Scenario Analysis of Pedestrian Flow in Public Spaces

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Abstract

Several modeling approaches in both microscopic and macroscopic scales have been already put forward into the pedestrian modeling literature. The most operational one of these models is the social force model, where forces are first defined by physical concepts (Newton's equation) and then have been applied to pedestrian behaviors. On the contrary, there are also models based on discrete choice modeling concept that go deeper in behavioral aspects of pedestrians' reactions rather than physical forces. In this paper, first we go through the literature in pedestrian modeling domain. Subsequently a real pedestrian simulation experiment conducted in the SV building at EPFL (Ecole Polytechnique Fédérale de Lausanne) is explored. In this building, at a medium sized entrance hall people's walking behaviors become extremely interesting at certain periods of the day since they take different entrances and exits depending on various destinations that they can reach by passing this hall. We have put a strong emphasis on model calibration. The simulator we used for calibration and simulation is called VISSIM. The VISSWALK add-on of the software (intended exclusively for pedestrians) has been mainly exploited which is based on the social force model. Another dataset is currently collected at a train station which experiences interesting passenger behaviors. The train station is a highly frequent multi-modal transportation hub. This second dataset can be of a high interest for more development in pedestrian modeling especially in the model calibration and validation. Basically, the SV building project is a part of a bigger project concerning pedestrian flow simulation/optimization in a transportation hub where the same methodology and calibration method tested for the SV building are going to be exploited. For the SV building experiment various forecasting (demand change) and optimization (supply change) scenarios are also built and simulated. The analysis of the results from these scenarios is presented.

Keywords

Pedestrian modeling and simulation, Model calibration, Pedestrian flow optimization

1 Introduction

In recent years, pedestrian flow modeling, simulation and optimization has received a surge in attention from the transportation research community. The focus of this attention is mainly on a) solving the tangible day-to-day problems of crowded public spaces, including, transportation hubs, shopping malls, etc. and b) optimizing the evacuation procedures from high occupancy buildings and centers in case of an unpredicted event. The prior could be of high interest for architects for design purposes to see how pedestrians move in buildings ans also for transport engineers tackling with safety and transportation facilities integration problems in big hubs. The later would be of obvious use for security and event planners organizing big sport matches, festivals, concerts, etc.

2 State of the art of pedestrian flow and behavior modeling

Models are considered as simplified representation of the reality. In fact, the goal is to find models which are as simple as possible, but at the same time could reflect realistic behaviors. Generally, pedestrian modeling is done in two different scales i.e. **microscopic or disaggregate models** and **macroscopic or aggregate models**. In microscopic models each pedestrian is represented separately as an individual agent and his/her behaviors are explored independently. While in macroscopic models pedestrians are analyzed in groups and crowds where the state of the system is generally described by mass densities, flow and average velocity (Schadschneider, Klingsch, Klüpfel, Kretz, Rogsch, and Seyfried, 2008).

Another scale between microscopic and macroscopic models might be seen in the literature as well, referred as **mesoscopic models** (Teknomo and Gerilla, 2008). These models don't distinguish each pedestrian individually and report pedestrian characteristics in aggregate terms. Nevertheless they could describe pedestrian behaviors at a microscopic level usually in terms of probabilities.

Theories of pedestrian dynamics normally take into account three different levels of behavior i.e. **Strategic level**, **Tactical level** and **Operational level** (S.P.Hoogendoorn, P.H.L.Bovy, and W.Daamen, 2001) and (Schadschneider et al., 2008).

At first level, pedestrian plan strategically what they intend to do. The desired activities, their order of performance and their locations are decided in this level. Pedestrians don't have any idea of the network or route alternatives at this point. This level is somehow a pre-trip decision process.

At tactical level, individuals start to gather information about the network and to make short-term decisions choosing the precise route. These decisions are usually based on obstacles location and macroscopic features of pedestrian flow (velocities, densities, flows). Contrary to the strategic level, in tactical level, pedestrians mostly have sufficient information to make a user-optimal decision.

Operational level describes the actual walking behavior of pedestrians, e.g. acceleration behavior, reaction or anticipation on obstacles and pedestrians walking in the opposite direction, their immediate decisions to avoid collisions etc. In general, operational level shows how pedestrian adjust their direction to achieve the goals set at previous levels (tactical and operational).

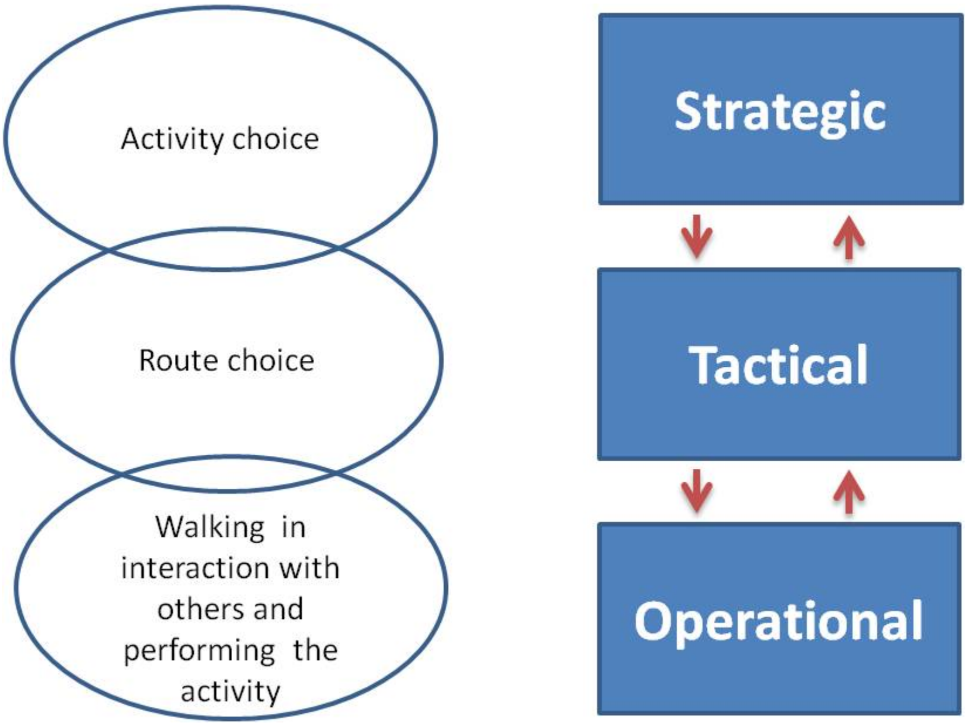

Figure 1: Different levels in pedestrian walking behavior

Discovering the way individuals think and decide in strategic and tactical levels would require information from other disciplines as well (sociology, psychology etc.). Models discussed in the following are mostly concerning the operational level of pedestrian behavior.

2.1 Macroscopic or aggregate models

In macroscopic models pedestrians are not analyzed as single individuals, but rather they are studied in human crowds where the aggregate attributes of the whole group such as flow, average velocity and density are taken into account. Thus, in macroscopic models, pedestrians can not be distinguished one by one. The earliest pedestrian dynamics models took inspiration from fluid or gas dynamics to describe how density and velocity change over time using differential equations.

2.1.1 Fluid dynamics and Gas kinetic models

Henderson (1971) who is basically a mechanical engineer monitored the movements of college students on a campus as well as children on a playground and realized that in both cases their motion fits the Maxwell-Boltzmann distribution, meaning that correspondingly to velocity of gas particles, the velocity of students also follows a Gaussian distribution.

Later, he developed a theory of the flow of a pedestrians fluid along a channel with variable width or partial obstruction. In order to apply the Maxwell-Boltzmann theory for pedestrians he had to make some assumptions and impose some restrictions on his data e.g. the crowd fluid had to be homogeneous meaning that every particle (pedestrian) must have the same mass and probability density function (pdf) for velocity and also the activity (walking, running or standing still) should be uniform among the particles (pedestrians). In summary, he proved that pedestrian motion could also follow a Gaussian curve if the crowd fluid was composed of independent, homogeneous particles of the same sex and in the same energy mode (activity).

The applicability of classical hydrodynamical models is based on several conservations; the conservation of mass, energy and momentum. The last two are not true for interactions between pedestrians.

