Numerical simulation and optimization models for socio-dynamical features of crowd evacuation

Anton von Schantz
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Abstract

The rapid increase of various mass gatherings and overcrowded festivals pose serious challenges, for example in case of emergency. Computational models may help to address issues related to these socio-physical systems, and in particular evacuating crowds. Physics-inspired self-driven particle models can describe most of the physics of moving crowds. However, there is still a need for comprehensive crowd models that can describe collective crowd effects, starting from individual crowd members' decision-making. In addition to models being able to describe harmful crowd phenomena, they should also prescribe solutions to prevent them.

This dissertation concerns the mathematical and computational modeling of an evacuating crowd. The main focus is on studying how individual decision-making causes the harmful physical effects in a bottleneck evacuation. How should rescue guides be used to minimize the evacuation time of a crowd? What is the effect of uncertain crowd movement patterns on the minimum time evacuation plan?

A multiagent framework is used to model the crowd. Its members are modeled as agents that interact with each other. The crowd dynamics are described using social force model based on Newtonian dynamics, and the agents' decision-making is described using evolutionary game theory. The model is studied by developing a simulation environment, which is implemented in a high-performance computing cluster.

Numerical simulations show that due to the locally played game, non-monotous dynamical effects emerge. In a bottleneck congestion, the back of the crowd behaves impatiently. It pushes the agents in front of it, and pressure increases. As a result, arch-like structures form, capable of interrupting the flow and slowing down the evacuation. The arches break down due to fluctuating loads. The results coincide with findings from behavioral and physical evacuation experiments.

New mathematical models and algorithms are developed to solve the minimum time crowd evacuation problem with rescue guides. The new methods are based on mathematical optimization, namely, on scenario optimization, genetic algorithms, numerical simulation-based optimization, and bi-objective optimization. Also, worst-case scenarios are accounted for with a risk measure. The solution to the minimum time evacuation problem gives the number of guides, their initial positions, and exit assignments. It is shown that there is a tradeoff between the evacuation plan that performs well across scenarios, and the one that performs well on the worst-case scenario. With enough guides, the uncertainty in the individual and crowd movement patterns is mitigated. This dissertation provides new practical tools for numerical simulation and optimization of dynamical features of crowd evacuation, and hopefully gives ways to prevent fatal accidents in emergencies.

Keywords crowd evacuation, multiagent system, evolutionary game theory, numerical simulation, mathematical optimization, non-monotous dynamics

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Suurten joukkotapahtumien sekä julkisen liikenteen kasvu aiheuttaa turvallisuusvaikutteita erityisesti hätätilanteissa. Väikijoukon evakuoinnin ongelmien ratkaisemiseen on kehitetty laskennallisia mallia. Nykyään kyetäänkin numerisesti simuloida niin matemaattisesti kuin geometrisesti ilmiöitä. Matemaattinen malli on kehitettävä, jotta se sopisi riittävästi laajempia tapahtumia. Tutkimus on toteutettu mallin keskustelussa ja siihen on käytetty matemaattisia ja fysiologisia mallinmäärityksiä.


Avainsanat väkijoukon evakuointi, monen agentin järjestelmä, evoluutiopelteoria, numerinen simulointi, matemaattinen optimointi, ei-monotonin dynamiikka

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List of publications

This dissertation consists of the present summary and of the following publications:


Author’s contribution

Publication I: “Spatial game in cellular automaton evacuation model”

Von Schantz is the main author. Von Schantz and Ehtamo initiated the paper together. Von Schantz coupled the game-theoretical model developed by Ehtamo et al. to a cellular automaton evacuation model. Von Schantz developed the simulation code and ran the experiments. The authors analyzed the results together. Von Schantz wrote the first draft of the paper. Von Schantz and Ehtamo wrote together the final version of the paper.

Publication II: “Twotype multiagent game for egress congestion”

Von Schantz is the main author. Ehtamo initiated the paper. Von Schantz and Pärnänen developed the simulation code, ran the simulations, and analyzed the results together. Von Schantz wrote the first draft of the paper. Von Schantz and Ehtamo wrote together the final version of the paper.

Publication III: “Pushing and overtaking others in a spatial game of exit congestion”

Von Schantz is the main author. Von Schantz and Ehtamo initiated the paper together. Von Schantz developed the evacuation simulation environment, designed the numerical experiments and implemented the simulation environment on the Aalto University supercomputer. The connection between non-monotonic dynamics and the agents’ decision-making was aroused by Ehtamo. He also emphasized the need to validate the results to the experiments done with real people. Von Schantz wrote the first draft of the paper. Von Schantz and Ehtamo wrote together the final version of the paper.

Publication IV: “Minimizing the evacuation time of a crowd from a complex building using rescue guides”

Von Schantz is the main author. Von Schantz and Ehtamo initiated the paper together. Von Schantz developed and implemented the algorithm on the Aalto University supercomputer. Von Schantz designed the numerical experiments. Von Schantz and Ehtamo analyzed the results together. Von Schantz wrote the first draft of the paper. Von Schantz and Ehtamo wrote together the final version of the paper. Sections 1, 2 and 6 are mainly written by Ehtamo.
Publication V: “Minimization of mean-CVaR evacuation time of a crowd using rescue guides: a scenario-based approach”

Von Schantz is the main author. Von Schantz initiated the paper. Von Schantz developed the solution algorithm, implemented it on Aalto supercomputer, and designed the experiments. The authors analyzed the results together. Von Schantz wrote the paper with input from both coauthors.
Abbreviations

ASET Available Safe Egress Time
CA Cellular Automaton
CSC Finnish IT Center for Science
CVaR Conditional Value-at-Risk
ESS Evolutionary Stable Strategy
GA Genetic Algorithm
GUI Graphical User Interface
HD Hawk-Dove game
HPCC High-Performance Computing Cluster
NSGA-II Nondominated Sorting Genetic Algorithm II
PD Prisoner’s Dilemma game
PRNG Pseudorandom Number Generator
VaR Value-at-Risk
VR Virtual Reality
VTT Technical Research Center of Finland
The doctoral research has been quite a journey for me. It would not have been possible for me to develop the ideas for this dissertation for so many years without the great support I received. Next, I wish to thank all the people and institutions that made this happen.

Officially, my doctoral studies started in fall 2014 with Harri as my thesis advisor and supervisor. His research group already had a strong experience of people flow research. They had collaboration with the elevator optimization group from Kone Corporation and the fire safety group from VTT (Technical Research Center of Finland). This gave me a solid foundation to build my knowledge.

I want to dedicate my thanks to Harri. Through the years we have known, I have very much enjoyed the lessons he has given me in science and life, and the times we have together made scientific discoveries. I also want to thank him for his ability to motivate and bring out the very best of me, and perhaps from himself, too.

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Helsinki, March 31, 2021,

Anton von Schantz
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1. Introduction

1.1 Background

Because of urbanization, increasingly large crowds are gathering in public spaces, which sets a higher requirement for crowd management, safety measures, and building design. In the case of, e.g., a fire, bomb threat, or active shooter, the crowd needs to evacuate efficiently; every second does matter. Sometimes, the threat to the crowd members is even the crowd itself; at high crowd densities, pressures can build up that even bend steel barriers (Helbing and Mukerji, 2012). For example, in early 2020, hundreds of thousands of people attended an Iranian military commander’s funeral. When the crowd moved to narrow roads that were blocked, panic ensued, and 56 people were crushed to death by the other crowd members (Safi and McKernan, 2020).

The behavioral study of crowds dates back to the 1950s (Mintz, 1951). Mintz’s experiment showed that escape panic is due to the reward structure inherent to the evacuation situation. Moving orderly towards the exit is rewarding, as long as everybody else does it. When one person starts to rush, rushing behavior becomes rewarding also for the other persons. In another famous experiment (Latane and Darley, 1968), it was shown that in an emergency, a person tends to look to the people around him to see how he should behave. The consensus among sociologists is that people behave rationally in emergencies (Quarantelli, 2001).

