Gregor Lämmel, Hubert Klüpfel, Kai Nagel

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Risk Minimizing Evacuation Strategies under Uncertainty

G. Lämmel[1] and H. Klüpfel[2] and K. Nagel[1]

[1]Technische Universität, ILS, 10623 Berlin, Germany
[2]TraffGo HT GmbH, Bismarckstraße 142a, 47057 Duisburg, Germany

Abstract This paper presents results on the simulation of the evacuation of the city of Padang with approximately 1,000,000 inhabitants. The model used is MATSim (www.matsim.org). Three different strategies were applied: shortest path solution, user optimum, system optimum, together with a constraint that moves should reduce risk whenever possible. The introduction of the risk minimization increases the overall required safe egress time (RSET). The differences between the RSET for the three risk minimizing strategies are small. Further quantities used for the assessment of the evacuation are the formation of congestion and the individual RSETs (in comparison with the available SET).

Introduction: Safety, Risk, and the Need for Simulation

Safety is a basic need for individuals and societies. Safety can be roughly defined by: existing risk < acceptable risk. It can also be discriminated from security by dealing with non-intentional threats. In this paper, the potential threat is a natural hazard: a submarine earthquake in the Indian Ocean causing a Tsunami wave hitting the coast of Sumatra, Indonesia and the city of Padang. The risk, and consequently also the safety if the acceptable risk is specified can be quantified based on the following formula:

$$R = \int D \cdot (1 - C) \cdot P(t)\,dt \qquad (1)$$

The damage is denoted by *D*, the coping capability by *C*, and *P(t)* is the probability of the wave reaching the coast. The criterion usually applied to assess a risk is: *R* < acceptable risk. Please note that there is always a residual risk (*RR*>0), which cannot be reduced by technical or management means. In case of a tsunami, the physical safety or lives of people are at risk. Evacuation is one means in ensuring the safety, especially to avoid the risk and threat to human life. Evacuation reduces the damage. Another strategy would be to build tsunami safe buildings which would increase *C*. This is beyond the scope of this paper. We focus on the evacuation.

The condition for a safe egress is RSET < ASET, where ASET is the available safe egress time and RSET is the required safe egress time. In this paper, we present the calculation of RSET (based on a microscopic multi-agent simulation). ASET is provided by inundation simulations that show the consequences of an earthquake off-shore the island of Sumatra (Indonesia) for the coastal city of Padang. The overall egress time is one major criterion for assessing an evacuation plan. Such a plan addresses – among many other issues – evacuation routes for the endangered population. There are many models that find optimal routing strategies (i.e. minimizing RSET) for a given road and walkway network. In the case of large-scale inundation, the network changes with time. Links or edges (i.e. roads or lanes) become impassable due to flooding. The evacuation simulation based on a dynamic network works only as long the advance warning time is known beforehand, though. When this is not the case, the optimal routing strategy might increase the risk for some persons on some stretch of way. This issue is addressed in the next section on utilities of evacuation strategies. Implementation details are given in section 3, experimental results discussed in section 4. The paper concludes with a discussion of the simulation results (section 5) and a conclusion and recommendations (section 6).

Utility of an Evacuation Strategy

The utility of an evacuation path often depends on uncertain aspects. One uncertain aspect is the advance warning time τ_{warn}. We assume that τ_{warn} follows an unknown probability distribution with, for this section, $P(\tau_{warn} > 0) = 1$, i.e. there is always a warning *before* the event. Let us consider a situation with two different evacuation paths p_0 and p_1; p_0 does not depend on the advance warning time τ_{warn} but has considerably longer travel time than p_1. The path p_1 first leads "towards danger" for a time period *T* before it leads to safety, i.e. when the warning time is too short one cannot take it. An example is a bridge close to the shore heading to a safe area. If an evacuee takes p_1, she moves towards the shore (danger) in order to reach the bridge. As a result the utility of p_1 depends on τ_{warn}. The utility for p_0 and p_1 can be formulated as follows:

