A methodology to calibrate pedestrian walker models using multiple objectives

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Abstract

The application of walker models to simulate real situations require accuracy in several traffic situations. One strategy to obtain a *generic* model is to calibrate the parameters in several situations using multiple-objective functions in the optimization process.

In this paper, we propose a general methodology for calibration of walker models. This methodology is a generalisation of existing calibration procedures adapted to walker models. The fundamental aspect of the methodology is the use of several scenarios representing different calibration objectives. One of the advantages of the general methodology is that by applying it, the process of calibration helps understanding the model and how to adjust it according to the intended application. As an example, the methodology is applied with synthetic generated trajectory data using the Nomad model to investigate the influence of the mathematical specifications of the objective functions and the flow configurations in the accuracy of estimations and significance of individual parameters.

Keywords

Pedestrian models, calibration, multi-objectives

1 Introduction

Pedestrian traffic is usually very complex, presenting many situations, bidirectional, unidirectional and crossing flows. Also, locally densities can vary from zero to 10 peds$/m^2$ (Helbing et al. (2007)). These conflicting conditions tend to require complex models with several parameters. A model with many parameters raise problems about the accuracy of an estimation process. Was the reference data and the calibration procedure adequate to properly estimate the parameters? Also the intended use of the model and its specialisation is important. Optimal parameters are estimated for certain aspects of the traffic system. These can be: the positions of the individual pedestrians, fundamental diagram relations or distributions of travel times. But once the parameters are estimated there is no guarantee that the walking model is reproducing other aspects on an acceptable level. The same applies for different flow configurations, a unidirectional flow does not present avoidance situations in a frontal direction. This lack of *behavioural information* may cause parameters estimated with data from unidirectional flows not to simulate well other flow configurations (e.g. bidirectional flows or crossing flows).

The accuracy and robustness of the calibration of walking models can be summarized by these two questions:

1. Are all of the estimated parameters significant and therefore truly estimated?
2. Is the behaviour of the real system best approximated by the estimated parameters?

These questions are valid for any type of simulation model and in these paper they will be answered for walker models. The first question refers to the accuracy of the estimation process. Was the reference data and the calibration procedure adequate to properly estimate the parameters? The second question addresses the intended use of the model and its specialization. What can be done to assure that set of parameters is *generic* (robust) enough to be applied in situations different than those used in the calibration.

This paper shows how to find answers to these questions by introducing in section 2 a methodology that formalizes the key components of calibrations of pedestrian models. The methodology is generic and can be used to calibrate any walking model with any aspect of pedestrian traffic. The methodology explicitly divide the optimisation process into parallel scenarios to easily allow for the influence of different aspects of pedestrian traffic. Scenario is a complete set of reference data, objective function and boundary conditions necessary to estimate the model parameters. The methodology proposes the use of multi-objectives (combination of one or more objective functions) to estimate more generic parameters to be used in simulation. The use of multiple-objectives minimises the problem of lack of information or traffic aspect specialization.

Another important aspect of the methodology is the use of trajectories to estimate parameters reflecting the behaviour of individual pedestrians. This important aspect accounts for differences in walking behaviour between pedestrians (inter-pedestrian heterogeneity) as well as differences that occur in different walking situations. Consequently the result of calibrations using the methodology are distributions rather than average parameter values.

The methodology is applied in the Nomad Model to show differences in estimation accuracy due to three different flow configurations, a bidirectional, a crossing and a narrow corridor bottleneck. The accuracy is increased when the calibration involve parallel scenarios. We show that calibrating using three parallel scenarios combining errors of all flows is more accurate than the individual flows calibrations.

2 A generalised calibration methodology

Figure 1 shows the scheme of the developed calibration methodology for the estimation of the parameter set θ. The calibration consists of two parts: the clockwise loop describing the iterative process for estimating the optimal parameter set and the sensitivity analysis to calculate the significance of each estimated parameter. This methodology does not require trajectory data (individual data about all pedestrians) but by assuming their existence it allows for much wider application. Given the generalised nature of the methodology, this paper will assume the existence of trajectory data.