However, in his theory the interpretation of some hydrodynamical variants is not entirely clear for pedestrian context. What would be the equivalents of pressure and temperature in the context of pedestrian motion? (Henderson, 1974)

Helbing (1992) founded a better fluid-dynamical based description of pedestrian movement. In his model several differences of pedestrian movement to normal fluids were pointed out such as anisotropy of pedestrian interactions or the fact that pedestrians have usually a personal preferred direction of motion. He considered different types of pedestrian motion representing different intended directions of walking. At each time, pedestrians of each type (meaning those who have the same intentions in their direction and movement) are characterized by their place, their actual velocity and their intended velocity. Then, the density of each type of motion is calculated in a given area A. It represents the number of pedestrians of each specific type within the area A. From these calculations he derives differential equations for the spatial density, mean velocity and velocity variance of motion types. The resulting equations resemble the equations for ordinary fluids.

According to Helbing the changes in densities of these different motion types can be explained by four effects:

- Tendency of pedestrians to approach their intended velocity.
- The interaction between pedestrians.

- Pedestrians who change their motion type (direction) accounting for turning left or right in reality.
- Density gain and loss which make it possible to model entrances and exits where pedestrians can enter or leave the system.

For a macroscopic approach, the gas-kinetic models would have problems at low densities (see Helbing (1992)).

2.2 Microscopic or disaggregate models

Macroscopic models aggregating pedestrian movement into flows, average speed or density might be efficient but they are not entirely capable of reflecting basic behaviors and interactions between individuals. Today due to improvements in computing power, microscopic models have become feasible and more attention is paid to them.

2.2.1 Cellular Automata

Cellular Automata models are named after the principle of automata (moving mechanical entities that perform a function according to a set of instructions) occupying cells according to localized neighborhood rules of occupancy.

By using these local rules, Cellular Automata models attempt to consider also the psychological factors of pedestrian rather than just applying mathematical and physical equations.

These models are discrete in space, time and state variable. Time discreteness means that there are defined time steps according to which agents positions are updated. In other words in simulation, all pedestrians move simultaneously at each time step. Space discreteness refers to the cell size.

As mentioned previously, in these models, the dynamics are defined by specific rules regarding pedestrians motion and probabilities to move to one of the neighboring cells. Actually, Cellular Automata models differ in the specification of these rules and probabilities.

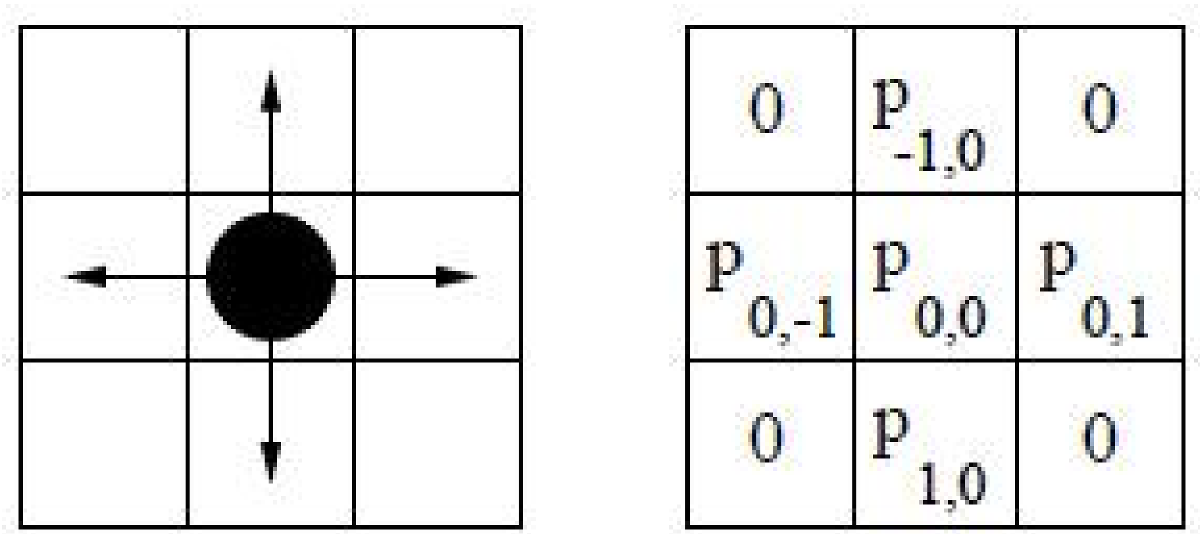

Figure 2: A particle, its possible directions of motion and corresponding probabilities for the case of a von Neumann neighborhood

For instance, the bidirectional Cellular Automata model created by Blue and Adler (2001) employs a set of several rules (such as two walkers that are laterally adjacent may not sidestep into one another, gap identifying rules, etc.) in order to take into account 3 fundamental elements of pedestrian motion i.e side stepping (lane switching), forward movement (attaining the desired speed) and conflict mitigation.

It is worth mentioning that although these models might capture to some extent pedestrian behaviors at the micro-level but they result in realistic macro-level group behavior. They have never been microscopicly validated.

2.2.2 Social force model

Social force model describes pedestrian behavior through so-called social forces where interaction with environment and other people is explained by attractive and repulsive forces. This model uses Newton's equation to calculate the forces. Basically the approach looks like:

$$\frac{d\overrightarrow{v_\alpha}}{dt} = \overrightarrow{F}_\alpha(t) + fluctuations \tag{1}$$

In this "*Acceleration equation*" the fluctuation term takes into account random and unsystematic variations of behavior and $\overrightarrow{F}_\alpha(t)$ gathers the social forces influencing pedestrian α. The later is constituted of several forces:

$$\begin{aligned}\overrightarrow{F}_{\alpha}(t) &= \overrightarrow{F}^{0}_{\alpha}(\overrightarrow{v}_{\alpha}, v^{0}_{\alpha}\overrightarrow{e}_{\alpha}) + \sum_{\beta\neq\alpha}\overrightarrow{F}_{\alpha\beta}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}_{\beta}) + \sum_{B}\overrightarrow{F}_{\alpha\beta}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}^{\alpha}_{B}) \\ &+ \sum_{i}\overrightarrow{F}_{\alpha i}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}_{i}, t)\end{aligned} \tag{2}$$

Where:

$$\overrightarrow{F}^{0}_{\alpha}(\overrightarrow{v}_{\alpha}, v^{0}_{\alpha}\overrightarrow{e}_{\alpha}) = \frac{1}{\tau_{\alpha}}(v^{0}_{\alpha}\overrightarrow{e}_{\alpha} - \overrightarrow{v_{\alpha}}) \tag{3}$$

Equation 3 represents the acceleration term depicting the intention of the pedestrian α to deviate his/her actual velocity $\overrightarrow{v}_{\alpha}(t)$ toward the desired direction $\overrightarrow{e}_{\alpha}$ and desired velocity v^{0}_{α} within a certain relaxation time τ_{α}.

The terms $\sum_{\beta\neq\alpha}\overrightarrow{F}_{\alpha\beta}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}_{\beta})$ and $\sum_{B}\overrightarrow{F}_{\alpha\beta}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}^{\alpha}_{B})$ denote respectively the repulsive forces describing attempts to keep a certain distance from other pedestrians (β) and obstacles borders (B) such as buildings, walls, etc. $\overrightarrow{r}_{\alpha}$ and $\overrightarrow{r}_{\beta}$ represent the positions of pedestrians α and β and $\overrightarrow{r}^{\alpha}_{B}$ is the location of that piece of border which is nearest to pedestrian α.

