# SENSITIVITY ANALYSIS OF PEDESTRIAN SIMULATION ON TRAIN STATION PLATFORMS

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**Abstract.** As the concerns for pedestrian safety in station design are growing, multi-agent simulation becomes more widely used nowadays. While the difference between inputs in regard to their impacts on simulation outputs needs further research, previous studies fail to provide a global analysis of it in complex environments with limited computation resources. Therefore, regression-based SRC and revised Morris Method are employed in a sensitivity analysis of train station platform simulations. Results show that preference for escalators and alighting rate are influential parameters to all three concerned outputs while the standard deviation of walking speed is negligible. Given that most simulation users have limited time and resources, this paper provides a list of parameters that deserve the time and effort to calibrate together with a factor fixing method that can be applied in similar scenarios. In this way, simulation users can lower the uncertainty of train station simulations more efficiently.

**Keywords.** Sensitivity analysis; Train station; Pedestrian; Simulation; Morris Method.

## 1. Introduction

As the concerns for pedestrian safety in station design are growing, multi-agent simulation becomes more widely used nowadays. A great number of studies focuses on pedestrian heterogeneity, which deals with how pedestrians vary in regard to their walking speeds(Ma, 2011), group sizes(Moussaïd et al., 2010), luggage(Ye, Chen and Jian, 2012) and so on. However, when train station designers try to integrate all of them into simulation practice, they will end up with overparamaterized models which are impractical for designers because they have no time to calibrate all the parameters mentioned in those studies. Train station designers need to figure out the most influential inputs which need further calibrations without wasting time on negligible ones.

That's when sensitivity analysis stands out as a tool for evaluating the importance of different inputs in pedestrian simulations. But two shortcomings are identified in related studies. First, most of them focus on simple scenarios like tunnels(Teknomo and Gerilla, 2005), bottlenecks(Gödel, Fischer and Köster, 2020), and evacuations(Lord et al., 2004). But sensitivity analysis in complex environments like train stations has not been thoroughly discussed. Second, the

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sensitivity measures used in many previous studies are either local measures which fail to explore the entire space of inputs, or time-consuming ones which are not suitable to simulations for complex environments.

Fortunately, recent studies have provided numerous observation data and behavioral models in train stations, which paved the way to the sensitivity analysis in such complex environmenets. As for the second gap, two sensitivity measures which have rarely been used in previous pedestrian simulation studies may help. First, although regression-based methods like SRC can only deal with linear or monotonic parts of the models(Borgonovo and Plischke, 2016), they consume far fewer computation resources. Besides, screening methods like Morris can also conduct low-cost analysis by a coarse exploration of input space(Saltelli et al., 2004, p. 93; Campolongo, Cariboni and Saltelli, 2007).

Therefore, based on observation data and models from various studies, this paper tries to make new contributions by a sensitivity analysis for pedestrian heterogeneity in a complex environment rather than simple scenarios. Besides, with the help of the two measures above, a global sensitivity analysis is carried out with far fewer computation resources compared to previous research.

The paper is organized as follows: In Section 2, the selected train station platform and simulation software is briefly introduced. Then eight inputs and their probability spaces are summarized through literature reviews and observations, followed by the selection of three outputs. The briefings of the two sensitivity measures are also provided. Section 3 presents the results, verifications, and validations of the method. The last section covers conclusions and outlook on future work.

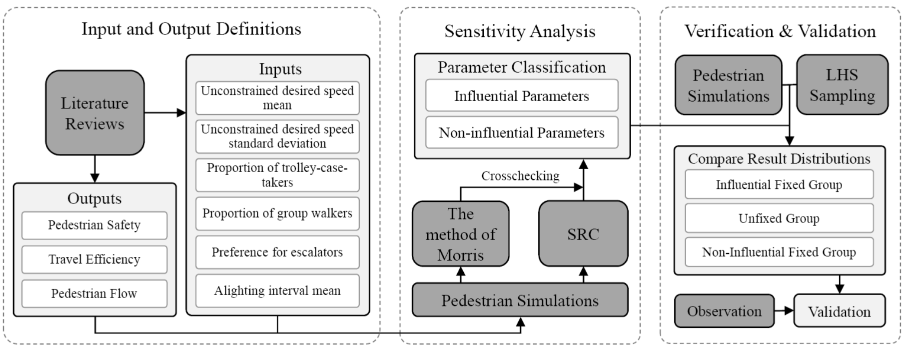


Figure 1. The analytical framework of this paper.

