

Modelling Traveller Behaviour under Emergency Evacuation Conditions

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Dynamic traffic simulation models are frequently used to support decisions when planning an evacuation. This paper focuses on limitations in the modelling of travellers' behaviour with respect to traffic information and compliance to evacuation instructions. More specifically, we propose a model framework where the traffic simulation is executed only once (instead of many times within an iterative traffic flow convergence framework, e.g., yielding a user-equilibrium assignment). Within this one-time execution of the traffic simulation (or dynamic network loading procedure), travellers are initially assigned to their instructed route (and destination), yet may continuously update their destination and route during their trip - while accounting for the possibly disutility associated with non-compliance - thereby responding to the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by an iterative user-equilibrium assignment). This way, the realized departure time, destination and route decisions are a result of the trade-off that travellers make between complying with the prescribed travel behaviour and following their preferred travel behaviour (i.e., the travel decisions that would have been made in absence of an active evacuation plan). Also, this approach allows modelling full compliance, no compliance, and any state in between. The face-validity of the model characteristics are illustrated using a hypothetical test example. The results show the importance of capturing compliance and information levels in the traffic simulation model, as they have a large impact upon the evacuation efficiency.

Keywords: Compliance, Evacuation, Network modelling, Road infrastructure dynamics, Traffic information, Traveller behaviour

1. Introduction

The occurrence of many natural and man-made disasters can be anticipated on, for instance, wild fires, hurricanes, floods, terrorist attacks, and industrial accidents. This implies that, up to a certain level, we can predict how such a disaster may affect a certain region and evolve in a specific way. A most probable disaster scenario can then be used to plan the best way of avoiding or mitigating the effects of the disaster, for instance by planning an evacuation. The success of an evacuation strongly depends on many factors, such as warning time, public preparedness and response time, information and instructions dissemination procedure, evacuation routes, traffic

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conditions, dynamic traffic management measures, etc. (Dash and Gladwin 2007, Lindell and Prater 2007). Due to the complexity of the underlying processes and the multitude of factors influencing these processes, model-based approaches are helpful or even indispensable for the analysis and planning of emergency evacuations (Barrett et al. 2000, Hardy et al. 2010). Such an evacuation simulation model can be applied to obtain a better understanding of the network conditions and the effect of traffic regulations and control measures hereon, by predicting departure and arrival patterns, travel times, average speeds, queue lengths, traffic flow rates, etc. Insight into this dynamic process is necessary to make well-supported decisions on, for instance, the latest possible time to order the start of the evacuation, the best evacuation routes, or the most suitable traffic management measures.

Many dynamic traffic simulation models have been used to forecast, plan, or optimize the traffic operations for a possible evacuation. In this paper, focus lies on the behavioural assumptions that are generally made while modelling travel behaviour and infrastructure dynamics, and their suitability to the case of evacuation conditions. To this end, in the next section, we present an overview of evacuation traffic simulation models and argue that many of these past and current traffic models used in evacuation studies have shortcomings. These model limitations, relating to traveller behaviour and model flexibility with respect to traffic information and travellers' compliance, are discussed in Section 3. Subsequently, Section 4 formulates a mathematical model aimed at relaxing these limitations. The characteristics and face-validity of the proposed evacuation traffic model, called EVAQ, is shown on a small test-network and hypothetical disaster scenario. The impact of varying levels of compliance and traffic information is tested and discussed. In the closing section, we discuss the presented modelling approach, and show the applicability of the proposed model by making reference to a few larger-scale case studies described elsewhere. Finally, some remarks are made concerning issues on model calibration and validation, which remains a general challenge to these models due to the lack of sufficient quantitative empirical data.

The contribution of this article lies in the conceptual framework and mathematical model formulation which relax some of the identified limitations and produce face-valid predictions on partial traveller compliance and traffic information under exceptional conditions, such as evacuation. Hence, the work presented here may be beneficial to those who develop evacuation traffic simulation models, as it provides a discussion on the proposed model formulation which incorporates travellers' response behaviour towards traffic information and road infrastructure dynamics, and their compliance with evacuation instructions. Also, the discussions and model results may benefit those who apply these models to forecast, plan, or optimise an evacuation as it helps in understanding the role of these behavioural aspects in the evacuation process and the design and evaluation of evacuation plans, including testing for robustness towards uncertainties in travellers' behaviour.

2. Past and Current Practices in Evacuation Modelling

Since the late 1970's, evacuation simulation models are developed to analyse and evaluate emergency evacuation plans. Early studies in the 1980's focused mainly on evacuation in case of nuclear power plant emergency due to the Three Mile Island reactor incident in 1979. Then, after a number of extremely devastating hurricanes hitting the coast line of the U.S. in the 1990's, much evacuation research shifted focus to hurricane evacuation. Since the September 11, 2001, attack in the U.S., also mass evacuation due to bomb threats and terrorist attacks is getting more attention. Due to tsunamis and otherwise-caused floods in Eastern Asia and bush fires in Australia, evacuation research in these countries typically focuses on these types of evacuation. For the Dutch situation, rising sea levels and a perceived increasing threat of flooding has led to the start

of a national program initiating flood evacuation research and applications within the Netherlands.

In many of the earlier studies, evacuation is recognized as an exceptional event regarding different travel demand patterns, driver behaviour, traffic management, etc., resulting in new traffic models being developed specifically for evacuation studies. A few of these earlier models have also been applied more recently and on reasonably large scale, such as the microscopic model OREMS (Rathi and Solanki 1993), and the macroscopic models DYNEV (KLD 1984) and MASSVAC (Hobeika and Jamei 1985). A note can be made here that MASSVAC can be seen as a successor of the earlier developed evacuation traffic simulation model NETVAC (Sheffi et al. 1980), and OREMS is based on the microscopic traffic simulation model CORSIM, which is developed for regular daily traffic conditions.

More recently, a large number of evacuation studies are conducted using well-established dynamic traffic simulation models developed for regular daily traffic applications, including both microscopic models, such as PARAMICS (Cova and Johnson 2003), CORSIM (Williams et al. 2007), VISSIM (Han and Yuan 2005) and mesoscopic or macroscopic models, such as DYNASMART (Murray-Tuite 2007), DynaMIT (Balakrishna et al. 2008), DynusT (Noh et al. 2009), TransCAD (Wang et al. 2010), and INDY (Klunder et al. 2009). In a number of studies using microscopic models, model parameters describing driving behaviour (such as headway, acceleration, reaction time) have been adjusted for the case of emergency evacuation (e.g., Tu et al. 2010). Other than that, the model structure and parameter settings are typically not changed.

In all these models, the origin-destination travel demand matrix describing travellers' evacuation participation and destination decisions is either model input or is computed using a gravity-model based trip distribution model, or a combination of the two. The departure times are generally determined by applying an exogenous response curve stating the percentage of departures in each time interval. Such a response curve has been assumed to follow a number of different distributions, for example, instantaneous departure (Chen and Zhan 2004, Chiu et al. 2006), a Uniform distribution (Liu et al. 2006, Yuan et al. 2006), a Poisson distribution (Cova and Johnson 2002), a Weibull distribution (Lindell et al. 2002) and sigmoid curve (Kalafatas and Peeta 2009, Xie et al. 2010). Although debated, the latter two are often claimed to be most realistic. A user-defined dynamic origin-destination matrix allows evaluating (mandatory) evacuation instructions, since the matrix can be chosen following dedicated departure time (windows) and destinations.

These trips are then in most models assigned to the road network according to the (dynamic or static) user-equilibrium assignment assumption, although one may wonder whether an equilibrium assumption will hold in an emergency evacuation. In addition, most models allow user-defined routes as model input, thus enabling evaluating (mandatory) instructions regarding prescribed evacuation routes. Exceptions are the route choice model incorporated in, for instance, PARAMICS, INTEGRATION, DYNASMART and DynaMIT, modelling en-route route switching based on prevailing (and predicted, in case of DynaMIT) traffic conditions.

In most models, traffic flow is simulated in which road network characteristics are mostly static. In some models, road network characteristics such as capacity and maximum speed vary to incorporate the damaging effect of the hazard on the road infrastructure (e.g., links becoming less accessible due to flooding) and dynamic traffic management and control measures (e.g., contraflow operations to increase outbound capacity). For example, MASSVAC allows modelling several consecutive time intervals (time-sliced static traffic assignment) in which road network characteristics change, and INDY incorporates so called 'events' in which network characteristics and model parameters can be different within a specified time window.

3. Modelling Shortcomings Reviewed

Furthering the discussion in Section 2, a more complete overview of modelling approaches, including a discussion on current and future challenges in evacuation transport research and applications, is given elsewhere (Pel et al. 2011). Here, we highlight the main limitations in the modelling approaches applied in the various evacuation models. Two typical shortcomings, both relating to travellers' behaviour, are on traffic information and compliance.

Regarding traffic information, since evacuation is an unfamiliar situation, it needs to be considered that travellers cannot rely on prior experience and knowledge on future traffic conditions. This makes the user-equilibrium assignment assumption inappropriate stating that travellers are fully aware of, and anticipate on, future network conditions in their route choice decisions. Instead, travellers need to rely on the available traffic information, and hence a more myopic choice behaviour is to be expected. This is supported by empirical findings from, for example, Knoop (2009), Lindell et al. (2005), and Robinson and Khattak (2010).

The second limitation relates to travellers' compliance. Since the evacuation instructions (on, e.g., departure time, destination, and route) may differ from the travellers' preferred travel decisions, the travellers' level of compliance need to be considered. This makes modelling travellers' behaviour equal to the instructed behaviour inappropriate. Instead, partial compliance is to be expected. Empirical findings supporting this can be found in studies by, for instance, Dash and Morrow (2001), De Jong and Helsloot (2010), Dow and Cutter (2000), Knowles (2003), and Rasid et al. (2000).

