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Effects of mobile traffic information on pedestrian traffic efficiency at public transport stations

Abstract

At public transport stations, groups of waiting pedestrians usually form in front of variable message signs displaying public transport information; real time departure times and platforms, delays, etc. However, in recent years the emergence of mobile public transport information systems that provide the same information directly to the travelers mobile phones has started to change this; instead of stopping in front of a sign, a fraction of the population can access the information from their mobile phones, either while walking or standing still.

When designing a public transport station, accurate prediction of the pedestrian traffic within the station is necessary to ensure that the pedestrians can get to their platform efficiently and comfortably. Waiting groups of pedestrians may significantly decrease the traffic efficiency, i.e., delay passing pedestrians. However, pedestrians using their mobile phones while walking may also do so; observational data indicates that their walking speeds are significantly decreased.

To evaluate the pedestrian traffic effects of mobile public transport information systems, and investigate the effects in terms of traffic efficiency, a microscopic modeling approach has been used to simulate a part of Stockholm Central Station. The microscopic approach facilitates explicit modeling of the interactions between both the waiting and the mobile phone using pedestrians with the passing pedestrians.

Both local and global measures of the efficiency of the pedestrian traffic are presented for a range of scenarios, examining the effect of the penetration level of the mobile application.

Keywords and topics: Pedestrians, Microsimulation, ITS, Public Transport.

Research domain: Intelligent transport systems — ITS & Traffic

CONTENTS

1 INTRODUCTION

The main purpose of a public transport station is to enable efficient and comfortable access to and exit from public transport modes, and transfers between them. This purpose requires that the stations are compact, so that the walking distances, and thus the transfer times, between the public transport modes are minimized. However, a small sized station also causes higher densities of pedestrians, which increases the risk of congestion, which in turn causes delays and discomfort. Thus, an efficiently designed public transport station needs to compromise between minimizing the walking distances and minimizing delay and discomfort caused by congestion. This is a complex task since it involves predicting the movements of the pedestrians.

At a public transport station, the movements of the pedestrians depend on the information available to them regarding departure time and place of the public transport modes. This information is usually communicated to the pedestrians via variable message signs, displaying the departure times and places of the next few public transport modes. These signs are usually placed carefully, so that the maximum number of people can read them without deviating too much from their paths. However, this placement may cause the people stopping or slowing down in front of the information sign to negatively affect the efficiency and comfort of the passing pedestrian flow.

As a complement to the information signs, public transport operators and authorities have started to supply the information on the information signs also over the internet, making it accessible through smart phones. The availability of this mobile information will likely lead to that some people use their phones to obtain the information while walking, instead of reading the information signs. This will cause fewer people to stop or slow down in front of the information signs and the efficiency of the passing flow will increase. However, while using their phones, people will behave differently from the rest of the population, probably walk slower and maybe react less to surrounding traffic, so they will also affect the efficiency of the surrounding flow negatively.

The purpose of this study is to estimate the efficiency effects of the introduction of traffic information accessible through smart phones, for different levels of usage of this information, compared to the base scenario that everybody in need of information has to read it from information signs. This is useful for station operators or transport authorities to decide to what degree mobile traffic information should be promoted.

The purpose is achieved by simulating one of the most heavily trafficked pedestrian corridors in Sweden, the lower level of Stockholm Central Station, in which an information sign is placed. This base scenario is compared to scenarios where a fraction of the people stopping in front of the sign in the base scenario instead use their mobile phones to access the information while walking.

1.1 Method

Microsimulation is a suitable tool for the problem at hand since it is able to represent the heterogeneous population in an adequate way. This ability is critical since the phenomenon under evaluation consists solely of slight alterations of the behavior of a fraction of the population.

