Crowd Movement - DTCC Milestone Project

Research Report

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The importance of pedestrian movement for urban design and planning

Pedestrian movement has always been a main concern for urban design and planning but has become more important in the light of the Sustainable Development research agenda (UN Agenda 2030), especially related to Goal 11. 'Sustainable cities and communities'. The agenda clearly calls for promotion of sustainable mobility and transport (i.e., public transport, walking, cycling, micro-mobility) that targets especially climate and health. The decrease of private car usage and increase of public ridership reduces greenhouse gas emissions (e.g., Litman 2020), and the increase of active modes of transport promotes public health and well-being (e.g., Roe et al. 2020, Bird et al. 2018). Furthermore, sustainable mobility and active travel support social inclusion and cohesion because while walking, we are co-present in public space (e.g., Legeby et al. 2015, Legeby 2013). Also, pedestrian flows are recognized as an important driver of local economies (e.g., Hillier et al. 1993, Hillier 1996a, Litman 2020). Pedestrian movement is thus brought to the front of sustainable urban development (Stavroulaki, keynote SS13, 2022).

To explain, assess and predict pedestrian movement in the built environments, we need appropriate methods to model pedestrian flows. Such methods are currently lacking in transport and traffic modelling that are still highly car-oriented. Pedestrians are sometimes included in traffic modelling, but mainly as 'vulnerable users' in simulations of vehicle-pedestrian interactions aiming to improve safety (e.g. Rinke et al. 2016, Pascucci et al. 2015, Obeid et al. 2017).

Pedestrian movement has been studied with different approaches and on different scales for many decades. Within the field of Space Syntax, models have been developed that are primarily pedestrian-oriented and in accordance with the informal, unregulated, and free-flow nature of pedestrian movement (Stavroulaki, keynote SS13, 2022). They explain pedestrian flows based on characteristics of the built environment, primarily the spatial configuration of the street network and built density.

The prediction of pedestrian flows can be based on statistical models where characteristics of the built environment (e.g., street centrality, activities along these streets and built density) are calibrated against hourly observed pedestrian counts collected via any kind of pedestrian-sensing technology (for a review of such technologies, see Dong et al. 2020). Different types of models are used, where a rough distinction can be made between macroscopic and microscopic models. Macro- and microscopic refers in this case to the size of the area studied that in the first case typically is a city district or complete city and in the latter case a public square, street crossing or small neighbourhood. In both situations, the pedestrian flows are predicted in the level of the individual street.

From a macroscopic perspective, different modelling methods have been developed to simulate pedestrian flows on the street network. Route-choice models are adapting traffic-modelling methodologies to simulate pedestrian trajectories from origins to destinations on a street network, e.g. Basu and Sevtsuk (2022); Sevtsuk et al. (2021). Network models are predicting aggregated pedestrian flows on the street level based on the characteristics of the network itself using for instance measures of centrality, e.g. Stavroulaki et al. (2020); Berghauser Pont et al. (2019a); Bolin et al. (2021); Ozbil et al. (2011, 2015). While route-choice models have a high accuracy, they are highly data demanding and rely on many predictors that are too detailed to specify in the early design and planning stages (e.g., specific attractions, sidewalk width, street lighting, exact land-use mix) or include socioeconomic predictors that are not predefined in development plans (e.g., income, age). Network models have moderate accuracy but can be more directly applied in scenario analysis and assessment to guide the early design and planning stages, since they only rely on spatial predictors that can be affected by design, as street centrality and urban density.

A typical example of microscopic models are cellular automata models. They divide the walking space for pedestrians into a discrete grid, through which pedestrians move based on constraints defined in the model (Blue et al. 1997). In contrast, the social force model represents pedestrians in a continuous space with force-based interactions and movements (Chen et al. 2017, Helbing 2000). Other examples are activity-choice-models and velocity-based models of pedestrians (see Blue et al. 1997, Helbing et al. 2000, Hoogendoorn and Bovy 2004 and Paris et al. 2007). The activity-choice-model is a continuation of the social force model adding an active route choice for pedestrians, whereas in the velocity-based model pedestrians choose their path based on knowledge of surrounding obstacles to get to their destination as directly as possible. In most examples, agents move on OD (origin destination) paths. Other approaches assume a random walk, where pedestrians do not aim to reach a predefined destination (Hanna 2021, Turner and Penn 2002).

Besides having a macro- or microscopic perspective, the model described above varies in what is modelled. The macro-simulations described above model the built environment to explain, simulate or predict the pedestrian flows (the phenomenon), while the micro-simulations model the flows of agents with certain rules that include the agents' behaviour. Rarely, approaches for hybrid models that combine macro- and macro- simulations and models of structure (built environment) and flows (agents/pedestrians) have been developed, e.g. Xiong et al. (2009), who created a multi-resolution model by coupling an agent-based and a flow-based model. Another example is agent-based models developed within the field of Space Syntax where agents' random walks depend both on visual parameters (i.e., angle and field of view) and the configurational properties of the spatial layout (urban or building layout) (Turner and Penn 2002).

The Crowd Movement Milestone Project, initiated by the Digital Twin City Centre, aims to develop such a hybrid model, coupling a macroscopic network model of the built environment and a microscopic agent-based model of pedestrians.

The technological deliverables of the project are stand-alone solvers for macroscopic and microscopic simulations and the coupling of the macroscopic network model and a microscopic agent-based model. Requirements for a user-friendly decision support tool as web app in the DTC platform has not been developed but is an obvious next step. This requires close collaboration with the developers of this milestone project and the developers of the DTC platform.

In this report, we summarize the findings of the project by first, highlighting some principal differences in modelling pedestrian movement. The next two sections summarize the work done in relation to the macroscopic network and microscopic agent-based model respectively, as well as their coupling. The following section presents use cases where such models can be valuable in urban planning and design practice based on a workshop with urban stakeholders. The report ends with a summary of the results and next steps to be taken in the understanding of pedestrian movement and its use in urban planning and design practice.

Aligning ontologies in modelling pedestrian movement

Based on unpublished chapter of a book due 2024 (MIT press) by Lars Marcus[1]

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The shared conceptual understanding of cities, albeit interpreted with different emphases in different disciplines, can be summarized either as in traffic planning as a land use – transport problem (Lowry 1964), or as in urban modelling as a location – flows problem (Batty 2013), or as in architecture and urban design (Hillier 1996) as a morphology – movement problem. The common ground here is arguably, that cities are constituted by a series of locations characterized by some kind of attraction or activity that will generate interaction and flows between these locations, which in turn may influence the attractions and activities at each location. This serves for a neat division of labor between urban design, dealing with the stationary dimension of cities, such as buildings and public places, and transport planning, taking care of its mobile dimension, such as car traffic and public transport. Importantly, this also creates distinct foci on cities as structure-process entities, where urban design addresses its physical structure and only implies processes of mobility, while traffic planners do the opposite. While being a simplification, it is clear how this division increasingly is becoming an obstacle for contemporary urban development to reach its aims.

Importantly, in recent decades there has been a shift in emphasis that in principle at least, has opened for a closer exchange between these disciplines. Where urban models, such as traffic models, traditionally were built on the assumption that locations generate flows, the modelling of which could support the planning of new infrastructure, the more recent understanding is that flows define location, that is, that the patterns of infrastructures such as rail and roads create a landscape of locations with highly varying accessibility that to a high degree defines potential activity at the locations (Batty 2013). This means that traffic does not only serve place but to some degree generate and define place, which challenges the old division of labor.

