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van der Tuin, Marieke S.; Pel, Adam J.

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ORIGINAL PAPER

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The disruption transport model: computing user delays resulting from infrastructure failures for multi-modal passenger & freight traffic

Marieke S. van der Tuin*  and Adam J. Pel

Abstract

Transport infrastructure owners are moving from reactive toward proactive infrastructure management. This involves computation of costs associated with failure or maintenance, including expected transport delays. These delays are often computed by multiplying additional travel time by the number of travellers. However, this does not reflect the process of decision-making by travellers using the infrastructure asset, such as mode choices, departure time changes and trip cancellations to reduce time wasted in a traffic jam. Therefore, we introduce a multi-modal transport model that simulates travellers' behaviour after a large-scale infrastructure failure at a critical node in the European TEN-T network. We use a novel approach of modelling the region around the infrastructure disruption in a very detailed manner, whereas the rest of Europe is modelled in a more basic way. This enables us to model impacts of disruptions in high detail, whereas also effects throughout Europe are considered, within reasonable computation time.

Keywords: Transport model, Disruptions, Critical infrastructure, Traveller behaviour, Traffic assignment, TEN-T network

1 Introduction

In the recent years, the number of infrastructure failures has increased due to ageing of infrastructure, more extreme weather events due to climate change, and increased traffic loading. Accordingly, the number of maintenance projects and resulting (partial) closures of the transport network has increased. This leads to a growing interest for making robust, cost-effective decisions on maintaining and upgrading infrastructure to prevent failures. Transport infrastructure owners are moving from reactive infrastructure management toward proactive management, by prioritising upgrades for critical network assets. Nowadays, such predictive maintenance techniques incorporate measuring the condition of assets, combined with life cycle costs analysis (LCC). Associated costs do not only involve reconstruction costs, but also costs experienced by users of the transport network. For example, a broken freight rail track in

Germany resulted in €100 million loss for the logistics sector due to the limited amount of other freight rail tracks available in the region [20]. The LCC usually computes these user costs (e.g. loss of service due to congestion and detour) by multiplying the (assumed) increased travel time by the number of travellers using the link [13].

However, this basic method of computing and monetizing user delays does not incorporate the aspect of user behaviour during such disruptions. For example, travellers may depart a little late to reduce experienced congestion time, shift to another mode, or cancel the trip completely. Additionally, this might result in delays for travellers who do not travel along the failed infrastructure object, which can be noticeable in other countries. Likewise, a simple multiplication of assumed increase in travel time for a group of travellers does not suffice.

Therefore, this paper introduces the Disruption Transport Model that simulates decisions made by travellers during infrastructure closures, both planned (e.g. maintenance) and unplanned (e.g. sudden failure caused by a natural hazard or ageing infrastructure). We focus on

* Correspondence: m.s.vandertuin@tudelft.nl
Department of Transport and Planning, Delft University of Technology, P.O. Box 5048, 2600, GA, Delft, The Netherlands

infrastructure failures in the European TEN-T network, consisting of the main roads, railways and inland waterways, for both passenger and freight traffic. Our model is built to simulate large-scale disruptions at critical nodes in the network, that possibly result in user delays propagating throughout Europe. The output of our model can be incorporated in advanced LCC analysis to consider effects of user delays in developing maintenance plans.

The Disruption Transport Model simulates the effects of a disruption by incorporating behavioural responses shown by travellers during such failures – which are typically different than simulated by a normal transport model. We first identify and quantify these behavioural responses by analysing literature and reports on previous occurring infrastructure failures. Following these results, our transport model simulates route changes, mode choices, departure time choices and trip cancellations. It uses a novel approach of modelling the region around the infrastructure disruption in a very detailed manner using dynamic traffic assignment, whereas the rest of Europe is modelled in a more basic way employing a static traffic assignment. This enables us to model disruption effects in high detail, whereas also effects throughout Europe are considered – within reasonable computation time. We finally demonstrate our transport model in a case study, involving the impacts of a potential infrastructure failure in the Port of Rotterdam.

2 Literature review: impact of infrastructure disruptions on behaviour of travellers

Behavioural responses of travellers are most likely not included in normal transport models. For example, it is unlikely that directly after an incident occurred a perfect equilibrium in traffic flows is achieved – that is, the situation where no traveller can improve its travel time by switching to another route or mode. Therefore, this section gives an overview of impacts of disruptions on passenger and freight traffic, based on reports on previous disruptions. We analyse 9 different studies reporting about 85 different infrastructure disruptions, both planned and unplanned. The durations of the closures range between a few weeks and 10 years. A full overview on analysed studies can be found in D2.2 of the SAFE-10-T project (to be published in July 2019).

2.1 Passenger transport during disruptions

Passenger transport in the TEN-T network comprises road and railway. Both transport networks have a different lay-out and density: Europe has a very dense network of road links, but a sparse network of rail links. This has its implications in available detours during disruptions. It is likely that a closed road link can be avoided easily by choosing another route, whereas this is not the case for a closed railway link.