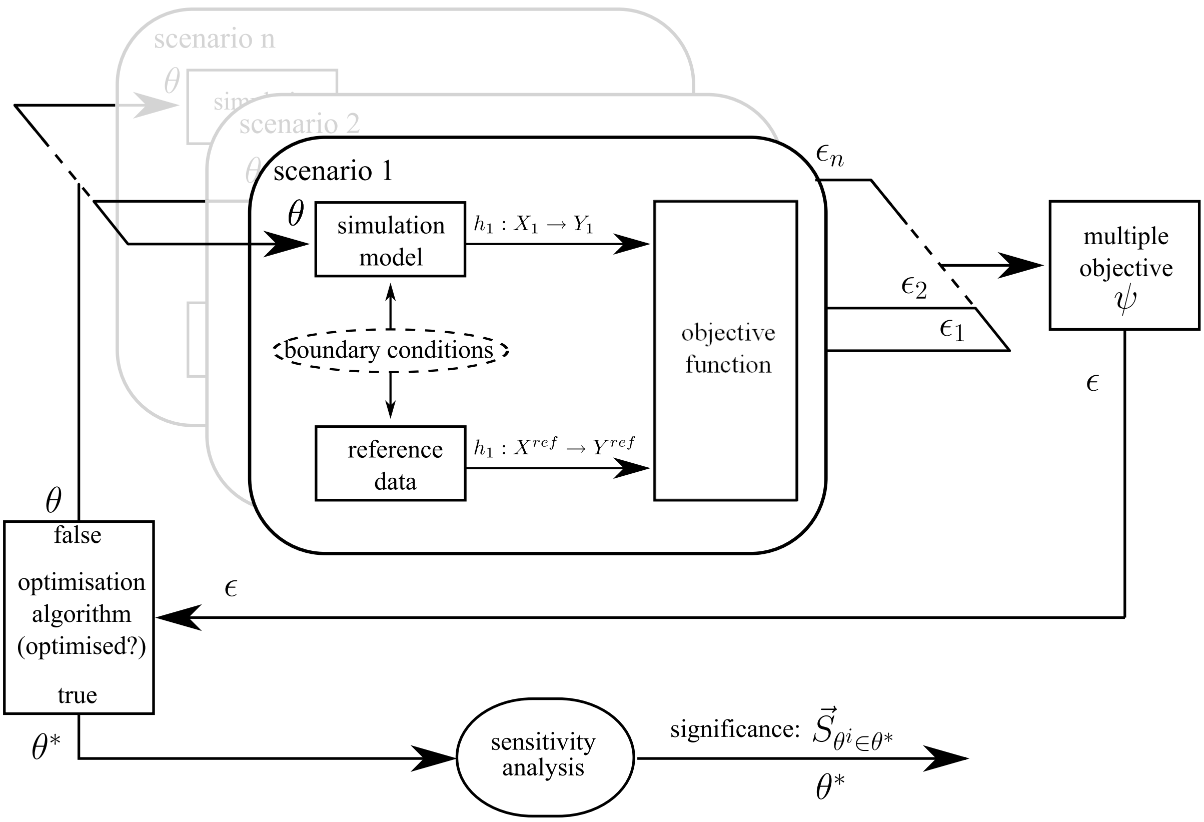


Figure 1: Calibration methodology for walker models. The outcome is the optimised parameter set $\theta^*$and the significance values S of all parameters from θ^*.

The estimation loop is based in the scenarios that incorporate everything that is necessary to simulate the pedestrians; boundary conditions such as demands, description of the walking facility, population demographics ...) and everything necessary to calculate the deviations of the model from the reference system (reference data, mappings and objective functions). Scenario 1 in figure 1 shows how parameter set θ is input to the simulation model (top left) to output trajectories X_i. The trajectories are mapped by

h_i to calculate the traffic aspect Y_i that will be input in the objective-function outputting the error ϵ_i (right side). An example of a traffic aspect is the position r of pedestrians. Positions can be directly obtained from the trajectories and the error ϵ_i can be calculated as the sum of all the differences between the positions of all pedestrians $p \in$ trajectories in the trajectory $\epsilon_p = \sum r(t)_p - r_p^{ref}(t)$. A calibration with more then one scenario will generate errors that are combined in a multiple-objective function. The resulting error ϵ is submitted to an optimisation process that compares the current error with errors from previous iterations. While the error is not minimal (optimal condition is not met) a new set of parameters is generated and a new iteration is performed. When the minimum error is found the parameters are considered optimal (equation 1).

$$\theta^* = \text{arg min}\ \epsilon\,(\theta) \tag{1}$$

Finally, for each parameter θ_i^* from the optimal set a sensitivity analysis is performed calculating their significance $S_{\theta_i} \in \vec{S}$. The significance tells the sensitivity that the model has for all parameters. If the significance is small than the model is not very affected by variations of the parameter. This can signify that the parameter is not useful and could be eliminated from the model or that there was not enough *information* in the empiric data to optimise the parameter. For example, if the trajectory data does not present pedestrians walking close to each other or with colliding trajectories then parameters that produce interaction behaviour cannot be optimised.