Similar ideas have in more recent research in architecture and urban design put an emphasis on the configuration of urban space as defined by built form, giving rise to a system of streets and open spaces, and its influence on pedestrian movement patterns (Hillier 1996). The street system often constitutes the primary infrastructure in cities, used by various transport modes over time, including rail based (such as trams), why it also comes to structure these. In parts of architecture and urban design this has meant an important shift from a focus on the built form of cities in itself, to the spatial system it defines and in turn the flows that it structures.

Hence, we can see recent developments that on the one hand, has made transport planning more concerned with the active role of patterns of built form, such as street networks, in distributing flows and in turn defining land use at different locations, and on the other hand, has made urban design more attentive to patterns of space and how they influence flows and how that in turn allocates land use. That is, we see a convergence between disciplines that for a long time have developed knowledge and trained practices isolated from each other.

The disciplinary development as described above, has affected the modelling of cities in more particular the modelling of flows, including pedestrian flows.

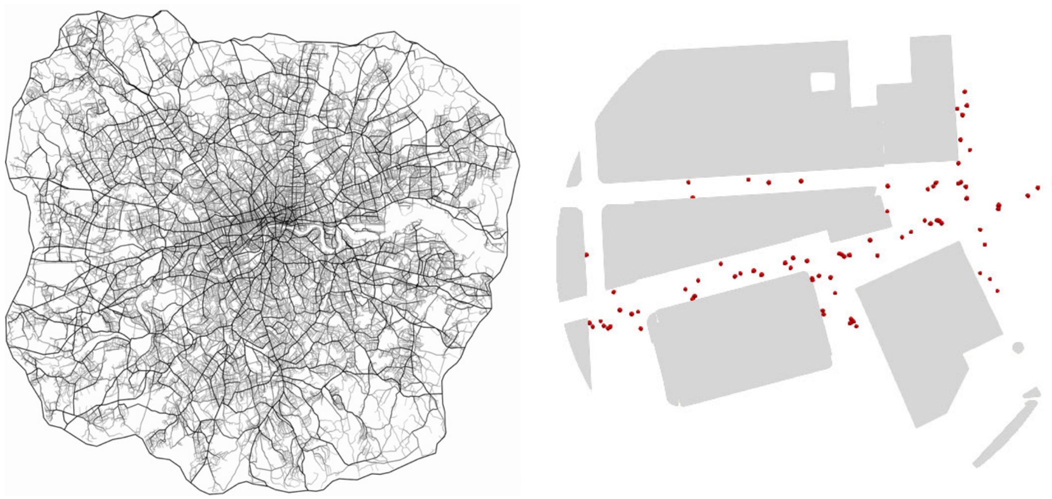

Figure 1. Varieties of spatial representation in urban modelling: Network representations of urban space as developed in the particular form of urban modelling called space syntax (left, source: UCL Bartlett) and agent-based models (right, source: FCC).

As we discussed in the introduction of this report, a distinction can be made between route-choice models that are adapting traffic-modelling methodologies to simulate pedestrian trajectories from origins to destinations and network models that base their prediction of aggregated pedestrian flows on qualities of the network itself.

Both models are simplified representations of an entity of interest, constructed in accordance with certain methodological needs and theoretical assumptions, directed by a particular line of enquiry concerning the entity at hand. We therefore need to pay attention to the theoretical assumptions when it comes to how they are interpreted. Of particular interest is what kind of representation is used for the spatial variable in these different models.

Besides these two different types of space-based models, agent-based models are relevant for simulating pedestrian movement and used in this project for the microscopic modelling of pedestrian behaviour. In essence, agents do not have fixed locations but act or interact with one another as well as the environment.

Despite differences, the models share the similar aim to capture how the urban environment affects pedestrian behaviour. The difference is that the network model emphasizes the physical environment to predict pedestrian flows, while the agent-based model emphasizes the agent's behaviour implied by the behavioral rules of the agent to predict pedestrian flows. Observed pedestrian count data is used in both cases to calibrate the models. And, as will be discussed later, the two models can be coupled to forecast the aggregated flow.

Modelling pedestrian movement on city scale

Based on abstract of unpublished paper 'Street network simulation for predicting pedestrian flows on the streets of existing and planned urban areas' by Ioanna Stavroulaki[1], Oscar Ivarsson[2], Meta Berghauser Pont[1], Vilhelm Verendel[2]

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In this paper (in development, to be published 2023), a street network simulation is presented that can be used in urban design and planning from the early stages of an urban development plan. It is based on a machine learning model using LASSO regression (Least Absolute Shrinkage and Selection Operator), that predicts pedestrian flows (i.e., numbers of pedestrians) on the level of street segments and can be applied on neighbourhood scale or on entire cities.

The street network simulation can be used for estimating both the volume and the distribution of pedestrians on future streets with the aim to support scenario analysis, assessment and decision making in urban design and planning. It can also be used to simulate pedestrian flows in existing streets, where this information cannot be collected through real-world observations with manual counts or with the use of sensors or cameras because of time, budget or GDPR constraints.

The simulation is built on street network modelling and relies on a handful of predictors, namely local street network centrality, density, number of lanes and speed limit, walking accessibility to local markets and street segment length, all of which can be calculated or easily estimated for a planned urban area or an infrastructural change, already from the early stages of design and decision making.

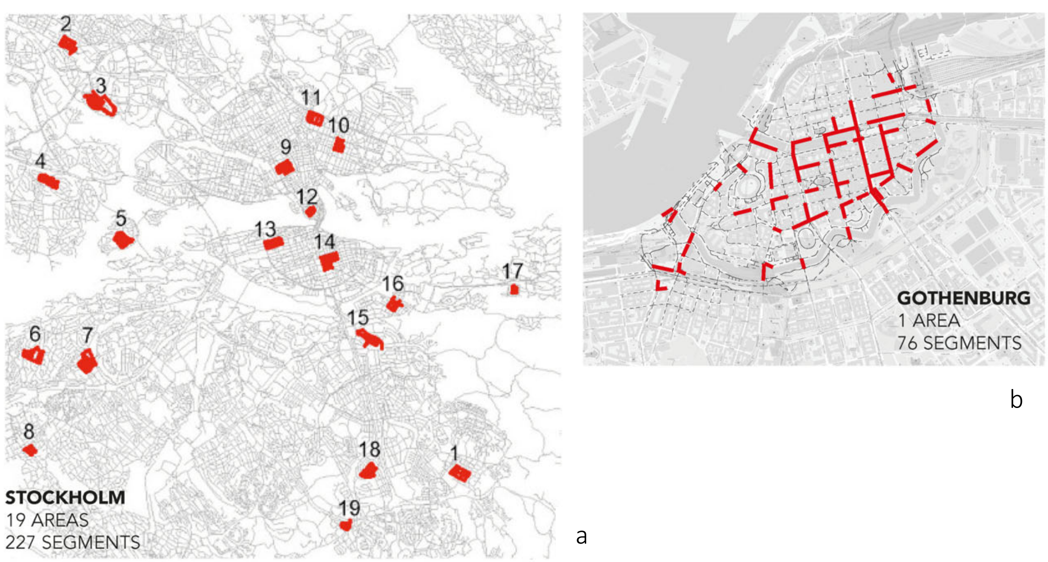


Figure 2. Neighborhoods included in the training data from Stockholm (a), Street segments included in the model validation in Gothenburg (b).

