Department of Mathematics and Systems Analysis

People Flow in Buildings – Evacuation Experiments and Modelling of Elevator Passenger Traffic

Juha-Matti Kuusinen

Aalto University

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Juha-Matti Kuusinen

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Abstract

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Abstract

This dissertation studies people flow in buildings, especially the process of how passengers arrive at elevator lobbies, estimation of elevator passenger traffic, and human behaviour and decision making in evacuations. The arrival process is studied by taking into account, for the first time, that passengers do not always arrive and use elevators individually but rather in batches. The results suggest that the common assumption that individual arrivals follow a Poisson distribution may not hold when the proportion of batch arrivals is large.

To estimate the elevator passenger traffic in a building, new mathematical models and algorithms are developed. The new methods are based on mathematical optimization, namely, linear programming, integer least squares and constraint programming. The results from numerical experiments show that the new approaches satisfy real-time elevator control requirements. In addition, randomized algorithms result in better quality passenger traffic statistics than traditional deterministic algorithms. The dissertation presents also an experimental evacuation study. The results show that people may not be able to select the fastest exit route and that cooperation may slow down the evacuation.

The new estimation models and algorithms presented in this dissertation enable better elevator control and some of them are already being implemented by KONE Corporation. The results also give new insights into the process of how passengers arrive at the elevator lobbies and use elevators and into human behaviour in evacuation situations, which affect elevator and building safety planning.

Keywords people flow, building, evacuation, experiment, behaviour, elevator, arrival process, origin-destination matrix, estimation, integer programming

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Tiivistelmä

Tässä väitöskirjassa tutkitaan rakennusten henkilöliikennettä, erityisesti henkilöiden saapumisprosessia hissiauloihin, hisseillä tapahtuvan henkilöliikenteen estimointia sekä henkilöiden käyttäytymistä ja päätöksentekoa rakennuksen evakuoinnissa. Saapumisprosessia tutkitaan ottaen ensimmäistä kertaa huomioon, että henkilöt eivät aina saavu ja käytä hissiä yksin vaan isommissa joukoissa. Tulokset osoittavat, että yleinen olettamus yksittäisten saapumisten Poisson jakautuneisuudesta ei välttämättä päde, kun joukkosaapumisten osuus on suuri.

Rakennuksen henkilöliikenteen estimoimiseksi väitöskirjassa kehitetään matemaattisia malleja ja algoritmeja, jotka perustuvat lineaariseen optimointiin, pienimmän neliösumman kokonaislukuoptimointiin ja rajoiteoptimointiin. Numeeristen testien tulokset osoittavat, että menetelmät toteuttavat todellisen hissiohjauksen reaaliaikavaatimukset. Lisäksi satunnaistetut algoritmit tuottavat laadultaan parempia henkilöliikennetilastoja kuin perinteiset deterministiset algoritmit. Väitöskirjassa esitetään myös kokeellinen evakuointitutkimus, jonka tulokset osoittavat, että ihmiset eivät välttämättä kykene valitsemaan nopeinta poistumisreittiä ja että evakuoitavien pyrkimys yhteistyöhön voi hidastaa poistumista.

Väitöskirjassa kehitetyt henkilöliikenteen estimointimallit ja -algoritmit mahdollistavat hissien tehokkaamman ohjaamisen ja osa menetelmistä on jo tuotannossa KONE Oyj:ssä. Väitöskirjassa esitetyt tulokset myös lisäävät ymmärrystä henkilöiden saapumisprosessista hissiauloihin ja käyttäytymisestä evakuointitilanteissa, ja niitä voidaan hyödyntää rakennusten hissi- ja turvallisuussuunnittelussa.

Avainsanat henkilöliikenne, rakennus, evakuointi, kokeellinen tutkimus, käyttäytyminen, hissi, saapumisprosessi, lähtö-kohdekerrosmatriisi, estimointi, kokonaislukuoptimointi

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[II] Kuusinen, J-M., J. Sorsa, M-L. Siikonen, H. Ehtamo. 2012. A study on the arrival process of lift passengers in a multi-storey office building. *Building Services Engineering Research & Technology* **33**(4) 437–449.

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[V] Kuusinen, J-M., A. Malapert. 2014. The effect of randomization on constraint based estimation of elevator trip origin-destination matrices. *Proceedings of the 4th Symposium on Lift and Escalator Technologies, Northampton*, 115–126.

Author's contribution

Publication [I]: The paper was initiated by Heliövaara and primarily jointly written by Heliövaara and Kuusinen.
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Publication [V]: The paper was jointly initiated and written by Kuusinen and Malapert.

Preface

I want to express my gratitude to several people who have made this dissertation possible.

First, I want to thank my supervisor, Professor Harri Ehtamo, who initially took me into his research group in the Systems Analysis Laboratory, and until the end of my doctoral studies and this dissertation, has been there for me for any scientific guidance and support. Then, I want to thank Dr. Simo Heliövaara and Dr. Timo Korhonen for the fruitful collaboration in the beginning of my research career. I am also grateful to the head of the laboratory, Professor Raimo Hämäläinen, for creating an encouraging working atmosphere, not forgetting all the other people in the laboratory with who it was always a pleasure to socialize between the long hours of work.

At KONE Corporation, I have had the privilege to work in a team of highly skilled people. I owe a special thanks to my advisor, Dr. Marja-Liisa Siikonen, and Mr. Janne Sorsa who have greatly contributed to this dissertation, and whose guidance and expertise in the field of the dissertation have made it possible for me to accomplish it. I want to also thank my colleagues, Mr. Mirko Ruokokoski, Mr. Henri Hakonen and Mr. Tuomas Susi, who have devoted their time to help me with any problems related to my work and research. It has been a great pleasure to work with all of you at KONE, and I look forward to the mutual challenges and achievements that the future may bring to us.

A special thanks goes to one of my co-authors, Professor Arnaud Malapert, whose interest in my research has broaden my understanding about some of the topics handled in this dissertation, and with who it has been very inspiring to discuss and develop new ideas. I also wish to thank the preliminary examiners, Professor Clas Rydergren and Professor Richard D. Peters, for their valuable comments, which helped me to improve the dissertation at the last minute.

Finally, I want to thank my family, my parents Jorma and Kirsti-Liisa, and my brother Antti who have always given me their support both in everyday and academic life. My last words go to my wife Heidi. Thanks to your love and support, it has been easy to concentrate and finish this work.

Helsinki, March 2015

Juha-Matti Kuusinen

Contents

1 Introduction

1.1 Background

It has been estimated that currently about 54% of the worlds population is urban and that by 2050 this number will be about 66% (Populations Division, Department of Economic and Social Affairs, United Nations 2014). It can be expected that many of these people will be living and working in multi-storey buildings, where people move mainly using elevators. The value of a building is thus largely dependent on the performance of the elevators. For example, the occupants of a building easily start to complain if they have to wait for the elevators too often too long.