$$U\left(p_0 | \tau_{warn}\right) = \begin{cases} -\infty \quad \text{if} \quad \tau_{warn} \leq 0 \\ -t_{travel}\left(p_0\right), \quad \text{otherwise} \end{cases} \tag{2}$$

$$U\left(p_1 | \tau_{warn}\right) = \begin{cases} -\infty \quad \text{if} \quad \tau_{warn} \leq T \\ -t_{travel}\left(p_1\right), \quad \text{otherwise} \end{cases} \tag{3}$$

where $t_{travel}(p_1)$ denotes the travel time for path p_1. Taking the information of the probability distribution for τ_{warn} , we can calculate the expectation value for each utility:

$$E\left(U\left(p_0 \mid \tau_{warn}\right)\right) = E\left(U\left(p_0\right)\right) = t_{travel}\left(p_0\right) \tag{4}$$

$$\begin{aligned} E\left(U\left(p_1 \mid \tau_{warn}\right)\right) = \quad & P\left(\tau_{warn} < T\right) \cdot \left(-\infty\right) \\ & + \left(1 - P\left(\tau_{warn} < T\right)\right) \cdot t_{travel}\left(p_1\right) = -\infty \end{aligned} \tag{5}$$

Based on these expectation values, risky evacuation paths p_1 are banned in the remainder of this paper, as long as a non risky solution p_0 exists. If no risk-free path exists, then the solution with the lowest risk should be chosen. Implementation details are given in the following section.

Routing strategies

In this section we discuss three different routing strategies. The most straightforward approach to an evacuation problem is the shortest path solution, where every evacuee takes the shortest path to safety. The Dijkstra shortest path algorithm [] finds the shortest path in a weighted graph from one node to any other. The weights for a link are defined by a time- and/or distance-dependent cost function. The algorithm relies on the information about the free-flow travel time τ_a for every link *a*. Algorithm 1 shows the shortest-path routing logic.

The shortest path solution does not take congestion into consideration, though. In reality, the link travel time depends on the level of congestion. In the underlying traffic flow simulation every link has a specific flow capacity; if this capacity is exceeded, congestion occurs and increases the link travel time. Since the demand on a link is not constant over time the link travel time is time dependent. There are different optimization approaches to find better solutions than the shortest path solution. In this paper we discuss the Nash equilibrium (NE; = user optimum) and the system optimum (SO).

Algorithm 1. Shortest path routing

1. initialize τ_a with the free-flow travel time for all links
2. calculate routes based on link costs $C_a = \tau_a$

The NE is named after John Forbes Nash and describes a state in a competitive two or more player game where no player can gain by unilateral deviation from her current strategy []. In the evacuation context the NE describes a state where no evacuee can improve her evacuation performance by unilateral deviation from her current evacuation route (user optimum). In most (but not all) evacuation situations, the NE leads to a shorter overall evacuation time than the shortest path solution. In the NE nobody has an incentive to change his path. It is therefore a solution that can be reached by appropriate training. In multi-agent simulations the solution can move towards the NE through iterative learning [,]. An iterative learning algorithm starts with a given starting solution and tries to improve it through trial and error. Learning means re-planning agents paths. The learning algorithm uses a cost function based on travel times. Formally, the real-valued time is divided into K segments ("bins") of length T, which are indexed by k=0,…K-1. The time-dependent link travel time when entering link a in time step k is denoted by $\tau_a(k)$. Implementation details are given in [10]. Algorithm 2 shows the Nash-equilibrium routing logic.