The paper describes the methodology of developing the machine learning model and its results. The model is written in Python and is published in Github (https://github.com/SMoG-Chalmers/crowd-movement)**. First,** the model was trained using data gathered in Stockholm, Sweden in 2017 including real-world data on full-day pedestrian counts collected by capturing anonymised wi-fi signals from mobile phones (see Stavroulaki et al. 2019, 2018). Then the model was tested by predicting full-day pedestrian counts in a different city, specifically on 75 street segments in central Gothenburg (Fig1). The model was tested against real-world observations collected in Gothenburg using the same method, i.e., by capturing anonymised wi-fi signals from mobile phones in October 2018 (Traffikontoret 2019). Two variations of the model were tested; one was trained in 224 street segments distributed in 19 different areas in Stockholm and one was trained in 121 street segments of central Stockholm[1] (areas 9-14) (Figure 2).

LASSO is a regularized regression method that constrains the sum of the absolute values of the model coefficients (i.e. penalization of coefficients). This results in a sparse model where some of the coefficients are exactly zero, indicating that they do not contribute to the prediction of the response variable, avoiding overfitting and handling redundant information and multicollinearity. So, while a large number of coefficients were tested initially in the model building the final predictors were only a small subset.

To select the optimal set of predictor variables and avoid overfitting to the training data, a cross-validation approach was used when in each iteration one neighborhood area from the training data was left out. MAPE (Mean Absolute Percentage Error) was used as the evaluation metric for the cross-validation. Since the response variable is strictly positive and its distribution right skewed, a log transformation before fitting the model and an inverse transform before computing any performance statistics was done to compute the error measures in the original scale and avoid negative predictions.

45 predictor variables were added initially (Figure 3), including the Space Syntax network centrality measures (Angular Betweenness and Angular Integration in 10 radii from 500m to 5000m walking distance) (Hiller and Iida 2005), built density (i.e. accessible Floor Space Index in 500m walking distance), land division (i.e. accessible Plots in 500m walking distance), three accessibility variables (i.e. accessibility to public transport, local markets and schools)[2] and two weighted Betweenness centrality measures (i.e. attraction betweenness centrality to local markets and built density[3]). Also, several street characteristics (i.e., sidewalk width, street segment width and length, number of lanes, street greenery, speed limits) and socioeconomic variables (e.g., working and residential population density) were included. In addition to the continues variables, different categorical variables were added, including the density types and multiscalar non-motorised street centrality types developed by the SMoG (Berghauser Pont et

[1] For the complete list and type of areas included in Stockholm data, please see Berghauser Pont et al. 2019

[2] Datasets of building polygons (including FSI attribute), plot polygons, and attraction points were developed by SMoG based on source datasets from Lantmateriet (i.e. Oversiktskarta) and Open StreetMaps (i.e. Point of Interest). All network centrality and accessibility measures were calculated with PST (Place Syntax Tool, https://www.smog.chalmers.se/pst)

[3] Angular betweenness centrality weighted with attractions. Attraction betweenness is calculated with PST (Place Syntax Tool, https://www.smog.chalmers.se/pst)

al. 2019), and transport road classifications used by the Swedish Transport Administration (i.e., functional class, road type[4]).

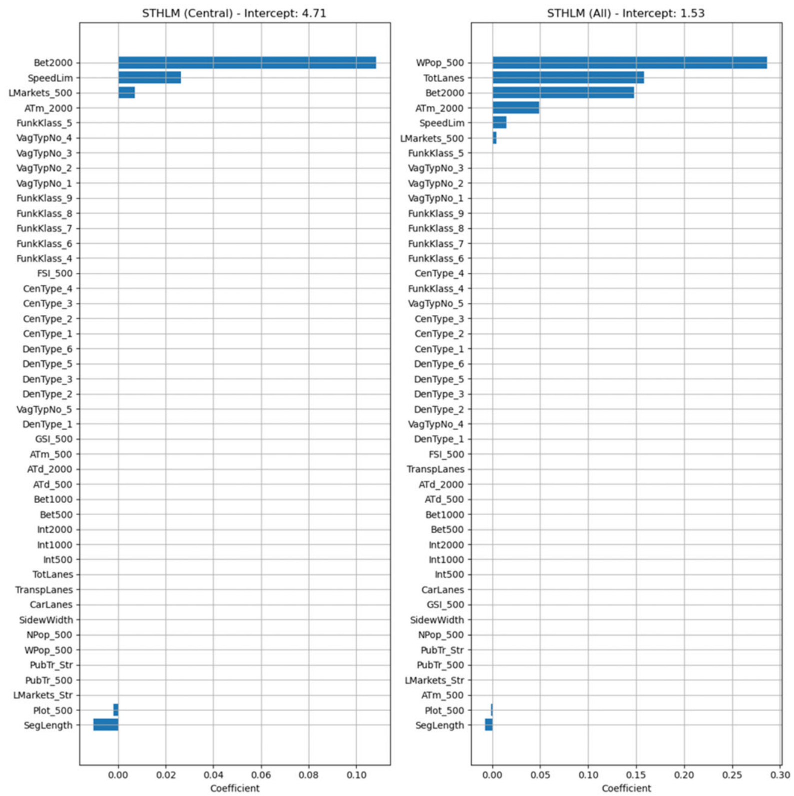


Figure 3. Initial list of predictor variables. In blue the significant predictors included in the final models (left: model trained in 6 areas in central Stockholm, right: model trained in 19 areas in all Stockholm).

The final model generated is based on a subset of predictors. The equation for the model trained in central Stockholm is:

$$\ln(FullDayCount) = \beta_0 + \beta_1 Plot\_500 + \beta_2 LMarkets\_500 + \beta_3 SegLength + \beta_4 SpeedLim + \beta_5 \ln(Bet2000) + \epsilon$$

$$\begin{aligned} \beta_0 &= 4.712 \\ \beta_1 &= -0.002 \\ \beta_2 &= 0.007 \\ \beta_3 &= -0.010 \\ \beta_4 &= 0.026 \\ \beta_5 &= 0.108 \end{aligned}$$

where,

'Bet 2000' is Angular Betweenness centrality of the street segment, calculated on the non-motorised street network and based on the shortest walking path in terms of angular

[4] 'Funktionell väg- klass' and 'VagTyp' included in the National Swedish Road database (NVDB).

distance (i.e. total degrees turned). Analysis radius was 2000m walking distance around every street segment.

'SpeedLim' is the speed limit of the street segment

'LMarkets_500' is the number of local markets (retail and services, food and drinks) reached within 500m walking distance from the street segment

'Plot500' is the number of properties (plots) reached within 500m walking distance from the street segment.

'SegLength' is the metric length of the street segment

The predictors were calculated using the PST (Place Syntax Tool) for spatial analyses (Stavroulaki et al. 2023a, https://www.smog.chalmers.se/pst).

For Angular Betweenness centrality, the following equation is used:

$$B_{(x)} = \sum_{s \neq x \neq t} \frac{\sigma_{st}(x)}{\sigma_{st}} \quad (1)$$

where s and t are all nodes (i.e. street segments) in the network different from x

σst = the number of shortest paths from s to t

σst(x) = the number of shortest paths from s to t that pass-through x

To calculate the number of local markets and plots within 500m walking distance from each street segment, the equation for Attraction Reach in PST was used:

$$AR_{(o)} = \sum_{a \in A} \left(f(a) w\big(D(o,a)\big)\right) \quad (2)$$

where,

A = the set of reachable attractions (i.e. local markets, plots) within given radius,

f(a) = attractions value associated with attraction a, or 1 if not attraction value is used as in this case

D(o,a) = shortest distance from origin o to attraction a,

w(x) = attenuation function (no attenuation function is used in this case)

The models have a regression coefficient (R^2) of 0.50 (trained in whole Stockholm) and 0.52 (trained in central Stockholm) (Figure 4), which can set a good stage for scenario analysis and early assessment of urban development plans and infrastructural changes in relation to estimated pedestrian flows. Apart from predicting the volume and distribution of full-day pedestrian counts, the model is also tested for predicting hourly counts, simulating fluctuations during the day. The results or this test will be presented in a following publication.