In modern multi-storey buildings, elevators are typically combined into groups and the elevators in the same group are controlled by the same group control unit. The task of the group control is to dispatch the elevators to passengers' pickup requests, e.g., up and down calls. Modern group controls use advanced mathematical methods to dispatch the elevators to the requests (Tyni and Ylinen 2001, Koehler and Ottiger 2002, Utgoff and Connell 2012). The best elevator is typically selected by minimizing passenger waiting or journey time, or both. It is, however, a difficult task to select the best elevator for each request. This is because a change in the traffic conditions, e.g., a new request, may require a change to the previous dispatching decisions if they are no longer optimal. Forecasts of future passengers help to avoid bad dispatching decisions and to improve passenger service level (Luh *et al.* 2008).

The forecasts should be based on measurements about the elevator passenger traffic, which can be defined by passenger journeys. A passenger journey is the journey of one passenger from an origin floor to a destination floor inside an elevator car. The problem is that without a dedicated system to identify every passenger, the passenger journeys cannot be directly measured. Although some passenger identification systems exists, they are not commonly used in elevator systems.

The passenger journeys can, however, be estimated by finding the passenger counts for the origin-destination (OD) pairs of every elevator trip occurring in a building. An elevator trip in an up or down direction starts at a stop where passengers board an empty elevator and ends at a stop where the elevator becomes empty again (Yoneda 2007). The OD pairs of the trip define the possible routes of the passengers, and these are determined by the passengers' delivery requests, e.g., calls given inside the elevator car.

An elevator trip can be mathematically defined as a directed network of nodes $N = \{1, 2, \ldots, m\}$, and arcs A defined by the OD pairs (i, j), $i, j \in N$. The nodes correspond to the stops made by the elevator and the arcs to the OD pairs. Figure 1 shows an elevator trip with five nodes, $m = 5$, and five OD pairs. In this case, the OD pairs are defined as follows. The passengers who board the elevator at the first node register delivery requests to nodes 3 and 4, which define the OD pairs $(1, 3)$ and $(1, 4)$. The passengers who board the elevator at the second node register a new delivery request to node 5, which defines the OD pair $(2, 5)$. Furthermore, the passengers who board the elevator at the second node may be travelling also to nodes 3 and 4, which results in OD pairs $(2, 3)$ and $(2, 4)$. Let b_i and a_i denote the observed count of passengers who board and alight the elevator at node or stop i, respectively. They can be measured, e.g., with an electronic load-weighing device (Siikonen 1997). Finally, let X_{ij} be the unobserved number of passengers or the OD passenger count from the origin node i to the destination node j. The goal is to find the OD passenger count for every OD pair $(i, j) \in A$ of the trip, i.e., the elevator trip OD matrix, based on the measured counts.

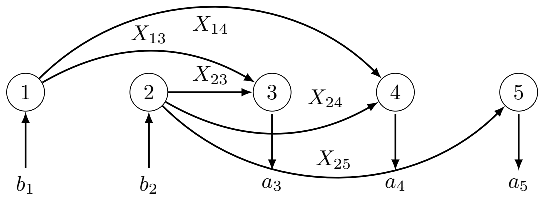


Figure 1: An elevator trip with five nodes and OD pairs.

The unobserved OD passenger counts are related to the measured boarding and alighting counts through the so called flow conservation constraints. These constraints simply require that the sum of the OD passenger counts out of or into a node is equal to the measured boarding or alighting count at the node, respectively. Hence, the flow conservation constraints can be mathematically defined as:

$$\begin{aligned} \sum_{j|(i,j)\in A} X_{ij} &= b_i \quad \forall i \in N, \\ \sum_{i|(i,j)\in A} X_{ij} &= a_j \quad \forall j \in N. \end{aligned} \tag{1}$$

In addition to the flow conservation constraints, the OD passenger counts must satisfy a set of other constraints. Since there cannot be partial passengers, the OD passenger counts must be positive integers, but actually more stringent lower bounds can be defined. For example, it is assumed that each delivery request corresponds to at least one passenger, which means that $X_{ij} \geq 1$ if a delivery request is registered from origin i to destination j. Since an OD passenger count is the sum of the passenger journeys from the origin to the destination, they provide an estimate of the elevator passenger traffic in a building.

Elevator systems in new buildings are planned based on theoretical calculations and often, especially in cases involving advanced group controls or unusual building configurations, simulation (Siikonen *et al.* 2001, Barney 2003). The results of the traffic calculations and simulations depend on the assumption of how passengers arrive at the elevator lobbies to register pickup requests. Hence, to be able to plan appropriately dimensioned elevator groups where, e.g., the number and size of the elevators is not too large or small, the simulated arrival process should match the real arrival process.

The traffic calculations and simulations are typically based on the assumption that passengers arrive at the elevator lobbies according to a Poisson process. In this process, passengers arrive individually with exponentially distributed inter-arrival times (Ross 1992). Alexandris (1977) found that this assumption holds in the real world during an up peak traffic period. During such a period, most people travel from the main elevator lobby or ground floor to the upper floors. For example, in office buildings, up peak occurs in the morning when people arrive at work.

The arrival process has not been studied since Alexandris (1977). Hence, the validity of the Poisson distributed arrivals has not been confirmed for other than up peak traffic. It can, however, be assumed that the process does not remain the same throughout the day. For example, during lunch hour, people move often in batches rather than alone. Since lunch peak is one of the most demanding traffic periods in an office building, it is important to accurately model the arrival process also during this period.

In addition to the possibility for smooth elevator traffic, the quality of a building depends on safety, especially safe evacuation in emergency situations. Evacuation calculations and building safety designs are typically based on computational evacuation models where internal algorithms are used to simulate human behaviour (Kuligowski *et al.* 2010, Heliövaara 2014). Naturally, the results of the simulations and adequate safety design largely depend on how well the algorithms describe human behaviour in reality. Although the outcome of an evacuation is a combination of many things, false assumptions of how people actually behave during emergencies may result in bad safety designs and in the worst case, lives will be lost in actual disasters.

A natural goal for the people in an evacuation situation is to get out of danger fast. This, however, may cause problems because in a large crowd, hurrying people often push forward which, because of increased pressure and friction forces between the evacuees, causes congestion in front of the exits (Helbing *et al.* 2000, Heliövaara *et al.* 2013). One unfortunate example of this effect is the fire at The Station nightclub in Rhodes Island, USA, in 2001, where 100 people were killed and 230 injured (Grosshandler *et al.* 2005). In addition, hurrying people may not be able to make optimal decisions which may result in slower evacuation.

One important decision evacuees' usually face is what exit to use. There are a few previous experiments on evacuees' exit selection behaviour (Muir and Cobbett 1995, McLean *et al.* 1996, Drury *et al.* 2009, Was 2010, Galea *et al.* 2011). These experiments, however, were not designed to study the evacuees' ability to select the fastest exit route. One reason is that the geometries in the experiments were such that the fastest route was trivial for the majority of the participants and no real decision making was required.

1.2 Objectives

The two research questions that Publication [I] aims to answer are: Are people able to select the fastest exit route in an evacuation situation? Which one of the two behavioural objectives, cooperative or selfish, results in faster evacuation?

Publication [II] studies the passenger arrival process by taking into account the fact that elevators serve passengers in batches that are often based on a social connection, e.g., colleagues or a family. The first objective is to study the size of the batches, and the second whether the individual and batch arrivals can be modelled as a Poisson process during the morning up peak and lunch peak periods.