## 2. Model and Methods

### 2.1. TRAIN STATION PLATFORM MODEL

A train station platform in China is selected in this study. And this study focuses on simulations of alighting events, when passengers get off train carriages, leave the platform, and enter the arriving hall. The simulation model is illustrated in figure 2, consisting of platforms, gates from which passengers alight, together with stairs and escalators which are connected to the arriving hall. As this paper mainly focuses on alighting events of one single terminal shift, boarding passengers are not taken into considerations and the model ends with the entrances to the arriving hall, not including the entire process of leaving the station.

Previous studies have explored various agent-based pedestrian models. Social-force-based models, firstly introduced by Helbing(Helbing et al., 2005), are the most widely used ones. In the realm of simulation applications in microscopic environments like train stations, open-source or licensed software like AnyLogic(Chen, 2014), Legion(Wang, 2011) and MassMotion(Lang, 2018) are often chosen as pedestrian simulators. This paper uses MassMotion 10.6 with related SDK as the simulation platform, which has been used and validated by other researchers(Rivers et al., 2014; Arup, 2015; Mashhadawi, 2016).

Figure 2. Train station platform model shown in MassMotion .

2.2. INPUT PARAMETERS

According to a previous study(Davidich and Köster, 2013), parameters can be categorized into stationary inputs, quasi-stationary inputs and dynamic inputs according to their changing speed. And inputs that are picked for sensitivity analysis should be suitable for the aim of the study. As this paper aims for simulations at the design stage of train stations, dynamic parameters like the number of passengers are fixed during sensitivity analysis because they are mainly used in simulations for routine operations. Besides, as this paper focuses on pedestrian-related parameters, stationary inputs like built environment geometries are also fixed in this paper.

Therefore, inputs in this paper are mainly quasi-stationary inputs, which may change gradually but can be treated as stationary ones for the prediction period, ranging from pedestrian characteristics to facility preferences. All probability spaces of input parameters are summarized by literature reviews. Since this paper focuses on evaluating the impacts of the inputs in the context of the whole China, a majority of reviewed data is in the context of China and the probability spaces are set by picking maximums and minimums among all reviewed surveys.

All inputs with their possibility spaces are summarized below. Besides, in order to detect which inputs are negligible, a control parameter which is actually not used in the simulations is added to the model.

Table 1. Uncertain inputs and their probability spaces used for the sensitivity analysis.

| | Parameter and the source of related observations | Abbr. | Unit | Range |
|---|---|---|---|---|
| 1 | Unconstrained desired speed mean | avg_spd | m/s | $\mathcal{U}(1.25, 1.4)$ |
| 2 | Unconstrained desired speed standard deviation<br>Zhang(2009), Ma(2011), Chen(2014), Wu(2016) | std_spd | m/s | $\mathcal{U}(0.15, 0.3)$ |
| 3 | Proportion of passengers who carry large luggage like trolley cases<br>Pearce et al.(2008), Ye(2009), Ye, Chen and Jian(2012), Chen(2014), Tang(2017), Jin(2018) | trl_shr | | $\mathcal{U}(0.4, 0.7)$ |
| 4 | Proportion of passengers who walk in groups<br>Chen(2014), Tang(2017), Moussaïd et al.(2010) , Zhang et al( 2019) | grp_shr | | $\mathcal{U}(0, 0.65)$ |
| 5 | Preference for escalators*<br>Cao(2009), Zhang, Zhang and Zhang(2015), Zacharias and Tang(2015) | str_cst | | $\mathcal{U}(10, 40)$ |
| 6 | Alighting interval mean<br>Yuan(2007) | avg_int | s/ppl | $\mathcal{U}(1.3, 2.2)$ |
| 7 | Control parameter | ctrl_par | | $\mathcal{U}(0, 1)$ |

* This parameter is applied in MassMotion by configuring the additional distance cost of stairs. The probability space is set to be in parallel with observation data in related studies.

