

Preliminary Result of a Large Scale Microscopic Evacuation Simulation for the City of Padang in the Case of Tsunami

Gregor Lämmel¹, Hubert Klüpfel², and Kai Nagel¹

¹ Berlin Institute of Technology (TU Berlin), Transport Systems Planning and Transport Telematics, Berlin, Germany

laemmel@vsp.tu-berlin.de

² TraffGo HT GmbH

Bismarckstraße 142a – 47057 Duisburg – Germany

kluepfel@traffgo-ht.com

Abstract. The evacuation of whole cities or even regions is an important problem, as demonstrated by recent events such as evacuation of Houston in case of Hurricane Rita or the evacuation of coastal cities in case of Tsunamis. The city of Padang, Western Sumatra, Indonesia is located in a zone of extreme risk due to severe earthquakes and possibly triggered tsunamis. A robust and flexible simulation framework for such large-scale disasters helps to predict the evacuation process, in order to give evacuation relevant recommendations for a better preparedness for a real event of tsunami. Existing methods are either geared towards smaller problems (e.g. Cellular Automata techniques) or are not microscopic (e.g. methods based on dynamic traffic assignment). This paper presents a technique that is both microscopic and capable to process large problems. The simulation framework is applied to the city of Padang in the case of a Tsunami warning. In this paper we give a description of the simulation framework. Although the results are still preliminary, we show first simulation results and give an analysis with respect to evacuation time, evacuation process, and the outflow rate of evacuees.

1 Introduction

The evacuation of whole cities or even regions is an important problem, as demonstrated by recent events such as the evacuation of Houston in the case of hurricane Rita or the evacuation of coastal cities in the case of tsunamis. As a consequence of these events, disaster and evacuation planning has become an important topic in science and politics.

Congruent with the importance of the topic, there is a large body of research regarding emergency evacuations. As a first classification, one may differentiate between two situations: (i) evacuation from within buildings, ships, airplanes, etc.; (ii) large-scale citywide or regional evacuations, e.g. because of nuclear power plants failures or because of hurricanes. Case (i) usually concerns pedestrian evacuation; case (ii) usually uses traffic-based evacuation.

A good overview of pedestrian evacuation modeling and software can be found in the books of the bi-annual conference series “Pedestrian and Evacuation Dynamics” [44, 14, 15, 1]. Pedestrian evacuation simulations can be classified into microscopic and macroscopic ones. Microscopic models represent space, time, and persons on a fine-grained level. Possible microscopic approaches are Cellular Automata (CA) [30], discretized differential equations (“molecular dynamics (MD)”) [23, 22], or movement rules based on random utility modelling [5]. Examples of software packages based on microscopic models are Exodus [13], Myriad (www.crowddynamics.com), Egress (www.aeat-safety-and-risk.com/html/egress.html), and PedGo [29]. Macroscopic models use the analogy of flows of pedestrians and liquids. Examples of software packages based on macroscopic models are Aseri [43] and Simulex (www.iesve.com). See Refs. [27] and [31] for surveys. Compared to what is known in terms of field measurements (e.g. [39, 48]), most if not all packages lead to similar results [40].

Once the pedestrian movement model is selected, it is necessary to define the evacuation directions. For more complex geometries, this is no longer a single movement towards one or two exits, but may involve rather complex movements in a building or in a street network. The arguably simplest solution is a grid-based potential function where the “uphill direction” leads to the nearest exit [37]. The same can be done using essentially continuous spatial variables, at the expense of much larger computing times [26]. Alternatively, routing can be done along graphs [20, 17], which is a much faster technique when the abstraction to a graph is possible.

Another line of research concerns citywide or regional evacuations, i.e. case (ii). The development of these tools was much influenced by the development of tools in the areas of transport planning and traffic management. At the core of many of these methods is a static assignment routine (e.g. [45, 38]). A typical example for traffic-based evacuation simulation based on static concepts is MASSVAC [25] although later versions contain dynamic aspects.