For infrastructure failures in road transport networks, changing route is therefore considered as the most viable option. Up to 50–60% of travellers switch to another route during an infrastructure failure [3, 8, 11, 12, 22]. If the road is only blocked partially, “doing nothing special” accounts for 90% of the travellers [17]. However, evidence shows that some passengers tend to avoid the location of a failed infrastructure element completely even though there may still be capacity available (e.g. partially closed due to a slope failure) due to the perception of a safety risk [5]. Besides switching to another route, changing departure time is also often reported. This is valid for 20–40% of the travellers [11, 12, 22]. It is often seen that the peak period lasts twice as long as normal.

Additionally, more severe disruptions – such as the Workington case where all bridges beside a train bridge collapse [8] – show high percentages of trip cancellations (33%). Another bridge collapse in Australia in 1975 requiring a 50 km additional drive to the next bridge [22], resulted in even higher percentages of 60% of trip cancellations. On the other hand, most other disruptions lead to a 2–5% of trip cancellation, as was shown by comparing traffic counts of 70 different road construction works [3]. Switching to alternative travel modes is less evident and done by 2–8% of travellers [11, 17, 22]). However, these values increase rapidly if public transport is made more attractive by introducing additional train stations (25%, [8] or by running more frequent services (19.5%, [12]). Other behavioural responses such as sharing travels with family members or switching to other destinations are sometimes reported, but less common.

Public transport disruptions tend to cause a large shift toward travelling with different modes: 50–60% chooses to travel by car during public transport strikes [19]. Additionally, sharing of travels (e.g. carpooling) is reported in 10–30% of the cases. Both observations can be explained by the structure of the network: if a public transport link fails, not much other options are left than to switch to car. Another possibility is to cancel the trip completely, which is reported in 10–15% of the analysed studies. A choice for other destinations was not reported, but this might be caused by the analysed periods, which are all peak periods. These periods are recognized by the high number of commuter trips, and one does not easily change its residential or work location.

2.2 Freight transport during disruptions

None of the analysed studies mentioned previously report impacts on freight separately. Although freight traffic might be limited at some corridors, there simply does not seem to be much attention to the impact for the logistics sector – except if it involves failure of a freight-specific link. One study that focussed on such a freight incident described the Rastatt failure [9]. During this

incident, a freight-rail track was blocked for 7 weeks. The network of freight tracks is limited, making it very hard to change route. At the end, 33% of freight volume had been transported by train – albeit with severe delays as well as during unfavourable time slots. This is in line with expectations given descriptions of the freight market structure, where generally contracts run for long periods of time and freight trains are scheduled more than a year in advance [16, 21]; rescheduling is to some extent possible, but only at unfavourable time slots or by incurring long waiting times.

Additionally, 32% of freight volumes were transported by different modes: 23% by truck, 9% by ship. The remaining, 35% of goods did not reach its destination at all. These shortcomings possibly have been resolved by using flexibility in the logistic & supply chain (e.g. using goods stored elsewhere). This agrees with the findings of McKinnon [14], who described in detail what would have happened if there was a strike by truck drivers in the UK. He concluded that trucks are most of the time irreplaceable by other modes due to lack of rail or water terminals at consumption locations. The fictitious disruption led to a shut-down of the country within a few days, relying mostly on stock levels rather than alternative transport modes.

2.3 Day-to-day variability

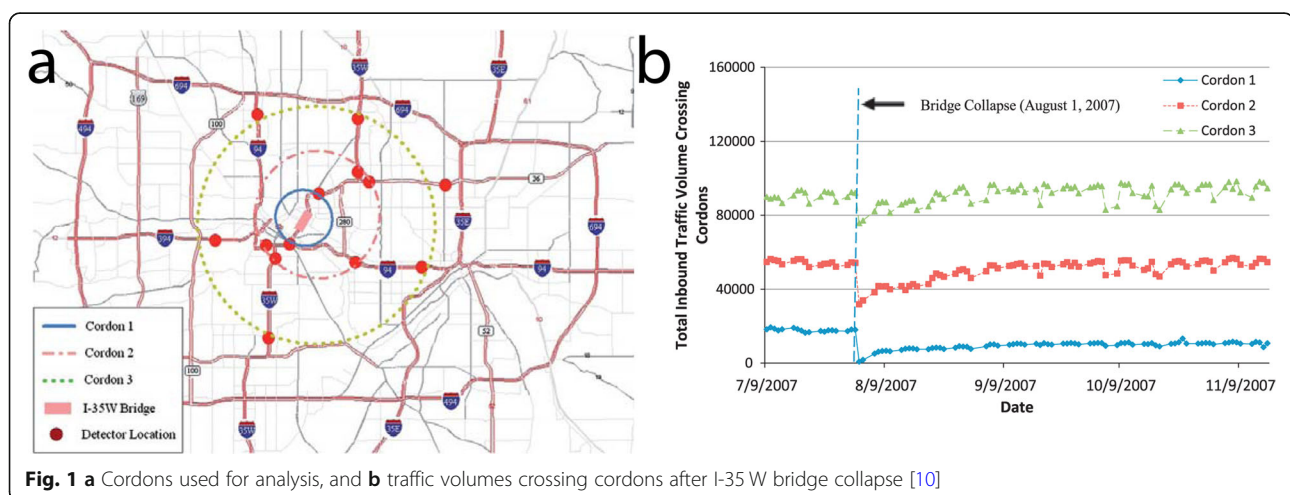
The behavioural responses mentioned in the previous sections are likely to result in a new equilibrium of traffic flows. However, evidence shows that this may take several weeks [5] due to habitual patterns and routines. Evidence has also shown that disruptions tend to lead to overreactions in passenger behaviour [4], leading to oscillating traffic among several routes (e.g. first a severe congestion on detour A, followed by a severe congestion on detour B the next day whilst detour A is underused). This day-to-day variability in choices made by travellers

