EJTIR

Issue 16(3), 2016
pp. 490-511
ISSN: 1567-7141
tlo.tbm.tudelft.nl/ejtir

A general activity-based methodology for simulating multimodal transportation networks during emergencies

Jeroen P.T. van der Gun[1]
Department of Transport and Planning, Delft University of Technology, The Netherlands.

Adam J. Pel[2]
Department of Transport and Planning, Delft University of Technology, The Netherlands.

Bart van Arem[3]
Department of Transport and Planning, Delft University of Technology, The Netherlands.

Many possible emergency conditions, including evacuations, negatively affect the urban transportation system by substantially increasing the travel demand and/or reducing the supplied capacity. A transportation model can be used to quantify and understand the impact of the underlying disasters and corresponding management strategies. To this end, we develop an efficient methodology suitable for simulating multimodal transportation systems affected by emergencies, based on the novel integration of an activity-based choice model with both pre-trip and en-route choices, and a macroscopic or mesoscopic dynamic network loading model. The model structure first estimates the daily equilibrium and then uses that result as a starting point to simulate the emergency situation without further iterations. Unlike previous efforts, our methodology satisfies all requirements identified from literature regarding transportation modeling for emergencies, and is sufficiently general to investigate a wide range of emergency situations and management strategies. An evacuation case study for Delft shows the feasibility of applying the methodology. Furthermore, it yields practical insights for urban evacuation planning that stem from complex system dynamics, such as important interactions among travel directions and among modes. This supports the need for a comprehensive modeling methodology such as the one we present in this paper.

Keywords: *urban emergencies, evacuation modeling, choice modeling, activity-based modeling, dynamic network loading, multimodal networks.*

1. Introduction

In today's world, many types of disasters can pose significant challenges to the transportation systems of urban areas. Ample studies have hence been undertaken to understand the impact of these disruptions and disasters, ranging from extreme weather to large-scale accidents. Notwithstanding the specifics of the consequent emergency situations, from a transport perspective we can also discern three ways how such emergencies commonly differ from a normal situation. First of all, there may be a reduced capacity for daily traffic. That is, disruptions and disasters tend to reduce the capacity of the road infrastructure and public transport network, e.g. because of adverse or extreme weather conditions (Hoogendoorn, 2012; Litman, 2006;

[1] A: Stevinweg 1, 2628CN Delft, The Netherlands T: +31 152784030 F: +31 152787956 E: j.p.t.vandergun@tudelft.nl
[2] A: Stevinweg 1, 2628CN Delft, The Netherlands T: +31 152784874 F: +31 152787956 E: a.j.pel@tudelft.nl
[3] A: Stevinweg 1, 2628CN Delft, The Netherlands T: +31 152786342 F: +31 152787956 E: b.vanarem@tudelft.nl

Lindell, 2008), traffic accidents (Knoop, Hoogendoorn and Van Zuylen, 2010), damaged infrastructure (Brachman and Dragicevic, 2014) and public transport failures (Tahmasseby, 2009). These capacity reductions can lead to substantial delays. Second of all, there may be evacuation traffic leaving the affected area or sheltering in-place. That is, in case of notice, evacuation may precede the disaster event, with evacuees trying to return home (Trainor, et al., 2013; Kolen, 2013), or to reach a hotel, family or public shelter (Murray-Tuite and Wolshon, 2013; Deka and Carnegie, 2010), possibly including intermediate trips (Trainor, et al., 2013; Murray-Tuite & Mahmassani, 2003; Yin, et al., 2014), where heavy road congestion is likely to occur (Litman, 2006). And third of all, there may be emergency services trying to reach the disaster site. That is, many disasters require the transportation of a significant amount of emergency services personnel, e.g. for delivery of medical care, water, food and utility maintenance (Litman, 2006), traffic regulation (Tu, et al., 2010), helping stranded vehicles and protect and evacuate non-self-reliant people (Litman, 2006) and rescue operations (Dombroski, Fischhoff and Fischbeck, 2006).

As urban transportation systems typically have a modest capacity compared to the local population and workforce, they can easily become overloaded by the surge in travel demand and/or reduction of supplied capacity caused by the characteristics of the emergency situation listed above. This poses a problem for the resilience of the system and necessitates authorities to have proper transportation management strategies. In this regard, the added value of a transportation model is twofold. Firstly, such a model enables quantifying the effects of disruptions as well as management strategies, where the former is often used to identify the most critical emergency conditions and vulnerable parts of the network, and the latter assists in ranking alternative strategies and measures. Secondly, such a model predicts the manner in which these effects take place with respect to travelers' decisions and traffic flow operations, which is helpful in understanding the underlying causes why certain effects occur and certain measures are successful, or not. Evidently, for a transportation model to be of value, its predictive validity is essential.

This brings us to what requirements such a transportation model should satisfy. Based on literature and the previously discerned commonalities of emergencies, we can identify seven main model features that are needed to capture the transport-related characteristics of an emergency. Each affects the choice model for the behavior of the affected people, the network loading model for the propagation of traffic, or both. We find that a transportation model for emergencies should:

- *Be dynamic*. An emergency situation and the emerging traffic conditions are time-varying (Fu and Wilmot, 2004), and consequently people's choices also have a time dimension. It is important that such time dynamics are taken into account (Lin, et al., 2009). The time range depends on the type and severity of the disaster, but would typically vary from about one hour for no-notice and short-notice disasters to a few days for hurricane evacuations.
- *Describe the relevant choice behavior*. An emergency is an unusual situation and as mentioned above, people need to make choices dynamically over time, instead of planning the whole day in advance. They may even need to adjust their choices en-route based on the information then available to them at that moment (Pel, Bliemer and Hoogendoorn, 2012; Robinson and Khattak, 2010). The emergency can also put people in entirely new choice situations, such as evacuation-related decisions, resulting in unusual behavior.
- *Predict the initial conditions of the emergency* or otherwise allow specifying these starting conditions if determined exogenously. The initial locations of people evidently affect the travel demand pattern, as it determines where people depart from (Noh, et al., 2009) or where people need to be picked up (Murray-Tuite and Mahmassani, 2003), while the

initial traffic pattern affects the network performance, together with aspects of possible capacity reductions and induced emergency traffic flows.

- *Include interactions between individuals*. Particularly for evacuations, households tend to act as a unit (Murray-Tuite and Mahmassani, 2003) due to activities at the household level, such as the pick-up of household members (Murray-Tuite and Mahmassani, 2003; Trainor, et al., 2013) and necessary purchases (Yin, et al., 2014). It has been shown that these activities may have important implications for traffic flows (Murray-Tuite and Mahmassani, 2004; Lin, et al., 2009). We presume that interactions within or across households may also play a role in other disasters that severely disrupt the transportation system.
- *Be multimodal*. Emergencies may directly affect various transport systems, or may cause severe spillover effects especially in urban regions with interacting transport modes, as, for example, public transport and pedestrian traffic play an important role as fallback alternatives for people without a car or in case of severe congestion (Shiwakoti, et al., 2013).
- *Include travelers who are not directly affected* and their behavior. This may pertain to, for example, background traffic that itself is not affected by the emergency but does affect the situation as they co-consume road and public transport capacity, or is affected indirectly by changes in the traffic situation or the availability of destinations (Murray-Tuite and Wolshon, 2013).
- *Include emergency services*. This can be either to enable evaluating the deployment of emergency services (as decision variable) or evaluating how these traffic flows affect the situation similar to the previous requirement.

Despite the existence of models that address subsets of this set of challenges, we lack methodology and tools to satisfy all requirements in an integrated manner, hampering disaster planning. In this paper, we address this knowledge gap by presenting a generic modeling methodology to simulate the impacts of emergencies on urban transportation networks. To adequately incorporate the choice behavior of the affected people, we propose using an activity-based escalation model for travel choices, which we show to connect well to the existing literature on travel choices during emergencies. Additionally, our paper contributes a new and computationally efficient methodology to couple such a choice model with macroscopic or mesoscopic dynamic network loading models for the simulation of evacuations as well as other emergency conditions, in a way that satisfies the listed requirements. We retain a high amount of flexibility in the specification of the choice model that can even include en-route choices, and we show that with the escalation-based formulation we propose, this is sufficiently flexible to incorporate insights from earlier studies on choice behavior in a wide range of emergencies.