Finally $\sum_{i}\overrightarrow{F}_{\alpha i}(\overrightarrow{e}_{\alpha}, \overrightarrow{r}_{\alpha} - \overrightarrow{r}_{i}, t)$ considers the fact that pedestrians can be attracted by objects (advertisements, shops, displays...) and other persons (friends, street artists...) located at $\overrightarrow{r}_{i}$. Logically this term contains also a parameter of time t meaning that pedestrians will not stay talking to a friend or looking at an announcement for the whole time and at a certain point they will continue their main route. Attractiveness decreases by time. (Helbing and Molnàr, 1995)

Social force model is the most operational pedestrian model that currently exists, meaning that its used by the most well-known simulators (VISSIM, SIMWALK, etc.) and in the majority of pedestrian projects and studies. On the contrary this model has never been microscopicly (behaviorally) validated. In general, validation of microscopic pedestrian models is performed by comparing aggregate (macroscopic) model parameters (flows, speeds, densities, etc.) or emerging patterns (dynamic lane formation, formation of diagonal strips in crossing flows) with empirical data. The social force model has been validated in the same macroscopic way for self-organization phenomena i.e. bottleneck oscillations, lane and strip formation. In doing so, it has been shown that the model is able to predict macroscopic flow conditions with reasonable accuracy. But it is unclear if it only provides reasonable "average" macroscopic predictions or it is able to describe individual walking behavior accurately as well. (P.Hoogendoorn and Daamen, 2007)

In social force model, forces are firstly defined by physical concepts (Newton's equation) and then have been applied to pedestrian behaviors. It is more of a physical model than a behavioral one. On the contrary, behavioral models attempt to get mathematical representative formulas based on human characteristics. Some of these models which are based on discrete choice framework are briefly explained in the next section. The simulator we are using in this project (VISSIM) has this Social force model implemented in it.

2.2.3 Pedestrian behavioral models (based on discrete choice modeling)

In a more **microscopic** and **behavioral** approach, Daamen sticks to the common hypothesis that individuals make different decisions, following a hierarchical scheme: (strategical, tactical and operational). She developed a model and a simulator tool called SimPed that could take into account the whole walking process (along successive strategic, tactical and operational levels) containing walking behavior, route choice (done at two levels in her model), activity performances and also interaction with public transport services. (Daamen, 2004)

Destinations and activities are chosen at strategical level, route choices are performed at the tactical level and instantaneous decisions while walking and interacting with others are taken at the operational level.

Robin (2011) focused more on pedestrian walking behavior, naturally identified by the operational level. By using discrete choice modeling concepts he went deeper into behavioral aspects of pedestrians reactions contrary to models utilizing pure mathematical or physical concepts to estimate pedestrian behaviors. He succeeded to develop a model called "Next step model" that proposes a walking pattern where pedestrians choose their next step among 33 alternatives in a discrete choice framework. These 33 alternatives make provision for 11 possibilities of changing direction and 3 of changing speed i.e. Constant speed, Acceleration and Deceleration.

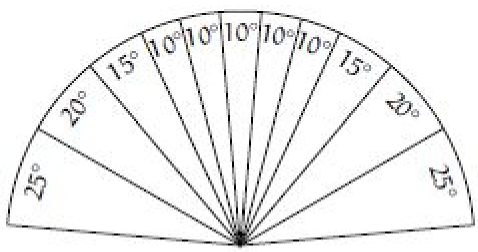

Figure 3: Discretization of directions in the next step model

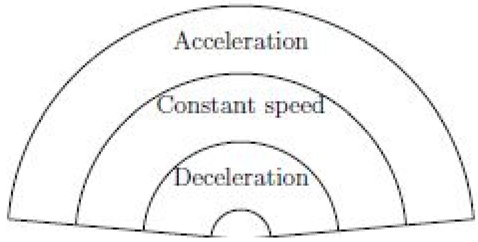

Figure 4: Discretization of speed regimes in the next step model

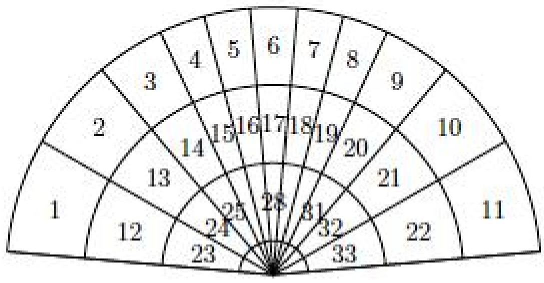

Figure 5: Choice set representation in the next step model

Although his model might not yet be as operational as other models exploited by simulators, it is scientifically very useful because of its high capability to explore and analyze different pedestrian characteristics and their effects on the walking pattern.

Next step model has been microscopicly calibrated on real pedestrian trajectories data which proves that it can to a large extent reflect a realistic pedestrians walking behavior. But on the other hand it encounters some problems modeling pedestrian restart walking again after a short break and it has not been implemented in a simulator yet either.

3 Model calibration

The social force model, like all models, is only a simplified representation of reality. In order to produce realistic results, its parameters have to be precisely adjusted. In this calibration process, parameters are tuned such that the predicted pedestrian behavior matches real behavior as closely as possible for the scenario of interest.

According to Buchmueller and Weidmann (2006) the walking speed of individuals in an unimpeded pedestrian flow follows a normal distribution with an estimated mean of 1.34 m/s and a standard deviation of 0.37 m/s (see figure 6). This information has been used for our calibration. Therefore, parameters related to pedestrians' speed has been tuned manually (since VISWALK has no automatic calibration routine implemented), such that the speed results could fit as closely as possible the above-mentioned normal distribution.

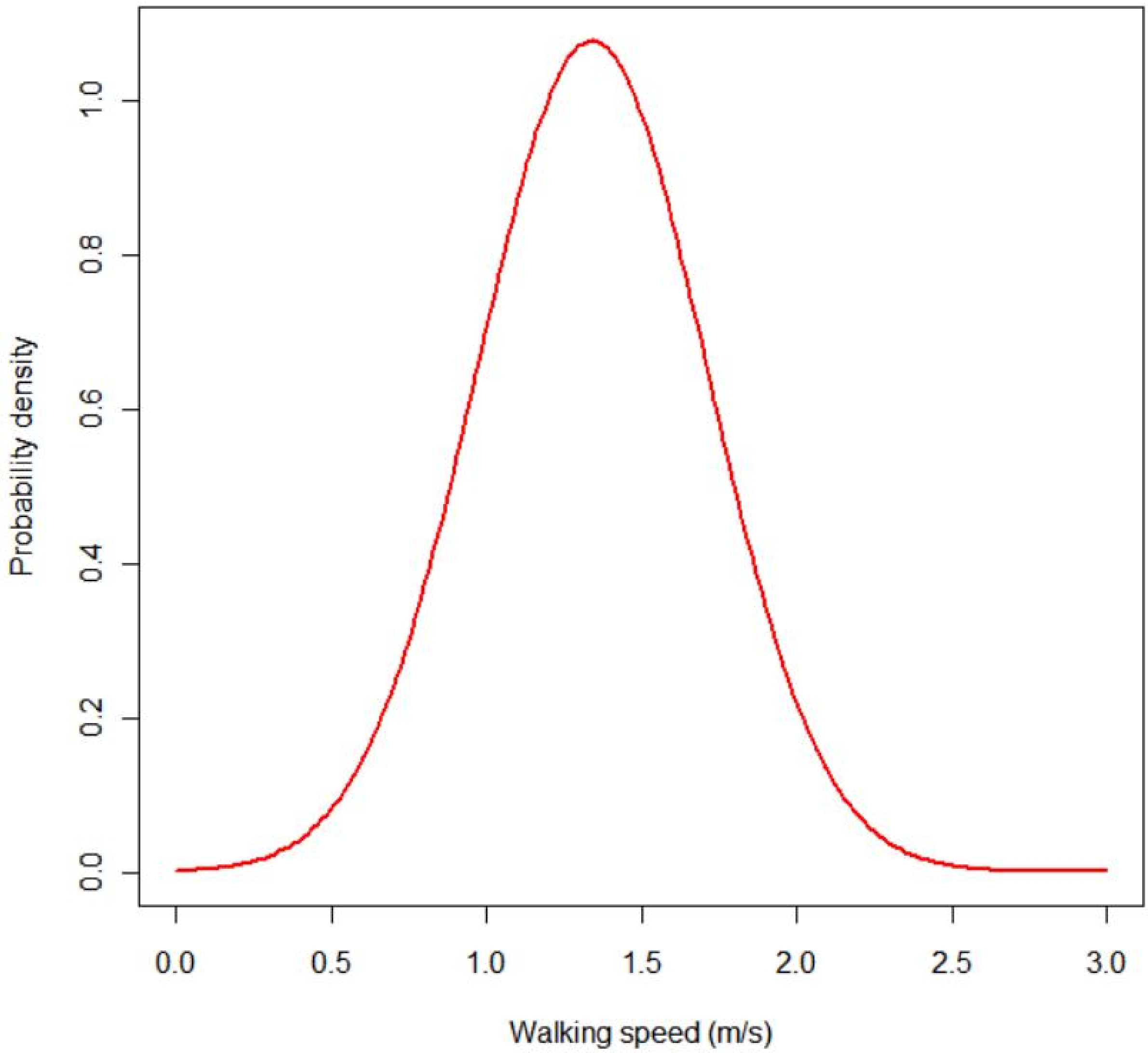

Figure 6: The walking speed of pedestrians is distributed normally with an estimated mean of 1.34 m/s and a standard deviation of 0.37 m/s according to Buchmueller and Weidmann (2006)