These important aspects are often insufficiently incorporated in evacuation models, and hence in the scenario analyses that use these models, although they have occasionally been identified as a promising future research direction (e.g., Abdelgawad and Abdulhai 2009, Chiu 2004, Peeta and Hsu 2009). As to travellers' compliance to advice under non-evacuation conditions, a number of studies have been done on identifying the factors that affect travellers' willingness to comply, and how this traveller compliance can be modelled endogenously (for an overview, see Chorus et al. 2009). The body of research empirically studying compliance behaviour may prove helpful when generating hypotheses on the explanatory variables which determine travellers' compliance. Although one may question whether the explanatory factors found under daily conditions (such as travel time variability, network familiarity, information quality, relative travel times under normal conditions, and a range of traveller characteristics) and their relative importance can be directly transferred to the case of an emergency evacuation, the research efforts nevertheless give direction to further study on travellers' willingness to comply with an evacuation plan.

In the remainder of this paper, we formulate a traffic model specifically aimed at relaxing these limitations on travellers' partial compliance and their lack of prior experiences and hence reliance on traffic information. Thereby, the model is tailored to the circumstances of an extreme event such as evacuation. Although these two limitations are highlighted, to a lesser extent, also other limitations need to be dealt with. One of the more important ones is driving behaviour, since the behaviour of drivers (i.e., driver-vehicle combinations) under mentally demanding and emergency conditions is suspected to differ from that expressed in normal conditions. This is supported by experimental and empirical findings (e.g., Hamdar 2008; Hoogendoorn 2010; Hoogendoorn et al. 2010, 2011; Knoop et al. 2009; Ni 2006). Before going into the proposed model formulation in Section 4, first, it is explained why driving behaviour is not (explicitly) dealt with in this paper.

The driving task is not considered throughout this thesis since the proposed model formulation is macroscopic and thus considers aggregated traffic flows instead of (the interactions between) individual driver-vehicle combinations. Hence, the impact of changes in driving behaviour under

evacuation conditions on, for instance, average speeds and road capacity, would be incorporated through the model input. The way this should be done is certainly not trivial, nor sufficiently studied yet. Nonetheless, there are strong arguments for defining the evacuation model at a macroscopic level of analysis (within the evacuation planning studies considered here):

Scalability, computation time, memory usage; The model applications in mind for the model developed here, relate to region-wide evacuation planning and model-based optimization of evacuation plans/instructions (typically done within an iterative search-and-evaluate framework). These require efficient model scalability, computation time and memory usage. These requirements are better met by macroscopic traffic simulation models than microscopic models.

Model complexity matching data availability; Given the lack of detailed empirical data, a more detailed (microscopic) level of traffic simulation which yields a higher model flexibility and complexity leads to problems regarding underdetermined (and hence unreliable) model calibration and validation. The principle of parsimony here strongly favours a macroscopic approach.

The formulation of the proposed macroscopic evacuation traffic simulation model is discussed next.

4. Model Formulation

In this section, it is shown how the previously identified limitations on traffic information and travellers' compliance can be relaxed. In short, this is done by modelling a one-time dynamic network loading (instead of an iterative traffic flow convergence algorithm yielding, e.g., a user-equilibrium assignment). Within this one-time execution of the dynamic network loading procedure (i.e., the traffic simulator), the impact of the prevailing available traffic information and infrastructure dynamics are incorporated by combining pre-trip route assignment and en-route route switching. In the pre-trip assignment, travellers are assigned to the prescribed evacuation routes to the prescribed safe destinations (coming from an evacuation plan). While en-route, travellers can decide to switch routes to any of the safe destinations, thereby responding to the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by an iterative user-equilibrium assignment). This way, the realized departure time, destination and route decisions are a result of the trade-off that travellers make between complying with the prescribed travel behaviour and following their preferred travel behaviour (i.e., the travel decisions that would have been made in absence of an active evacuation plan). For the departure time choice, the level of compliance is modelled exogenously. For the destination and route choice, compliance behaviour is modelled endogenously by introducing an additional attribute representing the possible disutility associated with non-compliance. This approach allows modelling travellers full compliance, no compliance, and any state in between. The mathematical formulation modelling these processes is given in the ensuing. The way in which both pre-trip and en-route route choices are incorporated is derived from a hybrid route choice model developed in an earlier study (Pel et al. 2009).

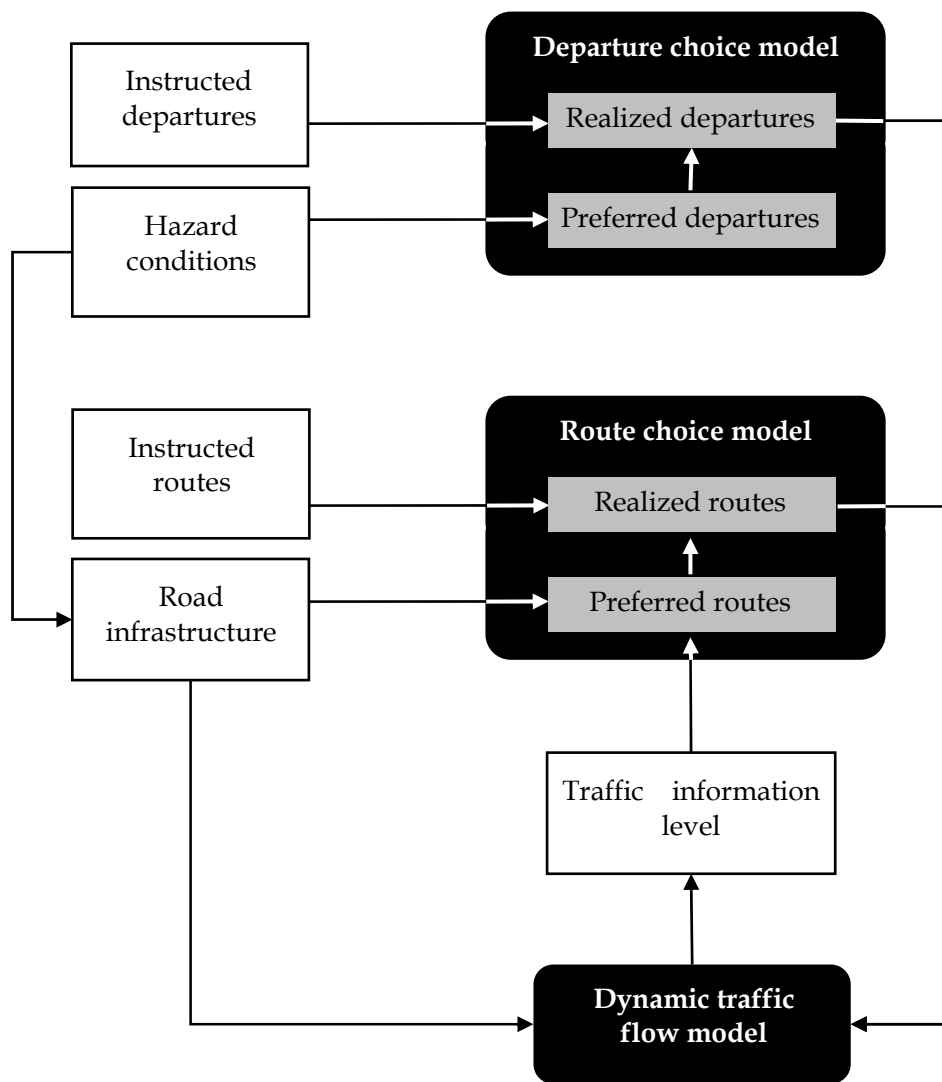


Figure 1. EVAQ model framework

4.1 Model Framework

The general framework of the proposed model, called EVAQ, is in line with that of any traditional transportation model, and is presented in Figure 1. The conceptual framework shows the three model components describing how travellers' departure time decisions, and destination and route decisions are realized (here assumed independent), and the traffic flow propagation over the road network (implicitly modelling driving behaviour). The model input comprises of: the hazard conditions, influencing the preferred departure times of evacuees, and (the accessibility of) the road infrastructure; the evacuation instructions, having an effect on the actually realized travel decisions, as travellers' decisions are a trade-off between their preferred decision and the instructed departure time, destination, or route; and the level of traffic information, as this influences which routes are preferred. Each of the three model components is described in more detail in the remainder of this section.

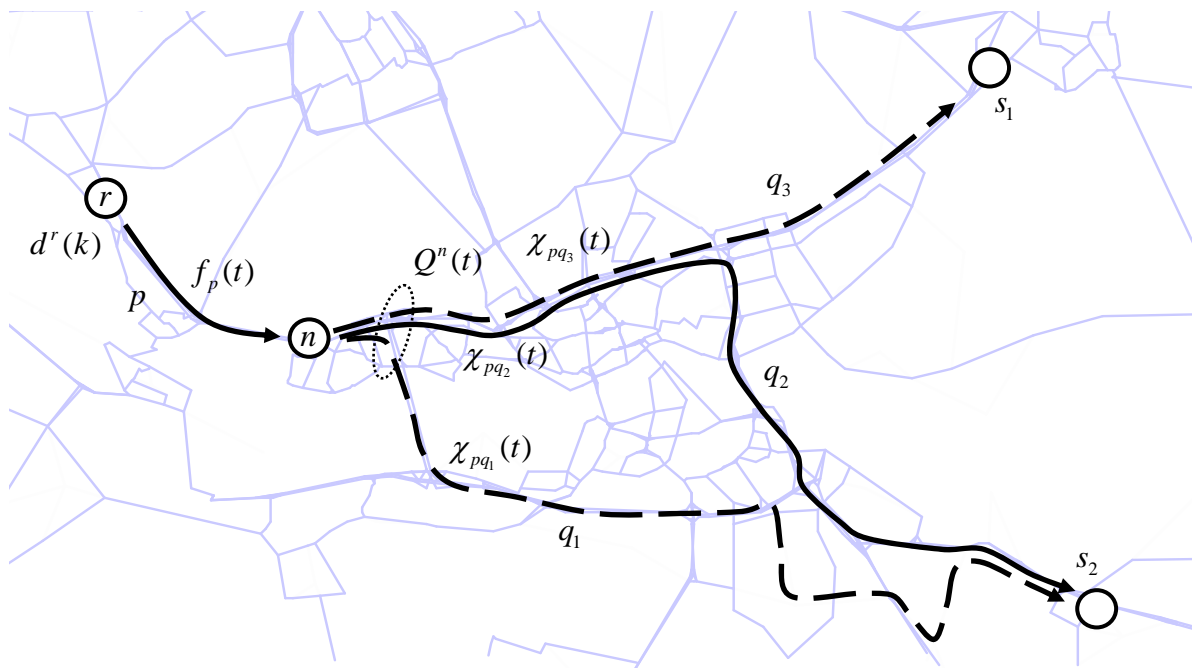


Figure 2. Model variables: Origin r , intersection n , and safe destination s . Dynamic travel demand rate $d^r(k)$, route flow rate $f_p(t)$, instructed evacuation routes p , (relevant) route choice set $Q^n(t)$, with for each route $q \in Q^n(t)$ a route-specific flow fraction $\chi_{pq}(t)$.