is hardly reported, probably caused by the methodology generally used to obtain results: by performing a survey at a single point in time.

The only study found that reported on the day-to-day variability, described the I-35 W bridge crash in Mississippi [10]. Immediately after the collapse, the traffic counts dropped significantly at the 3 cordons to 0%, 40% and 20% of the original traffic volumes as shown in Fig. 1. It is shown that cordon 1 (the area near the bridge) stabilizes quickly due to a lack of alternative routes in the area. The traffic flows at cordon 2 and 3 recover after about eight weeks and four weeks, respectively. The researchers believe that recovery of traffic volume was mainly due to route and time adjustments – not due to changes in origins or destinations. Additionally, they also reported overall traffic volumes throughout the morning peaks following the collapse, reflecting the variability in the number of trip cancellations. They showed that the demand did not exhibit any drastic changes, fluctuating within the bounds of weekly variation. The lone exception is on Thursday 2nd of August, the day after the collapse: a large decrease in traffic compared to other Thursdays was seen.

2.4 Conclusion

Following the review on behaviour after infrastructure failures, it can be concluded that four types of behaviour are shown regularly and should be included in a transport model simulating disruption: route changes, departure time choices, mode shifts and trip cancellations. Exact percentages differ greatly among the several analysed disruptions, depending on the area and type of disruption. Additionally, it was shown that travellers tend to change their behaviour as days since the closure occurred progress, recalled as the day-to-day variability.



3 Methods: the transport model

Our model should analyse large scale impacts of failing critical nodes on the European TEN-T network. This TEN-T network consists of a multi-modal network of relatively high density which provides all European regions (including peripheral and outermost regions) with an accessibility that supports their economic, social and territorial development as well as the mobility of their citizens [7]. European transport models built for analysing the TEN-T network usually have a very low level of spatial detail (e.g. considering highways and neglecting local roads) and temporal detail (e.g. only modelling four time periods: weekday peak, weekday off-peak, holiday, weekend). Therefore, these models are not sufficiently detailed to model all detours in the vicinity of the infrastructure failure, as well as not detailed enough to model the built up and propagation of traffic over time and excluding any changes in departure times. Generally, static traffic assignments are employed, whereas a dynamic assignment would be more suitable for modelling disruptions. In a dynamic assignment, smaller time-periods are modelled, and traffic flows are modelled realistically instead of based on arbitrary functions of experienced travel time given a certain amount of vehicles.

Performing dynamic traffic assignments on a detailed European network is computationally very expensive and currently not feasible. But it should be noted that most effects of disruptions are not noticeable throughout Europe: they are resolved within a small area around the disruption. We therefore assume that disruptions only directly affect traffic in the vicinity of the infrastructure object in terms of choices made. On a European level, only secondary effects are noticed (e.g. congestion). The Disruption Transport Model therefore combines these two types of models: a detailed dynamic model for the region in the vicinity of the infrastructure element, referred to as Local Disruption model (LD) and a static traffic assignment model for the rest of the network of interest, referred to as Global Spill-

over model (GS). One can see it as zooming in around the object of interest, while zooming out when looking at a European level, as can be seen in Fig. 2. This simulation approach ensures that disruption effects are modelled accurately, whilst also considering the broader impacts at European scale.

The complete model overview is shown in Fig. 3, with the transport model of the LD model on top, the GS model below. Both transport models are based on the well-known 4-step passenger [15] and 5-step freight transport models [18], combined in a shared traffic assignment step. As stated before, we assume that disruptions only affect choices made in the vicinity of the infrastructure object. As such, trip cancellations, modal shifts and departure time changes are only modelled at the detailed model. The resulting choices and delays are used in the GS model. The number of *iterations* (i.e. steps toward reaching an equilibrium) are used to model the day-to-day variability. We believe that the process of reaching an equilibrium by a transport model reflects the process of travellers adjusting toward a new situation in selection of routes.