## 2.3. OUTPUT PARAMETERS

### *2.3.1. Output definitions*

The assessment objectives of previous studies mainly focus on travel efficiency, pedestrian flow and pedestrian safety. These types are discussed below respectively with parameter definitions for this paper.

As for efficiency, criteria like average pedestrian speed(Hoogendoorn, Hauser and Rodrigues, 2004), total time cost(Chen, 2014; Bao, 2019) and speed ratio(Bao, 2019) is widely used. Since walking speed has been set as input in this paper, average time cost ratio, a measure which is similar to speed ratio is adopted to eliminate direct impacts from changing walking speed. The formula is presented as below

$$ATR = \frac{1}{N}\sum_{i=1}^{N}\frac{T_i}{\frac{D_i}{v_i}} \tag{1}$$

where N is the total amount of passengers in the simulation, T is the actual time cost for a specific pedestrian, D is the pedestrian's travel distance and v is the unconstrained desired speed of a specific individual. Therefore, ATR indicates the mean value of the ratios of actual time costs to expected ones.

Maximum flow rate(MFR) is a common measure for description of pedestrian flows so this paper picks it. In addition, flow rate data are calculated as averages of 41-second-long periods so as to get more stable results. The formula of MFR is presented as below

$$MFR = \max \left\{ \frac{\sum_{t-b \leq i \leq t+b} F_i}{2b+1} \right\} when\{b \leq t \leq L-b\} \tag{2}$$

where L is the time length of the simulation in seconds, F is the number of passengers who just left the simulation in a given time i, 2b+1 is the length of the period sample.

Maximum densities at bottlenecks are often selected for safety measure(Hoogendoorn, Hauser and Rodrigues, 2004; Gödel, Fischer and Köster, 2020) so this paper picks the same measure. The formula is presented as below

$$MDB = \max \left\{ \frac{\sum_{t-b \leq i \leq t+b} P_i}{2b+1} \times \frac{1}{A} \right\} when\{b \leq t \leq L-b\} \tag{3}$$

where L is the time length of the simulation in seconds, A is the area of the bottlenecks in square meters, P is the population of bottlenecks in a given time i, 2b+1 is the length of the period sample.

### *2.3.2. Behavioral uncertainty management*

As pedestrian simulations are executed by generating randomized agents. Model can produce different outputs in multiple runs even if the same inputs are provided. This phenomenon is described as behavioral uncertainty of the model by Ronchi, Reneke and Peacock(2014). Therefore, model needs to be executed several times to get the mean value of the results for every set of inputs. According to the study of Ronchi, the number of runs for the same scenario can be determined by calculating this:

$$TET_{convj} = \left| \frac{TET_{avj} - TET_{avj-1}}{TET_{avj}} \right| \tag{4}$$

where $TET_{avj}$ is the average of the output from $j$ runs, $TET_{avj-1}$ is the average of the output from $j-1$ runs. When $TET_{convj}$ is less than 0.5%, $j$ can be used as the optimal number of runs. So each set of inputs is repeatly executed until $TET_{convj}$ reaches below 0.5%.

## 2.4. SENSITIVITY MEASURES

As discussed in the Introduction above, this paper prefers methods that don't take too much computation time. So regression-based methods like SRC become desirable choices because their time cost is not related to the number of inputs(Borgonovo and Plischke, 2016). However, SRC only works for linear parts of the model(Saltelli et al., 2004, p. 10). So a model-independent measure should be applied as a complement. Since this paper aims to detect the most and the least important parameters in train station platforms rather than discomposing the variance of the model, screening methods like Morris can be put into use. The computation cost of this method is a linear function of the number of inputs(Saltelli et al., 2004, p. 107), which consumes fewer resources than variance-based methods(Dellino and Meloni, 2015, p. 116).

Therefore, this paper uses SRCs firstly, which is the square root of the fraction of the output variance due to each input(Saltelli et al., 2004, p. 9). After that, a revised method of Morris is applied as a cross-checking tool. By generating sample trajectories(Campolongo, Cariboni and Saltelli, 2007), two measures are calculated. The first one is named σ, which is used as a measure for detecting factors involved in interactions with other factors. The other one, which is named μ * , is used to detect inputs with an important overall influence on the outputs. The Morris Method is executed by SALib(Herman and Usher, 2017) on the Python platform.