The Social force model (SFM), proposed by Helbing and Molnár (1995), is one of the most prominent microsimulation models for pedestrian traffic, having been investigated thoroughly in the literature; it has, for example, been calibrated by A. Johansson et al. (2007), A. Johansson (2009), Zanlungo et al. (2011), and Ma et al. (2010). The main idea of the model is to model all desires of the pedestrians by social forces; one force that drives the pedestrian toward its destination, one force that makes it avoid collisions with other pedestrians, etc. The theoretical foundation of the model was strengthened by Hoogendoorn (2001), who showed that it can be derived in a utility maximization framework from reasonable assumptions on the utility functions of the modeled pedestrians. The version of the model derived by Hoogendoorn (2001) was applied to investigate the placement of ticket vending machines by Daamen et al. (2009), a problem similar to that investigated in this paper. A multitude of versions of the SFM has been proposed, see e.g., F. Johansson (2013b) for an overview. The version of the model applied in this study, and its implementation, is described in detail by F. Johansson (2013a), and the waiting model extensions proposed and analyzed by F. Johansson et al. (2015).

To simulate the effects of the two different information sources, two models are clearly of special importance: the waiting model and the model describing people actively using mobile phones while walking. There are no calibrated and validated waiting models available in the literature. However, F. Johansson et al. (2015) proposed a set of three waiting models and provided estimates of the effects of choosing model and parameters. These models are not validated but are given some credibility by being the natural extension of the SFM to include waiting. The model applied in this study is the preferred position model, motivated by the observations described in section 2.3. The model assumes that each pedestrian chooses a preferred waiting position and strives to stay there. If another pedestrian passes by, the waiting pedestrian will react according to the standard SFM, and then return back to its preferred waiting position.

The phone user model is assumed to be covered by the same model as for regular walking pedestrians, but with another set of parameters, most prominently the preferred speed. The parameters of both regular and phone using pedestrians where obtained from calibrations using data extracted from video recordings at Stockholm Central Station, as described by Lagervall and Samuelsson (2014). This data is further described in section 2.

1.2 Simulated scenario

To test the effect of availability of mobile public transport information, the most trafficked pedestrian corridor in Sweden was chosen: the tunnel corridor connecting the subway with the long distance and commuter trains at Stockholm Central Station. As depicted in figure 1, the corridor contains an intersection with exits up to the entrance level of the station, and immediately after this intersection there is a public transport information sign. This results in pedestrians gathering in front of the sign, partially blocking the way for pedestrians on their way to the trains.

The exits a – d lead toward the subway, and the exits e – f toward the commuter trains and most of the inter city trains. There are doors at e and f that only opens in one direction, which results in left hand traffic in the main corridor. Both stairs g and h lead to the main waiting hall of the station.

All four corridors connected to the intersection are covered by automatic counters, as described in section 2, enabling a rudimentary OD estimation. However, the situation is complicated by the presence of a number of shops and restaurants within the area enclosed by counters. In this study we will focus on the morning rush hour, and the fraction of the population that visit the shops during this hour is assumed to be negligible.

A number of scenarios was simulated, all with the same geometry and the same OD matrix, and the same fraction of the population in need of the traffic information, but different fractions of these using the phone to obtain the information. These scenarios are summarized in table 2.

