A Real-Time Decision Support Approach for Managing Disruptions in Line-Haul Freight Transport Networks

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A Real-Time Decision Support Approach for Managing Disruptions in Line-Haul Freight Transport Networks

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***Abstract*— Unexpected disruptions in road freight transport caused by poor weather conditions, traffic accidents, etc., are quite frequent and have negative effects on the whole supply chain. Therefore, an intelligent disruption management system is necessary to revise the transport plan directly after disruptions have occurred. The literature presents several approaches for managing disruptions in road freight transport. However, most of them focus on urban freight distributions where disruptions are often handled by vehicle rerouting. The current work, in contrast, addresses disruption management in a line-haul freight transport network that connects urban distribution systems. We present a novel hybrid approach combining a simulation model, optimization algorithms, and a cost-effectiveness analysis. When a disruption occurs, the proposed approach can be used to analyze the impacts of the disruption, identify the affected trips, and revise their plan quickly in real time. Six re-planning strategies are proposed to handle the disruptions and are evaluated in terms of cost, reliability (expressed in time delays), and CO2 emissions. Cost-effectiveness analyses are conducted to rank the obtained solutions and identify the best strategy. Moreover, we suggest a decision support system architecture, based on the proposed approach, to enable disruption management in real-time settings. Real data is used to evaluate the proposed approach in different disruption scenarios. The results provide transport planners with useful insights into possible re-planning strategies and how to identify the best cost-effective strategy to minimize the disruptions' effects and be more economically sustainable. This work also supports carriers in the transition towards intelligent disruption management.**

***Index Terms*— Real-time disruption management, freight, line-haul transport, carbon emissions.**

I. Introduction

TRAFFIC accidents, extreme weather, and vehicle breakdown are examples of Unexpected Events (UEs) that disrupt and delay road freight transport. Transport delays might result in more transport costs (salary costs, vehicle costs, etc.) and several indirect effects such as lower service quality, loss of reputation, or sales at receiving factories. When UEs occur, Disruption Management (DM) is needed to dynamically adjust the transport plans to minimize the transport delays or to put them within the allowed limits, thus reducing their negative consequences on the transport system [1]. In practice, human planners handle various disruptions based on their experiences rather than identifying and ranking possible re-planning options. With increasing the fleet size and dynamism in the transport environment, DM becomes more complex, and human decision making might result in a poor rescheduling solution or overlooking good re-planning options [2]. This raises the need for using Decision Support Systems (DSSs) in DM to bring together the human experience and the use of advanced re-planning algorithms with Information and Communication Technologies (ICTs) tools.

Managing transport disruptions has been widely studied in the supply chain and transport literature. The Supply Chain (SC) literature addresses different types of disruptions related to supply, demand, transport, and facilities. Regarding transport disruptions, the SC studies particularly focus on the strategic level where strategies such as holding safety stock and extra capacity are investigated for handling disruptions occurring between different echelons of the supply chain. For example, Albertzeth *et al.* [3] proposed a simulation model to study the effectiveness of different strategies to mitigate the impact of a transport delay between a production plant and a distribution center. The transport literature, in contrast, focuses on handling various disruptions causing deviations of the actual transport operations from their original plan. In particular, variants of the Real-time Vehicle Routing Problems (RVRP) are widely used to revise the original routing plan in real time once a disruption happens during transport execution. Visentini *et al.* [1] reviewed the literature on real-time vehicle schedule recovery methods in transportation services. They classified the existing literature based on the transport mode. i.e., road, train, and air transport, and discussed the problem formulation and solution methods used in each transport mode. There is also growing research on DM in multimodal transport chains that combine multiple transport modes to transport freight among countries. For example, Hrušovský *et al.* [4] developed a real-time DM approach along with three strategies to deal with disruptions occurring in transport networks combining rail, road, and sea transport.

The present work is related to the literature on DM in road freight transport. Four review papers identified the relevant

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literature and discussed many variants of the RVRP in different transport modes and sectors [1], [5]–[7]. Existing literature mostly addresses DM in urban distribution systems where small vehicles deliver or collect shipments between a distribution center (often named a depot) and the customer locations inside urban areas. In urban distribution, scholars studied disruptions caused by changing customer demand, vehicle breakdown, and uncertain travel times due to traffic jams [8], [9]. Moreover, rerouting of the operating vehicles is the most common re-planning strategy, where the important decisions are which operating vehicles should serve the disrupted customers [7]. The literature extensively proposed mathematical models and heuristic algorithms for revising the transport operations based on real-time information while the use of simulation modelling is limited only to the evaluation of the revised plan, see for example [10], [11]. In addition, a few studies discussed real-time DSSs, based on the proposed algorithms, for DM [2], [12].

In a two-tier freight transport system, urban distribution systems are connected through an intermediate network, named an intercity line-haul network, which uses large vehicles for transporting freight among cities, and thus achieving transport economies of scale [13]. The intercity line-haul transport network includes a number of terminals (often named consolidation terminals) where terminals are located in various cities. At each terminal, the shipments received from the urban distribution system are sorted and consolidated into large capacity vehicles based on the destination terminal from which urban distributions are performed. Compared to the VRP with pickup and delivery used in urban distributions, line-haul transport resembles many-to-many routing problems where each terminal acts simultaneously as an origin and destination of trailer or semitrailer trips. In addition, the trips among the terminals are performed by large vehicle combinations, e.g., modular vehicle combinations, in which tractors are used for performing semitrailer/trailer trips among different terminals [14]. The operational and tactical planning decisions of the line-haul transport networks have been widely addressed in the literature. The service network design problem is solved to design a tactical load plan describing how shipments are routed through the line-haul terminal network, see for example [15]. For operational planning decisions, vehicle combination routing problems are solved to determine the routes and number of drivers, tractors, and trailers to execute the load plan, see for example [16].

Based on the literature analysis, the literature focuses mainly on tactical and operational planning of line-haul transport operations while studies addressing road disruptions in the line-haul freight transport context are rare, in contrast to the significant literature on managing disruptions in the urban freight distributions [1], [5]–[7]. The line-haul transport networks are often prone to road disruptions, such as accidents or extreme weather, that close the highways for some time [17]. DM in line-haul road transport is important because heavy-duty vehicles are used more than small vehicles in road freight transport. In Europe, for example, 79 % of the tonne-kilometers of road transport, in general, were made by heavy-duty vehicles with a gross vehicle weight of over 30 tonnes [18]. Moreover, 60 % of the tonne-kilometers of road transport, in general, made in Europe were over distances of more than 300 km while 6.5 % of the tonne-kilometers made were over distances of less than 50 km [19].

In practice, transport planners add a little buffer time to handle small disruptions caused by traffic congestion [20]. A key to efficient DM is to maintain, as much as possible, the initial transport plan rather than make changes for the affected and unaffected vehicles, causing chaos in the system [7]. For this reason, the first step of efficient DM is to identify the line-haul trips whose delays exceed the built-in buffer time. Then, the identified trips are rescheduled using algorithmic approaches. Identifying the affected trips is not simple since real-time information represents only an instant picture of transport operations when the UE has occurred. This raises the need for simulating the evolution of the transport network in real time to identify all affected trips, in contrast to the available literature where the affected trips are assumed to be known when the disruptions have occurred. Real-time decision making also necessitates fast simulation methods, so that there is enough time for making decisions on the best way to manage the disruption.

