

First International Conference on Evacuation Modeling and Management

## Evacuation modeling including traveler information and compliance behavior

Adam J Pel <sup>a,\*</sup>, Serge P Hoogendoorn <sup>a</sup>, Michiel CJ Bliemer <sup>a</sup>

<sup>a</sup> Delft University of Technology, Transport and Planning Department, Stevinweg 1, Delft, The Netherlands

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### Abstract

Traffic simulation models are often used to support decisions when planning an evacuation. Scenario analyses based on these models then typically focus on traffic dynamics and the effect of traffic control measures in order to locate possible bottlenecks and predict evacuation times. A clear approach to incorporate traveler information and compliance behavior in evacuation modeling is however lacking. The consequence is that the impacts hereof are often insufficiently accounted for. In this contribution, we show how traveler information and compliance behavior are included in the evacuation model EVAQ by applying a hybrid route choice model and internalizing the generalized costs of deviating from the instructions. The impact of traveler information and compliance behavior is discussed using a case study describing the evacuation of the Rotterdam metropolitan area in the Netherlands.

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*Keywords:* Compliance; information; instructions; evacuation modeling

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### 1. Introduction

Many natural and man-made disasters can be anticipated on, for instance, bush fires, hurricanes, floods, terrorist attacks, and industrial accidents. This implies that, up to a certain level, we can predict that such a disaster may occur and may affect a certain region in a certain manner. 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, response time, information and instructions dissemination procedure, evacuation routes, traffic flow conditions, dynamic traffic management measures, etc. Due to the complexity of the underlying processes and the multitude of factors influencing these processes, model-based approaches are required for the analysis and planning of emergency evacuations. The model can be applied to obtain a better understanding of the evacuation conditions and the effect of traffic regulations and control measures hereon, by predicting departure and arrival patterns, travel times, average speeds, queue lengths,

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\* Corresponding author. Tel.: +31-152-784-981; fax: +31-152-783-179.  
E-mail address: [a.j.pel@tudelft.nl](mailto:a.j.pel@tudelft.nl).

traffic flow rates, etc. Insight into this dynamic process is necessary to make founded decisions on, for instance, the latest possible time to start evacuation, the best evacuation routes, or the most suitable traffic management measures.

A multitude of dynamic models have been developed and used to forecast evacuation conditions on a road network. A large number of these studies are conducted using traffic models originally developed for regular day-to-day traffic applications. For example, microscopic simulation models such as PARAMICS, CORSIM, and VISSIM were used for evacuation scenario analyses in [1]–[3] and for evaluating the impact of control measures, such as staged evacuations in [4] and contraflow operations in [5], [6]. In a number of these studies, model parameters describing driving behavior, such as headway, acceleration, and reaction time, are adjusted for the case of emergency evacuation. In other studies, evacuation is recognized as a special case regarding different travel demand patterns, driver behavior, traffic management, etc., resulting in new models dedicated to evacuation. For example, microscopic models, such as IMDAS [7], OREMS [8], and CEMPS [9], and macroscopic models, such as DYNEV [10], MASSVAC [11], and TEDSS [12], have been developed and used in the past decades.

Since the late 1970s, some of these models were developed to analyze and evaluate emergency evacuation plans. Early studies in the 1980s 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 1990s and in the past years, much evacuation research shifted focus to hurricane evacuation. Since the September 11, 2001, incident in the U.S., also mass evacuation due to terrorist attacks is getting more attention. Due to tsunamis in China and bush fires in Australia over the past years, evacuation research in these countries focus on these types of evacuation. For the Dutch situation, rising sea levels and increasing threat of flooding has led to the start of the Dutch national TMO (Taskforce Management Flooding) program, initiating flood evacuation research and applications within the Netherlands.