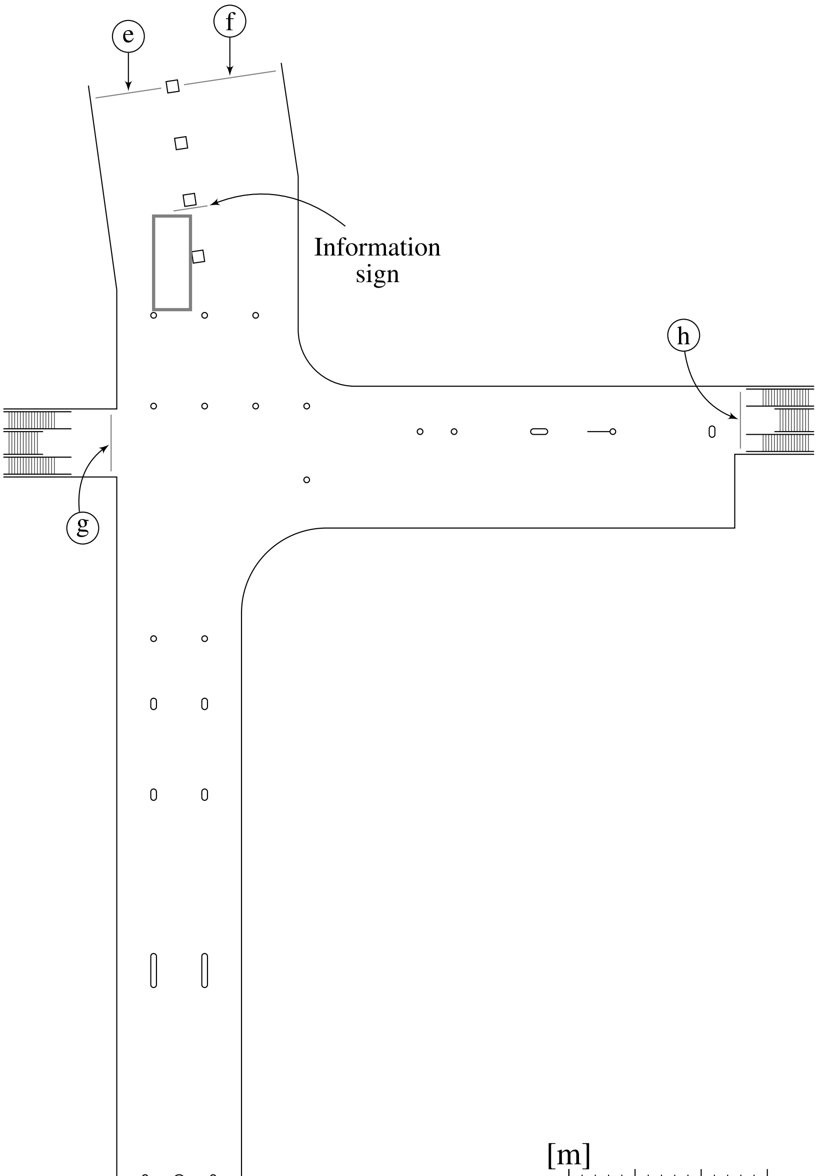

Figure 1: The geometry of the simulated scenario.

2 EMPIRICS

Three sets of empirical data was used in this study: a set of trajectory data used for calibration, a set of observations of waiting behavior in front of an information sign, and one set of flow data collected in all the entrances and exits from the investigated area. These sets are described in the following subsections.

2.1 Flow data

Jernhusen, the state-owned company that owns, develops and manages all major Swedish railway stations, routinely collects data on the number of passages in and out of the simulated area, obtained through automatic counters at the passages marked by the letters a–h in figure 1. The provided data is in the form of directed passages each hour of the day, averaged over a regular working week in November 2014. The total flow in and the total flow out of the simulated area is depicted in figure 2, in which the morning and afternoon peaks are clearly visible at around 09:00 and 17:00, respectively.