An evacuating crowd is a complicated system due to the large number of people involved and the nonlinear interactions between them (Bellomo et al., 2012). Also, socio-psychological and external factors, such as building geometry, influence human behavior. As a result, the study of evacuating crowds has received attention from different fields, including sociology, psychology, engineering, physics, and artificial intelligence. In evacuation research, three main research streams can be identified: the behavioral study of evacuating crowds, their descriptive mathematical modeling, and mathematical optimization of evacuation and building design (Vermuyten et al., 2016).

A particularly critical situation of a building evacuation is a crowd moving through a bottleneck. A large crowd clogging a bottleneck can seriously slow down the evacuation (Hoogendorn and Daamen, 2005). Also, due to the high crowd density, physical phenomena start to take place (Helbing et al., 2000). In the experimental study with real humans by Heliövaara et al. (2012b), a group of students evacuated a corridor under two behavioral objectives: non-competitive and competitive. Under the competitive objective, the individual students moved faster. Multiple trials were performed, and the students’ initial positions were randomized between trials. The study showed that under the competitive objective, the whole group evacuated significantly faster. However, if the level of competitiveness is further increased, the evacuation starts to slow down due to increased pushing and shoving (Haghani et al., 2019). This faster-is-slower effect was shown to take place in the experimental research by Garcimartin et al. (2014). Also, increasing the crowd size might have a similar effect.
Even though isolated features of a bottleneck evacuation have been experimentally studied, a fundamental issue in evacuation research is that real danger cannot be replicated in an experimental setup. Recent advancements in virtual reality (VR) have opened up the possibility of evacuation experiments in VR (Kinateder et al., 2014; Hürst and Geraerts, 2019). Still, we mainly rely on video footage of some crowd disasters and post-disaster interviews of participants. As a result, to tackle the issue, very realistic computational evacuation models have been developed. Numerical simulation of these models can be used to study different evacuation situations.

The first computational evacuation models were the fluid dynamic model by Henderson (1971) and the network model by Chalmet et al. (1982). In both of them, the focus is on modeling macroscopic quantities of a crowd. The advantage is their computational efficiency, but they cannot model individual interactions or decision-making. Probably owing to the increase in computing power, microscopic models were developed. In them, individuals’ movement and interactions are modeled, typically with physics-inspired self-driven particle models. The most used microscopic models are the social force model (Helbing and Molnár, 1995), and its refinements (Karamouzas et al., 2014), that are based on Newtonian dynamics, and the cellular automaton (CA) model, where agents move in a discrete square grid according to probabilistic rules (Schadschneider et al., 2008).

While the self-driven particle models can produce most physical phenomena of evacuating crowds, it has to be done by manually altering the model parameters. Also, crowds do not only follow the laws of physics. The conservation of momentum does not apply to people, and they can change their movement direction at will (Still, 2000). There is a need for more comprehensive models that would take human decision-making into account (Gwynne et al., 2016).

A multiagent system framework allows us to model the evacuating crowd’s physical movement and decision-making (Pan et al., 2007). A multiagent system consists of interacting agents and their environment (Shoham and Leyton-Brown, 2008). In this case, the evacuees and the building, respectively. Since people in evacuations are rational, their decision-making can be modeled with game theory (Coleman, 1990). Thus, the interaction between agents can be modeled by coupling a self-driven particle model with a game theoretical decision-making model (Heliövaara et al., 2013).

In the study by Heliövaara et al. (2013), the decision-making was mainly studied in a static environment, where the agents do not move. Thus, the study gives mainly insight into the game dynamics. What is lacking is a comprehensive explanation for the physical phenomena at a bottleneck based on individuals’ decision-making. If the full mechanism is understood, it can give us insight into how to prevent or mitigate the inefficiency and physical dangers.

However, emphasis should also be put on direct solution-oriented modeling (Haghani, 2020). We should not only ask the question of why the crowd evacuates slowly but how to evacuate it in minimum time? There is a vast literature on mathematical optimization of building evacuation, but most of these studies share the shortcoming that they do not suggest practical solutions. Some suggestions are quite extreme, like sending individualized evacuation plans to the crowd members’ cell phones (Wong et al., 2017). Also, the evacuation plans are not robust to changes in conditions. Even small changes in positions can affect
the crowd evacuation time (Helbing et al., 2003).

Most public spaces have security staff or rescue guides that can be utilized in case of an emergency. People are known to respond to clear orders from authorities in an emergency (Gwynne et al., 2016). Moreover, rescue guides improve evacuation efficiency (Proulx, 2002). Most of the research on optimal usage of rescue guides are comparative studies that numerically simulate different guide configurations. There are a couple of studies using mathematical optimization, but, in those, only a certain aspect of the use of guides are optimized (Albi et al., 2016; Zhou et al., 2018, 2019). Besides, the studies (Zhou et al., 2018, 2019) have a completely deterministic setting. Thus, they do not consider the uncertain nature of an evacuating crowd.

### 1.2 Objectives and scope

The topic of this dissertation is numerical simulation and optimization models for dynamical features of crowd evacuation. The aim is twofold: (i) to develop a simulation environment and analyze phenomena emerging from agents’ decision-making; (ii) to develop a mathematical framework for solving the minimum time crowd evacuation using rescue guides. The four main research questions derived from the aims are listed below, and how they are interconnected is shown in Table 1.1.

RQ1. Seek and analyze appropriate computational movement models taking into account simple agent decision-making rules in exit congestion.

RQ2. How does the agents’ behavior (e.g., competitive or non-competitive) affect the dynamical and mechanical features of an exit congestion?

RQ3. What is the mathematical framework needed to solve the minimum time crowd evacuation using rescue guides?

RQ4. How should uncertain crowd movement patterns be taken into account in the minimum time crowd evacuation using rescue guides?

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Table 1.1. Scope of Publications I-V.

The focus is on the physical movement of the agents and their decision-making. The
modeling is limited to microscopic agent-based models. Most physical parameters have been verified and validated by other researchers in the field (Korhonen and Hostikka, 2009; Karamouzas et al., 2014).

There are many thoughts crowd members may think in an evacuation, but in Publications I-III, we focus on some basic thoughts and decisions related to their survival in exit congestion. On the other hand, in Publications IV and V, we focus on the agents’ exit choice and interaction with rescue guides. In Publication V, different behavioral situations are modeled as probabilistic scenarios.

In Publications I-III, the results are qualitatively validated with observations from a real-life experiment. Quantitative validation is left for future research. In Publications IV and V, the focus is on the mathematical formulation, algorithm development, and its implementation on a supercomputer and analyzing the solution’s properties. Experimental validation is left for future research.

1.3 Organization of dissertation

Publications I and II are preliminary studies of exit congestion in a discrete environment. In Publication III, we analyze the dynamical and mechanical features of an exit congestion. We model crowd movement with the social force model to which a spatial exit congestion game is coupled. The crowd dynamics are studied by numerical simulation. Macroscopic physical quantities of the crowd are calculated with a Voronoi method (Steffen and Seyfried, 2010). We connect the resulting non-monotonous physical patterns to our observations from a real-life experiment.

In Publication IV, we consider the minimum time crowd evacuation problem using rescue guides. We make some behavioral assumptions to idealize the stochastic optimization problem. We reformulate the problem as a scenario optimization problem to handle its computational complexity. Then, the problem is solved with numerical simulation-based optimization, which we implement on a supercomputer. The proposed framework is applied for the evacuation of a fictional conference building. The solution, its convergence, and aspects related to stochasticity are analyzed.

Publication V answers the question of how uncertain crowd movement patterns should be accounted for in the problem of Publication IV. We suggest describing the uncertain movement patterns as probabilistic scenarios. A second performance measure, a risk measure, is introduced, and a bi-objective optimization problem is formulated. This framework is applied to a toy example to illustrate how qualitatively different evacuation plans there can be under different objectives.

