Model-based Optimal Evacuation Planning
anticipating Traveler Compliance Behavior

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Abstract  Instructing evacuees on their departure time, destination, and route can lead to more efficient evacuation traffic operations. While current evacuation plan optimization techniques are limited to assessing mandatory evacuation where travelers strictly follow the instructions, in reality a share of travelers likely decides not to comply. Here we show how 1) traveler compliance behavior affects evacuation efficiency, and 2) evacuation efficiency can be improved in case of less than full compliance when this traveler compliance is anticipated on. To this end, we use heuristic ant colony optimization in combination with the evacuation network model EVAQ in which compliance behavior is explicitly accounted for. The method is described and illustrated using the case study describing the evacuation of the Walcheren peninsula, the Netherlands. The method and application underline the conclusion that traveler compliance is an essential consideration while deciding on the appropriate evacuation instructions to be given. Also, the approach proposed here gives direction to further research along this line contributing to the understanding of the impact of traveler compliance behavior and its assessment in evacuation planning.

1. Introduction and Problem Definition

One of the many factors determining the success or failure of an evacuation is the set-up of the evacuation plan regarding how evacuees are instructed to select their individual departure time, destination, and route. Optimizing these evacuation instructions has been researched extensively. One way to distinguish different methods to optimize instructions is by whether an evacuation model is used. Optimization methods which do not make use of an evacuation model typically require unrealistic assumptions regarding, for instance, static travel times and link capacities (e.g., Baumann and Skutella 2006), no dynamic queuing and spillback (e.g., Liu et al, 2005), and static network characteristics. These constraints clearly limit

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1 Note that these same assumptions are made when optimizing using a static evacuation traffic model.
the applicability of the method to real-life cases. This can be regretted since the merit of these methods is faster computation, as time-consuming simulations are avoided. Model-based optimization methods on the other hand exploit the evacuation model to map evacuation instructions onto network outflow rates (e.g., Hibregts et al. 2009, Afshar and Haghani 2008, Chiu et al. 2007, Liu et al. 2006). Alternative evacuation instructions are then evaluated in an iterative manner until an optimum is found or the optimization procedure is terminated. The main advantage of these model-based search methods is that realistic situations can be addressed, including factors such as traffic flow dynamics and time-dependent network characteristics (due to both the progress of the hazard in space and time and prevailing traffic regulations and control).

Model-based optimization methods principally also allow including the effect of traveler compliance. However, this has been lacking until now, even though it is numerously identified as a crucial future research direction. The main reason why compliance behavior is neglected is that the evacuation models which are used as grounding model for the optimization process are unable of modeling traveler compliance behavior. As a consequence, model-based optimization studies to date typically assume full compliance, and the evacuation operations under optimized evacuation instructions for full compliance are then presented as an upper bound for network performance. This approach is too limited, since 1) it provides no insight into the impact of traveler compliance on the evacuation, and 2) it disables the trade-off made in real-life evacuation planning between investing in enforcement of instructions and reaping the possible benefits thereof in terms of, for instance, less congestion, lower travel times, and faster evacuation.

In fact, only very few studies have investigated the impact of traveler compliance on evacuation efficiency. For instance, Yuan et al. (2007) evaluate the impact of a fixed compliance rate with respect to route choice on an existing evacuation plan. In this study using VISSIM, \( n \% \) of the travelers complies and is thus assigned the instructed evacuation route, while the remainder share of travelers, that is \( 1-n \% \), is assigned to the nearest destination and the route following from the user-equilibrium. The value of \( n \) is systematically varied between 100\% (full compliance) and 0\% (no compliance). One of the main conclusions of the study is that less than full compliance may increase evacuation efficiency since less than full compliance allows travelers to deviate to under-utilized non-designated routes and thus compromises for ‘flaws’ in the original evacuation instructions. The preset compliance level and user-equilibrium assumption are relaxed in Pel et al. (2009b) where the authors accept that travelers follow a route over a period of time and during this period of time they can continuously choose whether to comply or not. Thus, travelers are assumed to 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 (intersection). This choice process describing traveler compliance behavior is modeled by applying the hybrid route choice model allowing for pre-trip and en-route travel decisions (Pel et al. 2009a). The minimum (relative) travel time gain for travelers to deviate from the instructed route is then systematically varied. The conclusions on the impact hereof in case of straight-
forward evacuation instructions are in line with the findings by Yuan et al. On the contrary, less than full compliance towards optimized instructions cannot benefit the evacuation efficiency by definition. This is also illustrated by Huibregtse et al. (2009) by evaluating the impact of variations in compliance levels towards optimized evacuation instructions, where the evacuation instructions were optimized based on the full compliance assumption. In the presented case study application, evacuation efficiency - measured as the number of safe arrivals within the limited amount of time available - dropped by 5 to 15 percent in case of less than full compliance. The latter two studies by Pel et al. and Huibregtse et al. make use of the same evacuation model used in this study.