Along with identifying the affected trips, re-planning strategies are another important aspect of the DM. In particular, existing studies rarely discuss the use of re-planning strategies other than rerouting such as detouring, hiring capacity from the spot market, or mixed strategies. Another challenge is how to select the most appropriate strategy since this often depends on multiple, conflicting criteria such as the cost of the strategy and its effectiveness in reducing the delay. Existing studies often use a delay cost per unit time to convert the time delays into a cost value. This way enables aggregating multiple criteria into a weighted cost function such that the re-planning solution with the lowest cost can be selected [2], [21]. In practice, a delay cost per unit time is, however, very hard to measure since indirect costs of time delays are in many cases implicit costs related to loss of reputation or low service level [20]. Moreover, this weighted cost approach would not always be desirable since it might fail to satisfy the preferences of the decision makers regarding one criterion or meet the budget limitation. Nevertheless, this challenge has not been adequately considered in the existing literature. Even though CO_2 emissions have been an increasing concern of road freight transport, a recent review [7] reported that the existing re-planning algorithms often have an objective of minimizing a weighted sum of operating, service cancellation, fixed vehicle, and delay costs while the emission considerations into DM are ignored.

In light of the above considerations, the present work makes several contributions to the literature as follows:

First, we develop a novel hybrid approach for managing disruptions occurring in line-haul freight transport networks, in contrast to the existing literature where the focus is placed on the urban distribution systems. The developed approach combines a Discrete Event Simulation (DES) model, optimization algorithms, and an Incremental Cost-Effectiveness Ratio (ICER) method. After detecting disruptions, a DES model is used to mimic how the planned line-haul transport operations will evolve in real time. This allows for identifying which vehicles and their trips will be affected within the durations of the UEs and evaluating the extent to which the trips are impacted by the disruption. Second, six re-planning strategies are proposed and applied using optimization algorithms to revise the transport plan quickly in real time. The proposed re-planning strategies are based on four distinct strategies and their combinations including accepting delays (no action is taken), detouring, rerouting, and hiring extra capacity from the spot market or a partner. The DES model also evaluates the re-planning solutions using real-world data in terms of three indicators: cost, reliability (expressed in time delays), and CO2 emissions. Third, the tradeoff between the cost of the strategy and its effectiveness in reducing the delays has been an important challenge in deciding on which re-planning strategy to select. The present work addresses this challenge by using the ICER method to compare the difference in costs between two competing strategies to the difference in their degrees of effectiveness in reducing delays. Thus, the present work not only evaluates different re-planning solutions but also supports the planner in choosing the most cost-effective solutions. Fourth, a real-time DSS, based on the proposed approach, is also suggested for integrating different transport planning phases including planning and execution, detecting disruptions, analyzing their impacts on the transport plan, and revising the transport plan quickly in real time. Furthermore, the proposed approach is applied to real data provided by a Danish logistics company. This allowed for conducting extensive numerical experiments in real settings and therefore, several managerial insights could be concluded on the proposed re-planning strategies and how the characteristics of UE affect the three indicators.

II. Problem Description

To better illustrate the problem, we use a simple example of a generic line-haul transport network as shown in Fig.1. Without loss of generality, we use the tractor-semitrailer combinations for illustrating the problem, but other vehicle combinations can be handled by the proposed approach. Before transport starts, offline planning is performed to develop the operational transport plan on a daily basis. The operational transport plan describes the number of tractors and the route of each tractor. A route is a feasible sequence of semitrailer trips, satisfying different operational constraints such as maximum driving distance and available resources [14]. As shown in Fig. 1, route 1 starts and ends at terminal C and includes three trips among terminals C, E, and A. Each trip may be a loaded-semitrailer trip, an empty semitrailer trip, or a tractor running alone.

Offline planning often takes into consideration small disruptions, e.g. traffic congestion, by adding little buffer times [20]. Delays in a previous trip, if not absorbed by the added buffer times, cause additional delays for its following trips in the same route. In addition, this might cause delays in other routes since the same shipment might be handled by different tractor-semitrailer combinations to reach its destination terminal. This in turn might affect the delivery performances of the urban freight distributions as well. Therefore, it is quite clear that designing an efficient DM in the line-haul tier is important for increasing the competitiveness of line-haul carriers.

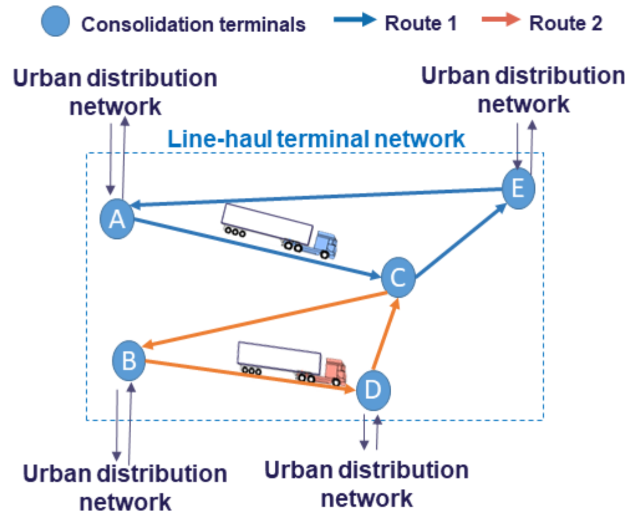


Fig. 1. An illustration of the line-haul transport network.

The type of disruptions considered in this work is a link or road disruption caused by UEs such as accidents or extreme weather. Each UE is defined by its location, occurrence time, and estimated duration. When the UE happens, it first delays the trip being served currently by the affected tractor. This trip is referred to as the first-affected trip while reactionary-affected trips refer to the trips following the first-affected trip in the same route. In contrast to offline planning, online planning deals with disruptions by revising the transport plan in real time according to pre-defined re-planning strategies. Based on the literature review, e.g., [3], [4], [22], [23], and our field experience, six re-planning strategies are identified. The six re-planning strategies are illustrated using an example in Fig. 2. In the illustrative example, the UE occurs on the link between terminals A and C. Trip A-C of tractor 1 is the first-affected trip from which the delay will transfer to its following trip C-F. Tractor 2 performs the last trip in its route and is not affected by the UE.

- Accepting strategy (S1): it means that no action is taken and tractor 1 waits in front of the UE and arrives late to the next terminal as shown in Fig. 2a. In some cases, e.g., time-sensitive cargo or a strict delivery time, accepting the delay is not an option and other strategies are necessary to reduce the delay.
- Detouring strategy (S2): it searches for a detour of the potentially affected trip before reaching the affected link as shown in Fig. 2b. The reactionary-affected trips also benefit from detouring since they will have a reduced delay. Detouring strategy requires a detailed link-node network representation (see Fig. 2), in contrast to offline planning (see Fig. 1) where a simple representation of the road network as single links is used.
- Rerouting strategy (S3): it reroutes unaffected tractors to serve potentially reactionary-affected trips with respecting the operational constraints. As shown in Fig. 2c,

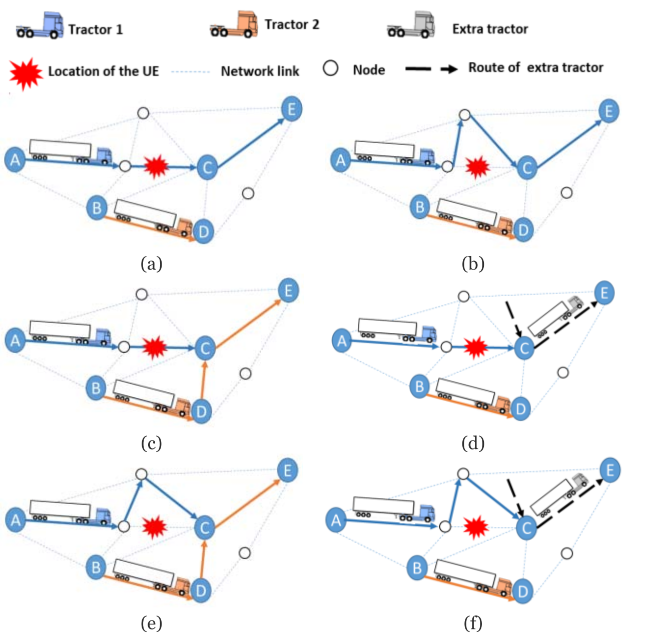


Fig. 2. The proposed re-planning strategies: accepting strategy (a), detouring strategy (b), rerouting strategy (c), extra-tractor strategy (d), detouring-rerouting strategy (e), detouring-extra tractor strategy (f).

tractor 2 is rerouted to serve trip C-E of tractor 1, resulting in a repositioning trip D-C and waiting time might be incurred if tractor 2 arrives before the planned departure time of trip C-E. Since tractors are typically working with small slack times in their schedules, the effectiveness of this strategy is limited.