A severe shortcoming of static assignment is that it does not possess any consideration of the time-of-day dynamics. Dynamic traffic assignment (DTA) is defined as a distribution of time-dependent trips on routes. A typical approach to implement DTA is day-to-day re-planning: The traffic flow simulation (also called network loading) is run with pre-specified routes, route costs are extracted, some or all of the routes are modified, the traffic flow simulation is run again, etc., until some stopping criterion is fulfilled. Examples of stopping criteria are that either every trip uses a route which minimizes expected travel time (time-dependent Nash equilibrium), or it selects between different route alternatives following a pre-specified distribution function (time-dependent SUE).

Many DTA packages have been tested in the evacuation context: MITSIM [28], Dynasmart [32, 10], PARAMICS [9], and VISSIM [21]. Oak Ridge National Laboratory has a package named “OREMS” (cta.ornl.gov/cata/One_Pagers/OREMS.pdf) explicitly for evacuation traffic. Publications stressing dynamic aspects of traffic-based evacuation as a novelty can be found as recent as 2000, e.g. [41, 3]. For a review, see [2].

A further distinction is if travelers can re-route while they are on their way (within-day re-planning; en-route re-planning), or only before their trip (day-to-day re-planning; pre-trip re-planning) [8]. Clearly, en-route re-planning capability is more realistic. It is, however, also more demanding: Adaptation of the plans needs to be called frequently from within the network loading, rather than only having to alternate between the network loading and the mental layers as one does in day-to-day re-planning.

To our knowledge, none of the above approaches is able to simulate large-scale scenarios (with millions of entities) while remaining microscopic:

- With a CA model, an area of $40\text{ km} \times 40\text{ km}$ translates into 10^{10} cells. Even if every cell only needs 1 Byte, this still translates into 10 GByte of memory, resulting in large simulation times.
- For the MD approach, the problem are the sub-second time resolutions that are typically used [12].
- DTA approaches seem the most likely candidates, but to our knowledge their implementation of the traffic flow dynamics usually is still too time-consuming for scenarios of that size.

One way to achieve faster computation with a microscopic model is to use a model with deliberately large time steps and to computationally concentrate on those areas (links) where the pedestrian movement actually takes place [18]. Another approach is based up on a modified queuing model [16, 46]. The queuing model simplifies streets to edges and crossings to nodes; the difference to standard queuing theory is that agents (particles) are not dropped but spill back, causing congestion. This graph-oriented model is defined by lengths/widths, free speed and flow capacity of the edges. This simplification leads to a major speedup of the simulation while keeping results realistic. The combination of these two approaches (switching off unused links; queue model) is used in this paper.

A robust simulation framework will help to find feasible solutions for arbitrary evacuation scenarios. The aim of this work is to find feasible evacuation solutions for an evacuation of large cities or regions by foot. This means we are looking for solutions from which it is possible to derive recommendations for the real world. This work is part of the current multi-disciplinary project “Last-Mile” [6]. The overarching goal of “Last-Mile” is to develop jointly with local partners a numerical last mile tsunami early warning and evacuation information system on the basis of detailed earth observation data and techniques as well as hydraulic numerical modeling of small-scale flooding and inundation dynamics of the tsunami including evacuation simulations in the urban coastal hinterland for the city of Padang, West Sumatra, Indonesia. It is well-documented that Sumatra’s third largest city with one million inhabitants is located directly on the coast and partially sited beneath the sea level, and thus, is located in a zone of extreme risk due to severe earthquakes and tentatively triggered tsunamis.

To develop an evacuation simulation for such a big city one needs much preparatory work, i.e. one needs detailed picture of the walkable area of the city, the socio-economic profile and of the expected extension of the inundation. In this article we will not go into detail how this information was explored. The

interested reader is referred to [33] for more information about how to get the necessary input data.

2 Simulation framework

The simulation framework is based on the MATSim framework for transport simulation [35]. Since MATSim is focused on simulation of motorized traffic, several adaptations were necessary. The key elements are:

- The agent database, where every agent represents one evacuee.
- The simulation network, based on links and nodes.
- The traffic flow simulator, where all the agents plans are executed.
- The plans generator, which generates an escape plan for every agent.
- There is a mechanism that allows improving the performance of the agents' plans by repeatedly trying to find faster evacuation routes.