To conclude, the structure of the dissertation summary is as follows. In Chap. 1, the background is presented, and the dissertation is outlined. In Chap. 2, the theoretical framework is presented. In Chap. 3, the contributions of Publications I-V are presented. In Chap. 4, the main contributions, their implications, limitations, and future research directions are discussed.
2. Theoretical framework

The theoretical framework starts with the behavioral assumptions made for the models presented in this dissertation. In all papers, a multiagent framework is used. For a detailed presentation of multiagent systems and game theory; see (Shoham and Leyton-Brown, 2008). The crowd members are described as agents interacting with each other and the building (Pan et al., 2007). Then, the multiagent exit congestion game for modeling agents’ interactive decision-making is presented. For studying the physics of the evacuating crowd of agents, the social force model and its numerical simulation are described together with the Voronoi method for calculating macroscopic physical quantities. Finally, the minimum time crowd evacuation problem and its computational complexity are discussed.

2.1 Behavioral assumptions

Exit congestion In the experimental study (Heliövaara et al., 2012b), students evacuated from a corridor under a non-competitive and competitive scenario. In the competitive scenario, the students were instructed to minimize their own evacuation time. Whereas, in the non-competitive scenario, the students were instructed to minimize the whole group’s evacuation time. Multiple trials were performed for both scenarios, and the initial positions were randomized between trials. In Publication III, based on the video material and data from the experiment, we make the following experimental observations (EO):

EO1. The number of overtakers in the group increases with the distance to exit.

EO2. In a competitive scenario, faster students overtake their predecessors, whereas, in a non-competitive scenario, students stick to their positions within the group throughout the egress.

EO3. The number of overtakers is not dependent on students’ initial positions.

EO4. In a non-competitive scenario, students are willing to give space to others; they are careful not to push or even touch other students around them.

EO5. Overtaking others makes an evacuation faster because, if faster students do not overtake slower ones, the whole group ends up moving at the slowest ones’ speed.

These items will be referred to later on when the results of Publication III are presented. Furthermore, if the competitiveness level is increased, it is assumed that if pushing and shoving are permitted, the evacuation will get slower, and more severe crowd conditions could be witnessed (Garcimartin et al., 2014).
Evacuation with rescue guides  Before solving the minimum time crowd evacuation with rescue guides, we make some assumptions about crowd behavior. First of all, we assume the fire alarm has been given, and rescue guides are ready to lead the crowd out of the building. The crowd consists of exiting agents and guide agents. Exiting agents represent people who do not have full knowledge of the building and head toward their familiar exit, a typical mode of behavior in evacuations (Sime, 1980; Proulx, 1993). The guide agents represent safety personnel who use routes instructed by the evacuation planner. People in serious situations have been shown to follow safety personnel (Proulx, 2002; Nishinari et al., 2004). Thus, guide agents are assumed to have enough authority to influence the route choices of exiting agents. More specifically, in Publications IV and V, we assume the following interaction rules:

Assumption 1. An exiting agent heads to its familiar exit by default.

Assumption 2. A guide moves from its starting position to its target exit using the shortest path.

Assumption 3. If an exiting agent moves towards its familiar exit, and a guide comes within a interaction range $r_{guide}$, it starts to move to the same exit as the guide. If multiple guides are within the $r_{guide}$ range, it starts to follow the closest one.

Assumption 4. If an exiting agent follows a guide, it will not switch to follow another guide.

Assumption 5. If an exit is within a visibility range $r_{exit}$ from an exiting agent, it heads there, whether or not it previously was following a guide or heading to its familiar exit. If multiple exits are within the $r_{exit}$ range, it heads to the closest one.

Note that other modeling assumptions could be made. However, tackling various behavioral aspects and associated modeling issues is not within the scope of this dissertation. It is also known that individuals participate in activities that do not directly take them to the exit (Gwynne et al., 2016). However, we assume these activities to be rare when authorities guide the crowd.

For situations where a large part of the crowd decides to deviate from their usual rules of motion, we take the modeling approach to describe the different behavioral situations as probabilistic scenarios.

2.2 Exit congestion game

Social theorists are unanimous that people behave rationally in evacuation situations (Quarantelli, 2001). Game theory is a theoretical framework for rational agents in an interactive decision-making situation. Thus, the decision-making of people in competitive exit congestion can be modeled with game theory (Coleman, 1990).

People can only observe the behavior of the ones near them. Based on these remarks,
Heliövaara et al. (2013) proposed a spatial exit congestion game. In it, the agents play the game against their nearest neighbors. The agents have two strategies to choose from: Patient and Impatient. It is assumed that these strategies correspond to the agents’ patient and impatient actions in an actual play of a competitive evacuation, respectively. See Fig. 2.1 for a depiction of the game setting. Note that we consider a non-competitive evacuation to be such that all agents are patient throughout it.

Since time is a limited resource, the reward structure should change based on how much time an agent has to evacuate safely. The estimated evacuation time $T_{ij}$, together with the available safe egress time (ASET), or $T_{ASET}$, determines the game played. More precisely, $T_{ij}$ is the average estimated evacuation time of neighboring agents $i$ and $j$, whereas $T_{ASET}$ is a widely-used measure in the fire and evacuation research literature. It describes the time it takes for the fire conditions to become physically harmful (Cooper, 2002). The game will be either Hawk-Dove (HD) or Prisoner’s Dilemma (PD) game in the sense of evolutionary game theory (Maynard Smith, 1982).

The agents choose their strategies according to the best-response rule, i.e., they choose the strategy that minimizes their cost against the other agents. The agents are myopic in the sense that they only consider the previous period play of their opponents, not the play at farther history or future periods. In a discrete setting, the game is played on a square grid against the agents in the neighboring 8 cells. A continuous setting works similarly; there, the game is played against neighbors within a certain distance. Both in the discrete and continuous settings, the agents update their strategies in a randomized order.

The game dynamics converges rather straightforwardly to an equilibrium, i.e., to a situation where no agent can lower its cost by unilaterally deviating (see Fig. 2.2). The lower $T_{ASET}$ is, the higher is the proportion of impatient agents in the crowd. Also, in an equilibrium, the proportion of impatient agents increases with the distance to the exit. In fact, along any semicircle centered at the exit, the proportion of impatient agents approximates the matrix game’s evolutionary stable strategy (ESS) (Maynard Smith, 1982). Meaning that even if the agents’ strategies were perturbed, the game would quickly return to its equilibrium.
Figure 2.2. A snapshot of an evacuation simulation in a continuous setting. The agents’ strategies are effectively in the evolutionary stable equilibrium along any semicircle centered at the exit. Among the semicircles $A$, $B$, and $C$, the proportion of impatient agents is $0.75$, $0.50$, and $0.25$, respectively.

2.3 Numerical simulation and macroscopic physical quantities

**Numerical simulation** The physical movement of the $N$ circle-shaped agents in the crowd is modeled with the social force model (Helbing and Molnár, 1995). In it, the agents move in the building and interact with other agents and walls. A mixture of socio-psychological and physical forces is assumed to affect an agent’s motion in a crowd. The motivation of agent $i \in N$ to change its velocity to its desired velocity $v_i^0(t)$ within a reaction time $\tau_i^{\text{reac}}$ evokes an acceleration force called the driving force. A social repulsion force describes the psychological tendency to keep distance to other agents $j \neq i$ and walls $W$, $f_{soc}^{ij}(t)$ and $f_{soc}^{iW}(t)$, respectively. In the original social force model (Helbing and Molnár, 1995), social repulsion depends on the distance, but rather on time-to-collision if the agents are about to collide.