The few studies referenced here show how limited the research is on the impact of compliance levels on evacuation efficiency. Yet, to the best of our knowledge, no evacuation optimization method has been applied to date in which traveler compliance behavior is anticipated on. This is unfortunate since earlier sociopsychological studies (e.g., Leach 1994, Quarantelli and Russell 1977) argue that the full compliance assumption is invalid, and evacuation efficiency can be improved in case of disseminating evacuation instructions which anticipate this less than full compliance. The latter is shown in this paper. To do so, we use a heuristic based on ant colony optimization (Huibregtse et al. 2009) in combination with the evacuation network model EVAQ (Pel et al. 2008) in which traveler compliance behavior in explicitly incorporated. The EVAQ model and heuristic optimization method are explained next. Thereafter, we apply the optimization framework to a real-life case setting describing the evacuation of the Walcheren peninsula, the Netherlands. In this application, we numerically show the (beneficial) impact of anticipating on traveler compliance behavior. The final section discusses the presented research and concludes that the modeling approach and application presented here can be used to give direction to future research along this line contributing to 1) the understanding of the impact of traveler compliance behavior, and 2) its assessment in optimal evacuation planning and management.

2. Optimization Approach

We have spoken until now on optimizing evacuation efficiency by means of the evacuation model EVAQ and an ant colony based optimization heuristic. Let us first define a measure for evacuation efficiency and present the framework using EVAQ and the optimization heuristic, after which we describe the evacuation model and optimization algorithm in more detail.


2.1 Objective and Framework

Optimizing evacuation instructions basically means generating instructions which maximize the evacuation efficiency. Various measures of evacuation efficiency can be thought of, depending on the evacuation objective and scenario constraints. Straightforward efficiency measures, such as network clearance time and system travel time, are used extensively. Other formulations evaluate, for instance, the risk exposure of evacuees while being at home waiting to depart and en-route (Yuan and Han 2009), or the number of arrivals considering the possibility of a non-complete evacuation (Miller-Hooks 2008). For other measures of evacuation efficiency that are appropriate in case of scenario-based uncertainties a distinction can be made between stochastic criteria evaluating the expected efficiency given probabilities of anticipated scenarios, and robust criteria evaluating the minimal efficiency given all anticipated scenarios (Huibregtse et al. 2010).

Here, we define evacuation efficiency as the weighted network outflow rates integrated over time:

\[ w(E \mid S) = \int_0^T e^{\beta t} f(E, S, t) dt. \]  

The evacuation efficiency \( w \) is determined by the evacuation instructions \( E \) (i.e., designated departure times, destinations, and routes) which clearly are conditional to the scenario \( S \) (i.e., network degradation and traveler compliance behavior). The evacuation efficiency measure has one parameter, \( \beta \in [0, \infty) \). For \( \beta = 0 \), the value of \( w \) is equal to the total network outflow, \( \int f(t) dt \). When \( \beta > 0 \), earlier arrivals are appreciated more than later arrivals. In other words, given that the same number of travelers successfully arrives at their destination, evacuation instructions leading to a situation in which travelers arrive earlier are considered as more efficient. The reason for choosing this formulation adopted from Huibregtse et al. (2010) is, because of its simplicity and ability to incorporate uncertainties with respect to the scenario conditions, including (uncertain) factors such as the window of available evacuation time and traveler compliance behavior.

Fig. 1. Optimization framework using optimization heuristic and evacuation model
In the proposed method, we maximize the evacuation efficiency as defined by Equation (1) by alternatingly calling the evacuation model EVAQ which uses evacuation instructions $E$ (and traveler compliance behavior) to compute the dynamic network outflow rates $f$, and calling the optimization heuristic which uses these dynamic network outflow rates $f$ to compute better evacuation instructions $E$. This procedure is illustrated in Figure 1.

