruptions, it is necessary to create the transportation plans at the beginning and then to monitor the transportation and identify potential disruptions. Therefore a hybrid simulation-optimization approach is created which integrates the different phases of the transportation process as described in the next sections.

## 3. Problem description

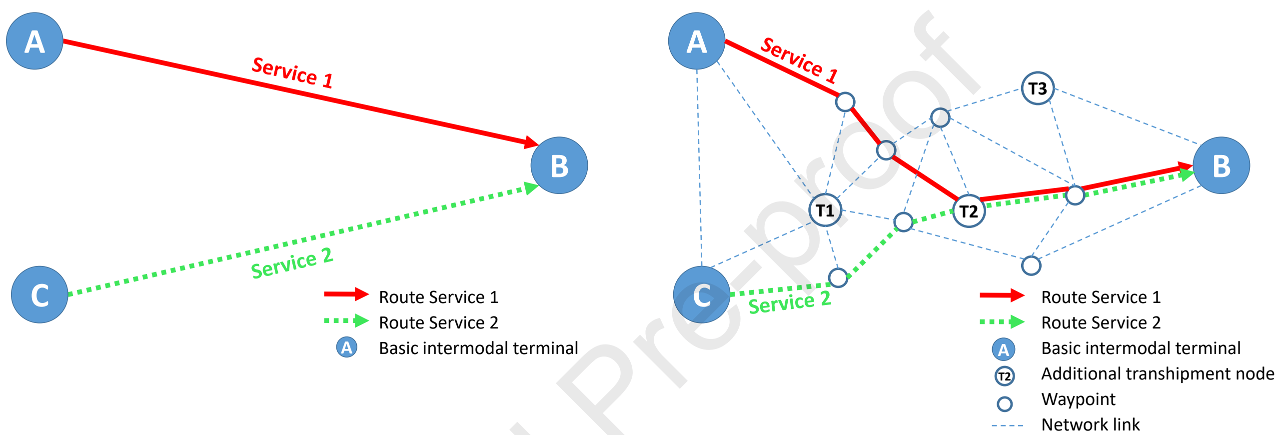
As mentioned in the previous sections, planning and execution of intermodal transportation is highly complex due to the need for coordination of different transportation modes with specific characteristics in one transportation chain. As an example, some modes (e.g., rail) are running according to fixed schedules and/or have only limited network available (e.g., IWT), whereas others have a quite dense network and flexible departure times (e.g., road). These factors influence planning as well as possible reactions to disruptions. Consequently, an appropriate TMS is needed in order to cover all these issues.

In this research, our aim is to develop a decision support system which covers all important phases of a transportation process, including planning, monitoring of execution and disruption management. In this way, the system should support transportation planners and facilitate their decisions since it should show them available alternatives and suggest the best possibility how to deal with an occurred unexpected event.

In this context, two planning phases can be distinguished: offline planning and online planning. Within offline planning, a transportation plan has to be created for each order received from a customer before the transport is started. For this, a network of terminals connected by transportation services is used to find the best route for each order according to its characteristics (origin, destination, pick-up and delivery time, etc.) and objectives (e.g., minimal costs or $CO_2$e emissions). Consideration of unexpected events in this phase is rather limited since the models are either deterministic (see, e.g., Crainic, 2007) or include demand or travel time uncertainty to increase the reliability of the plans (see, e.g., Demir et al., 2016; Hrušovský et al., 2018). However, these plans are only resistant to smaller disturbances since extensive buffer times and capacities would be needed for including all possible disruptions.

Major disruptions are handled in online planning, which is activated whenever a plan becomes infeasible. This usually happens during transportation execution, when a new plan has to be found in a fast way, so that vehicles can be rerouted before they arrive to the disruption location. Moreover, it is important to consider only services and orders which are really affected by the disruption instead of re-optimizing the whole network, since frequent changes of plans could cause chaos in the system. Therefore, an effective re-planning approach has to be used in order to find new plans for affected orders.

Offline and online planning require diverse inputs and granularity, as shown in Figure 1. In general, the network consists of different types of nodes that are linked together. The basic intermodal terminals represent the nodes which are origins and destinations of the available planned intermodal services. In addition to these basic terminals, there might be additional transshipment nodes without regular services or simple waypoints where two links are crossing. In general, each service has a strictly defined route including all links located between its origin and destination node. However, this granularity is not necessary in offline planning, where the task is to find the best sequence of services connecting the origin and destination of an order, whereby the number of available services can be high and the details about the exact route of a service are not necessary. Therefore in offline planning a service is only considered as a direct connection between two terminals in order to decrease the network complexity. This is also shown in Figure 1a for Service 1 and Service 2.




**(a)**
a) Offline planning network

**(b)**
b) Online planning network

**Figure 1**
Transportation network representation for offline and online planning

When it comes to transportation monitoring and online planning, it is necessary to adapt the network and consider the exact route with additional nodes and links as shown in Figure 1b. Although this network representation is more complex, it allows a quick identification of possible alternative routes. In addition to that, it also shows which links are used and shared by the planned services. As an example, despite the fact that Service 1 and Service 2 are treated as separate services for offline planning, Figure 1b shows that they use the same network links between additional transshipment node *T*2 and their destination *B*. Therefore, if an unexpected event occurs on this part of the route, both services might be potentially affected. However, this might not be necessarily the case as shown in the following example, which is based on the network from Figure 1b and illustrated in Figure 2.

In this example, it is assumed that both Service 1 and Service 2 are rail services. As shown in Figure 2, an unexpected event occurs on the last link before terminal *B* at the moment when Service 1 already left node *T*2 and Service 2 is close to its origin *C*. For Service 1 this means that it will probably be delayed, since it is close to the event location. Therefore, it is necessary to evaluate possible reactions to this event. In this case, the service can either wait (Alternative 1) and arrive with delay to terminal *B*, or alternative routes can be used - either detour via another waypoint (Alternative 2) or detour to node *T*3 and from there using another service (e.g., road) to terminal *B* (Alternative 3). The best alternative is dependent on the event duration and the planned following services for orders transported by Service 1 and has to be chosen within the online planning process. For Service 2, the situation is different - since it is still quite far away from the event location, it might not be affected at all if the event duration is relatively short. Even if the event duration is longer and Service 2 is affected, there are much more links and nodes available for alternative routes than it is the case for Service 1.

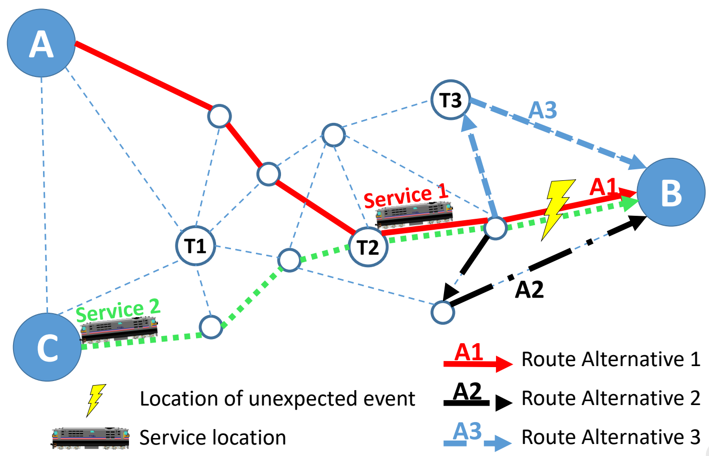



**Figure 2**
Online planning example

As also illustrated by the example, the effect of an unexpected event on the services and orders has to be evaluated individually in order to avoid re-planning of orders which are not affected and find the best solution for affected orders. This can help transportation planners to find an alternative solution quickly and immediately communicate it to drivers of the vehicles en route, so that changes can be implemented very fast. However, before looking at transportation monitoring and online planning, it is necessary to create offline plans, since they are the basis for each transport. Therefore the proposed decision support system combines offline and online planning as it is described in the next section.