2.1 Definitions

2.1.1 Trajectories

Commonly, trajectories obtained from video tracking methods consist of instantaneous positions at regular time moments[1]. In this methodology we assume that speeds and accelerations are available at each time step regardless of the way they are obtained. If they are not measured directly then a simple way to calculate the speeds in the x, y and eventually z directions is to divide the distances covered during successive frames by the time between the frames. The speeds in the directions are then used to calculate the velocity vector. A similar procedure using the calculated velocities can be used to calculate the accelerations.

The first step is to define the minimum set of properties that contain all the information necessary to predict the next position of a pedestrian. This set of information is the pedestrian *walking state* z. What define the pedestrian state is model dependent. Pedestrian models such as those presented in section **??** mainly need the dynamic properties of movement such as the positions $\vec{r}$, velocities $\vec{v}$ and accelerations $\vec{a}$ to estimate the next state of the pedestrians. Note that other type of models may require different information such as stress or fatigue levels. Equation 2 shows the state of pedestrian p with three movement properties.

$$\vec{z}_p = (\vec{r}_p, \vec{v}_p, \vec{a}_p) \tag{2}$$

[1] In this and subsequent sections we assume that the interval between two time frames in every trajectory is equal. This common time interval is the trajectory time step ΔT.

The area where pedestrians are walking is defined as the walking facility A. The considered period of time T starts at $t = t_0$ and ends at $t = t_N$. Suppose that the pedestrian p enters A in time $t = t_n$ and leaves it at $t = t_{n+k}$. The set of all the states $\vec{z}_p$ of this pedestrian during T is called a trajectory X_p.

$$X_p = \{\vec{z}_p(t_n), \vec{z}_p(t_{n+1}), \ldots, \vec{z}_p(t_{n+k})\} \tag{3}$$

The set of all pedestrians that walked in A during T is then P. The set of all trajectories X is thus the microscopic representation of the traffic system in A during T.

$$X = \{X_i \mid i \in P\} \tag{4}$$

2.1.2 Mappings and objective functions

The set X can then be used to map other aspects of traffic Y. Mappings are defined as function h that transforms X to Y.

$$h : X \to Y \tag{5}$$

It is important to note that there is no assumption on the form of h (only that it is a computable function). The most basic mapping is the identity h_I that maps the trajectory into it self:

$$h_I : Y = X \tag{6}$$

The outcome of h in this case are the values representing one (or more) pedestrian state variable. In section 2 we mentioned the position to be used in the error calculation. The general form of h is presented in equation 7 where s represents extra parameters of the mapping function:

$$h : Y(s) = h(X) \tag{7}$$

Fundamental diagram relations are examples of functional mapping in the form indicated by equation 7. In these relations the variable s represents other parameters necessary to calculate the diagrams such as space and time discretization (Edie (1963)). Other forms of mappings can also be used for calibration such as distributions of headways and travel times.

Equation 8 presents the definition of objective functions.

$$\epsilon = f\left(Y^{ref}, Y(X)\right) \tag{8}$$

3 Experimental design

This paper will apply the calibration methodology (section 2) with different scenarios to compare how the estimation accuracy is affected by flow configurations. To be able to measure the estimation accuracy it is necessary to compare the estimated parameters with a ground truth. For that, we use synthetic trajectories which were created using the Nomad model. The model runs once with known parameters $\overline{\theta}^{sy}$ and the trajectories of pedestrians recorded. These trajectories are created by pedestrians that differ from each other, therefore introducing heterogeneity in the population. The heterogeneity is created in some parameters of the synthetic pedestrians by means of normal distributions $\mathcal{N}(\overline{\theta}^{sy}, \overline{\sigma}^{sy})$. The means were taken from previous estimations with real data Campanella et al. (2009) and the standard deviations were based on calibrations presented in Hoogendoorn et al. (2005).