A major part and objective of this dissertation is to solve the elevator trip OD matrix estimation problem. The motivation is to construct passenger traffic statistics that can be used to forecast and model future passengers. Publications [III]–[V] present new mathematical models and algorithms to solve the problem.

1.3 Research methods and dissertation structure

Evacuation experiments

The results of Publication [I] are based on two experiments which took place at the Aalto University School of Science and Technology at Espoo, Finland, on 2 and 24 March 2010. The experiments were organized in a corridor with a lobby at one end and with two exits to a classroom at the other. One of the exits was closer to the participants' starting positions than the other, as shown in Figure 2. In order to select the fastest exit route in this geometry, one has to consider the distances to the exits as well as the queues in front of the exits. Hence, the selection of the fastest exit route was not trivial, which might be the case in a symmetric setting. Such an asymmetric setup is also interesting for the validation and testing of evacuation simulation models. Most models perform well in simple symmetric geometries but realistic simulations in the described setting require more sophisticated exit selection algorithms.

Figure 2: A snapshot of a trial of one of the experiments presented in Publication [I].

The first experiment consisted of six and the second of 10 trials. The trials were recorded with five digital video cameras. For each participant and trial, the video recordings were used to define the time from a whistle, indicating the start of a trial, to the moment of entering the classroom. To find out how cooperative or selfish behaviour affects the evacuation outcome, the instructions given to the participants were altered between the trials of the experiments. The objective of the participants was either to minimize their individual evacuation times, i.e., to act selfishly, or the evacuation time of the whole group, i.e., to cooperate.

To isolate the effects of interest, the following experimental measures were applied. To avoid any bias due to individual characteristics and to prevent learning, the starting positions were randomly assigned to the participants before each trial. The selfish trials were carried out before the cooperative trials since the randomization of the order of the objectives might have confused the participants about the objective in question. In addition, the participants of the experiments were healthy male and female undergraduate students, and thus, formed a homogeneous group which eliminates variability of the outcome variable, i.e., evacuation time, due to individual differences.

A case study on the arrival process of elevator passengers

The results of Publication [II] are based on a case study that was carried out in Finland in a 16-storey high office building with two entrance floors and a group of four elevators. The data consists of digital video recordings and the elevator monitoring system (EMS) data. The EMS records data from each elevator stop including time stamps of the stopping elevator state, e.g., stop time, number of passenger boarding and alighting the elevator, and requests registered by the passengers.

The video recordings were used to determine the arrival times of the passengers at the entrance floor elevator lobbies during the morning up peak and lunch peak periods. A single camera was placed on each of the two entrance floors, as shown in Figure 3. Since the passengers seemed to completely ignore the cameras, they did not disturb passenger movement and cause any bias to the data. This may not be the case with observers who may disturb the passengers and skew the results (Robertson *et al.* 1976, Alexandris 1977).

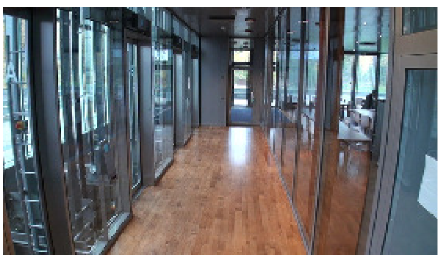


Figure 3: A snapshot of the video recordings of Publication [II] showing the first floor elevator lobby and the position of the camera.

Together with the video recordings, the EMS data was used to determine the batches in which the passengers arrived at the elevator lobbies. This requires the definition of a batch. In Publication [II], a batch was defined to consist of passengers who satisfy all of the following rules:

1. arrive at the elevator lobby at the same time;

2. arrive at the elevator lobby through the same door or from the same direction;
3. enter the same elevator;
4. travel to the same destination.

Rules 1 and 2 are related to the actual arrival process, and rules 3 and 4 specify sub-processes based on social relationships. The sub-processes are the ones that the elevators are actually serving, and thus, they have a great impact on the elevator performance. More specifically, the more there are batches, the less there are passengers with different destinations, which results in fewer stops and faster service. The arrival time of a batch was defined as the arrival time of the first passenger belonging to the batch. The observations were divided into 15-minute intervals to guarantee a sufficient number of observations for each interval.

Estimation of elevator passenger traffic

One issue in finding an OD matrix that satisfies the flow conservation and lower bound constraints is that it may not be unique, i.e., there may be more than one OD matrix satisfying the constraints. Nevertheless, these OD matrices can be found by minimizing a linear objective function with respect to the constraints. This results in the Linear Programming (LP) formulation presented in Publication [IV].

Another issue is that an OD matrix satisfying the flow conservation and lower bound constraints may not exist at all, i.e., the problem may be inconsistent. This is because of possible measuring errors in the boarding and alighting counts and the integer constraints. The Box-Constrained Integer Least Squares (BILS) and the Constraint Programming (CP) formulation (see, e.g., Chang and Han 2008 and Rossi *et al.* 2006) presented in Publications [III] and [V], respectively, extend the LP formulation to inconsistent problems. They both minimize a least squares objective function with respect to the lower bound and integer constraints. The CP formulation is, however, based on different assumptions than the LP and the BILS formulation. Since there cannot be partial passengers, the elevator trip OD matrix estimation problem is an integer programming problem. A solution to an integer programming problem can be found, e.g., with a branch and bound algorithm which is the standard method to solve such problems (Bertsimas and Tsitsiklis 1997, Li and Sun 2006). The algorithms presented in Publications [III]–[V] are based on this method.

For implementing an estimation algorithm in a real elevator group control application, the algorithm must be fast to reduce CPU load, and to have the most recent information about the passenger traffic all the time. Another criterion for the algorithm is quality of the estimation results. The better the quality of the results, the more reliable the information about the future passengers based on them. To study the performance of the algorithms with respect to these criteria, they were used to estimate the OD matrices of elevator trips obtained from simulated data. The simulations were run using the Building Traffic Simulator (BTS) which includes a real elevator group control and accurate models for elevator dynamics (Siikonen *et al.* 2001). One advantage of simulation compared to collecting data from a real elevator system is that it is fast, e.g., the simulation of a whole day's traffic takes typically only a couple of minutes. Another advantage is that, in simulation, traffic, elevator and building parameters can easily be changed. Hence, large amounts of appropriate test data can easily be obtained.

Dissertation structure

The rest of this dissertation overview is organized as follows. Sections 2 and 3 discuss the theoretical foundation related to pedestrian exit selection behaviour and elevator passenger traffic modelling, respectively, and present the key contributions or results of this dissertation related to the topics. Section 4 summarizes the implications of the results and suggests future research directions.

2 Exit selection behaviour in evacuations

2.1 Theoretical foundation

When evacuating a building, people are typically part of a large crowd moving towards the exits. A typical goal of everyone in the crowd is to reach an exit as fast as possible. People may, however, be unable to select the fastest exit route. It has been observed, e.g., that people tend to prefer familiar exit routes even if faster emergency routes were available (Proulx 2001). Another observed phenomenon in real crowds, which also affects pedestrian exit selection, is herding where people tend to follow each other (Helbing *et al.* 2002).