## 4. Decision support system based on hybrid simulation-optimization

A hybrid simulation-optimization approach is used combining offline planning, transportation monitoring, detection of unexpected events and online planning. The components of the model and the connections between them are depicted in Figure 3 and will be described in this section.

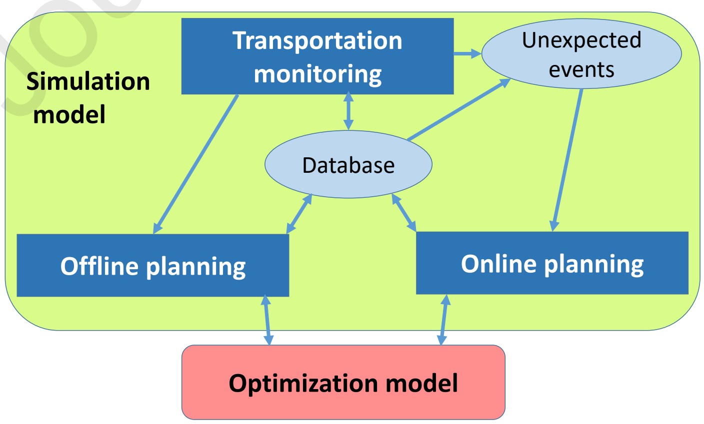



**Figure 3**
Components of the proposed DSS model

The simulation model mimics the transportation system and the influence of planning and unexpected events on transportation execution. Here, the transportation network and movements of vehicles and orders are modeled in real time. Simulation time is stopped every time when offline or online planning is started so that changes can be implemented immediately. The model combines agent-based and discrete-event simulation, where separate agents are created for each node, vehicle and order within the network. The agents for vehicles have their own internal statecharts which regulate the travel speed, the links which the vehicle is traveling on, and possible changes or intermediate stops on the route. It can be distinguished between vehicles with fixed (e.g., rail, IWT) and flexible (e.g., road) departure times, where in case of flexible departure the vehicle agent is responsible for waiting until all orders are ready to be picked up. The discrete-event elements are used to model the loading and unloading processes in terminals, the transportation of goods as well as sourcing of vehicle and order agents.

The whole system is coordinated by the transportation monitoring component which is responsible for controlling the model execution. This includes calling offline planning in regular intervals, updating the database and creating unexpected events which trigger the online planning process.

All components are connected to the database, where all necessary information is stored either as static or as dynamic data. The static data defines all nodes, services and orders with their characteristics. Examples for dynamic data are available service capacities, transportation plans for orders, changed arrival times and delays due to disruptions or changes in routes and costs due to online planning.

The actual process starts with the offline planning component, which is responsible for creating offline plans for received orders. The arriving orders are stored in the database and the plans have to be created for all orders received until the time of planning. Offline planning is repeated in regular intervals in order to reflect the work of planners who are usually planning the orders on a daily basis. In order to limit the size of the planning instance, the number of services is limited since only services departing within a certain planning horizon from the time of planning (e.g., one week) are included. After all necessary data is prepared for planning, the optimization model is called by the offline planning component.

The optimization model is based on the service network design approach, which is suitable for representing specific characteristics of different transportation modes (see, e.g., Crainic, 2007). Since this paper focuses on the combination of optimization and simulation and on the online planning, we adopted a mixed-integer linear programming model previously used by Hrušovský et al. (2018), which is in detail described in their paper. This model combines multiple optimization objectives (i.e. costs, time, emissions) and takes into account the specific constraints of intermodal transport, such as (partly) fixed schedules, transshipments or limited capacities of the different services.

When the offline plans are created, they are added to the database and the free capacities of each used service are decreased accordingly, so that the booked capacity cannot be used for further planning. Besides that, the departure times of services with flexible departures are adjusted according to the results from planning. Afterwards, the transportation execution process is simulated, where all activities are monitored in order to be able to identify every deviation from the plan.

The deviations are usually caused by unexpected events occurring randomly on different locations within the network. Each unexpected event affects a certain pair of links between two nodes (one link in each direction) whereby its exact location on the link is chosen randomly. In addition to the location, the event is characterized by its duration and its starting and ending time, which are assumed to be deterministic and known. Each unexpected event can potentially cause a disruption of the transportation plan, therefore each unexpected event automatically triggers the online planning module.

The online planning module is responsible for reactions to disruptions. However, since not every unexpected event might lead to a disruption causing infeasibility of the plan, the first step is to find out whether and for which orders a new plan has to be found. The identification of affected orders is the task of the so-called feasibility check, where the aim is to reduce the number of orders and services considered in online planning and to reduce the number of changes in the network. When affected orders are identified, the re-planning process can be started. Since these two phases of the online planning process are one of the main contributions of this paper, they are described in more detail in Section 4.1 and Section 4.2. They are also shown in Figure 4 and a pseudocode of the whole process is given in Algorithm 1 and Algorithm 2.

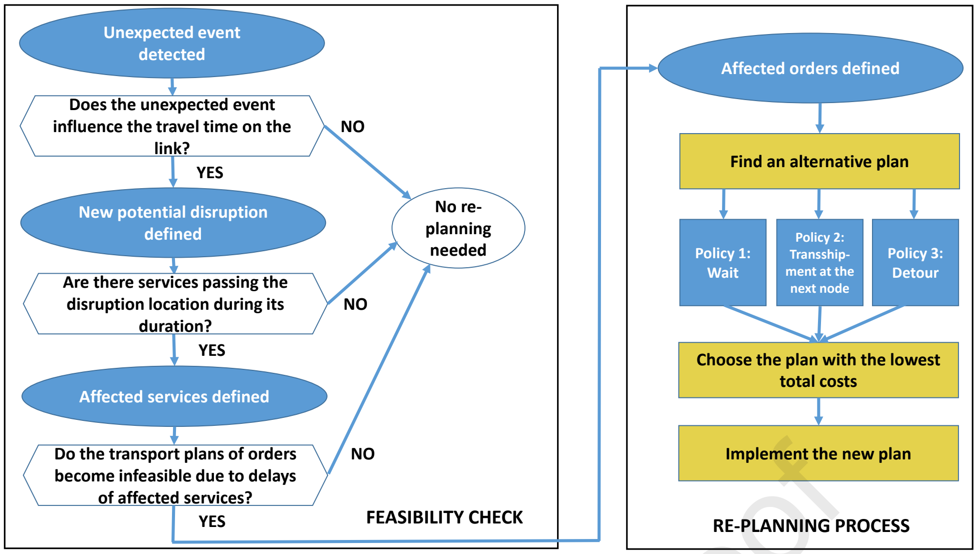



**Figure 4**
Online planning process

**Algorithm 1:** Feasibility Check

**input :** Unexpected event $UE$ defined by link pair $x$, time of occurrence $STE_x$ and end time $ETE_x$, set of links $L$ including start time $ST_l$ and end time $ET_l$ of the last recorded unexpected event at link $l$, set of services $S$ including set of links $RL_s$ included in the route of each service $s$, set of planned orders $O$ including set of services $OS_o$ used by each order $o$, order origin $OR_o$ and order planned departure time $DT_o$