We present this methodology in Section 2. Through a case study for a hypothetical evacuation of the city of Delft, we discover a number of important modeling issues, such as to capture interactions between transportation modes and between inbound, outbound and background traffic, as these show to potentially cause failure mechanisms that may be overlooked with a less comprehensive model. This model application is presented in Section 3. In Section 4 we conclude with a discussion on the model structure, its performance, and the modeling issues highlighted by the case study.

2. A general methodology to model travel choices and traffic propagation

As mentioned in the introduction, emergency conditions may both affect the choice behavior of the affected people and the propagation of traffic. Therefore, we derive specific structures of the choice model in Subsection 2.1 and the network loading model in Subsection 2.2 that satisfy the indicated requirements. We couple them in Subsection 2.3 resulting in a general modeling methodology for the complete transportation simulation of an emergency. Finally, Subsection 2.4 provides a brief summary.

2.1 *Travel choice modeling*

To describe travel choices, we start by acknowledging that the demand to travel is derived from the demand to undertake activities at different locations (Bowman, 2009; Ortúzar and Willumsen, 2011). By modeling complete activity patterns, rather than individual trips, one can consider resource (e.g. vehicle) and task allocation within households, whether people travel together, how activities are dynamically rescheduled, and the consequences for the load on the transportation system. When applied in the context of emergencies, this means that an activity-based model can predict the locations and activities of individuals and the vehicles they use at the time of an emergency event (i.e., the initial conditions), as well as it can simulate background traffic that is unaffected by the event, including transition effects from normal conditions to emergency conditions.

As we propose an activity-based approach, implying microscopic agent-based choice models, this generalizes earlier methods where a normal day model forms the basis for an emergency model. Noh, et al. (2009) use normal day demand matrices to estimate evacuation demand matrices per time-of-day. Lin, et al. (2009) use an activity-based model for determining evacuation demand, and later Yin, et al. (2014) use a more advanced one, but they cannot include time dynamics in the choice process. However, unlike these previous attempts, the framework we present here should ensure sufficient flexibility to specify how people dynamically respond to the emergency, e.g. by rerouting, rescheduling activities or evacuating.

To this end, we define an escalation model to categorize behavioral responses to emergencies, consisting of three possible behavioral states of individuals at any moment in time. These are an initial state, for those who are not or not yet affected by the emergency, an adaptation state for those responding to the disruption of the transportation system and an evacuation state for those directly threatened by the emergency. As individuals become increasingly affected, their choice behavior escalates, causing shifts in preferences and resulting in changes compared to the original activity-travel patterns.

Relying on existing literature, let us now summarize the most important choice behavior associated with the elements of the activity-based escalation model we propose:

1. In the initial, *normal state* the individual performs its (equilibrium) travel and activity plans as usual, that is consistent with a normal day.
2. In the *adaptation state* the individual responds to the disruption and may adapt its activity and travel plans accordingly by e.g. switching routes or rescheduling activities. For example, Kitamura and Fujii (1998) and Joh, Timmermans and Arentze (2006) propose models that, given an initial schedule, evaluates the utility of possible changes to the activities and their durations, sequencing, locations and modes, to see if a significant improvement can be found that outweighs the (mental) effort of the re-evaluation process. However, these models are not yet specifically targeted to within-day re-planning in response to unforeseen events, that additionally requires an estimate of perceived future travel times. Illenberger, Flötteröd and Nagel (2007) do propose a model for this, focusing on the time and route choices in the schedule and comparing various assumptions on the availability of travel time information. Knapen, et al. (2014) reschedule begin and end times of planned activities in response to unforeseen events and use an explicit model to dynamically estimate the perceived travel times from a combination of normal day travel times and incident characteristics. Analyzing empirical data, Knoop, Hoogendoorn and Van Zuylen (2010) find that the presence of a traffic

incident is an even stronger encouragement to switch routes than travel time differences alone, and that the response of travelers is delayed.

3. In the *evacuation state* the individual either evacuates or seeks shelter. Obviously, this third state is only relevant when imminent danger is present, as well as acknowledged and acted upon (Leach, 1994; Vorst, 2010), which, for example, Dixit, Wilmot and Wolshon (2012) incorporate by modelling risk attitudes. Besides this choice on whether and when to engage in evacuations, which can be captured with e.g. a sequential binary logit model, research on evacuation behavior has traditionally focused on two other choices related to the evacuation trip itself, namely the accommodation type and destination choice, with family and friends as the most favored and public shelters as the least favored accommodation types, and the mode choice, where, if possible, evacuation by car is the most preferred option. Murray-Tuite and Wolshon (2013) give a comprehensive overview of knowledge and models resulting from this. Nonetheless, there is increasing attention to activity-based aspects of evacuation modelling (Trainor, et al., 2013). In particular, returning home for pick-up activities within households is an important aspect (Murray-Tuite and Mahmassani, 2003; 2004), which was recently re-emphasized by the Great East Japan Earthquake (Hara and Kuwahara, 2015). Yin, et al. (2014) formulate and estimate a detailed activity-based model for evacuation behavior, including child pick-up activities, shopping activities to make necessary purchases and joint travelling with other households. Regarding route choice, Sadri, et al. (2014) have found that people tend to choose familiar routes during evacuations. Despite this, Robinson and Khattak (2010) find that more people are willing to make en-route choices than in normal circumstances. Pel, Bliemer and Hoogendoorn (2012) recommend to model choices both pre-trip and en-route.

From this overview, we see that in addition to satisfying the requirements listed in the introduction, our proposal of an activity-based escalation model relates well to existing literature on both adaptation and evacuation behavior. This allows existing choice models to be embedded in our framework: the agent-based models can be directly incorporated whereas aggregate-level models can be easily translated to the agent level. Our setup requires a description of under what conditions the behavior of an agent may escalate as well as of dynamic choices within each state. In general, these choice models can be a function of the plans and experiences on a normal day, the characteristics and attitudes of the considered agent, the on-going emergency event, and the information available to the agent. Interaction with other agents can be included here as well, in the sense of either joint decision-making or responding to perceived previous choices of others. Overall, our model structure thus provides a high level of flexibility with respect to the specification of the choice behavior, which, given a particular emergency situation, can be filled in accordance with the cited literature.

For clarity, note that, unlike the activity-rescheduling model by Knapen, et al. (2014) and the evacuation model by Lin, et al. (2009), the above choice modeling includes route choice which is hence also performed at agent-level. This ensures that at any time, an explicit location is defined for each individual, so that not only pre-trip but also en-route choices can be modelled, which in turn increases the realism of local traffic dynamics in the model (Knapen, et al., 2014). Furthermore, this allows to explicitly incorporate observed heterogeneity in route choice, e.g. the tendency of people to choose familiar routes during evacuations, allowing to further increase the predictive validity of the model.

2.2 Transportation network loading

Following our list of requirements, here we prescribe a multimodal dynamic network loading model that can include emergency services. A key characteristic to decide upon is whether the traffic simulation will be microscopic, mesoscopic or macroscopic, i.e. whether traffic is represented as individual vehicles, vehicle packets, or aggregated flows (Hoogendoorn and Bovy, 2001). Note that our microscopic (agent-based) representation of travelers in the previous choice models does not necessitate also having a microscopic traffic representation for the network loading model. At the same time, mesoscopic and macroscopic traffic flow simulation models typically are computationally more efficient, which is beneficial for applications that are large-scale or require iterative optimization, as well as suffice with aggregated data for calibration and validation purposes, which is beneficial since current empirical knowledge is limited with respect to individual driving behavior, e.g. during emergency conditions (Hoogendoorn, 2012; Tu, et al., 2010) and adverse weather conditions and due to heavy vehicle loads (Litman, 2006; Lindell and Prater, 2007) and traffic incidents during evacuations (Robinson, et al., 2009; Fonseca, et al., 2013). For these reasons we propose a network loading model with mesoscopic or macroscopic traffic representation.

Note that such a traffic representation relates to all vehicles on the road network, potentially distinguishing separate user classes with specific properties for describing affected individuals, background traffic, emergency services and public transport vehicles. Further details are discussed in the next subsection. Furthermore, this approach can be extended to the pedestrian network, e.g. using a uni- or bidirectional pedestrian fundamental diagram (Flötteröd and Lämmel, 2015), allowing a relatively simple extension of the model to multimodal networks. If the amount of pedestrian traffic is significant, one could also model the interaction between pedestrians and cars macroscopically (Meschini and Gentile, 2009).