In the case that agents come in close contact with each other or walls, the physical contact forces $f_{iW}^{c}(t)$ arise, analogously with driven granular material (Helbing et al., 2000). The time-dependent motion of agent $i$ with mass $m_i$ is modeled with Newton’s equation of motion,

$$m_i \frac{dv_i}{dt} = m_i \frac{v_i^0 - v_i}{\tau_i^{\text{reac}}} + \sum_{j, j \neq i} (f_{soc}^{ij} + f_{ij}^{c}) + \sum_{W} (f_{soc}^{iW} + f_{iW}^{c}) + \xi_i,$$  \hspace{1cm} (2.1)

where intentional or unintentional deviations from the usual rules of motion are modeled by an additive Gaussian force $\xi_i(t)$. The change of the center of mass of agent $i$, $x_i(t)$, is given by the velocity,

$$\frac{dx_i(t)}{dt} = v_i(t).$$  \hspace{1cm} (2.2)

To numerically simulate the motion of a crowd of agents, we need to solve a system of nonlinear differential equations. It is done with a numerical integration method like the Velocity Verlet algorithm (Vattulainen et al., 2002).

An agent’s desired velocity points to the direction that gives the shortest path towards the exit it is heading. We calculate it using the detailed method presented in (Kretz et al., 2011).
The theoretical framework involves solving the continuous shortest path to an exit. It is solved using the fast marching method, which first discretizes the building floor into a grid. The method works almost like Dijkstra’s algorithm for finding the shortest paths between nodes in a graph. The solution is a distance map from each point, or grid node, in the building to the exit. The direction to which an agent should head towards, in each point, can be calculated using the gradient direction of the distance map. Before the start of numerical integration, the distance maps, i.e., the distances from each grid node to every exit, are calculated offline and stored.

The offline computations and numerical simulation of the social force model and exit congestion game are implemented in Python; for code, see (von Schantz, 2018). Fig. 2.3 shows a screenshot from the graphical user interface (GUI) of the simulation environment.

![Figure 2.3. Snapshot of the GUI of the simulation environment.](image)

When we couple the exit congestion game to the social force model, we set the game parameter $T_{ASET}$ to decrease in proportion to time $t$. Impatient agents have a higher desired speed and a smaller social force magnitude than patient agents. Furthermore, the agents update their strategies according to independent Poisson processes. We set them to update frequently enough compared to their physical movement so that their strategies are always in equilibrium. In the case of a non-competitive evacuation, we fix all the agents’ to patient throughout the whole numerical simulation.
Theoretical framework

Calculating macroscopic physical quantities As agents are discrete objects all around the continuous space, macroscopic physical quantities like density, speed, and kinetic pressure are not self-evident concepts. There is not a single correct method to approximate these quantities. We focus here on the Voronoi method (Steffen and Seyfried, 2010). In it, the building floor $\Omega \subset \mathbb{R}^2$ is discretized into square cells $\omega$ of size $0.1 \text{ m} \times 0.1 \text{ m}$. Then, the Voronoi region of agent $i$, $R_i$, is defined as

$$R_i = \{ y \in \Omega \mid \| x_i - y \| \leq \| x_j - y \| \text{ for all } j \neq i \}. \quad (2.3)$$

So, $R_i$ includes the points $y \in \Omega$ that are closer to agent $i$ than to any other agent $j \neq i$; see Fig. 2.4.

![Figure 2.4. The Voronoi region $R_i$ consists of all the points closer to agent $i$ than to any other nearby agents $j_1, j_2, j_3,$ or $j_4$. Also, the building floor $\Omega$ is discretized into square cells $\omega$ of size $0.1 \text{ m} \times 0.1 \text{ m}.$](image)

At time $t$, agent $i$ produces a density distribution,

$$d_i(y, t) = \begin{cases} \frac{1}{S(R_i)} & \text{for } y \in R_i \\ 0 & \text{otherwise,} \end{cases} \quad (2.4)$$

where $S(R_i)$ is the area of $R_i$. At time $t$, agent $i$ also produces a velocity distribution,

$$V_i(y, t) = \begin{cases} v_i(t) & \text{for } y \in R_i \\ 0 & \text{otherwise.} \end{cases} \quad (2.5)$$

Let us denote the area of $\omega \cap R_i$ by $\beta_i$. We define the density field at time $t$ in point $y \in \omega \subset \Omega$ as the weighted sum of the individual agents’ density distributions,

$$\rho(y, t) = \frac{\sum_i \beta_i d_i(y, t)}{\sum_i \beta_i}, \quad (2.6)$$

and likewise, the velocity field at time $t$ in point $y \in \omega \subset \Omega$ as the weighted sum of the individual agents’ velocity distributions,

$$v(y, t) = \frac{\sum_i \beta_i V_i(y, t)}{\sum_i \beta_i}. \quad (2.7)$$

Notice that $v(y, t)$ is a vector field. Hence, the speed at time $t$ in point $y$ is calculated as $v(y, t) = \| v(y, t) \|$.
The kinetic pressure is related to an agent falling down in a crowd and crowd turbulence (Helbing and Mukerji, 2012). It is defined as the time-averaged density times the variance of speed,

\[ \langle \rho(y, t) \rangle_t \cdot \langle [v_E(y, t) - \langle v_E(y, t) \rangle_t]^2 \rangle_t, \ y \in \omega \subset \Omega, \]

over a suitable time-interval, where \( v_E \) is the component of \( v \) in the direction of the exit. Note that in some definitions, the variance of velocity is used instead of just the component towards the exit (Helbing and Mukerji, 2012; Garcimartín et al., 2017).

**Discretization considerations** Let us consider the different uses of discretization. In the continuous setting, we use it as a numerical approximation method. We use it to approximate the continuous space in the shortest path calculation and the Voronoi method. On the other hand, in the optimization problem that we discuss later, the discretization has a different purpose. The guides’ starting positions are optimization variables, and we discretize the building floor to reduce the solution space. A smaller discretization gives more accurate results for all use cases, but otherwise, they are not related.

There are also discrete movement models, which we do not discuss in detail in this dissertation summary. In this case, discreteness is a built-in feature of the model. In the preliminary studies in Publications I and II, we use a discrete CA movement model (Kirchner et al., 2003). In it, agents move in a square grid according to probabilistic rules, and a single agent occupies one grid cell at a time. A grid cell’s size is 0.4m × 0.4m, which is also the level of detail the model can go into. The CA model allows for high-speed computation, but its drawback is that it cannot model physical contact forces or the build-up of pressure (Zheng et al., 2009).

### 2.4 Computational complexity

**Optimization problem** Next, we discuss the computational complexity of solving the minimum time crowd evacuation from a complex building using rescue guides. Let us define \( T_{last} \) to be the crowd’s evacuation time, i.e., the time when the last agent has evacuated the building. The optimization variables are evacuation plans that include the number of guides, their starting positions, and exit assignments. We discretize the building floor into a square grid, and the possible starting positions are prespecified points in the grid cells. Let us denote an evacuation plan with \( \pi \in \Pi \), where \( \Pi \) is the set of feasible evacuation plans. We define the following function:

\[ \phi(\pi; \theta) := T_{last}, \]

where \( \theta \) is a random variable, with a known probability distribution, that describes the uncertainties in the crowd evacuation. Thus, \( T_{last} \) comes out as a random variable having its distribution that depends on the choice of \( \pi \). The minimum time evacuation using rescue guides is formulated by using the mean,

\[ \min_{\pi \in \Pi} \mathbb{E} [\phi(\pi; \theta)], \]
subject to the initial positions of the agents, Eqs. (2.1) and (2.2), and Assumptions 1-5.

Essentially, we are dealing with a hard combinatorial optimization problem. To illustrate the computational complexity of it, let us consider the example case from Publication IV. Numerical simulation of one realization of the evacuation can take up to 1 h. The number of starting grid cells is 62, and the number of exits five. Let us assume that an inactive guide is mapped to a dummy grid cell. Then the number of cells is 63. For example, to search through all the solutions with less than or equal to ten guides, \((63 \cdot 5)^{10}\) evacuation plans have to be evaluated. Using a single processing unit, it would take approximately \(1.1 \cdot 10^{21}\) years to evaluate all solutions. Note that we assumed that just one numerical simulation with given \(\pi\) is enough to evaluate the mean from Eq. (2.10). Actually, we have to evaluate it by taking multiple samples.