**output:** List of affected services $AS$ and affected orders $AO$

1 Let $AS$ be the set of services affected by $UE$ and $AO$ be the set of orders affected by $UE$
2 **if** $ETE_x > ET_x$ **then**
3     $ET_x \leftarrow ETE_x$ and $ST_x \leftarrow STE_x$
4 **else**
5     **return**

// Identification of affected services

6 **for** $s \in S$ **do**
7     **if** $x \in RL_s$ **then**
8         Calculate planned time $PTA_{sx}$ when service s will arrive to link x and $PTD_{sx}$ when service s will leave link x
9         **if** $PTD_{sx} > ST_x$ *or* $PTA_{sx} < ET_x$ **then**
10             Calculate planned delay $DEL_s$ due to unexpected event and add it to planned travel time for $x$ and all links between $x$ and service destination
11             Add $s$ to $AS$
12 **if** $AS == \emptyset$ **then**
13     **return**

// Identification of affected orders

14 **for** $s \in AS$ **do**
15     **for** $o \in O$ **do**
16         **if** $s \in OS_o$ **then**
17             Calculate buffer time $BT_{sr}$ between planned arrival of affected service $s$ and following service $r$ or planned delivery time if affected service is the last planned service
18             **if** $BT_{sr} < DEL_s$ **then**
19                 Add $o$ to $AO$
20 **if** $AO == \emptyset$ **then**
21     **return**

### 4.1. *Feasibility check*

Before the effect on services and orders is investigated, the feasibility check starts with the affected link pair and searches for potential active events on that link (lines 2-5 of Algorithm 1). If there is still an active event from the past which ends after the end time of the current event and is located before the new event in the transportation direction, then the new event does not have any effect at all, because the services using the link are blocked by the previous event. In this case no re-planning is needed and the process terminates, in all other cases a new potential disruption is defined and its time of occurrence and end time are saved to the affected link. Afterwards, the feasibility check continues with the search for affected services.

In order to identify a service as affected (lines 6-13), it is necessary to know whether the affected link is included in its route and what is the exact location of the service when the unexpected event occurs. Therefore, the planned arrival times to each intermediate node on the route are stored in the database and the exact service location on each link based on the planned travel time can be detected. In this way it can be decided whether the service will arrive to the affected place before the planned end time of the unexpected event or, if the service is already on the affected link, whether it still did not pass the affected place before the event has occurred. In these cases the service is affected and the planned delay is added to its travel time. This delay is the time which the service has to wait until the disruption is resumed, whereby it is assumed that the service can continue with its planned speed until the event location and then wait there until the event is resumed. The delay is added to the planned arrival times of all intermediate nodes on the rest of the route and the expected arrival time to the destination is adjusted. Finally, the service is added to the set of affected services and the process continues with the next step.

When the new expected arrival time of the affected service is known, the last step is to identify the affected orders (lines 14-21). Since containers need to be transshipped between services with mostly fixed schedules, offline plans usually include some buffer time between two planned services. If the planned delay is shorter than this time, then the original plan of the order is not affected, since the next planned service can be used without problems. However, if the delay is longer than the buffer time, the order is affected and a new plan is needed. When all orders transported by an affected service are checked, the feasibility check is concluded and the affected orders are further treated in the re-planning process.

### *4.2. Re-planning process*

The aim of the re-planning process is to find a new plan for the affected orders in a fast way based on the current network situation. The plans are optimized by the same optimization model that is used for offline planning. However, since a quick solution is needed, the number of considered services has to be reduced. In order to achieve this, pre-defined policies in form of simple rules are used which define how the affected service will continue. Since all orders on a service are transported together on one vehicle, only one policy can be chosen for all orders on a particular service. In this paper, three possible policies are considered: waiting, transshipment at the next node, and detour. The applicability of these policies is dependent on the position of the vehicle at the time when the event is announced. It is assumed that the vehicle cannot turn back easily and therefore if the vehicle is already on the affected link, only the waiting policy is applicable. If the vehicle did not reach the affected link yet, all policies can be used (lines 5-9 of Algorithm 2).

Policy #1 (Waiting, lines 1-4 ): In case of the waiting policy, the service uses the planned route, waits in front of the disruption location and arrives to the destination with delay. As a consequence, the orders need a new plan from the destination of the service. Therefore, the service destination is set as a new origin of the order and the delayed service arrival time is set as a new order release time. Afterwards the optimization model is used to find a new plan whereby the number of services is reduced including only services which have not started yet. The advantage of this policy is that re-planning can be started earlier and therefore available capacities, which might be already blocked by other orders at the time of arrival to the destination, can be used. Moreover, if no feasible plan can be found within the existing network, an emergency truck service can be organized for the direct delivery of goods to their destination.

Policy #2 (Transshipment at the next node, lines 10-15): The second policy can be applied if there is a transshipment terminal on the route before the vehicle reaches the affected link. In such case the vehicle can be stopped at this node and containers can be transshipped to an alternative service. In this case the

**Algorithm 2:** Re-planning process

**input :** Set of affected orders $AO$, set of affected services $AS$
**output:** Updated plans of all affected orders

// Policy 1: Waiting

1 **for** $o \in AO$ **do**
2 Set new origin of $o$ equal to the destination of the affected service $s$ used by order $o$
3 Set new departure time to the delayed arrival time of the affected service $s$ to the destination
4 Find an alternative plan $AP_{1o}$ for order $o$ between the new origin and planned destination
// Checking availability of Policy 2 and 3
5 Identify the current link $cl$ on which service $s$ of order $o$ is located at the time of occurrence of UE
6 **if** $cl == x$ **then**
7 Policy 2 and 3 not available
8 **else**
9 Identify the next node $n$ to which the affected service $s$ used by order $o$ will arrive
// Policy 2: Transshipment at next node
10 **if** *n is a waypoint* **then**
11 Policy 2 not available
12 **else**
13 Set new origin of order $o$ equal to $n$ and new departure time of $o$ equal to the arrival time of service $s$ to $n$
14 Add truck services from $n$ to all other basic nodes to the set of services
15 Find an alternative plan $AP_{2o}$ for $o$ between the new origin and planned destination
// Policy 3: Detour
16 Find an alternative path from $n$ to the planned destination of the affected service $s$
17 Calculate the additional costs of this path and the new arrival time to the destination
18 Save the new plan to $AP_{3o}$
// Choice and implementation of the new plans
19 Choose the plan with the lowest cost (i.e., $\min\{AP_{1o}, AP_{2o}, AP_{3o}\}$)
20 Implement the new plan
21 Cancel the parts of original plans which became infeasible due to $UE$
22 Block capacities on the newly used services
23 Release capacities on services from canceled plans
24 **return**

arrival time to this node is known and it is assumed that the service waits in the terminal until containers are unloaded. However, the service has to continue to its destination, as the vehicle might be planned for another service starting from the service destination. Therefore there still exists a possibility to use the original service for orders which are loaded on the vehicle but are not affected by the disruption, but additional delay is possible. However, the unplanned stop offers additional possibilities for re-planning of affected orders. In order to find a new plan, the intermediate node is set as a new order origin and the arrival time to that node is set as a new order release time. Moreover, since this node might not have any regular services, additional truck services from this node to all basic network nodes are considered in addition to planned services in order to facilitate the search for the new route, including also the direct emergency truck, since the destination of each order is always a basic terminal.

