CETRA[2020*] 20-21 May 2021, Zagreb, Croatia
6th International Conferenceon Road and Rail Infrastructure

SELECTION AND ANALYSIS OF INPUT PARAMETERS INFLUENCING PEDESTRIAN MICRO-SIMULATED CROSSING TIME

Chiara Gruden[1], Irena Ištoka Otković[2], Matjaž Šraml[1]
[1] *University of Maribor, Faculty of Civil Engineering, Transportation Engineering and Architecture, Slovenia*
[2] *Josip Juraj Strossmayer University of Osijek, Faculty of Civil Engineering and Architecture, Croatia*

Abstract

Pedestrian unrestrained behaviour, sudden movements and vulnerability are elements, which can highly affect road safety, especially when interacting with motorized vehicles. Therefore, it is important to have a deep insight in pedestrian behaviour. A way to tackle this issue is micro-simulation. Modern micro-simulation tools, indeed, allow, thanks to the implemented mathematical formulation of the problem, to model and repeat a real situation in a virtual environment. Nevertheless, they need to well-fit the real observed behaviour: the calibration step allows to make the model reliable, by adapting selected, influential model input parameters. By dealing with pedestrian issues, software Vissim/Viswalk has been selected for micro-simulation, which implements Helbing's Social Force model. This model is based on several parameters, like relaxation time, side preference, strength and range of pedestrian interactions, amount of anisotropy, parameters governing the forces among pedestrians, noise, number of reacting pedestrians, queue order and straightness, which need to be set by the user when creating the model, but they can be hardly measured. This paper presents a selection of the recalled input parameters, on which statistical tests are carried out to understand their influence on the behavioural output – crossing time - that is supposed to describe pedestrian crossing behaviour. This is the first step towards the development of a new calibration methodology, which will keep advantage of artificial intelligence tools to fine-tune micro-simulation input parameters.

Keywords: pedestrian, micro-simulation, input parameters, statistics

1 Introduction and related works

Moving through urban area by foot, i.e. been a pedestrian, is one of the most wide spreading transportation ways. On the one hand it is an eco-friendly way of moving, it is healthy and it permits to easily and fast reach close facilities. On the other hand, the increase of walkers produces a greater interaction with motorized vehicles, letting the problem of pedestrian safety arise. As a matter of fact, pedestrians are the most free-to-move, but also the most vulnerable road users, and their behaviour is often not totally predictable for the other traffic participants. All these statements found the need of a deeper knowledge about walking behaviour, specifically in areas where interaction with motorized users exists. A way to tackle this problem, without affecting reality, is micro-simulation. This powerful and very promising tool allows, indeed, to reproduce and study a selected location on a virtual environment (computer), and to repeat many times the same external conditions – which in reality would always change. One of the most relevant issues highly affecting the results of a micro-simulation model is the choice of the parameters to fine-tune. [1] carried out an overview of all parameters used in previous research studies about traffic simulation model calibration, noticing that the most redundant ones are mean headway, mean reaction time, speed and, more generally, driver behavioural parameters. As regarding pedestrian simulation model calibration, the efforts spent in that way are much lower than for motorized traffic. In Table 1, the main works about calibration found in literature are reported and the utilized parameters are listed. 8 of the listed papers deal with social force model –may it be implemented in Vissim, or in a modified version of the recalled approach.

Table 1 Literature review about calibrated micro-simulation model parameters.

Authors	Calibrated parameters
[2]	free speed, anisotropy of social force; interaction strength and its range
[3]	not specifically told
[4]	parameters related to attractive and repulsive forces
[5]	interaction strength and range, obstruction effects of physical interactions, 4 social force parameters + 8 scenario specific parameters
[6]	pedestrian count, flow, passage time, no of overlaps
[7]	radius and comfort speed; comfort speed, neighbor distance, radius, time horizon; comfort speed, radius, 2 error-quantifying parameters
[8]	radius of pedestrians, A social, B social, B physical, border, A social Isotropie, B social Isotropie, τ, friction force, side preference right, velocity dependence, λ, longitudinal scale consider at maximum n pedestrians
[9]	pedestrian size, desired speed, time pressure
[10]	interaction strength and range, anysotropy
[11]	Interaction strengths and ranges for repulsive and attractive forces, relative distance, relative conflicting time, “footprint” effect.