Algorithm 2. Nash equilibrium routing

1. initialize $\tau_a(k)$ = free-flow travel time for all links a and time steps k
2. repeat for many iterations:
   (a) recalculate routes based on link costs $C_a(k) = \tau_a(k)$
   (b) load vehicles on network, obtain new $\tau_a(k)$ or all a and k

The SO can be achieved by applying a similar learning algorithm as for the NE approach. The only difference is that for a SO, the travel time based on which agents evaluate their routes needs to be replaced by the marginal travel time []. The marginal travel time of a route is the amount by which the total system travel time changes if one additional evacuee takes that route. It is the sum of the cost experienced by the added evacuee and the cost imposed on other evacuees. The latter is denoted here as the "social cost" (C^s). Implementation details for the approximated system optimum (SO) in the evacuation context are discussed in []. An application of this result to a system optimal route assignment requires to calculate $C_a^s(k)$ for every link a and entry "time bin" k in the network and to add this term to the time-dependent link travel time that is evaluated in the route re-planning of every agent. Algorithm 3 outlines the arguably most straightforward implementation of this approach.

Algorithm 3. System optimum approach

1. initialize $C_a^s(k)=0$ and $\tau_a(k)$ with the free-flow travel time for all links a and time steps k
2. repeat for many iterations:
   (a) recalculate routes based on link costs $C_a(k)=\tau_a(k)+C_a^s(k)$
   (b) load vehicles on network, obtain new $\tau_a(k)$ and $C_a^s(k)$ for all a and k

Risk costs

In this section we propose a strategy that allows only risk-decreasing moves, as long as such moves exist. This approach is similar to the system of priority levels proposed by Hamacher and Tjandra [7]. A move is defined as risk-decreasing if it increases the evacuee's distance to the danger. Inside the endangered area the distance describes the temporal distance. For inundation scenarios this means that the evacuee's position before the move will be flooded earlier than the position after the move. But even people outside the area directly affected should keep some distance to the danger. This is important because otherwise those people could block evacuees from leaving the endangered area. Therefore we propose an additional buffer around the endangered area that also has to be evacuated. Within this buffer a move is defined as risk-decreasing if it increases the evacuee's spatial distance to the danger. In general, some evacuation paths might always be risk decreasing others not. In our simulation, the only decision points are at nodes. As soon as an evacuee has entered a particular link she has to travel along that link until the next node. Therefore we calculate risk levels for nodes. If a link leads from a node with lower risk to a node with higher risk than that link will be charged an additional penalty. This is achieved by adding a risk cost term C^r to the cost function C. The cost terms for algorithms 1, 2, 3 are thus extended by the static risk cost C^r.

The cost term for the shortest path routing and the NE approach is now:

$$C_a^k = \tau_a(k) + C_a^r \tag{6}$$

for the NE; for the system optimal approach it is

$$C_a(k) = \tau_a(k) + C_a^s(k) + C_a^r \ . \tag{7}$$

The risk cost for link a connecting nodes (i, j) with risk levels r_i and r_j :

$$C_a^r = \begin{cases} l_a \cdot penalty & \text{if } r_i < r_j \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where l_a is the length of link a and $penalty$ is a constant that has to be chosen so that the cheapest risk increasing path is more expensive then than the most expensive risk decreasing path. In the underlying scenario, $penalty$ has been set based on a heuristic estimate to 30 hours per 100 meters. We conducted experiments for each of the three routing strategies (shortest path, user optimum, system optimum) with risk avoidance and compared them to the NE (user optimum) approach without additional risk costs. The results of the experiments are given in the following section.

Simulation results

The risk minimizing routing strategy has been investigated through the application to a real world evacuation scenario namely the evacuation of the city of Padang in the case of a tsunami warning. Padang is located at the West Coast of Sumatra Island and is exposed to earth quakes triggered tsunamis (see, e.g. [8]). The city has more then 800 000 inhabitants, where several hundred thousand are living in the endangered area. The geographical data, socio-economic profile and expected inundation scenarios for the city have been discussed in many of our previous publications (see, e.g. [9]). The simulations have been performed in the MATSim simulation framework. The MATSim simulation frame work and its adaptation to pedestrian evacuation simulation have also been discussed broadly (see, e.g. [4,10]). We conducted four runs to investigate the risk minimizing strategy. *Run 1* implements the NE approach (w/o risk costs), *Run 2* implements the risk minimizing shortest path solution, *Run 3* the risk minimizing NE approach and *Run 4* the risk minimizing SO approach. The synthetic population is the same for all runs. It consist of 277 299 agents. The number of agents and the initial distribution corresponds to the real population of Padang.