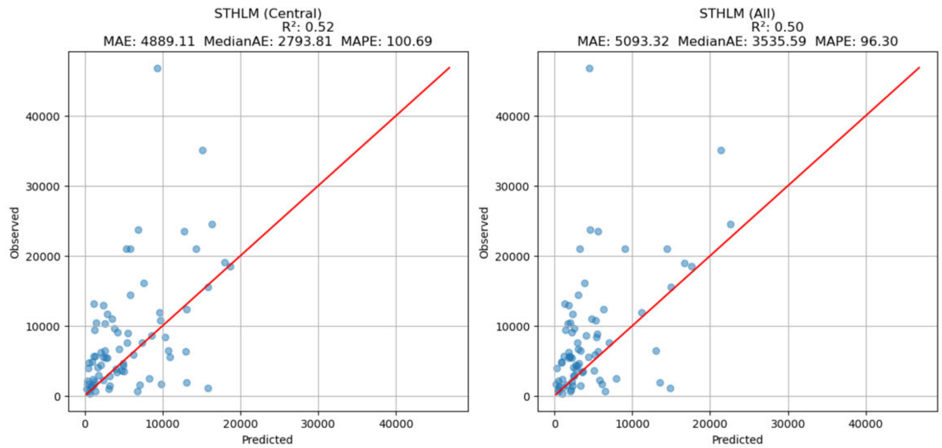


Figure 4. Plots of Observed (y axis) vs Predicted values (x axis) for the two models a. trained in 6 central areas of Stockholm, b. trained in all 19 areas in Stockholm. The values represent daily number of pedestrians and the dots represent each of the 75 street segments tested. The results show R^2, Mean Absolute Errors (MAE), Median Absolute Error (Median AE).

Modelling pedestrian movement on local scale

The agent-based model (ABM) that is used in this study is a variation of the well-established class of social force models. It aims at resolving the local pedestrian flow in an urban environment. The social force model has commonly been used for crowd movement and emergency evacuation simulation. Here, the model shall be used to model the daily movement of pedestrians in open spaces. The common procedure of calibrating has usually been done in literature with small experiments. We follow the same procedure for validating our model with simple settings. Yet for the simulation in the urban environment, we calibrate the parameters with real-world data from a simple pedestrian crossing.

A. Force Equations

The agents are simulated with a social force model based on (Helbing, et al., 2000). The ABM and its force models have been implemented as an extension to the particle solver Demify® (Quist, et al., 2021) for efficient handling of the agents and their interaction partners. The applied particle model that represents a pedestrian consists of three spheres modelling their body, head and nose. The nose indicates the orientation of the pedestrian.

A social force is implemented according to (Helbing, et al., 2000) acting between the centres of two pedestrians. Let r_{ij} be the sum of the body radii given for agent i and agent j and let d_{ij} be the distance between their centres. Then, the social force is defined as

$$F_{PSY} = k_1 exp\left(\frac{r_i - d_{ij}}{k_2}\right),$$

where k_1, k_2 are empirical constants.

Similar to the social force, a wall social force between pedestrians and the obstacle geometries. Let r_i be the radius given for pedestrian i and d_{iW} the distance of pedestrian i and wall W. Then, the wall social force is defined as

$$F_W = k_{W1} exp\left(\frac{r_i - d_{iW}}{k_{W2}}\right),$$

where k_{W1}, k_{W2} are empirical constants. The pedestrian can see buildings and obstacles in their field of view of 120°, which is determined by a ray tracer.

To drive the pedestrians towards their assigned destination with their desired speed, a motive force is included according to (Langston, et al., 2006). Let V_D denote the desired and V_i the actual velocity of pedestrian i, m_i the mass and τ_i the characteristic time of pedestrian i, then the motive force is defined as

$$F_M = m_i \frac{V_D - V_i}{\tau_i}.$$

Finally, a model to adapt the pedestrian speed for tilting floors is implemented according to (Wang, et al., 2013). Let the horizontal velocity without the adaptation for tilting floors be v_0. The adapted horizontal velocity is then given by

$$v_h = v_0(1 - c \tan\theta),$$

with θ the slope gradient and c a constant.

Inspired by (Li, et al., 2021), a simplified curiosity model is included based on information gap theory. Every pedestrian is assigned a curiosity value that represents how curious this pedestrian is. Instead of emergencies as in (Li, et al., 2021), attractors are defined in this model which are represented by geometry meshes. When an attractor lies in the field of view of a pedestrian, they decide with a probability based on the pedestrian's curiosity if they head towards the attractor. If the pedestrian's curiosity is triggered, the attractor location is put as a temporary destination. Otherwise, the pedestrian continues its original path. Each pedestrian is given a cool-down time, after which the pedestrian is receptive to attractors again.

Note, that the curiosity model has been utilised in a workshop with urban planners, however, is not included in the following simulation scenarios.

B. Model Classification

Classifying the presented ABM, is done by discussing the model characteristics as well as defining the model's capability due to defined base cases and features as shown in (Duives, et al., 2013).

The core of this model is based on a social-force model both for pedestrian-pedestrian and pedestrian-obstacle interaction. It includes motive forces and an adaption for tilting floors. Additionally, the direction of a pedestrian is updated based on obstacles lying in the field of view of the pedestrian. The walking direction is chosen as close to the direct path towards the destination as possible without collision with obstacles. Thus, the ABM shares characteristics with the velocity-based model as well. Moreover, the model is equipped with a curiosity that distracts pedestrians from their original path. This does not coincide completely with the activity-choice model as the distraction is no tactical decision, but a (randomized) choice of activity, which excludes knowledge over ground types such as streets, crosswalks, or greenery. The model can easily be extended with more complex behavioural rules and tactical planning when e.g., empirical rules are present.

Considering the base case according to (Duives, et al., 2013) plausibility tests have been setup to ensure the tool's base capability. The simulations, which are not shown here, confirm the correct pedestrian behaviour in the following base cases:

- Unidirectional flow
- Unidirectional rounding corner
- Unidirectional entering
- Unidirectional exiting
- Bidirectional flow
- Crossing flow, 2 flows
- Crossing flow, 4 flows
- Crossing flow, random

C. Validation

To evaluate the performance of the ABM, two validation cases, a corridor, and a stair, are considered. Both cases are experiments performed by (Frantzich, et al., 2007) and the simulation results are compared to the experimental measurements as well as simulation results obtained by (Martén & Henningsson, 2014) with the crowd movement simulation tool Viswalk.