3.1 Procedure for running the model

The general steps for running the Disruption Transport Model as shown in Fig. 3 are as follows:

1. Initially, the area in the region of the infrastructure failure (i.e. detailed study area) is defined. This area is modelled with high level of detail and referred to as the *Local Disruption model (LD)*. The remainder of the network is modelled with a lower level of detail, referred to as the *Global Spill-over model (GS)*.
2. The trip generation, trip distribution and mode choice models for passengers, as well as the alike production/consumption, trade patterns, logistic

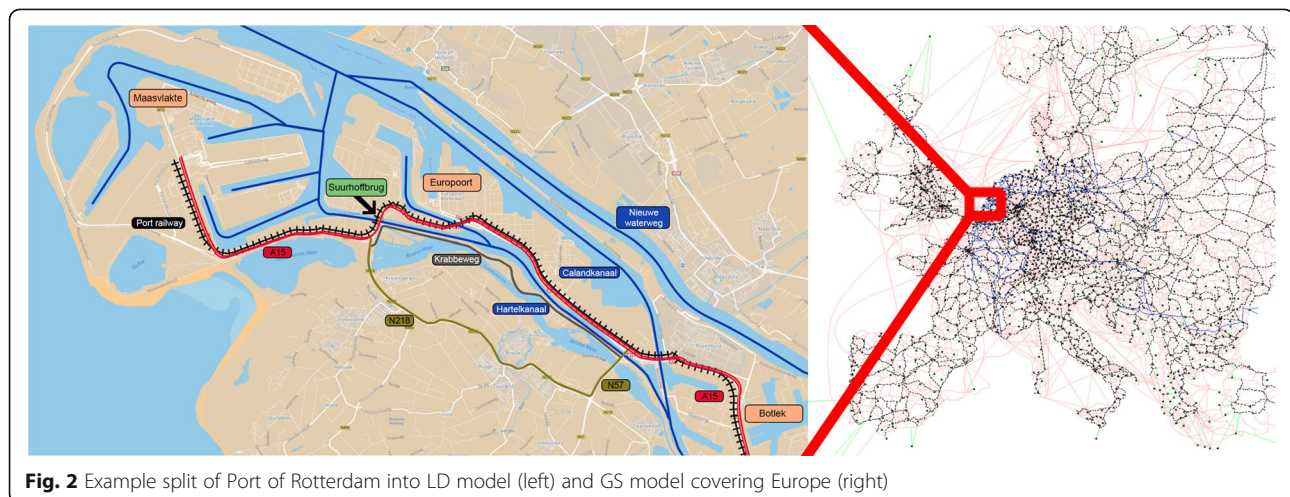


Fig. 2 Example split of Port of Rotterdam into LD model (left) and GS model covering Europe (right)

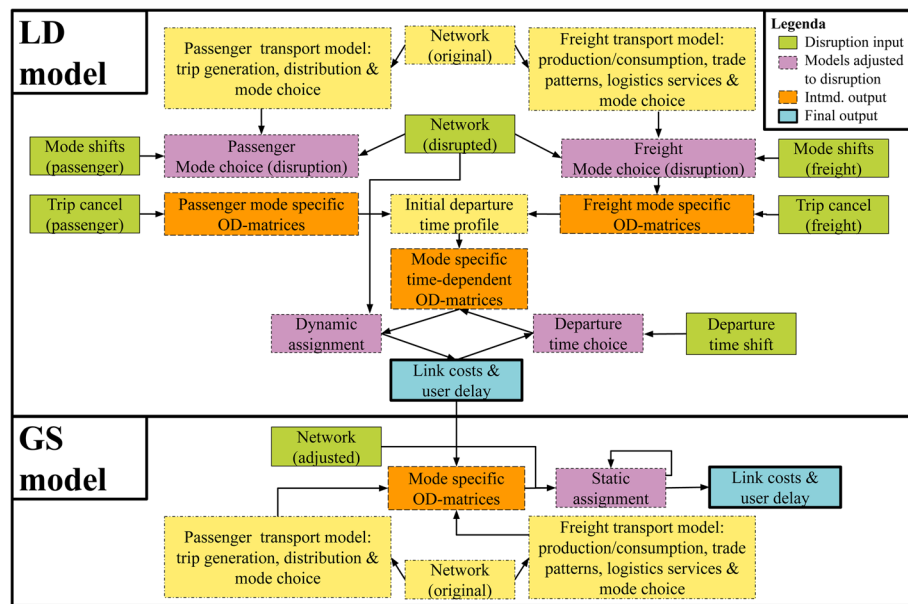


Fig. 3 Overview of the Disruption Transport Model

choice and mode choice models for freight, are performed on the *LD model*. No disruption is assumed at this stage – basic models are run.