**Scenario optimization** In both Publications IV and V, the evacuating crowd’s stochastic nature is handled using scenario optimization (Calafiore and Campi, 2006). However, the approaches in these papers are different.

In Publication IV, the uncertainty \(\theta\) equals the random force terms \(\xi_i(t), i \in N, t \in [0, T_{\text{last}}]\). To solve problem Eq. (2.10), samples of the random force are generated, and the mean crowd evacuation time is approximated with the sample mean. In practice, we use a pseudorandom number generator (PRNG) to generate realizations of the random force terms. For each scenario, we store the seed of the PRNG. Thus, the realizations of the random force terms are replicable. Then, for a specific seed, the social force equations are solved with the Velocity Verlet numerical integration scheme, and the evacuation time is calculated. The sample mean is obtained by averaging over the sampled evacuation times.

In Publication V, the focus is on situations where a large part of the crowd deviates from its usual rules of motion. For simplicity, in Publication V, we use a deterministic social force model, i.e., Eq. (2.1) without the random force term. There, the uncertain variable, \(\theta\), describes the familiar exits and desired speeds of the agents. The different behavioral situations are modeled as a finite number \(K\) of representative probabilistic scenarios. The associated realizations of the uncertain parameters are \(\theta_1, ..., \theta_K\) and their probabilities \(p_1, ..., p_K\), where \(\sum_{k=1}^{K} p_k = 1\). Fixing \(\pi\), we can numerically simulate the scenarios and obtain the evacuation times \(T_{\text{last}}^1, ..., T_{\text{last}}^K\). In Publication V, the mean evacuation time is then calculated as

\[
E[\phi(\pi; \theta)] = \sum_{k=1}^{K} p_k T_{\text{last}}^k.
\]

**Numerical simulation-based optimization** As already stated, we cannot use analytical methods to solve the problem of Eq. (2.10). Thus, we resort to numerical simulation-based optimization. Genetic algorithms (GAs) are often used on combinatorial problems (Goldberg, 1989). Hence, we combine a GA with numerical simulation. In the GA, a population of solutions is maintained in consecutive iterations. The GA iteratively searches for the optimal solution, while the solutions’ sample means are evaluated with numerical simulation. As the evaluations of the solutions in one iteration of the GA are independent, they can be parallelized and implemented on a high-performance computing cluster (HPCC).
After the evaluation, we perform three operations: i) selection, ii) crossover, and iii) mutation. Selection ensures the best solutions survive to the next iteration as parent solutions. The crossover operation combines the parent solutions to create child solutions, and mutation operation alters them. The GA is considered to have converged when the best solution has not changed for a predefined number of iterations.

In a GA, the solutions consist of genes. A gene defines the starting grid cell and destination exit of a guide. Usually, the number of genes in each solution should be the same. However, in our problem, the number of guides is also a variable. Thus, we use a particular version of the GA, the hidden genes GA (Abdelkhalik, 2013). In it, a gene can be either hidden or active. If the gene is hidden, the corresponding guide is idle and does not participate in the evacuation. See Fig. 2.5 for a depiction of the gene encoding and how the crossover operator works in the hidden genes GA.

![Figure 2.5. Crossover operation applied on the two parent solutions to create child solutions.](image)

**Computational complexity of numerical simulation**  Next, we discuss computational issues related to numerical simulation. In Eq. (2.1), the social repulsion force is calculated between all $N$ agents, which means that the computational complexity is $O(N^2)$. However, the social repulsion force is exponentially decaying, meaning that its effect vanishes quickly with distance. Without loss of accuracy, a cell-list algorithm can be used to divide the building into domains so that the forces are cut off at a distance of 3 m, which reduces the complexity to $O(N)$ (Yao et al., 2004).

Also, in Eq. (2.1), the agent-wall social repulsion is calculated between all agents and wall segments. However, we can omit these interaction forces by constructing the agents’ desired velocities to point heavily away from walls, once agents come near them (Cristiani and Peri, 2017). The construction is done offline, before the numerical simulation, increasing efficiency.

The main source of inefficiency in numerical simulation is the step size. When crowds move in bottlenecks, crowd density increases, and the nonlinear contact forces of Eq. (2.1) come into play. Large changes in forces can happen very quickly. Thus, in numerical simulation, the step size needs to be very small for stability and accuracy. Studies claiming real-time simulations with large crowds omit these contact forces and use a larger time step...
Theoretical framework

(Johansson et al., 2007). Hence, they are not accurate in describing dense crowds and the associated physical dangers.

Risk measures  Using the mean evacuation time as the objective function is useful if the evacuation times are relatively normally distributed. However, for right-skewed distributions, we might want to consider using a risk measure like Conditional Value-at-Risk (CVaR) (Rockafellar and Uryasev, 2000). Note that CVaR is only used in Publication V. Hence, it is here defined only for a finite probability distribution.

For a finite number of scenarios, and probability level \( \alpha \in (0, 1) \), we first define Value-at-Risk (VaR),

\[
\text{VaR}_\alpha [\phi(\pi; \theta)] = \inf \left\{ \zeta \in \mathbb{R} : \sum_{k, T_{k}^{last} \leq \zeta} p_k \geq \alpha \right\} .
\]  

(2.12)

Suppose the crowd evacuation times associated with the scenarios are ordered, from fastest to slowest. In that case, VaR is the fastest evacuation time for which the scenarios’ cumulative probability equals or exceeds \( \alpha \). On the other hand, C\( \text{VaR}_\alpha \) measures the mean of the \((1 - \alpha)\) slowest scenarios,

\[
\text{C\( \text{VaR}_\alpha \)} [\phi(\pi; \theta)] = \frac{1}{1 - \alpha} \sum_{k, T_{k}^{last} \geq \text{VaR}_\alpha [\phi(\pi; \theta)]} p_k T_{k}^{last} .
\]  

(2.13)

Note that \( \text{C\( \text{VaR}_\alpha \)}\) may be obtained for a fractional number of scenarios. In that case, Eq. (2.13) has to be modified (Rockafellar and Uryasev, 2002).

Pareto-optimality  Optimizing only CVaR can give an overly conservative evacuation plan. A bi-objective formulation can be used to account for both mean and worst-case performance. The optimization problem is otherwise as before; now, there are just two objective functions, mean and CVaR, of evacuation time (Rockafellar and Uryasev, 2000). To compare two solutions, we use the concept of dominance. Solution \( \pi_1 \) dominates solution \( \pi_2 \) iff:

\[
\mathbb{E} [\phi(\pi_1; \theta)] \leq \mathbb{E} [\phi(\pi_2; \theta)] , \text{ and } \text{C\( \text{VaR}_\alpha \)} [\phi(\pi_1; \theta)] < \text{C\( \text{VaR}_\alpha \)} [\phi(\pi_2; \theta)] ,
\]

or

\[
\mathbb{E} [\phi(\pi_1; \theta)] < \mathbb{E} [\phi(\pi_2; \theta)] , \text{ and } \text{C\( \text{VaR}_\alpha \)} [\phi(\pi_1; \theta)] \leq \text{C\( \text{VaR}_\alpha \)} [\phi(\pi_2; \theta)] .
\]

(2.14)

The set of solutions not dominated by any other solutions is called nondominated or Pareto-optimal solutions. By definition, they are the solutions of the bi-objective optimization problem. They can also be solved using a numerical simulation-optimization procedure like nondominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002). Instead of measuring the goodness of the solution by the sample mean of the evacuation time, the solutions are ranked based on how many solutions they dominate.
3. Contributions of the publications

3.1 Publications I and II

Publications I and II are preliminary studies on how agents’ decision-making affects the dynamical features of exit congestion. The exit congestion game is coupled to the computationally light CA evacuation model (Kirchner et al., 2003). The agents move in discrete time steps towards the exit in a square grid according to probabilistic movement rules. The game is updated frequently enough so that agents’ strategies are in equilibrium at each evacuation simulation time step. Despite its apparent simplicity, it can qualitatively reproduce some important collective crowd phenomena in an evacuation. Publication II extends the model by introducing two types of agents with low and high attitude towards impatience. The simulations show the self-evident fact that high impatience agents overtake the low impatience agents.