Parameter	Unit	Value
m_i	kg	Uniformly distributed (63.0, 77.0)
r_i	m	Uniformly distributed (0.18, 0.22)
$\|\|V_D\|\|$	m/s	Uniformly distributed (1.0, 2.0)
c	-	1.6336
Δt	s	10^{-4} (DEM timestep)
τ	-	0.1
k_1	N	600.0
k_2	m	0.3
k_{W1}	N	600.0
k_{W2}	m	0.053

Table 1. Choice of model parameters for indoor environments

The model parameters have been chosen such that they result in a good agreement with the experimental data as well as with the other available simulation data and are summarised in Table 1. In outdoor scenarios with larger open spaces and a more undisturbed flow, the pedestrian behaviour is expected to be significantly different than in indoor scenarios, hence the parameters are re-calibrated as presented in section C.

a. Corridor

The corridor experiment consists of in average 42 people walking through a corridor that has a narrow passage at its end. The corridor is 2 m wide, and 10 m long and the passage starts after 9.6 m. Different widths of the passage are investigated where scenario A is completely open, scenario B has a door opening of 60 cm, scenario C 75 cm and scenario D 90 cm. However, scenario A corresponds to a unidirectional flow without obstacles and thus, that scenario is skipped. Scenario E, which consists of two separate doors, is skipped as well as the movement pattern is of different nature than for one door. The velocity distribution measured in the experiments is approximated by the uniform distribution stated in Table 1. The three quantities for comparison are:

- Total time: The time difference between when the last pedestrian exits the corridor and when the first has walked 2.4 m into the corridor.
- Flow: Number of pedestrians passing the passage opening in 5 second intervals divided by the time interval length.
- Density: Number of pedestrians inside an area of 2.88 m^2 divided by the area that is measured in two zones. One in the beginning of the corridor and one directly in front of the passage opening.

Total Time Mean [s]

Scenario	Frantzich	Martén	ABM
B	43.00	41.00 (-4.65 %)	44.90 (4.42 %)
C	37.00	41.00 (-10.81 %)	36.30 (-1.89 %)
D	31.00	36.00 (-16.13 %)	31.80 (2.58 %)

Flow Mean [p/s]

Scenario	Frantzich	Martén	ABM
B	1.10	1.20 (9.09 %)	0.93 (-15.46 %)
C	1.30	1.20 (-7.69 %)	0.99 (-23.75 %)
D	1.60	1.40 (-12.50 %)	1.15 (-28.13 %)

Density Zone 1 Mean [p/m²]			
Scenario	Frantzich	Martén	ABM
B	1.80	1.20 (-33.33 %)	2.35 (30.35 %)
C	2.00	1.10 (-45.00 %)	2.05 (2.53 %)
D	1.90	1.10 (-42.11 %)	1.84 (-2.99 %)

Density Zone 1 Mean [p/m²]			
Scenario	Frantzich	Martén	ABM
B	1.80	2.40 (-33.33 %)	1.99 (10.53 %)
C	1.80	2.30 (-27.78 %)	1.87 (3.78 %)
D	1.70	2.00 (-17.65 %)	1.72 (0.96 %)

Table 2. Measurements of the corridor experiment, simulation results of Martén and simulation results of the present ABM with the difference to the experiment following in % in parentheses.

In Table 2 a comparison of the experiment and simulation results of Martén and the ABM are shown. The ABM results are an average over ten simulations. Overall, the results depict the trends from the experiments well and are similar to the results of Martén. For the mean total time the presented tool shows the same trend as the experimental results with a decreasing time for a wider opening and a quantitatively very good agreement with a maximum difference of 5 % to the experiment. Considering the flow, the simulation results show a larger difference than Marténs. Nevertheless, the trend of the flow is captured by the simulation results with an increasing flow for a wider opening. Moreover, the density is approximated well by the simulation for scenarios C and D with differences of below 5 % while in scenario B the density is overestimated, yet in the same error range as the results of Martén. All in all, the simulation results deliver a good approximation of the experiments and achieve an agreement of similar quality as the results obtained by Martén.

b. Stair

The second validation case is a theatre stair experiment where pedestrians are walking from one floor in a theatre to a lower one by passing a narrow stair. The experiment is performed with two groups of people, the first one consists of 61 (scenario S) and the second one of 91 pedestrians (scenario M). The two quantities for the comparison are:

- Total time: The time difference between the first and the last participant passing the stair.
- Flow: Total time divided by the number of participants.

Total Time Mean [s]			
Scenario	Frantzich	Martén	ABM
S	52.00	51.00 (-1.92 %)	60.00 (15.38 %)
M	83.00	72.00 (-13.25 %)	75.90 (-8.55 %)

Flow Mean [p/s]			
Scenario	Frantzich	Martén	ABM
S	1.17	1.19 (1.71 %)	1.03 (-12.39 %)
M	1.11	1.27 (14.41 %)	1.20 (8.47 %)

Table 3. Measurements of the stair experiment, simulation results of Martén and simulation results of the present ABM with the difference to the experiment following in % in parentheses.

In Table 3 a comparison of the theatre stair experiment and simulation results of Martén and the presented ABM are shown. Again, the ABM results are an average over ten complete simulations per scenario. With focus on the difference to the experimental results, our simulations show satisfactory agreement with a maximum difference of 15 %, just as Marténs. The increase in total time for the higher number of participants is captured as well. However, both simulation tools show a different trend for the flow mean which is slightly decreasing in the experiment but increasing in the simulations for more pedestrians.

With this comparison, the general functionality of the model is confirmed and thus the model is applied to outdoor scenarios hereafter with the model parameters chosen as in Table 5.

D. Validation with measurement data for real-world case pedestrian crossing

The following case is an area downtown of Gothenburg, Sweden, consisting of a pedestrian crossing including a shopping mall entrance and a bus stop, see Figure 5.

The experimental recording was performed for 3 days with focus on pedestrians passing the shopping mall entrance where the hourly variation of the number of pedestrians, their velocity distribution and positions on the measurement lines were analysed.

A comparison of direction, density and velocity between the measurements and simulation results is performed to validate the presented simulation tool for real-world outdoor urban scenarios.

The measurements show significant differences in the amount of people for different times of day. Often, the pedestrian density was so low that only few pedestrian interactions could be observed. We thus chose a time with maximum occupancy to validate the ABM.

The chosen time is a 15-minute interval starting at 8.00 AM on Tuesday, the 11th of October 2016.

a. Real-World Measurements

The real-world measurements are provided by Viscando AB[5] and are performed with grids of smart stationary sensors. Based on 3D vision and artificial intelligence, the sensors detect, classify and track all types of road users 20 times per second and the data from several sensors is fused for large measurements. The images are processed in embedded computational units, and permanently deleted within 20 ms after acquisition. Only road user trajectories are stored. Therefore, images are neither recorded nor transmitted, ensuring full GDPR compliance.

b. Case Setup

The building and ground geometries of the measurement area are provided by the Swedish National Land Survey (Lantmäteriet). The raw data is processed by the DTCC Builder (Logg, et al., 2022); (Naserentin & Logg, 2022) to generate the building and ground triangle meshes without detailed information on e.g., entrances or roads.

The measurement area, shown in Figure and underlaid with a Google Maps snapshot[6], is divided into 4 sections. In the simulation, the pedestrians are generated in each of the sections and are statistically assigned a path towards one of the other sections according to an origin-destination-matrix, which is based on the measurements. The exact numbers are summarized in Table 4. With a total of 347 pedestrians in a 15-minute interval, the maximum pedestrian density on a normal workday is expected to be such that the pedestrians can move freely.

[5] www.viscando.com

[6] access date 2023-03-28, https://www.google.com/maps/place/Nordstan/@57.7087039,11.9708397,47m/data=!3m1!1e3!4m6!3m5!1s0x464ff363f5374bcb:0xfc7ac7ea2ddb942!4b1!8m2!3d57.7087091!4d11.9691425

The choice of generation, target and measurement areas has been based on the real-world data and is visualized in Figure . The generation areas are given as red boxes with side widths of 2.5 m, the target areas are visualized as dark blue boxes with a side width of 5 m and are located behind the generation areas to avoid unintentional conflicts due to the insertion of new pedestrians.
The crosswalk has a large impact on the movements as it binds the pedestrians to cross the street in that area. To capture this effect in the simulation, the crosswalk is modelled with an in-between target (light blue box). The measurements and simulations have been evaluated along two lines at the crosswalk (dashed line in Figure) and at the sidewalk (solid line in Figure).
The chosen simulation parameters for the simulation cases are given in **Error! Reference source not found.** and have been calibrated with the measurement data in this setup.