2.3 *Integration of the choice model and network loading model*

In combining the dynamic network loading model and the choice model, attention needs to be paid to their interaction, which is challenging in this case because the latter operates at a microscopic level of detail while the former does not. To this end we develop a new method to tightly integrate these models, considering both equilibrium and emergency conditions, with the inclusion of en-route choices, public transport and emergency services. This method relies on both a serial procedure and a parallel procedure.

The *serial procedure* solves the user equilibrium assignment, representing a normal day. One runs the choice model to yield dynamic route demand, that is then input to the network loading model to yield dynamic travel times, that are then input to the choice model, and so on (Lin, et al., 2009). The method of successive averages (Ortúzar and Willumsen, 2011), which is usually applied to macroscopic flows, can be adapted to find the equilibrium of agents: to simulate flow averaging, one can fix the choices of a random share of agents that increases in size over iterations, eventually yielding agent choices that reproduce the equilibrium situation. This may be extended further into, e.g., the more comprehensive approach by Raney and Nagel (2006).

The *parallel procedure* solves the non-equilibrium assignment, representing the emergency situation. During execution of the network loading model, one can already determine dynamic travel times up till the current time. While tracking individuals throughout the network, we repeatedly alternate between the network loading model and the choice model as time progresses: after each network loading time step, the choice model receives the locations of travelers and the current travel times, and provides the (possibly adapted) departure and route choices for the next time step.

The results for the normal day equilibrium, to be found using the serial procedure, serve as input to the emergency choice model described previously, so that the system remains in equilibrium until the emergency situation causes a disturbance, to be simulated via the parallel procedure. The overall process is illustrated in Figure 1. The parallel procedure does require the emergency choice model to be causal, which is a realistic assumption as people can only base their (expectations and) choices on the conditions up till now (Pel, Bliemer and Hoogendoorn, 2012; Qian and Zhang, 2013).

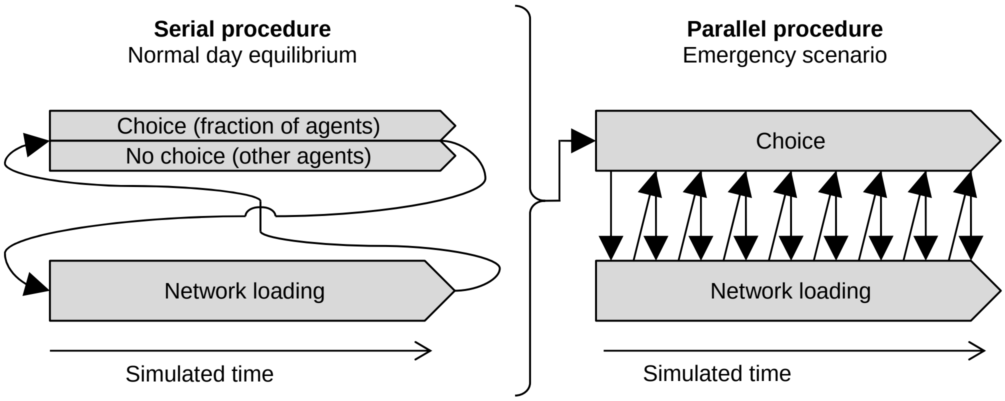

Figure 1. Flow charts of procedures for the overall model

Although a serial procedure can simulate the emergency scenario as well (Lin, et al., 2009), the parallel procedure skips the construction of intermediate infeasible solutions where some people depart for their next trip before they arrived from their previous trip. The absence of iterations makes this method also much more efficient. For these reasons, we propose the parallel procedure in our methodology. Of course, the parallel procedure does require the software of the choice model and the network loading model to be tightly integrated so that the overall model can rapidly alternate between them.

Figure 2 shows a more detailed flow chart for the parallel procedure for simulating the emergency scenario. Here, we added an optional control component that represents the actions undertaken by authorities during the emergency situation, which affect the transportation system either directly via traffic control and deployment of emergency services or indirectly by influencing the choice behavior of the population.

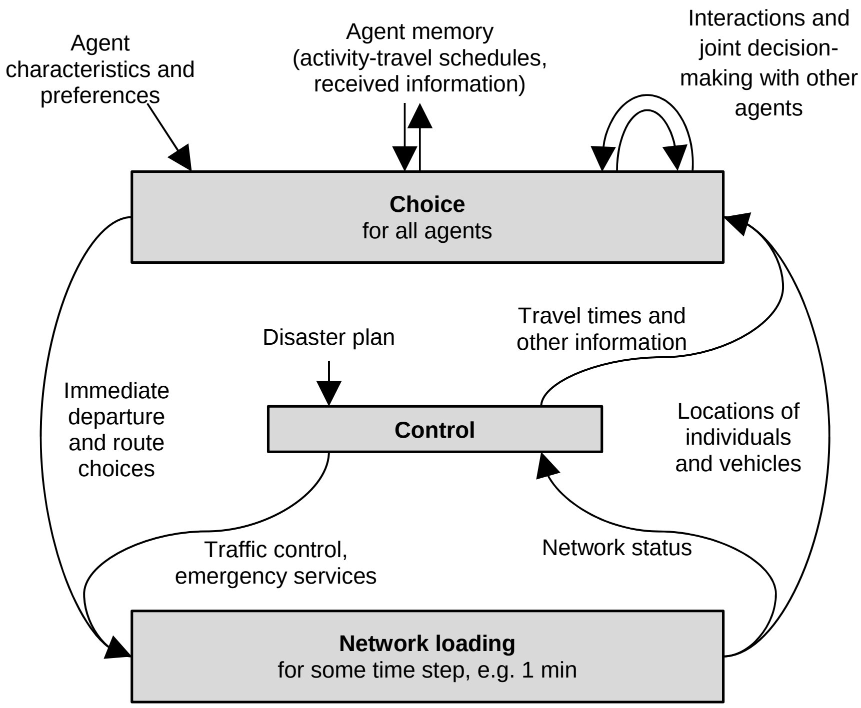

Figure 2. Detailed flow chart of the parallel procedure for the emergency scenario

Tracking individuals and handling en-route choices

One requirement for the parallel procedure is that the network loading model continuously informs the choice model of the location of individual travelers. In a microscopic network loading process, this is straightforward, and it is also easy to immediately apply, for example, a route change in response to an en-route choice. However, we will show that we can also do this in a macroscopic or mesoscopic network loading process by accurately tracking the location of individuals while the aggregated traffic flow is propagated through the network.

Dynamic network loading models propagate traffic at intersections based on turn fractions. However in this application these are not constant over time and the time dynamics depend on the delays the traffic encounters before reaching the intersection as well as the en-route choices that people make. As explained below, we solve this by disaggregating the traffic flow into various commodities with different routing behavior, so that the turn fractions are specified per commodity rather than for the total flow (Daganzo, 1995; Papageorgiou, 1990; Yperman, 2007). We thereby choose the disaggregation such that we can both track the location of individual travelers and delay the definitive route choice of a traveler until she/he passes the relevant divergence point. More specifically, we define that each commodity is associated with exactly one spatial position, i.e. a link, a cell of a link, or a packet of vehicles depending on how space is discretized. At the next intersection, the commodity is converted into other commodities associated with downstream links, according to particular splitting rates (i.e. turn fractions). Furthermore, let us define that each individual microscopic vehicle is associated with exactly one of the commodities in the network. As soon as the first link outflow of a commodity is registered, its splitting rates are fixed and all associated individual vehicles are immediately associated with the corresponding commodities on the outgoing links of the intersection, even though, depending on the network loading model, not all corresponding flow may be able to pass the intersection within that single time step.

The spatial position corresponding to the currently associated commodity defines the current location for each individual vehicle. If an individual vehicle needs to switch to a different route due to an en-route choice, we can simply modify the splitting rates of the currently associated commodity. At an origin, all traffic with the same departure time and link can be grouped into a commodity, and this traffic will then split up into an increasing number of distinct commodities upon passing downstream intersections as their routes diverge. The above aggregation of traffic into commodities saves us computation time compared to creating separate commodities for every individual vehicle.

Incorporation of public transport

The previous definition of commodities considers only private transport. To incorporate public transport, we define an additional commodity for each public transport vehicle for each location along its route, such that the road traffic propagation model naturally simulates any interactions, including, e.g., occupancy of road space and adaptation of the speed of the vehicle subject to the traffic conditions. Of course, if the network loading model can differentiate user classes, these public transport commodities may have different dynamics than normal cars.