The overall run-time for *Run 3* was 12 hours and 21 minutes. For *Run 4* the overall run-time was 26 hours and 4 minutes. This demonstrates that the pedestrian flow model can deal with large-scale scenarios. Some visualizer screen shots of the first 30 minutes are shown in fig. 2. The agents are colored according to their evacuation time: green indicates fast, red slow escape. It is shown that *Run 1* (left column in the figure, reference case) performs best. In the visualizer snapshots, no major differences between the three risk minimizing runs (2 to 4) can be identified. In *Run 2* there are many red colored agents in the northern part of the city, indicating a longer evacuation time. *Run 3* and *Run 4* are almost identical. Based on the screen shots alone, no advantage of the risk minimizing approach (compared to the reference case) can be identified. A detailed examination of the results shows the advantage of the risk minimizing approach, though.

In fig. 3 (right) there are two visualizer screen shots of the Siti Nurbaya Bridge each taken after 5 minutes The left part shows *Run 1* (reference case) and at the right part *Run 3* (risk minimization). In *Run 1* agents cross the bridge towards the mountains in the south. This strategy would be a good strategy if the advance warning time was known to be long enough; otherwise, if the wave arrived earlier than expected, this strategy would be disastrous. In contrast in *Run 3* the agents avoid the bridge and move away from the river (and from the danger).

As a consequence of risk minimization, many agents in the northern part of the city do not have enough time to evacuate (RSET < ASET). This fact is also reflected in the evacuation curves. Fig. 4 (left) shows the evacuation curves for the four runs discussed The simulation results show that the risk minimization does in our scenario comprise agents which do not have enough time for evacuation.