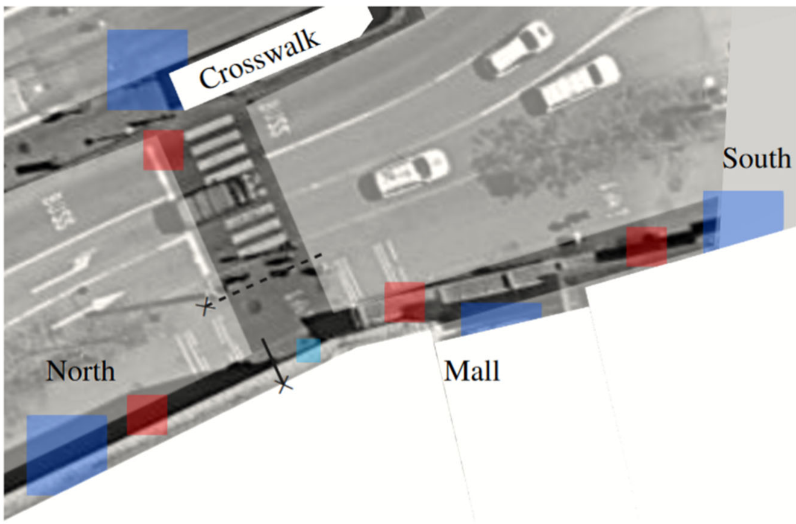


Figure 5. Sections of measurement areas: North, Crosswalk, Mall and South. Choice of generation (red), destruction (dark blue) and target points (light blue). The counting line at the crosswalk (dashed) and the sidewalk (solid) are included with the ×-symbol indicating the line origin. The main simulation domain is the dark area. The white domains are obstacles received from the building geometry.

From \ To	North	Crosswalk	South	Mall	Total
North	0	11	43	65	119
Crosswalk	13	0	47	91	151
South	17	40	0	7	64
Mall	5	5	3	0	13
Total	35	56	93	163	347

Table 4. Distribution of pedestrians from generation areas to target points.

c. *Comparison*

Due to large statistical variance in pedestrian movements, the comparison focuses on qualitative agreement rather than quantitative accuracy.

Figure shows the pedestrian trajectories over the whole 15-minute interval, with the simulation output to the left and the real-world data to the right. The two representations show a similar trajectory pattern. The real-world data has a more chaotic nature than the simulation results which is caused by the force-driven nature of the model.

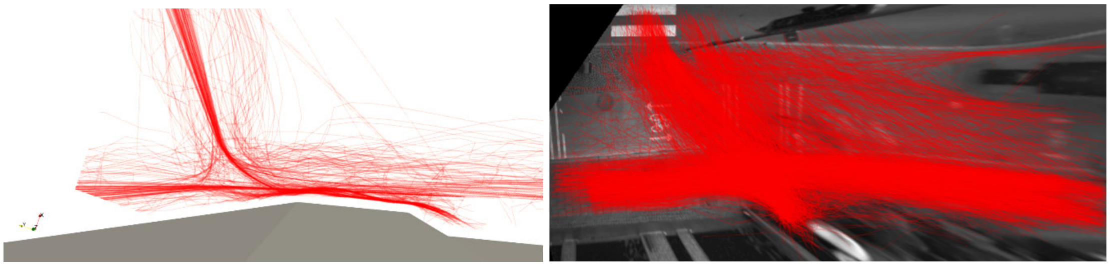


Figure 6. Comparison of pedestrian trajectories of simulation results (left) and real-world data (right)

This difference is expected for the given number of pedestrians as there are only few occurrences where pedestrians in the simulation alter their paths from the shortest path to avoid collisions with others. Furthermore, no refined psychological models are included, which would lead pedestrians to take a shortcut resulting in trajectories on the bicycle lane whereas such behaviour can be interpreted from the measurements. Note that the difference at the entrance of the mall stems from a modelling artifact to avoid unintended conflicts due to pedestrian generation. Additionally, heat maps of the pedestrian densities, i.e., number of pedestrians per square meter and hour, are shown in Figure . Besides the location of the densest sections, the simulation results agree well with the real-world data. Both, the data range, and the locations of the densities are similar. The difference for the densest sections is discussed above.

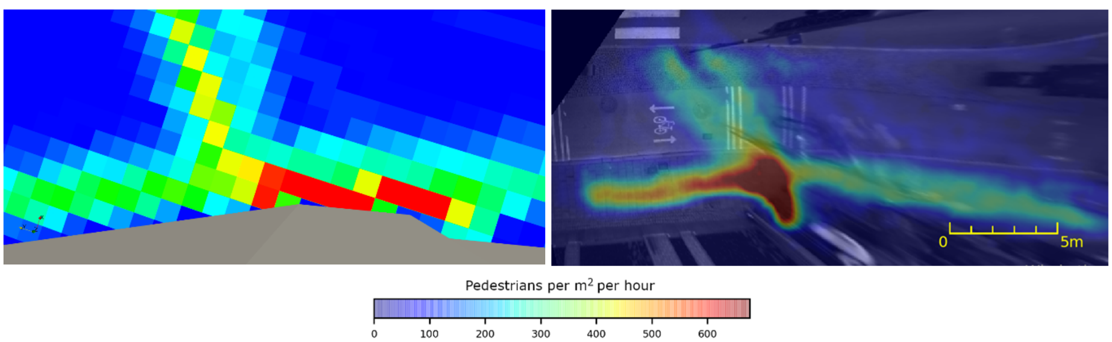


Figure 7. Comparison of heat map of the number of pedestrians per square meter and hour of simulation results (left) and real-world data (right).

Velocity distributions of pedestrians crossing the two measurement lines during the whole simulation are visualized in Figure 8 a) and Figure 8 b). The distributions are in reasonable agreement, yet at the crosswalk the velocity distribution for the real-world data is broader confirming with the reasoning above. On both lines, the peak position has a slight offset between simulation and real-world data. The peak at 1.5 m/s in the simulation results is a reasonable outcome for the given simulated velocities that are distributed uniformly between 1 and 2 m/s.

Pedestrian position distributions across the measurement lines are presented in Figure 8 c)-f). It can clearly be seen that modelled pedestrians walk predominantly on specific paths whereas real-world pedestrians utilise the entire sidewalk, which is particularly visible in Figure 8 c) and f). This characteristic is expected as pedestrians in the simulation chose the shortest way to reach the target if the way is undisturbed while real-world pedestrians chose the position on the sidewalk more freely. Since Figure 8 d) and e) have a better agreement between simulation results and real-world data this indicates that more disturbances occur for the modelled pedestrians.

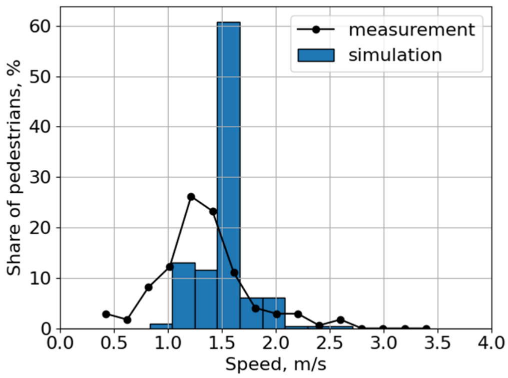
Fine-tuning of the simulations was kept to a minimum with as little target specifications as possible in order to test the model's general performance in urban pedestrian movement.

