Calibration of Nomad Parameters Using Empirical Data

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Abstract This paper describes the results of calibration of the Nomad pedestrian simulation model using empirical data from laboratory experiments. The results of the calibration show that complex walker models with large amounts of parameters can indeed be calibrated. The estimated average parameter values are shown and discussed, as well as their significance and correlation. Furthermore, pedestrian behaviors are investigated using the estimated parameters values in various conditions, among which flow configuration, pedestrian heterogeneity and traffic conditions.

1 Introduction

The microscopic pedestrian simulation model Nomad has (like other simulation models) a large amount of parameters. The calibration of such complex models is not a simple process given the reliability and correlation of parameters, as well as the problem of the information richness of the available data. Furthermore, pedestrian behaviours are complex and vary according to several factors such as walking area configurations, traffic conditions and pedestrian heterogeneity. Therefore, it is important to know to which situations a model can be applied for prediction. One way to estimate the general applicability of a walking model is to compare the parameter estimates when varying the different factors. Differences in the estimated parameter samples will reflect the inability of the model to correctly predict differences in the behaviours. If the parameter samples are significantly different then the model is not general enough and the samples reflect variations of pedestrian behaviours. As a positive consequence the estimated parameter samples

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can therefore be used to investigate how pedestrians are behaving in the different situations.

This paper therefore presents the calibration results of Nomad using data from several controlled experiments. The parameters are simultaneously estimated for each individual pedestrian using trajectory data. The calibration results are then used to investigate the reliability, parameter correlation and general applicability of Nomad.

In the following, first a short description is given of the laboratory experiments of which the data are used. Then, the Nomad parameters that will be estimated are introduced, followed by the calibration results. Finally, we show the effect of the flow configuration, the population heterogeneity and the traffic conditions on the estimated parameters. We end with conclusions and recommendations for future research.

2 Laboratory Experiments

The data used for the model calibration come from the controlled experiments described in Daamen and Hoogendoorn [1]. Figure 1 shows the infrastructure layout and flow directions of the four configurations discussed in this paper: unidirectional flow, bidirectional flows, crossing flows and a narrow bottleneck. All experiments have been performed under normal walking conditions, while only in the narrow bottleneck experiment congestion occurred. Since the congestion occurred upstream of the corridor, the area of this experiment has been split into two: one (possibly) congested area upstream of the bottleneck and an area inside the bottleneck where capacity occurred. Trajectory data have been collected for 0.1 s and smoothed and interpolated to time-steps of 0.2 s to minimize numerical errors in the estimation process.

3 Microscopic Pedestrian Simulation Model Nomad

The microscopic pedestrian simulation model Nomad has been developed at the department Transport & Planning of the Delft University of Technology [2, 3]. Nomad is an agent-based model, covering the tactical and operational levels of human behaviour, including route choice behaviour, activity (area) choice behaviour, walking behaviour, waiting behaviour and behaviour in special infrastructure elements, such as revolving doors and turnstiles. The Nomad model is composed of linearly added components that correspond to specific pedestrian behaviours: path following, pedestrian and obstacle interaction. The parameters shown in Table 1 are included in the calibration process.

The parameters describing the lateral avoidance between pedestrians (A_I and R_I) are only estimated in the experiments in which these lateral movements