Generally speaking in VISSIM social force model parameters can be divided into two groups; model parameters by pedestrian types set for each type of pedestrian and global model parameters having a global effect on all pedestrians. Equations 1 and 3 can be descriptively reformulated as:

F = Driving force + Repulsive forces from other pedestrians + Repulsive forces from obstacles + Attractive forces

Different parameters in VISSIM could modify the effect any of these forces. For instance, λ, $A_{soc-isotropic}$, $B_{soc-isotropic}$, $A_{soc-mean}$, $B_{soc-mean}$ and VD govern forces between pedestrians. There is also a “noise” parameter that simply reflects the strength of the random term in the social force model in order to take into consideration taking the unsystematic variations of pedestrian behavior.

Since our calibration is a speed-related process, we mainly adjust the parameters having direct impact on the driving force.

In the following subsection we proceed to a brief explanation of the social force parameters adjusted in VISSIM for the sake of calibration.

Desired speed distribution: Obviously, the most relevant parameter that can have a direct impact on the speed results of pedestrians is the desired speed distribution. In social force model, the desired speed represents the speed pedestrians are willing to reach and is a determinant term in defining the driving force in equation 3. In VISSIM this parameter can be defined by a linear function between a lower and upper bound.

Relaxation time (τ): In equation 3, τ is a part of the driving force (the systematic force toward the desired direction and velocity) without which a pedestrian would never reach his/her destination. It is in time unit and also interpreted as reaction or inertia time. The higher this value is the smaller the force becomes and vice versa. To understand better the effect of this parameter in the simulation let's imagine the case of pedestrians entering a bottleneck. If the value of τ decreased the driving force would increase, which would generate higher density and flow through the bottleneck. Increasing τ would also result in smaller accelerations and larger radius when the pedestrian has to turn around a corner.

In SV building there exists 9 origins and destinations in total i.e. Cafeteria (CA), Elevator (EL), Balcony (BA), Main door (MD), Secondary door (SD), Second floor (SF), North door (ND), Couches (CO) and Restaurant (RE). Every pedestrian can enter or exit from either of these ODs. (see figure 7)

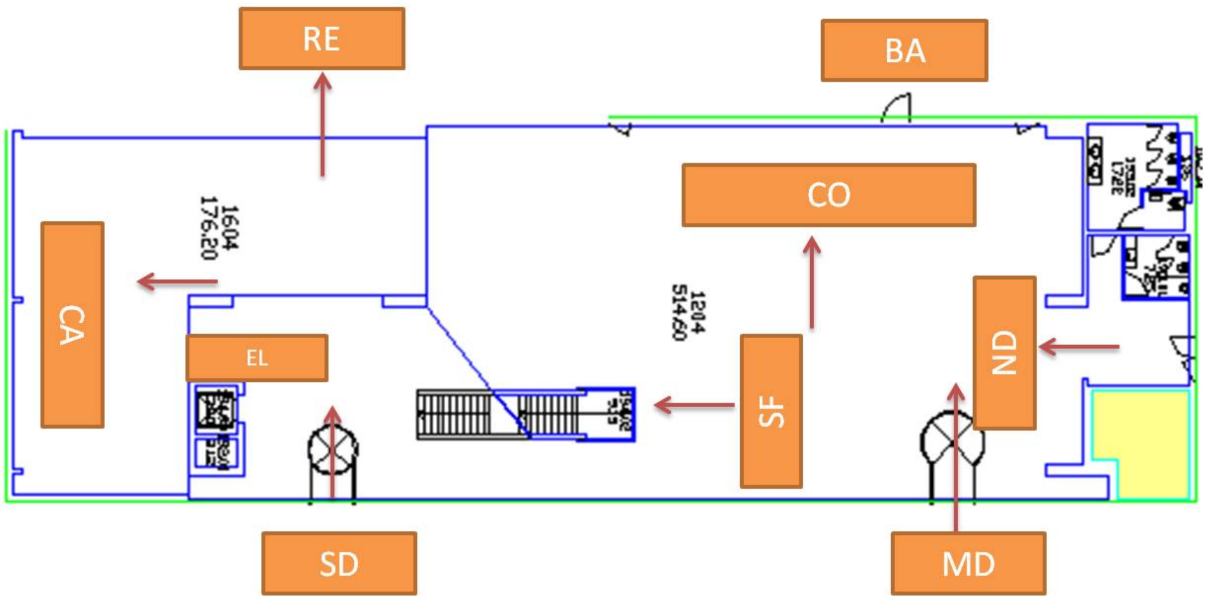

Figure 7: SV origins and destinations

Data collection in the SV building has been done by the use of two cameras capturing pedestrians' movements. The scene was filmed from 11:30 am to 01:30 pm (Wednesday) which is considered as the rush hour of the building when different students, collaborators, employees come along to have lunch, take coffees and take a rest. To have a dynamic OD, 2 hours of simulation have been divided into 8 (15min) intervals (11:30 - 11:45, 11:45 - 12:00, 12:00 - 12:15 ... 01:15 - 01:30).

From preliminary descriptive data analysis it was obvious that the restaurant and the cafeteria of SV are the main destinations for which people are passing by this hall at noon. There are two doors that give access to the building from the outside (the main door and the secondary door). Main door is much more used than the secondary door. Since main door and restaurant constitute the most important origin-destination pair, our calibration and scenarios' simulation are based on results of pedestrians' behavior on this trajectory.

Most microscopic traffic simulation models have the property to represent random variations in the behavior of the simulated traffic. In microscopic models this randomness, or stochasticity is used in many of the simulated processes. Examples are the arrival process of vehicles or pedestrians at the entries to the simulated network, the distribution of driver characteristics such as desired speeds, route choice preferences etc. Since the simulation has these random and stochastic processes as components several runs are required to generate valid predictions. One single simulation does not recognize the stochastic nature of simulation, may erode the confidence and credibility of the recommendation or decision, and may unintentionally mislead the decision-maker and the public. For this project we have run every simulation scenario 20 times. In order to do this, we chose the first 20 prime numbers (from 2 to 71) as random number generator seeds in VISSIM for 20 runs. As previously mentioned, the main and the most used itinerary in the building is the main entrance-restaurant path which conducts the highest number of people to the restaurant to have their lunch. Consequently, we have based the calibration process and scenarios on the results extracted from this trajectory. Simulation speed is set to 10 (simulation seconds/real seconds) where each simulation second represents 10 real seconds. Therefore our simulations have a duration of 720 simulation seconds equal to 2 real hours. Moreover, the simulation resolution has been defined as 5 time steps/simulation second meaning that the state of the simulation (pedestrians' speed, coordinates, etc.) is being recalculated and updated 5 times per simulation second. Given the uniform distribution of the desired speed defined in VISSIM and the large number of speed measures during simulation (5 times per simulation second) according to the Centeral Limit Theorem (CLL) we can conclude that pedestrians' speed results would already follow a normal distribution (see figure 8). So it remains only to verify how they fit (in terms of average and standard deviation) the normal distribution proposed by Professor Weidmann. The central limit theorem is one of the most remarkable results of the theory of probability. In its simplest form, the theorem states that the sum of a large number of independent observations from the same distribution has, under certain general conditions, an approximate normal distribution. Moreover, the approximation steadily improves as the number of observations increases.