Three flow configurations were selected, a unidirectional flow with a narrow bottleneck (*narrow*), a bidirectional corridor (*bidi*) and a 90 bidirectional crossing flows (*cross*). These configurations present a wide variety of different traffic situations between pedestrians and pedestrians; and also between pedestrians and obstacles creating a large amount of behaviours that need to be properly covered by the model. Furthermore, they represent the most used flows in calibration and validations procedures. In these configurations pedestrians need to avoid incoming pedestrians, follow or overtake leading pedestrians, interact with pedestrians coming from the sides and deal with conflicts near bottlenecks.

The model used in these calibrations is the modified Nomad model (Campanella et al. (2009)).

3.1 Scenarios

The objective-function follows the calibration framework developed in Hoogendoorn & Daamen (2010) and Hoogendoorn & Hoogendoorn (2010). In the following we will recall and describe the parts of the framework. For more details refer to original references.

The basic idea is to select one trajectory from the set X and use it to calculate the likelihood that the model can predict the states of this pedestrian along his/her trajectory. The other pedestrians will have their state always set according to the reference trajectories (and not by the model). By doing so we make sure that we will estimate the parameters that will best represent the walking behaviour of this single pedestrian when all the rest is following the *reality*. To apply this type of estimation requires that the pedestrian states are known in relatively small time intervals to avoid autocorrelation problems (Hoogendoorn et al. (2005)).

3.1.1 Maximum likelihood mapping for single trajectories

To estimate the parameters θ_p of a walking model for a single pedestrian p we must use a microscopic mapping Y_i that reflects his/her individual behaviour. The most common are her state variables: position $\vec{r}_p$, velocity $\vec{v}_p$ or acceleration $\vec{a}_p$ but any microscopic mapping such as current headway, or a combination of mappings can be used as well. The difference between the mappings at a time t_k subjected to parameter set θ is expressed by:

$$\epsilon(t_k \mid \theta_p) = \left\| Y_i^{ref}(t_k) - Y_i(t_k \mid \theta_p) \right\| \tag{9}$$

If we assume that the incorrect model predictions $\epsilon(t_k \mid \theta_p)$ of the mappings are independent and normally distributed $\mathcal{N}(0, \sigma^2)$ we can obtain the probability p_k of the estimation at time t_k from the probability density $f(\epsilon)$ of the normal distribution:

$$p_k(\theta_p, \sigma_p) = \frac{1}{\sigma_p \sqrt{2\pi}} \exp \frac{-\epsilon^2(t_k \mid \theta_p)}{2\sigma_p^2} \tag{10}$$

A natural definition of a likelihood function L combines all n time instances observed for pedestrian p:

$$L(\theta_p, \sigma_p) = p(\epsilon(t_1 \mid \theta_p), \ldots, \epsilon(t_n \mid \theta_p)) = \prod_{k=1}^{n} p_k(\theta_p, \sigma_p) \tag{11}$$

The log-likelihood is then:

$$\tilde{L}(\theta_p, \sigma_p) = -\frac{n}{2} \ln(2\pi\sigma_p^2) - \frac{1}{2\sigma_p^2} \sum_{k=1}^{n} \epsilon^2(t_k \mid \theta_p) \tag{12}$$

The parameter estimation equation defined in (1) can be expressed in terms of the log-likelihood:

$$\theta^* = \text{arg max } \tilde{L}\,(\theta) \tag{13}$$

By applying the optimality condition in the log-likelihood we obtain the Maximum-Likelihood-Estimate (MLE) condition:

$$\frac{\partial \tilde{L}}{\partial \sigma_p^2} = 0 \Rightarrow \hat{\sigma}_p^2 = \frac{1}{n} \sum_{k=1}^{n} \epsilon^2(t_k \mid \theta_p) \tag{14}$$

Substituting (14) in (12) we are able to write the MLE only as a function of the errors (15).

$$\tilde{L}(\theta_p, \sigma_p) = -\frac{n}{2} \ln \left(\frac{2\pi}{n} \sum_{k=1}^{n} \epsilon(t_k \mid \theta_p)^2 \right) - \frac{n}{2} \tag{15}$$

The maximum value of the MLE can then be found by determining the θ that maximizes its value by means of a numerical optimization. Note in the equation 12 that maximizing the MLE is equivalent of finding the θ that minimizes the mean square error (MSE) (**??**).