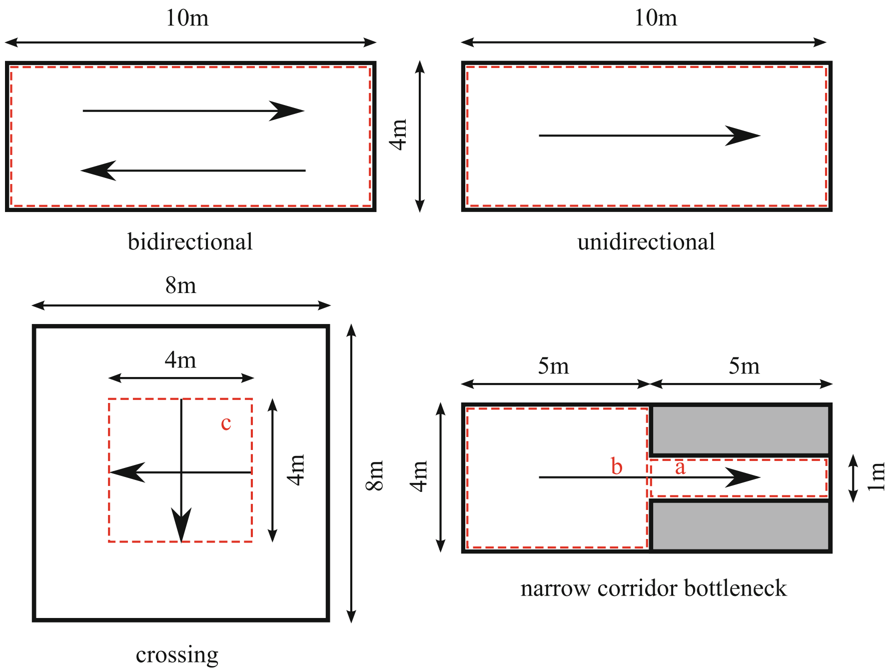

Fig. 1 Overview of laboratory experiment infrastructure configurations

occurred, that is, the bidirectional and the crossing flows. The parameter describing the interaction with obstacles is only estimated in the experiment with the narrow corridor, the only experiment where obstacles were present. All other parameters were estimated in all experiments.

Another important parameter in the Nomad model is the free speed V_0. Since this free speed is specific for each pedestrian, this speed is measured using the beginning of the trajectories (first 0.2 s), when the densities are low and it can be assumed that a pedestrian is walking in free flow conditions.

The parameters used to calculate the physical forces have been excluded from the calibration as previous tests have shown these parameters to be insensitive to calibration results. The parameters have been set to very large values to prevent compressions of pedestrians ($K_0 = 1{,}000$, $K_1 = 1{,}000$). The stochastic noise that accounts for modelling errors and behavioural variations was always set to zero, preventing it to influence the estimation. This way, the estimated parameters are optimal regardless of the size of the modelling errors and the behaviour variations can be measured by the differences of the parameters for different individuals.

Table 1 Overview of Nomad parameters estimated in this paper

Symbol	Explanation
T	Acceleration time (s), the time required to accelerate towards the free speed V_0 in the direction of the desired path. Small values of T will force pedestrians to walk very close to their desired path with their free speeds and any deviation from the path will generate large path following accelerations
A_0	Interaction strength (m/s^2), controls the intensity in which pedestrians are avoiding each other. Larger values of A_0 when other parameters are kept equal indicate an increase of importance of the avoidance accelerations due to other pedestrians
R_0	Interaction distance (m), controls how responsive the avoidance accelerations are to the distance between pedestrians. Small values of R_0 ($\sim$0.0 m) signify that only small distances between pedestrian cause avoidance accelerations
c_0^-	Transform the shape of the influence area behind pedestrians from circular (value = 1) to an ellipsoid. For values smaller than one the main axis of the ellipsoid is in the walking direction otherwise in the perpendicular direction
c_0^+	Transform the shape of the influence area in front of pedestrians from circular to an elongated ellipsoid similarly as c_0^-
ie_f	Influence area extension in the front (m), the largest distance at the front in which a pedestrian will provoke the avoiding behaviours
ie_b	Influence area extension in the back (m), the largest distance at the back in which a pedestrian will provoke the avoiding behaviours
A_1	Frontal interaction strength for pedestrians (m/s^2), controls the intensity of the extra lateral component of the avoidance accelerations when pedestrians are walking towards each other
R_1	Frontal interaction distance for pedestrians (m), controls how responsive the extra lateral avoidance accelerations are to the lateral distances of pedestrians walking towards each other
A_T	Anticipation time (s), the time in the future that pedestrians project the current locations of neighbouring pedestrians
A_W	Obstacle interaction strength (m/s^2), controls the extent in which pedestrians are avoiding obstacles. Larger values of A_W when other parameters are kept equal (*ceteris paribus*) indicate an increase of importance of the obstacle avoidance accelerations

4 Model Calibration Results

For the calibration results, samples of estimated parameters have been derived. A parameter set θ for an experiment consists of all the estimates of each parameter ($\theta_i = T, A_0, \ldots$). A single calibration thus results in an optimal parameter set θ^*, consisting of all samples $\theta_i^* \in \theta^*$. An estimated value is only part of the parameter set if it is significant, while values on the boundaries of the estimation interval are excluded from the set, since their optimality is not guaranteed. An overview of the