3.2 Publication III: non-monotonous dynamics

In Publication III, we consider the competitive evacuation of a large crowd of agents through a narrow exit. We model it by coupling the spatial exit congestion game to the social force model. We study game-theoretical, mechanical and dynamical features with numerical simulation. These features are qualitatively validated by our experimental findings EO1-EO5. Using the Voronoi method, we also calculate the crowd speed and kinetic pressure patterns. Most importantly, as a result of the exit congestion game, we obtain non-monotonous patterns, which are not observed with the pure social force model; see Fig. 3.1. All results of the paper are found to be robust to reasonable parameter variations.

Next, we give a detailed summary of the main results. First, recall the game equilibrium in Fig. 2.2. The farther the agent is from the exit, the more beneficial it is for it to be impatient. Let us take the perspective of a single agent in our model. An impatient agent has a higher desired speed and a smaller magnitude of social force. Thus, it pushes and overtakes the agents in front of it. If the crowd is sparse, it manages to overtake its patient predecessors; see EO1 and EO2. In Fig. 3.1a note that the average crowd speed is relatively high far away from the exit.

If the agent gets closer to the exit, it turns patient. The agent’s strategy is not a permanent characteristic but rather changes according to its distance to the exit and the neighboring agents’ strategies; see EO3.

The closer the agent is to the exit, the higher the crowd density is, which decreases its speed (notice the drop in the speed in Fig. 3.1 a). Also, before the exit, a human arch has formed, which almost completely stops the agent’s movement. These arches are mechanical structures that can totally interrupt the crowd flow. Their existence has been shown in crowd simulations (Helbing et al., 2000; Parisi and Dorso, 2007) and experiments with
driven granular material that share some physical properties with humans (Zuriguel et al., 2014). The combination of the friction force between agents and the driving force of the back of the crowd causes human arches to form. They break down due to imbalances in the system caused, e.g., by the random fluctuation force. When the human arch breaks, the agents in front of the exit can freely move and evacuate in a burst-like manner. Hence, the average speed right at the exit is relatively high (see Fig. 3.1 a).

**Figure 3.1.** Macroscopic physical quantities of a simulated crowd of 200 agents evacuating. The results are averaged over the interval when the number of agents in the room is between [190, 146]. The red curves correspond to simulations with the game for different game parameters $T_{ASET}$. The lower $T_{ASET}$ is, the higher the proportion of impatient agents is, with $T_{ASET} = 0$ corresponding a crowd with only impatient agents. On the other hand, the black curves correspond to simulations with the pure social force model, where all agents, $i \in N$, have the same desired speeds, $v_0^i = v_0$.

As agents with higher speed overtake their way forward, there is a transportation of momentum from the back of the crowd, which causes kinetic pressure (see Figs. 3.1 b,c). It is related to the risk of falling bodies and crowd disasters (Helbing and Mukerji, 2012).

Note that when the agents behave similarly, or have the same physical parameters, non-monotonous patterns are not seen (see Figs. 3.1 a,c,d). Numerical simulations reveal that in a crowd with only patient agents, i.e., in a non-competitive evacuation, the agents are careful not to push and overtake each other; see EO4. If all agents are impatient, they all push so hard towards the exit that there is no room to overtake.
In the paper, we also calculate the average flow at the exit for different proportions of impatient agents. In the non-competitive evacuation, the flow is smaller than in the case there is a small proportion of impatient agents; see EO5. An explanation for this is that the flow is under the exit capacity when only patient agents are in the crowd. Adding a small proportion of impatient agents increases the flow.

With an even further increase in impatient agents, the flow starts to decrease. This is the well-known faster-is-slower effect (Helbing et al., 2000). The underlying mechanism for this is the human arch formation. The more there are impatient agents, the more stable human arches are formed, decreasing the flow. We confirm this by collecting data from the time lapse between two successive agents’ passage through the exit. A long time lapse between successively evacuated agents indicates that a human arch has formed in front of the exit. We statistically infer that the probability for a long time lapse is always higher, the more there are impatient agents in the crowd. Similar results have been found in real-life evacuation experiments (Garcimartin et al., 2014).

### 3.3 Publication IV: minimum time evacuation with rescue guides

We propose a new framework to minimize the crowd evacuation time from a complex building. We consider an emergency after a fire alarm has been given, and there are enough rescue guides with skill and authority to lead the crowd out. Both a novel formulation and solution algorithm are presented. We choose the number of guides, their initial positions, and exit assignments to solve the optimization problem.

We reformulate the problem as a scenario optimization problem to deal with the stochasticity. The mean evacuation time is replaced with its sampled version. After this, we still have a hard combinatorial optimization problem. Its solution space is large, and evaluating a solution is computationally costly. A combined numerical simulation and GA procedure is then developed to solve it. To account for the variable number of guides in the solutions, we use the hidden genes GA. The GA iteratively searches for the optimal solution, whereas the numerical simulations evaluate the found solutions and steer the random search process.

As a single iteration of the algorithm can be parallelized, we implement the algorithm on a supercomputer. Preliminary computations were done on a supercomputer of Finnish IT Center for Science (CSC), and the project was finished with the Triton supercomputer of Aalto University. The operating system of Triton is Linux. Thus, the GA is implemented in shell script that calls the simulation environment written in Python; for codes see (von Schantz, 2020).

The framework is applied to the evacuation of a fictional conference building; see Fig. 3.2. We depict the guides with large yellow circles and their optimal paths with red arrows. A guide influences exiting agents within its interaction range and leads them to its target exit. Without guides, the exiting agents move to their familiar exits, as depicted by the blue arrows. A large congestion will occur at one of the concert hall entrances, which is the main source of evacuation inefficiency.

Typically, the GA parameters are adjusted manually in a problem-specific manner. Thus, before solving the conference building case, we first construct a test case, for which we
Contributions of the publications

Natural crowd dynamics

Rescue guide in evacuation

Guide’s optimal path

Figure 3.2. Illustration of the evacuation from a conference building using rescue guides. For visualization purposes, the problem setting is slightly altered compared to the actual setting found in Publication IV. Note that not all blue arrows are drawn here.

beforehand can anticipate the optimal solution. Then, we try different parameter configurations to get the GA to converge as efficiently as possible to the optimal solution. It is known for GAs that in a problem with a large number of local minima, introducing noise to the objective function and evaluating it by taking multiple samples improves convergence to the global minimum (Hammel and Bäck, 1994). This further assures that the found solution is optimal for our inherently noisy problem.

When we apply the found parameter configuration to the conference building case, the algorithm converges to the optimal solution. To again demonstrate the problem’s computational complexity, it took 6 days and 8 hours to reach convergence with the supercomputer. Intuitively, in the optimal solution, a large congestion never emerges. The agents that would cause it are steered to other parts of the building, yet so as not to create other jams or counterflows, and all exits are also used equally. These both have been recognized as efficient crowd evacuation strategies in other studies as well (van Toll et al., 2012; Hou et al., 2014).

Some other aspects of the solution are noteworthy in that they highlight the effect of modeling assumptions made. As the objective is not to minimize the number of guides, there can be redundant guides in the solution that do not interfere with the evacuation plan, e.g., positioned next to exits. Also, Assumption 5 states that if there is an exit within a visibility range of an exiting agent, it will head there. In the solution, there is an exit to which no guide is set to move. Instead, some guides are set to walk close to it, and in this way, divert exiting agents to it. Without Assumption 5, guides would have to be assigned to that exit.