Policy #3 (Detour, lines 16-18): Within the third policy, a detour is used to bypass the affected link. The detour is defined as the shortest path which minimizes the increase in total costs and reduces the planned delay. The costs are calculated based on average costs for each link and the travel time is based on average speed of the vehicle according to the planned travel time. If a detour can be found, then the delay can be reduced, which means that orders can be transported according to the original plan or can use services with departures between the arrival time of the detour policy and the arrival time of the waiting policy.

The optimal plans for each applicable policy are created separately and the total costs based on the preferences of the customers are calculated for each plan and policy. When all plans are available, they are compared and the plan with the lowest total costs is chosen as relevant plan for implementation. This plan is then valid for all orders loaded on the affected service (line 19).

The last step within the online planning component is the implementation of the chosen plan (lines

20-24). This means that the route of the service has to be adapted if the third policy is chosen, arrival times to all nodes on the route have to be changed, and possible delay in the intermediate terminal if the second policy is chosen has to be considered. The changed plans for orders mean that the capacities of the original services which are not used anymore and the capacities of the newly used services have to be changed accordingly. Moreover, the new route is implemented and additional costs, times and $CO_2$e emissions connected to the new route are recorded for each order. Analogically, the costs, times and emissions for the services in the canceled part of the route are not considered in real total costs. In this way the additional costs caused by the disruption and the need for re-planning can be calculated.

## 5. Case study: Disruption management in European intermodal network

To investigate various planning stages of the proposed solution methodology, we developed a case study based on real-life network. Intermodal transportation is mainly used for long-distance routes, therefore intermodal services of various European countries are included. These services are not only used for intracontinental transports, but represent also hinterland network of intercontinental transports going through the port of Hamburg. The basic network was already used for a case study in Demir et al. (2019a), but it has been extended for this paper by increasing the number of services and possible connections as well as by developing the detailed network with its links and intermediate nodes. The transportation network, input parameters as well as the results are described in the following subsections.

### *5.1. Transportation network and inputs*

The intermodal transportation network includes 30 basic terminals, which are located in Germany, Austria, Czech Republic, Slovakia and Hungary. Each terminal, which can be both a starting and an ending point for transportation orders, is connected to other terminals by means of road, rail or inland waterway transportation (IWT), depending on the available infrastructure and schedules. As a result, only selected connections are available, which are summarized in Table 1. The position of all basic terminals in the network is depicted in Figure 5.

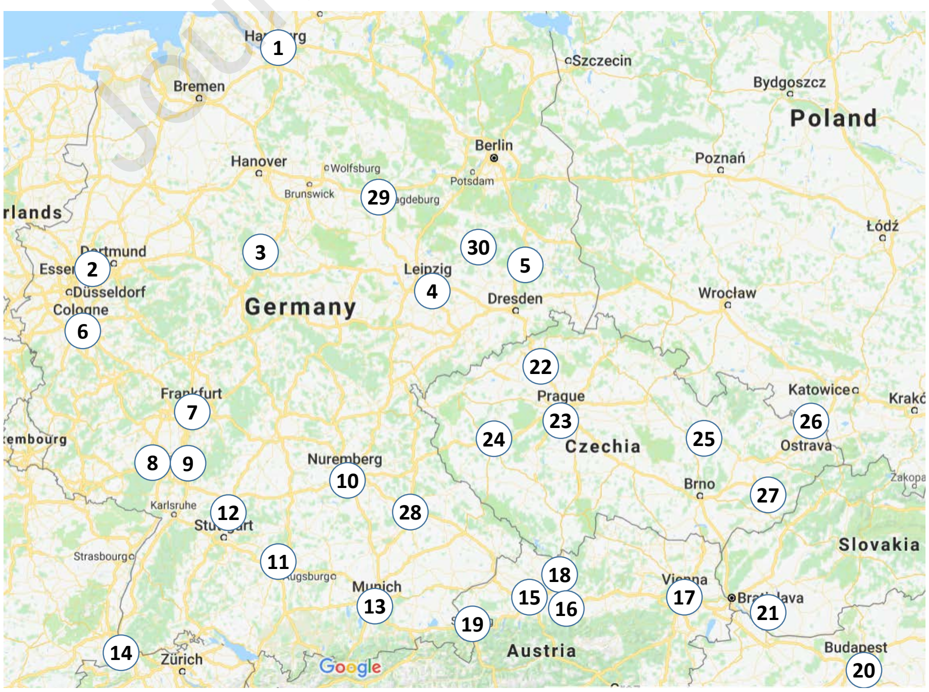



**Figure 5**
An illustration of basic terminals in the network

**Table 1**
Basic terminals with available transportation modes and connecting services

| Terminal no | Terminal name | Road | Rail | IWT | Connecting services by Road to terminals | Rail to terminals | IWT to terminals |
|---|---|---|---|---|---|---|---|
| 1 | Hamburg | | x | x | | 2,3,4,5,6,7,8,9,10,11,12,13,14,16,17,20,22 | 29 |
| 2 | Duisburg | x | x | x | 3 | 1,4,8,13,15,17,20,22,23 | 7 |
| 3 | Göttingen | x | x | | 2,7,29 | 1 | |
| 4 | Leipzig | x | x | | 28 | 1,2,5,13 | |
| 5 | Schwarzheide | x | x | | 4,22 | 1 | |
| 6 | Cologne | | x | | | 1,11,12,13,14 | |
| 7 | Frankfurt | x | x | x | 3 | 1 | 2,10 |
| 8 | Ludwigshafen | x | x | | 9 | 1,2,13,15 | |
| 9 | Mannheim | x | x | | 8,12 | 1 | |
| 10 | Nuremberg | x | x | x | 12,29 | 1,13 | 7,28 |
| 11 | Ulm | x | x | | 13 | 1,6 | |
| 12 | Kornwestheim | x | x | | 9,10 | 1,6 | |
| 13 | Munich | x | x | | 11,14,19,28 | 1,2,4,6,8,10 | |
| 14 | Basel | x | x | | 13 | 1,6 | |
| 15 | Wels | x | x | | 18,19 | 2,8,17,20 | |
| 16 | Enns | x | x | | 18,24 | 1 | |
| 17 | Vienna | x | x | x | 21,27 | 1,2,15,25 | 18,20 |
| 18 | Linz | x | | x | 15,30 | | 17,28 |
| 19 | Salzburg | x | x | | 13,15 | 23 | |
| 20 | Budapest | | x | x | | 1,2,13,15,17,21 | 17 |
| 21 | Dunajska Streda | x | x | | 17,26 | 20,25 | |
| 22 | Lovosice | x | x | | 5,23 | 1,2 | |
| 23 | Prague | x | x | | 22 | 2,19,24,25 | |
| 24 | Plzen | x | x | | 16 | 23 | |
| 25 | Ceska Trebova | | x | | | 17,21,23,26,27 | |
| 26 | Ostrava | x | x | | 21 | 25 | |
| 27 | Zlin | x | x | | 17 | 25 | |
| 28 | Regensburg | x | | x | 4,13 | | 10,18 |
| 29 | Magdeburg | x | | x | 3,10 | | 1,30 |
| 30 | Riesa | x | | x | 18 | | 29 |

The available connections are served by transportation services running at different intervals ranging from once per week up to multiple times per day. Thereby rail and IWT services are operated based on real-world fixed schedules (Metrans, 2019; Kombiverkehr, 2019) which are repeated in weekly cycles . These services are extended by flexible truck services that cover mainly the areas with insufficient rail and IWT connections.