Table 2 Average values of all parameters for the five data sets

			Pedestrian interactions									
		Path follow	Ped avoid		Influence area				Lateral avoid		Antici-pation	Obstacle
	rad	T	A_0	R_0	c_0^-	c_0^+	ie_f	ie_b	A_1	R_1	A_T	A_W
bidir		0.32	2.02	1.24	0.94	1.01	1.30	1.98	7.08	0.69	0.53	
unidir		0.27	2.39	1.45	1.01	1.03	1.42	1.82			0.61	
cross		0.62	2.42	0.99	1.00	1.00	0.96	1.10	4.71	×	0.52	
bneckDown		0.63	4.51	1.28	1.07	1.06	1.04	1.51			0.56	9.43
bneckUp		0.57	2.84	1.06	0.99	0.96	1.36	1.14			0.60	9.02

estimated parameter values can be found in Table 2, where the × indicates that no significant estimations could be achieved.

Low values of the acceleration time T indicate a strong tendency of pedestrians to stay close to their desired paths. In general, the values of T are around values obtained in other calibrations [4, 5]. The unidirectional and the bidirectional flows resulted in significantly smaller values of T when compared with the other normal walking experiments, which is due to the lower densities in these experiments. In these relatively free situations, pedestrians have smaller probabilities to interact with other pedestrians and therefore only need small corrections to keep their desired path.

Larger values of the interaction strength A_0 alone do not indicate large avoidance accelerations because the final acceleration value depends on distances to other pedestrians and the interaction distance R_0. The relatively large values of A_0 and R_0 indicate that pedestrians in normal walking conditions are more reactive due to the presence of other pedestrians. This implies that when necessary pedestrians need to apply larger accelerations at larger distances to anticipate the longer distances between pedestrians (lower densities). The most reactive behaviours are encountered inside the narrow corridor (*bneckDown*), when they settle in a laterally displaced position that was identified by Hoogendoorn and Daamen [6] as the 'zipper-effect'. This arrangement puts pedestrians very close to each other and simultaneously close to the corridor walls, while the speeds inside the corridor are relatively high. With such high speeds, natural variations cause pedestrians to apply large accelerations to prevent collisions. The largest R_0 is estimated in the unidirectional flow (*unidir*) indicating that pedestrians are more sensitive to pedestrians further away than in the other experiments. This is largely due to the low densities in the experiment that make short distances very unlikely.

c_0^+ remained reasonably constant along the normal walking experiments with values around 1.0 indicating that pedestrians seem to be isotropic (scanning equally in all directions) contrary to previous findings [6]. However, further in this paper we show that for most walking experiments the slower the pedestrians walk the more they consider pedestrians walking near their walking paths (larger anisotropy). This is supported by the experiment *bneckUp* with the lowest average speeds presenting

Table 3 Percentages of significant parameters in each experiment (percentages below 5 % highlighted in bold)

Parameters	Path follow	Pedestrian interactions: Ped avoid		Influence area				Lateral avoid		Anticipation	Obstacle
Experiments	T	A_0	R_0	c_0^-	c_0^+	ie_f	ie_b	A_1	R_1	A_T	A_W
bidir	49	58	10	66	62	62	68	7	**1**	57	
unidir	75	62	17	60	71	71	71			56	
cross	52	36	**3**	40	55	43	28	**2**	**0**	48	
bneckDown	72	91	32	72	81	72	79			61	28
bneckUp	66	75	21	55	66	58	53			53	13

the largest anisotropy in the frontal part of the influence area. The opposite happens in the back part of the influence area where pedestrians are clearly reacting to pedestrians immediately at their shoulders and lesser by those behind them. This is probably due to the large densities. As for c_0^+, the values of c_0^- are around 1 with the largest anisotropy for the bidirectional experiments (*bidir*) due to the self-organised presence of lanes that align the pedestrians and also makes them consider less the pedestrians in the nearby lanes.

In all but the last experiment pedestrians clearly consider more what happens in their back than in their front ($ie_b > ie_f$). This surprising result is counter-intuitive since pedestrians are certainly more attentive to what they see in front, especially in relatively uncomplicated traffic situations and low densities that usually do not require special attention to the surroundings. These results may reflect a deficiency of the model rather than pedestrian behaviours. Campanella et al. [4] already showed the necessity of the so-called 'push from behind' in the Nomad model to come up with good validation results. This effect is stronger in the experiments in which pedestrians are more aligned with each other (larger differences between ie_b and ie_f and larger values of ie_b).