2.1 Synthetic population, plans, agent database

MATSim always start with a synthetic population of all involved individuals. A synthetic population is a randomly generated population of individuals which is based as much as possible on existing data such as census data. For evacuation, the synthetic population is the collection of all synthetic individuals that are involved in the evacuation.

Every synthetic individual possesses one or several plans. These plans are “intentions” of the synthetic individuals, to be tested in the traffic flow simulation described later, and scored afterwards. For evacuation, the plans are evacuation strategies. For example, such a strategy may be to leave the building 5 minutes after a second warning, and follow a predetermined route to safety. The collection of agents together with their plans is sometimes called an agent database.

People can have different positions within the city when a warning occurs. For example, they can be at home or at work. Therefore, also in the evacuation context it makes sense to consider MATSim plans in their more conventional meaning, as a description on what a synthetic traveller intends to do during a normal day. One can then run a regular traffic flow simulation with these plans, stop it at the time of an evacuation warning, and use the positions of all agents at the time of that warning as the initial condition to the evacuation.

2.2 Simulation network

The simulation network represents the area that is accessible by the evacuees. In the case of a vehicular evacuation this network consists of all accessible streets. Each street segment defines a link. The parameters of the links are the length, capacity and the free flow speed. For a pedestrian evacuation the links in the simulation network also consist of squares and sidewalks. The flow capacity is

given by the width of a link as described in the next section. A good way of creating the simulation network is by extracting the needed information from satellite imagery.

In the case of an evacuation simulation the network has time dependent attributes. For instance large-scale inundations or conflagrations do not cover all the endangered area at once. In fact the spreading of the threat could be seen as a function of time. One solution would be by modeling this as a time variant network. This means streets, bridges etc. will be blocked as soon as they no longer passable. In MATSim time variant aspects of the network are modeled as network change events. A network change event modifies parameters of a link in the network (e.g. free speed or flow capacity). As soon as a link is no longer passable its free speed will be set to zero.

2.3 Traffic flow simulator

The traffic flow simulation is implemented as a queue simulation, where each street (link) is represented as a FIFO (first-in first-out) queue with three restrictions [16]. First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link flow capacity is defined which limits the outflow from the link. If, in any given time step, that capacity is used up, no more agents can leave the link. Finally, a link storage capacity is defined which limits the number of agents on the link. If it is filled up, no more agents can enter this link. The difference to standard queueing theory is that agents (particles) are not dropped but spill back, causing congestion.

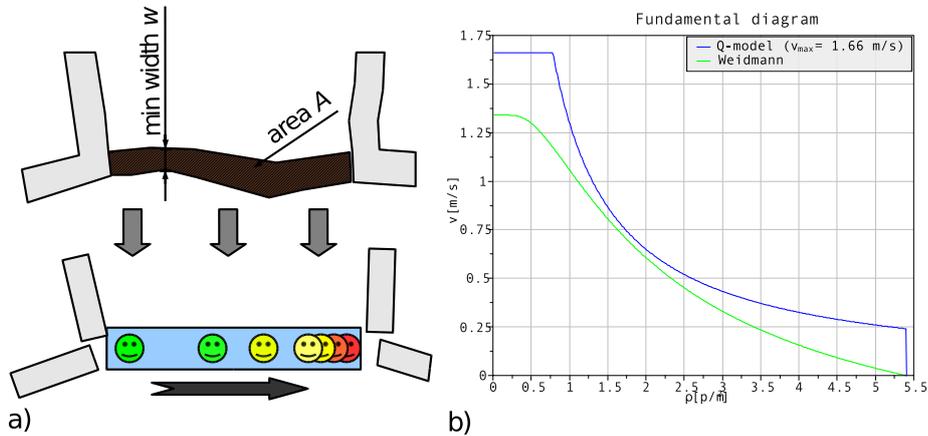


Fig. 1. Functioning of the queue model is shown in (a) and its corresponding fundamental diagram in (b).