We model road infrastructure as nodes and links, where N is the set of network nodes and A is the set of directed network links (arcs). The set of all nodes N consists of origin nodes $r \in R \subset N$ (where travellers depart and enter the network), safe destination nodes $s \in S \subset N$ (where travellers arrive and exit the network), and intersections $n \in N \setminus (R \cup S)$ (where travellers can change the remainder of their route). All nodes are connected by directional links, representing roads or connector links. Links are indicated by subscript $a \in A$, and have characteristics, such as maximum speed, length, number of lanes, and inflow capacity. Figure 2 can be used as reference for clarification of the variables introduced below.

4.2 Departure Time Choice Model

Let the modelling time horizon be given by T . The cumulative dynamic travel demand from a specific origin r until time instant $k \in T$ is then computed as

$$D^r(k) = \gamma D_{\text{instr}}^r(k) + (1 - \gamma) D_{\text{pref}}^r(k). \quad (1)$$

Here, the actual travel demand $D^r(k)$ depends on the (cumulative) instructed travel demand $D_{\text{instr}}^r(k)$ and the travellers' (cumulative) preferred travel demand $D_{\text{pref}}^r(k)$ (in case of no instructions). More precisely, we assume that the fraction $\gamma \in [0, 1]$ of travellers complies and follows the instructed departure time, while the remaining travellers (equal to fraction $1 - \gamma$) do not comply and depart at their preferred departure time. The cumulative instructed travel demand $D_{\text{instr}}^r(k)$ follows from the evacuation instructions regarding the prescribed departure time window for origin r .

The cumulative preferred travel demand is determined by the preferred departure times of travellers in case of no instructions. A method of predicting preferred departure time decisions is by applying a sequential binary Logit model (e.g., see Fu 2004, Fu and Wilmot 2004). In this method, the shares of people who prefer to evacuate and depart in the current period, or to postpone evacuation, are predicted repeatedly over time. The share of people choosing to evacuate at a specific time is determined based on the prevailing conditions, relating to factors such as the hazard force and the velocity with which it approaches. Such a departure time choice model and accompanying utility functions have been estimated for the case of wild fires (Alsnih et al. 2004) and hurricanes (Fu et al. 2007) using surveys on stated preference and post-disaster revealed preference.

The sequential binary Logit model describes how people choose their preferred time of departure depending on their socio-demographic characteristics and the hazard's spatial temporal dynamics. The outcome of this choice process yields an evacuation response curve. In the hypothetical example in Section 5, it is assumed that travellers' preferred departure times can be represented by the sigmoid curve,

$$D_{\text{pref}}^r(k) = \left(1 + \exp\left[-\alpha^r(k - h^r)\right]\right)^{-1} B^r . \quad (2)$$

Here, $D_{\text{pref}}^r(k)$ denotes the cumulative preferred travel demand from origin r at time k . The total number of travellers who wish to evacuate from this origin r is denoted by B^r , while the bracketed term in front of it determines the share of travellers who prefer to depart at time instant k or earlier (since we are computing the cumulative demand). This way the bracketed term is the departure time profile, of which the shape is determined by two parameters (for an example see Figure 3(b)). The response rate α sets the slope of the curve, such that low values of α produce a more uniform departure profile (slower response). The half loading time h sets the midpoint of the curve, and thus states the time at which half the travellers have departed. As mentioned earlier, the values for the parameters α and h have to be estimated for each origin separately based on the outcomes of the sequential binary Logit model.

The use of the sigmoid curve fits the purpose of testing the impact of traffic information and the level of compliance in the synthetic example in this paper. However, it should be noted that, in general, this assumption may not be representative of many emergency conditions that provoke evacuation as a means of risk mitigation. Specifically, the sigmoid curve adopted is symmetrical and strictly monotonic, while conditions provoking evacuation often generate risk that develops more rapidly as time progresses, making a symmetrical response likely less appropriate. Also, some factors influencing the evacuation response, for example, opening and closing of contraflow to increase outbound capacity, yield non-smooth evacuation departure patterns over time.

Given the cumulative dynamic travel demand, the corresponding dynamic travel demand rates describing the total travel demand from origin r at departure time k is given by

$$d^r(k) = \frac{\partial D^r(k)}{\partial k} . \quad (3)$$

4.3 Destination and Route Choice Model

Pre-trip route assignment

Suppose that a traveller from origin r is assigned a prescribed evacuation route $p \in P^r(k)$ upon departure, implying also a specific destination, where $P^r(t)$ is the set of instructed routes from origin r to any (safe) destination $s \in S$ at time t . Throughout the article we assume that each

route has its own index and thus once a route is defined, also its start and end point is known. Therefore, to keep the notation short, indices for origins, destinations, and other nodes on the network are left out when they are implicitly known through the route index. The route flow rate of travellers being prescribed to a specific route p at departure time k is given by

$$f_p(k) = \chi_p(k)d^r(k), \text{ for } p \in P^r(k). \quad (4)$$

In other words, the total travel demand rate from origin r , $d^r(k)$, can be distributed according to prescribed route fractions $\chi_p(k) \in [0,1]$. Since $P^r(k)$ denotes the set of all routes that are prescribed from origin r when departing at time instant k , evidently $\sum_{p \in P^r(k)} \chi_p(k) = 1$, since all travellers are assigned a route. Travellers with the same prescribed route p can be seen as belonging to the same class of travellers. Hence, the formulation in this section can also be seen as a multiclass formulation where each class p is a distinct prescribed route.

Travellers are assigned to an initial route upon departure, after which they may adapt their route (and destination) during their trip. They might do so when prevailing traffic conditions are such that travellers are better off (or have the feeling of being better off) by deviating to another route (possibly with another destination). Evidently, travellers need to be aware of these traffic conditions in order to switch routes. This way the level of available traffic information plays a role in (en-route) destination and route switching decisions. We distinguish two phenomena: *route updating decisions* and *route choice decisions*. These are described in the following sections.

Route Updating Decisions

Travellers decide to *update* their route based on *changes* in the perceived route travel times. Presumably, slight changes in traffic conditions are ignored (or go unnoticed) and therefore do not affect route flow rates, whereas larger changes do lead to travellers deciding on considering switching to a new route. For example, travellers are insensitive to, say, ten percent change in route travel times on alternative routes. Then route flow rates remain the same while travel times vary within this ten percent margin compared to the prevailing route travel times when the route was last updated. As soon as route travel time variations exceed this ten percent margin, new route flow rates are computed.

This route updating rule shows similarity with the bounded-rationality route switching rule in the DYNASMART model where an alternative route must provide some minimum improvement in order for drivers to switch routes (Mahmassani 2001). The main difference is that in the mesoscopic DYNASMART model the route updating is checked for each specific driver, while in our proposed macroscopic model the route updating is checked for each intersection node.

We let $Q^n(t)$ denote the set of all alternative routes from intersection node n to any (safe) destination $s \in S$ at time instant t . Then the set of nodes for route updating, denoted by $\mathcal{N}(t) \subseteq N \setminus S$, is given by

$$\mathcal{N}(t) = \left\{ n \in N \setminus S \mid \exists q \in Q^n(t), \text{ for which } \left| \frac{\tau_q(t) - \tau_q(\theta)}{\tau_q(\theta)} \right| \geq \tau_{\min} \right\}. \quad (5)$$

In words, the set $\mathcal{N}(t)$ consists of all nodes $n \in N \setminus S$ for which the travel time on at least one of the alternative routes $q \in Q^n(t)$ from this node n to any safe destination, denoted by $\tau_q(t)$, differs from the travel time on this same route q at an earlier time instant when the route flow rates were last updated, $\tau_q(\theta)$, by more than τ_{\min} . Here, θ denotes the time instant when

routes from node n where last updated, while τ_{\min} denotes the minimum relative travel time difference as a threshold for route updating.

As an example, consider travellers from an upstream link coming onto an intersection node n . Say, there are three relevant routes from this node n to any of the safe destinations. At a certain time, the prevailing travel times on these routes are (perceived as) 45, 48, and 52 minutes. When assuming travellers require a minimum relative travel time difference of 10 per cent, i.e., $\tau_{\min} := 0.1$, then travellers coming onto this intersection are assumed to only consider rerouting when, for at least one route, its travel time drops below 41.5, 43.2, respectively 46.8 minutes, or exceeds 49.5, 52.8, respectively 57.2 minutes. Then, $n \in \mathcal{N}(t)$. As long as the (perceived) travel times of all three routes stay within these margins, travellers continue on their earlier chosen route, as $n \notin \mathcal{N}(t)$.