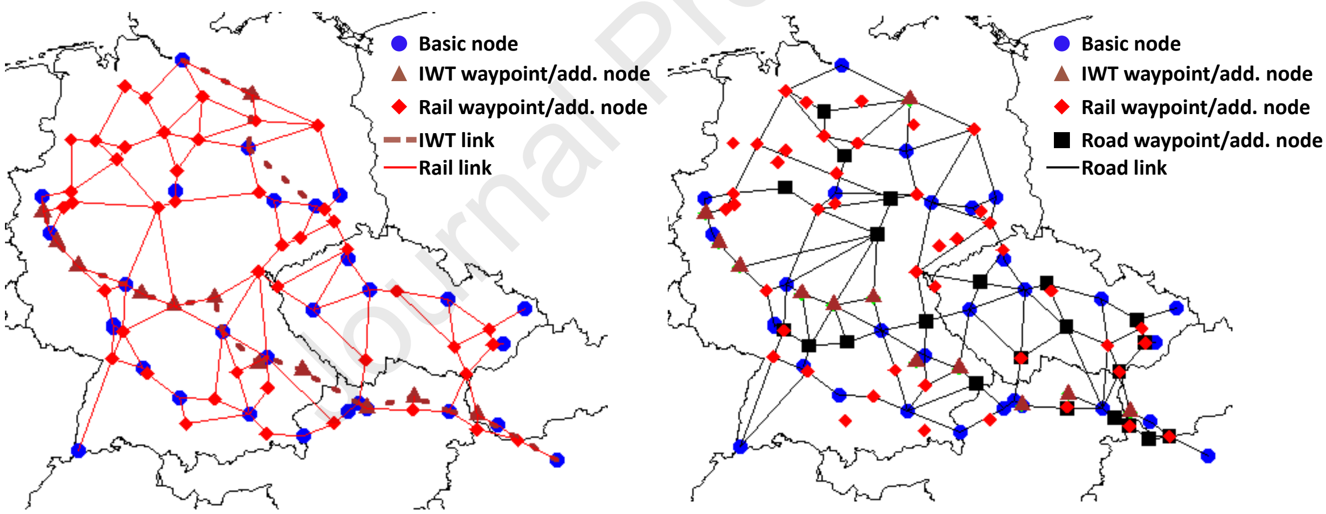
In order to show the ability of the proposed methodology to adapt online as well as offline plans according to occurred unexpected events, the planning and monitoring processes over a longer time horizon need to be considered. Therefore, the simulation is run over one month, with services departing on each of the 31 days. In total, 2,792 services are available during one month, out of which 74% are rail services, 21% are road services and 5% are IWT services, covering mainly the rivers Danube and Elbe. This means that on average 90 services are dispatched per day with higher number of services during the working days and lower number during the weekends. We define service with its origin, departure and travel time, costs and $CO_2e$ emissions (per container) and destination information.

Transportation costs and $CO_2e$ emissions for each service are pre-calculated before the simulation is started. As a result, a fixed cost factor and a fixed emission factor per TEU is calculated for each service. The cost factors are dependent on the distance, travel time, vehicle characteristics (e.g., engine, capacity, utilization, traction) and route characteristics (e.g., gradient, infrastructure charges). The necessary parameters are calculated based on PLANCO (2007), via donau (2007) and PTV (2019). In case of $CO_2e$ emissions, a specific method for each transportation mode is used for calculation. As also described in detail by Hrušovský et al. (2018), the important factors are again vehicle and route characteristics. As an example, emissions for trucks are mainly dependent on the fuel consumption and vehicle utilization, whereas train emissions are influenced by the traction (diesel or electric) and total weight of the train. In case of IWT, the sailing direction is an important factor since sailing upstream requires much more energy than sailing downstream. Since the emissions are considered in form of emission costs in the model, a reference value of 70 Euro per ton of $CO_2$e emissions was used to convert emissions into costs (PLANCO, 2007). As the described factors might vary between the services, the cost and emission factors are also different. Table 2 shows the ranges of used costs and emissions per TEU–km.

**Table 2**
Cost and $CO_2$e emission factors for transportation services

| Transportation mode | Transportation costs (EUR/TEU–km) | $CO_2$e emissions (kg/TEU–km) |
|---|---|---|
| Road transportation | 0.6–0.8 | 0.55–0.65 |
| Rail transportation | 0.2–0.6 | 0.15–0.30 |
| Inland waterway transportation | 0.2–0.4 | 0.1–0.4 |

Each transportation service connecting two basic nodes has assigned a certain route consisting of different network links and nodes which the vehicle is passing through. This is necessary to be able to identify the effect of an unexpected event on a specific vehicle. Therefore, the basic network consisting of 30 terminals is extended by 78 additional nodes, consisting of 32 additional transshipment nodes and 46 waypoints. The basic terminals and additional transshipment nodes can be used by multiple transportation modes whereas the waypoints are separate for each transportation mode. These nodes are connected by a total of 570 links, whereby each connection is bi-directional and includes two links. Each link is also transportation mode-specific. The available links are illustrated in Figure 6.




**(a)**
Rail and IWT network

**(b)**
Road network

**Figure 6**
Transportation network with nodes and network links

In addition to the network and services, transportation orders have to be considered. The orders are characterized by their origin, destination, release time and due date, penalty costs for late delivery, inventory costs for each hour in transit and the number of containers. They were created randomly over the whole simulation period, which means that the number of orders can fluctuate from day to day.

The routes for the orders are optimized in regular offline planning cycles that are performed every day at midnight. Within one cycle, all orders with release times during the following day are planned and the planning horizon is limited to seven days, including 623 services on average. This means that 25 offline planning cycles are performed within the one month, so that also the last cycle can have the full planning horizon of seven days. In total, 247 orders are considered, which means that on average 10 orders are planned per day, fluctuating between seven and 16 orders. The number of TEU for each order varies between one and 30, the planned due date is between 24 and 168 hours after release time and the cost factors are 10 EUR/h as penalty costs for late delivery and one euro per hour as inventory costs.

The decision support tool is run on an Intel(R) Core(TM) i5-5300U CPU with 2.3Hz and 8GB of memory. The mathematical model is solved with CPLEX 12.63 (IBM ILOG, 2020) and Anylogic University 7.2.0 was used for simulation model (AnyLogic, 2016). The analysis can be divided into two parts: at first, the effect of different objectives on the optimal routes is analyzed in Section 5.2. Afterwards the effect of unexpected events and the necessary changes in online planning are examined in Section 5.3.