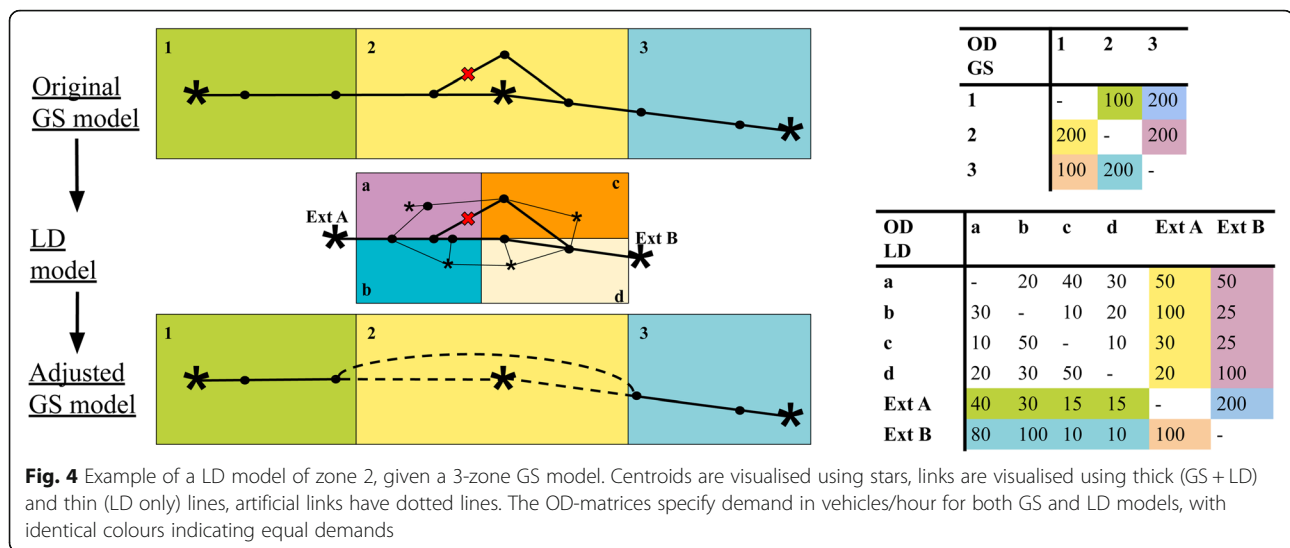
- The mode choice model is performed again on the *LD model* for a percentage of the travellers assuming a disrupted network (i.e. including the broken link). The percentages of travellers per mode and user class (passenger/freight) that can shift modes are given by the parameter “Mode shifts”.
- The OD-matrices of the *LD model* are adjusted given a certain percentage of trip cancellations.
- An initial departure time profile is used to split the OD-matrices into time-dependent OD-matrices on the *LD model* (i.e. specifying demand for every 5 min).
- The dynamic assignment is run on the *LD model*. The number of iterations specifies the adaptability toward route change, typically increasing after multiple days.
- The output of the dynamic assignment is used as an input for the departure time choice model. The percentage of travellers willing to shift departure time is used as an input.
- Procedure 6 and 7 are repeated depending on the amount of iterations specified.
- The final link flows and travel times of the *LD model* provide the input to the *GS model*.
- A static assignment is performed at the *LD model*.
- The total user delays associated with the disruption are calculated as the sum of those predicted by the *LD model* and the *GS model*.

Due to the learning effect of travellers resulting in day-to-day variability, the model should be rerun for every time period of interest, each involving a different set of parameters (e.g. the percentage of travellers that want to shift mode or departure time), as well as the number of iterations ran. Typically, every additional day corresponds to one additional iteration, with equal number of iterations specified for every module.

3.2 Constructing the LD & GS model

The transport model uses two networks: a detailed one covering the region of the infrastructure failure (local disruption model, LD), and one covering Europe completely (global spill-over model, GS). Both networks differ greatly in the level of detail, spatial and temporal resolution. The LD model should be selected in such a way that all mode, route or departure time changes are made by people travelling (partly) via the LD model area. Of course, it is possible that traffic jams propagate over the boundaries of the LD model. Dependent on the area of interest, the LD model covers 30–50 km around the infrastructure object. Additionally, a large level of detail is required: typically, all roads, rail tracks and waterways should be included. During severe disruptions, even very unattractive roads (e.g. with speed limits of just 30 km/h) might provide viable alternatives to the broken link.

The boundaries of the LD network should correspond with the boundaries of one or more of the zones of the GS model to correctly model demand. A small example is shown in Fig. 4, where zone 2 is replaced by the LD model. The LD model splits the GS-zone(s) of interest into multiple smaller zones. For every ingoing and



outgoing link of this detailed model, an external centroid should be added. To ensure correspondence of both models, it is not allowed to have any link crossing the boundary of the LD network that does not exist in the GS model. After addition of the external centroids in the LD model, the original nodes and links in the GS model should be replaced by artificial links, that represent travelling the zone.

Once both networks have been constructed, the (mode-specific) OD-matrices of both LD and GS model should be calibrated. Traffic entering or exiting the LD model should correspond to the GS model: both through-traffic (e.g. from zone 1 to 3) as well as departing (e.g. from zone 2 to 3) and arriving traffic (e.g. from zone 1 to 2). An example OD-matrix of the example networks is shown next to the example networks. For example, 200 veh/h travelling from zone 2 to zone 3 (GS model) correspond to the sum of vehicles travelling from zones a, b, c and d to external zone B (LD model). This calibration process requires to know affected OD-pairs (i.e. OD-pairs (partly) travelling via the zone of interest), which can be obtained by analysing a basic traffic assignment of the GS model. Since multiple routes between a single OD-pair might be used, weight factors (i.e. a percentage of traffic normally travelling through the affected zone) might be necessary.