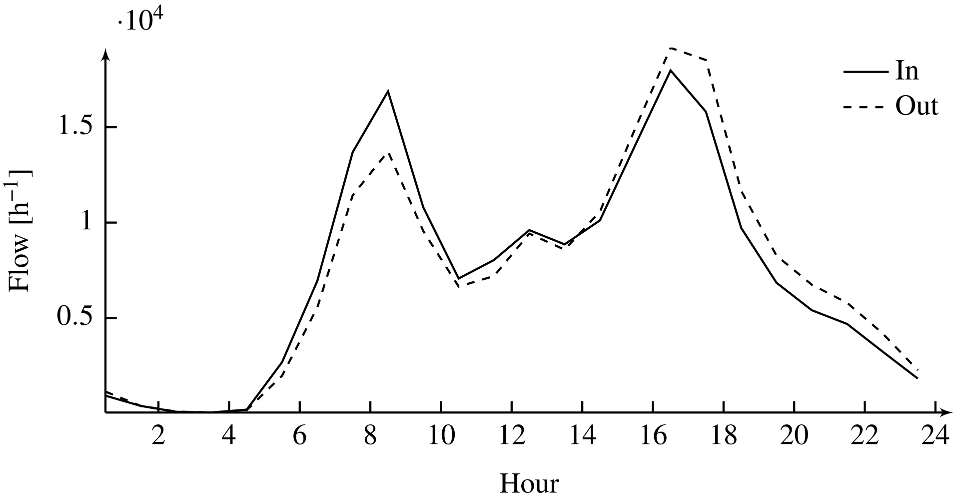

Figure 2: The total flow in and out of the simulated area during an average workday.

From the flow data it is obvious that the measurements contain significant errors, which is to be expected for automatic counters. In this study we focus on the morning peak hour, where the flow in is 16 877 h^{-1} and the flow out is 13 727 h^{-1}, according to the data. This difference is far to large to be accurate, so we assume that the actual flow is the average of the measured in and out flows, that is, 15 302 h^{-1}.

To estimate the origin destination flows from the provided flow data, we assume that the flow vanishes between all the origins and destinations a–d, between e and f, and between g and h, since any flow between these would imply that people go back to where they came from. We estimate the OD flows by assuming that the flow from each origin is distributed among the remaining feasible destinations according to the fraction of the total flow arriving at each destination. Thus, the necessary simulation input consisting of a flow from each origin to each destination is obtained.

2.2 Trajectory data

As described by Lagervall and Samuelsson (2014), pedestrian trajectory data was collected at the ground floor of Stockholm Central Station. This data set is here used to calibrate the basic model for both normal pedestrians as well as phone users. The data was collected in the main hall of Stockholm Central Station on April 29, 2014, 16:30–17:15, which according to the flow data presented in section 2.1 is close to the middle of the afternoon peak at the station. The data consists of the trajectories of 1870 pedestrians, 7 % of which were identified as looking at some kind of mobile device, most likely a smart phone.

The calibration is performed similarly to the process outlined by A. Johansson (2009); each pedestrian is simulated with surrounding pedestrians moving according to the observed trajectories. The simulated pedestrian is initiated at the position of the observed pedestrian with its current velocity. The simulation is repeatedly run a short time T_{sim}, and the integrated difference, E_i, between the simulated trajectory of pedestrian i and the observed one, is calculated according to

$$E_i = \sum_{t_0 \in \mathscr{T}_0} \int_{t_0}^{t_0+T_{\text{sim}}} \left\| \mathbf{x}_i^{t_0}(t) - \mathbf{X}_i(t) \right\| dt, \tag{1}$$

where t_0 is the staring time of the simulation, $\mathbf{X}$ is the observed trajectory, $\mathbf{x}_i^{t_0}$ is the simulated trajectory with initial conditions $\mathbf{x}_i^{t_0}(t_0) = \mathbf{X}_i(t_0)$ and $\dot{\mathbf{x}}_i^{t_0}(t_0) = \dot{\mathbf{X}}_i(t_0)$, and the sum is taken over the set of starting times, $\mathscr{T}_0$. In equation (1), the dependence of E_i and $\mathbf{x}_i^{t_0}(t)$ on the parameters of the SFM, are suppressed for clarity.

The rationale for the repeated resetting of the simulated position to the observed trajectory is that as soon as the simulated pedestrian deviates significantly from the observed trajectory, there is no reason to promote behavior that returns it toward the observed trajectory, since it is reacting to a different surrounding than the observed pedestrian.

In this study, $T_{\text{sim}} = 2$ s was used; long enough to be sensitive to slow reactions, but short enough to prevent the simulated pedestrian to drift too far from the observed trajectory.