Pedestrian exit selection is an important part of agent-based evacuation simulation models where the preferred exit is often selected based on a rule or a more advanced algorithm. The agents may, e.g., select the nearest exit or observe the situation and make optimal decisions (Gwynne *et al.* 1999, Ehtamo *et al.* 2010). It is, however, questionable whether people in a threatening situation are able to make optimal decisions. For example, the information available and the time to process it may be limited. Although people in an emergency situation are typically in a hurry, panic is unlikely to occur in large crowds (Proulx 2001, Cocking *et al.* 2009). In addition, people often attempt to move towards familiar people, and try to evacuate within this group rather than as individuals, i.e., they tend to cooperate rather than act selfishly (Cocking *et al.* 2009).

In their evacuation experiments conducted in an aircraft, Muir and Cobbett (1995) found that cooperative behaviour results in faster egress than selfish behaviour, while the results of McLean *et al.* (1996) suggest the contrary. These results, however, are not fully comparable because of different incentive systems used to encourage the participants to stronger devotion. In the experiments of Muir and Cobbett (1995), selfish behaviour was produced by offering a monetary reward for the participants who evacuated the aircraft cabin among the first 75%. Hence, the participants who were clearly among the first 75% did not have a reason to hurry. On the other hand, because of the reward, the other participants probably concentrated on competing with each other rather than on getting out of the cabin fast. Cooperative behaviour was produced by giving a monetary reward to all participants, if the whole group evacuated the cabin within a given time limit. Hence, under the cooperative evacuation, the participants truly concentrated on getting out fast.

In the experiment of McLean *et al.* (1996), selfish behaviour was produced by giving monetary rewards to those participants who evacuated among the first 25% when averaged over all the five trials where the initial seating orders were rotated. Cooperative trials did not include any rewards. Hence, the participants had an incentive to hurry only during the selfish trials.

2.2 Results

Selecting the fastest exit route

In Publication [I], the ability to select the fastest exit route was studied based on the exit specific queue clearance time, which, for a given exit, was defined as the time from the whistle to the moment when the last participant who used that exit entered the classroom. A statistically significant difference between the queue clearance times of the two exits suggests that the participants may not have been able to select the fastest exit. To test the statistical significance, the sign test was applied (Siegel 1956). This test was selected since the sample size was small and the sign test does not involve any distributional assumptions. The only assumption underlying the test is that the outcome variable is continuous, which is the case with the evacuation time.

Based on the results, the queue clearance time was statistically significantly shorter for the exit that was closer to the participants' starting positions. This result implies that many participants ended up selecting the further exit even if they would have evacuated faster through the nearer one. As the objective was to evacuate as fast as possible, the result suggests that the participants systematically made suboptimal decisions to head to the exit through which the egress was slower.

There are at least two explanations for this outcome. First, the participants may have falsely estimated that the evacuation time through the further exit was shorter than through the nearer one. This is possible because when estimating the queue lengths, one should consider both the people in the queues as well as the ones still moving to join the queues. This explanation is also supported by the results of a questionnaire filled in by the participants after the experiments. Based on the answers, the most common criterion for exit selection was the shorter queue. Hence, the participants tried to select the shorter queue, but the experimental results show that they had a bias of favoring the further exit.

Second, the setting of the experiment was such that the participants who started from the back of the group arrived to the queue in front of the nearer exit and faced the decision whether to join that queue or to keep moving to the further exit. The fact that these participants decided to move even if the queue at the nearer exit was shorter might be explained by the idea that people in a hurry tend to prefer moving instead of standing still and queuing. This possible explanation is based on the authors' intuition and does not have any support in the existing literature.

Cooperative versus selfish evacuation

The effect of evacuation objective was studied based on the total evacuation time which was defined as the time from the whistle to the moment when the last participant entered the classroom using either of the two exits. To test whether the evacuation objective has a statistically significant effect on the evacuation outcome, i.e., the total evacuation time, the analysis of variance with blocking was applied (Montgomery 1997). Blocking is a method where the variability caused by any external nuisance factor is removed from the data so that the experimental error will consist only of the random error. Blocking was necessary since the test was based on the observations from the two experiments which were run on different days with a different number of participants. The results suggest that the total evacuation time was significantly shorter, i.e., evacuation was significantly faster when the participants were instructed to act selfishly.

Even if the result may seem somewhat surprising, an explanation was found from the video recordings. When the participants were acting cooperatively, they were careful not to push or even touch each other and overtaking was uncommon. Under the selfish objective, the participants were able to pass through the exits more efficiently and even overtake slower predecessors. If faster individuals do not overtake slower ones, the whole crowd ends up moving at the speed of the slowest individuals. Proulx (1995) identified this as a characteristic typical for a people forming a group. Hence, the cooperative objective made the participant behave as if they were part of a large group.

Also McLean *et al.* (1996) found that evacuation is faster under selfish than under cooperative behavioural objective, while Muir and Cobbett (1995) found the opposite. The different results can be largely explained by the different incentive systems in the two experiments. The experiments presented in Publication [I] did not include any incentives. This is because, in order to compare the evacuation times of selfish and cooperative behaviour and to draw any causal conclusions about the possible differences, it is enough or actually necessary that the devotion is at the same level under both objectives. In addition, in a real emergency, the people involved are not competing with each other but try to save themselves from the situation before getting in mortal danger. In this sense, the behaviour of the participants in the experiments of Publication [I] corresponds better to the behaviour of people in actual emergencies.

3 Modelling of elevator passenger traffic

3.1 Theoretical foundation

In the elevator group control, measurements about the passenger traffic are usually stored in statistics using a given time interval. A typical interval length is at least 5 and at most 15 minutes (Strakosch 1983, Leppälä 1991). With shorter than 5-minute intervals, the dynamics of the passenger and elevator traffic start to disturb the statistics, or result in noisy data. On the other hand, during a peak traffic period, a 15-minute interval may result in statistics that do not accurately describe the changes in the traffic.

Typically once a day, the statistics of the current day are combined with the long-term statistics that store the traffic data for each day in a cycle. A typical cycle is one week. To learn the passenger traffic and to adapt to possible changes in the population of the building, the combination of the current day and the long-term statistics can be done using, e.g., exponential smoothing (Siikonen 1997). The long-term statistics can also be used to estimate a forecasting model that tries to capture the dynamics of the traffic and to forecast the future based on recent observations in the short-term statistics. There are several learning and forecasting methods (e.g., Siikonen 1997, Powell *et al.* 2000, Huang *et al.* 2003, Xiang *et al.* 2005, Luo *et al.* 2005, Yan *et al.* 2006, Imrak and Özkirim 2006, Jianru *et al.* 2007).