### 2.2 Evacuation Model

We use the evacuation model EVAQ to predict the dynamic network outflow rates depending on the evacuation instructions regarding departure time, destination and route, and the traveler compliance behavior. Compared to other evacuation traffic models, the distinguishing features of EVAQ are: 1) modeling of dynamic road infrastructure, 2) incorporation of adaptive traveler choice behavior, and 3) incorporation of evacuation instructions and traveler compliance behavior. EVAQ models time-dependent road infrastructure. This means that 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 regulation and control measures (e.g., contraflow operations to increase outbound capacity). While other models typically relate time-varying road infrastructure only to an impact in traffic flow propagation (e.g., lower speed limits results in drivers experiencing higher travel times), in EVAQ this also affects en-route travel choice behavior (e.g., lower speed limits leads to drivers making a detour). That is, when evacuation-related dynamic traffic control measures and hazard-inflicted network degradation lead to (sufficiently large) changes in the network, then travelers can choose to adapt their route at the next decision point (intersection). For a complete model description we refer to Pel et al. (2008). In the ensuing, we focus on how traveler compliance towards evacuation instructions is dealt with.

We distinguish traveler compliance towards the instructed evacuation participation and departure time, and towards the instructed destination and route. We assume that participation and departure time compliance can be modeled as:

$$D'(t) = \gamma D'(t) + (1 - \gamma) \hat{D}'(t).$$

Here, $D'(t)$ denotes the actual travel demand from origin $r$ at time instant $t$. The actual travel demand depends on the instructed travel demand $\hat{D}'(t)$, which is given by the evacuation instructions, and the preferred travel demand $\hat{D}'(t)$. 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 pre-
ferred travel demand can be predicted by the sigmoid curve given by Radwan et al. (1985) as:

\[ \hat{D}'(t) = \left[1 + \exp\left(-\alpha' \left(t - h'\right)\right)\right]^{-1} F'. \]  

(3)

The number of inhabitants at origin \( r \) is denoted by \( F' \). The preferred travel demand curve determined by the bracketed term in front of \( F' \) has two parameters. 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 population at origin \( r \) has departed.

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, we assume that at each decision point (intersection) travelers make a trade-off between following the instructed route and deviating to a route which is (perceived as being) more attractive. Thus, the generalized route costs are modeled as:

\[ c_{pq}(t) = \tau_q(t) + \ell_{pq} \max\{\tau, \phi \tau_q(t)\}. \]  

(4)

Here, \( c_{pq}(t) \) denotes the costs of following route \( q \) as perceived by travelers who are actually instructed to follow route \( p \). These costs consist of the costs associated with traveling route \( q \), modeled here as travel time \( \tau_q(t) \), and a minimum gain that the traveler wishes to achieve in case of deviating from the instructed route \( p \) to the new route \( q \). This minimum gain is modeled by the \( \max\{\ast\} \) term, while the deviation is modeled by \( \ell_{pq} \). The deviation \( \ell_{pq} \in [0,1] \) denotes the relative length of route \( q \) which does not coincide with the instructed route \( p \). Consequently, we assume that the more route \( q \) deviates from the instructed route \( p \), the larger the gain should be to switch routes, since the \( \max\{\ast\} \) term is strictly positive, which seems reasonable. The gain \( \max\{\ast\} \) term then states that the new route \( q \) should be \( \phi \) percent faster, with a minimum of \( \tau \). Route choice decisions at all intersections are then modeled by the pathsize logit model (Ben-Akiva and Bierlaire 1999). Traffic is propagated over the network by the link-based dynamic queuing model described by Bliemer (2007).

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

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2 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 (Stepher et al. 2004) and hurricanes (Fu et al. 2006) using surveys on stated preference and revealed preference. The sigmoid curve is used here due to lack of data and for the sake of generality and simplicity. The presented method of anticipative optimization will not be affected by defining the preferred departure time choices differently. How a different definition may impact the model outcomes in Section 3 is beyond the scope of this paper.
choice sets (at the intersections) the destination choice compliance is embedded in the route choice compliance.

For reasons of simplicity, the model framework is formulated here for homogeneous travel behavior. In EVAQ, differences among travelers in, for instance, departure time and route preferences, evacuation instructions, and compliance behavior are dealt with by applying a multiuser class assignment. Thus, travel demand and route flow costs and flows are computed per class, where each class has its own parameters determining traveler preferences and compliance behavior.