An illustration of the queue model is shown in Fig. 1 a). The parameters of the model are:

- Link minimum width w
- Link area A
- Link length l
- Flow capacity $FC = w * C_{max} = w * 1.3 \frac{p}{m*s}$
- Free flow speed $v_{max} = 1.66 \frac{m}{s}$
- Storage capacity $SC = A * D_{max} = A * 5.4 \frac{p}{m^2}$

where C_{max} is the maximum flow capacity per unit width, and D_{max} is the maximum density per unit area.

The parameters have been chosen to approximate Weidmann's fundamental diagram [48].³ He pointed out that the relation between density and velocity is adequately captured by the so-called Kladek-formula:

$$v_{F,hi}(D) = v_{F,hf} \times [1 - e^{-\gamma \times (\frac{1}{D} - \frac{1}{D_{max}})}]$$

With:

- $v_{F,hi}$ the velocity at a particular density [m/s],
- $v_{F,hf}$ the velocity at free flow [m/s],
- γ a free parameter [$persons/m^2$],
- D the actual density [$persons/m^2$] and
- D_{max} the density at which no flow occurs [$persons/m^2$].

Empirical studies showed the best results with $\gamma = 1.913 \text{ persons}/m^2$, $v_{F,hf} = 1.34 \text{ m}/s$ and $D_{max} = 5.4 \text{ person}/m^2$.

Our study uses the same maximum density, but the free flow speed was set to $1.66 \text{ m}/s$. This value is slightly higher than the $1.34 \text{ m}/s$ used by Weidmann, but the values presented by Weidmann reflect the pedestrian flow under normal conditions and not in a case of emergency.

Our queuing model, however, generates a speed-density relationship of the form $v = \min[v_{max}, FC/D]$ [47]. The flow capacity FC is a free parameter that has to be chosen to fit the desired fundamental diagram. Even if a complete agreement is not possible, with $FC = 1.3 \frac{p}{m*s}$ the flow dynamics produced by our queue model is not too far away from Weidmann's fundamental diagram (cf. Fig. 1 b)). Furthermore, Predtechenskii's and Milinskii's [39] empirical study supports a value of approx. $1.3 \frac{p}{m*s}$ for the flow capacity.

2.4 Plans generation

Initial plans use the shortest path (according to free speed travel time) out of the evacuation area for all agents. Within the MATSim framework a shortest

³ Newer studies [42] imply other fundamental diagrams than those from Weidmann. An adaptation of these values could, in consequence, become necessary in future.

path router based on Dijkstra’s shortest path algorithm [11] has been implemented. This router finds the shortest path in a weighted graph from one node to any other, whereby the actual weights for a link are defined by a time- and distance-dependent cost function. Since we want to evacuate the city as fast as possible, the weights represents the (expected) travel time. There is, however, no particular node as the target of the shortest path calculation, as the evacuees have more than one safe place to run to. Instead, in the underlying domain every node outside the evacuation area is a possible destination for an agent that is looking for an escape route. To resolve this, the standard approach (e.g. [34]) is to extend the network in the following way: All links which lead out of the evacuation area are connected, using virtual links with infinite flow capacity and zero length, to a special “evacuation node”, and all paths are routed to that special evacuation node. Doing so, Dijkstra’s algorithm will always find the shortest route from any node inside the evacuation area to this evacuation node and, in consequence, to safety.