What can be noticed is that the main parameters, which are modified by the authors to better fit real data, are the ones linked to the interaction strength and range of repulsive and attractive forces: these are also the parameters that majorly influence the dynamics in Vissim/ Viswalk social force model. As stated in [12], the most important difficulty when thinking about parameter selection, fine tuning and calibration, is the interpretation of these magnitudes, which greatly affect various and different behavioural aspects. Focusing on Vissim/ Viswalk social force model, the parameters which can be set up in the model are: reaction time, anisotropy, strength and range governing the interaction forces among pedestrians, time VD connected to pedestrian relative speeds, noise, number of pedestrians influencing the considered agent, queue order and straightness and side preference [13]. In the calibration attempt developed in [14], the authors use as initial parameter set a group of 13 magnitudes (Table 2, second column), which have been reduced to 4 in the other sets (Table 2, third column). As can be inferred from Table 2, not only the number of parameters changed, but also their values.

Table 2 Literature review about calibrated micro-simulation model parameters.

Parameters	Initial parameter values	2nd parameter set values	3rd parameter set values	Unit of measure
Radius of pedestrians	0.15			m
A social	0.5	0.1	2.5	m/s²
B social	2.8 m			1/s²
B physical, border	100			1/s²
A social, isotropic	25	10	100	m/s²
B social, isotropic	0.2	0.05	0.3	m
T	0.4			s
Friction force	0			
Side preference	Right			
Velocity dependence VD	2 s			s
λ	0.1			
Longitudinale scale	0.25			
maximum n pedestrians	5	15	15	

The present research focuses on pedestrian behaviour at roundabout crossings and aims at modelling pedestrian crossing time. Specifically, it will be developed in further steps a prediction model for the selected output (i.e. pedestrian crossing time) thanks to neural networks, which will be the tool to calibrate the developed micro-simulation model. The first step towards the development of such a calibration, is the selection and statistical analysis of the input parameters chosen as starting point for both models, as well as the understanding of their influence on pedestrian crossing time. In the following structure, the first chapter will recall the studies about pedestrian parameter selection and the choice made for this research. The second paragraph will describe the normality test held on the parameter datasets, while the third part will focus on the two statistical tests: non-parametric Kruskal-Wallis and parametric one-way ANOVA tests. Finally, the discussion of the results is provided and the first important conclusions of this statistical analysis are drafted.

2 The selection of input parameters

This study focuses on the problem of pedestrian crossing action, described by pedestrian crossing time. An existing roundabout located in an urban area and specifically the unsignalized crossing set on the main entry leg of the same have been chosen as study area. The crossing is 10.25 m long and 4 m wide and passes through two traffic lanes. After the definition of the geometrical features of this zone and their setting up in Vissim/Viswalk micro-simulation software, the most important step is the identification of which model parameters are influencing the expected output, i.e. crossing time. As summarized in the introduction, many authors already dealt with the right selection of input parameters to achieve an accurate model of pedestrian behaviour. Following the cited examples about parameter fine tuning [1] [2] [3] [4], it has been decided to select for this study 5 pedestrian parameters - tau, lambda, Asoc_iso, Bsoc_iso, side_pref - and their ranges (Table 3). Since in the situation analysed in this study there is a strict interaction with vehicular flow, also vehicular parameters have to be considered: the selected model to rule vehicular behaviour is Wiedemann 74, and the parameters chosen to be used are the three most affecting the car-following model, i.e. average standstill distance, additive part of safety distance and multiplicative part of safety distance (Table 3).

Table 3 Selected micro-simulation model input parameters.