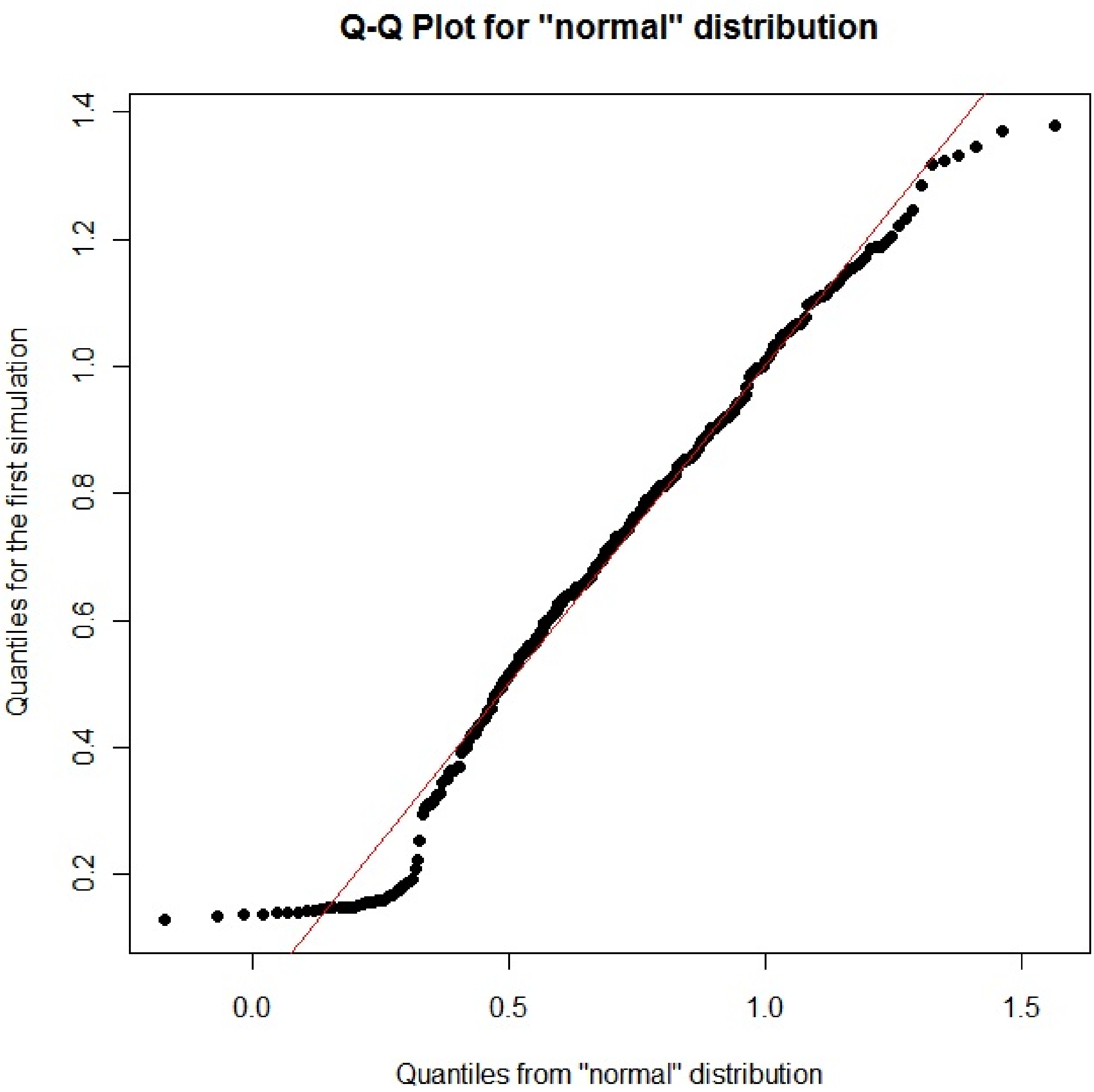

Figure 8: The normality test for the speed results of the first run with default parameter values through quantile-quantile plot

To cut the long story short, the calibration process consists in adjusting one of the model parameters at each stage, running the simulation 20 times, extracting pedestrians' speed results, calculating the average of them along the 20 runs and compare it to figure 6 so as to observe the extent our speed results fit the normal distribution proposed by Weidmann (Buchmueller and Weidmann, 2006). This comparison is done through the Kolmogorov-Smirnov test (K-S test). The Kolmogorov-Smirnov test (K-S test) is a nonparametric test for the quality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution, or to compare two samples. The Kolgomorov-Smirnovtest is defined by:

- H_0: The data follows a specified distribution (in our case figure 6)
- H_a: The data do not follow the specified distribution

The null hypothesis (here means good fitness of our results) is rejected if the test statistic, D is greater than the critical value obtained from a reference table. There are several variations of these tables in the literature that use somewhat different scalings for the K-S test statistic and critical regions. D is the maximum difference between the theoretical cumulative distribution of the distribution being tested with the reference distribution. For our calibration we refer to the table published by The University of York (Lee, 2005). Accordingly, since we have 20 runs given a Significance level of α = 0.05, the critical D value will be 0.2647.

The SV model is calibrated for the base scenario (actual situation) and the same calibrated model has been used for the following scenarios (optimization and forecast scenarios).

Default parameter values: Here are the default values for parameters that are going to be eventually modified for the sake of calibration.

- Desired speed distribution = it is defined as a linear function between 3.5 km/h (0.97 m/s) and 5.8 km/h (1.6 m/s) for men and between 2.6 km/h (0.72 m/s) and 4.3 km/h (1.2 m/s) for women.
- The default τ is equal to 0.4.

The following table illustrates the D-value resulting from the Kolmogorov-Smirnoff test. The K-S verifies for the good fit of the average distribution curve of 20 simulation runs default parameters' value in comparison with figure 6. In this scenario D-value is far greater than the critical D-value (see table 1. The null hypothesis can be rejected and the model needs to be calibrated.

Table 1: Comparison of D value from K-S test for simulation results (default values) with the critical D value

$D_{default}$	$D_{critical}$
0.6375	0.2647

Desired speed distribution change: To find a rational range for pedestrian speed, we referred to the literature. According to Teknomo (2006), the average speed of elderly pedestrians vary between 37 and 55 m/min equal to 0.62 and 0.92 m/s. Knowing that most of the pedestrians at EPFL are students and young collaborators we consider the minimum speed of 1m/s for calibration.

Regarding maximum speed the world walking speed record is 4.6 m/s held by Mikhail Shchennikov which is far beyond the speed rate at which people walk during their lunch break. Consequently we hold it as to be 3 m/s.

Therefore a linear function varying from 1 to 3 m/s has replaced the default desired speed distribution. Having modified this parameter, run 20 simulation, calculated the average of them, gone through the K-S test, the model has been ameliorated. The D value has decreased to (2). However the model is still not well calibrated and needs more parameter changes.

Table 2: Comparison of D value from K-S test for simulation results (desired speed distribution change scenario) with the critical D value

$D_{default}$	$D_{critical}$
0.4125	0.2647

Adjusting τ: When a group of pedestrians has to pass a bottleneck all except for the very first pedestrians have to slow down due to the social forces. If the value of tau is decreased the driving force would become stronger relative to the repelling social force term. As a consequence the density in front of the bottleneck increases and with it the flow through the bottleneck. Therefore to decrease the density in entrance and exit of the building we increase the value of τ to 1. The same steps as for the previous two scenarios have been proceeded here as well which lead to a better K-S test results (table 3). This time the test D-value becomes lower than the critical threshold.

Table 3: Comparison of D value from K-S test for simulation results (τ change scenario) with the critical D value

$D_{default}$	$D_{critical}$
0.1861	0.2647

4 SV simulation scenarios

Early studies considered only the infrastructure properties (sidewalk width...) to characterize the level of service in walking facilities. More recently, not only did researches consider infrastructure characteristics, they also took into account pedestrian movement properties (pedestrian density, travel time, queue length, etc.) in order to have a better idea of the offered service quality.