Traffic simulation models used in past evacuation studies generally focus on traffic flow dynamics to identify possible bottlenecks and compute expected evacuation times. As a consequence, a number of aspects relating to traveler behavior under evacuation conditions are insufficiently incorporated in the scenario analyses when applying these models [13]. In this contribution, we show how travel behavior relating to departure time and route choice under uncertainty (traveler information) and instructions (compliance behavior) can be modeled, and what the impacts are in terms of the model outcomes. We start by explaining how traveler information and compliance are incorporated in the evacuation model EVAQ in the next section. Thereafter, we use the case study of Rotterdam to discuss the impact of traveler information and compliance behavior. First, the research approach is presented, including the case setting and experimental set-up. Then, the numerical results are presented and elaborated on. In the final section, we conclude that aspects of traveler information and compliance may strongly dictate traffic states and evacuation times in a non-linear manner, and thus should be included in future research and evacuation model applications.

## 2. Modeling approach

The following is based on how traveler information and compliance behavior is modeled by the evacuation model EVAQ [14]. EVAQ is a model to predict traffic flow conditions on a road network for a wide range of emergency situations, such as hurricanes, bush fires and floods. Compared to other evacuation traffic models, the distinguishing features of EVAQ are: i) modeling of dynamic road infrastructure, ii) incorporation of adaptive traveler choice behavior, and iii) incorporation of evacuation instructions and traveler compliance behavior. The first advantageous feature of EVAQ is that it models time-dependent road infrastructure. Characteristics such as speed limits, capacity and flow direction can be time-varying due to the hazard's progress in space and time (e.g., links becoming inaccessible due to flooding) and prevailing traffic regulations and control measures (e.g., contraflow operations to increase outbound capacity). 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 degradation plays a major role in the evacuation process. To realistically model the impact of time-varying road infrastructure, travelers need to be able to update their route at the next decision point whenever traffic conditions change (drastically) due to changes in the network. This route-updating behavior occurs in case of evacuation-related dynamic traffic management measures and hazard-inflicted network degradation. The same route-updating behavior is reasonable to assume in case travelers face uncertain traffic conditions and receive

(limited) traveler information, as shown in Section 2.1. How EVAQ deals with traveler compliance behavior by internalizing the generalized costs of complying with or deviating from the instructions is then shown in Section 2.2.

### 2.1. Traveler information

If we accept that evacuation is an unfamiliar situation, then we need to consider the fact that travelers cannot rely on experience, which invalidates the often-applied user-equilibrium assignment assumption. Instead, EVAQ uses a “one-shot” assignment in which travelers’ decisions depend on the uncertain and changing conditions. These decisions include the effect of dynamic traffic management measures, network degradation, traveler information, evacuation instructions, and compliance towards these instructions. These effects are included in EVAQ by applying the hybrid route choice model proposed in [15]. In this model, travelers decide on an initial route upon departure, possibly the instructed route, after which they may adapt their route during their trip if necessary. This is necessary in case of changing traffic conditions. Evidently, travelers need to be aware of these (changing) traffic conditions in order to adapt their route. To this end, we distinguish two phenomena. First, travelers update their route based on changes in the perceived route travel times. Presumably, “slight” changes in traffic conditions are ignored and therefore do not lead to changes in route flow rates, whereas “larger” changes do lead to travelers choosing a new route. For example, if we say that travelers are insensitive to a 10 percent increase or decrease in route travel times, then route flow rates remain the same while route travel times vary within this 10 percent margin. As soon as route travel time variations exceed this 10 percent margin, new route flow rates (and if necessary route choice sets) are computed. Second, once travelers have chosen to update their route, then travelers select their route based on perceived route travel times. These perceived route travel times are closer to (further away from) the actual route travel times when travelers receive more (less) information. Thus, more information leads to a larger share of travelers selecting the currently shortest route, while less information leads to a more uniform share of travelers selecting each route.