2.5 Agents learning

After an execution of the traffic flow simulation, every agent will score the performed plan. The score of a plan is calculated by a scoring function as it is described later. The scored plans remain in the agents’ memory for further executions. For the learning procedure two different learning strategies were used. The **ReRoute** strategy generates new plans with new evacuation routes based on the information of the experienced travel times from the last run. This uses the router described in the previous section, but using time-variant link travel times as link costs. The other strategy is called **ChangeExpBeta**. This strategy decides if the just performed plan should be used again, or if a random plan out of the memory should be selected for the next iteration. The probability to change the selected plan is calculated by

$$p_{change} = \min(1, \alpha * e^{\beta * (s_{random} - s_{current})/2})$$

With:

- α : The probability to change if both plans have the same score
- β : A sensitivity parameter
- $s_{\{random, current\}}$: The score of the current/random plan

If the system is “well-behaved”, this set-up converges to a steady state where the probability that agent a uses plan i is

$$p_{a,i} = \frac{e^{\beta * s_{a,i}}}{\sum_j e^{\beta * s_{a,j}}},$$

i.e. the standard multinomial logit model (e.g. [4]).

The plans score (utility) is determined by the scoring function:

$$U_i = \beta_{tr} t_{tr,i} + \beta_{dist} d_i$$

where U_i is the (dis)utility of plan i , β_{evac} is the marginal utility (in $1/h$) for travel (normally negative), $t_{tr,i}$ is the experienced travel time for plan i , β_{dist} represents the marginal utility (in $1/km$) of distance (normally negative), and d_i the distance covered by executing plan i .

Each strategy is selected with a certain probability. These probabilities are assigned before the simulation starts, but they can be varied during the iterations. Typically, **ReRoute** is called with a relatively small probability, say 10%, and **ChangeExpBeta** is called in the remaining cases.

After re-planning every agent has a selected plan that will be executed in the next iteration. Repeating this iteration cycle of learning, the agents' behavior will move towards a Nash equilibrium. If the system were deterministic, then a state where every agent uses a plan that is a best response to the last iteration would be a fixed point of the iterative dynamics, and at the same time a Nash Equilibrium since no agent would have an incentive to unilaterally deviate. Since, however, the system is stochastic, this statement does not hold, and instead we look heuristically at projections of the system. From experience it is enough to run 100 iterations until the iterative dynamics has reached a steady state. In most (but not all) evacuation situations, the Nash equilibrium leads to a shorter overall evacuation time than when everybody moves to the geographically nearest evacuation point. On the other hand, a Nash equilibrium means that nobody has an incentive to deviate. The Nash equilibrium in an evacuation situation can therefore be considered as a solution that could be reached by appropriate training.

3 Scenario

The evacuation procedure of a city depends on the distribution of the population. The distribution of the population changes over the time of day. That means one has to develop different evacuation scenarios for different times of day. Here we present a scenario called: "evacuation at 3 am". That means we assume all inhabitants are at home. It is then straightforward to derive the necessary information about the population from existing census data. The presented simulation relies upon the census for 2005 and was provided by the statistical bureau of Padang [7]. Another important aspect is the information about safe places. In future it is planned to identify buildings that are suitable for a vertical evacuation. For the time being we use a simpler approach: All areas with an elevation of more than 10 m above sea level are defined as safe. Fig.2 shows an image of the city with the safe area. However, based on models of small-scale flooding and inundation dynamics of the tsunami [19] it is not expected that all the area below 10 m will be flooded. Based on these simulations, one also learns that the estimated time between the earthquake and the inundation of the city is about 28 min. The results are backed by the results of large-scale tsunami simulations for the west coast of Sumatra Island [36]. Adding this to the simulation, the framework makes the agents learn a more risk averse behavior, they are not only trying to reach the safe area as fast as possible, but they also try to avoid the flooding.