Travellers arriving at any of the nodes $n \in \mathcal{N}(t)$ at time t decide to update their route (since here the threshold for route updating is exceeded). Once travellers have decided to do so, they *choose* their route based on the *perceived* route costs. This is explained next.

Route Choice Decisions

At time t , travellers can switch routes at any intersection node $n \in \mathcal{N}(t)$. That is, travellers may decide on switching to any route $q \in \mathcal{Q}^n(t)$, where $\mathcal{Q}^n(t)$ denotes the set of all alternative routes from intersection node n to any safe destination $s \in \mathcal{S}$ at time instant t . The fraction of travellers of class p (i.e., having route p instructed) selecting route q is given by the probability that route q minimizes their *perceived* generalized route costs,

$$\chi_{pq}(t) = \Pr(c_{pq}(t) \leq c_{pz}(t), \forall z \in \mathcal{Q}^n(t)). \quad (6)$$

Here $\chi_{pq}(t)$ is the fraction of class p travellers switching to route q at time instant t , based on the prevailing perceived generalized route costs, $c_{pq}(t)$. These costs, $c_{pq}(t)$, are the costs of following route q (to any of the safe destinations) as perceived by travellers who are actually instructed to follow route p (to their instructed destination). These generalized route costs are computed as

$$c_{pq}(t) = \tau_q(t) \left(1 + l_{pq} \omega \right), \quad (7)$$

where $\tau_q(t)$ is the travel time on route q , and $(l_{pq} \omega)$ is the additional disutility of non-compliance. This additional disutility depends on the perceived costs, $\omega \geq 0$, and the route deviation proportion, $l_{pq} \in [0, 1]$. The perceived costs, ω , state that the new route q should be fraction ω faster in order to make this route more attractive than the prescribed route p . The route deviation proportion is the relative length of route q which does not coincide with the instructed route p ,

$$l_{pq} = \frac{\sum_{a \in A} \delta_{aq} (1 - \delta_{ap}) l_a}{\sum_{a \in A} \delta_{aq} l_a}, \quad (8)$$

where l_a is the length of link a , and δ_{aq} is the link-route incidence indicator that equals 1 if link a belongs to route q , and zero otherwise. Consequently, we assume that the more route q deviates

from the instructed route p , the larger the additional disutility is to switch routes, which seems reasonable.

Here, we base travellers' route choice decisions on travel time. We wish to point out that clearly, in case of empirical evidence, other attributes can be added, such as travel distance, perceived travel time reliability, network familiarity, and risk exposure (see e.g., Chiu and Mirchandani 2008 for a discussion hereon).

Presumably, the perceived route travel times used in Formula (7) to compute the generalized route costs are more accurate (i.e., closer to the actual route travel times) when travellers receive more information, and vice versa. This means that more information principally leads to a larger share of travellers selecting the present fastest route, while less information principally leads to a more uniform share of travellers selecting each alternative route (depending on the route compliance behaviour). The traffic information may relate to the expected future traffic conditions accounting for future traffic dynamics, or relate to the instantaneous traffic conditions where the current traffic state is expected to continue during the remainder of the trip. In the hypothetical example in Section 5, route updating and switching is based on instantaneous prevailing travel times, since this is available information nowadays from most information sources, such as, radio broadcasting, variable message signs (VMS), dynamic road-side information panels (DRIPs), in-car navigation systems, etc. (the impact of considering predictive information instead, is discussed in Section 5.3, while presenting the numerical results to the test example).

The perceived route travel times on a route q , denoted by $\tau_q(t)$, can be computed as

$$\tau_q(t) = \sum_{a \in A} \left[\delta_{aq} \theta_a(t) \right] + \varepsilon_q(t) . \quad (9)$$

Here the route travel times consist of the travel times on all links belonging to the route, where $\theta_a(t)$ denotes the actual instantaneous link travel time. The route error $\varepsilon_q(t)$ is the error between the perceived (instantaneous) route travel time and the actual (instantaneous) travel time on route q . Or, in case the error terms are specified on link level then the perceived route travel times are computed as

$$\tau_q(t) = \sum_{a \in A} \left[\delta_{aq} (\theta_a(t) + \varepsilon_a(t)) \right] , \quad (10)$$

where $\varepsilon_a(t)$ is the error between the perceived link travel time and the actual travel time on link a . Actual instantaneous link travel times are computed by the dynamic network loading model (discussed in Section 3.4). The route-based error formulation of (9) can be solved by a logit model, while the link based error formulation of (10) can be solved by a probit model. The choice between these model formulations is made as a trade-off between the computational costs (as logit provides a closed form expression, yet probit requires simulation) and some drawbacks (as probit automatically accounts for spatially overlapping route alternative, while logit need a correction term for this). A more detailed discussion is given in Appendix 1. This trade-off leads to the choice to use the probit formulation in the test example in Section 5 in this paper, and to use the logit formulation in larger case studies presented elsewhere (Pel et al. 2010a, 2010b, 2010c).

We assume that the error terms follow a distribution where the variance (>0) is related to the prevailing level of available traffic information. This way, high information levels are implied in case of small variance in the error distributions. The perceived travel times then closely resemble the actual travel times as the effect of the error term becomes negligible. As a consequence, route fractions (given by the probabilities in Formula (6)) are only non-zero on the fastest route(s)

(depending on the route compliance behaviour). On the other hand, low information levels are implied in case of large variance in the error distributions. The perceived travel times are then dominated by the error term, and route fractions are more uniformly distributed over alternative routes in the route choice set $Q^n(t)$.

Synthesis

In sum, the previous sections on the destination and route choice model describe the following. The dynamic travel demand rates, $d^r(k)$, at the origins $r \in R$ are distributed over the set of prescribed evacuation routes, $P^r(k)$, according to route fractions, $\chi_p(k)$, following from the evacuation plan. During their trip, travellers may switch routes in case of a more attractive route. They may do so when the perceived travel times on any of the alternative routes $q \in Q^n(t)$ varies more than a certain threshold for route updating, τ_{\min} . The share of class p travellers then switching to a new route q , $\chi_{pq}(t)$, is based on the perceived route travel times and an additional disutility of deviating from the instructed evacuation route. This additional disutility of non-compliance depends on the route deviation proportion, l_{pq} , and the perceived generalized costs of non-compliance, ω . Travellers then follow this new route q until variations in the perceived route travel times again exceed the route updating threshold compared to the prevailing route travel times when the route was last updated. And so forth until they have reached any of the safe destinations.

This way, the dynamic network loading (DNL) procedure is executed only once (instead of many times within an iterative traffic flow convergence framework yielding, e.g., a user-equilibrium assignment). Within this one-time execution of the DNL procedure, travellers are initially assigned to their instructed route (and destination), yet may continuously update their destination and route during their trip – while accounting for the disutility associated with non-compliance – thereby responding to the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by an iterative user-equilibrium assignment).

The mathematical model has been implemented in Matlab, with a user-defined road network, hazard scenario, and traveller behaviour (in terms of model parameters) as model input. For readers who are interested in model implementation, we refer to Appendix 1 where we discuss how the proposed model formulation can be solved, and provide a step-wise algorithm to do so.

4.4 Special Cases

The parameters γ and ω describe the traveller compliance behaviour, where γ determines departure time compliance (Formula (1)), while ω determines destination and route compliance (Formula (7)). These parameters are influenced by the *travellers' willingness* to conform and the *authority's enforcement* to control. Hence, the authority can steer the evacuation by deploying information and instructions as well as by enforcement to which the evacuees respond in their travel behaviour. By the latter we can discriminate the effect of discretionary advice (e.g., route guidance via information panels) and mandatory orders (e.g., applying police force and road blocks to regulate the evacuation traffic flows).

Regarding departure time compliance, in the limiting case that $\gamma = 1$, we get $D^r(k) = D_{\text{instr}}^r(k)$ indicating full compliance. On the contrary, $\gamma = 0$ leads to $D^r(k) = D_{\text{pref}}^r(k)$ such that all travellers depart at their preferred departure time. For $0 < \gamma < 1$, a share of travellers complies and departs at the instructed departure time, while the remainder of travellers does not comply and departs at their preferred departure time.

Similarly for route compliance, full compliance can be simulated when a high value is chosen for ω . In this situation, the generalized route costs are predominately determined by the term associated with the additional disutility of deviating from the instructed route. Consequently, the costs of deviating from the instructed route p (that is, when $l_{pq} \neq 0$) become very large (or approach infinity) such that all travellers comply. Non-compliance can be simulated by setting ω equal to zero. The additional disutility for deviating from the prescribed evacuation route then equals zero, such that travellers always follow the perceived fastest route, independent of which route is instructed. Partial compliance, depending on the traffic conditions, is modelled as $0 < \omega < \infty$, where a higher value of ω allows for higher compliance rates, since travellers then require larger (travel time) gains before deviating from the instructed route.

4.5 Dynamic Network Loading Model and Road Infrastructure Dynamics

The dynamic network loading (DNL) model simulates the departing traffic flows $f_p(k)$ (given by Formula (4)) through the road network, while accounting for the dynamic class-specific route flow fractions $\chi_{pq}(t)$ (given by Formula (6)) given at all intersections. The DNL model yields the traffic conditions (travel times) used to provide information to the travellers, based on which they may update their route (thus determining the route flow fractions), see Figure 1. Essentially any traffic flow simulator or DNL model can be used, such as a queuing model, cell transmission model (Daganzo 1994) or link transmission model (Yperman 2007).