Note also that in a more sophisticated model, the guides could be set to wait in place for

1The correct term is near-optimal solution as we solve the problem with a heuristic. For brevity, we drop the prefix and use the term optimal solution instead.
the exiting agents. The found solution circumvents this deficit by positioning a guide farther away so that it crosses paths with the exiting agents at the right time and steers them to an exit.

We evaluate the effects of uncertainty in our problem by comparing the sample distributions of the minimum time evacuation and the unguided evacuation. The sample standard deviation is small compared with the large deviation found in the unguided evacuation. It appears that the optimal evacuation plan inadvertently mitigates the effect of uncertainty. Numerical simulations show that the guides in the minimum time evacuation plan clear all major congestions. Thus, it can be that the nonlinear contact forces in Eq. (2.1) do not come into play. Hence, the additive Gaussian random force term has a minor effect on the evacuation time.

We can also think about the uncertainty from another point of view. It has been experimentally shown that even small changes in the crowd members’ positions alter the evacuation time (Helbing et al., 2003; Huang and Guo, 2008). Because we take the mean of multiple samples of the crowd dynamics to evaluate the objective function, the optimal solution is, in some sense, robust to position changes (Tsutsui and Ghosh, 1997).

3.4 Publication V: minimization of mean-CVaR evacuation time with rescue guides

After Publication IV, the question arises: what happens if many agents can simultaneously deviate from their usual rules of motion? As a toy example, we consider a passenger terminal with a cross-shaped floor plan. The agents arrive and depart there, and go about their business unless instructed otherwise. We construct a finite number of probabilistic scenarios, which represent the possible crowd movement patterns. Most probably, the agents move to their nearest exits. However, with some probability, a counterflow occurs, i.e., multiple groups of agents move in opposing directions at the cross-shaped terminal’s intersection.

The rescue guides are assumed to be trained for a single evacuation plan used in all scenarios. We will here take an approach from the literature of portfolio optimization (Rockafellar and Uryasev, 2000), and optimize both the mean evacuation time and that of CVaR at suitable probability level $\alpha$. We then have a bi-objective problem, so that we consider optimality in the sense of Pareto-optimality. We use the solution algorithm developed in Publication IV, but change the GA to NSGA-II suitable for bi-objective problems (Deb et al., 2002). When there is a constraint for the number of guides, we obtain multiple Pareto-optimal solutions and face a genuine tradeoff between mean evacuation time and CVaR. To illustrate the qualitative difference in the mean- and the CVaR-optimal solutions separately, let us consider the problem with two guides; see Fig. 3.3.

In the mean-optimal solution, the guides are positioned behind two agent groups and lead them to the nearest exits; see Fig. 3.3 (left). This “near exit” plan has also, in other studies, been found to improve evacuation time (Wang et al., 2012; Zhou et al., 2018). Nevertheless, in Fig. 3.3 (left) counterflows may arise, as the two groups with no guides may encounter at the intersection with some probability. Counterflows are known to slow down the evacuation and even cause mutual blockages (Isobe et al., 2004; Heliövaara et al., 2012a).
On the other hand, the CVaR-optimal solution completely eliminates this kind of effect. The algorithm produces a "turning the corner" plan for the guides. They have the same initial positions as in the mean-optimal solution. Nevertheless, they walk towards the intersection without colliding with each other, turn the corner, meet the remaining two groups, and lead all agents to the left or right exit. Note that there are also Pareto-optimal solutions that are combinations of these two extreme solutions. We analyze them in detail in Publication V.

The scenario approach we above propose is appropriate when the possible crowd movement patterns are notably different. Then, an evacuation plan that performs well across all scenarios usually does not exist. Our bi-objective optimization approach provides a tool to analyze tradeoffs between different evacuation plans. In practice, our framework can be applied to passenger terminals. There, the crowd traffic is highly fluctuating, crowd size is uncertain, and various dangers like bomb threats, although rare, are of concern (Schultz and Fricke, 2011). Also, these days, in the years 2020-2021, fast everyday operations without crowd congestion are needed in passenger terminals to prevent epidemic spread.
4. Discussion

The topics of the dissertation are numerical simulation and optimization models for dynamical features of crowd evacuation. The research questions posed before in Sec. 1.2 are answered here. We have made the following research contributions:

RC1. We have applied two computational movement models to an exit congestion, where the agents play spatial evolutionary games (Publications I-III).

RC2. We show that non-monotonous physical patterns emerge from agents’ local decision-making, and qualitatively validate the results with a real-life experiment (Publication III).

RC3. We formulate a new problem to minimize the crowd evacuation time using rescue guides. We formulate the optimization problem and develop a solution algorithm to solve the computationally hard problem. The algorithm solves the number of guides, their starting positions and exit assignments that minimize the evacuation time (Publication IV).

RC4. The considerably very different movement patterns with each other are described as probabilistic scenarios. In addition to mean evacuation time, we use CVaR as a second objective, and analyze tradeoffs between the two objectives (Publication V).

In the evacuation literature, behavioral aspects has been modeled less compared to physical features (Gwynne et al., 2016). We noticed that a pure physics-based model results in quantities that monotonically vanish as the distance to exit increases. Maybe this is also the reason why in the evacuation literature physical quantities are mainly studied near the exits.

In Publication III, we consider the competitive evacuation of a crowd of agents through an exit. We model it with a spatial exit congestion game coupled to the social force model. We numerically simulate the microscopic dynamics and measure the resulting macroscopic quantities with the Voronoi method. We show that agents’ local behavioral rules result in non-monotonous physical quantities that are not witnessed with the pure social force model. More specifically, they result from impatient agents in the back of the crowd pushing and overtaking their way forward. Our observations of the real-life evacuation experiment qualitatively validate the results.

Using simple rules for behavior, we can simulate collective phenomena of exit congestion. Our results are also qualitatively in-line with other real-life evacuation experiments (Garcimartin et al., 2014; Pastor et al., 2015; Garcimartín et al., 2017). Nevertheless, we should not expect the faster-is-slower effect to hold if, in a competitive situation, aggressive pushing is not allowed (Haghani et al., 2019).

Publication IV considers the minimum time crowd evacuation problem using rescue guides.
The crowd dynamics are described by the social force model, and interaction rules between guides and exiting agents are given. We present a new treatment for the problem, where we first formulate it as a stochastic optimization problem. The computationally challenging problem is solved by first reformulating it as a scenario optimization problem. Then, we use a combined numerical simulation and hidden genes GA procedure. To our knowledge, Publication IV, for the first time, solves the number of guides, their starting positions, and exit assignments all in a single-optimization. We compute them for a complex building, with several irregularly shaped rooms.

The closest study to Publication IV is the simultaneous but independent study by Zhou et al. (2019). They studied the deterministic evacuation from a regular building geometry using two separate optimization problems. The initial positions of the guides were first solved using an appropriate criterion. Then, in a separate problem, the routes were solved for these initial positions. The evacuation plan they construct in this way is not a minimum time evacuation plan. Our minimization problem cannot be separated in this way, but is once and for all one problem. Other aspects of the efficient use of rescue guides have been studied with numerical simulations: the optimal proportion of guides (Pelechano and Badler, 2006; Wang et al., 2012; McCormack and Chen, 2014), the initial positions of guides (Wang et al., 2012; Aubé and Shield, 2004), and exit assignments of guides (Hou et al., 2014).

Mathematical optimization is in a central role in evacuation research (Vermuyten et al., 2016; Albi et al., 2019). Nevertheless, thus far uncertainties in crowd movement have almost entirely been ignored in evacuation optimization (Haghani, 2020). Both Publications IV and V consider such uncertainties. In Publication IV, the random force term in the social force model approximates small individual behavioral deviations, and we consider some effects it has on the optimization. In Publication V, we show how to treat scenarios that differ quite dramatically from each other. In that case, the mean evacuation time can by itself be a poor performance measure.

We make some simplifying assumptions about the interactions between guides and the exiting agents around them. It would be interesting to see how altering the assumptions would affect the optimal solution. Also, the optimal solution should be experimentally validated, for example, using experiments in VR or evacuation drills, like the ones made in VTT (Technical Research Center of Finland) (Hostikka et al., 2007).