To mathematically describe this process, route flow rates at each decision point (network node) are dictated by the Path Size Logit model [16], given by

$$f_q^{ns}(t) = \frac{\exp(\mu c_q^{ns}(t) + \phi_q^{ns})}{\sum_{q' \in Q^{ns}(t)} \exp(\mu c_{q'}^{ns}(t) + \phi_{q'}^{ns})} \quad (1)$$

Here  $c_q^{ns}(t)$  denotes the generalized travel costs of route  $q$  from intersection  $n$  to destination  $s$  at time  $t$ , and  $\phi_q^{ns}$  the path-size overlap factor measuring the weighted fraction of route  $q$  that overlaps with the other routes in the route choice set  $Q^{ns}(t)$  [16]. The scale parameter  $\mu$  can be used as a proxy for traveler information level, as it determines how travelers are distributed over the alternative routes. Low values of  $\mu$  lead to travelers being more uniformly distributed over the alternative routes, while higher values let more travelers select the most attractive route (i.e., the route with the prevailing lowest generalized travel costs).

These route flow rates are kept constant over time until the differences in route cost amongst the route alternatives exceed a certain threshold,  $\theta$ . Route flow rates, and possibly route choice sets, are subsequently updated. New route flow rates are computed based on the present traffic state, and using a scale parameter in the Path Size Logit model representing the present traveler information level. These new route flow rates are then kept constant until the difference between current route costs and the route costs which these route flow rates are based on exceeds the threshold, etc.

### 2.2. Compliance behavior

Traveler compliance behavior is essential in assessing the effect of an evacuation strategy. If we agree that the instructed departure time (route, destination) may differ from the traveler’s preferred departure time (route, destination), then it is possible that the traveler’s actual behavior is different from the instructed behavior. In EVAQ, we assume that departure time choice compliance can be modeled as:

$$D_m^r(t) = \gamma_m \tilde{D}_m^r(t) + (1 - \gamma_m) \hat{D}_m^r(t) \quad (2)$$

Here,  $D_m^r(t)$  denotes the actual travel demand from origin  $r$  at time instant  $t$ . The actual travel demand depends on the instructed travel demand  $\hat{D}_m^r(t)$ , which is given by the evacuation instructions, and the preferred travel demand  $\hat{D}_m^r(t)$ . Or, more precisely, we assume that the fraction  $\gamma \in [0,1]$  of travelers complies and follows the instructed departure time, while the remaining travelers (equal to fraction  $1-\gamma$ ) do not comply and depart at their preferred departure time. The preferred travel demand can be predicted by the sigmoid curve given in [20] as:

$$\hat{D}_m^r(t) = \left(1 + \exp[-\alpha_m^r(t - h_m^r)]\right)^{-1} F_m^r. \quad (3)$$

The number of inhabitants at origin  $r$  is denoted by  $F_m^r$ . The index  $m$  indicates the class of travelers, where each class has its own parameter settings. The preferred travel demand curve has two parameters. The effect hereof can be seen from Figure 1. The response rate  $\alpha$  sets the slope of the curve, such that low values of  $\alpha$  produce a more uniform departure profile. The half loading time  $h$  sets the midpoint of the curve, and thus states the time at which half of the group of travelers has departed.

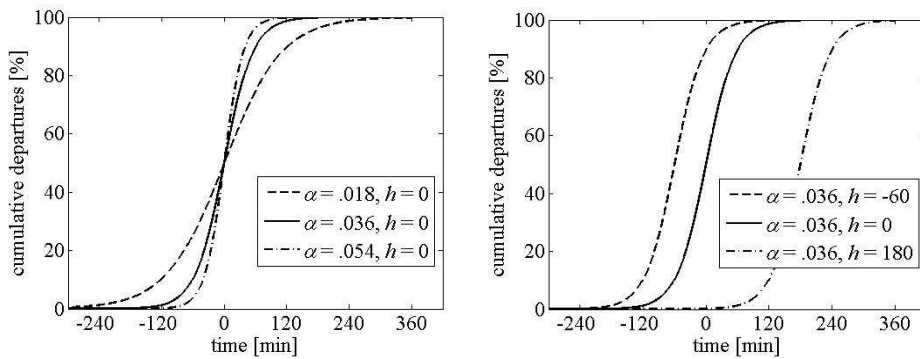


Figure 1: Preferred travel demand curve for different values of parameters  $\alpha$  and  $h$