The pedestrian Level of Service is defined as an overall measure of operation conditions on a given itinerary. The definition of the quality of a walking area might be dependent of several different parameters such as level of accessibility to destination, connectivity and quality of the pedestrian network paths, safety and security, etc.

Various definitions of level of service have been developed by different researchers so as we can find LOS A defined as “best”, “most safe”, “very satisfied” or “excellent” in different studies.

Fruin (1971) considered six level of services for pedestrian facilities (walkways, stairwells and queues) according the the average area occupancy (density) and flow. LOS breakpoints in Fruin’s standard has been determined on the basis of the walking speed, pedestrian spacing and the probability of conflict at various traffic concentrations.

Table 4: Pedestrian Walkway LOS according to Fruin

LOS	Maximum Density ($\frac{ped}{m^2}$)
A	< 0.308
B	< 0.431
C	< 0.718
D	< 1.076
E	< 2.153
F	≥ 2.153

Fruin’s standard has been rectified by the National Cooperative Highway Research Program (research board, 2008) and been reported in Highway Capacity Manual (HCM). In this standard breakpoints between the levels are set at smaller values than Fruin’s standard.

Table 5: Pedestrian Walkway LOS (density) according to NCHRP

LOS	Minimum Pedestrian Space Per Person or Maximum Density	Equivalent Maximum Flow Rate per Unit Width of Sidewalk
A	($> 60\ \frac{ft^2}{ped}$) or ($< 0.179\ \frac{ped}{m^2}$)	$\leq$ 300 peds/hr/ft
B	($> 40\ \frac{ft^2}{ped}$) or ($< 0.270\ \frac{ped}{m^2}$)	$\leq$ 420
C	($> 240\ \frac{ft^2}{ped}$) or ($< 0.455\ \frac{ped}{m^2}$)	$\leq$ 600
D	($> 15\ \frac{ft^2}{ped}$) or ($< 0.714\ \frac{ped}{m^2}$)	$\leq$ 900
E	($> 8\ \frac{ft^2}{ped}$) or ($< 1.333\ \frac{ped}{m^2}$)	$\leq$ 1380
F	($\leq 8\ \frac{ft^2}{ped}$) or ($\geq 1.333\ \frac{ped}{m^2}$)	$>$ 1380

In order to compare scenarios regarding level of service in SV building, the following results are generated by the simulator and analyzed.

- **Travel time** which can be a good evaluation measurement for comparing scenarios. Travel times are extracted for origin-destination having the most demand in each scenario i.e. main door and restaurant in the base scenario.
- **Density** according to HCM standard (table 5) will help us assess level of services in different scenarios.

Once the model is calibrated and reflects realistic results for the base scenario (current situation) we can proceed to produce future scenarios.

Several scenarios have been defined and simulated in the SV building of which three are of the most interest and are going to be analyzed in this research paper.

1. First scenario is the base scenario which has been created out of real collected data. It aims at describing the current situation in the building during the rush hours. Other scenarios are built based on a) trying to find an optimal solution to existing issues b) forecast effects of demand/infrastructure adjustments.
2. Second scenario consists in assigning one door (main door) exclusively for entrance and another one (secondary door) for exit. The results show how having separate doors for entrance and exit could influence pedestrian flow fluency.
3. Third scenario looks at increase of 20% in number of pedestrians choosing the restaurant as their destination. What would happen if more and more people decide to have their lunch in SV due to a better food quality or an overal increase in number of students and collaborators at EPFL?

The base scenario reflects the current situation in SV building. Figure 9 illustrates the time it took by every pedestrian to travel from main door to restaurant. Explicitly, the density of the dots on the the graph confirms that during the third and forth quarter-hour (from 180 to 360 in simulation time or between 12:00 and 12:30 in real time) the restaurant experiences the highest number of clients. The travel times increase consequently in this period as well.

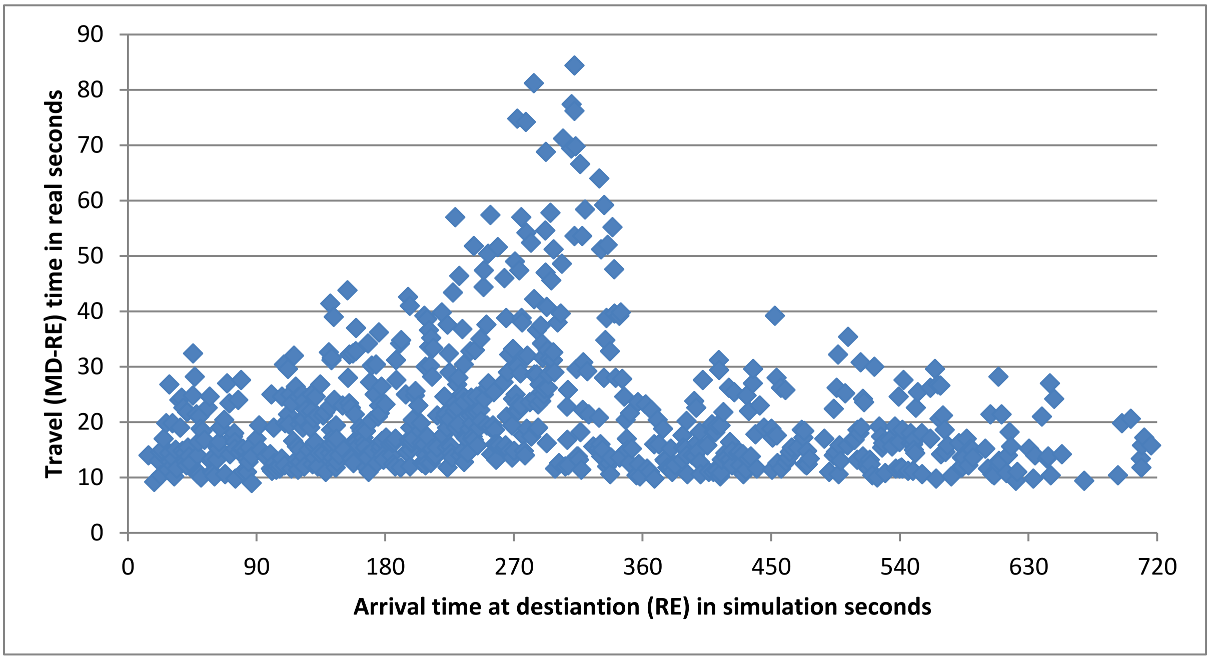

Figure 9: Pedestrians' travel times from MD to RE during simulation (scenario 1)

As discussed before, one of the standards based on which level of service can be evaluated is the Highway Capacity Manual standard. Figure 10 reflects the LOS of the whole studied area via colored heat maps drawn for 15min (90 simulation seconds) intervals. It is based on HCM standards. Pictures follow a chronological order from top left which is describing the LOS at the beginning and the bottom right picture which concerns the last 15 minutes of the simulation.