The location of the currently associated commodity of a vehicle, as defined for the unimodal case, will be the key to modeling how (individual) passengers propagate throughout the public transport network. For this, we require that network nodes containing public transport stops must have sink and source capabilities in the network loading model. We can then define the following system:

- Each public transport stop node has a queue of passengers waiting to board any of the lines.
- Each public transport vehicle has a list of passengers who are on board.

- Passengers arriving at a public transport stop via incoming links, e.g. of the pedestrian network, use the sink capability and are placed into the queue. If they arrive by private vehicle, this vehicle must be parked at the node, and this must fit within the parking capacity.
- Public transport vehicles arriving at a public transport stop via incoming links use the sink capability to stop.
- Passengers who want to alight from a vehicle, use the source capability to leave via outgoing links, e.g. of the pedestrian network, and are removed from the vehicle's passenger list. Alternatively, if they want to transfer to another public transport line at the same stop, they are removed from the vehicle and added to the queue of the public transport stop. If they continue by private vehicle, this vehicle is retrieved from the parking capacity of the node.
- Passengers in the queue, who want to board a vehicle, are added to the vehicle's passenger list and removed from the queue, until the vehicle's capacity is reached.
- Public transport vehicles, when ready, depart from stops using the source capability via outgoing links.

This fully defines the propagation of both public transport vehicles and passengers, and the transfers of passengers from and to the system of private modes. The next two rules complete the system with support for en-route choices of public transport passengers:

- Passengers in a vehicle may choose to switch to any other public transport route containing the part of the public transport line where they currently are.
- Passengers in the queue may choose to switch to any other route from the corresponding node, with or without public transport. If they do not need to board anymore, they use the source capability to leave via outgoing links, e.g. of the pedestrian network, and are removed from the queue.

Incorporation of emergency services
Finally, any emergency services may be modelled similarly to public transport, but without intermediate stops and passengers, and with the possibility of having multiple vehicles belonging to a commodity. Like public transport, it is up to the network loading model to correctly model the interaction with other traffic by treating the emergency services as a separate user class, potentially with dedicated infrastructure (Litman, 2006; Maassen, 2012), different speeds (Petzäll, et al., 2011) and priority at intersections (Teng, et al., 2010). The "timetable" of emergency services may be derived from the disaster plan. If emergency services are deployed to regulate traffic (Tu, et al., 2010), then the model may activate the regulation once they arrive at their destination.

Summary
Let us briefly summarize the proposed framework. The travel choices follow from an activity-based model. On a normal day the activity-travel patterns of agents are in equilibrium. We can find this equilibrium by adapting the method of successive averages to discrete agents, which iterates until the choices resulting from the choice model are consistent with the travel times resulting from the network loading model. In an emergency scenario agents begin executing their equilibrium activity-travel patterns, but may show adaptation behavior after noticing a disruption and evacuation behavior after being confronted with a threat, possibly interacting with other agents or influenced by information provision by authorities. Consequently, the traffic situation will gradually start deviating from that of a normal day. For the propagation, we use a macroscopic or mesoscopic dynamic network loading model, possibly including traffic control measures, in which we represent agents using commodities. The commodities allow us to track

the locations of agents and handle their en-route choices. We define additional commodities to represent public transport vehicles and vehicles of emergency services, and define mechanisms for agents to board and alight at public transport stops.

3. Delft evacuation model application

To demonstrate the feasibility and investigate the properties of our newly proposed methodology, we here present a case study application. The application describes the hypothetical multimodal evacuation of the city of Delft with the following setup. In our scenario, authorities take no action other than informing the public, and the public transport system operates according to the normal timetable. This means we are essentially investigating a do-nothing variant, whose results can be used as a starting point to develop more proper control strategies and as a reference point when evaluating such strategies.

Households living in external zones follow their normal activity-travel patterns, and households living in Delft start evacuating between 16:00 and 17:30, thus interacting with initially substantial background traffic due to the evening peak. The Delft transport network is plotted in Figure 3 and consists of motorways and provincial roads, main arterials, and urban streets for cars and busses as well as rail infrastructure. In total it contains 24 centroids (7 are external), 4 train stations (2 are external), 40 nodes with bus/tram stops and 437 other nodes. There are 1206 uni-directional vehicular links and 1092 uni-directional pedestrian links. Counting each direction separately, the public transport network contains 4 train lines, 2 tram lines and 14 bus lines. We based our network on the default network included with the OmniTrans modeling software that we also use for generating artificial public transport timetables and visualizing the results of our model.

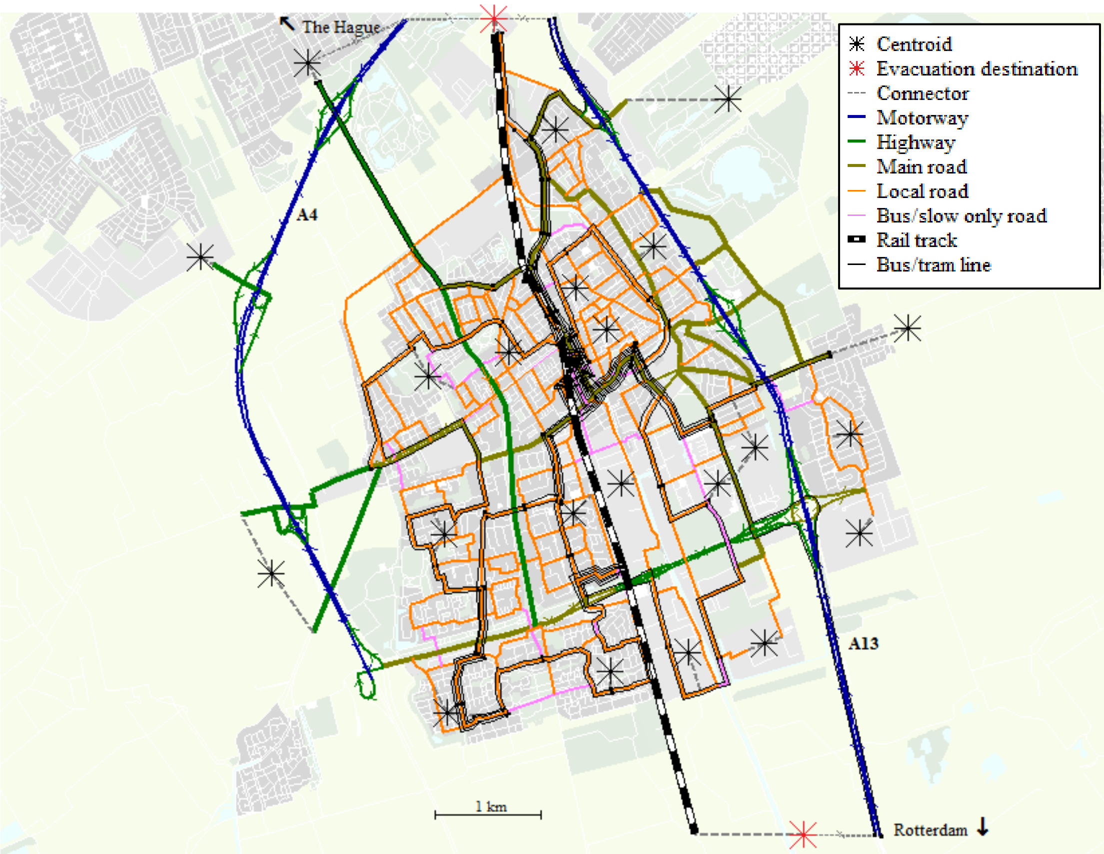

Figure 3. Network of the city of Delft used in our case study

For the evacuation choice model, we assume that people go home prior to evacuating, depart from home once all household members have arrived, use their car if possible, use public transport or walk if not, and choose their routes according to instantaneous travel times (i.e., based on current conditions) and household-level personal preferences. If multiple members of a household want to make the same trip, we assume they share a single car. Preferred evacuation destinations are assumed to be randomly distributed equally between the northern and southern safe destinations (see Figure 3). The southern destination is reachable only by the A13 motorway, by train and by bus, whereas the northern destination is also reachable by the A4 motorway, by a small local road and by tram.

Before we present the simulation results, in the next subsection we first discuss model implementation issues relating to the choice set generation, the activity-travel pattern generation for a synthetic population, and the multimodal dynamic network loading. Figure 4 summarizes the main points of the case-specific assumptions and methodology for the emergency scenario.