In this work, we use the multiclass dynamic spatial queuing model proposed by Bliemer (2007), consisting of a link model and a node model. The link model describes the flow propagation through each link, accounting for different speeds for different vehicle types (for the sake of simplicity not included in the explanation of the route choice model) and a dynamic horizontal queue. The link model thus computes the maximum traffic flow that may potentially enter a link based on the space availability, and the maximum traffic flow that may potentially exit a link as it reaches the downstream end. The node model then uses the potential inflows and outflows to compute the actual inflows into and outflows out of each node according to the dynamic route choice rates, accounting for possibly restricted flow capacities due to, for instance, queue spillback from downstream links, conflicting flows on the node, or traffic signal control. For details we refer to Bliemer (2007).

The (actual) instantaneous prevailing link travel times, $\theta_a(t)$, used in the route choice model are computed from the DNL model as the link travel time under free-flow conditions plus some additional delay (in case of a queue) determined by the current queue load divided by the current link outflow rate.

Road Infrastructure Dynamics

We model time-dependent road infrastructure, hence characteristics such as speed limits and road capacity can vary over time. These variations can be due to the hazard's evolution in space and time (e.g., road sections becoming inaccessible due to flooding) and prevailing traffic regulations and control measures (e.g., ramp metering and variable speed limits). Capturing these important changes in the road infrastructure over time makes the model (outcomes) more realistic. Also, this feature enables simulating an acute evacuation in which network disruption plays a major role in the evacuation process, and testing the robustness of an evacuation plan towards uncertainty in the hazard scenario. To realistically model the impact of road infrastructure characteristics which vary over time, travellers need to be able to adapt their route choice decisions during their trip in response to these unforeseen and changing conditions. The

way in which this is done is similar to the simulation of en-route route switching in case travellers receive new information on traffic conditions as explained previously.

As mentioned earlier, considering dynamic network characteristics necessitates time-dependent route choice sets $Q^n(t)$, since the choice set includes all relevant routes from a network node n to any safe destination that are relevant at time t . Therefore, these route sets are (when needed) generated during execution of the dynamic network loading model based on the prevailing traffic and network conditions.

4.6 Heterogeneous Travel Behaviour

For reasons of simplicity, the model framework is formulated here for homogeneous travel behaviour. That is, all travellers behave similarly when making departure time and route decisions, receive the same travel information, and react similarly towards this information and their instructions. In reality, there are differences between travellers regarding, for instance, preferred departure time and route, information availability, response to information, willingness to comply, etc. The differentiation in behavioural response is in line with findings from socio-psychological studies on emergency situations (e.g., Leach and Campling 1994, Quarantelli and Russell 1977).

When dealing with heterogeneous travellers, we may choose to form multiple discrete classes, where travellers belonging to the same class show (sufficiently) similar travel behaviour. In applying a multiclass assignment, each distinct class shows distinct travel behaviour and hence has its own parameter settings. Our model is generalized, in order to allow a (user-specified) number of classes with class-specific departure time choice parameters a and h , class-specific error variance in the perceived link costs $\varepsilon_a : N(0, \sigma_a^2)$, and class-specific traveller compliance behaviour represented by γ and ω . The variables in the formulas above are then appended with the subscript m to indicate the class of travellers. The total number of travellers from an origin, B^r , is then given per class, and dynamic travel demand, generalized route costs, and route flow rates are computed for each traveller class, while the route fractions aggregated over all traveller classes sums to 1.

Instead of discrete classes, heterogeneity in traveller behaviour and information level can also be represented by a continuous probability distribution for each of the parameters a , h , σ_a^2 , γ , and ω (similar to the Mixed Logit construct). Solving for the travel demand rates and route flow rates then requires simulation (as a closed form expression cannot be given).

5. Test example

Where Section 4 explained the mathematical formulation of the proposed model which generalizes the previously identified limitations in evacuation modelling, in this section the face-validity of the model characteristics is shown by applying it to a simple example of a test network and disaster scenario. The test network and disaster scenario are introduced first, after which we present the experimental setup and discuss the numerical results.

5.1 Case Description

The proposed model is applied to the hypothetical test network shown in Figure 3, containing two origins r , two destinations s , and nine bi-directional links. Each of the two origins inhabits 5,000 travellers, here for simplicity leading to a travel demand of 5,000 vehicles. The length of the network links is indicated in the figure. Other characteristics of all network links are set to be

equal, where capacity = 2,000 veh/h, speed limit = 80 km/h, and number of lanes = 1 lane. Furthermore, the maximum queue density (jam density) = 150 veh/km. The two connector links, starting from the origins, are assumed to have sufficient storage capacity (i.e., no spillback occurs upstream of these connectors).

The considered disaster is a hypothetical flood approaching from the South (see Figure 3). The linear flood front reaches the lower network links and origin r_2 1.5 hours after the start of the evacuation and propagates in upward direction with a speed of 2 km/h. Furthermore, the preferred departure times are assumed to be represented by the sigmoid curve shown in Figure 4 (where the actual realized departure times depend on the level of compliance as explained in the previous section).

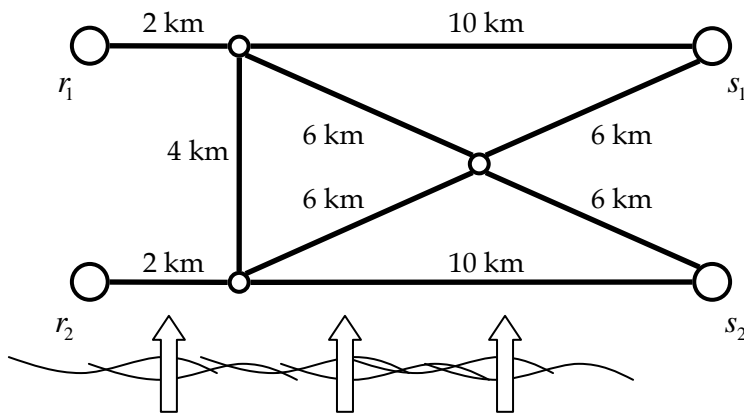


Figure 3. Test network and disaster scenario

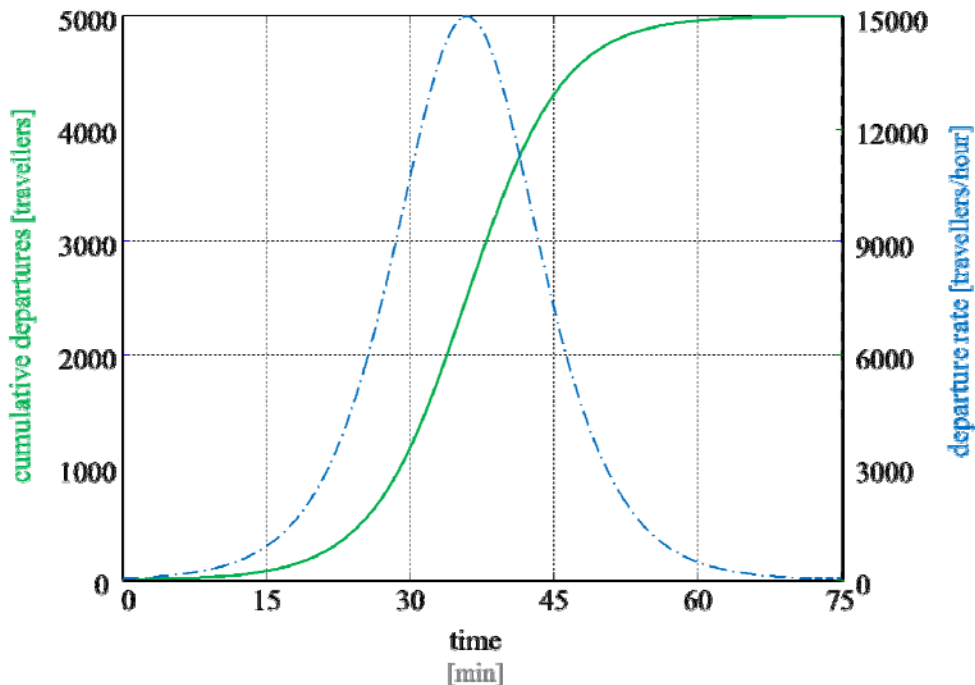


Figure 4. Preferred departure profile for a single origin ($a = 12$ and $h = 0.6$): solid green graph shows cumulative departures [travellers], and dash-dotted blue graph shows departure rate [travellers/hour]

5.2 Experimental Setup

A number of assignments are computed, while varying compliance behaviour and traffic information level. The setup of these assignments is discussed here, while the numerical results are presented in the next section.

To illustrate the impact of accounting for traveller compliance behaviour, we design straightforward evacuation instructions. Travellers at origin r_1 are prescribed to follow evacuation routes p_1 and p_2 (see Figure 5), while travellers at origin r_2 are prescribed to follow evacuation routes p_3 and p_4 . Each route is prescribed to 2,500 travellers in total. Departure times are instructed leading to constant departure rates of 2,000 veh/h (thus avoiding congestion to occur). The traveller compliance to these instructions is systematically varied to show the effect hereof. The tested parameter values for departure time compliance, γ , and destination and route compliance, ω , are listed in Table 1.

The effect of accounting for traffic information is shown by systematically varying the corresponding parameters. The tested parameter values for route updating (the minimum travel time difference τ_{\min}) and route selection (the link error variances σ_a^2) are listed in Table 2.