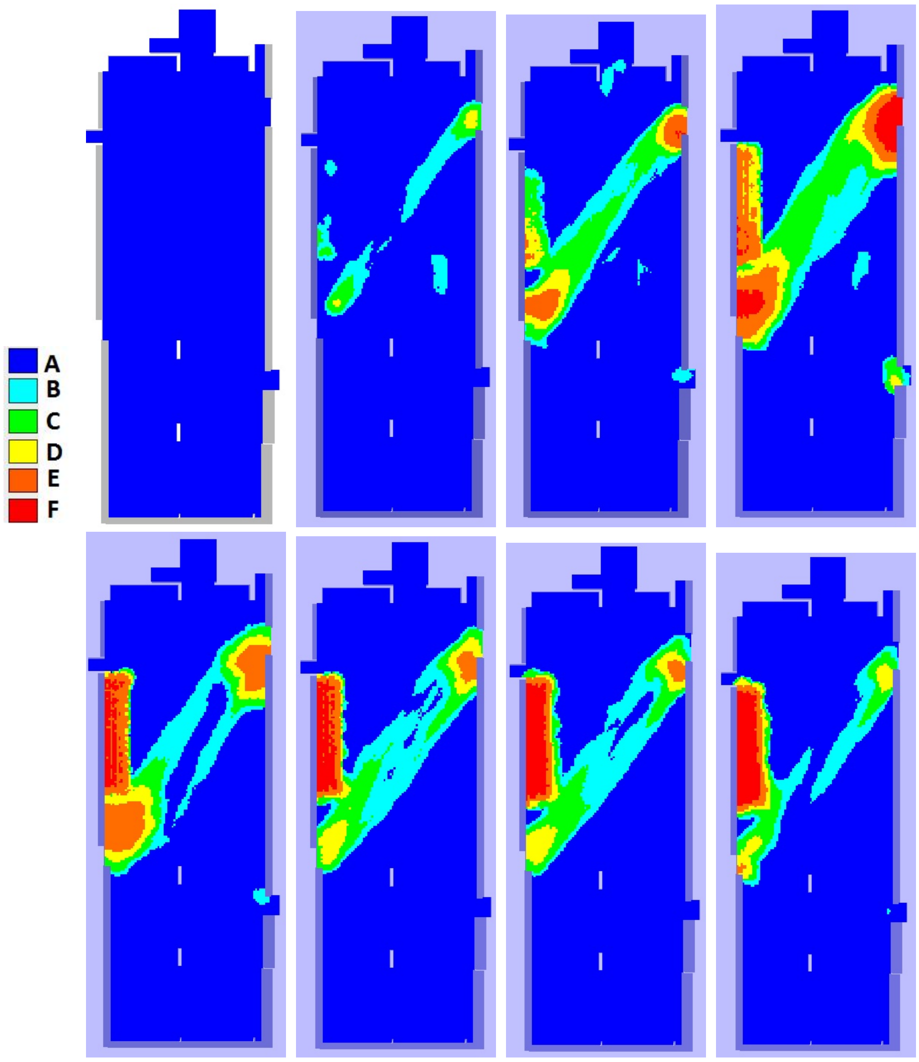

Figure 10: LOS for the first scenario based on HCM standards. On the top left is the first 15-minute interval and on the bottom right is the last 15-minute interval

Conceivably, the idea of having separate entrance and exit affect the important flow between main door and restaurant. Pedestrians' movement has become smoother and faster in this second scenario. By comparing the travel times figure 11 to those of the first scenario figure 9 we can obviously observe that the graph has moved down in many points leading us to the fact that travel times have mostly decreased for MD-RE trip.

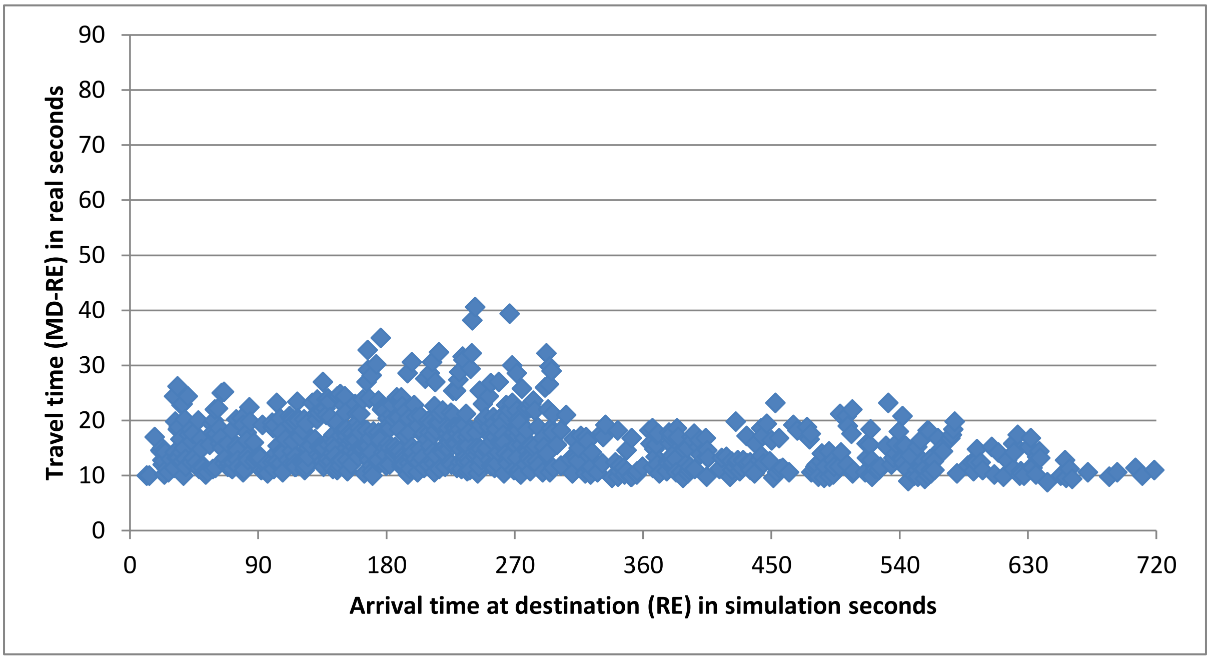

Figure 11: Pedestrians' travel times from MD to RE during simulation (scenario 2)

Moreover, if we follow the LOS at restaurant and main door and compare them to LOS of the first scenario, we comprehend that the LOS has ameliorated in the second scenario for these origin/destination.

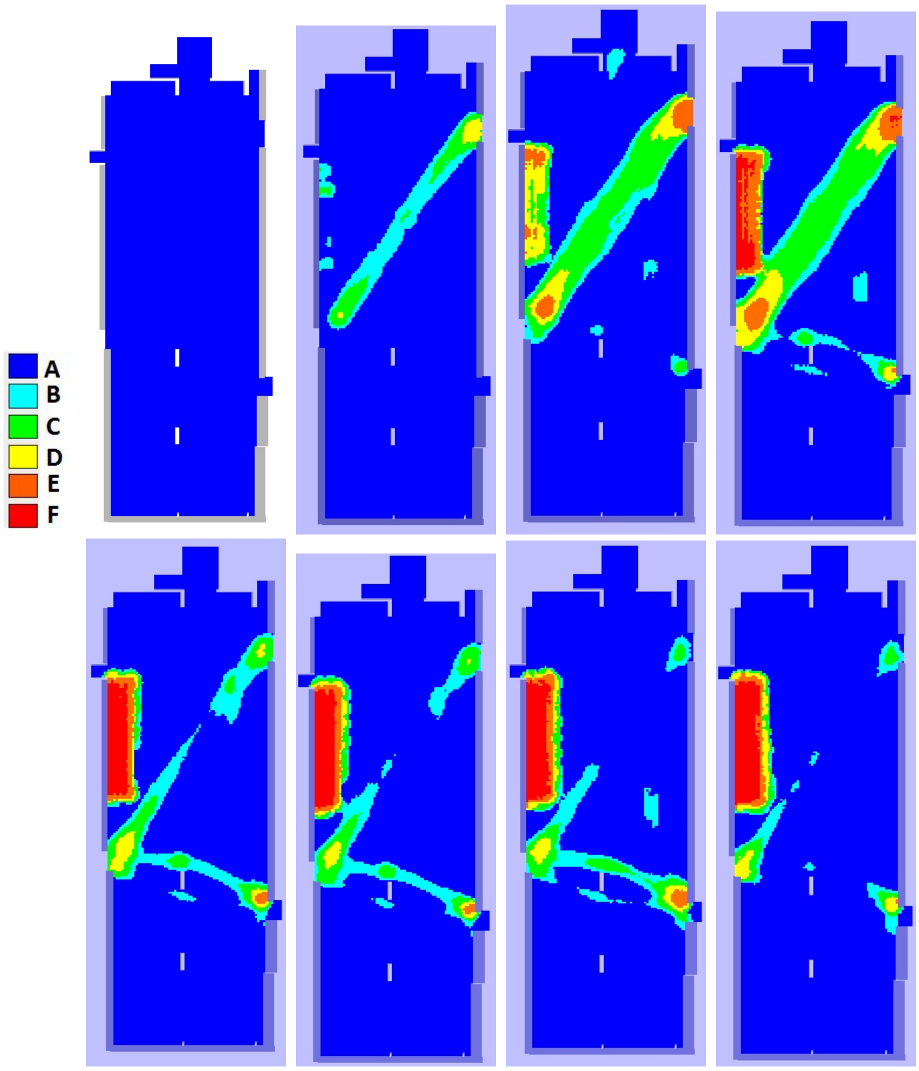

Figure 12: LOS for the second scenario based on HCM standards. On the top left is the first 15-minute interval and on the bottom right is the last 15-minute interval

Results of the third scenario demonstrate a significant increase in travel times (MD-RE) due to a 20% growth of the number of pedestrians going to the restaurant.