Travelers depart at a certain *time instant*. Upon departure they choose whether to comply or not. However, travelers follow a route over a *period of time*. During this period of time they can continuously choose whether to comply or not. Thus, a method directly similar to Equation (2) is not possible when modeling route choice compliance. Instead, we assume that travelers make a trade-off between following the instructed route and deviating to a route which is (perceived as being) more attractive at each decision point. Thus, the generalized route costs are modeled as:

$$c_{mpq}(t) = \tau_p(t) + \chi_{pq} \max\{\bar{\tau}_m, \beta_m \tau_p(t)\}. \quad (4)$$

Here,  $c_{mpq}(t)$  denotes the costs of following route  $p$  as perceived by travelers who are actually instructed to follow route  $q$ . These costs consist of the costs associated with traveling route  $p$ , modeled here as the travel time<sup>c</sup>  $\tau_p(t)$ , and a minimum gain that the traveler wishes to achieve in case of deviating from the instructed route  $q$  to the new route  $p$ . This minimum gain is modeled by the  $\max\{\cdot\}$  term, while the deviation is modeled by  $\chi_{pq}$ . The deviation  $\chi_{pq} \in [0,1]$  denotes the relative length of route  $p$  which does not coincide with the instructed route  $q$ .

<sup>b</sup> Another method of predicting aggregated departure time choice is by applying a sequential binary logit model where people repeatedly decide whether to evacuate and depart presently, or to postpone evacuation. This demand model and accompanying utility functions have been estimated for the case of bush fires in [17] and hurricanes in [18] using surveys on stated preference and revealed preference. Comparison in [19] with the sigmoid curve suggests that this method more closely models observed departure time decisions. The sigmoid curve is used here however for the sake of simplicity, since the focus here is on traveler compliance behavior and not on preferred departure time choice.

<sup>c</sup> Currently, we base travelers' route choice decision on travel time. Yet clearly other attributes can be added, such as travel distance, perceived travel time reliability, network familiarity, and risk exposure.

Consequently, we assume that the more route  $p$  deviates from the instructed route  $q$ , the larger the gain should be to switch routes, since the  $\max\{\bullet\}$  term is strictly positive, which seems reasonable. The gain  $\max\{\bullet\}$  term then states that the new route  $p$  should be  $\beta_m$  percent faster, with a minimum of  $\bar{\tau}_m$ . Route choice decisions are then modeled by the Path Size Logit model in the hybrid route choice model discussed in the previous section.

Note that the formulation in Equation (4) is not limited to routes with the same destination. Thus, by including routes with different destinations in the route choice set, the destination choice compliance is embedded in the route choice compliance.

The parameters  $\gamma_m$ ,  $\beta_m$ , and  $\bar{\tau}_m$  model the traveler compliance behavior. These parameters are influenced by the *travelers' willingness* to conform and the *authority's enforcement* to control. Hence, the authority can optimize the evacuation by information, instructions, and enforcement to which the evacuees respond in travel behavior.

### 3. Research approach

In this paper, we investigate traveler information and compliance and their impacts in terms of the model outcomes. To this end, we use the evacuation of the Dutch city of Rotterdam as a case study. Let us first briefly describe the considered case, after which we present the experimental set-up used to structure the analysis.

#### 3.1. Case study description

The metropolitan area of Rotterdam is situated in the west of the Netherlands (see Figure 2). With a population exceeding 600,000 inhabitants, the municipality forms the second largest in the country. Given the setting of the city, evacuation due to river flooding, coastal flooding, industrial accidents, or terrorist threats, can be considered conceivable. In fact, several programs on national, regional, and municipal level have been initiated over the past years dealing with the preparation for a possible hazard of these types. The road network used in the analyses<sup>d</sup> consists of approximately 500 links, and 220 nodes, including 80 origins and 3 destinations.



Figure 2: Rotterdam metropolitan area and evacuation exit points: motorways A15, A16, and A29

<sup>d</sup> Applying a time step of 20 seconds, CPU times for the individual scenarios range from 10 to 20 minutes.