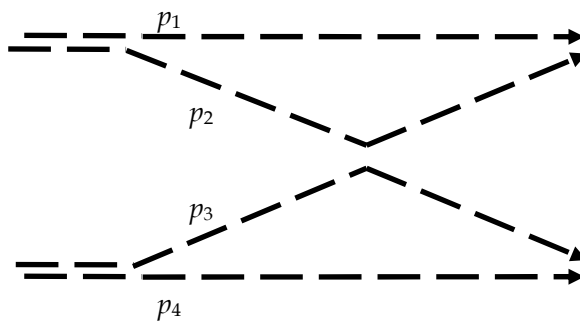


Figure 5. Instructed evacuation routes, P

Table 1. Parameter settings relating to traveller compliance behaviour corresponding to compliance levels which are tested for

parameter		compliance level										
		(none)	0	1	2	3	4	5	6	7	8	9
departure time	γ	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
route	ω	0	.05	.1	.15	.2	.25	.3	.35	.4	.45	inf

Table 2. Parameter settings relating to traffic information corresponding to information levels which are tested for

parameter		information level										
		(low)	0	1	2	3	4	5	6	7	8	9
updating	τ	.5	.45	.4	.35	.3	.25	.2	.15	.1	.05	0
selection	σ	.1	.09	.08	.07	.06	.05	.04	.03	.02	.01	0

5.3 Numerical Results

In the hypothetical example, all travellers, when they fully comply to the prescribed evacuation instructions, are capable of reaching their prescribed destination. With partial compliance, a number of travellers might not be able to evacuate in time before the flood causes the network links to become inaccessible and the evacuation to come to a halt. As expected, generally speaking, a lower compliance level has a larger negative impact on the number of arrivals. This is shown in Figure 6.

In this example, with higher traveller compliance levels, the reduction in the total number of arrivals (as compared to that in the full compliance case) is caused by the non-compliance with the departure time instructions. This is shown by the fact that an equivalent reduction can be seen when only varying traveller compliance towards the prescribed departure times, while simulating full compliance towards the destination and route instructions (dash-dotted graph). Relatively high network outflow rates are maintained since apparently (most) travellers still follow the dedicated evacuation routes, thereby avoiding (severe) congestion. Below a certain compliance level, the number of arrivals drops further, where the *additional* reduction is due to the lower compliance level towards destination and route instructions (as seen from comparison with the dashed graph showing the impact of varying traveller compliance towards the prescribed destinations and routes while simulating full compliance towards departure time instructions). This is explained as follows. The low traveller compliance level leads to a more peaked dynamic travel demand, as it more closely replicates the preferred departure profile. In turn, this results in a high network load. In such conditions, the impact of route guidance (i.e., compliance towards the prescribed evacuation routes) will be larger, as compared to when the network load is low. Or, in reverse, lower compliance (towards the prescribed destinations and routes) results in additionally lower network outflow rates and longer evacuation times (see Figures 7 and 8).

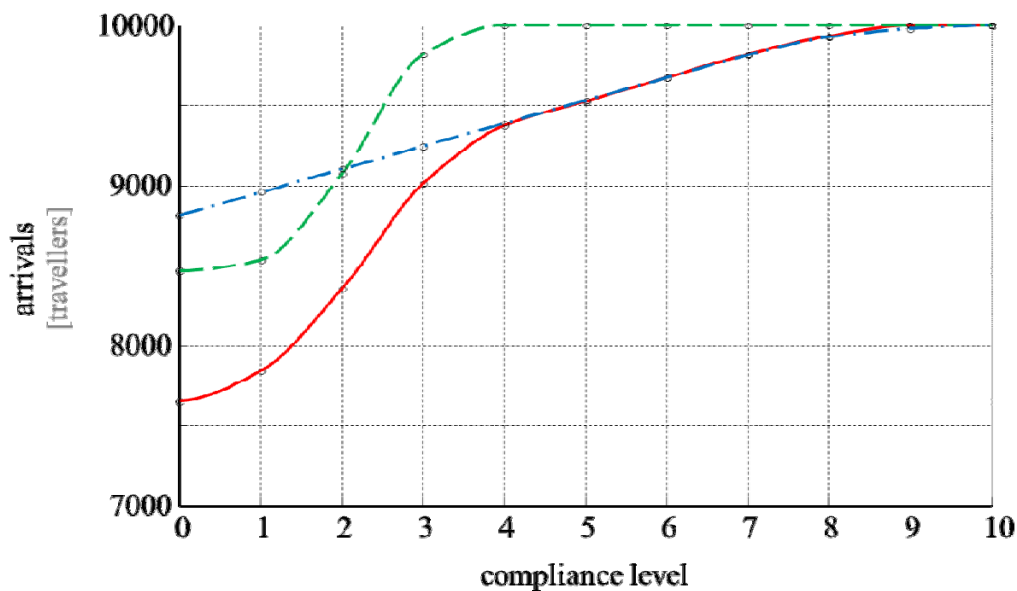


Figure 6. Total number of arrivals as a function of traveller compliance level: red solid line, varying departure time (DP) and destination and route (D&R) compliance level; green dashed line, varying D&R compliance level (with full compliance to DP); blue dash-dotted line, varying DP compliance level (with full compliance to D&R)

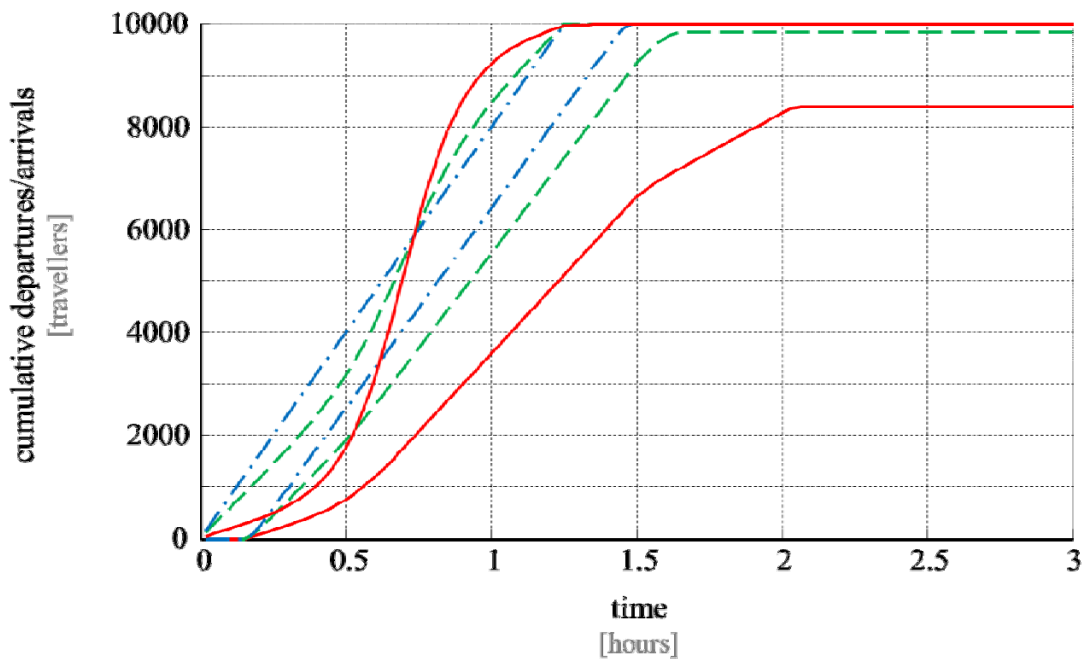


Figure 7. Cumulative departures (upper lines) and arrivals (lower lines): **red** solid lines, compliance level 2; **green** dashed lines, compliance level 7; **blue** dash-dotted lines, compliance level 10 (see Table 1)

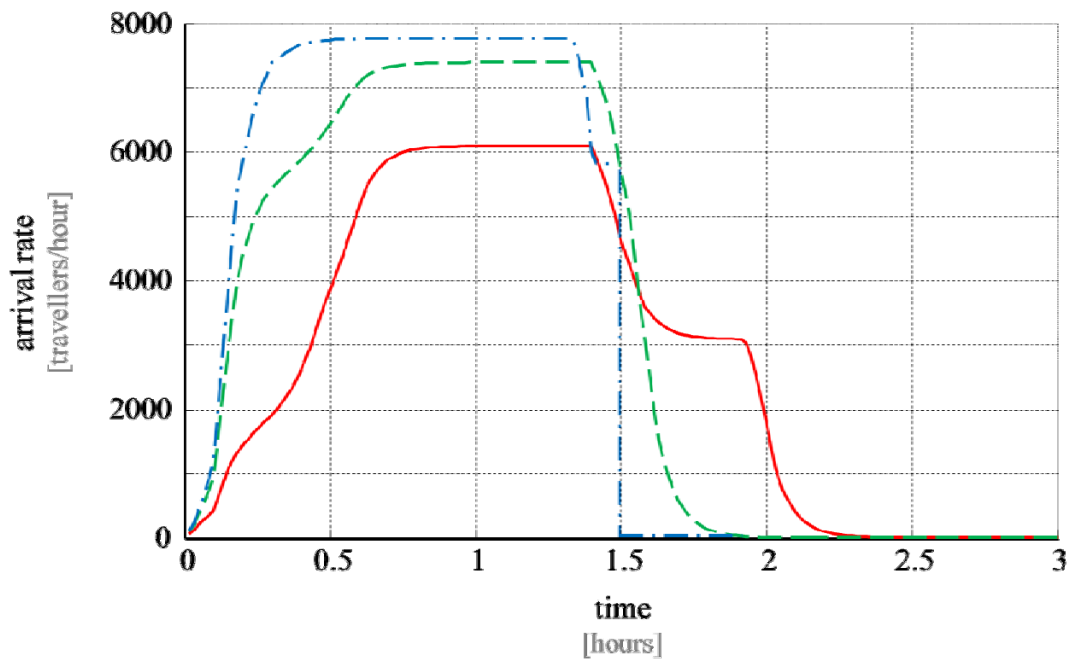


Figure 8. Network outflow rates: **red** solid line, compliance level 2; **green** dashed line, compliance level 7; **blue** dash-dotted line, compliance level 10 (see Table 1)

In contrast to traveller compliance, the impact of traffic information is non-monotonic. That is, a higher information level need not necessarily lead to a larger number of arrivals, and vice versa. This can be seen in Figure 9. When travellers receive complete traffic information (information level 10), then all travellers will select the (perceived and actual) fastest route. The fastest route from each of the origins is the direct route using the horizontal network links. The network

outflow rates in this case thus equal the capacity of these routes (see Figure 11). Note that queues build up on the connector links when departure rates exceed these route capacities, yet this does not lead to rerouting, since these routes remain fastest. In case of lowering the traffic information level, a share of travellers may perceive the alternative route using the diagonal network links as fastest and decide to reroute. The usage of the alternative parallel routes then increases the network outflow rate. Further lowering the traffic information level then leads to larger shares of travellers diverting to alternative routes. Initially, this reduces network outflow (rates) due to longer travel times and more (and larger) conflicting flows on the network nodes. However, lowering the traffic information below a certain level may spread the traffic more evenly over alternative routes, thus removing traffic from the (actual) fastest routes and consequently increasing throughput on these evacuation routes which slightly restores the overall network outflow (see Figures 10 and 11).