Thus, we have one optimization problem for each pedestrian, with a solution which is the set of parameter values describing that pedestrian. After solving all these optimization problems we obtain a sample of the distribution of parameters describing the population.

The parameters included in this study are relaxation time, τ, force strength, F_0, force distance scale, σ, anticipation time, T, and preferred speed v^p, resulting in five dimensional, potentially non-convex and discontinuous problems. The problems are solved using a commercially available genetic algorithm solver.

As is natural for this kind of real world trajectories, very few trajectories are significantly sensitive to all of the model parameters. However, random conditions will give a slight artificial sensitivity to practically all parameters, and this will get picked up by the optimization algorithm, which in most cases will push the solution to one of the borders of the feasible region. Thus, many of the optimal solutions will have an extreme value in the parameter set, even though the trajectories are insensitive to variations in the parameter. We solve this by applying box constraints to all variables of the problem, forcing the parameters to attain reasonable values, and remove all extreme values from the resulting parameter value distributions.

A summary of the calibration results can be seen in table 1, where the mean and standard deviation of each parameter distribution is given. The feasible set of the optimization problems is the Cartesian product of the intervals given. As can be seen, the distributions are all rather flat, with a slight exception in the preferred speed. The averages do not deviate greatly from the earlier results by A. Johansson (2009) and Zanlungo et al. (2011).

Table 1: Parameters.

	τ [s]	F_0 [m/s^2]	σ [m]	T_s [s]	v^p [m/s]
No phone	0.54 ± 0.21	0.58 ± 0.24	0.64 ± 0.18	1.2 ± 0.41	1.3 ± 0.30
Phone	0.57 ± 0.21	0.56 ± 0.25	0.62 ± 0.19	1.3 ± 0.46	1.2 ± 0.32
Constraints	$[0.1, 1]$	$[0.1, 1]$	$[0.3, 1]$	$[0.5, 2]$	$[0.4, 2.5]$

2.3 Waiting behavior data

To accurately simulate the waiting behavior in front of the information sign, the area in front of the information sign was filmed during the morning peak, 07:40–08:40, a regular Monday morning (May 4, 2015). From this film, several important observations were made.

Firstly, the overwhelming majority of the waiters stood at right half of the left ‘lane’, as indicated by the gray rectangle in figure 1, and almost only pedestrians going to destination e stopped to look at the sign. This rectangle was thus used as an intermediate destination for a fraction of the walkers going to destination e.

Secondly, the distribution of waiting times was obtained by randomly selecting 50 of the observed waiting pedestrians and manually measuring their waiting times. This resulted in a distribution similar to an exponential distribution with a mean of 39 s.

Thirdly, the average number of waiting pedestrians was measured by manual counting at 50 randomly selected times. By assuming that the total flow was according to the estimation from the automatic counters, as described in section 2.1, the fraction of waiting pedestrians, p, were obtained as

$$p = \frac{n}{qT} \approx 0.24,$$

where n is the average number of waiting pedestrians, q is the average flow, and T is the average waiting time. Thus, the fraction of the population going to destination e that stops to get information is 24 %. This is therefore used as the fraction in need of information in the simulations. The fraction of these that uses the mobile phone instead of the sign to get the information is varied from zero to 100 % of them, in steps of 20 %, as summarized by table 2.

Table 2: Simulated scenarios.

Scenario	A	B	C	D	E	F	G
Pen. rate	0	0	0.2	0.4	0.6	0.8	1
Frac. sign	0	0.24	0.19	0.14	0.095	0.047	0
Frac. phone	0	0	0.047	0.095	0.14	0.19	0.24

Finally, a qualitative description of the waiting behavior could be extracted from the video, and the waiting model adjusted accordingly. The waiting pedestrians reacted only weakly to passing pedestrians, and only moved slightly out of the way to let people pass when the crowding was rather severe. It seems, although it is hard to tell exactly, that the pedestrians after an interaction usually moves back to its position before the interaction. This behavior is in accordance with the preferred position waiting model. However, according to this model the waiting pedestrians should react as strongly to other pedestrians as walking pedestrians do. This is clearly contradictory to the observations made. Thus, the model was extended accordingly by the introduction of a parameter that decrease the reaction of the simulated pedestrians when waiting. By comparing simulations using the extended model to the observed behavior, the parameter could be estimated to be approximately 0.5, corresponding to half as strong reactions by waiting pedestrians as of walking pedestrians. This estimation is however highly uncertain, since no precise measurements could be made.