To avoid bad dispatching decisions in constantly changing traffic conditions, the learned or forecast statistics are used to model future passengers. Basically, at the moment of making a dispatching decision, it should be known when and at which floors passengers will register new pickup requests, what the number of passengers is waiting behind these requests and the existing requests, and what their destinations are. The reason is that first, the number of passengers waiting behind a request is not in general known, which means that the elevator that is dispatched to serve the request may not have enough space for all the passengers behind the request. Second, in conventional control systems where passengers use up and down calls or a single push button in the elevator lobbies to register pickup requests, the destinations of the passengers are not known before they board the elevator and register the delivery requests to their destinations. Hence, at the moment of making a dispatching decision, it is not known where the elevator has to stop before all the passengers are served, i.e., what the route of the elevator is. The route defines the serving time of other existing requests and passengers. In destination control systems this problem is avoided since in such a system passengers register their destinations already in the elevator lobby using special call buttons. Finally, it is not known on which floors future passengers will register new pickup requests, what number of passengers is related to each request, and what their destinations are. All these future events may make the previously defined routes suboptimal with respect to the passenger service level. The problem of how to model future passengers based on the traffic statistics is discussed, e.g., in Siikonen (1997) and Utgoff and Connell (2012). The problem of how to utilize the information about the future passengers in the elevator group control is addressed, e.g., in Siikonen (1997), Luh *et al.* (2008) and Utgoff and Connell (2012).

The statistics are typically based on direct measurements about the passenger traffic, e.g., boarding and alighting counts and passengers' requests (Siikonen and Kaakinen 1993, Siikonen 1997, Utgoff and Connell 2012). The statistics should, however, be based on complete information about the traffic, i.e., on passenger journeys. For example, the number of passengers waiting behind a pickup request to a given destination can be accurately modelled only if the statistics contain the passenger journeys from the origin to the destination. The problem is that the passenger journeys cannot be directly measured. They can, however, be estimated by finding the OD matrix for each elevator trip occurring in a building.

An elevator trip is analogous to a single transit route such as a bus line, where there is only one route connecting any OD pair, and usually counts on the boarding and alighting passengers are collected on all stops on the route (Nguyen 1984). A single transit route is typically defined in advance and remains unchanged for long periods of time. This means that it is possible to collect many counts on the same route during a given time period, e.g., a rush hour, and use these observations to estimate average passenger counts for the OD pairs of the route. A typical objective is to estimate an OD matrix that minimizes the distance to a target OD matrix with respect to a suitable distance measure (Tsygalnitsky 1977, van Zuylen and Willumsen 1980, Nguyen 1984, Ben-Akiva *et al.* 1985). The target OD matrix is usually based on historical data or a survey. When the boarding and alighting counts are not consistent, i.e., the sum of the measured boarding counts is not equal to the sum of the measured alighting counts, the unobserved OD matrix is required to minimize the distance between the predicted and measured counts, and usually also the distance to the target OD matrix (Maher 1983, Cascetta and Nguyen 1988, Bell 1991). The predicted boarding or alighting count at a node is the sum of the unobserved OD passenger counts out of or into the node, respectively.

Whereas a single transit route is defined in advance, an elevator trip is request driven, which means that there may not be two similar trips even within a day. In addition, every elevator trip has its own set of OD pairs, and boarding and alighting counts, i.e., the elevator trips are independent. This is why the OD matrix should be estimated separately for each elevator trip. In addition, especially in new buildings, the estimation must be based only on the measured counts since there is no target OD matrix available. For these reasons, the methods for a single transit route are not well suited for the elevator trip OD matrix estimation problem.

In general, when a problem is being solved, it is enough to find a single solution efficiently, and often algorithms are designed to meet this goal. An elevator trip OD matrix estimation problem may, however, have many optimal solutions and it is impossible to say which one of the optimal OD matrices corresponds to what happened in reality. The first solution found by an algorithm depends on the characteristics of the algorithm. For example, a branch and bound algorithm can be implemented with several different branching rules (Bertsimas and Tsitsiklis 1997, Li and Sun 2006). If the short-term statistics were constructed based on the first solution to each problem instance, then the long-term statistics would be biased towards the characteristics of the algorithm. Such statistics poorly describe the possible realizations of the passenger traffic, and thus, are not a good basis for passenger traffic modelling and forecasting. One way to overcome this issue is to find multiple solutions and select the final solution, e.g., randomly or as the average of the found solutions. In the long term, these strategies result in statistics that model better the possible realizations of the passenger traffic. This naturally requires that most of the solutions are found to each problem instance, which means that the algorithm must be fast.

One might wonder the necessity of the integer constraint in the elevator trip OD matrix estimation problem since in most other applications, such as a bus line, this constraint is relaxed. The main reason is that computing a continuous solution to each problem instance directly may also result in biased traffic statistics, as shown by the following example. Recall that a solution to a problem instance consists of the OD passenger counts for all OD pairs of the instance, and an OD passenger count is the number of passengers from the origin to the destination. Figure 4 shows the distribution of the integer solutions for an OD pair of one of the inconsistent example problem instances presented in Publication [III]. It also shows a continuous solution, which is not unique, and the average of the integer solutions. Clearly, the continuous solution is unlikely for the OD pair.

An important improvement provided by the statistics based on the elevator trip OD matrices is related to the modelling of the number of passengers behind a pickup request. A typical approach is to multiply the time the request has been on with the total passenger arrival rate to the direction of the request obtained from the statistics (Siikonen 1997). The longer the request remains unserved, the larger the estimated number of passengers behind it. In continuous allocation, where the pickup requests are typically reallocated periodically, e.g., twice a second, the above modelling approach works since if the elevator that is currently allocated to a given request does not have enough space for all estimated passengers behind the request, the elevator can be changed in the next allocation round. In immediate allocation, which is typically used in destination control systems, an elevator is allocated to a new pickup request immediately when the request is given, and the allocation decision cannot be changed. This means that the above approach fails because the time a request exists is zero, and thus, the estimate about the number of passengers is always zero, or one if at least one passenger per request is assumed. With the new statistics this problem is avoided since the number of passengers behind a pickup request to a given destination or direction can be estimated from the distribution of the OD passenger counts using a statistic,

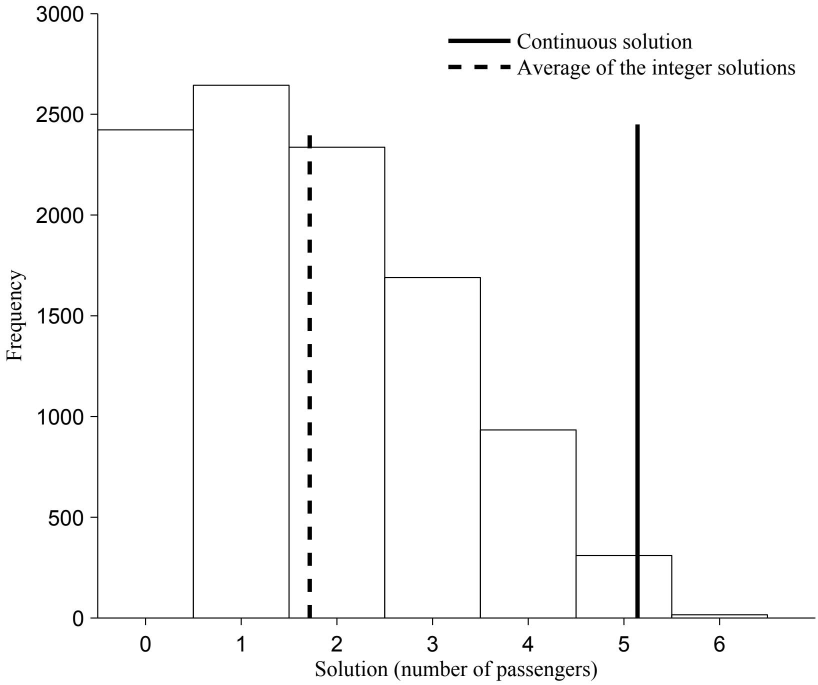


Figure 4: Distribution of the integer solutions, their average and a continuous solution for an OD pair of one of the inconsistent example problem instances presented in Publication [III].

e.g., average, of the distribution. Note that this distribution is not the same as shown in Figure 4 but the combination of such distributions.