Related research includes evacuation experiments with invisible guides. Invisible guides are ordinary crowd members that have been given a special role to move purposefully and guide people tacitly to a safe place. In the real-life experiment (Dyer et al., 2008), it was found that 5% of the crowd members have to be invisible guides to lead the crowd out optimally. On the other hand, we got that only 0.7% of the crowd have to be recognizable guide agents for a minimum time evacuation from a complex building. Also, in the numerical simulation experiment in (Albi et al., 2019), a comparison was made of guiding a crowd to a target exit using recognizable and invisible guides. It was noticed that if the guides are invisible, more guides are needed, and the evacuation is more sensitive to their positioning. Invisible guides might not be practical in an evacuation, but this research can help us understand the interaction between recognizable rescue guides and the agents following them.

Research on robot-assisted evacuation also has much overlap with Publications IV and
V. The technology is not at the stage that robots could guide the crowd out of a building. However, it seems to be advancing rapidly (Sakour and Hu, 2017). There is experimental research on how humans trust the paths taken by robots in evacuation (Robinette et al., 2017). The experimental findings with robots could help us validate our model. Or maybe our models could be applicable to robot evacuations, since our guides do not have any human features but obey mathematical interactions rules?

Physically realistic computational crowd models take agents’ contact forces into account. In their numerical integration, the step size needs to be set small, making computation slow. However, recently there have been some noteworthy computational advances in the research field. Karamouzas et al. (2017) presents a very efficient numerical integration scheme, which might be used for physically realistic faster than real-time simulations. In (Hu et al., 2020), a deep neural network was trained to predict the relationship between building environment and evacuation performance. With fast numerical simulations, we could rapidly solve minimum time evacuation plans for many different evacuation situations. These solutions could then be used to train a deep neural network to give optimal evacuation plans in milliseconds. It could open up avenues for real-time crowd control.
References


References


References


References


Errata

Publication I

page 4, column 2, paragraph 5, lines 30-32:

The risk of injury is described by a cost $C > 0$, which affects both agents. The constant $C$ is called the cost of conflict.

Correction (to be replaced by):

The risk of injury is described by a cost of conflict $C \Delta T$ that affects both agents. Here, $C > 0$ is a constant.

page 4, column 2:

Table I. The game matrix for the spatial evacuation game.

<table>
<thead>
<tr>
<th></th>
<th>Impatient</th>
<th>Patient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impatient</td>
<td>$C, C$</td>
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Correction (to be replaced by):

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Then the game matrix only depends on the parameter \( C/\triangle u(T_{ij}) \). When \( 0 < C/\triangle u(T_{ij}) \leq 1 \), the game played is PD, and the only Nash equilibrium is (Impatient, Impatient). If \( C/\triangle u(T_{ij}) > 1 \), the game played is HD, and there are two pure strategy Nash equilibria (Impatient, Patient) and (Patient, Impatient). There is also a mixed strategy equilibrium, where the strategy Impatient is played with probability \( \triangle u(T_{ij})/C \), and the strategy Patient with probability \( 1 - \triangle u(T_{ij})/C \).

**Correction (to be replaced by):**

Note from Eq. (3) that \( u'(T_{ij}) \approx \triangle u(T_{ij})/\triangle T \). Then the game matrix only depends on the parameter \( C/u'(T_{ij}) \). When \( 0 < C/u'(T_{ij}) \leq 1 \), the game played is PD, and the only Nash equilibrium is (Impatient, Impatient). If \( C/u'(T_{ij}) > 1 \), the game played is HD, and there are two pure strategy Nash equilibria (Impatient, Patient) and (Patient, Impatient). There is also a mixed strategy equilibrium, where the strategy Impatient is played with probability \( u'(T_{ij})/C \), and the strategy Patient with probability \( 1 - u'(T_{ij})/C \).

We will suppose that \( \triangle T = 1s \). Then the parameter \( C/\triangle(T_{ij}) \) appearing in the game matrix is

\[
\frac{C}{\triangle u(T_{ij})} \approx \frac{T_0}{T_{ij} - T_{ASET} + T_0}.
\]

(7)

Note that whether the game played is PD or HD, depends only on the value of \( T_0/(T_{ij} - T_{ASET} + T_0) \). Thus the game only depends on the estimated evacuation time \( T_{ij} \), since \( T_0 \) and \( T_{ASET} \) are constants. When \( T_{ij} \) increases, the game turns from HD to PD.

**Correction (to be replaced by):**

Then the parameter \( C/u'(T_{ij}) \) appearing in the game matrix is

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\frac{C}{u'(T_{ij})} = \frac{T_0}{T_{ij} - T_{ASET} + T_0}.
\]

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Note that whether the game played is PD or HD, depends only on the value of \( T_0/(T_{ij} - T_{ASET} + T_0) \). Thus the game only depends on the estimated evacuation time \( T_{ij} \), since \( T_0 \) and \( T_{ASET} \) are constants. When \( T_{ij} \) increases, the game turns from HD to PD.
Publication II

page 2, column 2, paragraph 6, lines 27-30:

The risk of injury is described by a cost $C > 0$, which affects both agents. The constant $C$ is called the cost of conflict.

Correction (to be replaced by):

The risk of injury is described by a cost of conflict $C\Delta T$ that affects both agents. Here, $C > 0$ is a constant.

page 2, column 2:

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<td>$\Delta u(T_{ij}), -\Delta u(T_{ij})$</td>
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</tr>
</tbody>
</table>

page 3, column 1, paragraph 3, lines 18-20:

Let us now go back to Eq. (2). If we for simplicity assume $\Delta T = 1$, we have $\Delta u(T_{ij}) \cong u'(T_{ij})$. So, the cost of being overtaken is approximately $u'(T_{ij})$. Let’s make another assumption about $u(T_{ij})$.

Correction (to be replaced by):

Let us now go back to the cost of being overtaken $u'(T_{ij})\Delta T$. 

...
page 3, column 1, paragraph 6, lines 36-39:

Now, substitute $\triangle u(T_{ij}) = u'(T_{ij})$ in the game matrix, and divide it by $u'(T_{ij})$. This does not affect the equilibria of the game. Finally, substitute $u'(T_{ij}) = T_{ij}/T_{ASET}$.

Correction (to be replaced by):

Now, divide the game matrix by $\triangle u(T_{ij})$, and substitute $\triangle u(T_{ij})/\triangle T = u'(T_{ij})$. This does not affect the equilibria of the game. Finally, substitute $u'(T_{ij}) = CT_{ij}/T_{ASET}$.

page 5, column 2, paragraph 2:

$$\sum_{j \in N_i} \frac{T_{ASET}}{T_{ij}} + (|N_i| - |N_i^{Imp}|) \leq |N_i^{Imp}|,$$

(5)

Correction (to be replaced by):

$$\sum_{j \in N_i^{Imp}} \frac{T_{ASET}}{T_{ij}} + (|N_i| - |N_i^{Imp}|) \cdot (-1) \leq |N_i^{Imp}|,$$

(5)

Publication III

page 9, paragraph 4, lines 16-19:

The random force $\xi_i$ in Eq. (4) is decomposed $\xi_i = \xi_i \eta_i$, where the magnitude $\xi_i$ is drawn from a truncated Gaussian distribution with mean zero, standard deviation of $0.1 m_i m/s^2$, and it is truncated at three times of the standard deviation. The components of the direction vector $\eta_i = (\eta_i^1, \eta_i^2)$ are drawn from uniform distributions on the intervals $[\cos(0), \cos(2\pi)]$ and $[\sin(0), \sin(2\pi)]$, respectively.

Correction (to be replaced by):

Finally, the components of the random force vector $\xi_i$ follow a truncated normal distribution with zero mean, standard deviation $0.1 m_i m/s^2$, and are truncated at three times of the standard deviation.