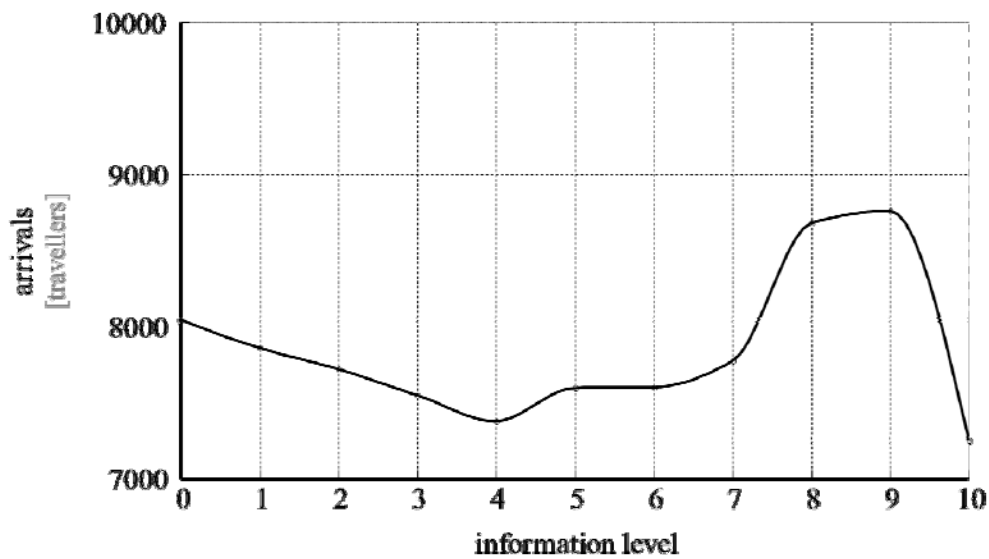


Figure 9. Number of arrivals as a function of traffic information levels

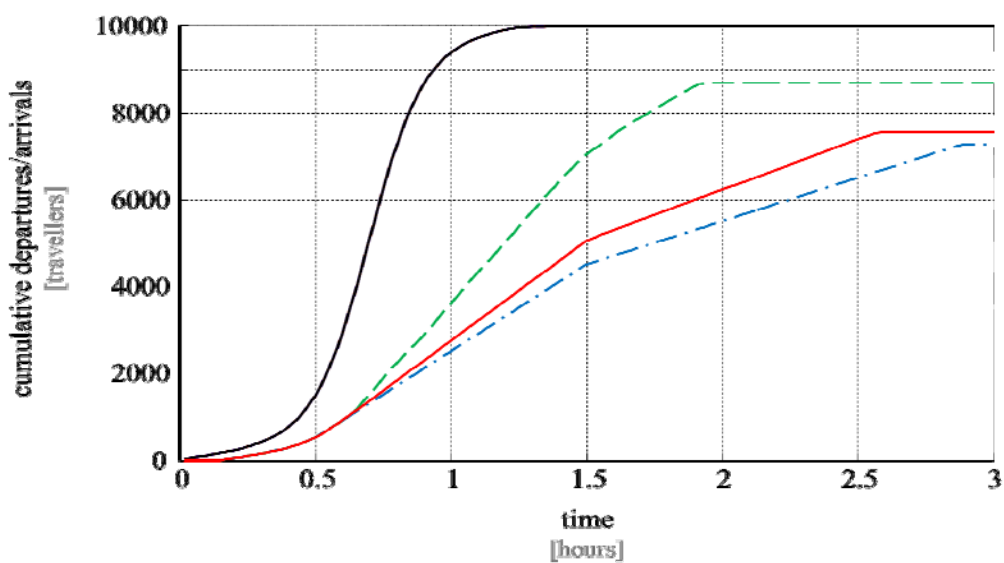


Figure 10. Cumulative departures (upper line) and arrivals (lower coloured lines): red solid line, information level 3; green dashed line, information level 8; blue dash-dotted line, information level 10 (see Table 2)

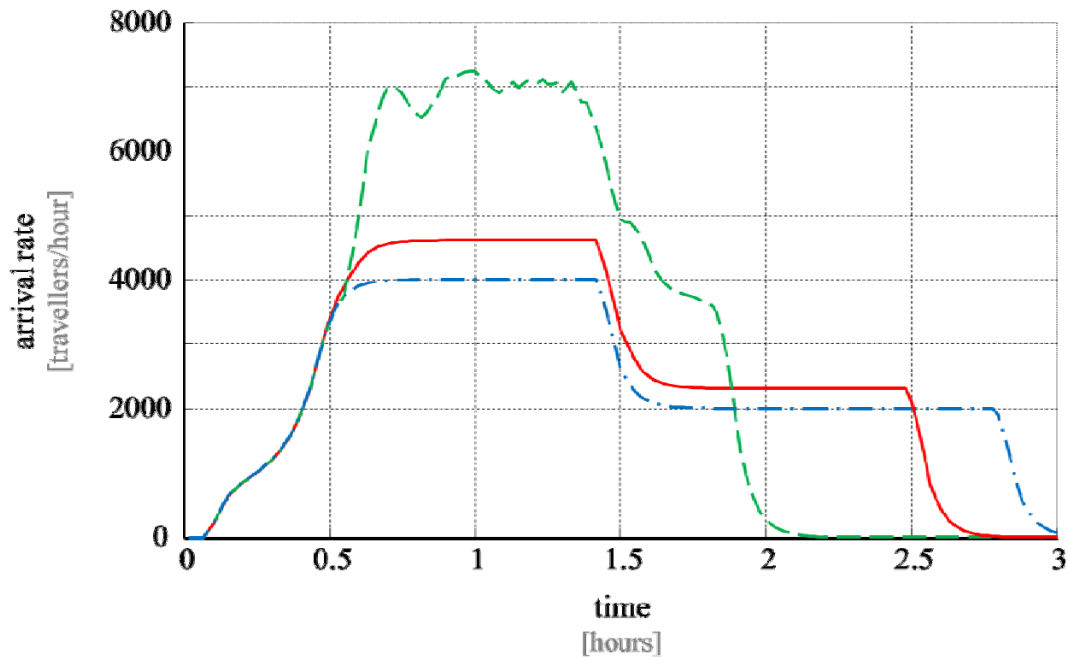


Figure 11. Network outflow rates: red solid line, information level 3; green dashed line, information level 8; blue dash-dotted line, information level 10 (see Table 2)

The cause of the very low arrival rates observed in case of full information (i.e., all travellers choosing the direct route and other routes not being used) is specific to the topology of the example network. However, the principal that fully informed travellers yield lower arrival rates than highly informed travellers is more general, as it may occur in many cases including the larger case studies reported in Pel et al. (2010a, 2010c). Similarly, when predicted travel times are to be used (recall that the traffic information provided here are the instantaneous travel times), in some cases all travellers are better off, while in other cases the results are worse due to the well-informed individualistic route choice behaviour.

6. Concluding Remarks

Dynamic traffic simulation models have proven to be helpful or even indispensable for the analysis, planning, and optimization of the traffic operations during a possible evacuation. Using an evacuation model allows obtaining a better understanding of the network conditions and the effect of traveller behaviour and traffic regulations and control measures hereon. In this paper, we relaxed some of the limitations in many traffic models used in evacuation studies regarding traveller behaviour and road infrastructure dynamics with respect to traffic information and compliance with evacuation instructions. The face-validity of the model characteristics are illustrated using a hypothetical example. The numerical analysis shows the importance of capturing compliance and information levels in the model, as they have a large impact upon the evacuation efficiency.

The practical applicability of the evacuation model developed, implemented, and tested in this paper has been shown on a few larger real-life networks. In collaboration with the strategic traffic management authority of the municipality of Rotterdam, the model is applied to a case study describing the evacuation of the Dutch metropolitan area of Rotterdam, see Figure 12. Multiple simulations have been run varying in possible network exit points, traffic information levels,

evacuation instructions, traveller compliance behaviour, and network dynamics. These behavioural and control settings determine departure patterns and route flows, and thus traffic states and network outflow utilization, where these relationships are shown to be (in some cases highly) non-linear and non-monotonic. More detailed information on the evacuation study can be found in (Pel et al. 2010a and 2010c).