3.3 Local disruption model

The first steps of the LD model consist of computing trip generation, distribution and mode choice for passengers, and production/consumption, trade patterns, logistic services and mode choice for freight. This results in mode-specific OD-matrices. The modules should be based on a non-disrupted situation – we do not assume any changes in residential location or job selection.

Next, the mode choice model is run on the disrupted network. Not all travellers are able to switch to a different mode (e.g. due to non-possession of a car) or are willing to do so. Additionally, the elasticities of switching to a different mode are not equal: switch from train to car is often easier than vice versa. For freight traffic, mode switching might not even provide a viable option due to absence of intermodal terminals. It is likely that these elasticities change gradually over time. The mode choice model can be implemented using a simple logit model based on travel times. At the first day of disruption, no travellers will make a mode shift due to absence of knowledge on the new traffic situation. For the second day, travel times of the first day are used as an input, etc.

Trip cancellations can be modelled by adjusting the trip generation module, or by adjusting the OD-matrices directly. The latter is assumed to represent the behavioural responses by travellers in a better way – it is seen as a temporary reduction in traffic, not a reduction in travel demand due to changes in residential locations or jobs. Trip cancellations also represent flexibility used within the supply chain in terms of cancelled freight trips.

Dynamic assignment is employed for modelling route changes due to a disruption. Two types of dynamic assignment algorithms are commonly used: en-route and equilibrium. The en-route assignment models traffic flows according to how drivers react to information received en route, for example via radio broadcasts or variable message signs. On the other hand, the equilibrium assignment only assumes that drivers have full knowledge on travel times accomplished during previous iterations. By running several iterations, an equilibrium in traffic state is reached. The LD model uses this equilibrium assignment algorithm such that iterations reflect the number of days that have passed by since the disruption started. The achieved traffic flows then

show the learning effect of travellers, i.e. acquiring knowledge on the traffic situation as days progress.

The dynamic assignment is combined with a departure time choice model. First, a time-dependent OD-matrix is initially generated using a departure time profile, and in further iterations updated according to the departure time choice model. This model reassigns portions of traffic to other (time-dependent) OD-matrices. Not all travellers are willing to change their departure time: this is reflected by a percentage of travellers being able to switch. Note that the departure time choice model requires input on travel times per timestep and is therefore only applied after the first time of applying dynamic assignment.

3.4 Linking the LD & GS model

After running the LD model, we need to link its output to the GS model. Therefore, we first need to compute mode-specific original OD-matrices (i.e. without assuming a disruption) using a basic transport model. Next, these matrices need to be adjusted according to mode choices and trip cancellations modelled by the LD model. For adjusting the GS OD-matrices, the final time-dependent OD-matrices of the LD model should be aggregated to one matrix per time period of the GS model (e.g. peak/off-peak). Next, the OD-matrices of the GS model are adjusted according to these aggregated OD-matrices. This is done in the same way as calibrating the OD-matrices (see Fig. 4): the sum of ingoing, outgoing and through-traffic should be equal. Linking both models in terms of route level (i.e. incorporating route choices and departure time choices) is done by updating travel times for every mode for each of the artificial links in the GS model. Departure time choices are thereby indirectly reflected by resulting delays (e.g. peak spreading results in less delay and thus lower travel times).

3.5 Global spill-over model

The only relevant part of the GS model is the static traffic assignment. The process of reaching an equilibrium state is achieved by running multiple iterations. However, the process used with dynamic assignment (i.e. “one iteration = one day”) is not suitable, because traffic further away is presumably not affected by the disruption and keeps its equilibrium state. Therefore, we use the output of an equilibrium assignment (without a disruption) as a starting point for running the traffic assignment. The number of iterations only reflects the changes as a result of introducing the disrupted network and adjusting OD-matrices according to the LD model output.

3.6 Running and comparing scenarios

To compute the final output of the model, for example the total travel time, the sum of travel time spent in the