There exists one approach to solve the elevator trip OD matrix estimation problem, but it has a different motivation than to construct passenger traffic statistics, namely, trace driven simulation (Yoneda 2007). In such a simulation, the passenger arrivals are based on the estimated elevator trip OD matrices instead of, e.g., the Poisson process. The disadvantage of this approach is that it may result in biased traffic statistics. The reason is that the approach finds only a single solution which is optimal with respect to a predefined criterion, e.g., the OD matrix is required to produce predicted boarding and alighting counts such that their totals are equal to the minimum of the totals of the measured boarding and alighting counts. The criterion can be changed but it is practically impossible to decide which criterion will result in statistics of best quality.

Elevators are typically planned using simulation but also traditional theoretical calculations are still used. The driving force behind the calculations and simulations as well as real elevators is the passenger arrival process which defines when and at which floors passengers arrive to register pickup requests, and what their destinations are. The theoretical calculations are based on queuing theory, and they can be used to study the performance of conventional elevator groups in up peak traffic conditions (Roschier and Kaakinen 1979, Peters 1990, Barney 2003, Al-Sharif 2010, Al-Sharif *et al.* 2014). Other traffic situations and elevator systems based on destination control require simulation.

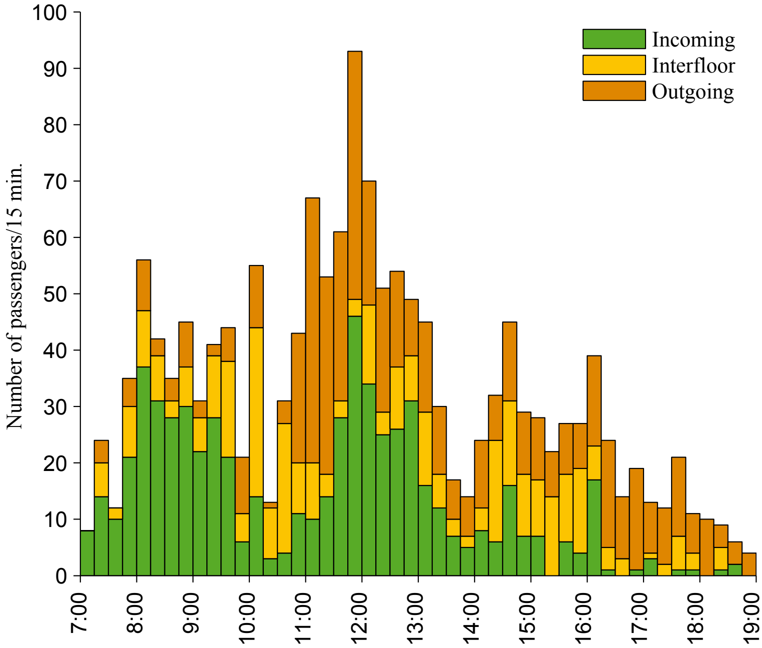


Figure 5: Daily traffic profile of a multi-tenant office building.

In a traffic simulation, the origin and destination floors are typically defined according to the assumed population distribution of the simulated building, and the proportions of three traffic components, namely, incoming, outgoing and inter-floor traffic (Siikonen *et al.* 2001). Incoming traffic consists of passengers travelling from the entrance floors to the upper floors, outgoing traffic of passengers travelling from the upper floors to the entrance floors, and inter-floor traffic of passengers travelling between the upper floors. The global arrival rate defines the number of passengers simulated during a given time interval. Figure 5 shows a typical traffic profile of a multi-tenant office building. The traffic of a given time interval is defined by the traffic component proportions and the global arrival rate. In the figure, a lunch peak period can be seen approximately between 11:00 and 13:00.

The passenger arrivals in the elevator lobbies are typically assumed to follow a Poisson distribution (Ross 1992). The assumption was confirmed by Alexandris (1977) who, by using observers, counted the individual passengers arriving on the main entrance floors of three tall buildings during the morning up peak period. Some other studies on the passenger arrival patterns in multi-storey office buildings cover, e.g., passenger arrival rates and waiting times but not the arrival process exactly (Carter and Whitehead 1976, Robertson *et al.* 1976, Green and Smith 1977, Peters *et al.* 1996, Siikonen *et al.* 2014).

3.2 Results

Arrival process of elevator passengers

The results on the batch size show that, in the studied office building, the size depends on the time of day. The batches are smaller during the morning up peak than during the lunch peak period. The reason is that during lunch hour, people go to and return from lunch together while in the morning they often arrive at work alone.

To find out whether the individual and batch arrivals can be modelled with a Poisson process, a test developed by Brown *et al.* (2005) was applied. This test was selected since the arrival rates of both the individual and the batch arrivals varied from interval to interval, which indicates that the two processes are time-inhomogeneous. The more common chi-square goodness of fit test for the Poisson distribution assumes a constant arrival rate, and thus, could not be applied.

The results suggest that the batch arrivals can be modelled as a time-inhomogeneous Poisson process with piece-wise constant arrival rates during both the morning up peak and the lunch peak period, whereas for the individual arrivals this process applies only when the proportion of batch arrivals is small, namely, during the morning up peak.

Estimation of elevator trip origin-destination matrices

Publication [IV] formulates the elevator trip OD matrix estimation problem as a network flow problem which is a Linear Programming (LP) problem (Bertsimas and Tsitsiklis 1997). The disadvantage of this approach is that it gives good estimation results only when the problem is consistent, i.e., it is possible to find an integer OD matrix such that the flow conservation and lower bound constraints are satisfied.

The problem of the LP formulation with inconsistent problems is that it may result in an OD matrix that produces small deviations between most of the predicted and measured counts, but accepts large deviations for some counts. It is, however, reasonable to assume that in a real application the goal is to measure the boarding and alighting counts as accurately as possible. Hence, it can be assumed that the measured counts are close to the true counts, i.e., possible measuring errors are small. A good solution, i.e., an OD matrix would then be such that the difference between each predicted and measured count on the elevator trip is small. Such solutions can be obtained by minimizing the squared deviation between each predicted and measured boarding and alighting count.