For the given pedestrian density, this can lead to pedestrians being able to move unhindered towards their target. However, trajectories that are of more chaotic nature (also seen in the position and velocity distribution) indicate that there are conflicts and interactions between pedestrians causing them to adapt their walking speed and their path. Thus, the simulations can be used to study pedestrian conflicts, being a change of the target velocity or a violation of their personal space.

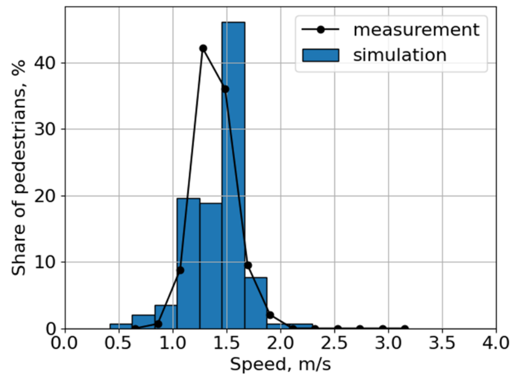
Parameter	Unit	Value
m_i	kg	Uniformly distributed (63.0, 77.0)
r_i	m	Uniformly distributed (0.18, 0.22)
$\|\|V_D\|\|$	m/s	Uniformly distributed (1.0, 2.0)
c	-	1.6336
Δt	s	10^{-4} (DEM timestep)
τ	-	1.0
k_1	N	6000.0
k_2	m	0.3
k_{W1}	N	2000.0
k_{W2}	m	0.08

Table 5. Choice of model parameters for outdoor environments.

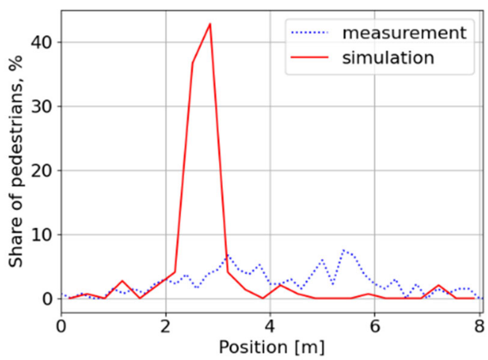
To summarize, the qualitative comparison to the experimental measurements is satisfactory and shows that the presented simulation tool can predict conflicts that arise from pedestrian movement in real-world outdoor scenarios and that general pedestrian movement can be reproduced in outdoor environments.



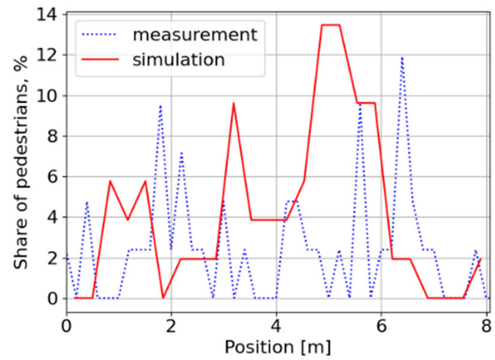
Subfigure a) Speed distribution at crosswalk line



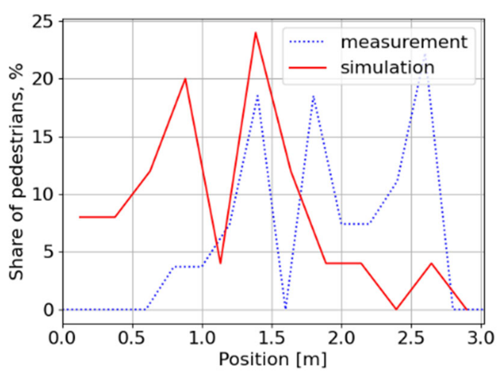
Subfigure b) Speed distribution at sidewalk line



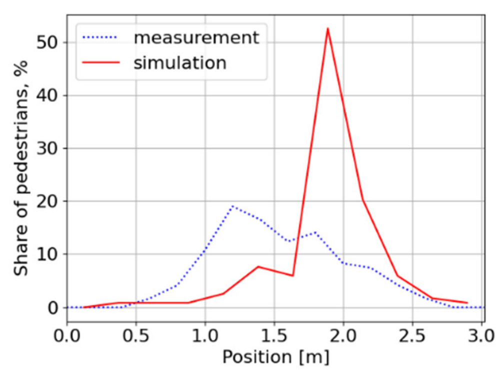
Subfigure c) Position distribution of pedestrians at the crosswalk line headed towards Mall.



Subfigure d) Position distribution of pedestrians at the crosswalk line headed towards Crosswalk.



Subfigure e) Position distribution of pedestrians at the sidewalk line headed towards North.



Subfigure f) Position distribution of pedestrians at the sidewalk line headed towards South.

Figure 8. Speed and position distribution at the two measurement lines (crosswalk and sidewalk) comparing the real-world measurements and simulation data.

Coupling pedestrian movement modelling on local and city scale

Based on abstract of paper (in review) 'Towards predictive pedestrian movement modelling: A workflow connecting a network and an agent-based model' by Anita Ullrich[1], Franziska Hunger[1], Ioanna Stavroulaki[4], Adam Bilock , Klas Jareteg[2], Yuri Tarakanov[3], Alexander Gosta[5], Johannes Quist[1], Meta Berghauser Pont[4], Fredrik Edelvik[1]

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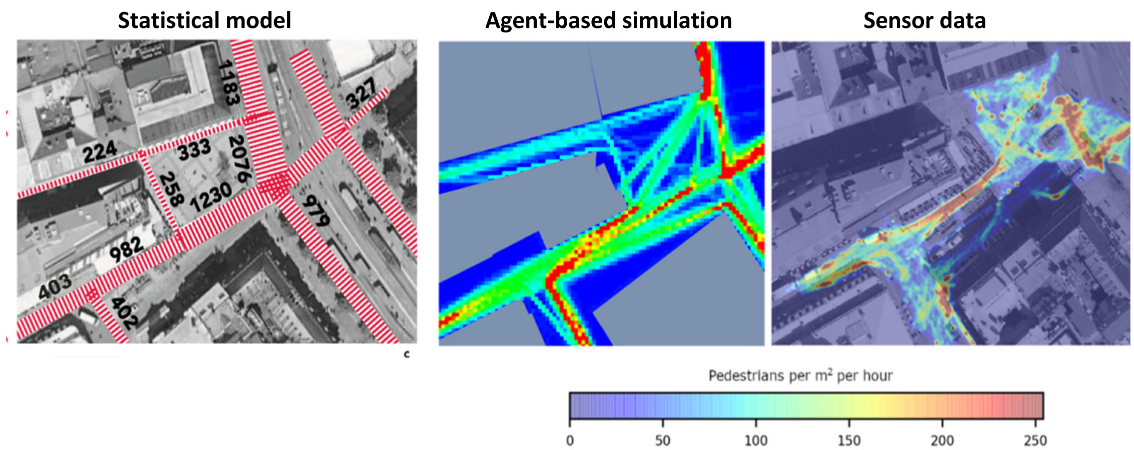

Figure 9. Comparison of the data from the statistical model (left) used to calculate the pedestrian occupancy on the local scale (middle) with the pedestrian occupancy recorded using sensor data (right) for a pedestrian precinct in the city centre of Gothenburg, Sweden.