3.1.2 Multiple-Objective

The combined likelihood of N different individual likelihoods is simply the product:

$$L_{multi}(\overline{\theta}) = \prod_{i=1}^{N} L(\overline{\theta}) \tag{16}$$

3.2 Flow configurations

Figure 2 shows the scheme of the three flow configurations. The dimensions of the walking areas are respectively for the bidirectional flow $10m \times 4m$, narrow bottleneck flow $10m \times 4m$ with a corridor of $1m$ in the middle and $8m \times 8m$ for the crossing flows. These dimensions were chosen because they have shown in walking experiments in Daamen & Hoogendoorn (2003) to present representative walking behaviours.

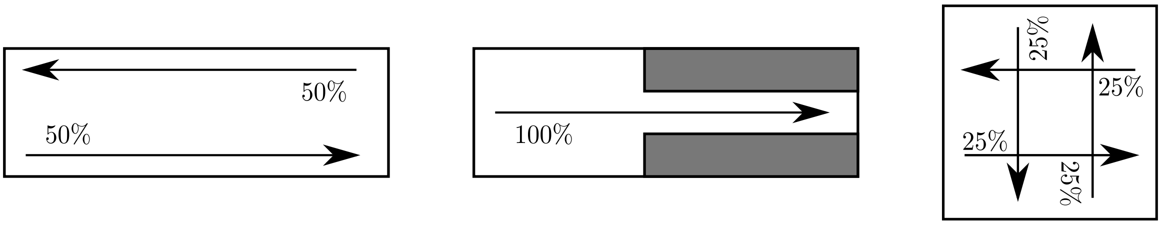


Figure 2: The three experimental set-ups: bidirectional flow, narrow bottleneck flow and crossing flow

The input flows were created in a stepwise ascending manner to assure that both free flow and congestion could occur in all flow configurations and that the densities could reach approximately 2 pedestrians$/m^2$. Figure 3 shows the graph with the demands per simulation time for the bidirectional flow. The demand value is then multiplied by the percentages shown ins figure 2 to obtain the amount of pedestrians that is generated in each origin (represented by the tail of the arrows on figure 2).

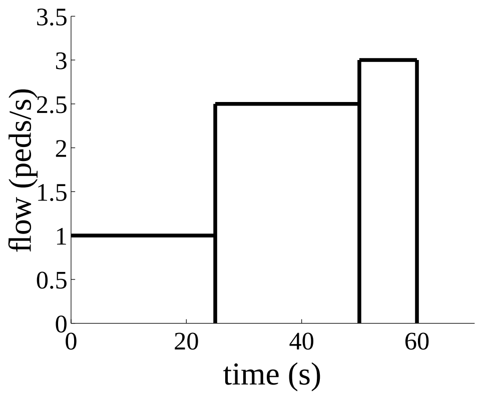


Figure 3: The stepwise inflow demands for the bidirectonal flow

The total time of the input flows is 60 seconds for all experiments to allow enough time for interactions between pedestrians but not extend too much the computational time of the calibrations. The total amount of pedestrians that walk in the simulations are respectively, 173 for the narrow bottleneck corridor, 200 for the crossing flow and 236 for the bidirectional corridor.

3.3 Parameters that created the heterogeneity and were estimated

Table 1 shows the means and standard deviations of the seven parameters of interest in the investigations. These are considered the most important in the Nomad model and in social force models.

The six parameters that were varied to create heterogeneity in the synthetic trajectories are, interaction strength (a_0) and interaction distance (r_0) responsible for the interaction between pedestrians, acceleration time (τ) responsible in keeping pedestrians walking along their intended path, the free speed v_0, the pedestrian radius rad and the stochastic noise ϕ. The noise was also varied to account for unknown and incorrect modelled behaviours. Table 1 shows a seventh parameter that represents the obstacle interaction strength between pedestrians and obstacles (a_W). It is also very important in determining pedestrian behaviours but it was not varied in the synthetic trajectories. This is due to a lack of evidence of how much it varies in the pedestrian population. The rest of the parameters necessary to run the Nomad model were kept fixed and equal through all the estimations.