The Box-Constrained Integer Least Squares (BILS) and the Constraint Programming (CP) formulation presented in Publications [III] and [V] are based on this approach. The BILS formulation also includes upper bounds for the OD passenger counts, hence the name of the method. Even if the objective function in the BILS and the CP formulation is the same, they may not result in the same solution. The reason is that they are based on different assumptions. The CP formulation is based on the assumption that passengers do not give false requests, i.e., it is assumed that the elevator does not make unnecessary stops where passengers neither board or alight the elevator. The disadvantage of this assumption is that sometimes passengers give false requests and the elevator makes unnecessary stops that should not be included in the formulation. To take such unexpected passenger behaviour into account, the BILS and the LP formulation use the measured boarding and alighting counts in the formulation. It is assumed that a node is an origin (resp. destination) node only if the measured boarding (resp. alighting) count is larger than zero. The disadvantage here is that a stop will not be included in the formulation at all if the measured boarding and alighting count at the stop are both zero. The validity of either of the modelling approaches depends on the situation, and other issues related to unexpected passenger behaviour may make them both invalid. Such issues are, however, difficult to take into account in practice. In addition, other problem formulations certainly exist, but it is difficult to come up with a one that would, independent of the situation, describe the reality better than those presented in this dissertation.

Publication [IV] presents a new branch and bound algorithm to find all solutions to the LP formulation. The new algorithm resembles the second phase of the one-tree algorithm presented in Danna *et al.* (2007), which can be used to find multiple solutions to a mixed integer programming problem. The new algorithm exploits the properties of the LP formulation for the elevator trip OD matrix estimation problem. For example, the algorithm can be used only when the solutions are integer valued. Hence, the new algorithm is somewhat simpler than the one presented in Danna *et al.* (2007).

Publication [III] presents two new algorithms to find all solutions to the BILS formulation. The first one can be used only when the number of OD pairs is smaller than the number of measured boarding and alighting counts, and the second otherwise. The first algorithm is based on the algorithm developed by Chang and Han (2008) and the second on the algorithm developed by Chang and Yang (2007b). These algorithms were selected based on literature and they are the most efficient ones among the BILS algorithms (Damen *et al.* 2000, 2003, Dayal and Varanasi 2003, Yang *et al.* 2005, Cui and Tellambura 2005, Chang and Yang 2006, 2007b,a, Chang and Han 2008, Yang 2008, Ku 2011). The algorithms are based on the branch and bound method and consist of two processes: reduction and search. The goal of the reduction process is to modify the search tree to make the typically more time consuming depth-first search process more efficient.

Publication [III] presents some important modifications to the original algorithms. First, the search processes were modified to find all instead of a single solution to a problem. Second, the bijective transformation proposed by Chang and Yang (2007b) was applied to the search process of the second algorithm to handle general lower and upper bounds, i.e., a general box-constraint. Third, the reduction process of the second algorithm was improved to make the search process for the elevator trip OD matrix estimation problem more efficient. Publication [III] also shows how a target OD matrix based on historical OD passenger counts can be taken into account in the estimation to obtain OD matrices that are historically more likely than the others.

Publication [V] studies the effect of randomization on the statistics constructed based on the elevator trip OD matrices. The motivation is that if only some optimal solutions to each problem instance can be computed within a real time limit, then, intuitively, a randomized search should result in better quality statistics for the reason that a deterministic search will always favor particular solutions. The presented CP formulation is a constraint optimization problem that can be solved with a branch and bound algorithm (Rossi *et al.* 2006). Publication [V] considers three deterministic, one partly randomized and one completely randomized algorithm to find a single or multiple optimal solutions to the formulation.

To compare the performance of the algorithms with respect to solving time, they were used to find all solutions to four example problems based on the simulations of Publication [III]. The results reported in Publications [III] and [IV] show that the BILS algorithms are faster than the LP algorithm. In addition, the disadvantage of the LP approach is that it is suitable only for consistent problems, but in practice some problems will be inconsistent.

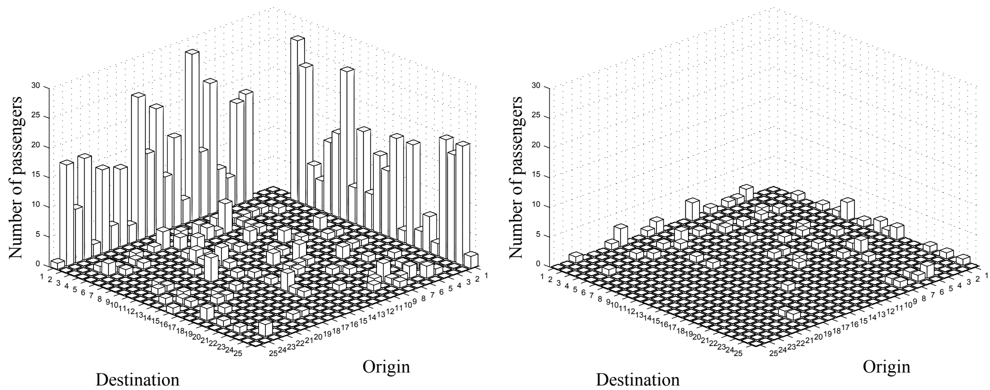
The results of Publications [III] and [V] suggest that the fastest deterministic CP algorithm is about as fast as the fastest BILS algorithm and even faster for very complex problem instances. The results from additional numerical experiments show also that the fastest BILS and CP algorithms fulfill real-time elevator group control requirements for solving elevator trip OD matrix estimation problems.

The results on the effect of randomization presented in Publication [V] suggest that randomization and multiple optimal solutions are a good compromise between solving time and quality. More specifically, the less time there is to find optimal solutions to each problem instance, the more preferable with respect to quality is an algorithm where the search is at least partly randomized. A completely randomized algorithm is too slow.

To illustrate the usability of the proposed formulations and algorithms in practice, consider the lunch hour traffic simulations in a 25-storey office building presented in Publication [V]. The duration of one simulation was 15 minutes, which is a typical interval length in traffic statistics. The elevator group consisted of eight elevators and a conventional control system. The traffic intensity was 25% larger than the handling capacity (HC) of the elevator group. When the traffic intensity exceeds the HC, the elevators become often fully loaded and make many stops during one up or down trip. This increases the number of difficult elevator trip OD matrix estimation problem instances. In addition, to obtain more realistic data, possible measuring errors were included by removing one passenger from each boarding and alighting count with 10% probability. Measuring errors increase the number of inconsistent problem instances which are typically harder to solve and include more solutions. The more there are solutions, the more uncertain are the estimated passenger journeys or OD passenger counts.

Furthermore, a conventional control system that was used in the simulations is the worst with respect to the uncertainty of the OD passenger counts. This is because in such systems, the destinations are defined by the requests registered inside the elevator cars, and thus, the destinations of the passengers from a given origin include also the destinations of the passengers who are already inside the elevator. In destination control systems, the OD pairs are defined only by the requests registered at the origin floor elevator lobbies. Hence, in conventional control systems the number of OD pairs in the problem instances is typically larger than in destination control systems, and thus, the instances are typically more difficult to solve and the estimation results become more uncertain.

Figure 6(a) shows the actual building OD matrix constructed based on the data of one simulation. An element in this matrix corresponds to the true number of passengers from an origin to a destination. Figure 6(b) shows the absolute deviation per OD pair between the actual and the estimated building OD matrix. In this example, the estimated building OD matrix was constructed by finding as many solutions as possible to each of the 50 elevator trip OD matrix estimation problem instances in the simulated data, selecting one of the found solutions to each instance randomly and adding up these solutions. The problem instances were formulated and solved using the BILS approach. The execution time limit for a single problem instance was 0.5 seconds. In the few complex instances where no solutions were found within this time limit, a possibly suboptimal but feasible solution was obtained fast by rounding a continuous solution to the nearest integer. In this case, the continuous solution was readily available since its computation is part of the BILS approach.