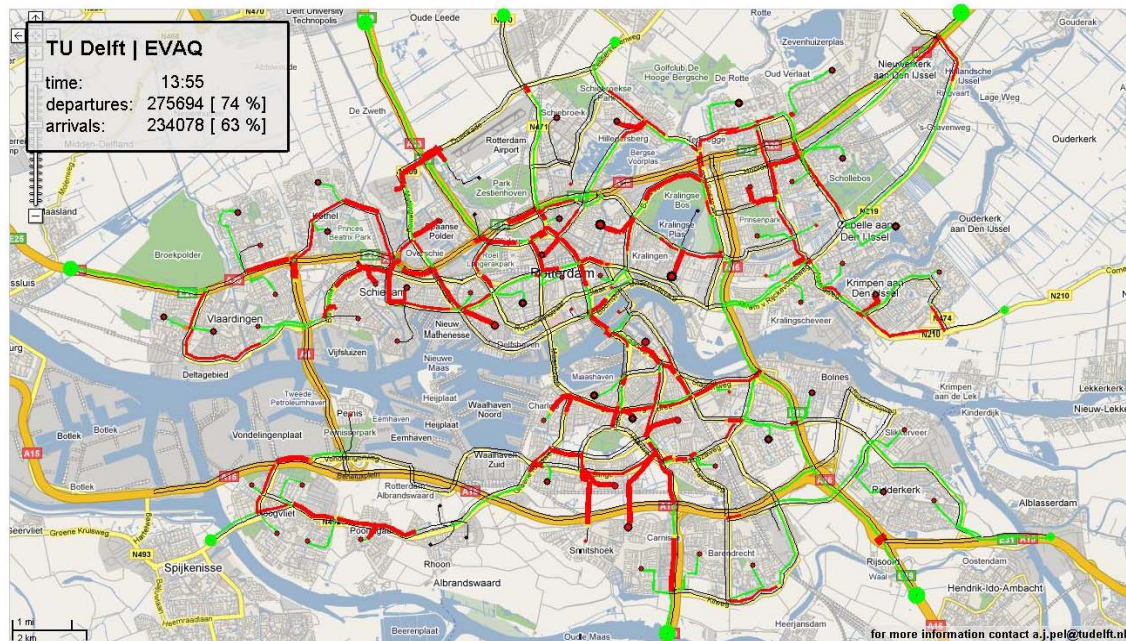


Figure 12. Rotterdam evacuation network (Source: Google Maps)

In other studies, the model is used as prediction model to optimize evacuation instructions. Optimization search methods have proven to substantially improve evacuation clearance times compared to evacuation by straightforward rules (such as evacuating towards the nearest exit, using the shortest routes, and spreading departure times to avoid the occurrence of congestion) (Huibregtse et al. 2009). More interestingly, the inclusion of traveller compliance in the model formulation has also been exploited to extend such an optimization method to design efficient evacuation instructions which anticipate this level of partial traveller compliance (Pel et al. 2010b).

Special attention needs to be paid to parameter settings, as traffic models that are used in evacuation studies tend to suffer from the lack of adequate real-life data, and our proposed model is no exception. The unfortunate consequence of this is that these models are often limitedly validated or inappropriately calibrated on traffic data representing regular daily traffic conditions. This need for appropriate data could possibly be addressed, first of all, by combining (i) the limited amount of post disaster evacuation data with (ii) data describing travellers' behaviour in equivalent conditions, for example, route guidance and rerouting behaviour due to large-scale incidents on the road. Second of all, the lack of appropriate empirical data can be anticipated and evacuation traffic models can be formulated such that model parameters have a clear behavioural interpretation. The latter is attempted in the model developed here in this paper and allows (with appropriate caution) simulations based on expert judgment or non-quantitative literature from the behavioural sciences. Finally, the uncertainty due to the lack of data can be relaxed by (elaborate) scenario analyses and sensitivity analyses on variations in both model parameters and factors determining travel demand and network supply. A detailed

discussion on the data requirements to manage and model evacuation situations is provided by Wilmot et al. (2009).

The presentation of the model, numerical analyses, and conclusions presented in this work provide a discussion on the role of incorporating travellers' response behaviour towards traffic information and road infrastructure dynamics, and their compliance with evacuation instructions, in evacuation models. Also, it helps in distinguishing and evaluating the various evacuation model formulations, and in understanding the role of the discussed behavioural aspects in the evacuation process and the design and evaluation of evacuation plans, including testing for robustness towards uncertainties in travellers' response.

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Appendix 1: Solution Algorithm

In this work, first of all, the set of all alternative routes $Q^n(t)$ is reduced to the set of all relevant routes which are likely to be chosen. Different route set generation models could be considered for this (for an overview see, e.g., Bekhor et al. 2006, Fiorenzo-Catalano 2007). Here, we choose to adopt a stochastic route generation algorithm proposed by Bliemer and Taale (2006) (based on Bovy and Fiorenzo-Catalano 2007). This method applies Monte Carlo (MC) simulations in which the generalized link costs are assumed to be random variables with a mean related to the prevailing instantaneous link costs. In each subsequent MC simulation, the fastest routes from each origin to any of the destinations are determined using Dijkstra's algorithm (Dijkstra 1959) and added to the route set (given that they show sufficient low overlap with existing routes in the route set). The dynamic route set is generated during the execution of the dynamic network loading model since we consider road infrastructure characteristics to be time-varying. In other words, some routes may be available and attractive during some time intervals, while being unavailable or unattractive during other time intervals.

Second of all, we choose here to let the travel time error distributions be specified on link level (using Formula (10)). We wish to point out that in case of using error distributions on route level (using Formula (9)) and assuming that the route error terms are identically and independently Gumbel distributed then the route flow fractions, given by Formula (6), can be computed with the Multinomial Logit (MNL) model. The scale parameter in the MNL model is then related to the variance in the error distributions and thus represents the prevailing level of available traffic information. In this case, a route overlap factor can be included to account for the effect of spatially overlapping routes on the route flow fractions (see, for instance, the pathsize formulation by Ben-Akiva and Bierlaire 1999, or the commonality factor formulation by Cascetta et al. 1996).

On the other hand, in case of error distributions on link level, as we use here, this effect of spatial route overlap is automatically accounted for. The route flow fractions in Formula (6) then however have no closed-form expression which necessitates solving these by means of simulation. A sufficiently large number of independent draws on the link-specific error terms is needed to replicate the error distributions. The route flow fractions then correspond to the relative number of draws in which the specific route $q \in Q^n(t)$ was the most attractive route compared to all alternative routes. That is, the number of times that $c_{pq}^{(x)}(t) \leq c_{pz}^{(x)}(t)$, $\forall z \in Q^n(t)$ where x denotes the draw.

To limit the required number of draws, low discrepancy sequences are used. In this work the Modified Latin Hypercube Sampling (MLHS) method is applied to generate a sample of X quasi-random draws (Hess et al. 2005). In case the link travel time error terms are assumed to be identically and independently Normal distributed, i.e., $\varepsilon_a(t) : N(\mu, \sigma^2)$, this approach leads to the Probit assignment model (Daganzo 1979, Sheffi 1985). Then, to obtain the link error terms, we evaluate the inverse of the cumulative error distribution function at the quasi-random draw x , $\pi_a^{(x)} \in [0, 1]$,

$$\varepsilon_a^{(x)} = \Phi^{-1}(\pi_a^{(x)})\sigma_a^2, \quad (11)$$

where Φ is the cumulative distribution function of the standard normal distribution, and σ_a^2 corrects for the link-specific error variance. Recall that we assume the mean to be zero (no structural bias) and the variance ($\sigma_a^2 > 0$) to be related to the prevailing level of available traffic

information. From Formula (11) it is directly observable how a larger variance leads to a larger error and hence a larger difference between the actual travel times and the perceived travel times, thus implying a lower traffic information level.

Below we present the step-wise algorithm corresponding to the destination and route choice model explained in Section 3. Here we use P to denote the full set of instructed evacuation routes from all origins to all destinations at all departure times, i.e., $P = \bigcup_{r \in R, k \in T} P^r(k)$.

Destination and route choice algorithm

Input: Network with for each link, prevailing instantaneous travel times, $\theta_a(t)$, and link lengths, ℓ_a , a set of safe destination, S , and for each node $n \in N \setminus S$ a choice set with relevant routes, $Q^n(t)$ (here generated using MC simulations and Dijkstra's algorithm), their overlap with the prescribed routes, ℓ_{pq} , $\forall p \in P, \forall q \in Q^n(t)$, and the time instant when routes from this node n were last updated, ϑ^n .

Parameters: number of iterations, J , link error variances, σ_a , route updating threshold, τ_{\min} , and perceived generalized costs of non-compliance, ω .

Output: Route fractions $\chi_{pq}(t)$ for all relevant routes $q \in Q^n(t)$ from all nodes $n \in N \setminus S$, for all classes $p \in P$.

Step 1: Compute node set for route updating, $\tilde{N}(t) = \left\{ n \in N \setminus S \mid \exists q \in Q^n(t), \text{ for which } \left| \left(\tau_q(t) - \tau_q(\vartheta^n) \right) / \tau_q(\vartheta^n) \right| \geq \tau_{\min} \right\}$.

Step 2: Set $j := 1$. Set $\chi_{pq}(t) := 0, \forall p \in P, \forall q \in Q^n(t), \forall n \in \tilde{N}(t)$.

Step 3: Compute link travel times $\theta_a^{(j)}(t) = \theta_a(t) \left(1 + \left| \varepsilon_a^{(j)} \right| \right)$, with $\varepsilon_a^{(j)} \square N(0, \sigma_a^2)$ (here using efficient MLHS draws).

Step 4: For all routes $q \in Q^n(t)$, from all nodes $n \in \tilde{N}(t)$, compute the (perceived) travel time, $\tau_q^{(j)}(t) = \sum_{a \in A} \left[\delta_{aq} \theta_a^{(j)}(t) \right]$.

Step 5: For all routes $q \in Q^n(t)$, from all nodes $n \in \tilde{N}(t)$, and for all classes $p \in P$, compute the travel costs, $c_{pq}^{(j)}(t) = \tau_q^{(j)}(t) \left(1 + \ell_{pq} \omega \right)$.

Step 6: For all routes $q \in Q^n(t)$, from all nodes $n \in \tilde{N}(t)$, and for all classes $p \in P$, if $c_{pq}^{(j)}(t) \leq c_{pz}^{(j)}(t), \forall z \in Q^n(t)$, then set $\chi_{pq}(t) := \chi_{pq}(t) + 1/J$.

Step 7: If $j = J$, then stop. Otherwise, set $j := j + 1$ and continue with Step 3.