The average value of A_T is around 0.55 s, whereas the lowest values are found for the bidirectional and crossing flows, indicating that the benefits of cooperation reduce the necessity of anticipation. However, these differences are too small to be conclusive.

4.1 Significance of Calibrated Parameter Values

Table 3 shows the percentages of significantly estimated parameters, which values were not on the limits of the interval used by the optimisation algorithm. Most parameters are seen to be significantly estimated for a large percentage of the trajectories: only 4 out of 46 significant parameters were constituted from less than 5 % of the total amount of available trajectories. This shows that the parameters are relevant to the model and that the calibration procedure is finding optimal values.

Table 4 Significant correlations between parameters (only correlations above an absolute value of 0.35 are shown)

Parameters		Pedestrian interactions									
		Ped avoid		Influence area				Lateral avoid		Antici-pation	Obstacle
Experiments		A_0	R_0	c_0^-	c_0^+	ie_f	ie_b	A_1	R_1	A_T	A_W
bidir	A_0							0.50			
	R_1			0.71							
unidir	R_0						0.41				
	c_0^+					0.42					
cross	A_0		−0.41					0.99			
	c_0^-						0.48				
	c_0^+					0.51					
bneckDown	A_0			0.39							0.84

The parameters describing lateral avoidance (A_1 and R_1) show very low significance. To test the relevance of these parameters, a model with these parameters has been compared to a model without these parameters using the likelihood ratio test. These tests show a surprisingly high level of success, indicating that even though the parameter is not significant, any value different from zero (that is the equivalent of removing it) improves the simulated behaviour. The reason for the low percentage of significant parameters is the lack of a sufficient amount of moments when pedestrians are walking towards other pedestrians, which is the situation A_1 and R_1 can be estimated.

Correlation Between Calibrated Parameters

Table 4 shows that from a total of 190 possible pair combinations for all experiments, only 10 show significant correlations above an absolute value of 0.35. The low amounts of significant estimations for A_1, R_1 and A_W did not allow for many valid pair comparisons between these and other parameters, thus only few correlations involve these parameters.

The only correlation between parameters from different components was between the obstacle component parameter A_W and the pedestrian avoidance parameter A_0 for the bottleneck experiment, suggesting that the three components have a large independence from each other. The bottleneck situation is in this case very specific, since pedestrians keep their relative distances to walls regardless of the local densities experienced by the pedestrians, thus pedestrian avoidance accelerations had to be large. Table 4 also shows that 50 % of the correlations included at least one parameter of the influence area, indicating that the variables shaping the influence area are not independent.

Table 5 Similarity statistics for the walking experiments

	bidir	*unidir*	*cross*	*bneckDown*	*bneckUp*
bidir	0.00	**1.19**	1.79	1.77	1.50
unidir		0.00	**1.84**	1.64	1.50
cross			0.00	1.47	1.40
bneckDown				0.00	1.50
bneckUp					0.0

5 Effect of Flow Configuration on Estimated Parameters

This section discusses the differences in pedestrian behaviour due to different flow configurations of the experiments. Table 5 shows the results of the similarity statistics ST that are the sum of the KS distances $D_{1,2}$ of every parameter sample $\theta^i \in \theta^*$ of a pair of experiments:

$$ST = \sum_{\theta^i \in \theta^*} D_{1,2}(\theta^i) \qquad (1)$$

It is important to note that the KS statistics can be used regardless of if the KS test is passed. Once ST is measured for all pairs of experiments, the pairs with the smallest results can be identified and, based on the KS distances, it can be determined whether these experiments present similar pedestrian behaviours.

Table 5 shows that in general the experiments display a similar value of the similarity statistic. The unidirectional and bidirectional experiments show the smallest value of the statistic, indicating that these experiments are most similar, which can be explained by the occurrence of lane formation in the bidirectional flows, thus effectively turning these into several unidirectional flows. The largest value of the statistic occurs between the unidirectional flow and the crossing flows, which is also intuitive, but the difference is not significant.

6 Pedestrian Heterogeneity

In this section we investigate the heterogeneity of pedestrian behaviours by calculating the coefficient of variation CV for the parameter samples. Table 6 shows the coefficients for variation for all parameters in all experiments. For most of the samples the CV is large. Only the parameters c_0^- and c_0^+ presented relatively low averages of 0.23 along all experiments. The last column with the average CV per experiment was calculated using only the parameters that were common to all experiments. The overall average of CV is 0.71, in itself a large value that shows that there is a significant amount of heterogeneity in the population.