### 5.2. *Offline planning*

The aim of offline planning is to find an optimal transportation plan for each transportation order based on the defined objectives. Since the optimization model combines three different objectives (costs, time and $CO_2$e emissions), which can have different weights based on planner's preferences, this section analyses the influence of these objectives on the resulting plans without taking the effect of unexpected events into consideration. For this purpose, various offline planning cycles were run over the whole planning horizon considering all objectives together and also each objective individually.

In most of the considered cases the optimal plans could be found relatively quickly (up to 720 seconds per planning instance for one day). However, if only the time objective was considered, the increase in computational times was very high and often no optimal solution could be found even after more than 3,600 seconds, since in this case there might exist multiple alternative solutions with equal or very similar time costs. Therefore, this case was excluded from the analysis and the results are compared for the following three cases: in Case A, all three objectives are considered with equal weight for each objective, in Case B, only transportation costs are considered in optimization and in Case C only the $CO_2$e emissions are minimized. In order to represent each objective, we now provide mathematical formulations for the three studied cases as follows.

$$\text{Case A:} \quad min \quad \sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}} x^{sp}c^{s} + \sum_{j\in\mathcal{N}} n_j c_j + \tag{1}$$

$$+\sum_{p\in\mathcal{P}} c_t^p (AD^p - \Gamma^p_{release}) + \sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}} a^p_{delay} c^p_{pen} +$$

$$+c_{emi}\sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}} x^{sp}e^{s} + \sum_{j\in\mathcal{N}} n_j e_j$$

$$\text{Case B:} \quad min \quad \sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}} x^{sp}c^{s} + \sum_{j\in\mathcal{N}} n_j c_j \tag{2}$$

$$\text{Case C:} \quad min \quad c_{emi}\sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}} x^{sp}e^{s} + \sum_{j\in\mathcal{N}} n_j e_j \tag{3}$$

where $\mathcal{P}$ represents the set of orders, $\mathcal{S}$ represents the set of services and $\mathcal{N}$ is the set of locations. We define four decision variables: (*i*) $x^{sp}$ is the number of containers of order $p$ carried via service $s$, (*ii*) $n_j$ is the number of containers transshipped at terminal $j$, (*iii*) $AD^p$ is the arrival time of order $p$ to its destination, and finally (*iv*) $a^p_{delay}$ shows the delay of order $p$ at its destination.

The parameters include the transportation costs per container and service $c^s$ (i.e., the fixed transportation costs per service allocated to one container as well as the direct transportation costs per container) and transshipment costs per container ($c_j$). The time-related costs are used to represent in-transit inventory costs for the total time spent since the release of containers at the origin until the arrival of the order to the destination. We also consider charges for delayed deliveries ($c^p_{pen}$) in time-related costs. $\Gamma^p_{release}$ shows the earliest release time of order $p$. Furthermore, $CO_2$e emissions-related costs per kilogram ($c_{emi}$) for the emissions consumed per container serviced ($e^s$) and transshipped ($e_j$) are also included.

**Table 3**
Comparison of total costs for different optimization objectives

| Case | Optimization according to | Transportation costs (EUR) | Time costs (EUR) | Emission costs (EUR) | Total costs (EUR) | Computational time (seconds) |
|---|---|---|---|---|---|---|
| A | Costs&Time&Emissions | 1,202,427 | 436,881 | 40,971 | 1,680,279 | 45–720 |
| B | Costs | 1,201,925 | 453,134 | 40,952 | 1,696,011 | 20–160 |
| C | Emissions | 1,269,887 | 460,459 | 37,946 | 1,768,281 | 20–160 |

The resulting costs and computational times are summarized in Table 3.

The results show significant differences with regard to the resulting routes and the computational times needed to solve each case. The variation in computational times between the daily instances can be explained by the varying number of orders and services per day (see Section 5.1) and the resulting differences in the problem complexity. In addition to that, differences between the three cases can be observed: whereas Case B and Case C need only 20 to 160 seconds to solve the planning instance for one day, the time increases to 45 to 720 seconds in Case A. This is due to the increased complexity of the problem caused by including the time objective. However, the time objective has a positive impact on the total costs, since the optimal routes in Case A tend to minimize waiting times in intermediate terminals in order to reduce the inventory costs and avoid penalty costs for late delivery. This is a difference to optimal routes in Case B and Case C, where the optimal solution often suggests to wait for a later service which has slightly lower costs or emissions, since inventory and penalty costs are not considered. Case A was also used for online planning in Section 5.3, since the unexpected events have here the highest impact due to the minimized waiting times in intermediate terminals.

The results in Table 3 also show the clear dominance of transportation costs, since the optimal plans are different only for five orders between Case A and Case B. However, these changes lead to savings of 3.6% within the time costs due to faster transports and reduced penalty costs. The changes in transportation costs and emissions costs are not significant. If Case A and Case C are compared, differences between the transportation plans for 70 orders can be observed, mainly aiming at the reduction of emission costs, which are decreased by 7.4% in Case C. However, this also leads to increases in transportation and time costs by more than 5%, which means that Case C has the highest total costs.

The changes in costs between the cases can be explained when the usage of services is analyzed. In each case between 650 and 700 services are used, with the highest number of services in Case A and the lowest number of services in Case C. The reason is that Case A uses more truck services due to the time costs and 76% of used services only transport one order. If the emissions are minimized, consolidation takes place so that only 72% of used services transport one order whereas 2–4 orders are transported by 28% of the services. The maximum of orders transported by one service is four.

When looking at the modal split of the used services depicted in Figure 7, it can be seen that train services are dominating for all three cases. However, whereas in the first two cases the share of train services is 45% and truck and IWT services have both about 27%, the situation changes when emissions are minimized in Case C. Here the share of train services increases to 58% whereas the shares of both truck and IWT services decrease to slightly more than 20%. This clearly shows the preference for electrical trains with very low emissions before the truck services. The decrease in the usage of IWT services can be explained by the fact that many services are sailing upstream, which also leads to increased emissions. The similar results for Case A and Case B can be explained by the fact that the transportation costs still have a very high weight for Case A and the consideration of time only leads to the situation where in both cases the optimal routes are the same but in Case A services on the same route with earlier departures (but slightly higher transportation costs) are chosen, as described before.