3 RESULTS AND CONCLUSIONS

Each of the scenarios in table 2 where simulated 10 times with different random seeds for the pseudo random number generator. The results were quantified in terms of the delay experienced by the simulated pedestrians, defined as the difference between the actual travel time and the travel time if the pedestrian would have walked at its preferred velocity. The delay can be localized both in space and time by considering the delay rate and the delay rate density, describing the rate at which the pedestrian is lagging behind its preferred movement, and the production of this rate averaged over an area, respectively.

In the results presented below, the waiting pedestrians are excluded from the calculation of the delay, since the delay is not well defined, or should be interpreted differently, for waiting pedestrians.

3.1 Results

The average delays experienced by simulated pedestrians on their way through the simulated area are presented in figure 3, for different penetration rates of the mobile information, scenario B–G. The error bars denotes 95 % confidence intervals. The delay is calculated both for all pedestrians, and for only the pedestrians going to destination e, since these are the ones that are affected most by the waiting pedestrians.

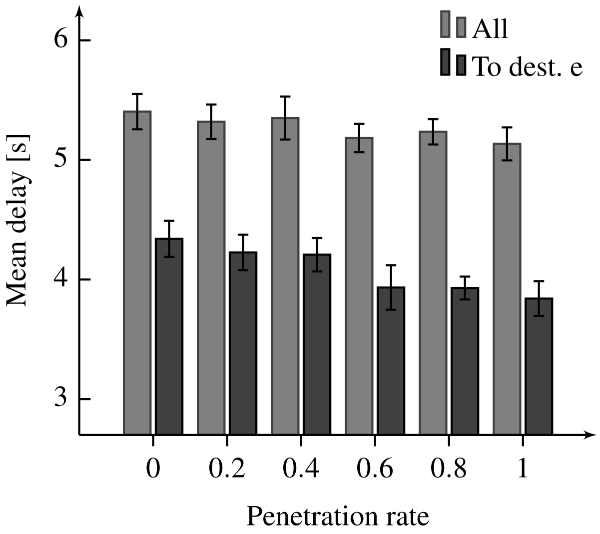

Figure 3: Mean delay

As can be seen in the figure, the dependence of the delay on the penetration rate is weak, but the difference between scenarios is significant, at least for large differences in the penetration rate. As expected, the dependence is slightly stronger if we only consider the pedestrians going to destination e, since then a larger fraction of the total delay is caused by the waiting pedestrians.

The average waiting time for scenario A, in which no pedestrians wait and no one uses phones, is 5.23 ± 0.19 s for all pedestrians and 3.94 ± 0.17 s for pedestrians going to destination e, which is very close to the corresponding numbers for scenario G.

Not only the average delay, but also the distribution of delays are of interest when assessing a facility; a hardly noticeable delay rate during a long time may be less annoying than a large delay rate during a shorter interval. Therefore the spatial distribution of delay rates are given in figure 4.