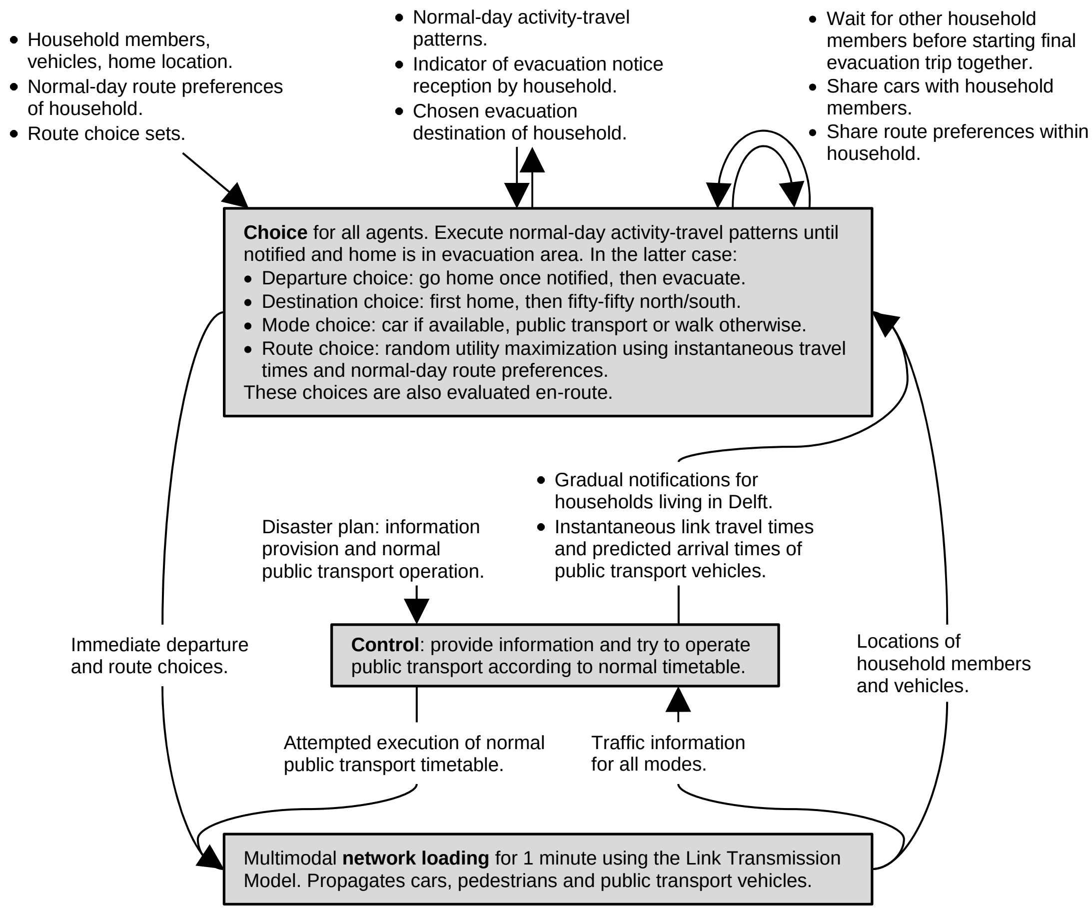

Figure 4. Overview of how the evacuation scenario implements the general framework of Figure 2

3.1 Case-specific methodology

Route choice sets

As stated previously, route choice, including en-route choices where individuals adapt to the prevailing conditions, is simulated microscopically. For sake of computational efficiency we generate explicit route choice sets beforehand, rather than repeatedly searching for a new fastest path for each individual. To include en-route choices, we need to generate a choice set for each location in the multimodal network where an individual may update his/her route. Furthermore, each choice set should include all destinations reachable from the corresponding location, with one or more alternative routes for each possible mode.

For the private modes, we generate choice sets at all road network links, including connector links. Here an accelerated Monte Carlo approach is used (Fiorenzo-Catalano and Van der Zijpp, 2001), where we repeatedly draw link travel times τ from normal distributions with mean equal to the free flow time τ_0:

$$\tau = \max\left(\tau_0 + \varepsilon\sqrt{\theta\tau_0}, 0\right) \text{ with } \varepsilon \sim N\left(0,1\right) \tag{1}$$

We repeat this for 500 iterations, linearly increasing the dispersion coefficient θ from zero to 0.0025 h. In each iteration the shortest paths are extracted using Dijkstra's (1959) algorithm and merged into the choice sets of the links if new. Note that we execute Dijkstra's algorithm backwards to efficiently generate routes from each destination centroid to each link. Turn prohibitions are taken into account by operating at link level rather than node level. For efficient storage in computer memory, routes are defined recursively as a combination of the first link and, if this is not the only link, a reference to the route after that link.

The inclusion of public transport is complicated by the common lines problem where travelers can choose among multiple lines for a single public transport leg (Kurauchi, Bell and Schmöcker, 2003). One possible solution is to merge all lines between the boarding and alighting stops into a single public transport link representing the effective level of service (Cominetti and Correa, 2001). This simplifies route choice as individuals then board the first departing vehicle along the lines. However, to include en-route choices, the location of an individual needs to be known in more detail to determine at which intermediate or later stops a traveler can choose to alight. In this application, we therefore define public transport links between each pair of consecutive stops, merging any lines serving that pair. We extend the previous route definition for the unimodal case to include a set public transport line numbers that may be used to traverse the link, which is constant over a leg.

Combining these public transport links with the links of the pedestrian network, we use a version of the branch-and-bound algorithm (Friedrich, Hofsäß and Wekeck, 2001) for the generation of public transport routes, again working backwards to construct routes from each destination centroid to each link. In the algorithm, we concatenate public transport legs and pedestrian legs, and save the generated route for each link in each leg. As input, we generate pedestrian legs for access, egress and transfers with Dijkstra's algorithm, considering only the shortest routes for simplicity. One public transport leg is generated for each possible combination of a boarding and alighting stop along each line, with common lines merged. While concatenating legs, we only use the following logical constraints:

- a route may not contain two consecutive pedestrian legs;
- a consecutive pedestrian leg and public transport leg (in any order) may not have any node in common, except for the boarding/alighting node, to prevent walking between stops of a used public transport line;
- routes may not be cyclic, except if the cycle is at the start of the route, since these circular routes could be chosen by travelers en-route to return to their origin;
- no individual pedestrian leg may exceed a specified maximum walking time (30 minutes), where the maximum is lower for transfer legs than for access/egress legs (5 minutes);
- a specified maximum number of public transport legs per route may not be exceeded (2).

Synthetic population, activity-travel patterns and route choice
For practical reasons, we use the existing Albatross model (Arentze and Timmermans, 2008) to generate synthetic households with normal-working-day activity-travel patterns, for its base year 2004. This model has been calibrated for the Netherlands using annual census data and travel diaries. From the Albatross output we extract all households that conduct any of their activities inside the study area, as well as households generating through traffic. For the latter, we extract households with one or more trips between any (near) location north and south of Delft, as Delft is situated in a corridor. The size of our synthetic population equals 20% of the representative population and hence all households are assigned a weight of 5 in the network loading simulation to get correct traffic volumes. Finally, note that Albatross constructs the activity-travel schedules for the adults of a household, and the synthetic households only indicate the age of the youngest child, but not the number of children. For simplicity, we assume that such households have one child, who needs to be picked up at home in case of an evacuation.

Albatross distinguishes a car driver mode, a car passenger mode, a public transport mode and a slow mode (Arentze and Timmermans, 2004). Note that this does not include park-and-ride separately, hence we assume the slow mode is the access and egress mode for public transport. To avoid explicit modeling of car sharing within and between households on a normal day – constraints that are principally handled within Albatross – we always create a car for users of the car driver mode, even if the number of cars owned by the household is lower according to Albatross. For trips not related to the evacuation, we "teleport" car passengers directly to their destination for simplicity, avoiding the need to explicitly couple every car passenger to a car driver as this has no influence on the traffic conditions. This also happens for public transport and slow mode trips without any route available from their origin, which may occur for some external zones in our case. The slow mode covers walking and cycling, and these users are also simulated jointly in our case study.

Supplementing these activity-travel patterns, route choice on a normal day is assumed to follow the (multimodal) dynamic stochastic user equilibrium, approximated by the serial procedure in Subsection 2.3. The weights used in the method of successive averages are set as $\alpha_i = i^{-2/3}$, where is the iteration number (Polyak, 1990), instead of the usual $\alpha_i = i^{-1}$, to emphasize the later iterations. Thus, in each iteration we randomly select $\lfloor \alpha_i N \rfloor = \lfloor i^{-2/3} N \rfloor$ households to update their choices, where N is the number of households. The sampling is stratified with respect to the number of iterations ago each household was last updated. Furthermore, we prioritize households who can gain more than 45 minutes of utility by changing the route of a single trip.