- Extra-tractor strategy (S4): it means that an extra tractor serves the reactionary-affected trips, starting from terminal C as shown in Fig. 2d. In reality, companies can achieve this strategy in two approaches; either the company owns some emergency tractors, or the company hires extra tractors from the spot market or one of its partner carriers. This research follows the second approach since carriers might not always afford the cost of extra capacity. In addition, the recent developments in ICTs have supported the implementation of advanced freight matching platforms enabling carriers to find extra capacity more efficiently in the spot market. An important feature of these platforms is that logistics data and operational updates continually flow from carriers' systems to the freight matching platform. Thus, these platforms can automatically match the disrupted trips to several tractors of other carriers in only a few minutes after disruptions, see for example [24], [25]. The line-haul network typically spreads along with the whole country and most likely overlaps with the service areas of other carriers. This makes finding extra capacity much easier, especially, since the hired tractors will serve the reactionary-affected trips which in turn provides the transport planner with enough time to find a partner carrier.
- Detouring-rerouting strategy (S5): it combines the detouring and rerouting strategies to achieve more delay reduction in all affected trips. As shown in Fig. 2e, S5 detours the first affected trip while the reactionary-affected trip is reassigned to route 2.
- Detouring-extra tractor strategy (S6): it combines detouring and extra tractor strategies as shown in Fig. 2f in which the disrupted tractor is detoured while its successive trips are handled by an extra tractor.

In re-planning strategies S3, S4, S5, and S6, we assume that there are no goods being cross docked among the semi-trailer trips of the delayed tractor. For example, trip C-E does not require goods from the affected trip A-C. It is also worth noting that the proposed approach conceptualizes that not all the re-planning strategies might be available when the disruption occurs. Based on the existing situation, one or more strategies may be available or even none except the accepting strategy. We assume that freight matches are always available since identifying possible freight matches requires modelling the transport operations of other carriers and solving an auction-based decentralized planning problem, which is beyond the scope of the current work.

The re-planning strategies are evaluated in terms of three performance indicators, i.e., operating cost of vehicles (OC), the time delay (TD), and CO2 emissions from the vehicles (CE). Thus, selecting the best strategy based on the least weighted cost might not be practical since time delays are hard to be measured in monetary values and have a tradeoff with cost and emissions. Another important consideration is that planners typically have a limited budget for DM. Therefore, identifying the cost-effective strategies is very useful since it would not be realistic to select an expensive strategy to reduce the delays more than needed when there is a less expensive strategy that can achieve the targeted delays. This raises the need for a cost-effectiveness analysis along with considering how much money the planner is willing to pay for reducing the delay.

III. The Proposed DSS Based on the Hybrid Approach

This section begins by describing a DSS architecture, based on the developed approach with illustrating the ICT settings and the DM procedure. Essential inputs to DM include real-time information on the transport operations, disruptive events, and the initial transport plan. Therefore, the proposed DSS integrates various planning phases such as transport planning, monitoring, execution, and detecting as well as managing the impacts of UEs.

Fig. 3 shows the proposed DSS architecture including three main components, i.e., the database, the interface, and the model components. The database component stores and processes different types of static and real-time data such as updates of the transport flow status, service prices, freight trips, and characteristics of resources. The model component retrieves the required input data from the database and updates it with obtained planning solutions. The interface component enables interactive communication among the DSS and the real world such as freight matching platforms and real-time sensing technologies. For example, transport planners can run the planning algorithms with different criteria while truck drivers

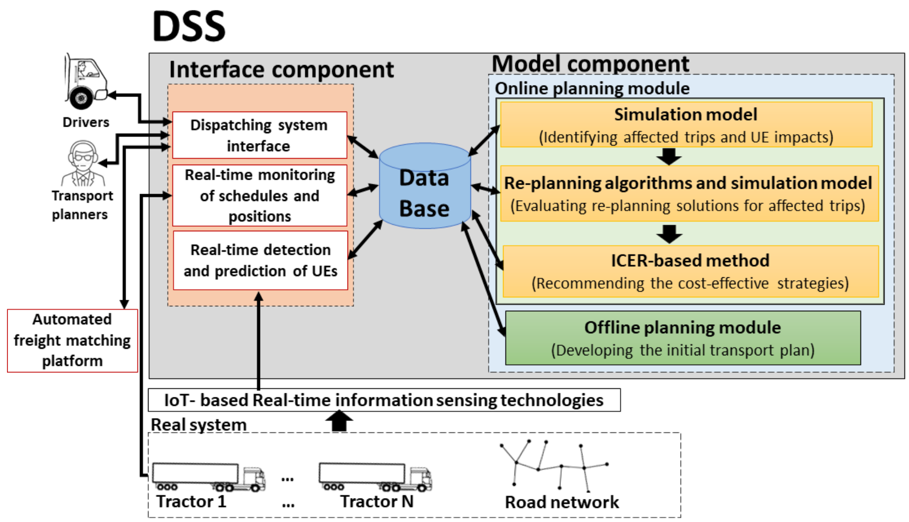


Fig. 3. The architecture of the proposed DSS.

can be updated quickly with recovery solutions. Detection and prediction of disruptions are important aspects of the proposed DSS. The earlier the disruption is detected, the more the re-planning strategies are available and the ability to reduce its effects. Disruptions can be detected through real-time monitoring of deviations in the actual status from the planned status. In addition, detecting disruptions can be based on real-time information on the surrounding system environment such as road traffic [26]. Prediction concerns estimating the duration of UE that might not be available when the UE is detected [27]. In current practices, traffic operators or police publish the estimates on incident durations based on their experience. However, the accuracy of these practices is questionable, raising the need for real-time prediction models [28]. The literature has developed several methods for prediction based on real-time information, historical data, and human experience [29]. Prediction methods are beyond the scope of the current work and might be considered in extending the present work.

This research focuses particularly on the model component that includes offline and online planning modules. Before transport starts, the offline planning module is used to develop the transport plan based on the information stored in the database. During transport execution, real-time information on work progress is constantly collected and stored in the database. The detection of disruptions calls immediately the online planning module that combines simulation, optimization, and ICER methods to evaluate possible re-planning strategies. Once re-planning solutions are identified, the DSS notifies the transport planner for making decisions. The offline and online planning modules will be described in more detail in sub-sections A and B.