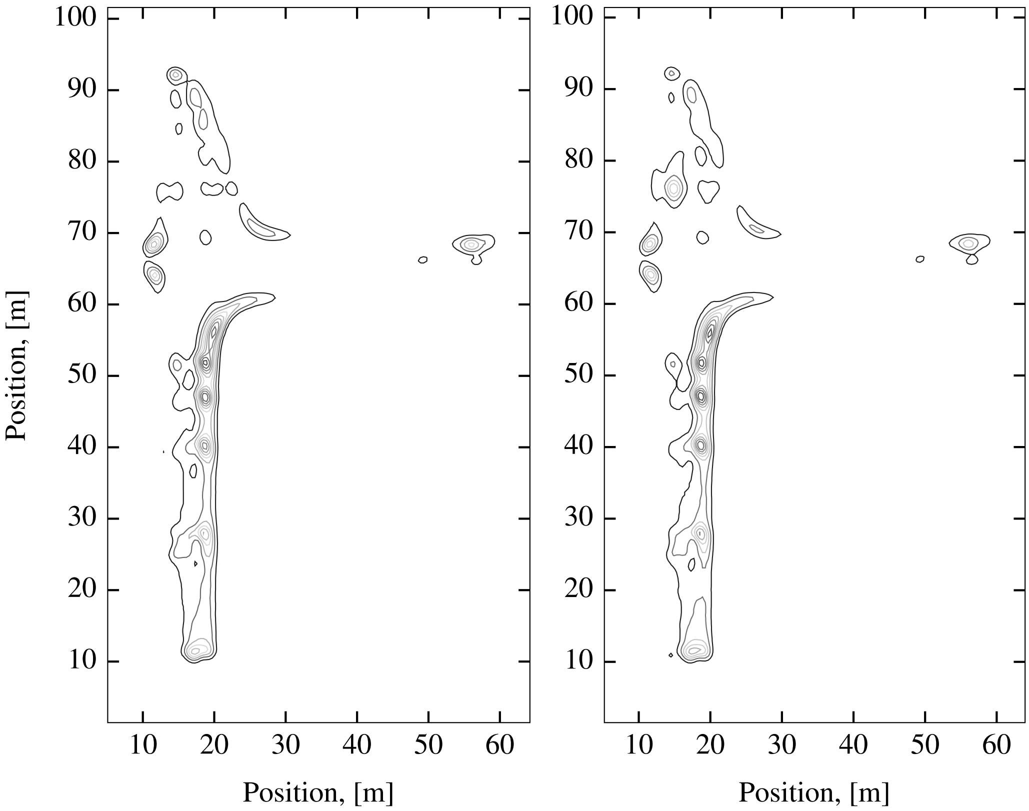

Figure 4: Delay rate density of scenario A (left) and scenario B (right).

As can be seen in the right part of the figure, there is an additional peak at the waiting area, around coordinate $(15,75)$, that is not present in the left part of the figure.

3.2 Conclusions and discussion

Is it preferable, in terms of traffic efficiency, that pedestrians use the mobile application instead of stopping and reading from a sign? The average delays presented in figure 3, suggests that there are some small but statistically significant differences, in favor of the mobile information. Also the delay rate distributions in figure 4 suggest that there is an observable increase in delay caused by the waiting crowd.

These results are strengthened by the fact that the waiting behavior observations, presented in section 2.3, were made in the morning rush hour, on a day without any delays or other disturbances to the train traffic, so almost everybody new where they were going. Thus, the result would almost certainly be stronger for other times of the day or other days of the week. It would clearly be a larger effect on a day with disturbances in the train traffic, causing the demand for information to rise dramatically.

However, there are several sources of errors that potentially can be larger than the error bars in figure 3. From figure 2, it is clear that the flow measurements have rather large errors; if the numbers were accurate, more than 10 000 persons would be within the simulated area in the middle of the day, which clearly is not the case. Experience from other automatic detectors suggest that the accuracy also is likely to be dependent on the flow, with a higher fraction of undetected passages at high flows, causing further uncertainties.

In addition to this, the flow data is aggregated on hourly level, averaging out any bunching of the traffic due to arrival of trains. Such bunching can have significant effects on the delays, especially if the capacity of some bottleneck is reached during the temporal peaks.

Another source of error related to the flow data is the rudimentary OD estimation; it is hard to even estimate the errors made at this stage without any further data.