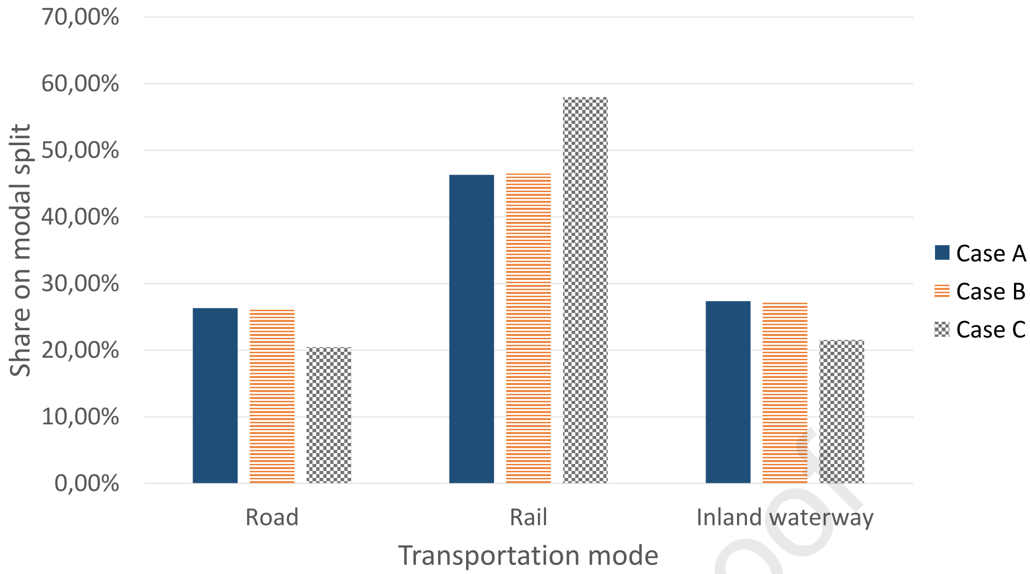



**Figure 7**
Modal split of used services for different optimization objectives

### 5.3. *Online planning*

This section discusses the influence of unexpected events (UE), whereby the aim is to identify which policies should be used for different durations of these events. To this end, offline plans are created taking into account all three objectives (Case A) and the extended network from Figure 6 is used. Out of the 570 links in that network, 324 links are used by planned services and therefore can be possible locations for an UE. The rest of the links are used for detours. Out of the used links, about 75% are used by 1–3 services per day, but the number of services per link can go up to 15 per day. The longest service uses 18 links, whereby most of the services use 2–3 links and a significant number of services have seven and 11 links in their route. For comparing possible detours with the planned route, each link has specific costs and $CO_2$e emissions assigned based on the proportional costs and emissions of services using the link. The travel time for a service on a certain link is based on its average speed according to its schedule.

Unexpected events are created in regular intervals whereby the affected links and the precise location of the event on the link are chosen randomly. In order to increase the significance of the results, the model was run 10 times with different randomly chosen event locations in each scenario and the average results over all runs are presented in this paper. The duration and frequency of occurrence of UE have been chosen based on the available literature as described in Section 2. In total, four scenarios were tested with durations of 2, 6, 12 and 24 hours. The intervals between two UE were two hours for the first two scenarios, since shorter events usually occur with higher frequency. For the rest of the scenarios, three events per day were created as suggested by Burgholzer et al. (2013). Although the time period used for planning was 31 days, it took another two days until all services have arrived to their destination, therefore 396 disruptions were analyzed in the first two scenarios and 99 disruptions were recorded in the two scenarios with longer durations.

As a first step of the feasibility check, Table 4 summarizes the affected services. In all scenarios multiple affected services could be identified whereby the average number of affected services per UE is increasing with its increasing duration. Whereas 396 events for the first scenario affect only 113 services, 99 events with durations of 12 and 24 hours are sufficient to affect 171 and 355 services, respectively. The average delay per service is in all cases around half of the event duration with delays evenly distributed throughout the whole range, reaching from one minute up to almost the duration of the unexpected event. With regards to the transportation mode of the affected services, a clear dominance of rail can be observed in all scenarios with about 90% of affected services. This corresponds to the expectations since rail services have major share on all services and usually have longer routes, which increases the probability that they will be affected by an UE. In contrast to that, trucks usually operate on shorter distances and IWT services are limited in this case study, therefore their share is much lower.

**Table 4**
Effect of unexpected events on services

| Duration of UE (hours) | Interval of UE (hours) | Total number of UEs | Number of affected services | Total delay (hours) | Average delay (hours) | Modal split of affected services (%) | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Road | Rail | Inland waterway |
| 2 | 2 | 396 | 113 | 110.65 | 0.98 | 8.93 | 88.32 | 2.75 |
| 6 | 2 | 396 | 350 | 1,043.01 | 2.98 | 8.68 | 89.08 | 2.25 |
| 12 | 8 | 99 | 171 | 1,008.45 | 5.90 | 11.05 | 87.50 | 1.45 |
| 24 | 8 | 99 | 355 | 4,244.52 | 11.98 | 9.10 | 89.25 | 1.65 |

The affected services might carry orders which can be potentially affected by the UE. However, this might not be valid for all orders as it is also shown in Table 5. Here the potentially affected orders are all orders that are carried by the affected services, ranging from 16 in the first scenario up to 48 in the last scenario. However, if only affected orders with infeasible plans are considered, these numbers are reduced to five and 24 orders respectively, which means that only 30-50% of potentially affected orders require re-planning. As a result, only five orders out of 247 have to be re-planned on average in the first scenario. This also illustrates the relevance of the feasibility check, since the number of re-planning activities can be significantly reduced, which contributes to higher stability of the whole system.

In addition to that, the computational time needed for optimization in the re-planning process can be also reduced. Whereas one offline planning cycle can last more than 10 minutes (see Table 3), the reduced number of orders and services in re-planning process reduces the computational time to less than 10 seconds for one run of the optimization model. As a result, the whole re-planning process including the comparison of all policies and implementation of the best plan can be concluded in less than one minute.

**Table 5**
Effect of unexpected events on orders

| Duration of UE (hours) | Potentially affected orders | Affected orders | Share of affected orders (% ) | Modal split of affected orders (% ) | | |
|---|---|---|---|---|---|---|
| | | | | Road | Rail | IWT |
| 2 | 16.2 | 4.9 | 29.22 | 7.15 | 79.20 | 13.65 |
| 6 | 48.6 | 17.5 | 35.84 | 11.69 | 79.34 | 8.97 |
| 12 | 24.8 | 10.7 | 42.92 | 16.51 | 77.37 | 6.12 |
| 24 | 48.1 | 24.5 | 50.99 | 17.24 | 74.98 | 7.77 |

As described in Section 4.2, three policies are considered within the re-planning process: Policy 1 is waiting until the problem is resolved, Policy 2 suggests transshipment at the next possible node and Policy 3 tries to find a detour which is more convenient than the disrupted original route. Although all policies are checked in every re-planning process, their availability is dependent on the affected link and the position of the affected service when the UE is announced. As a consequence, some policies might not be always available. This is illustrated in Table 6 which shows that Policy 3 was available in less than 50% of the re-planning processes in the first scenario. The reason is the relatively short event duration where the vehicles are usually very close to the event location when the event is announced, mostly one link before or directly on the affected link. In these cases the detour possibilities are very limited. With the increasing event duration, vehicles are usually far away from the affected link and more detours are available, which results in increased availability of Policy 3. Similarly, the options to tranship containers to other services are limited when the vehicle is very close to the affected link, therefore the availability of Policy 2 is also limited. In contrast to that, the waiting policy can be used in every situation.

The limitations of the policies are reflected in the shares of the implemented policies which are also shown in Table 6. Although the waiting policy has the highest share in all four scenarios, its dominance is especially clear in the first scenario where it is used by almost 98% of re-planned orders. The reason

**Table 6**
Availability and implementation of re-planning policies

| Duration of UE (hours) | Availability of re-planning policies | | | Implemented re-planning policies | | |
|---|---|---|---|---|---|---|
| | Policy 1 (%) | Policy 2 (%) | Policy 3 (%) | Policy 1 (%) | Policy 2 (%) | Policy 3 (%) |
| 2 | 100.00 | 77.63 | 49.12 | 97.98 | 1.11 | 0.91 |
| 6 | 100.00 | 78.97 | 60.67 | 87.13 | 6.77 | 6.11 |
| 12 | 100.00 | 85.02 | 73.72 | 73.13 | 4.83 | 22.05 |
| 24 | 100.00 | 90.28 | 80.49 | 53.72 | 2.75 | 43.53 |

for this is the relatively short event duration where it is more convenient to wait and accept additional penalty costs for late delivery than to organize a detour which is in most cases longer than the delay itself. Sometimes it is also possible to postpone the departure of the next service if this is a truck.