A. The Offline Planning Module

The proposed approach requires the initial transport plan as an input to develop the re-planning solutions. To create the initial transport plan shown in Fig. 1, the offline planning module solves the Tractor and Semitrailer Routing Problem with Many-to-Many Demand (TSRP-MMD) which fits the planning requirements of the line-haul freight network [14]. In the TSRP-MMD, the consolidation terminals and highway links represent the vertexes and arcs, respectively. Each consolidation terminal has some semitrailers waiting to be transported to other terminals and each terminal can be also the origin and destination of semitrailer trips simultaneously. Each semitrailer trip is defined by its origin terminal, destination terminal, freight weight, and its due departing time. The solution of TSRP-MMD describes the routes of tractors where each route is assigned to only one tractor. In each route, the tractor departs from terminal i to another terminal j, hauling one loaded or empty semitrailer or traveling alone. When arriving at terminal j, the tractor drops off the semitrailer, then picks up another semitrailer, and moves it to another terminal. The tractor must start and end its route at the same terminal. Moreover, the number of required semi-trailer trips among terminals is known in advance. All routes must satisfy three operational constraints: the number of available tractors, maximum driving time, and the time window on the trips' departing times. The objective of the TSRP-MMD is to minimize the total transport cost of tractors, including operating costs of vehicles and the cost of CO_2 emissions. To solve the TSRP-MMD, we utilized a variant of the Clarke and Wright Savings heuristic (CWSH) algorithm and local search previously developed by [14] and described in detail in their work. We have modified their algorithm to include the time window on the trips' departing times when solving the TSRP-MMD.

B. The Online Planning Module

Our approach to DM includes three main steps as shown in Fig. 4. When UE happens, the first step is to simulate how the initial transport plan will evolve after UE has happened. This allows for identifying which trips will be affected over the UE duration. For this purpose, a DES model is used to mimic the evolution of the transport network over time

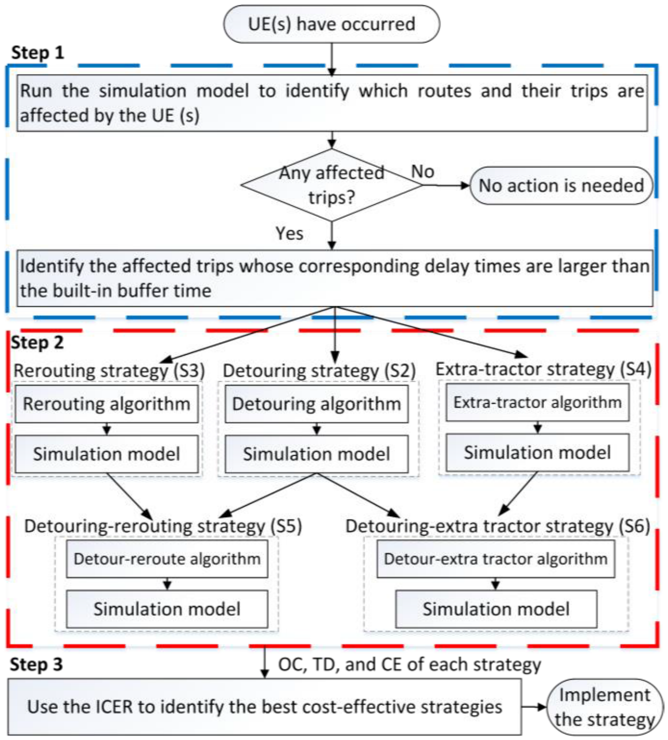


Fig. 4. The different procedures of the operational disruption management module.

after disruptions. In particular, the simulation can track the movements of tractors and the execution progress of their schedules in real-time, thus all trips that will be probably affected during the UE duration can be identified. Also, the simulation model evaluates OC, TD, and CE of the transport plan. In the second step, the re-planning algorithms take the results of the simulation model as input and search for a new plan that improves total delay time compared to the accept strategy (S1). Note that only the affected trips, whose delays exceeded the built-in buffer time, are planned. Afterwards, the simulation model evaluates OC, TD, and CE of each strategy. Finally, the best cost-effective strategies are determined based on the ICER in the third step. In the following, the simulation model, re-planning algorithms, and ICER method will be explained in detail.

1) The Proposed DES Model: The simulation model is a discrete event model built into the Arena environment. In the Arena environment, complex systems can be efficiently described by a flow chart with general-purpose modules. Therefore, Arena has been the most used simulation software in the logistics and supply chain literature [30]. The two important steps in our simulation model are building the terminal network and specifying the logic of freight flows among the terminals. The terminal network is modelled by STATION and ROUTE modules where each terminal is defined by a STATION module while ROUTE modules are used to define links connecting the terminals. Since there might exist several terminals, the Advanced Set module is used to build the network more efficiently. The Advanced Set module defines the terminals as a group where each terminal is referenced using an index. Regarding the logic of freight flows, tractors are modelled using entities where an entity is created for each route being unfinished when the UE has occurred. The attributes of unfinished routes are defined using a set of two-dimensional variables. For example, the transport plan obtained by the offline planning algorithm is defined as a two-dimension variable in which columns represent the tractor ID and rows represent the remaining unfinished trips of each tractor's route. At the start of the simulation, a READ module imports different simulation parameters, e.g., travel speed, distances among terminals, emission factor, cost per km, and UE's information. Entities are generated by the CREATE module. Following this, an ASSIGN module assigns the attributes of unfinished routes, e.g., sequence of trips and freight weight on each trip, to the generated entities. During the simulation, each entity travels through the transport network according to its trip sequence defined in the transport plan. The UE is defined in the simulation model by its occurrence time, location (disrupted link), and duration. A CHECK module is used to identify whether the trip is affected by the UE. For the first-affected trips, their travel times are increased by a delay time that is equal to the difference between the time at which the tractor reaches the UE's location and the time at which the UE ends. A DELAY module is used to model potential delay times due to the UEs. As the transport plan evolves with time, information on travelling distances, service times, and CO2 emissions of each tractor is collected. The tractor leaves the simulation once its planned route ends. To ensure the deliveries of all planned trips, the simulation time is run until all entities leave the simulation. The simulation model evaluates OC, TD, and CE of the transport plan taking into consideration uncertain travel times. Travel times along highways might vary due to several events such as congestion and stops for fueling, tolls, or short breaks. In this paper, the uncertainty of travel times is considered by the probability distributions of the travel speed which is assumed to be uniformly distributed between 60 and 80 km/hour. OC is calculated following the work in [31], based on a fixed cost rate (unit cost per hour) and a variable cost rate (unit cost per km). TD is calculated as the product of time delay per first-affected trip and the number of affected trips. The number of affected trips in each route includes the first-affected trip and reactionary-affected trips. The CO2 emission of each trip is calculated following the method described in [32] which used the Passenger car and Heavy-duty Emission Model to estimate the CO2-emission factors at different values of payload and speed. Linear interpolation and extrapolation were utilized to get the emission values at other payload values. The CO2 emission of the tractor while waiting for the disruption is estimated as 13.5 Kg CO2/hour, following the work in [33].

It is worth noting that the proposed simulation model reflects the same detail of abstraction used in the TSRP-MMD. This explains why consolidation operations at the terminals are not represented in the simulation model. Before using the simulation model, its accuracy should be investigated. According to Law *et al.* [34], verification and validation are two important tasks to test the accuracy of the simulation model. Verification of the model ensures that the developed simulation model behaves in the way it was designed. For verification, a variety of small transport plans (18 trips and 3 tractors) were input into the simulation model. After each run, the values of OC, TD, and CE obtained by the simulation were compared to the values calculated manually. Validation of the model is conducted to ensure the developed simulation model simulates accurately the line-haul transport plan developed by the CWSH procedures. For validation, a comparison is made between the results of the simulation model in deterministic settings and the results of the CWSH procedures for the same transport plans. The results proved the accuracy of the proposed simulation model.