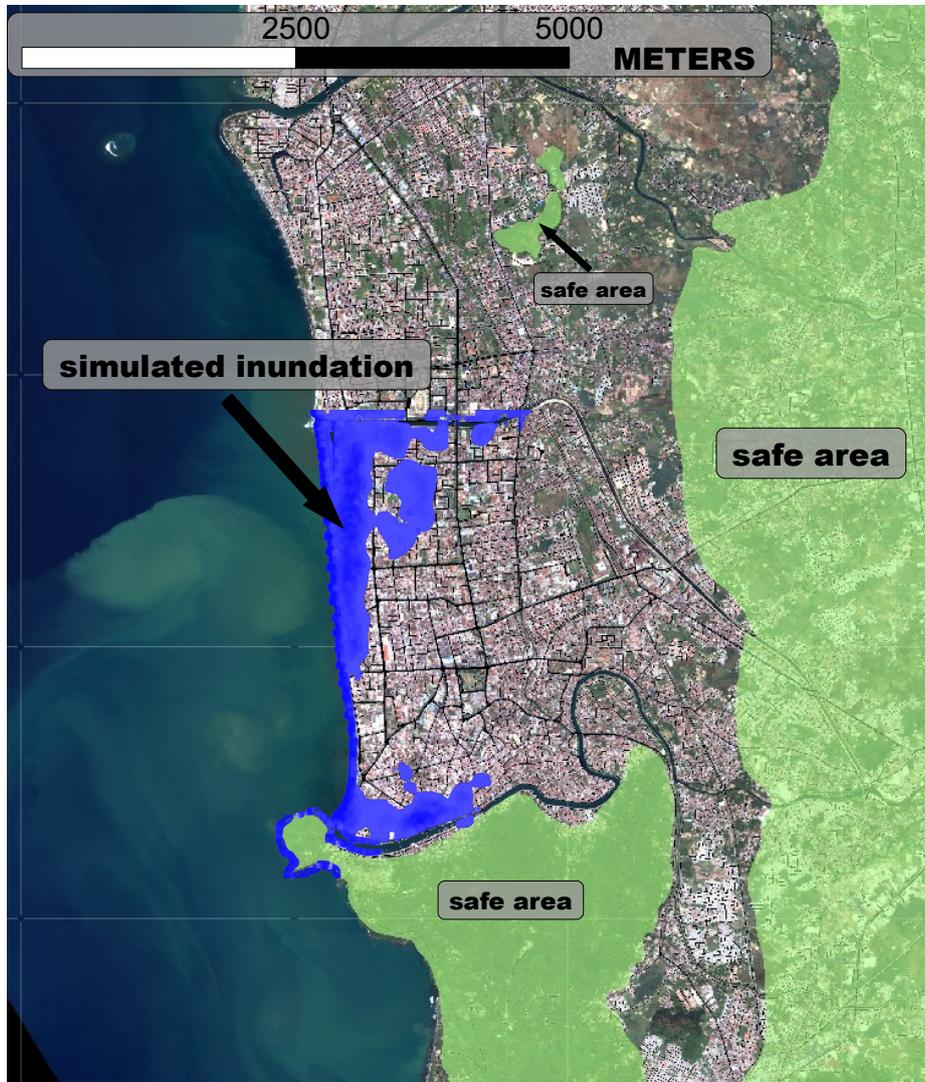


Fig. 2. Satellite imagery of the city shows the safe area (light green) and some preliminary results of the flooding simulation (blue area). Satellite imagery by the German Aerospace Center, Oberpaffenhofen (2007)