The (type of) hazard clearly affects the evacuation process characteristics in terms of warning time, scale of evacuation, safe destinations, possible network degradation, etc. In this paper, we choose a setting in line with the evacuation plans as currently developed by the municipality of Rotterdam in preparation for possible flood evacuation. We assume sufficient time to evacuate before the hazard occurs, and thus need not consider warning time and network degradation. Furthermore, we assume everyone prefers to depart within 48 hours ( $\alpha = -0.3$ ,  $h = 24$ ), leading to a maximal departure rate approximating 28.000 travelers per hour. The designated exit points are the freeways A15, A16, and A29 in southeast direction as indicated in Figure 2.

### 3.2. Experimental set-up

The impact analysis will focus on variations in traveler information and compliance. The table below shows an overview of the considered input factors and their ranges for which impact is discussed in the following section. Each factor is discussed below.

Table 1: Overview of traveler information and compliance variations considered in impact analysis

	Considered factor	Description of variation	Range
Traveler information	Route updating	Update threshold	10% – 100%
	Route selection	Path-size parameter	20 – 0.1
Traveler compliance	Departure time	Compliance fraction	1 – 0.1
	Route	Relative gain	100% – 10%
	Route	Minimum gain	60 – 5 min

#### 3.2.1. Traveler information

Travelers may receive information on the present traffic state. Based hereon they may decide to change their route (and destination). Travelers will be able to continuously select the present perceived fastest route when they receive abundant information. Otherwise, travelers will face the traffic conditions on their current route, unaware of the (possibly better) traffic conditions elsewhere on the network. The hybrid route choice model is used to model this adaptive route choice behavior based on traveler information as discussed in the previous section. In the following, we simulate a range of scenarios differing in the amount of information that is provided to, or acquired by, travelers. To model this, we simultaneously vary the threshold with which travelers update their route between  $\theta = 10\%$  and  $\theta = 100\%$ , and the path-size parameter by which travelers select their route between  $\mu = 20$  and  $\mu = 0.1$ . In the extreme, the worst-informed case may represent, for example, travelers being only periodically updated on travel times and traffic conditions via radio, while in the best-informed case, for instance, radio, and variable message signs (VMS) and dynamic route information panels (DRIPS) alongside the road are extensively used, and there is a high percentage of travelers using an in-car navigation system providing up-to-date traffic information.

#### 3.2.2. Compliance behavior

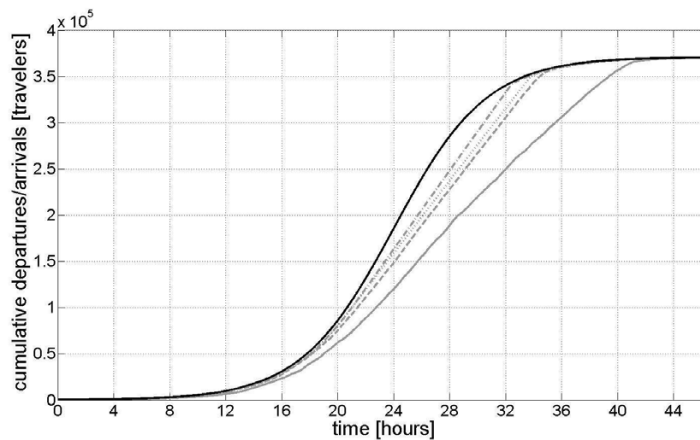
The evacuation is determined by travelers' departure time, destination, and route decisions. These decisions are influenced by giving evacuation instructions. Whether travelers comply depends on how distinct these instructions are from their preferred behavior, their willingness to conform and the enforcement executed by the regulating authority (e.g., police force, emergency services, and army). Little is known about travelers' compliance towards evacuation instructions. Also, it may differ strongly across settings and locations. We therefore refrain from picturing various likely scenarios, but instead compare different scenarios in which the same instructions hold, yet compliance levels are systematically varied. To model this, we simultaneously vary the departure time compliance fraction between  $\gamma = 10\%$  and  $\gamma = 100\%$ , the relative gain in route travel time between  $\beta = 10\%$  and  $\beta = 100\%$ , and the minimum gain in route travel time between  $\bar{\tau} = 60$  min. and  $\bar{\tau} = 5$  min. The straightforward evacuation instructions which travelers may conform to here appoint travelers to their nearest exit point via the fastest route under free flow conditions, and set departure times to obtain a uniform departure rate in order to limit congestion.