The parameters $\gamma$, $\tau$, and $\phi$ 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 both instructions and enforcement to which the evacuees respond in travel behavior. In the following, we focus on optimizing evacuation instructions while anticipating a constant compliance (enforcement) level. Bi-variate optimization including determining the optimal compliance (enforcement) level is considered future research. Regarding departure time compliance, in the limiting case that $\gamma = 1$, then $D'(t) = D'(t)$ indicating full compliance. While $\gamma = 0$, leads to $D'(t) = D'(t)$ such that all travelers depart at their preferred departure time. For $0 < \gamma < 1$, a share of travelers complies and departs at the instructed departure time, while the remainder of travelers does not comply and departs at their preferred departure time. Similarly for route (and destination) compliance, full compliance can be modeled when high values are chosen for $\tau$ and $\phi$ (or approach infinity). Then, the generalized route costs are predominately determined by the threshold term in Equation (4). Consequently, the costs of deviating from the instructed route $p$ (that is, when $\ell_{pq} \neq 0$) become very large (or approach infinity). Non-compliance can be modeled by setting $\tau$ and $\phi$ equal to zero. The threshold term in Equation (4) then equals zero, such that travelers always follow the (perceived) fastest route, independent of which route is instructed. Partial compliance, depending on the traffic conditions, is modeled as $0 < \tau \ll \infty$ and $0 < \phi \ll \infty$, where higher values of $\tau$ and $\phi$ allow for higher compliance rates, since travelers then require larger travel time gains before deviating from the instructed route.

2.3 Optimization Heuristic

We use the ant colony optimization based heuristic to assign evacuation instructions regarding departure time, destination and route to all travelers. Or, more precisely, we first generate promising instruction sets consisting of a designated departure time and route (where the route implies the destination), and subsequently assign travelers to these instruction sets. The concept of each of these both steps (1. generating sets, and 2. assigning travelers) will be described in the following. For a complete description of the optimization method we refer to Huibregtse et al. (2009).
In the first step, instruction sets are generated. Since we are dealing with time-dependent network characteristics due to hazard impacts and traffic control, different routes will be appropriate for different departure time intervals. For example, a specific route might be an efficient evacuation route at the start of the evacuation, yet become an inappropriate designated route once a section becomes inaccessible due to flooding. To take this into account, we first generate a master set of routes, denoted as $\bar{P}$, based on a fully accessible road network, from which we later select (sub)sets of routes that are available within specific time-intervals. These master route sets (from each origin to all destinations) are generated using an algorithm proposed by Bliemer and Taale (2006) which applies Monte Carlo (MC) simulations in which the generalized link costs are assumed to be random variables. In each subsequent MC simulation, the fastest routes from each origin to any of the destinations are determined using Dijkstra’s shortest path algorithm (Dijkstra 1959), and added to the master route set $\bar{P}$ if the newly found route shows sufficiently low temporal overlap\(^3\) with all other routes in the route set $\bar{P}$ having the same origin. The criterion of sufficiently low temporal overlap is to ensure distinct route alternatives in the route choice set and avoid adding routes which heavily coincide with other routes apart from, for instance, a slight ‘detour’ using an off-ramp and corresponding on-ramp.

Once we generated this master set of routes, we then select (sub)sets of routes $P([k, k + \Delta k]) \subseteq \bar{P}$, ‘available’ during departure time interval $[k, k + \Delta k]$. Available here means that travelers departing within the designated time interval will safely arrive at their destination via these routes under the condition of free flow travel time. Since links become inaccessible at specific time instances (conditional to a certain hazard scenario) we can define route sets on departure time intervals in between the successive failure of two links in the road network. This way, we create time-interval specific route sets containing departure time and route combinations that serve as possible evacuation instructions. For each origin, and each departure time interval, we then select potential evacuation routes as the routes with a travel time that is no greater than $m$ times the travel time on the fastest route, with a maximum of $M$ routes. In case less than $M$ routes were found, we try to append the route set by generating new routes for this origin-departure time pair using MC simulation on the limitedly accessible road network. This route selection is made to avoid instructing travelers to follow slow routes which they most likely will not comply to, and to speed up computation and limit memory usage.

Note that this first step of generating instruction sets is only performed once, while the second step of assigning travelers to these instruction sets is an iterative procedure executed a large number of times in which each iteration aims at improving the current-best solution. To ensure practicality, both regarding computational costs and real-life implementation of the evacuation instructions, travelers

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\(^3\) Temporal overlap is measured as the free flow travel time on the route section not coinciding with other routes, relative to the total free flow route travel time.
are not assigned individually, but in groups. For instance, all inhabitants of a neighborhood receive the same instructions\(^4\).