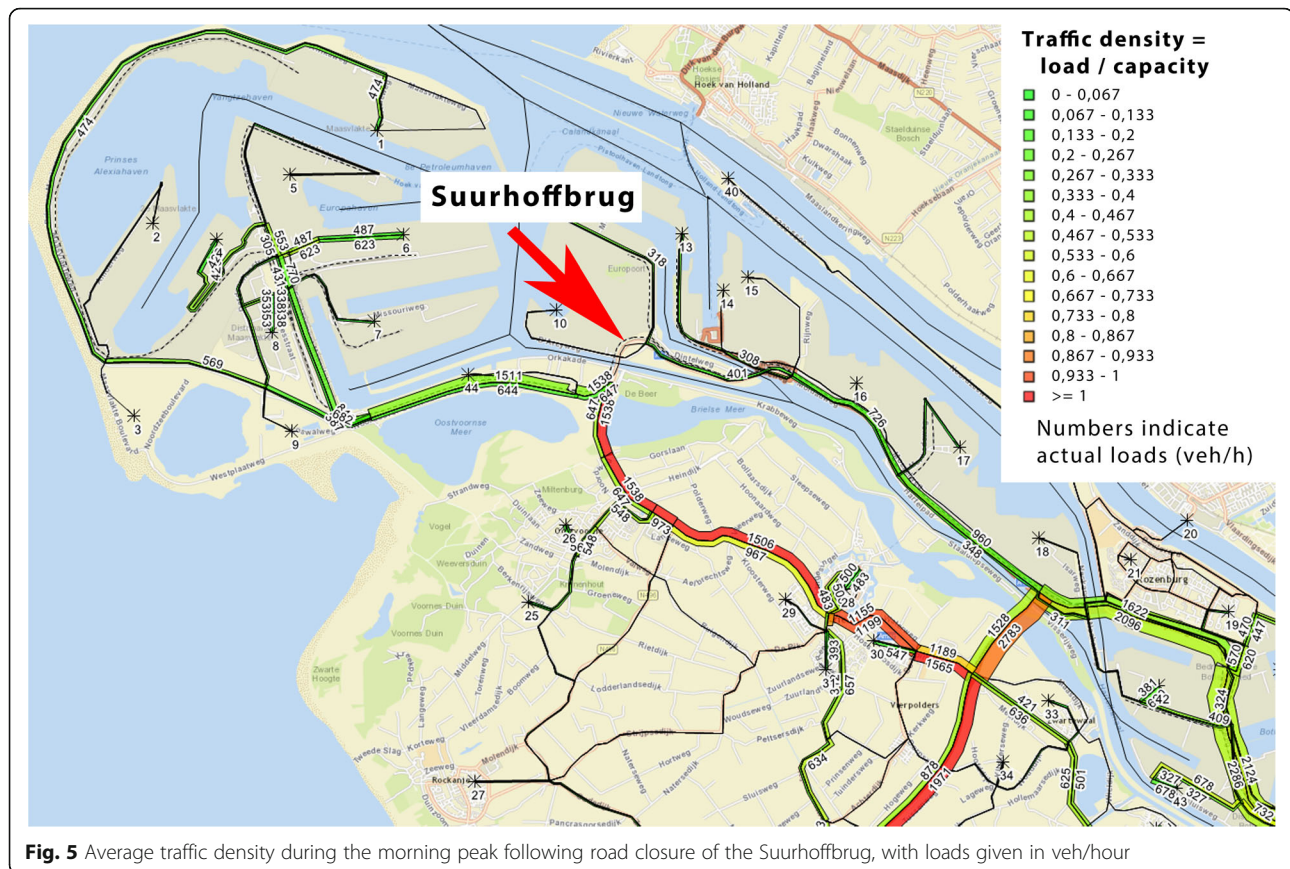
LD model and the GS model should be taken. To prevent counting delays in the detailed area double, the “artificial links” in the GS model within the zone of interest should be left out. Additionally, the travel time can be split per user class (passenger/freight, but also commuter, business, leisure and bulk, liquid, containerized) and per time period. This is helpful to consider monetary values – typically, the “Value of Time” of a freight vehicle is much higher than that of a leisure traveller. Also, cancellation of trips should be considered carefully in terms of monetary values.

4 Results and discussion: case study at the port of Rotterdam

We apply our transport model at a case study site in the Port of Rotterdam, The Netherlands. We examine a failure of the Suurhoffbrug, a steel bridge that connects the newest part of the port, the Maasvlakte. The bridge supports a 2×2 -lane highway connection and 2×1 rail tracks. We assess the impact of an unforeseen failure of the road bridge and compare the results to the situation where the Suurhoffbrug was fully functional.

The Disruption Transport Model was established using OmniTRANS 8.0 [6]; a multi-modal transport modelling platform. For the GS model, data was adopted from TransTools, a European transport model for forecasting effects of transport policies throughout Europe [2]. It consists of 138,072 km of railway lines, 136,706 km of roads and 15,715 km of inland waterways and has 1441 zones used for aggregating demand. The LD model was created using network data of the Port of Rotterdam and a traffic demand prediction for 2020 was obtained [1]. The boundaries of the LD model were selected in such a way that most vehicles can proceed their original route within the model boundaries after an infrastructure failure, and that the zones of the GS model overlapped (see Fig. 2). The LD model splits 1 GS zone into 44 smaller zones. Traffic data of the LD model was considered more reliable. Therefore, the GS model was calibrated such that the traffic demand corresponded to the LD model. The GS model employed a static assignment using volume averaging techniques using cost functions and parameters as specified by the TransTools project. The LD model used dynamic assignment module StreamLine (included in OmniTRANS). Travel time was used as the only component of the link costs functions.

User behaviour parameters were selected to reflect the situation 10 days after the infrastructure failure occurred. All iteration parameters were therefore set to 10. Additionally, it was assumed that 1% of truck trips were cancelled and 0% of passenger trips. Modal shifts were not considered. All freight traffic could change departure times slightly, against 20% of passenger cars. Passenger car traffic



mainly consisted of business/commuting traffic, where not much flexibility is possible.