This paper (in review) describes how an agent-based modeling approach targeting the resolved movement of pedestrians in outdoor urban environments is combined with the macroscopic network model predicting aggregated pedestrian flows to develop a methodology assisting (quantitative) scenario testing in various phases of urban planning. The study aimed at two main aspects. (1) Enable urban planners and designers to take pedestrian movement on a detailed scale in the different planning phases into consideration. (2) Create a tool that can be coupled to pedestrian flow predictions on the large scale as described in the previous section.

The agent-based model (ABM) that is used in this study is a variation of the well-established class of social force models as described in the previous section. It aims to give reliable micro-scale predictions of the pedestrian movement based on an origin-destination-matrix of the macro-scale pedestrian flow. The great advantage with this approach is the limited need for input data which enables the application in early design phases of future urban areas where no real-world data is available. Moreover, it enables pedestrian flow analysis seamlessly on different scales, allows scenario testing and facilitates optimized planning putting the pedestrian in focus.

The hybrid model has been applied to a more complex case in the city centre of Gothenburg, Sweden for which sensor data is available. The reasonable comparison with real-world data underscores the model's reliability.

The use of pedestrian modelling in urban design and planning practice

Based on a workshop 22-10-28 led by Alexander Gösta, Liljewall arkitekter, Sweden. The workshop aimed at gaining insight in how modelling pedestrian movement is useful in urban planning and design practice (for whom and when in the design process). Besides possible use cases, risks and difficulties are highlighted.

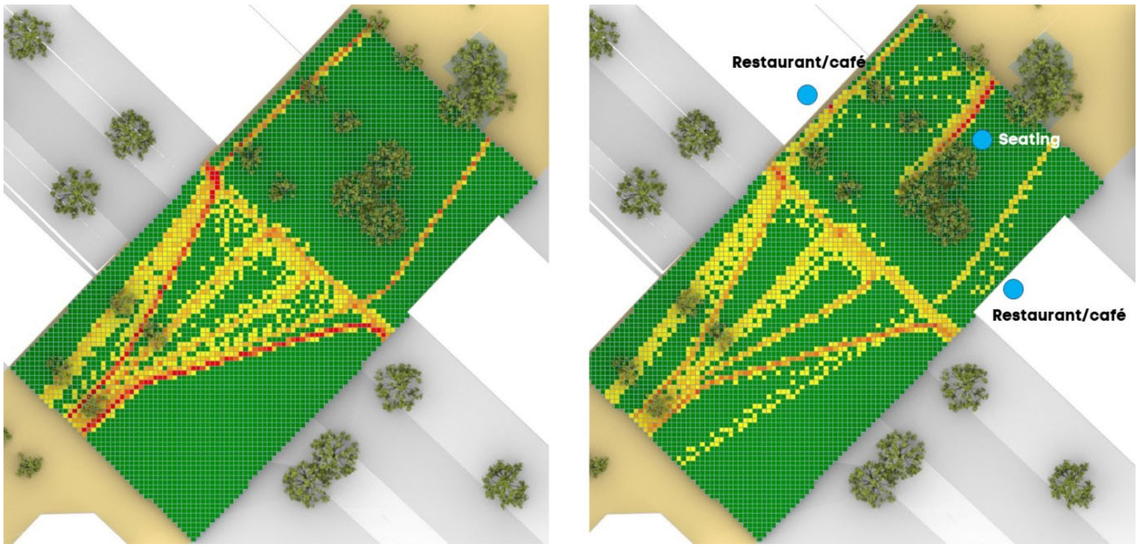

Figure 10. A comparison of pedestrian flow heatmaps with and without attraction points discussed during the workshop.

From the workshop, six categories of use cases of the models predicting pedestrian movement were identified:

- Understanding pedestrian behaviour (at various times and for separate groups)
- Directing people flows
- Evaluation of bottleneck situation
- Traffic safety
- Dimensioning of public space
- Evaluation of perception of a place

The use cases span from the detailed comprehensive planning to the building design phase with an emphasis on the detailed development planning. This means the tools and method can be of interest for municipalities but also for private developers, with different uses of varying interest.

More data in the early stages of design give more informed decisions for stakeholders. The ability to evaluate and compare different alternatives with data promotes a fairer, and maybe a more objective, decision-making process. Being able to visualize and communicate the effects on pedestrian movement in the early design and planning stages might lead to a more valued design solution. There is consensus among the workshop participants that other issues that are easier to simulate like motorized traffic, currently weigh more in the decision-making process. Another case in point raised during the workshop was cyclability, and how the movement of bicycles has been more in design focus, since simulations of cycling flows became available and used. There is an acknowledged need to simulate the pedestrian movement in a combined simulation with other traffic such as bicycles and cars.

Risks and difficulties that were highlighted include lack of data, lack of regulation and increasing planning costs. Further, there is a fear that lacking data and too many assumptions in the simulation will result in faulty and misleading prediction results. In areas where existing flows can be measured and included in the simulation model, more trust in the results might be achieved.

The workshop participants did not perceive that the Swedish Planning and Building Act (PBL)[7] includes regulations to secure a functional pedestrian environment, while such regulations are given for motorized traffic. Historically, PBL 1 kap § 1 has indeed mostly resulted in the evaluation of motorized traffic in the planning process. However, it might be argued to also include pedestrians and 2 kap § 6 point 6 says that land must be planned in such a way that it is suitable with regards to "traffic supply and the need for a good traffic environment". In the light of the Convention on the Rights of the Child which was signed by Sweden in 1990, a good traffic environment must include the child perspective as they do not drive cars and are highly dependent on functional pedestrian public space. We could thus argue that there are also juridical reasons to evaluate the impact of planning on pedestrian movement flows.

An obstacle to including the simulations in the design process might be added costs. There is no desire to pay for simulations with unclear benefits, given that there is no regulation that needs to be met by the design, which would require assessments and simulations. Either being able to show that simulations, good predictions, and assessments decrease costs long term or that they add monetary value to the design in the end (such as successful commercial spaces and added rent) might be needed to promote their use, depending on who the client is (municipality, private).

[7] See https://lagen.nu/2010:900, https://www.boverket.se/sv/PBL-kunskapsbanken/)

Next steps in modelling pedestrian flows

An obvious next step of the project is to develop a user-friendly decision support tool as web app in the DTC platform. This would also ease the use of the results of the project in decision making in urban development projects.

However, before doing so, we see a need to further develop the network model to improve the prediction of the aggregated number of pedestrians. The gathering of more real-world data on pedestrian movement is important to be able to do so and could be something DTCC takes the lead on. For the agent-based model, more studies in setups with different complexity and characteristics would be required to be able to include more real-world pedestrian behavior.

If this is in place, another development is to study the flow of pedestrians in combination with other modes (e.g. bicycles, e-bikes, cars, etc) and especially possible conflicts between these different modes.

Lastly, we see opportunities to combine the simulation of pedestrian flows with the analysis of other data. For example, the combination of pedestrian movement and the distribution of noise and air pollution could give insight in where to reduce car speed or plant trees to have a greater impact on the most vulnerable users of the streets, pedestrians. And where more people walk, the health impact will be higher.

The latter has been tested in a pilot project financed by the National Research Infrastructure for Data Visualization, Infravis (https://infravis.se/), where the hourly simulation of pedestrian flows was used in combination with hourly fluctuations in noise levels to visualise noise exposure during the day for a small area in Gothenburg. The simulations were developed both for the existing situation and for different design scenarios for the area. Although the pedestrian simulations were still in working progress, the small Infravis project tested their usefulness and applicability in combination with other types of simulations. This has also resulted in a joined EU application that is currently being prepared with the aim to develop methods for the assessment of the impact of future vehicles and equipment on the health and wellbeing of the urban population.

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