Assigning (groups of) travelers to the generated evacuation instruction sets is done based on ant colony optimization. The concept of the procedure is as follows. All instruction sets have a specific probability of being selected, where all these probabilities for instruction sets belonging to a specific origin add to 1 (how these probabilities are computed we will explain in a moment). For each of the origins, we randomly select an instruction set – accounting for the relative probabilities – and assign this set to a group of travelers. We continue doing so until all travelers have been assigned instructions. Note that this procedure allows the same instruction set to be assigned to multiple groups of travelers, in contrast to the original ant colony optimization algorithm. This way, an evacuation plan is generated consisting of instructions regarding departure time and route (implying destination) for all travelers. In one iteration, multiple evacuation plans are generated. Each of these evacuation plans, \(E\), is evaluated using the evacuation model EVAQ. Applying EVAQ leads to the dynamic network outflow rates, from which we can compute the evacuation efficiency according to Equation (1). This is computed for all evacuation plans. The evacuation plan in the current or previous iterations\(^5\) that leads to the most efficient evacuation is then selected. This overall-best evacuation plan is used to compute new probabilities of selecting each individual instruction set. These new selection probabilities are then used in the next iteration to select new instruction sets and thus generate new evacuation plans. This iterative procedure is continued until no further improvement is made over a number of successive iterations or the procedure is terminated.

As mentioned, the probabilities of selecting specific instruction sets are determined by whether the evacuation plans containing these instruction sets have proven to be overall-best. Thus, the probability of selecting instruction set \(u\) is computed as:

\[
Pr(u) = \begin{cases} 
\xi(w_{E}, B_u) Pr(u)^{-1} & \text{if } u \in \bar{E} \\
\zeta Pr(u)^{-1} & \text{otherwise}
\end{cases}
\]  

(5)

Here, the selection probabilities of instruction sets \(u\) belonging to the overall-best evacuation plan \(\bar{E}\), are increased, i.e. \(\xi(w_{E}, B_u) \geq 1\), while the remainder selection probabilities are lowered, i.e. \(0 \leq \zeta \leq 1\), to ensure that all probabilities of instruction sets belonging to the same origin add up to 1. The value of \(\zeta\) determines the impact of the overall-best evacuation plan on subsequent iterations. For higher values of \(\zeta\), the selection probabilities of instruction sets belonging to the overall-best evacuation plan will be higher, thus indicating more concentration of the

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\(^4\) This method is in accordance to current evacuation planning practices in the Netherlands and most other countries.

\(^5\) Using the overall-best evacuation plan for updating instruction-set-selection probabilities has been found to perform better than updating based on the iteration-best evacuation plan (Huibregtse 2008).
search heuristic in successive iterations and less exploration, and vice versa. We compute $\xi$ as a function of the evacuation efficiency $w_{EF}$ attained by the overall-best evacuation plan and the number of travelers assigned to the instruction set $B_{i\sigma}$, such that a higher evacuation efficiency or larger number of travelers receiving this instruction set leads to a higher increase in selection probability.

Equation (5) shows the concept of updating the selection probabilities. Initial probabilities for iteration $i = 0$ depend on the characteristics of the instructed departure time and route, where earlier departure times and faster routes (based on free flow travel time) receive a higher initial probability than later departure times and slower routes. We refer to Huibregtse (2008) for more details on the probability-initializing and updating functions and an analysis on optimal values for factors determining the exploration and concentration of the search method.

We wish to emphasize that the optimization method used here assigns groups of travelers to evacuation instruction sets based on a stochastic procedure in order to iteratively improve the evacuation instructions. As a consequence, the evacuation instructions found by this optimization framework in most cases are likely not optimal, but only approach optimality. This has an effect on the impact of traveler compliance as discussed in the model application presented next.

3. Model Application

In the following model application, we wish to illustrate the functioning and potential of the proposed optimization framework including traveler compliance behavior. To this end, we will use the evacuation of the Walcheren peninsula in the southwest of the Netherlands as a case study. Let us first briefly describe the considered case, after which we present the experimental set-up used to structure the application, and discuss the numerical results.

3.1 Case Study Description

The Walcheren peninsula is situated in the southwestern part of the Netherlands and contains both rural and build-up areas, as seen from Figure 2. The population of approximately 120,000 inhabitants (excluding the few residential areas with less than 500 inhabitants) is largely concentrated in the two cities of Middelburg and Vlissingen. Given the setting of the area, evacuation due to coastal flooding can be considered conceivable. In fact, several programs on national and regional level have been initiated over the past years dealing with the preparation for a possible flood. The flooding scenario 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 which the available time to evacuate before the flood occurs is critical for complete evacuation,
namely 8 hours\(^6\). After 8 hours, further evacuation is assumed no longer possible. We assume everyone prefers to depart within these 8 hours (following Eq. (3) with \( \alpha = 1.5, \ h = 4 \)), leading to the preferred departure profile pictured in Figure 3. Note that the actual departure profile is determined by the interaction between the preferred departure profile, the instructed departure profile, and the travelers’ compliance behavior, as discussed in Section 2.2. The designated exit points are the 2x2 lane motorway A58, and the 2x1 lane provincial roads N57, N665, and N254 in east and northeast direction, indicated in Figure 2. The road network used in the analysis consists of 146 links and 61 nodes, including 23 origins and 4 destinations (i.e., exit points).