2) Re-Planning Algorithms: These re-planning algorithms consider only the affected trips whose corresponding delay times exceed the built-in buffer time. In addition, the delay time of the accept strategy is set as an upper bound for accepting the re-planning solutions. Fig. 5 illustrates the detailed steps of re-planning algorithms.

```
1.  Initialization
2.  Let U be the set of all unaffected routes, indexed by u
3.  Let Q be the set of all affected routes, indexed by q
4.  Let R_q be the set of all affected trips of route q, indexed by r
5.  Let t_rq is the delay of trip r in route q as obtained from the accept strategy (S1)
6.  Let L be the set of affected links
7.  Detouring algorithm
8.  Input: L, Q, R_q ,t_rq
9.  Output:D (set of routes to be rerouted), d_rq (delay of trip r in route q in case of rerouting),
10.   Remove the affected links from the network
11.   For each route q ∈ Q
12.     For each trip r ∈ R_q , r=1 (r=1 means only the first-affected trip)
13.       If an alternative link (detour) is found by Dijkstra algorithm such that d_1q < t_1q, Then
14.          Add the route q to set D
15.       Else
16.          No detour is available
17.       End if
18.     End for
19.   End for
20. Rerouting Algorithm
21. Input: U, Q, R_q ,t_rq
22. Output: Updated version of U and Q, f_rqu (delay of trip r of route q if reassigned to route u),
23.   Sort the routes in Q in ascending order of its delay t_1q .
24.   For each route q ∈ Q
25.     For each trip r ∈ R_q , r>1 (r>1 means only the reactionary-affected trip)
26.       For each route u ∈ U
27.         Use the CWSH to find all least cost insertions of trip r into route u, such that f_rqu < t_rq
28.       End for
29.       Add trip r to the route in U that results in the lowest value of f_rqu
30.       Remove trip r from route q
31.     End for
32.   End for
33. Extra tractor planning algorithm
34. Input: Q, R_q ,t_rq
35. Output: E (set of the affected routes to be served by the hired extra tractors),
36.   Calculate TD_q which is the total delay time in route q as TD_q=(|R_q| − 1). t_1q
37.   Sort routes in Q in descending order of TD.
38.   Select a number of routes (defined by the planner) from the top of Q and add them to E
39. Detouring-rerouting algorithm
40. Input: U, D, Q, R_q , d_q , f_rqu
41. Output: Updated version of D and Q
42.   For each route d ∈ D
43.     For each trip r ∈ R_d, r>1 (r>1 means only the reactionary-affected trip)
44.       If trip r appears in the detouring and rerouting solutions, Then
45.          trip r is treated with the strategy that minimizes its delay time
46.       End if
47.     End for
48.   End for
49. Detouring-extra tractor algorithm
50. Input: D, E_q, R_q , d_q
51. Output: Updated version of D and E_q
52.   For each route d ∈ D
53.     For each trip r ∈ R_d, r>1 (r>1 means only the reactionary-affected trip)
54.       If trip r appears in the detouring and extra-tractor solutions, Then
55.          trip r is treated with the strategy that minimizes its delay time
56.       End if
57.     End for
58.   End for
```

Fig. 5. Steps of the re-planning algorithms.

a) Detouring algorithm: In Fig.5, Lines 7-19 show the detouring algorithm that is based on the Dijkstra method and considers only the first-affected trips. First, the transport network is modified by removing the affected links (line10). Then, the Dijkstra algorithm is used to find an alternative path (the shortest one) from the current location of the tractor to its destination terminal. If an alternative path is found, this path is accepted only if it results in a delay lower than that of S1 (line 13). Otherwise, the trip should wait until the end of the UE (line 16).
b) Rerouting algorithm: Lines 20-32 of Fig. 5 show the rerouting algorithm that is based on CWSH procedures. Priority is given to routes with large delays in the first affected-trips (line 23). The rerouting algorithm tries to find a least-cost insertion for each reactionary-affected trip into unaffected routes that are still in execution (line 25). To avoid changing the schedules of unaffected routes, the trip must be inserted into the beginning or the end of the route without violating the driving-time constraint. Besides this, the found insertion is acceptable only if it results in a delay lower than that of S1 (line 27). Particularly in this strategy, an important consideration is whether existing routes have slack times or not. The slack time should be enough for all additional times for rerouting such as repositioning, waiting, and travelling times of the trip. Since tractors have a high utilization rate, this strategy does not find many feasible insertions into existing routes.
c) Extra tractor planning algorithm: Lines 33-38 of Fig. 5 show the extra tractor-planning algorithm. In hiring extra tractors, decisions have to determine the number of hired tractors and which trips will be served by the hired tractors. A few extra tractors are often hired from the spot market since the re-planning budget is limited and spot prices are usually much higher than internal costs per km [35]. In addition, priority is typically given to routes that have many trips with relatively larger delays (lines 36-37). Once these decisions are made, the transport planner asks the partner carrier to send a number of extra tractors to specific terminals from which the service of trips will start. To calculate the CO2 emissions of the extra tractors, we assume that their initial locations are pre-defined, and they will serve the trips following the same order as was specified in the original plan.
d) Detouring-rerouting algorithm: Lines 39-48 show the detouring-rerouting algorithm. When combining the solutions of detouring and rerouting strategies, it might happen that one successive trip or more appears in the solutions of both strategies (line 44). In this case, only one solution has to be selected. We select the solution that will result in the lowest delay for the trip (line 45).
e) Detouring-extra tractor algorithm: Like detouring- rerouting algorithm, combining the solutions of detouring and extra-tractor strategies might lead to a case where one successive trip or more appears in the solutions of both strategies (line 54). In this case, the solution with the lowest delay is selected (line55).

3) The ICER Method: As stated before, each re-planning strategy is evaluated in terms of three indicators: OC, TD, and CE. Given the difficulty in measuring the cost of time delays and the tradeoff between the cost of the strategy and its effectiveness in reducing the time delays, a method is required to calculate, for each strategy, what will be the additional cost to reduce the time delay by one hour. For this purpose, we use the ICER proposed by Johannesson and Weinstein [36] which has been recently used in the supply chain literature on DM [3]. The ICER is by definition a comparison since it compares the difference in costs between two competing strategies to the difference in their degrees of effectiveness. Effectiveness represents any performance indicator that cannot be quantified in a monetary value. Therefore, our research considers TD obtained by each strategy as the degree of its effectiveness. The ICER for a strategy, i can be calculated as follows:

$$\mathrm{ICER}_i = \frac{\mathrm{C}_i - \mathrm{C}_{i-1}}{\mathrm{TD}_i - \mathrm{TD}_{i-1}} \tag{1}$$

where C_i and C_{i-1} are the total transport costs of strategy i and strategy *i-1*, respectively. C_i is calculated as $\mathrm{OC}_i + unitcost\ of\ Kg\ CO2 * \mathrm{CE}_i$. TD_i and TD_{i-1} are the total time delay of strategy i and strategy *i-1*, respectively. Since TD_i might be smaller than TD_{i-1}, the calculated ICER has a negative value. It is worth noting that operational transport cost is always significantly larger than the emission cost and, therefore, emission cost might not influence the ICER value. However, the consideration of emission cost makes the proposed ICER approach more comprehensive. For example, the ICER analyses can be made for only the emission cost or operational transport cost, or both. In addition, other negative impacts of transport on society (e.g., accidents and noise) might be considered along with emission cost, which in turn enables analyzing the trade-offs between the different transport costs. For decision-making, the ICER can be interpreted as the Willingness to Pay (WTP) which is the maximum amount of money the planner is willing to pay to switch from one strategy to another. In this sense, transport planners can use their expertise to find a good compromise between the re-planning costs and these real-world issues arising due to the time delay. To compare the six re-planning strategies in each case by using the ICER, a six-step procedure is utilized as follows:

Step 1: Sort all strategies in ascending order of their total transport costs, C.

Step 2: Find and remove weakly and strongly dominated strategies. A strategy, i is weakly dominated if its C_i equals to C of its preceding strategy but achieves more TD or if its TD_i equals to TD of its preceding strategy but has more C. A strategy, i is strongly dominated if its C_i and TD_i are higher than that of its preceding strategy.

Step 3: For each strategy, calculate ICER using equation (1).