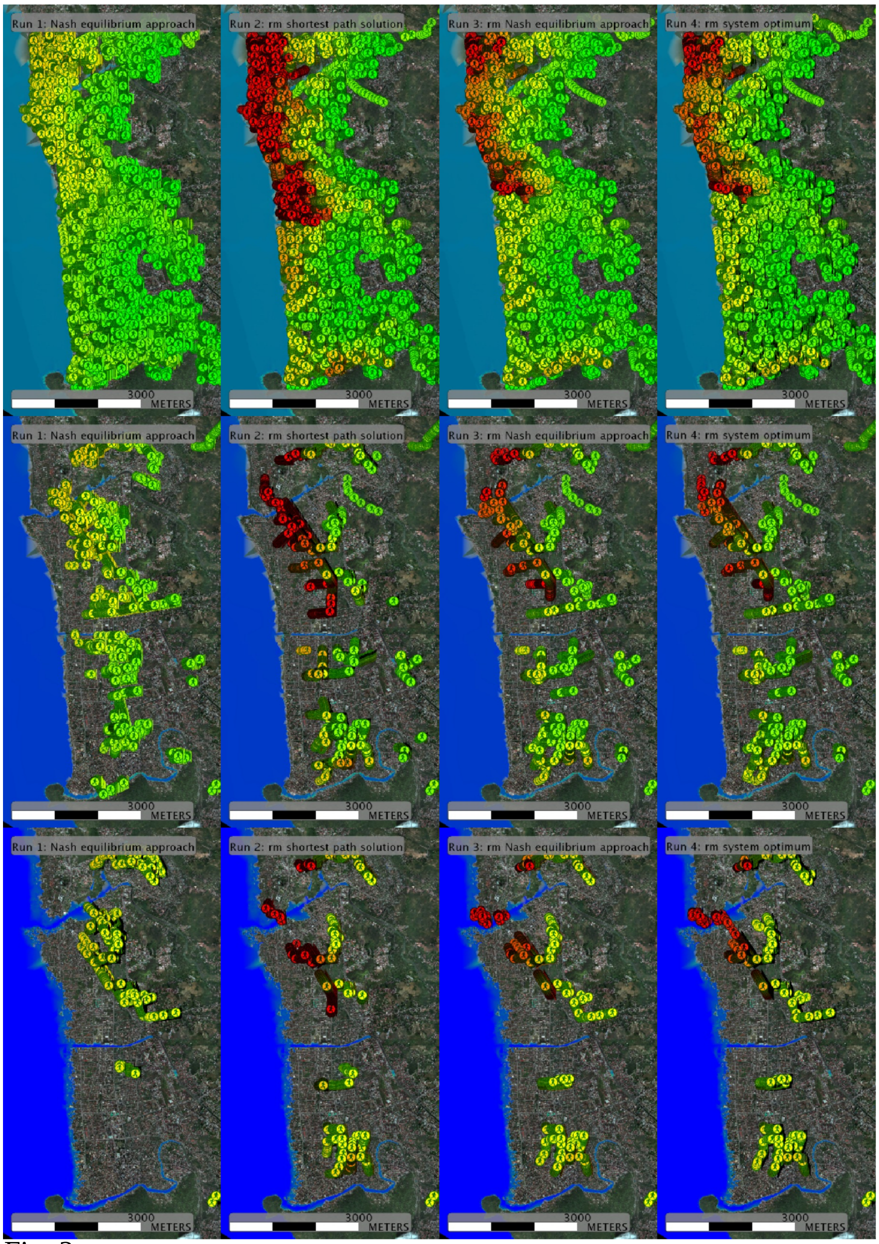

Fig. 2. From left to right: Nash equilibrium without risk, risk minimization (rm) for shortest path, Nash (user optimum), and approximated system optimum. Agents with RSET > ASET are shown in red. For all three risk minimizing strategies (column 2 to 4), namely shortest path rm, Nash rm, and approximated system optimum rm, the results are similar. The time is (from top to bottom): 1 minute, 15 minutes, and 30 minutes after the alarm. Please note that the warning time is the time between the alarm and the wave reaching the coast.

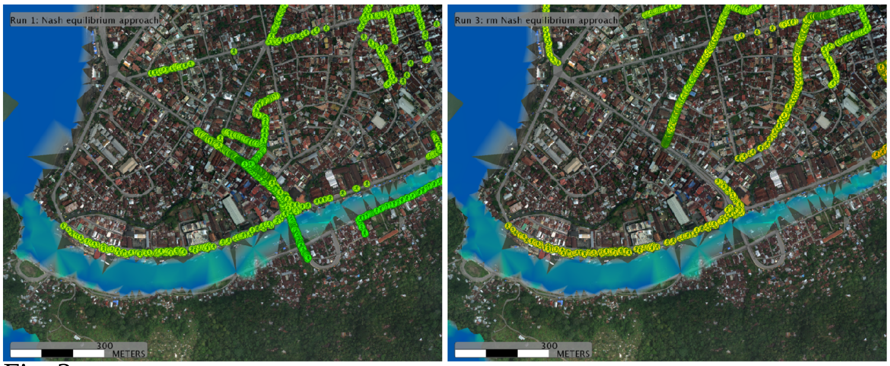

Fig. 3. Result of penalizing risk in the simulation: Agents use the dangerous bridge in the left case, but avoid it if its usage is more costly. In the right case, crossing the bridge is costly ($r_j > r_i$ in eq. (8), i.e. node *j* will be flooded earlier than node *i*).

Note that the evacuation curves for *Run 3* and *Run 4* almost coincide. Therefore, the risk costs are an additional constraint pushing NE and SO solution towards each other. There are still fundamental differences between both approaches, however. These differences are indicated by the area where ASET<RSET (available time<required time), e.g. the area in the north.