\[\text{Fig. 2. Walcheren road network and evacuation exit points: motorway A58 and provincial arterial roads N57, N665, and N254}\]

\(^6\) The combined capacity of the four network exit points equals 10,400 vehicles per hour. However, two exit points share an upstream bottleneck. Correcting for this, the maximum network outflow rate equals 8,400 vehicles per hour. Assuming average car occupancy of 2 travelers per vehicle leads to evacuating maximally 16,800 travelers per hour. A total of 121,842 travelers results in a minimal evacuation time of 7 hours and 15 minutes, excluding additional constraints, such as initial travel time from origins to exit points, incidental underutilization of exit points due to internal conflicts on the road network, lower network outflow rates due to capacity drop induced by congestion, etc. The available time horizon of 8 hours can thus be seen as critical, as also shown by the results presented in Section 3.3.
Fig. 3. Preferred travel demand pattern for Walcheren area: cumulative departures (black graph) and departure rate (grey graph)

3.2 Experimental Set-up

The model application consists of two related parts, both showing the relevance of incorporating traveler compliance behavior in evacuation optimization and the potential of the proposed optimization framework. First, we show the impact of traveler compliance behavior on evacuation efficiency when invalidly assuming full compliance. Second, we show the gain in evacuation efficiency when anticipating the traveler compliance behavior. Each approach is described next. The numerical results are presented thereafter.

Impact of Full Compliance Assumption

Evacuation instructions which are optimized based on the assumption of full compliance are typically reported as an upper bound on evacuation efficiency. Here, we investigate the impact on evacuation efficiency when applying these optimized instructions to the case of less than full traveler compliance. This is done by 1) generating optimized evacuation instructions assuming full compliance, and then 2) applying these instructions to evacuation scenarios in which we systematically
vary traveler compliance behavior. The impact of these variations in compliance levels on evacuation operations and efficiency is then analyzed.

In the following analysis, we investigate the impact of traveler compliance behavior towards departure time choice, route choice, and the combination of these. Departure time choice compliance is modeled by a fixed compliance rate according to Equation (2), as discussed in Section 2.2. Here, we vary this compliance fraction between \( \gamma = 1 \) and \( \gamma = 0 \), thus modeling the scenarios of full compliance, no compliance, and intermediate states of partial compliance. Next, route choice compliance (implying destination choice compliance) is modeled by a minimum travel time gain travelers wish to achieve in order to deviate from the instructed route to another route (with possibly another destination). The minimum gain is split into a minimum absolute gain \( \tau \), and a minimum relative gain \( \phi \). These are simultaneously varied between \( \tau = \phi = \infty \), and \( \tau = \phi = 0 \), thus again leading to the scenarios of full compliance, no compliance, and partial compliance. Third, we simultaneously vary traveler compliance behavior regarding departure time choice and route choice to investigate their combined impact.

Impact of Anticipating Traveler Compliance
The optimization framework proposed in Section 2 allows optimizing evacuation instructions while anticipating less than full compliance levels. This is done by iteratively searching for optimal instructions while accounting for traveler compliance behavior. Here, we investigate the gain in evacuation efficiency when applying instructions that anticipate traveler compliance behavior compared to instructions assuming full compliance. This is done by 1) generating optimal evacuation instructions that anticipate specific traveler compliance behavior, and then 2) comparing the evacuation efficiency resulting from these instructions against the efficiency resulting from the optimized instructions belonging to the full compliance assumption. This is done for a higher and lower level of traveler compliance behavior, modeled as 1) \( \gamma = 0.7 \), \( \tau = 30 \text{ minutes} \), and \( \phi = 100 \% \), and 2) \( \gamma = 0.3 \), \( \tau = 10 \text{ minutes} \), and \( \phi = 20 \% \). The impact of anticipating traveler compliance behavior on evacuation operations and efficiency is then analyzed.