Step 4: Check if $|\mathrm{ICER}_i| > |\mathrm{ICER}_{i+1}|$, then remove strategy i since it is considered to be dominated by strategy $i+1$.

Step 5: Repeat steps 3 and 4 if necessary.

Step 6: Obtain a list of the recommended strategies based on the ICER.

IV. Numerical Experiments

This section aims to test the proposed approach in different case studies with various road disruptions. First, the section presents the data of case studies, the transport network, and road disruptions. Following this, the results of several experiments with the proposed approach are discussed. The numerical experiments are run on a PC with an Intel(R) Core (TM) i7 and 8 GB of memory. The re-planning algorithms are implemented in MATLAB (R2018b) while the simulation model is implemented in Arena15.10.

A. Input Data

1) Case Studies: Three case studies are used to test the proposed approach. The use of multiple case studies enables a better understanding of the results since the results can be analyzed within each case study and across case studies. The case studies were provided by a logistics company operating a daily average of 210 line-haul trips among its main seven terminals in Denmark. Most of the line-haul trips are made between 18:00 and 6:00 AM. The real data describes the freight weight, planned departure time, origin, and destination terminals of each trip. Google map is used to obtain the distance matrix among the terminals. Each case study represents a daily TSRP-MMD that is solved using the CWSH algorithm described in section III. Table I describes the solution of each case study in terms of the number of trips, operating cost of vehicles (OC), CO2 emissions (CE), and the total transport cost (TC). Fixed cost rate is 45.50 \$/hour while the variable cost rate is 0.37 \$/km. The spot-market price of the hired tractor is 105.19 \$/hour and the number of hired tractors is two tractors. To convert the emissions into monetary value, a reference value of 0.04 \$ per kg of CO2 emissions is used [37]. Following the work in [33], the CO2 emission and fuel consumption of idling (waiting for the disruption) are estimated as 13.5 Kg CO2/hour and 6.00 liters per hour, respectively. To protect against small delays, transport planners often add a little buffer time to the line-haul transport plan. This is because the travel time reliability is often high along the motorways at night, as in our case. In addition to this, it makes sense to reduce the buffer time if real-time DM strategies are to be adopted, which in turn reduces the transport cost and maximizes resource utilization. In the case studies, the buffer time for the route is 0.75 hours and may be distributed over all the trips of the route to protect against small delays in each trip. If the delay due to UEs at any trip reaches 0.75 hours, this means that no buffer time is available for succeeding trips, and in this case, re-planning of transport operations is necessary.

2) The Road Transport Network: The detouring strategy requires knowledge of the road network. Fig. 6 shows a node-link representation of the highways connecting the freight terminals. For confidentiality reasons, the locations of the freight terminals cannot be shown in Fig. 6. The transport network is represented by 40 nodes connected by 60 links,

TABLE I
MAIN INDICATORS IN EACH CASE STUDY

Case study	Number of trips	OC ($)	CE (Kg CO2)	TC ($)
C1	227	37392.93	22191.00	38258.38
C2	220	34194.86	20293.10	34986.29
C3	220	37246.55	22104.10	38108.61

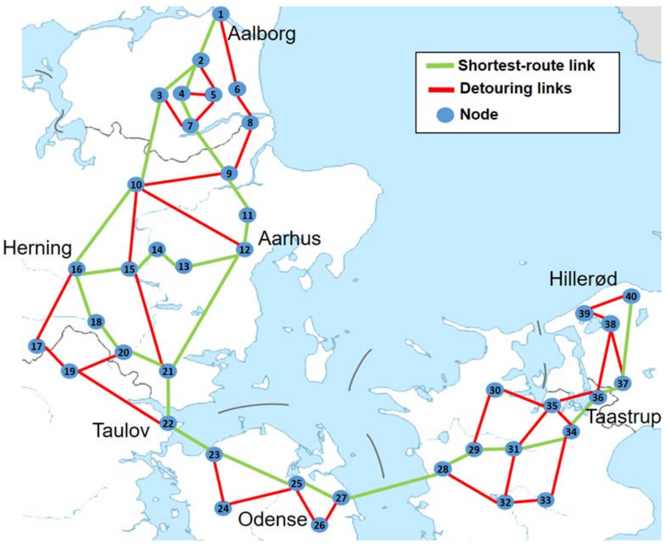


Fig. 6. A node-link representation of the transport network.

where each link is bi-directional. In addition, the network has two types of links, i.e., shortest-route links and detouring links. The shortest route connecting each pair of terminals is always composed of the shortest-route links. We assume that the vehicles always drive among terminals using the shortest routes. However, the vehicles might use the detouring links if the UE temporarily closed one of the shortest-route links.

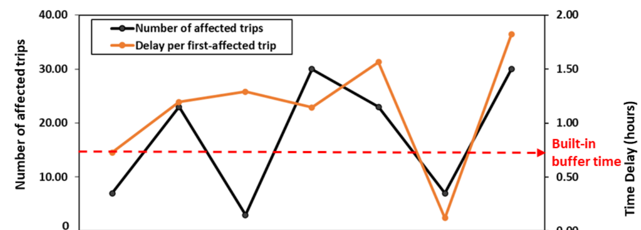
3) Road Disruptions Data: Road disruption data was obtained from the Danish road authority, covering four years from 2017 to 2020. The provided data describes the durations and locations of UEs that caused the closures of the highways (shortest-route links). To test the proposed approach in different disruption scenarios, a Monto Carlo sampling procedure is used to generate various UEs based on the historical data. To increase the diversity of the results and avoid conducting too many experiments, each case study is tested with seven UEs of different characteristics as shown in Table II. UEs whose durations are lower than the buffer time (0.75 hours) are not considered. In Table II, the second column ‘affected link’ refers to the link where UEs happened (see Fig.6). The DES model simulates the execution of the planned transport operations, and every time a UE occurs, the proposed approach is used to identify the best cost-effective re-planning strategies to deal with this UE.

B. Experimental Results

This section discusses the results of the six re-planning strategies and the ICER method in different cases. Since re-planning is made only for the affected trips which represent a small portion of the total trips, the average running time of the proposed approach in each case is around 30 seconds.

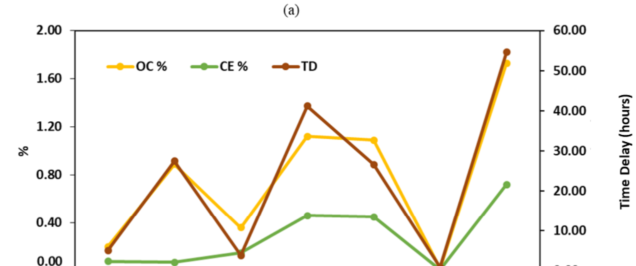
TABLE II
DATA OF THE SEVEN UES

UEs	Affected Link	Occurrence time	Duration (hour)
UE1	2-4	20.24	1.00
UE2	27-28	19.00	1.50
UE3	21-12	7.58	2.00
UE4	25-27	21.00	2.50
UE5	22-23	3.00	3.00
UE6	12-11	15.00	3.50
UE7	25-27	20.00	4.00



Case	C1(1)	C1(2)	C1(3)	C1(4)	C1(5)	C1(6)	C1(7)
Link	2-4	27-28	21-12	25-27	22-23	12-11	25-27
Start Time	20.24	19.00	7.58	21.30	3.10	15.00	20.00
Duration (h)	1.00	1.50	2.00	2.50	3.00	3.50	4.00

(a)



Case	C1(1)	C1(2)	C1(3)	C1(4)	C1(5)	C1(6)	C1(7)
Link	2-4	27-28	21-12	25-27	22-23	12-11	25-27
Start Time	20.24	19.00	7.58	21.30	3.10	15.00	20.00
Duration (h)	1.00	1.50	2.00	2.50	3.00	3.50	4.00

(b)

Fig. 7. The impacts of UEs on case study (C1) in terms of the number of affected trips and average trip delay (a) and the three performance indicators (b).