Households' route choice follows Random Utility Maximization, where route disutilities U^r are based on to-be-experienced travel times for choices on a normal day and instantaneous travel times for choices during the emergency conditions:

$$U^r = \sum_{a \in A^r} \left(\tau^a + \max\left(\varepsilon^a \sqrt{\theta \tau_0^a}, -\tau_0^a \right) \right) + \beta_{\mathrm{PT}} \max\left(\varepsilon^{\mathrm{PT}}, 0 \right) \left| P^r \right| + \sum_{p \in P^r} \left(t_{\mathrm{wait}}^p + t_{\mathrm{IV}}^p + \sum_{a \in A_p} \max\left(\varepsilon^a \sqrt{\theta \tau_0^a}, -\tau_0^a \right) \right) \tag{2}$$
$$\text{with } \varepsilon^\bullet \sim N(0,1)$$

Equation 2 sums up the travel times τ^a of private mode links $a \in A^r$, and the in-vehicle time t_{IV}^p, waiting time t_{wait}^p and a boarding penalty β_{PT} of public transport legs $p \in P^r$, where each component includes an error term to include heterogeneous preferences. For the computation of public transport in-vehicle time and waiting time, we use the departure and arrival times of all individual public transport vehicles as realized in the previous iteration, or as in the timetable for the first iteration; for simplicity we do not include the delay due to vehicles that cannot be boarded due to capacity constraints. In our application, we set β_{PT} to 8 minutes and θ to 0.0005 h. Stochastic error terms $\varepsilon^\bullet$ are generated and stored per household.

For choices during the emergency scenario, the same error terms are used as on the normal day, such that households' route preferences are fully correlated between these conditions. This effectively yields an increased likelihood that people choose familiar routes to evacuate. We use instantaneous travel times to predict the arrival times of each public transport vehicle at each of its stops, which in turn are used in the utility calculation of public transport routes in the emergency scenario.

Multimodal dynamic network loading
For the macroscopic dynamic network loading model, we use the Link Transmission Model (Yperman, 2007), derived from kinematic wave theory (Lighthill and Whitham, 1955; Richards, 1956). This model discretizes time at every node, but, unlike e.g. the Cell Transmission Model, does not need to discretize space within links, both yielding a high computational efficiency and a small numerical error. Here, we maximize the time step of each node, within the constraints set by the adjacent links, and process nodes in parallel when possible in order to minimize computation time. In order to prevent small amounts of traffic from travelling faster than the free flow speed due to numerical diffusion – this would give unrealistically small travel times on the microscopic level and negatively affect the possibilities for en-route choice behavior – we use a modified method to interpolate cumulative curves in our model, the details of which are however beyond the scope of this paper. The maximum time step of any node equals 1 minute, since travel demand at origins is aggregated per minute and, in the evacuation scenario, the choices of households are updated every minute as well. To avoid numerical errors in the arrival and departure times of public transport vehicles, all nodes with public transport stops are assigned a small time step of 1 second.

We define links and fundamental diagrams separately for vehicular and pedestrian traffic. The fundamental diagram for vehicular traffic is piecewise linear with three pieces, based on the link free speed, link critical speed, link capacity, and a jam density of 180 vehicles per kilometer per lane. For dedicated public transport links, we use a triangular fundamental diagram based on the public transport speed. For pedestrian traffic, lacking specific data, we use a rather arbitrary fixed triangular fundamental diagram with a free speed of 5 km/h.

Our node model is based on the Tampère, et al. (2011) node model for unsignalized intersections. Note that this model does not include the interaction of crossing flows on intersections, e.g. via red phases at traffic lights, but only the diverging and merging of flows. As described in Subsection 2.3, we need to extend our node model with various source and sink capabilities to handle public transport, which we implement as follows:

- For alighting pedestrians and departing public transport vehicles, we define a source immediately downstream of the node. We give this source traffic absolute priority over traffic coming from the intersection by subtracting the source traffic from the receiving flow provided to the node model.
- Pedestrians arriving at the node to board public transport and public transport vehicles arriving at their final stop, are part of the sending flow provided to the node model, but are destined to a virtual sink turn. Thus, they are constrained by the conservation of turn fractions, but do not show up on any outgoing link. For public transport vehicles, this is consistent with an assumption that the final stop is situated just upstream of the intersection.
- Public transport vehicles arriving at intermediate stops are part of the sending flow, use a regular turn and are also part of the transition flow of that turn, but are removed from the flow just before the transition flow is added to the inflow of the outgoing link. These vehicles thus go through the node model before stopping, consistent with an assumption that the public transport stop is situated just downstream of the intersection.

3.2 Simulation results

Below we present the case study results. First of all, Figure 5 indicates the trip departures over the day for a normal day, thus following directly from the Albatross output. The "teleportation" trips correspond to all trips not explicitly assigned to the network, of which almost all relate to car passenger trips (and almost none are public transport and slow trips for which no route exists in the case study network). The strange peaks in the figure exist because in Albatross, the time-of-day constraints on activity types are deterministic rather than stochastic, leading to many identical starting and ending times of activities among the synthetic population.

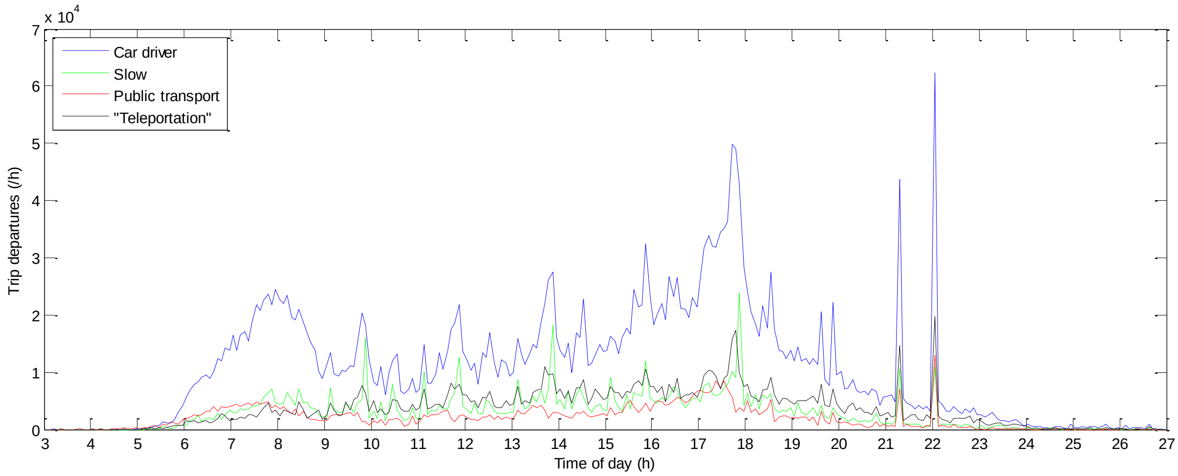

Figure 5. Trip departures per mode in Albatross activity-travel patterns for the case study

The next step is to perform route choices for the activity-travel patterns of Albatross. Let U_i^r denote the disutility of route r, as in Equation 2, using the travel times resulting from iteration i. Let r_i then indicate the chosen route in iteration i, based on the travel times resulting from iteration $i-1$. This allows us to define a duality gap DG_i and a maximum utility difference MUD_i for iteration $i>1$ as follows:

$$\begin{aligned} r_i &= \arg\min_r U_{i-1}^r \\ DG_i &= \frac{\sum\left(U_{i-1}^{r_{i-1}} - U_{i-1}^{r_i}\right)}{\sum U_{i-1}^{r_i}} = \frac{\sum U_{i-1}^{r_{i-1}}}{\sum U_{i-1}^{r_i}} - 1 \\ MUD_i &= \max\left(U_{i-1}^{r_{i-1}} - U_{i-1}^{r_i}\right) \end{aligned} \tag{3}$$

In a perfect stochastic Wardrop equilibrium, both convergence indicators would be zero since the included error terms are drawn explicitly and remain constant over iterations. From Figure 6, we observe it is difficult to obtain reasonable convergence using our current method, even though there is almost no road congestion outside the evening peak hours. This might partly be explained by the fact that the travel times allocated by Albatross may deviate from the travel times in our case study network, so that encountered delays in one trip affect later trips as well because departures are delayed. Additionally, in the public transport system, very subtle changes in traffic conditions and hence in running times may have a big impact for individual travelers, as this may force them to board a different vehicle, causing a very unequal distribution of the duality gap over the trips (Figure 6b). The indivisibility of agents (with a weight of 5 each) may also play a role (Bekhor, Kheifits and Sorani, 2014). Of course, in this study we focus on simulating an emergency, but better convergence for the normal day would be desirable. Here, we stop once the overall duality gap is lower than 0.003, which takes 340 iterations.