(a) Actual building OD matrix.

(b) Absolute deviation per OD pair.

Figure 6: Actual building OD matrix and the absolute deviation per OD pair between the actual and the estimated building OD matrix of the worst case example.

It can be seen from Figure 6(b) that the deviations between the actual and the estimated building OD matrix are small. In this worst case example, the difference between the matrices over all the deviations is about 10%. Because, in practice, elevator groups are designed to have enough HC, the elevator trip OD matrix estimation problems occurring in reality are likely to be less complex, and thus, the estimated building OD matrix closer to the actual building OD matrix. In addition, when learning the passenger traffic in a real building, the estimated building OD matrices are combined with the long-term statistics, and thus, the deviations in the individual matrices are smoothed out. Hence, it seems that at least the BILS and the CP approach can be successfully applied in practice. Furthermore, it has not been possible to obtain this kind of detailed description about the passenger traffic in a building before.

4 Discussion

4.1 Theoretical and practical implications

The results of the experiments presented in Publication [I] give new insight into human behaviour in evacuation situations and especially into the evacuees' ability to select the fastest exit route. Based on the results, people may not be able to select the fastest exit route. In addition, it was found that selfish behaviour results in faster evacuation than cooperative behaviour. This is an interesting result since many studies on real emergencies show that people in an emergency do not panic, tend to cooperate and act altruistically (see, e.g., Proulx 2001 and Cocking *et al.* 2009). Even if it may not be reasonable that people in emergency could or even should be encouraged to act more selfishly to speed up the evacuation, the result might be useful for building safety design. For example, a building could have different evacuation routes for people who are not able to move as fast as others because of a physical handicap or another similar reason. This would probably also decrease congestion on a particular evacuation route. Easier overtaking could also be used as a criterion in designing the routes.

The results of Publication [I] can be used to validate computational simulation models. The limitation of the results is that they, as the results from any other experimental study, are dependent on the geometry of the experiment. Nevertheless, the geometry used in the experiments is not uncommon, and thus, there is no reason to assume that the observed phenomena would be unique only for this specific setting. The results may not be generalizable to larger crowds where evacuees' attempt to move faster can cause slower flow through a bottleneck and slow down the evacuation under the selfish objective (Helbing *et al.* 2000).

The case study presented in Publication [II] considers the passenger arrivals at the elevator lobbies in an office building during the morning up peak period, and for the first time, during the lunch peak period. These are the most intense and most important traffic periods in an office building. In addition, the study is the first to consider the arrival process by taking into account the fact that passengers do not always move alone but rather in batches due to, e.g., a social connection. Hence, the results from the study increase the understanding of the passenger arrival process during the most demanding traffic periods.

The results suggest that when the average batch size is clearly larger than one passenger, i.e., passengers do not arrive individually, the usual assumption that the individual arrivals follow a Poisson distribution may not hold. It has also later been shown that results from theoretical up peak calculations match the reality better, e.g., with respect to the number of elevator stops, if the up peak equations are based on passenger batches instead of individual passengers (Sorsa and Siikonen 2014).

The passenger arrival process strongly affects the estimated service level and the selection of the number of elevators in a building (Sorsa *et al.* 2013). Hence, it is important that the model for the passenger arrival process used in planning the elevators is as realistic as possible. The results presented in Publication [II] suggest that the passenger arrivals can be modelled with a process where the arrivals occur in batches with exponentially distributed inter-arrival times, i.e., the batch arrivals follow a Poisson distribution. Application of this process in practice requires a distribution for the batch size. Publication [II] presents such a distribution in an office building for the morning up peak and the lunch peak period.

The size of the batches in which people move is naturally dependent on the building. In other countries and cultures, and in other types of buildings, e.g., hotels, the batch behaviour might be different. However, it can be assumed that also in other office buildings the batch size will vary with the time of day, namely, the batches will be larger during lunch hour than during other periods. Hence, the results may be applicable also in other office buildings.

This dissertation introduces the elevator trip OD matrix estimation problem, and presents new mathematical formulations and algorithms to solve the problem. The elevator trip OD matrix estimation problem is important since it makes it possible to obtain complete information and statistics about the elevator passenger traffic. The statistics can be used to model future passengers which, when taken into account in the elevator group control, helps to improve passenger service level (Luh *et al.* 2008). Hence, the formulations and algorithms presented in Publications [III]–[V] are undoubtedly of interest to the elevator industry.

One practical limitation of the presented formulations is that they define NP-hard problems, which means that there is no polynomial time algorithm to solve them. However, the simulations presented in Publication [III] show that most of the problems occurring in reality are relatively simple and can be solved, which in this case means finding all solutions, within a reasonable time considering a real application. Another limitation is that the numerical experiments were run with laptop PCs and not with a real elevator group control computer which is typically an industrial PC. Hence, the results related to the execution time of the algorithms do not fully correspond to those that would be obtained in reality. Nevertheless, the execution times of the fastest algorithms were for most of the problems so short that even if the real computer was less powerful, the execution time should still remain reasonable.

The new approaches provide a basis for any further research related to the problem. In addition, the numerical experiments and results presented in the publications can be used to compare new formulations and algorithms to those developed in this dissertation. Some of the algorithms are described in such a detail that it should be relatively easy to implement them from scratch, e.g., in a real application. Furthermore, the work done in this dissertation helps to decide what kind of approach is applicable in practice. Since elevators form a particular transit system where passengers reveal their destinations by registering delivery requests, it may be difficult to apply the presented formulations and algorithms in other transportation systems.

4.2 Future research directions

This dissertation opens up several future research directions. First, experiments about pedestrian behaviour in evacuations are rare. The experiments presented in Publication [I] concentrate on evacuees' ability to select the fastest exit route under selfish and cooperative behavioural objectives. Since the results are at least partly dependent on the geometry of the experiment, similar experiments should be run in different interesting geometries. Then, it might be possible to draw more general conclusions about the exit selection behaviour. Additional experiments would also provide a more comprehensive data set for the validation and development of computational evacuation simulation models.

Second, Publication [II] presents distributions for the size of the batches in which people move and use elevators in an office building. Since the distributions depend on the building and its usage, they should be measured also in other locations and building types. Then, it might be possible to define general distributions for the batch size and include the batches in traffic simulations. This is important to get as realistic simulation results as possible especially for the lunch peak period when people typically move in batches.

Third, the methods presented in Publications [III]–[V] can be used to measure the elevator passenger traffic in a building. They are based on finding the OD matrix for each elevator trip occurring in the building. This opens up at least three interesting future research topics in elevator group control development. The first is how to model future passengers based on the elevator trip OD matrices, and the second, how to use this information in elevator dispatching. The third is to develop a forecasting method that captures long-term historical traffic trends and adapts to the most recent information about the traffic. Some approaches already exist but they are not based on the elevator trip OD matrices.

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