## 4. Numerical results

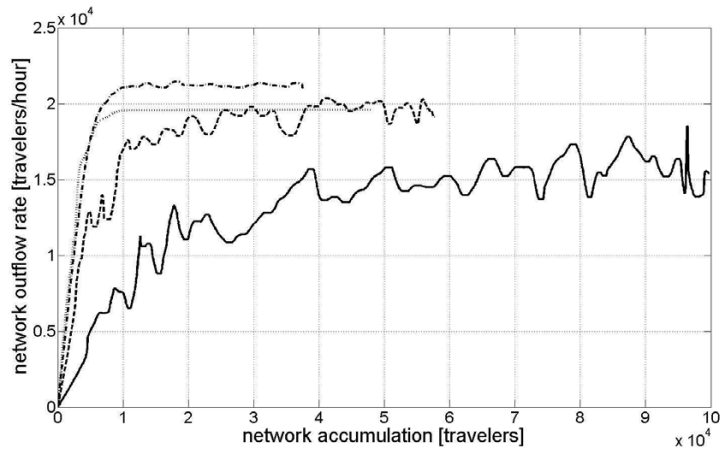
### 4.1. Traveler information

The arrival rate is bounded from above by the network outflow capacity. The network outflow capacity can be reached when all (roads towards the) exit points are optimally utilized. In case travelers are poorly informed and unfamiliar with the network, then certain exit points remain under-utilized, which can result in longer evacuation times compared to cases in which travelers are kept better informed on traffic conditions. This can be seen from the solid grey line in Figure 3(a) showing that cumulative arrivals are lower at each time instant for the situation in which route flow rates are updated least often and route flows are most spread over alternative routes, thus indicating a low information level as discussed before. When we gradually increase the information level, we can expect that network outflow rates will also increase up to a maximum approximating the network outflow capacity. This is because (more) exit points will then become (better) utilized. This is indeed the case when looking at the dashed and dash-dotted lines, representing intermediate and reasonably high information levels, respectively. Raising the information level after a certain point (when the traveler information level is already reasonably high) leads to lower network performance. This is a principle of system optimality. More information and network familiarity may enable a few more travelers to select a faster route and thus lower their travel time, yet consequently lengthen the travel time of many travelers already on this faster route. Thus on average everyone is worse off. Hence, in this case setting, best results are obtained from near-perfect information and familiarity.

One might suspect that increasing traveler information levels will stabilize the time-dependent network outflow rates. The reason is that travelers select their route to the exit points based on the perceived travel times on the alternative routes. When travelers are fully informed, then each traveler will continuously select the actual fastest route to the exit point. Hence, travel times on all used routes towards the exit points are equal. The traffic flow on the routes feeding the exit points are therefore steadier than in case travelers are less informed and travel times and flows on alternative routes vary strongly over time. This principle is illustrated in Figure 3(b) where network outflow rates as a function of network accumulation are related to different information levels. It can be seen that the variations in the time-varying network outflow rates are smaller for higher information levels.