1) Analysing the Impacts of Different UEs: UEs have unpredictable characteristics, i.e., location, start time, and duration. Therefore, we, herein, aim to investigate how OC, CE, and TD are influenced by the characteristics of the UE. For this purpose, the results of the case study (C1) with the seven UEs are analyzed when no action is taken (Accept strategy). The analyses are shown in Fig. 7 in which C1(1) refers to the case composed of case study C1 and UE1. In addition, the percent increases in OC and CE are calculated with respect to the initial transport plan while TD is expressed in hours since no delay exists in the initial transport plan. The general trends of the line graphs in Figs 7a and b show that the different impacts increase with increasing the UE duration. This is because the trip delay depends on the difference between the time at which the UE ends and the time at which the vehicle reached the UE

TABLE III
RESULTS OF CASE STUDIES

UEs	Re-planning Strategy	Case study 1					Case study 2					Case study 3				
		FA	TA	OC (%)	TD (Hour)	CE (%)	FA	TA	OC (%)	TD (Hour)	CE (%)	FA	TA	OC (%)	TD (Hour)	CE (%)
UE2	S1	6	23	0.89	27.47	0.07	5	24	0.66	23.06	0.08	7	28	0.80	24.81	0.16
	S2			—	—	—			—	—	—			—	—	—
	S3			0.89	24.23	0.07			0.66	22.34	0.08			1.31	23.72	0.68
	S4			4.11	16.81	0.10			3.25	13.34	0.10			3.62	14.58	0.21
	S5			—	—	—			—	—	—			—	—	—
	S6			—	—	—			—	—	—			—	—	—
UE3	S1	2	3	0.36	3.87	0.15	1	2	0.07	0.80	0.03	0	0	—	—	—
	S2			0.41	2.07	0.41			—	—	—			—	—	—
	S3			0.91	2.44	0.70			—	—	—			—	—	—
	S4			0.54	2.44	0.25			—	—	—			—	—	—
	S5			0.41	2.07	0.41			—	—	—			—	—	—
	S6			0.68	1.38	0.51			—	—	—			—	—	—
UE4	S1	6	36	1.12	41.20	0.46	2	20	0.49	30.54	0.20	2	10	0.55	18.55	0.23
	S2			0.79	21.73	0.57			0.23	7.14	0.23			0.46	13.60	0.25
	S3			4.11	37.29	2.40			0.75	25.48	0.46			0.79	14.26	0.47
	S4			3.46	17.47	0.62			4.50	3.48	0.27			2.50	3.71	0.30
	S5			3.80	17.81	2.51			0.50	6.43	0.50			1.20	10.50	0.99
	S6			3.29	6.91	0.77			4.54	1.17	0.34			2.53	2.72	0.35
UE5	S1	5	17	1.09	26.61	0.45	4	20	1.35	38.46	0.56	4	20	1.17	33.74	0.48
	S2			—	—	—			—	—	—			—	—	—
	S3			1.78	24.35	1.15			1.90	34.57	1.12			2.01	27.19	1.33
	S4			2.38	13.09	0.65			2.50	19.01	0.72			3.63	15.34	0.69
	S5			—	—	—			—	—	—			—	—	—
	S6			—	—	—			—	—	—			—	—	—
UE7	S1	9	30	1.73	54.60	0.72	5	25	1.82	59.46	0.75	11	43	3.28	97.64	1.37
	S2			1.26	34.22	0.89			0.76	15.72	0.65			1.74	32.76	1.34
	S3			2.45	52.31	1.45			2.02	58.46	0.96			3.70	93.32	1.80
	S4			3.76	23.65	0.89			4.05	34.15	0.85			5.50	76.53	1.44
	S5			1.98	33.50	1.62			0.76	15.72	0.65			1.74	32.76	1.34
	S6			3.50	10.10	1.21			3.47	13.57	1.41			4.20	20.57	1.76

location, thus longer UE probably increases the trip delays. However, the trendlines decrease in cases C1(3), C1(5), and C1(6). The reason is that the impacts of the UE also depend on the start time of the UEs since most trips start from 18.00. Thus, the closer the time of UE is to 18.00, the more the first-affected trips are at the beginning of the tractor schedule, resulting in at least 5 or 4 reactionary-affected trips. Fig. 7a shows that in most cases, the delay per first-affected trip is more than half of the UE duration. In addition, some delays exceeded the built-in buffer time, raising the need for DM to reduce the negative consequences of the delays. Fig.7b shows that the changes in OC % and CE % are small, ranging from 0.02% to 1.73% and 0.01% to 0.072 %, respectively. This is because the ratio of first-affected trips to all trips is low. In fact, in some cases, the impacts of the UE also depend on the affected link. This includes, for example, the case where UEs occur on a link that the company rarely uses. It can be concluded from Fig. 7 that the proposed approach supports transport planners in identifying quickly the critically affected trips, i.e., those trips whose delays are more than the built-in buffer time, taking into consideration the UE characteristics (i.e., location, start time, and duration) and planned routings of the tractors. So, only the affected trips can be considered into the DM. This is of great importance, especially in large fleet sizes where identification of the affected trips becomes more complex, and human decision making might result in a poor rescheduling solution.

2) Results of the Re-Planning Strategies: The combinations of the three case studies with the seven UEs resulted in 21 cases. 14 out of the 21 cases have trips whose delays exceeded the built-in buffer time. Thus, the six re-planning strategies are applied to these 14 cases and the results are compared to the initial transport plan. The experimental results of the 14 cases are shown in Table III. Note that '—', in Table III, means that the strategy is not available since a feasible solution could not be found or it could not reduce the total delay time compared to the accepting strategy. As stated before, a road closure delays the first-affected trip, and the resulting delay is transferred to the successive trips (i.e., reactionary-affected) made by the same tractor. Therefore, the second and

TABLE IV
RECOMMENDED STRATEGIES BASED ON ICER

UEs	Case study 1			Case study 2			Case study 3		
	Recommended strategy	TD (hour)	WTP ($/hour)	Recommended strategy	TD (hour)	WTP ($/hour)	Recommended strategy	TD (hour)	WTP ($/hour)
UE2	S3	24.23	—	S3	22.34	—	S1	24.81	—
	S4	16.81	162.29	S4	13.34	107.619	S4	14.58	102.86
UE3	S1	3.87	—	—	—	—	—	—	—
	S2	2.07	9.94	—	—	—	—	—	—
	S6	1.38	147.15	—	—	—	—	—	—
UE4	S2	21.73	—	S2	7.14	—	S2	13.60	—
	S6	6.91	62.10	S5	6.43	137.94	S5	10.50	89.10
	—	—	—	S6	1.17	287.37	—	—	—
UE5	S1	26.61	—	S1	38.46	—	S1	33.74	—
	S4	13.09	35.787	S4	19.01	22.12	S3	27.19	47.10
	—	—	—	—	—	—	S4	15.34	51.22
UE7	S2	34.22	—	S2	15.72	—	S2	32.76	—
	S6	10.1	34.7115	S6	13.57	473.73	S6	20.57	75.42