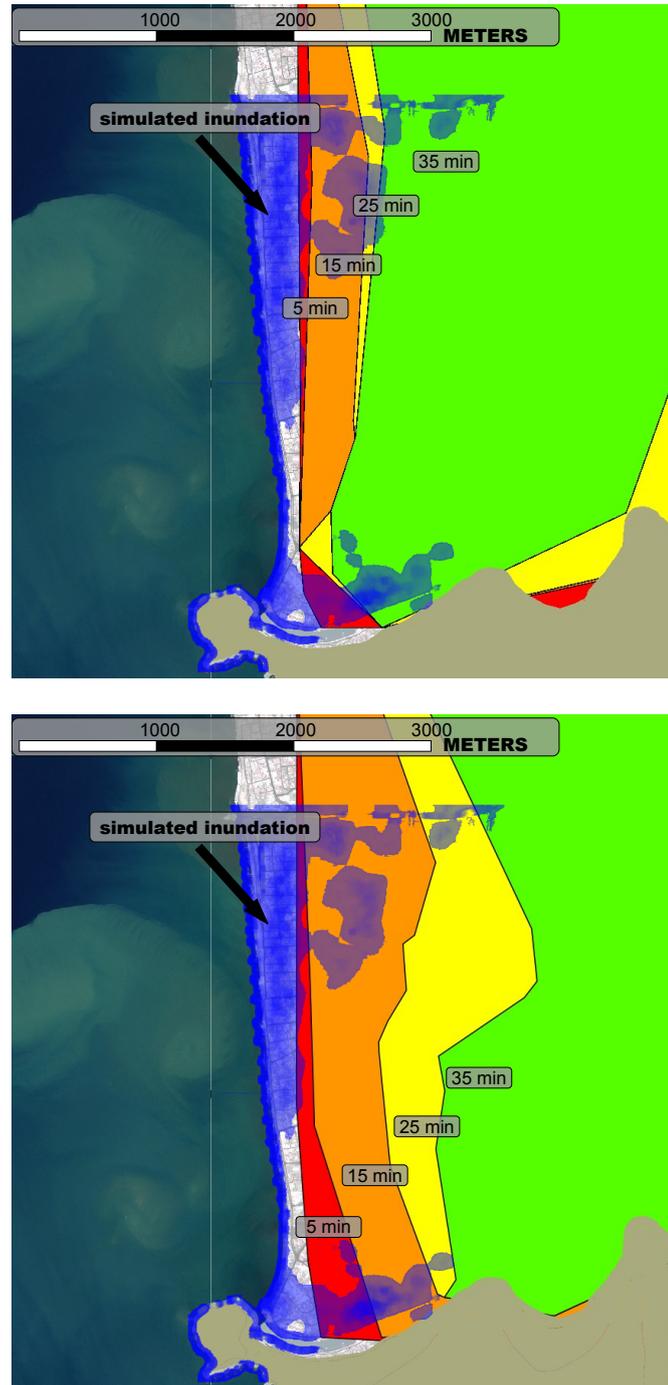


Fig. 3. Evacuation progress after 5 min, 15 min, 25 min and 35 min. Top: Results of the first iteration (shortest path solution). Bottom: Results of the last iteration (“Nash equilibrium” approach). One observes that, in the last iteration, for given times much larger areas are evacuated. Satellite imagery by the German Aerospace Center, Oberpfaffenhofen (2007)

In some places the flooding will reach locations that are more than 2 km away from the shoreline.

4 Results

The simulation run was stopped after 200 iterations of learning. The overall runtime was about 15 hours on a 3 GHz CPU using up to 2 GB of RAM. After 200 iterations of learning, the evacuation time is about 75 min. This is the time that is needed to evacuate all the area with an elevation lower than 10 m. An interesting aspect is the time that is needed to evacuate all the area that is expected to be inundated.

Fig. 3 shows the evacuation progress of the coastal strip for the first and the last iteration. The first iteration could be seen as a strategy where every evacuee follows the path that would be fastest in an empty network. The last iteration is the “Nash equilibrium” approach discussed earlier, where, via iterations, every evacuating person attempts to find a route that is optimal for him-/herself under the given circumstances. The results show that the “Nash equilibrium” approach leads to a substantially faster evacuation of the coastal strip. But not only the evacuation of the coastal strip is much faster, but also the overall evacuation of all the area below 10 m. Fig. 4 shows the evacuation progress for the first and the last iteration. After 200 iterations of learning, the overall evacuation time is about 75 min. This is much better compared to the first iteration, where only 75

5 Discussion

As described earlier, the iterations start from a solution where all agents take the fastest path to safety, and iterate to a stochastic version of the Nash equilibrium. The fact that the number of evacuated persons per time unit increases during the iterations (Fig. 4) indicates that the initial solution is overly congested on some evacuation paths, and some evacuees are better off taking a longer route.