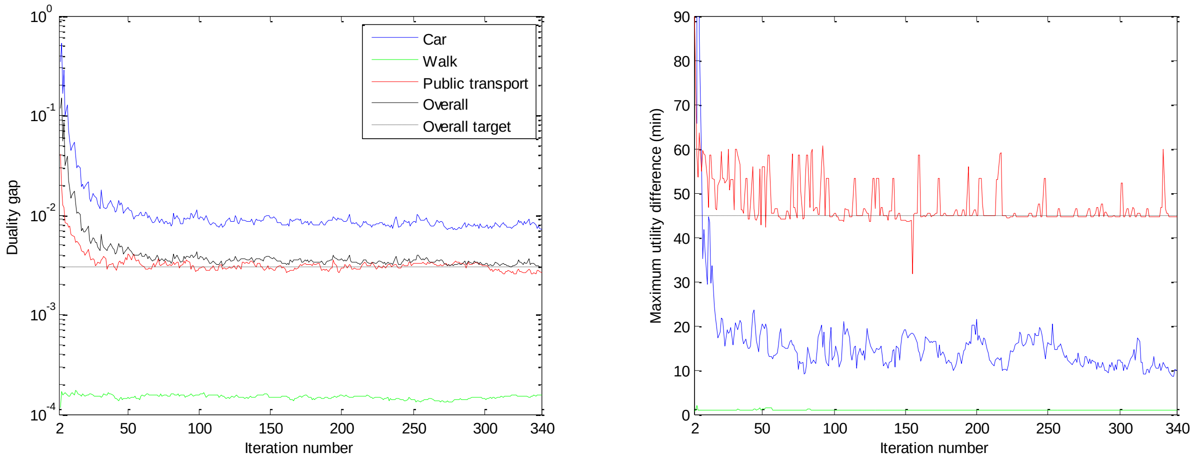

Figure 6. Convergence of (a) the duality gap (b) the maximum utility difference

Proceeding with the simulation of the emergency conditions, the average status of the transportation system between 17:30 and 18:00 is visualized in Figure 7 for vehicular traffic and in Figure 8 for the public transport network (the pedestrian traffic is omitted here for brevity). For the vehicular traffic (Figure 7), we notice many traffic jams on roads inside Delft. Because of the combination of inbound, outbound and background traffic with various destinations each, we observe no clear pattern regarding the directions of traffic jams on the urban roads – at various places, both directions of the same road are heavily congested simultaneously. Looking at access points to the motorways, the traffic conditions are especially bad for the people that try to evacuate to the south.

One main origin of congestion is the southernmost A13 motorway on-ramp directed towards the south. This bottleneck is also active in the evening peak of a normal day, but in the evacuation scenario we can see it spill back over the urban arterial, via one of its intersections back in the other direction of the same arterial, and then onto the opposite direction of the motorway. The route of this shockwave is indicated with an arrow in Figure 7b. This is a major conflict between outbound, inbound and background traffic, causing very large delays for through-traffic travelling on the A13 northbound *towards* Delft – this motorway queue does not resolve until 21:30. If the disaster plan would require emergency services to access Delft from the south, they would also be severely delayed.

Due to the same southbound on-ramp, the southbound A13 also suffers from heavier congestion than on a normal day, with much more spillback into the urban network at the other two on-ramps as well. In response, we see many people evacuating to the north using the A4 motorway instead. Looking at the A4, at the circled off-ramps in Figure 7b, we see traffic heading into Delft blocking the through-traffic on the motorway. Although to some extent this also occurs on a normal day for southbound traffic, this problem starts earlier due to the inbound evacuation traffic and now also blocks outbound evacuation traffic heading north. Hence, at this moment in time, all three motorway routes towards Delft are simultaneously congested, which again could be problematic for emergency services.

For the public transport network (Figure 8), all outbound trains are fully loaded until 19:30. The bus and tram lines are however almost not used, due to road congestion as indicated in Figure 7. Both tram and bus in the northern evacuation direction show zero passenger flow out of the network between 17:00 and 18:30, as traffic jams cause delays so large that they are too unattractive for evacuating travelers. The next half an hour, the road congestion between Delft central station and The Hague reduces a bit and the tram line is boarded up till capacity before leaving Delft. Later, the passenger flow of the tram line reduces again as for most people taking the train is faster, while the demand from residential zones near the tram line is already

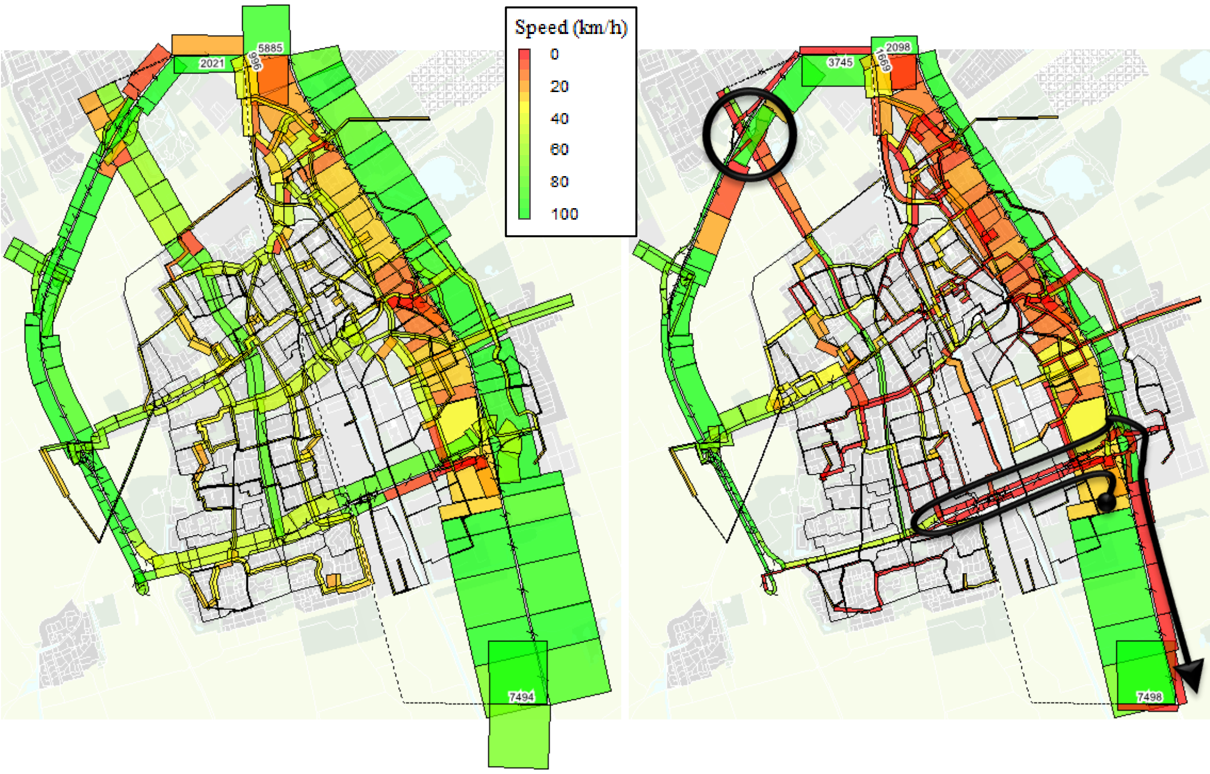

Figure 7. Average vehicle traffic flows (h^{-1}) between 17:30 and 18:00 for the Delft case study
(a) on a normal day (b) in the evacuation scenario
Bar widths are proportional to flow, colors indicate traffic speed