As the narrow corridor experiment has been split up into two separate areas, it is possible to see whether the behaviour of exactly the same pedestrians changed in

Table 6 Coefficient of variation for all estimated parameter samples

			Pedestrian interactions										
		Path follow	Ped avoid		Influence area				Lateral avoid		Anticipation	Obstacle	
	rad	T	A_0	R_0	c_0^-	c_0^+	ie_f	ie_b	A_1	R_1	A_T	A_W	μ
bidir		0.92	1.54	1.49	0.22	0.24	0.68	0.58	0.95	1.21	0.51		**0.77**
unidir		0.75	1.20	1.34	0.23	0.24	0.51	0.50			0.48		**0.65**
cross		1.07	1.20	1.54	0.24	0.23	0.32	0.32	1.22	×	0.47		**0.67**
bneckDown		0.74	1.34	1.47	0.23	0.22	0.57	0.54			0.49	1.02	**0.70**
bneckUp		0.92	1.39	1.58	0.21	0.24	0.65	0.62			0.50	1.00	**0.76**

the upstream and the downstream part, the so-called intra-pedestrian heterogeneity. Table 6 shows the differences between the estimated parameters for each pedestrian i walking upstream of the narrow corridor θ_i^{up} and inside the narrow corridor θ_i^{in}. This difference *dif* is calculated as

$$dif = \frac{\left|\theta_i^{up} - \theta_i^{in}\right|}{\max\left(\theta_i^{up}, \theta_i^{in}\right)} \tag{2}$$

The results show that pedestrians show significantly different walking behaviour upstream of and inside the narrow bottleneck, which is already indicate by the relatively large similarity statistic (1.5) in Table 5. Especially the parameters relating to the influence area, and specifically the ones transforming its shape (c_0^- and c_0^+) show large differences, while the small *CV* values (see Table 6) indicate that the parameters are not much affected by external conditions. We can thus conclude that natural variations of pedestrian behaviour (intra-pedestrian heterogeneity) causes these differences.

The median values for the path following, pedestrian avoidance, anticipation time and obstacle avoidance parameters show median values well above 0.6. This confirms the hypothesis that the behaviours are significantly different and we can conclude that natural variations occur here as well (Fig. 2).

7 Influence of Traffic Conditions

In this section, we investigate how the parameters vary for traffic conditions. Here, we take the speed as the independent variable, since it is relatively easy to measure and it always reflects the local conditions. For each pedestrian, the average speed encountered during his entire trajectory is calculated and assigned to an interval of 0.2 m/s. The average values of the estimated parameters per interval are then compared to see whether pedestrian behaviours change with speed. Table 7 shows for which experiments which parameters are statistically different.

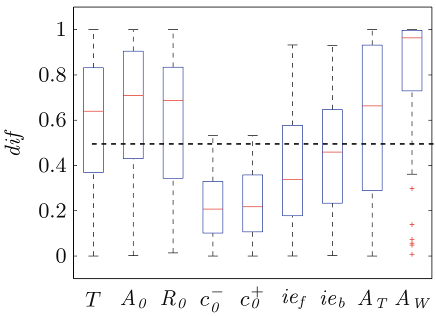

Fig. 2 Box-plot with normalised differences of parameters estimated for the same trajectories in the upstream and inside the narrow corridor

Table 7 Parameters for each experiment that have been shown a statistical difference for various speed intervals

	Path follow	Pedestrian avoidance		Influence area				Antici-pation	Obstacle
	T	A_0	R_0	c_0^-	c_0^+	ie_f	ie_b	A_T	A_W
bidir									
unidir		×				×			
cross	×	×							
bneckDown		×				×			
bneckUp	×	×			×		×	×	

Only the interaction strength appears to be statistically different for four out of five experiments, while the interaction distance, the shape transformation of the influence area behind pedestrians and the obstacle interaction strength does not seem to differ over speed. The samples of the frontal interaction strength and distance (A_1 and R_1) were too small to perform the test. Most significant difference were found for the upstream area of the narrow bottleneck experiment, which is also the experiment with congestion, and thus the largest speed range, whereas no significant differences were found for the bidirectional flow experiment, which might be caused by the self-organisation in the form of lane formation in which pedestrians simply follow other pedestrians. The relation between the significantly different parameters T, A_0 and are shown in more detail in Fig. 3, where the graphs on the left hand side show the experiments for which the parameter was significantly different, and in the graphs on the right hand side the parameter was not significantly different for the various speed intervals.