(a) Cumulative departures (black line) and cumulative arrivals (grey lines)



(b) Network outflow rate as a function of network accumulation

Figure 3: Model results for different information levels: dotted lines  $\theta = 10\%$ ,  $\mu = 20$ , dash-dotted lines  $\theta = 30\%$ ,  $\mu = 2$ , dashed lines  $\theta = 50\%$ ,  $\mu = 1$ , and solid lines  $\theta = 100\%$ ,  $\mu = 0.1$  ( $\theta$ : update threshold,  $\mu$ : path size parameter)

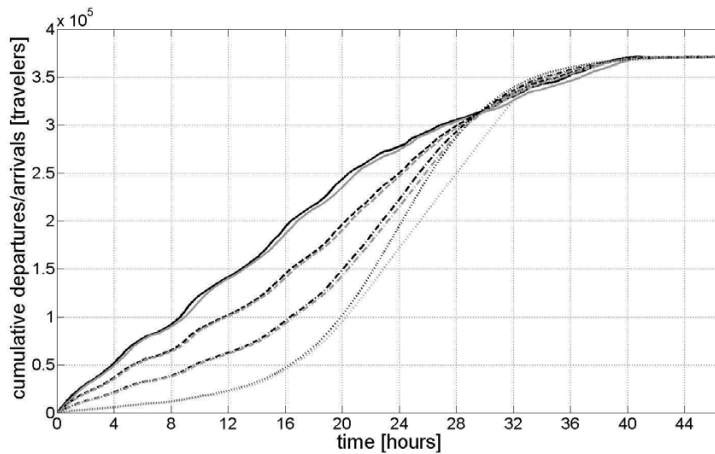
To conclude, the route flow rates have an impact on how (the routes feeding) the exit points are utilized, and thus on the arrival pattern. Figure 3(a) shows that this impact is highly non-linear. Also, a higher traveler information level and network familiarity does not necessarily result in lower network accumulation or higher network performance, and vice versa. This is shown by the domains for which network accumulation are observed and ranges for which network outflow rates are observed, respectively, in Figure 3(b).

#### 4.2. Compliance behavior

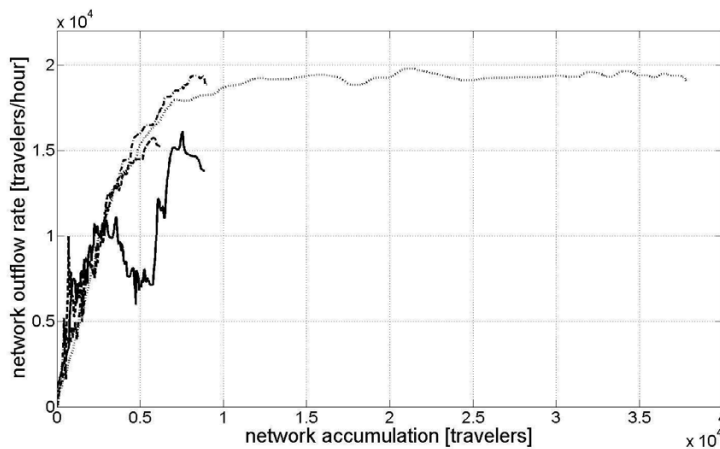
The impact of compliance behavior strongly depends on how well the evacuation instructions perform with full compliance. When instructions are optimized and thus perform well with full compliance, then non-compliance will worsen the evacuation. Network outflow rates will decrease and evacuation times increase. However, when instructions are deduced from straightforward rules such as the ones considered here, non-compliance does not necessarily worsen the case. Let us first consider departure time. The evacuation instructions given here aim at removing the peak demand and leading to a more uniformly distributed travel demand pattern, which in principle helps to lower the network load. Generally, this indeed occurs, as seen from Figure 4(a) showing the cumulative departures and arrivals for different compliance levels. A higher compliance level leads to a uniform travel demand, while a lower compliance level leads to a peak demand. This peak demand in turn results in higher network loads. The network load at each time instant can be deduced from the vertical distance between the black lines representing cumulative departures and the grey lines representing cumulative arrivals. The network load for the lowest compliance level is clearly much higher than for higher compliance levels. The difference in network load for higher compliance levels is smaller, and is mainly due to evacuation routes.