3.3 Numerical Results
The ACO-EVAQ optimization method is implemented in Matlab. Applying a time step of 30 seconds and group size of 500 travelers (resulting in 253 groups), CPU times on a Windows XP driven 2.2 GHz processor range from less than one minute to approximately three minutes for computing individual scenarios. Here, full compliance leads to lower CPU times since the route choice set generation during the traffic flow propagation procedure is omitted (since travelers will not deviate from their route). For the less than full compliance case, CPU times and memory usage are proportional to the number of traveler groups, since most link and node variables are computed for each group of travelers with the same prescribed depar-
ture time or route. To find efficient instruction sets for lower compliance levels typically fewer iterations are required, compared to higher compliance levels, since the remaining flaws in these evacuation plans are partially remedied by travelers deviating to a different departure time or route. The results presented in the ensuing are obtained after 72 hours of computation, equivalent to approximately 550 iterations (of 10 simulations each) for the full compliance setting and 150 iterations for the anticipating compliance settings.

Impact of Full Compliance Assumption
The effect of traveler compliance behavior when applying instructions based on full compliance is shown for evacuation efficiency and number of arrivals in Figure 4. The traveler compliance parameter settings for which this is tested are listed in Table 1. The solid line is Figure 4 represents the case of simultaneously varying compliance towards departure time choice and route choice. The same effect of compliance level is observed in both evacuation efficiency and number of arrivals. Starting from full compliance and gradually lowering compliance leads initially to better performance. This shows that the optimized instructions are not optimal. As mentioned earlier, this can be due to too few iterations (solution has not converged yet), and the optimization method assigning too large groups of travelers at once (hence less than full compliance allows 'breaking' these groups and increasing performance). That the presented method is capable of finding near-optimal solutions is underlined by the decreasing performance when further lowering the compliance level. That is, more travelers complying with the optimized instruction sets leads in principal to more arrivals and higher evacuation efficiency, however, in case of full compliance travelers are stuck to following designated routes regardless of prevailing traffic conditions and hence remaining conflict in traffic flows are not resolved (which are typically resolved in case of very high, but not full, compliance).

The independent effect of departure time compliance and route compliance are analyzed next. In Figure 4, the dash-dotted lines show the impact of varying departure time choice compliance (while modeling full compliance towards instructed evacuation routes), and the dashed lines show the impact of varying route choice compliance (while modeling full compliance towards instructed departure times). Departure time compliance appears to have a much larger influence on the number of arrivals and evacuation efficiency than route choice compliance does. This is to be expected since when travelers do not comply with the instructed departure times this results in a more peaked travel demand (instead of a more uniform demand) which leads to higher network inflow rates. Higher network inflow rates in turn lead to higher network accumulation, leading to lower network outflow rates as congestion sets in, which in turn again leads to a further increase in network accumulation, etc. On the other hand, when travelers do not comply with the instructed routes, they make en-route route decisions based on provided traffic information which allows travelers to utilize all possible routes towards the designated evacuation exits equally. Thus, non-compliance towards route guidance can up to a certain level be remedied by giving sufficient traffic information and ex-
pecting travelers to easily switch routes (thus also assuming a reasonable level of network familiarity).

(a) Evacuation efficiency as a function of compliance level

(b) Percentage of arrivals as a function of compliance level

Fig. 4. Model results for full compliance assumption: solid lines for both departure time and route compliance levels, dash-dotted lines for only departure time compliance levels, dashed lines for only route compliance levels. Compliance levels correspond to parameter settings listed in Table 1.
Table 1. Traveler compliance behavior parameter settings corresponding to compliance levels presented in Figure 4.

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<td>φ [%]</td>
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<th>.9</th>
<th>.8</th>
<th>.7</th>
<th>.6</th>
<th>.5</th>
<th>.4</th>
<th>.3</th>
<th>.2</th>
<th>.1</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>route</td>
<td>τ [min]</td>
<td>60</td>
<td>54</td>
<td>48</td>
<td>42</td>
<td>36</td>
<td>30</td>
<td>24</td>
<td>18</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td>φ [%]</td>
<td>100</td>
<td>90</td>
<td>80</td>
<td>70</td>
<td>60</td>
<td>50</td>
<td>40</td>
<td>30</td>
<td>20</td>
<td>10</td>
<td>0</td>
</tr>
</tbody>
</table>

Impact of Anticipating Traveler Compliance

We may decide on anticipating the expected traveler compliance behavior while searching for optimal evacuation instructions. This leads to higher evacuation efficiency than when the previously-found full compliance-based instructions are applied. This is shown in Table 2 below presenting the evacuation efficiency as computed by Equation (1) for the various cases. Though the difference is minor, we observe that evacuation efficiency in case of low compliance with anticipation hereon is higher than in case of high compliance without anticipation hereon. This underlines the relevance and potential of anticipating traveler compliance behavior.