Figure 3a shows that the acceleration time follows a sigmoid curve for both the narrow bottleneck experiment (upstream part) and the crossing experiment, where the speed is constant for low and high speeds. For the other experiments the acceleration time is constant, and thus independent of the speeds. However, especially in the unidirectional and bidirectional experiments no high densities, and thus no low speeds, have been observed, so the sigmoid curve could still be possible

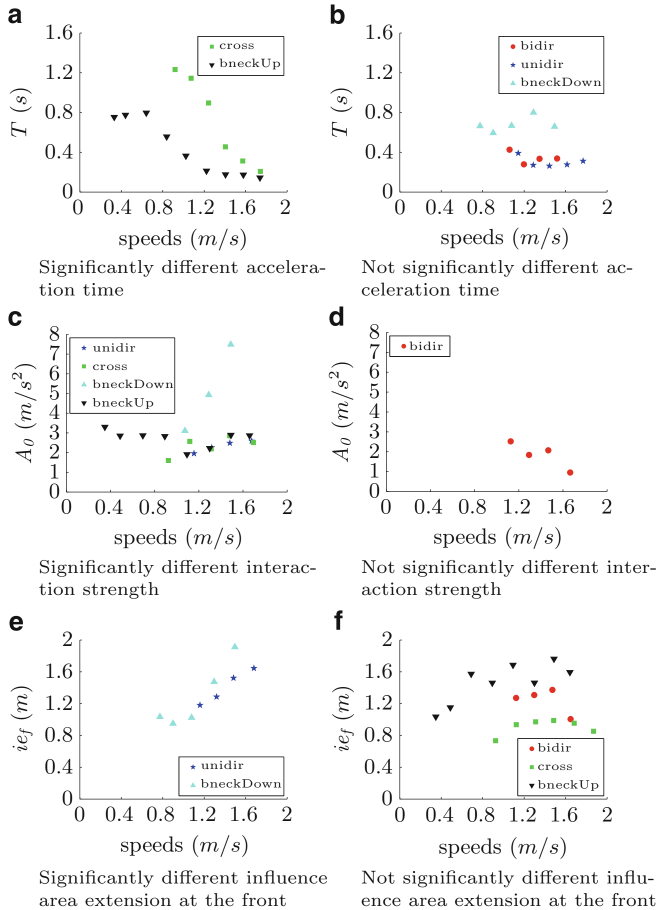

Fig. 3 Graphs with average parameter values of acceleration time (**a** and **b**), interaction strength (**c** and **d**) and influence area extension at the front (**e** and **f**) over speed

for these situations. The larger value of T is due to the more complex manoeuvres that are needed in congestion, especially when pedestrians also have to cross.

Figure 3c shows that A0 follows a U shaped curve, with a minimum value at speeds around 1.0 m/s for the narrow bottleneck experiment. For higher densities larger A_0 values are caused by the fact that pedestrians become more reactive and manoeuver more intensively, while for lower densities, pedestrians are compensating for the larger distances between pedestrians to avoid accelerations (more anticipation). Also Fig. 3e shows that pedestrians consider a longer horizon to perform their avoidance behaviours when walking faster: in more dense situations pedestrians are less likely to see pedestrians further away and even if they would they are more concerned with those nearby that are more likely to cause a conflict.

8 Conclusions and Recommendations

The main contribution of this paper is the extensive calibration of pedestrian behaviours using multiple sets of trajectories from several experiments, including different flow configurations, population characteristics and traffic conditions.

All parameters of the Nomad model could be calibrated, and are therefore necessary to be included in the model. Results of the calibrations from trajectories of different experiments show that flow configurations have a strong influence on pedestrian behaviours, and resulted in different parameters. Pedestrians in unidirectional flows behaved similar to pedestrians in bidirectional flows, showing that lane formation effectively separates the area in unidirectional regions. In congestion, pedestrian behaviour is quite different: in low densities pedestrians are more reactive due to the presence of other pedestrians, while in congestion pedestrians tend to follow other pedestrians and do not strain from their paths. The latter is also shown in the clear relation between some of the parameters and the (local) speed.

The clear differences between the parameters estimated for different situations show that a simulation model needs a specific parameter set to optimise prediction of pedestrian behaviour in a specific situation. However, simulation models are not applied for specific situations, but for a combination of situations, so future research aims at the assessment of the different parameter set for different situations.

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