Input	Name	Description	Min.	Max.
I1	Tau	Relaxation time	0.05	2
I2	Lambda	Amount of anisotropy	0	0.4
I3	Asoc_iso	Parameter governing pedestrian forces	3	7
I4	Bsoc_iso	Parameter governing pedestrian forces	0.1	10
I5	Side_pref	Side preference	-1	1
I6	Avg standstill distance [m]	Average standstill distance	1	3
I7	Additive part of safety distance [m]	Additive part of safety distance	1	5
I8	Multiplicative part of safety distance [m]	Multiplicative part of safety distance	1	6

Starting from this selection of input parameters and their ranges, a database of 100 random combinations of the same has been produced by applying a changing step of 0.1. Each one of these combinations has been then simulated via Vissim/Viswalk, and the simulated pedestrian crossing time has been added to the database. The following analyses have been based on the complete dataset, containing both the input combinations and their relative simulated output.

3 Results

3.1 Normality Test for crossing time simulation results

The first features that are essential to be discovered are the main statistical characteristics of the data and the type of distribution followed by the same. Descriptive statistics (Table 4) run on Vissim/Viswalk simulation results, shows that on a set of 100 data, the mean value is 6.407 s, while the median is 4.575 s. This let us infer that the distribution of the data could be non- normal.

Table 4 Descriptive statistics about pedestrian crossing time.

variable	N	N*	Mean [s]	StDev	Min [s]	Q1 [s]	Median [s]	Q3 [s]	Max [s]
VISSIM	100	0	6.407	3.502	2.440	3.673	4.575	7.773	14.5

To confirm this result, Anderson-Darling test has been set up. This test is based on the hypothesis that if the calculated p-value is lower than the set significance level, the distribution is not normal (null hypothesis for this test). Otherwise, it cannot be stated that the distribution is not normal – the null hypothesis is rejected, but no additional conclusions about the normality of the distribution can be made. In this study a significance level of 0.05 has been set, and the results reported in Table 5 have been obtained.

Table 5 Numerical results of Anderson-Darling test

Mean	StDev	N	AD	P-Value
6.407	3.502	100	6.355	<0.005

Also, the data plotting shows the non-normality of the selected dataset (Figure 1).

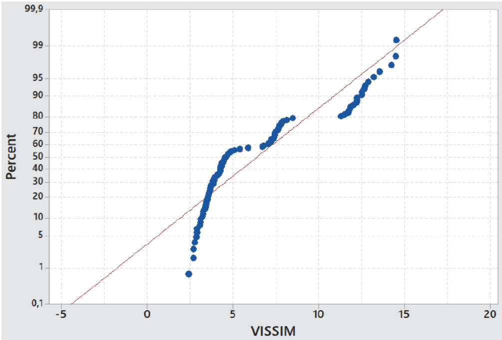

Figure 1 Probability plot of pedestrian crossing time: normal vs. data distribution.

3.2 Comparison of non-parametric and parametric test results

The next outcome, which will provide very useful information, is about the influence of the parameters on the selected output. Since the previous analysis confirmed the non-normal distribution of the data, firstly the non-parametric Kruskal-Wallis test has been used to examine this factor. Considering the large amount of available data and the strength of ANOVA, and following the suggestions of various authors [15]–[17], who recommend the use of this method also on data partially deviated from normality, when the recalled preconditions are available, the parametric ANOVA test has also been applied.

3.3 Kruskall-Wallis test

Kruskal-Wallis test is based on the comparison of the differences between medians. Specifically, it compares this magnitude to the set significance level – in this case 0.05 – and states if the null hypothesis „the population medians are all equal" is valid or must be rejected. If the p-value is less than the chosen significance level, the null hypothesis must be rejected, otherwise it can be confirmed. In the considered study, Kruskall-Wallis has been applied to all the selected input parameters to understand their influence of the output „crossing time". It turned out that all P-values are lower than the significance level (Table 6), and therefore all parameters are important in the calculation of the chosen outcome. For seek of completeness it has to be clarified that P-values reported in Table 6 (as regarding Kruskal-Wallis test) and Table 7 (referring to ANOVA analysis) are all null: actually, they differentiate one from the other for such low values, that do not influence the results, when compared to the significance level and thus they have been omitted. To understand which parameter influences the most the crossing time, the same test provides H-values. The greater this value is, the most influential the relative parameter. Table 6 summarizes also these results.
From Table 6 it can be inferred that the 3 most influential parameters are I1, I3 and I8, i.e. τ, Asoc_iso and multiplicative part of safety distance.