## 3. Results

### 3.1. SRC AND THE METHOD OF MORRIS

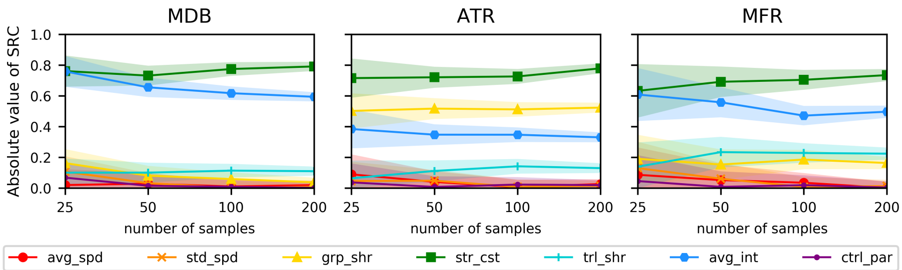


Figure 3. Absolute values of standardized regression coefficients(SRC) of inputs, changing as the number of samples increases. Each light-colored area refers to the 95% confidence interval of each SRC.

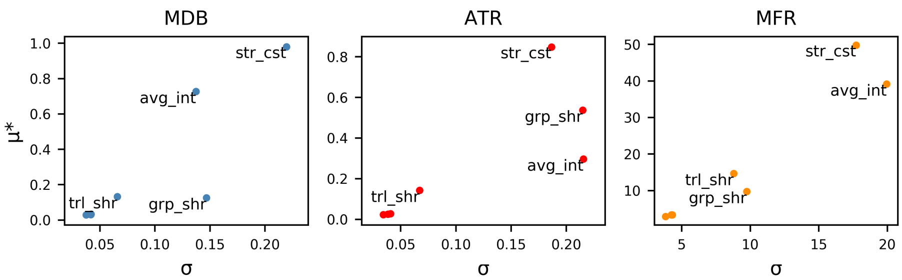


Figure 4. Scatterplots of the result of the method of Morris. The most influential inputs are annotated.

Linear regression models are built for three outputs respectively and SRCs are shown in Figure 3. All regression models reject the null hypothesis of an F test with coefficients of determination which are over 0.9, even though the models in this paper are assembled by non-linear parts. As for the method of Morris, 50 trajectories are evaluated and the results are shown in Figure 4.

As the figure illustrates, both methods produce similar results. Preference for escalators (str_cst) and alighting interval mean (avg_int) are prominent parameters for all three outputs. It indicates that if more people prefer to use escalators and people alight from carriages more quickly, there will be significantly more severe congestion at bottlenecks, lower flow rates, and people will spend longer time on travel than they expected. Besides, it also suggests that good management of alighting events can significantly reduce congestion at bottlenecks.

The mean value of walking speed distribution(avg_spd) also plays a part in MDB and MFR, but its impacts are smaller than the two inputs mentioned before. It is noticeable that the proportion of group walkers(grp_shr) is important to ATR, while avg_spd becomes negligible. The impact of the standard deviation of walking speed is not detected in both measures, indicating that it is a negligible parameter.

### 3.2. VERIFICATION: FACTOR FIXING

The findings of the two methods are testified by the observations of result distributions when different inputs are fixed to constant values. As figure 5 implies, when negligible inputs are fixed(see Fixed 1 group), the result distributions rarely change, indicating that they can be set to any value within the probability spaces in simulation practice. Meanwhile, when influential parameters are fixed(Fixed 2 group), the result distributions sharply shrink, suggesting careful calibrations of such inputs will lower the uncertainty of the simulation results greatly. The distribution of ATR is not narrowed to an ideal range in Fixed 2 group because influential inputs for ATR are different from the other two outputs, which is shown in the previous section.