third columns of Table III show the number of first-affected trips (FA) and the total number of affected trips (TA) for each case. TA is calculated as the sum of the first-affected trips and reactionary-affected trips in all routes. In all cases, the TA ranges from 0 in C3(3) up to 43 trips in C3(7). In general, the impacts of UEs on FAs and TAs differ among the three case studies. This implies that the impacts of the same UE might vary from one day to another, depending on the freight flows among the terminals and the characteristics of UEs, confirming the observations obtained in the previous section. As stated before, TD is the sum of time delays in all affected trips. For example, in case study C1 and UE2, FA of 6 means that six routes are affected by UE2. The numbers of affected trips in these six routes (from the first route to the sixth route) are 3, 5, 3, 4, 4, and 4, respectively. This results in TA of 23 trips. The time delays per first-affected trip in these six routes (from the first route to the sixth route) are 1.30, 1.30, 1.12, 1.00, 1.01, and 1.37 hours, respectively. Note that we consider the buffer time of the route a delay if it is completely consumed at one trip. Accordingly, the buffer time of the route is not deducted from the delay in the first-affected trip when calculating TD in the 14 cases. Thus, TD of the six routes can be calculated as the sum of multiplying the number of affected trips in each route by its corresponding time delay per first-affected trip. This results in TD of 27.47 hours. Regarding the performance of re-planning strategies, we can notice from Table III that although all strategies achieve different effectiveness levels of reducing the total delay times, they increase the transport cost and carbon emissions compared to the initial transport plan. On average, the cost-based rankings of the strategies are S2 < S1 < S5 < S3 < S6 < S4 while the emission-based rankings are S1 < S4 < S2 < S6 < S5 < S3 and the lowest delay time-based rankings are S6 < S4 < S5 < S2 < S3 < S1. The differences in the three rankings imply that there are tradeoffs among the different performance indicators for each strategy. In most cases, the results suggest that S2, if available, is the best in terms of transport cost but it is not always the best in terms of total delay time and emissions either. S1 has the least amount of emissions, and it provides the second lowest cost but is the worst in term of total delay time. S3, S4, S5, and S6, if available, can reduce the total delay time, but they incur more costs and emissions. For instance, S4 is the worst in term of transport cost due to the relatively high cost of adding extra tractors, and it is not always the best in terms of total delay times or emissions. In all cases, S6 has the lowest delay time, and its added costs are slightly lower than that in S4, but it still results in relatively higher emissions. At the first glance, one can notice that in most cases, S3 has higher costs and emissions since it requires additional repositioning trips and waiting times. In addition, it slightly reduces the total time delay compared to the other strategies. However, S3 might result in the lowest transport and emissions if there are no repositioning trips and waiting times required. An example of this is C1 (2). S5 combines the advantages of S1 and S3 but still has their shortcomings.

3) Strategy Selection Based on the ICER: The results of the previous section indicated multiple trade-offs among the three performance indicators, i.e., cost and emissions often increase when planners try to reduce the delay time or improve the service level. Clearly, the six re-planning strategies compete against each other and there is no clear dominance of one strategy on the performance indicators across all cases. Thus, this confirms the need for a method supporting the planners in selecting the appropriate strategy. Table IV shows the recommended strategies obtained by the procedures of ICER for each case in Table III. As already mentioned, the WTP in Table IV is the maximum amount of money the planner is willing to pay to switch from one strategy to another. Taking case study 3 and UE5 as an example, three strategies S1, S3, and S4 are identified as the most cost-effective re-planning strategies. If the planner prefers the cheapest one and is satisfied with its delay reduction, then S1 is selected. If the planner needs to reduce the time delay by 5 hours compared to S1 but he is willing to pay 47.10 USD for each one-hour reduction, then S3 is selected. If the planner still needs to reduce the time delay with paying more than 51.22 USD for each one-hour reduction, then S4 is selected. This example shows the ability of the ICER to guide the best possible decisions by combining the intuition of the planners and the results from the proposed approach. The overall results of Table IV show that the cheapest, recommended strategies are S1(Accept) and S2 (detouring). This implies that planners who are not willing to invest in DM will always select S1 and S2. In contrast to that, S4 and S6 will be selected if the planners have a high willingness to invest in DM. It is worth noting that S3 and S5 appear in a few cases compared to the other strategies since they are often weakly or strongly dominated strategies and so, are eliminated by step 2 of the ICER procedures. Generally, S3 and S5 appear when other strategies are not available. The results of the ICER analysis showed that the best cost-effective strategies differ from one case to another and depend on different parameters including the characteristics of the UEs, the fright flows, and the willingness of the planners to pay for reducing the transport delays. The results also showed the fact that switching from one strategy to another can achieve a significant reduction in time delays while the additional cost is relatively small. An example of this is C1 with UE5. Thus, transport planners are advised to evaluate possible re-planning options instead of accepting the delay.

V. Conclusion

The present work contributes to the literature by developing a DSS, based on a hybrid simulation-optimization approach and ICER-based method, for managing road disruptions in the line-haul transport network. The proposed DSS enables the integration of various planning phases including transport planning, execution, monitoring, and evaluation of six re-planning strategies for managing impacts of detected disruptions. The six re-planning strategies, namely the accepting strategy (S1), the detouring strategy (S2), the rerouting strategy (S3), the extra-tractor hiring strategy (S4), and the combination of the detouring and the rerouting strategies (S5), and the combination of the detouring and the extra-tractor hiring strategies (S6). For each detected UE, the re-planning strategies are evaluated in terms of three performance indicators: cost, reliability (expressed in time delays), and CO2 emissions. In addition, an ICER method is used to compare the benefits of these strategies against each other in terms of total transport cost and their effectiveness in reducing time delays.

We tested the proposed DSS by using 21 real cases based on a line-haul transport network of a Danish logistics company. Therefore, the results give useful insights into how the road disruptions affect the line-haul transport operations and how effective the proposed re-planning strategies are in reducing the impacts of these disruptions. The results showed the impacts of road disruption not only depend on its duration but also on the extent of matching among the disruption characteristics (location and start time) and the driving times and roads used by the company. In all cases, the proposed approach could obtain re-planning solutions for each detected disruption in around 30 seconds. Although the re-planning strategies proved their effectiveness in reducing the delay times, they increase the transport cost and carbon emissions. On average of all cases, the cost-based rankings are S2 < S1 < S5 < S3 < S6 < S4 while the emission-based rankings are S1 < S4 < S2 < S6 < S5 < S3 and the lowest delay time-based rankings are S6 < S4 < S5 < S2 < S3 < S1. These rankings indicate a trade-off among the different performance indicators for each strategy. In addition, the six re-planning strategies compete against each other and there is no clear dominance of one strategy on the performance indicators across all cases. Accordingly, the ICER method is useful to decide on the best strategy considering multiple criteria and their inherent trade-offs. The results of the ICER analysis showed that the best strategy differs from one case to another and depends on different parameters including the willingness of the planners to pay for reducing transport delays. The overall results showed that planners who are not willing to invest in DM will always select S1 and S2 while S4 and S6 are recommended if the planners have a higher willingness to pay. S3 and S5 are viable options in a few cases when other strategies are not available. The results also showed the fact that switching from one strategy to another can achieve a significant reduction in time delays while the additional cost is relatively small. Therefore, incorporating the ICER method into DM enables the planners to select the strategies that reduce the delay times at a low increase in cost.

There are several future directions based on this study. First, expanding the proposed approach by considering the prediction of road disruptions instead of assuming that the length of disruptions is known as in this paper. Second, expanding the simulation model by considering the handling operations inside the consolidation terminals. The proposed approach can handle disruptions resulting from vehicle breakdowns only if the failed vehicle can be repaired where it has broken down and can resume its journey after being repaired. Thus, future research might extend the proposed approach to consider vehicle breakdowns where the failed vehicle cannot resume its journey and its load must be transferred to an active vehicle. In addition, other types of disruptions related to terminal operations such as labor shortage and machine breakdown can be also considered. Future work might also consider different combinations of UEs occurring at the same time, following the work of Hrušovský [4]. This can enable making more general conclusions on the best mitigation strategy to use in different levels of disruptions, i.e., highly and slightly disrupted networks.

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