Table 6 Results of Kruskal-Wallis test on the selected parameters.

Input parameters	Description	H-values	P-values	Significance level
I1	Tau	80.63	0	0.05
I2	Lambda	47.67	0	0.05
I3	Asoc_iso	80.65	0	0.05
I4	Bsoc_iso	69.69	0	0.05
I5	Side_pref	27.15	0	0.05
I6	Avg standstill distance	48.04	0	0.05
I7	Additive part of safety distance	53.55	0	0.05
I8	Multiplicative part of safety distance	80.68	0	0.05

3.4 ANOVA

One-way ANOVA is a parametric test, which is considered by many authors [15]–[17]strong also for large dataset, which do not follow a normal distribution. In this case, ANOVA has been applied to compare the results achieved by Kruskal-Wallis test and establish if they agree or not. Being a parametric test, the precondition of ANOVA should be that means and medians equal each others, and its null hypothesis states that „the population means are equal “. When p-value is lower than the significance level this hypothesis must be rejected, otherwise it cannot. Analogously to Kruskal-Wallis test, there is a value, F-value, which highlight the degree of influence which each parameter has on the output. In Table 7 the results of ANOVA test, p- and F-values, are reported.

Table 7 Results of one-way ANOVA test on the selected parameters.

Input parameters	Description	F-values	P-values	Significance level
I1	Tau	229.52	0	0.05
I2	Lambda	27.85	0	0.05
I3	Asoc_iso	144.562	0	0.05
I4	Bsoc_iso	108.67	0	0.05
I5	Side_pref	10.25	0	0.05
I6	Avg standstill distance	19.76	0	0.05
I7	Additive part of safety distance	21.70	0	0.05
I8	Multiplicative part of safety distance	202.02	0	0.05

4 Discussion

The parametric and non-parametric statistical analysis of the same large database has allowed to make some considerations about the parameters chosen as influential on pedestrian behaviour, specifically pedestrian crossing time. Indeed, the first selection of those parameters has been made based on literature considerations and observations, but the application of these tests provides an insight in the importance and influence of the preliminary chosen parameters from a mathematical point of view. It is very promising that both the parametric one-way ANOVA test and the non-parametric Kruskal-Wallis test turn the same results. As can be seen from previous paragraphs, both tests underline the importance of all parameters, which – consequently – have to be considered in the further model. They also allow to score the parameters, from the most to the last influential, underlining that multiplicative part of safety distance, τ and Asoc_iso are the most powerful ones, followed respectively by Bsoc_iso, additive part of safety distance, average standstill distance, lambda and side preference. The only difference between the results of the two methods is that ANOVA recognizes a more powerful parameter in τ, followed by the multiplicative part of safety distance, Asoc_iso and Bsoc_iso. Also, the comparison between the two methods confirms the suggestions that ANOVA can be a strong statistical tool also for non-normal distribution datasets, if they are large enough.

5 Conclusions

Micro-simulation is a powerful tool to study traffic dynamics. This is valid also when dealing with pedestrians. In this paper the selection of input parameters for a micro-simulation model and its further calibration is presented. The first set of parameters has been chosen on the basis of literature observations, and a database with 100 random combinations of the selected parameters has been produced. Each one of this combination have been simulated via Vissim/Viswalk in order to obtain the chosen output, pedestrian crossing time. A first statistical analysis of the output results showed that it does not have a normal distribution. This statement led to the decision of applying a non-parametric test, Kruskal-Wallis one, to the database in order to analyse parameter influence on pedestrian crossing time.
Since the data base was large enough, it has been established the precondition set by [15] – [17], who states that also one-way ANOVA can be strong enough to statistically analyse which parameters are influential for the considered problem. The achieved results confirmed that the two methods were equivalent for the studied issue. Both Kruskal-Wallis and ANOVA tests turned out that all selected parameters are influential in the calculation of crossing time and must be considered in further elaborations. Also, thanks to H- and F-values respectively, they allowed to score the parameters from the most to the last influential. The results of this study are essential for next steps: indeed, they will be used as input parameters not only for the micro-simulation model, but they will also be implemented in the creation of a prediction model of crossing time. This independent model, developed thanks to neural networks, will be the tool used to develop a methodology to calibrate pedestrian micro-simulation models.