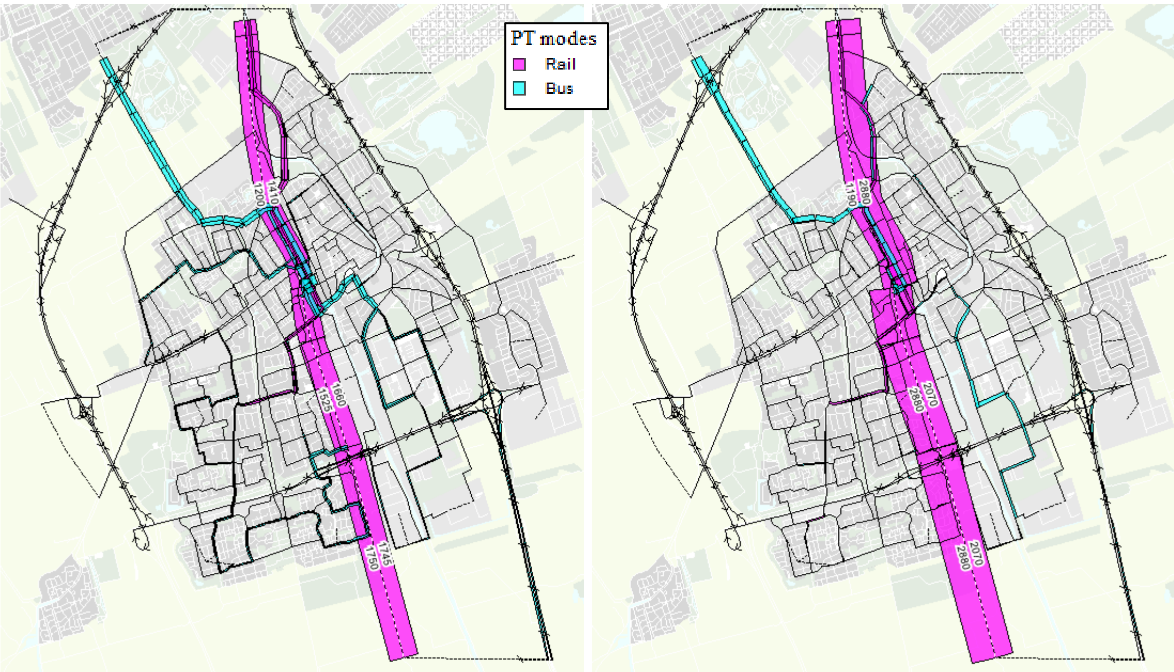

Figure 8. Average public transport flows (h^{-1}) between 17:30 and 18:00 for the Delft case study
(a) on a normal day (b) in the evacuation scenario
Bar widths are proportional to flow, colors indicate public transport mode

decreasing. The bus line remains practically unused by passengers, but it is also barely used on a normal day. Overall there appears to be a difference between user-optimal and system-optimal evacuation in public transport, although this may be overestimated because the *choice* model does not take into account that the train services are overloaded with passengers.

Also, we note that since the last traffic jam resolves after 23:30, there is a large period of time of four hours in which the train lines have spare capacity, but the roads are still congested. This suggests that a true multimodal evacuation plan, where authorities try to convince car owners to use public transport, may significantly reduce the time required to evacuate the city, in this case especially for people with a destination south of Delft. A public transport schedule specifically designed for evacuations may further increase the network production.

We plot the overall progress of the evacuation in Figure 9. Here, we see that not all, but a large majority of households can gather at home quickly, yet the final evacuation trip from home to the safe destination takes substantially longer. This supports our earlier expectation that early outbound traffic together with background traffic will activate prominent network bottlenecks, and due to these traffic jams then also late inbound traffic gets delayed.

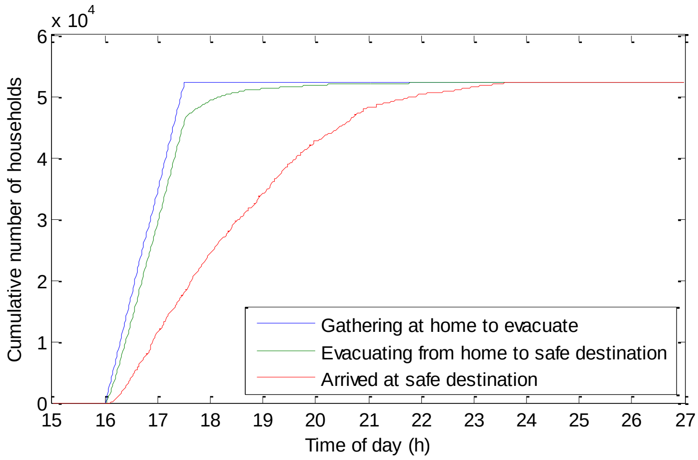

Figure 9. Evacuation progress over time for the Delft case study

Finally, we look at computation time. From Table 1, we see that although a lot of time is spent finding the normal day equilibrium – simply due to the very many iterations – the actual evacuation simulation is very fast: it takes only about two and a half minutes on our PC. This makes the model suitable for efficiently investigating a large number of possible emergency scenarios and candidate disaster plans. Note that if the overall model is ran with increased accuracy by enforcing a maximum time step of 1 second for all nodes, the convergence of the normal day equilibrium takes a lot longer, but the increased accuracy does not significantly affect the results reported above, indicating that the use of larger time steps was adequate.

Table 1. Computation time per model component

Model component	Computation time*
Network and population import	62.1 s
Car/walk route choice set generation	8.9 s
Public transport route choice set generation	11.7 s
Normal day equilibrium simulation	158.8 min†
Emergency simulation	154.0 s

* Measured with a C++ implementation on a Dell Precision T3600 PC with 12 logical processors
† On average 28.0 s per iteration

4. Conclusions

In this paper, we propose a methodology to simulate a multimodal transportation network during emergency conditions. Starting with model requirements identified from literature, we included an activity-based escalation model for the choice behavior of individuals in the network and a macroscopic or mesoscopic multimodal dynamic network loading model. We show that such an escalation-based choice model captures the choice behavior found in literature, and subsequently presented a new method to integrate it with the network loading model for efficient simulation of emergency conditions. As a result, the overall methodology supports arbitrary pre-trip and en-route choice models with interactions among individuals and is agnostic regarding the modeling of traffic propagation, so that it is flexible and thus general enough to study a wide range of emergency situations, and corresponding management strategies of authorities. Our case study application showed that the resulting model structure is indeed very efficient for the simulation of emergencies. This for example allows model users to compare various alternative management strategies and to check the robustness of a strategy by varying simulation inputs.

The Delft case study application yielded the following insights, which both provide directions for the development of urban evacuation plans, as well as emphasize essential model requirements and thus the need for our comprehensive modeling methodology that includes these complex system dynamics:

- One should consider the interaction of inbound, outbound and background traffic. Within the endangered area, congestion may occur in multiple directions simultaneously. Due to spillback, important roads *towards* the endangered area may become seriously congested. This may have important consequences for emergency services trying to reach this area.
- One should also consider the interaction between modes. Urban public transport may fail due to road congestion. Consequently, public transport users may need to adapt their route.
- User-optimal route choice may not be system-optimal. This is well-known for car traffic, but during evacuations this can also be the case within the public transport network, as this network has its own capacity restrictions.
- Spare capacity may become available in public transport while the road network is still congested. Encouraging car owners to use public transport may hence reduce the total evacuation time.

Once candidate strategies have been developed, preferably with these insights in mind, these can again be assessed with the same framework and model. Important aspects of the case study that need further verification are the equilibrium traffic pattern for a normal day, the emergency choice model, and the emergency driving behavior in the network loading model. At the same time, relying on an activity-based choice model for a normal day for all members of the population and the need for an accurate model that predicts all travel choices of people during an emergency are likely important practical limitations of our methodology. To remedy the latter, we plan to develop and calibrate an emergency choice model through a stated-preference experiment in a later stage of this research project. The methodology presented in this paper is flexible enough to handle any outcome of such further research.

Acknowledgements

This research effort is funded by the NWO-NSFC project *Optimal Multimodal Network Management for Urban Emergencies*, part of the China-Netherlands joint research program *The Application of Operations Research in Urban Transport*. The authors wish to thank Theo A. Arentze from Eindhoven University of

Technology for generating synthetic households with activity-travel patterns for our case study using Albatross. An earlier version of this paper has been presented at the *3rd International Conference on Evacuation Modeling and Management*, June 2015, Tainan. Parts of this paper are based on a paper presented at the *Joint Chinese-Dutch Seminar on Transportation Management and Travel behaviour for Urban Emergencies: Past, Present, and Future Research*, June 2014, Shanghai.

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