As discussed earlier, this can only be considered as a benchmark solution. Still, given a warning time of about 30 min, even the “rational” Nash equilibrium solution does not seem to leave enough time. However, the situation is not only a question of Nash equilibrium vs. system optimum vs. “non-rational” behavior: The preliminary inundation simulations indicate that our evacuation area is too large for most situations, i.e. the tsunami wave will not reach that far. A problem here, however, is that even if one assumes a functioning warning system, it will probably not include the tsunami wave height, and so a tailored evacuation seems not possible. At the same time, it seems impossible to implement an evacuation scheme that makes people evacuate for about an hour when this is not necessary in most cases: The compliance rate will not be very high. Tsunami proof shelters for vertical evacuation could be a solution for those areas from where horizontal evacuation takes a long time. Since the local government in Padang plans to build some kind of shelters for vertical evacuation, one could use the simulation

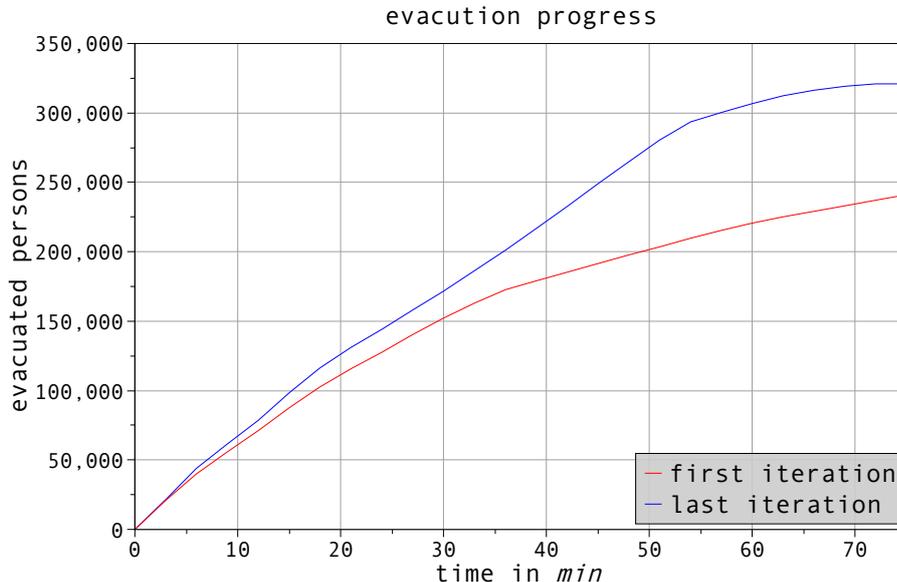


Fig. 4. Comparison of the evacuation curves of the first iteration (shortest path solution) and the last iteration (“Nash equilibrium” approach). The curves are truncated at 75 min.

to find appropriate locations for these shelters. It might also be possible to use the roofs of stable buildings for shelter. Another issue concerns the mode choice: The investigation assumes that all evacuation is done by foot while it might be reasonable to assume that some people use cars or cycles, and they might even leave vehicles in the street to continue on foot if progress by vehicle becomes too slow. For the time being, such issues are not considered. The queue model could, to a certain extent, be parameterized to deal with mixed traffic, as long as all modes move with the same speed. The effect of “stranded” vehicles could be included by a parameterization of the flow capacity of the queue model, although a behavioral model for abandoning vehicles would be needed. Beyond that, one would arguably need to switch to a true two-dimensional model such as [24] or [29]. Such models could still operate on networks [17].

6 Conclusion

We introduced the evacuation related part of the “Last-Mile” project. The microscopic large-scale evacuation simulation is based on the MATSim framework. It is implemented as a Multi Agent Simulation, where every agent tries to optimize its individual evacuation plan in an iterative way. We discuss the simulation framework, the necessary input data, show preliminary results, and discuss these

results. In the current base case it is assumed that all people are at home. Currently we are working on more detailed picture of the population. Based on census data and the results of a survey with 1000 households, that took place in April/Mai 2008, we are developing a synthetic population with individual daily plans. From this synthetic population it will be possible to derive a model of the population distribution at any time of day. In future work it is also planned to integrate tsunami proof shelters into the simulation framework. Therefore the simulation framework could be extended in a way to find optimal location for the tsunami proof shelters.

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