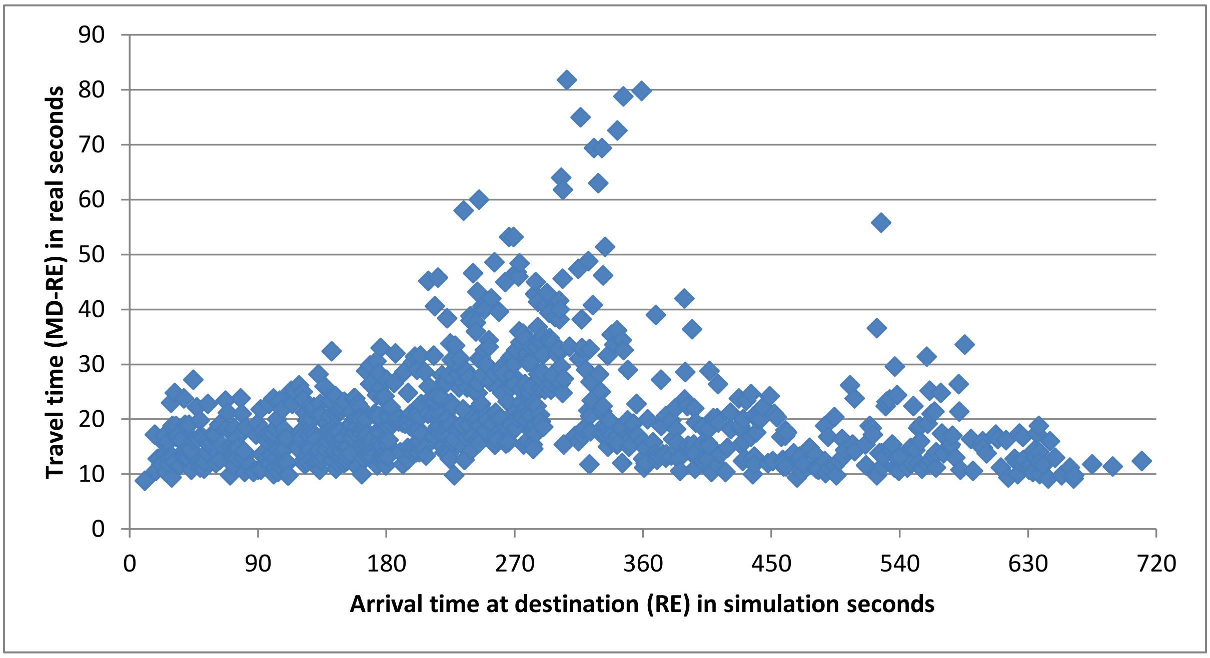

Figure 13: Pedestrians' travel times from MD to RE during simulation (scenario 3)

More number of clients (we tried with 30% and 50% increase in restaurant demand) can even lead to a complete congestion state at the restaurant and the main door.

Level of service strongly declines in the third scenario (figure 14).

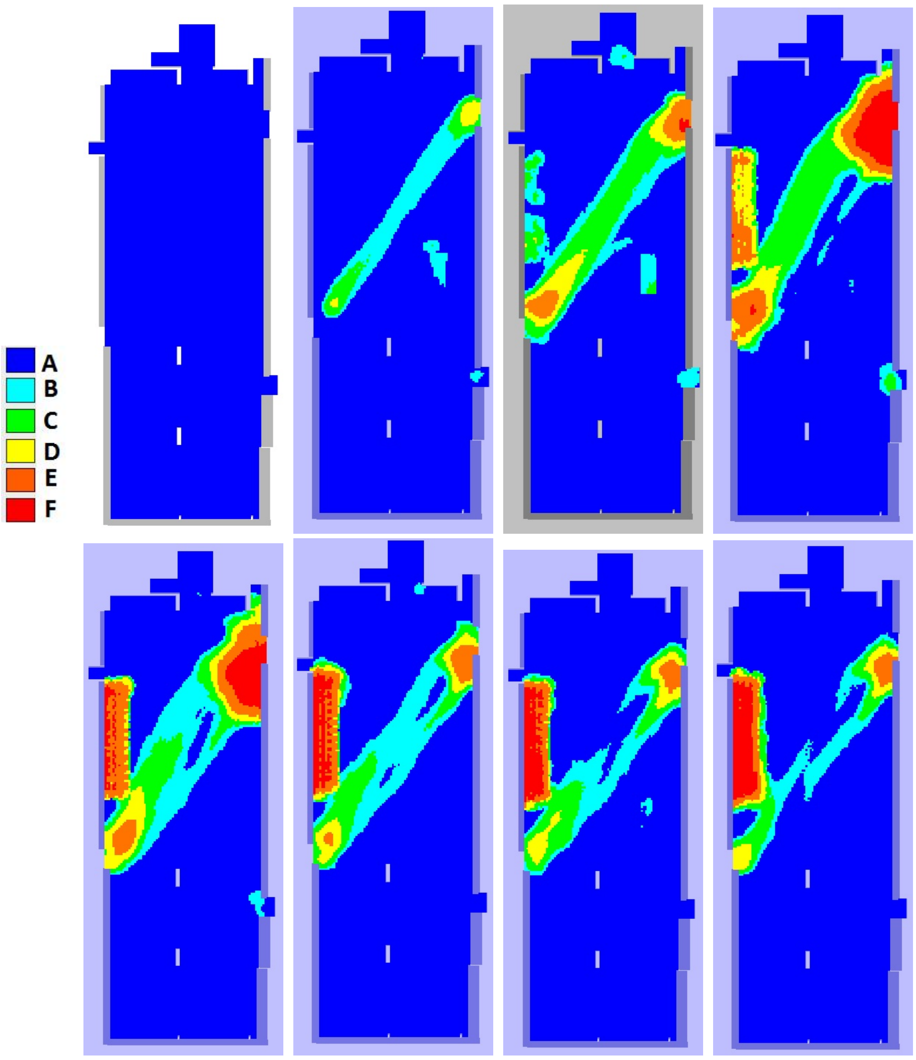

Figure 14: LOS for the third scenario based on HCM standards. On the top left is the first 15-minute interval and on the bottom right is the last 15-minute interval

5 Conclusion

In this project a comprehensive review of pedestrian modeling literature helped us put together and compare what had been already done in this domain. We could eventually establish a methodology to deal with pedestrian optimization problems. More importantly a real experiment has been conducted in this regard on which the project was based. The data was collected by two cameras in the SV building and was processed manually with the naked eye. Data processing is a time consuming but important task that can have a direct impact on the precision of the simulation. For the train station project, the data is collected by professional cameras and processed by image processing algorithms that can follow pedestrians from their origin to their destination in order to get pedestrians' trajectory data. Then, the model can be calibrated and validated using the same principle as in SV experiment.

Finally, the situation of the SV building was entirely studied in terms of pedestrian movement at lunch time. In SV building the most frequent trajectory at this period is the one from the main door to the restaurant. An optimization scenario of having one exclusive door as entrance and another one exclusively for exit was elaborated. This scenario leads to more fluent flow at peak periods. Travel times from the main door to the restaurant are smaller than the base scenario. A forecasting scenario (demand change) was also studied. The results prove that with approximately 1.5 times more restaurant clients than the current situation, the flow will get stuck in the building and pedestrians will not be able to move.

With regard to prospects associated to this project, we can mention that the methodology established in this thesis can be used for other pedestrian simulation projects as well.

Furthermore gathering the trajectories data would not only allow us to take into consideration route choices and have more realistic simulation results.

More detailed optimization scenarios with different characteristics can be defined and analyzed, for instance: scenarios regarding pedestrian flow in different periods of the day or different days of the week, scenarios concerning the service rate inside the restaurant and its effects on pedestrian movement and queues, etc.

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