We modelled a morning peak period (7:00–9:00 am) on an average working day. The aggregated output of the LD model is visualised in Fig. 5. Due to the absence of the Suurhoffbrug a high density of traffic occurs on the N218 and N57, both small local roads through villages. After the N57-bridge, traffic densities at the highway A15 are almost identical to the situation without a failure.

A delay of around 200 vehicle hours per morning peak in the LD model was predicted due to a failure of the Suurhoffbrug. This means that if there are 4000 vehicles in the region around the Suurhoffbrug, each vehicle would encounter a 3-min delay due to the failure of the Suurhoffbrug. After adjusting the OD-matrices of the GS model given the LD model output, the GS model traffic assignment was performed. This resulted in much lower values of only 83 vehicle delay hours per morning peak, which indicates relatively low values of congestion propagating along the borders of the LD model – as we could already see in Fig. 5. Overall results for total travel time delays per user class are shown in Table 1.

An additional evaluation of the traffic disruption in the period immediately following the closure of the Suurhoffbrug was also performed. Figure 6 illustrates the

traffic disruption caused to road users in the period following the bridge closure, which shows that an equilibrium is reached after approximately 3 days. The figure also shows that the differences in total travel time on day 1 following the bridge closure and the equilibrium state (day 3) are not significant. This can be explained by the lack of redundancy of the road network in the vicinity of the Suurhoffbrug: there are only two roads connecting the Maasvlakte to the mainland.

It can be concluded that a road bridge failure results in significant additional travel time in the vicinity, but not throughout Europe. The outputs have the potential to be used as part of a life cycle cost analysis. For a more extensive analysis it is advised to not only incorporate these user delays, but also environmental impact due to a large increase of traffic flows on local roads (i.e. N57 and N218), possibly exceeding air or noise quality

Table 1 Total travel time delays in hours, specified per user group, per model

	LD model	GS model	Total
Freight	94.0	22.9	116.9
Passenger: Business/commute	89.6	56.6	146.2
Passenger: Leisure	11.1	3.6	14.7

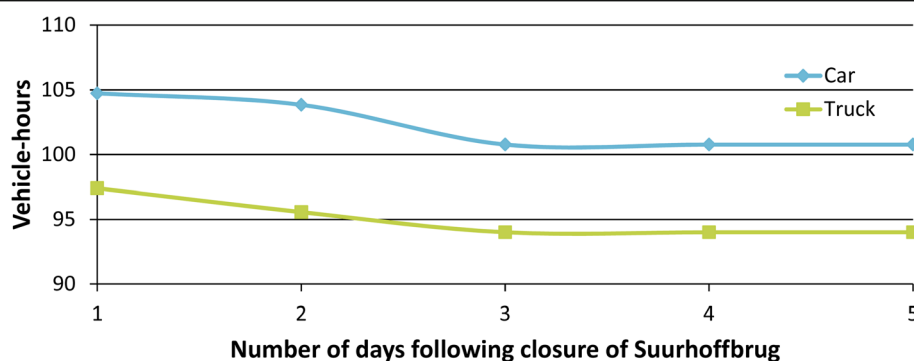


Fig. 6 Delay in vehicle-hours for road users following a closure of the Suurhoffbrug as a function of time since road bridge closure

standards. It is assumed that a failure of the rail bridge results in a larger impact, as it provides the only rail connection toward the Maasvlakte.

5 Conclusion

In this paper, we introduced a transport model used for simulating user delays as a result of a disruption. The proposed framework uses a detailed model of the region around the infrastructure failure and combines this with a basic European model. This enabled us to model impacts of disruptions in high detail, whereas also effects throughout Europe are considered. We applied the transport model in a case study at the Port of Rotterdam. The case study showed that a failure of the road bridge results in significant additional travel time in the vicinity, but not throughout Europe. We expect that a failure of a rail or waterway link – having a sparse network with limited alternative routes – will result in a more significant impact on a European level.

Further research is recommended among the calibration of the behavioural response parameters. It was shown that every disruption is characterized with different percentages of travellers showing certain responses. This makes it hard to predict exact values for a specific case study, which would require expert judgement. A better insight in the uncertainty can be made by using sensitivity analysis of the model or by viewing these parameters as a design variable that can, to a certain degree, be accomplished via appropriate policy measures. It is especially recommended to track traffic volumes as well as mode choices and trip cancellations during actual disruptions.

Setting up the Disruption Transport Model (including obtaining a detailed network, calibrating the GS model, and setting behavioural parameter values) is a time-expensive process. A “plug-and-play” interface where an infrastructure manager can select any infrastructure object on a map and directly retrieve the associated delays during failures is still a future challenge, but at least a first attempt has been presented to model user delays following an infrastructure closure.

Abbreviations

Acronym: Definition; GS-model: Global Spill-over model; LD-model: Local Disruption model; OD-matrix: Origin-Destination matrix

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Authors' contributions

MvdT reviewed the literature, programmed and calibrated the model, performed the case study simulation, and drafted the manuscript. Both authors contributed to the model design, interpreted the model results, and edited and approved the final manuscript.

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Availability of data and materials

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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