When comparing the average delay in scenario A, in which no pedestrians waited or used phones, with scenario G, in which all pedestrians in need of information used the mobile information and no one looked at the sign, it becomes clear that the difference between regular walkers and phone users is very small to non-existent. This is of course expected by the parameter values presented in table 1, but there seems to be practically no effect of the lower preferred speed of the phone users on the delay.

The similarity between the parameters of regular pedestrians and phone users casts some doubt on the sufficiency of the data set used for calibration, or alternatively, the calibration method. The data set may indeed contain an insufficient number of interactions to give an accurate picture of the behavior of the population. In addition to this, it is possible that the waiting model needs a separate set of SFM parameter values to adequately reproduce waiting behavior.

The conclusion must be that even though unusually good input and calibration data is available, the uncertainties are still too large to draw any certain conclusions regarding the pedestrian traffic efficiency effects of mobile public transport information.

REFERENCES

Daamen, W., Hoogendoorn, S. P., Campanella, M. C., and Eggengoor, E. (2009). "Ticket Reservation Posts on Train Platforms: Assessment Using Microscopic Pedestrian Simulation Tool NOMAD". *Transportation Research Board 88th Annual Meeting*. 09-1853.

Helbing, D. and Molnár, P. (1995). "Social force model for pedestrian dynamics". *Physical Review E: Statistical, nonlinear and soft matter physics* 51, pp. 4282–4286. DOI: `10.1103/PhysRevE.51.4282`. arXiv: `cond-mat/9805244 [cond-mat.stat-mech]`.

Hoogendoorn, S. (2001). *Normative Pedestrian Flow Behavior, Theory and Applications*. Delft University of Technology, Faculty of Civil Engineering, Geosciences, Transportation, and Traffic Engineering section. URL: `http://resolver.tudelft.nl/uuid:f3802ff0-33a2-4013-8661-84de4e59c7dd`.

Johansson, A. (2009). "Data-Driven Modeling of Pedestrian Crowds". PhD thesis. Technische Universität Dresden. URL: `http://nbn-resolving.de/urn:nbn:de:bsz:14-qucosa-20900`.

Johansson, A., Helbing, D., and Shukla, P. K. (2007). "Specification of the social force pedestrian model by evolutionary adjustment to video tracking data". *Advances in Complex Systems* 10.SUPPL. 2, pp. 271–288. DOI: `10.1142/S0219525907001355`. arXiv: `0810.4587 [physics.soc-ph]`.

Johansson, F. (2013a). *Pedestrian traffic simulation platform*. VTI notat 16-2013. Swedish National Road and Transport Research Institute, Linköping. URL: `http://www.vti.se/en/publications/`.

Johansson, F. (2013b). *Microscopic Modeling and Simulation of Pedestrian Traffic*. DOI: `10.3384/lic.diva-101085`.

Johansson, F., Peterson, A., and Tapani, A. (2015). "Waiting pedestrians in the social force model". *Physica A: Statistical Mechanics and its Applications* 419, pp. 95–107. DOI: `10.1016/j.physa.2014.10.003`.

Lagervall, M. and Samuelsson, S. (2014). "Microscopic Simulation of Pedestrian Traffic in a Station Environment: A Study of Actual and Desired Walking Speeds". MA thesis. Linköping UniversityLinköping University, Communications and Transport Systems, The Institute of Technology.

Ma, J., Song, W., Fang, Z., Lo, S., and Liao, G. (2010). "Experimental study on microscopic moving characteristics of pedestrians in built corridor based on digital image processing". *Building and Environment* 45.10, pp. 2160–2169. DOI: `10.1016/j.buildenv.2010.03.015`.

Zanlungo, F., Ikeda, T., and Kanda, T. (2011). “Social force model with explicit collision prediction”. *Europhysics Letters* 93.6, p. 68005. DOI: `10.1209/0295-5075/93/68005`.