When the event duration increases, Policy 1 loses its share in favor of Policy 3. If the event duration reaches 24 hours, for more than 43% of the orders a detour was the optimal solution. Although the transportation costs were higher for the majority of the detours, this increase was compensated by significant delay reductions resulting in reduced inventory and penalty costs. In some cases even faster and cheaper solutions than the original route could be found where the vehicle used alternative links that are usually not used under regular conditions. However, it cannot be claimed that the detour policy would be the best option in general, since its advantages are dependent on various factors.

First, the location of the vehicle at the time of event occurrence is important. Although longer distance of the vehicle from the affected link is in general more convenient, if the distance is too long and the effect of the event on the service is thus relatively short, usually the detour is more expensive than waiting.

Second, the network density plays an important role. In this respect it could be observed that the detour policy was mainly used for disruptions in Germany, where the network density is high especially around Munich, Frankfurt, Cologne and their links to Hamburg, so that an alternative route can be found easily. On the other hand, detour possibilities were limited in Austria where only the main corridor between Vienna and Salzburg was modeled, so that only long detours via Czech Republic were possible.

Thirdly, the average speed of the vehicle is also important. This is especially valid for some rail services with very long travel times and low average speed, so that waiting is better than the detour. In contrast to that, fast services usually use the detour. In this way the services can be also prioritized, since fast services use the scarce capacity on the detour and slower services wait until the problem is resolved.

Last but not least, the detour policy is also limited by transportation modes since vessels sailing on the river usually do not have any alternative routes.

Policy 2, transshipment at the next node, has clearly the lowest share in all scenarios. This is partly caused by the fact that very often transshipment nodes are not available on the route, but the main reason is that this policy is too expensive because in most cases the solution is to use an emergency truck to the destination at high costs. Therefore this policy was mainly used when the vehicle was too close to the affected link to find a detour and the delay was too long for employing the waiting policy or in cases where IWT service was affected and this policy was the only option. In a few cases it also happened that the next node was the destination of the order, where the service should not stop according to the plan, but employing Policy 2 led to the earlier and cheaper delivery of the goods to their destination.

The re-planning process and the implemented solutions also influence the total costs for the affected orders. Since the proportion of affected orders to all orders is rather low, the effect of changes on total costs of the system is also very low, ranging from 0.26% to 0.81% increase across the four scenarios. Therefore the focus here is put only on changes in costs of re-planned orders illustrated in Table 7.

As the table shows, the costs are changing in accordance with the implemented policies. In the first scenario, the vast majority of orders used the waiting policy and therefore almost no changes in transportation and emission costs took place. The small negative change in transportation costs was caused by the orders where Policy 2 was implemented and the direct emergency trucks were cheaper than the original solution. The highest increase was recorded for time costs since goods arrived later

**Table 7**
Changes in costs for re-planned orders

| Duration of UE (hours) | Cost category | Planned costs (EUR) | Actual costs (EUR) | Change in actual vs. planned costs (%) |
|---|---|---|---|---|
| 2 | Transportation | 26,637.40 | 26,620.80 | –0.02 |
| | Time | 7,234.60 | 7,581.10 | 4.14 |
| | $CO_2$e emission | 925.88 | 925.31 | 0.00 |
| | Total | 34,797.88 | 35,127.22 | 0.91 |
| 6 | Transportation | 96,360.40 | 93,878.70 | –2.39 |
| | Time | 24,055.10 | 26,487.90 | 10.46 |
| | $CO_2$e emission | 3,102.01 | 3,077.84 | –0.81 |
| | Total | 123,517.51 | 123,444.44 | 0.07 |
| 12 | Transportation | 57,843.90 | 57,535.50 | –0.63 |
| | Time | 14,752.40 | 16,968.60 | 14.09 |
| | $CO_2$e emission | 1,932.90 | 1,950.89 | 1.04 |
| | Total | 74,529.20 | 76,454.99 | 2.22 |
| 24 | Transportation | 139,572.50 | 140,361.50 | 0.54 |
| | Time | 27,275.70 | 33,197.90 | 23.53 |
| | $CO_2$e emission | 4,758.33 | 4,987.11 | 4.78 |
| | Total | 171,606.53 | 178,546.51 | 4.13 |

than planned, but the delays were not too long due to short event duration. A similar situation was in the second scenario, where the share of Policy 2 was the highest among all scenarios, thus the transportation costs were decreasing. In the third scenario, the use of direct trucks in Policy 2 still had some influence on decreasing transportation costs, but the emission costs increased due to the negative impact of trucks on environment. In the fourth scenario a substantial increase in time costs can be observed, since the long delays influence the penalty costs for late deliveries. This increase was only partly mitigated by the time savings of orders which used the detour policy. However, some of the detours were more expensive than the original plan which resulted in higher transportation and emission costs.

## 6. Conclusions

Intermodal transportation is a viable alternative to single-mode transports since it combines advantages of various modes and contributes to economic as well as environmental efficiency. Despite this fact, its usage is quite low in Europe due to several reasons, one of them being insufficient support for intermodal transportation planning and monitoring within the existing TMS software. In order to respond to this problem, we developed a DSS model which combines transportation planning and monitoring and is able to react to potential disruptions. This approach was tested on several scenarios with different durations of unexpected events that have occurred on different links all over the transportation network. Thereby different policies were employed and their suitability for different situations was analyzed. As the results based on a real-world case study covering wide parts of the European transportation network highlight, the chosen policies are helpful when dealing with unexpected events with different durations in intermodal transportation chains. In general, the proposed policies can be used for the following situations:

- The waiting policy can be used for all scenarios, but it is especially convenient for shorter delays up to two hours where other policies lead to much higher costs. However, these short delays could be included into offline planning where uncertainties in travel times can be considered.

- Transshipment of the goods at the next node often leads to high costs since many of the nodes do not have regular planned intermodal services, which means that an expensive emergency truck service needs to be organized, which in reality also requires additional time and effort to find a suitable vehicle. Therefore, this option is not preferred to react to disruptions.

- Increasing delays increase the usage of detour policy, if the vehicle is not very close to the affected link and if the network density is sufficient. Its applicability is also dependent on the affected transportation mode: whereas inland vessels usually do not have any option for detour, trucks can use the dense network and find an alternative route easily. In case of rail, even if a detour is found, in practice it still needs to be checked whether the train can be diverted since other factors such as track capacity or other barriers could cause infeasibility of this solution. However, these factors were not part of the developed model and would need to be considered by the actual planner.

Generally, the consideration of real-time and stochastic data is very limited in current TMS software. The future developments in such software packages and platforms should enable aggregation of information from several sources that is shared between partners and transportation information providers. Using advanced models and algorithms can help improve the modal split and reduce transportation times and slack, as well as response times to unexpected events during transportation. Future research directions include:

- More effective hybrid algorithms that can support very large-scale network simulations.
- Incorporating well-studied complex time-space service network design problems with simulation.
- Focusing on social impacts of intermodal transportation policies at local, regional and international levels.

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**Declaration of interests**

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