The instructions assign travelers to the fastest routes under free flow conditions. Since these instructed routes are not optimal, traffic conditions can actually improve when a fraction of travelers deviate from the instructed route to under-utilized routes that are currently (believed to be) faster. This leads to travel time reduction for both non-complying travelers on the faster routes, and complying travelers who now face lighter traffic conditions. The same can be concluded from Figure 4(b). Here, network outflow rate is given as a function of network accumulation for different compliance levels. In case of full compliance, travelers strictly follow the instructed routes. This leads to lower network outflow rates as some routes towards the exit points are used, while other attractive routes remain

under-utilized. A reasonably high compliance level solves this by allowing travelers to deviate from their route in case of a faster alternative. Routes towards the exit points are better utilized and network outflow rates increase. This in turn lowers network load, as seen from the domain on which network accumulation is observed. For the Rotterdam case, a further decrease in compliance level leads to higher network outflow rates, yet also higher network load due to the peak demand as discussed earlier. Decoupling the compliance level of departure time and route may lead to better results, but is outside the scope of this paper.



(a) Cumulative departures (black lines) and cumulative arrivals (grey lines)



(b) Network outflow rate as a function of network accumulation

Figure 4: Model results for different compliance levels: dotted lines  $\gamma = 10\%$ ,  $\tau = 5$  min,  $\beta = 10\%$ , dash-dotted lines  $\gamma = 40\%$ ,  $\tau = 20$  min,  $\beta = 40\%$ , dashed lines  $\gamma = 70\%$ ,  $\tau = 35$  min,  $\beta = 70\%$ , and solid lines  $\gamma = 100\%$ ,  $\tau = 60$  min,  $\beta = 100\%$  ( $\gamma$  : departure time compliance,  $\tau$  : minimum travel time gain,  $\beta$  : relative travel time gain)

To conclude, the impact of compliance behavior heavily depends on the evacuation instructions. This impact is likely non-linear, since compliance behavior determines travel decisions and the relationship between travel decisions and resulting traffic states and evacuation times is non-linear. Considering that a higher compliance level does not necessarily lead to a lower network load or faster evacuation, and vice versa, it is strongly recommended to incorporate traveler compliance behavior in evacuation models such that evacuation plans can be tested for robustness regarding different compliance levels.

## 5. Discussion and final remarks

Due to focusing on traffic flow dynamics, important aspects relating to how travelers deal with traveler information and evacuation instructions are typically neglected in evacuation traffic models and hence also scenario analyses. This contribution shows how traveler information can be modeled by applying a hybrid route choice model, thus enabling travelers to adapt their route when new information becomes available, and how traveler compliance can be modeled by internalizing the generalized costs of deviating from the evacuation instructions. The impacts of traveler information and compliance behavior are then numerically investigated by systematically varying the introduced model parameters in the evacuation model EVAQ. The case setting for which this is done describes the evacuation of the city of Rotterdam. We discussed how different information and compliance levels substantially affect traffic state and evacuation time. Increasing information and compliance levels may improve network conditions for some cases, while worsen conditions in other cases. These effects are highly non-linear. Furthermore, the impact of traveler compliance strongly depends on the instructions. The instructions used in the analysis in Section 3.3 follow from straightforward rules for the sake of simplicity. In other studies, EVAQ is used as grounding model to optimize evacuation instructions using Ant Colony Optimization (ACO) [21]. This ACO search method has proven to substantially improve evacuation times compared to evacuation by straightforward rules similar to those considered here. These optimized evacuation strategies are analyzed in [22] to show why certain strategies perform well, where others fail. The optimization method has been extended to design robust optimal evacuation strategies which perform well under uncertain traveler compliance behavior in [23].

The results, discussion and conclusions presented in this paper confirm the stated need to further incorporate traveler information and compliance into evacuation models, as well as assess the impact of these (uncertain) aspects in future scenario analyses. Scenario analyses on information and compliance levels can then be used to investigate the trade-off between costs associated with (collecting and disseminating) traveler information and enforcement of instructions and benefits hereof in terms of less congestion, lower travel times, and faster evacuation. Future research may relate to the impact of time-varying information and compliance levels, and cross-variations in traveler information and compliance (e.g., the impact of compliance level variations in case of higher or lower traveler information).

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