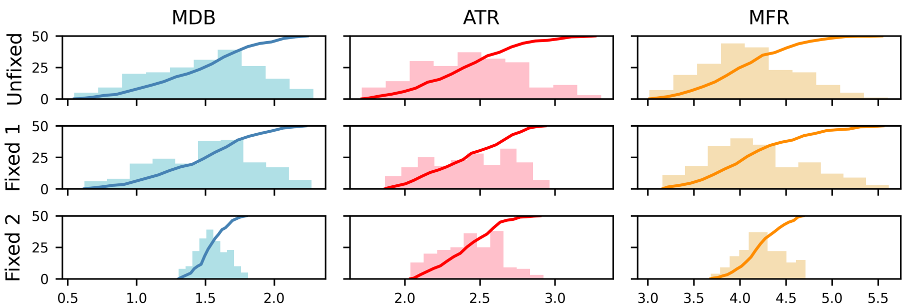


Figure 5. Histograms of simulation results under different input conditions. Cumulative distribution functions are also plotted. Unfixed: All inputs are sampled by LHS(Latin Hypercube Sampling) method. Fixed 1: Negligible factors(std_spd, grp_shr) are fixed to their midpoints of probability spaces while others are sampled by LHS. Fixed 2: Influential factors(avg_int, str_cst) are fixed.

### 3.3. VALIDATION

The model is validated by observation data in the train station platform. Firstly, the number of passengers and the most influential inputs(avg_int, str_cst) derived from the previous section are calibrated by observation data. Other inputs that are identified as non-influential, are set to the medium values of the probability spaces in section 2.2. The input settinng is shown in Figure 6 (right). Then, the simulation is executed 30 times. After that, the cumulative population and flow rate of the simulation are compared with empirical data.

| | Parameter | Value |
|---|---|---|
| 1 | avg_spd | 1.325 |
| 2 | std_spd | 0.225 |
| 3 | trl_shr | 0.55 |
| 4 | grp_shr | 0.325 |
| 5 | str_cst * | 15 |
| 6 | avg_int * | 1.41 |

* Calibrated parameters

Figure 6. (left) Empirical data is extracted from video recordings. (right) The parameters of the validation process.

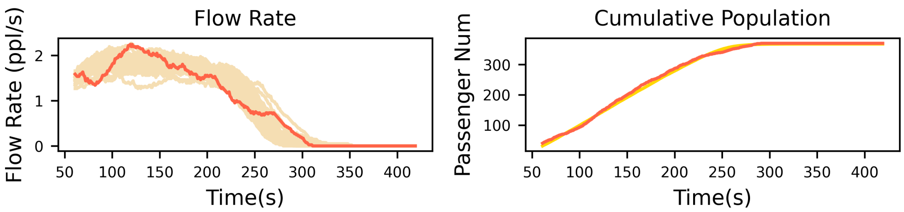


Figure 7. Flow rate at the vertical walking facilities(left) and the cumulative number of people who exited the simulation(right). Empirical data is illustrated by dark orange lines. And light yellow lines represent simulation results.

The results show that the model with only two inputs calibrated can predict the time when a majority of passengers leave the simulation very well. And the tendency of flow rate variation can also be simulated. The result of MFR(2.02) is close to the empirical data(2.24) but this should be further studied with more observations. Due to the limitations of the measuring method, the other two outputs are difficult to observe so they are not included in the validation process.

## 4. Conclusion and outlook

For train station designers, this paper helps them figure out the most influential parameters in alighting event simulations by conducting a sensitivity analysis. So they can just focus on calibrations of important inputs without losing the result accuracy in similar simulations. Specifically, the standard deviation of walking speed distribution, though widely studied and measured in other studies, is identified as a non-influential parameter in this paper. So it can be fixed for further similar studies and simulation practice. Preference for escalators and alighting rate are the most influential inputs to all three outputs so they need more careful calibrations. Other inputs impose smaller impacts on the results so simulation users can treat them differently according to their own needs.

Besides, this study also suggests a more time-efficiently sensitivity metric when designers need to conduct a new sensitivity analysis in other simulations which involve complex environments. Although the simulation model is often made up of non-linear parts, as long as the combination shows strong linearity, linear-regression-based SRC can be put into use to save computation resources.

However, the limitations still exist. Firstly, all inputs are assumed to be independent of each other in this study while the reality may not be the case. So the relative importance between influential inputs needs further research by considering dependencies between the inputs. Besides, while this study has been validated by empirical data, a larger-scale validation is needed to prove its compatibility. Also, the sensitivity analysis in this paper is restricted to alighting event simulations on train station platforms. It's worth applying the same methodology to other scenarios to compare the results between different environments. Finally, putting the findings into architectural design practice can be part of future work.

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