Table 2. Evacuation efficiency for anticipating traveler compliance

<table>
<thead>
<tr>
<th>Compliance level</th>
<th>Full compliance assumption</th>
<th>Anticipating compliance</th>
</tr>
</thead>
<tbody>
<tr>
<td>High compliance level</td>
<td>(γ = 0.7, τ = 30 min, φ = 100 %)</td>
<td>84,344</td>
</tr>
<tr>
<td>Low compliance level</td>
<td>(γ = 0.3, τ = 10 min, φ = 20 %)</td>
<td>78,957</td>
</tr>
</tbody>
</table>

The gain in evacuation efficiency is mainly due to travelers arriving earlier when applying instructions anticipating the compliance behavior, in contrast to a possible gain due to a larger total number of arrivals. This is apparent from the cumulative departures and cumulative arrivals plotted for each case in Figure 5(a) and the time-dependent network outflow rate (i.e., arrival rate) shown in Figure 5(b). Anticipating traveler compliance behavior here leads to instructing (possibly other) travelers to departure times and routes letting them evacuate earlier than they would do otherwise.

Moderating departure rates and guiding travelers to efficient evacuation routes results in lower network accumulation (i.e., the total number of travelers on the network over time), since both the network inflow is lower and the network outflow is higher. Figure 5(c) shows that when anticipating traveler compliance behavior higher network outflow rates are maintained at similar network accumulation (thus showing efficient evacuation route instructions), and maximal network accumulation is limited. This is apparent from the ranges for which network out-
flow rates are observed and the domains for which network accumulation are observed, respectively.

(a) Cumulative departures (solid lines) and cumulative arrivals (dashed lines)

(b) Time-dependent network outflow rate
These same patterns are valid for anticipating low compliance. However, here the gain in evacuation efficiency and number of arrivals is primarily due to efficient evacuation departure time instructions. This can be seen from Figures 6(a)-(c). Instructions anticipating low compliance behavior lead to larger departure rates at the start of the evacuation resulting in larger early arrival rates, thus limiting network accumulation later on. Note that network accumulation over time is shown by the vertical distance between the cumulative departures (i.e., network inflow) and cumulative arrivals (i.e., network outflow). That the effect of route instructions anticipating compliance is limited additional to the same effect for the full compliance assumption is illustrated in Figure 6(c). Here, network outflow rates for similar network accumulation levels are comparable between cases.
(a) Cumulative departures (solid lines) and cumulative arrivals (dashed lines)

(b) Time-dependent network outflow rate
4. Discussion, Conclusions, and Future Research

The optimization framework proposed here applies an ant colony based optimization heuristic in combination with an evacuation model in which traveler compliance behavior is explicitly accounted for. This allows for the first time to 1) analyze the impact of traveler compliance behavior on evacuation efficiency, and 2) generate optimal evacuation instructions while anticipating traveler compliance behavior. In that, the modeling approach and application presented here can be used to give direction to future research along this line contributing to 1) the understanding of the impact of traveler compliance behavior, and 2) its assessment in optimal evacuation planning and management.

The model application shown here relates to anticipating certain traveler compliance behavior. However, the presented method is clearly also applicable to designing robust optimal evacuation instructions while anticipating uncertain traveler compliance behavior by defining (the parameters describing) compliance behavior as a probability distribution and, for example, using Monte Carlo simulations in which the compliance behavior is a stochastic variate.
Current drawbacks in the ACO-EVAQ framework are in line with common disadvantages of model-based iterative optimization techniques and relate to that 1) no guarantee can be given on finding the optimal solution, and 2) the convergence towards a near-optimal solution can be relatively slow in specific cases. Future research on the ACO-EVAQ framework thus will aim at improving these aspects, which then allows illustrating the benefit of anticipating traveler compliance behavior more clearly. Finally, we wish to argue that further research in this line of study is needed 1) on realistic levels of traveler compliance behavior for different settings (i.e., model calibration on behavioral parameters for various scenarios differing in, e.g., traveler information level, network familiarity, instruction dissemination method, and hazard characteristics), and 2) on bi-variate optimization, such that both evacuation instructions and compliance enforcement are simultaneously optimized to obtain a balanced trade-off between the benefits of more efficient evacuation by applying instructions and the costs of disseminating and monitoring the compliance towards these instructions.

References