References

[1] Lee, J. B., Ozbay, K.: Calibration of a Macroscopic Traffic Simulation Model Using Enhanced Simultaneous Perturbation Stochastic Approximation Methodology, 2008.

[2] Liao, W., Chraibi, M., Seyfried, A., Zhang, J., Zheng, X., Zhao, Y.: Validation of FDS+Evac for pedestrian simulations in wide bottlenecks, 17th IEE International Conference on Intelligent Transportation Systems, ITSC 2014, 2014, pp. 554-559.

[3] Berrou, J.L., Beecham, J., Quaglia, P., Kagarlis, M.A., Gerodimos, A.: Calibration and validation of the Legion simulation model using empirical data, Pedestrian and Evacuation Dynamics 2005, Springer Berlin Heidelberg, 2007, pp. 167-181

[4] Rudloff, C., Matyus, T., Seer, S., Bauer, D.: Can Walking Behavior be Predicted? Analysis of Calibration and Fit of Pedestrian Models, Transportation Research Record: Journal of the Transportation Research Board, 2264 (2011) 1, pp. 101-109, doi: https://doi.org/10.3141/2264-12

[5] Zhong, J., Hu, N., Cai, W., Lees, M., Luo, L.: Density-based evolutionary framework for crowd model calibration, Journal of Computer Science, 6 (2015), pp.11-22

[6] Voloshin, D., Rybokonenko, D., Karbovskii, V.: Optimization-based Calibration for Micro-level Agent based Simulation of Pedestrian Behavior in Public Spaces, Procedia Computer Science, 2015, pp. 372-381

[7] Wolinski, D., Guy, S.J., Olivier, A.-H., Lin, M., Manocha, D., Pettrè, J.: Parameter estimation and comparative evaluation of crowd simulations, Comput. Graph. Forum, 33 (2014) 2, pp. 303-312

[8] Kretz, T., Hengst, S., Vortisch, P.: Pedestrian Flow at Bottlenecks: Validation and Calibration of Vissim Social Force Model of Pedestrian Traffic and its empirical Foundations

[9] Hongfei, J., Lili, Y., Tang, M.: Pedestrian Flow Characteristics Analysis and Model Parameter Calibration in Comprehensive Transport Terminal, Journal of Transportation Systems Engineering and Information Technology, 9 (2009) 5, pp. 117-123

[10] Johansson, A., Helbing, D., Shukla, P.K.: Specification of a Microscopic Pedestrian Model by Evolutionary Adjustment to Video Tracking Data

[11] Zeng, W., Chen, P., Yu, G., Wang, Y.: Specification and calibration of a microscopic model for pedestrian dynamic simulation at signalized intersections: A hybrid approach, Transportation Research Part C: Emerging Technologies, 80 (2017), pp. 37-70

[12] Kretz, T., Lohmiller, J., Sukennik, P.: Some indications on How to Calibrate the Social Force Model of Pedestrian Dynamics, Transp. Res. Rec. J. Transp. Res. Board, 2672 (2018) 20, pp. 228-238

[13] VISSIM 5.30-05 User Manual, 2011.

[14] Kretz, T., Hengst, S., Vortisch, P.: Pedestrian Flow at Bottlenecks – Validation and Calibration of Vissim's Social Force Model of Pedestrian Traffic and its Empirical Foundations, May 2008.

[15] McDonald, J.H.: Handbook of Biological Statistics, Second Edition, 2014.

[16] Hoskin, T.: Parametric and Nonparametric: Demystifying the Terms

[17] Kitchen, C.M.R.: Nonparametric vs Parametric Tests of Location in Biomedical Research, American Journal of Ophthalmology, 147 (2009) 4, pp. 571-572