Therefore, this area is highly endangered and an alternative strategy is required. A first step is the detailed analysis of this area. Therefore a GIS based analysis of the number of endangered agents has been performed (fig. 4, right). This analysis demonstrates the differences between *Run 3* (NE) and *Run 4* (SO). Even if there are no big differences in the spatial distribution of the endangered agents for *Run 3* and *Run 4*, the figure shows one important aspect of the social cost optimization: The number of endangered agents further inland is higher in *Run 4* than in *Run 3* and vice versa at the coastline. The agents starting near the coast gain through the social cost optimization and the agents further inland lose. The latter make space for others in order to reduce their own social costs. Such behavior reduces the average evacuation time and also increases the number of rescued agents. The price, however, is the organized "sacrifice" of some. In reality, this is does not seem to be an option and therefore we argue in support of the NE approach.

Summary and Discussion

We have presented simulation results for the coastal city of Padang. The results are based on the MATSim multi-agent simulation framework (www.matsim.org) adapted for evacuation simulation. The introduction of risk costs (eq. (8)) increases the overall evacuation time (RSET) considerably. This result holds irrespective of the routing strategy. Three different routing strategies have been investigated: shortest path, Nash equilibrium (NE; = user optimum), and system optimum (SO). The SO is realized by introducing social costs on each link; those social costs do not represent an intrinsic motivation but have to be enforced externally, i.e. they depend not only on the agent's own travel time but also on the travel time of others. The NE approach leads to a shorter overall evacuation time than the shortest path strategy. In the simulation, the NE is approximated by iterative simulation runs with re-planning based on the results of the previous run.

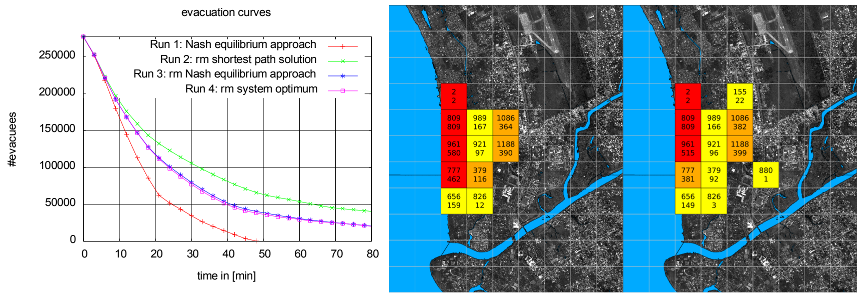

Fig. 4. Left: Evacuation curves of the four runs. Right: GIS analysis of the highly endangered area on a 300 meter grid. From left to right: Run 3 (rm for NE) and Run 4 (rm for SO). The colors of the squares describe the percentage of agents for whom ASET<RSET (red: ≥50%, orange: ≥25% and yellow: <25%). The numbers in the squares denote the total number of agents departing from that square (top) and the total number of agents with ASET<RSET.

Conclusion and Recommendations

In the case of an evacuation, re-planning as described in the previous section does not take place. An evacuation is – other than commuter traffic – a singular event. This distinguishes evacuation simulations from traffic simulations. On the other hand, the results of the evacuation simulation are intended to provide a basis for an evacuation plan which has to be implemented by local authorities and groups. And for a recommendation, a stable and acceptable solution is required. Such a solution, in terms of evacuation paths, is provided by the NE approach: no single agent can gain by unilateral deviation and there is no gain based on the loss of someone else. Of course, the evacuation paths have still to be communicated to the population, e.g. by signage, the authorities, police, and volunteer groups. One of those groups is KOGAMI (kogami.multiply.com), which provides training for the local population to prepare for Tsunamis. The recommendations of KOGAMI turn out to be most similar to the NE solution for the risk minimization case. One prominent example to illustrate this is the bridge shown in fig. 3. In one sentence, the strategy derived from the simulations could be summarized as “avoid bridges and keep away from the water”. But the simulation allows more detailed analysis, including how much one loses through the “risk minimization” approach, or the possibility to evaluate changes to the scenario such as capacity expansions, shelters, or changes to the whereabouts of people when the evacuation starts.

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