Table 1: Distribution means and deviations for the parameters that produced heterogeneity or were estimated.

parameters	**mean** $\overline{\theta}^{sy}$	**deviation** $\overline{\sigma}^{sy}$
a_0	10.0	0.7
r_0	0.16	0.02
τ	0.25	0.04
v_0	1.45	0.20
rad	0.22	0.02
ϕ	0	0.001
a_W	20.0	-

The free speeds and pedestrian radius are always obtained in literature and are consider input of walker models, therefore will not be estimated. The four important parameters that are estimated, a_0, r_0, τ and a_W have their estimated θ^* and known $\overline{\theta}^{sy}$ values compared and analysed. The first three parameters allow for a comparison of distributions since the population was generated using normal distributions and are referred in the following sections as *distributed parameters*.

3.4 Number of calibration runs

The analysis of the mean calibrated parameter values for the distributed parameters should not be affected of statistical errors due to insufficient sample size. A too small sample, may result in an values outside of the accuracy desired due to large stochastic variations. When in reality if enough calibrations would have been performed, the sample average could have fallen within the accuracy boundary. Therefore we determine for each distributed parameter the minimum sample size that guarantees an accuracy of 5% of the mean parameter value $\overline{\theta}^{sy}$.

To determine the amount of calibrations necessary of the distributed parameters we apply a dependent t-test for paired samples with 95 % confidence. The samples are generated with $\mathcal{N}(\overline{\theta}^{sy}, \overline{\sigma}^{sy})$ for the three distributed parameters until the sample size consistently gives the desired accuracy. The following calculations show that samples with 25 individuals are sufficient:

$$n > \left(\frac{z\sigma_p}{d}\right)^2 \qquad n_{a_0} = \left(\frac{1.96 * 0.7}{0.5}\right)^2 = 8$$

$$n_{r_0} = \left(\frac{1.96 * 0.02}{0.008}\right)^2 = 24 \qquad n_{\tau} = \left(\frac{1.96 * 0.032}{0.0125}\right)^2 = 25$$

$$n_{v_0} = \left(\frac{1.96 * 0.17}{0.0725}\right)^2 = 21 \qquad n_{rad} = \left(\frac{1.96 * 0.02}{0.011}\right)^2 = 13$$

where:

n	number of runs needed to obtain the sample accuracy
z	confidence multiplier (1.96 for 95% confidence for the two tailed distribution)
σ_p	is the standard deviation of the sample test
d	desired accuracy of the sample (5% of the mean parameter value $\overline{\theta}^{sy}$)

3.5 Heterogeneity and input uncertainty

In this paper we investigate the influence of heterogeneity in the population and the input errors in the accuracy of the calibrations. Five parameters are heterogeneous and therefore different sets are created with increasing numbers of heterogeneous parameters. The input errors of the simulations are the differences between the assigned values of rad. In the set-up of the simulations, values of rad are assigned to each pedestrian either with the same value as encountered in the synthetic trajectory or randomly assigned according to the distribution. Therefore, differences in the rad values add errors to the model noise. This additional source of errors is created to account for the effect of input errors that are encountered in calibrations with real trajectories when the rad of real pedestrians are not known.

The reference data are composed of three sets of synthetic trajectories created by the Nomad model (one for each flow configuration). The sets have pedestrians created with heterogeneity and input errors and table 2 show their composition.

Table 2: The reference set with their heterogeneous parameters and input errors

	heterogeneity	input error	noise
reference	a_0, r_0, τ, v_0, rad	rad	ϕ

The three flow configurations and four levels of heterogeneity required 12 reference synthetic trajectory sets. These sets are used in all calibrations in this paper.

3.6 Measuring accuracy

To compare the results of different calibrations we need to establish which calibration procedures generate the smallest estimation errors. In this paper we mainly look at deviations from the refernce parameter values. The error of the mean estimated values are the differences between the estimated and the synthetic values of the parameter. To be able to compare the accuracy of different parameters, errors are normalised:

$$\text{relative error } = \frac{\overline{\theta}_i^{sy} - \theta_i^*}{\overline{\theta}_i^{sy}} \tag{17}$$

3.7 Simulation set-up

The numerical set-up of the simulations was the same for all flows and trajectories with the values described in table 3. These values have proven to simulate stable trajectories and not demand too much computational power.

Table 3: Numerical set-up of the simulations

name	ΔT	**update**	**route cell size**
values	$0.02s$	parallel	$0.1m$

The reset-step used is the smallest possible i.e. the simulation time-step $\Delta T = 0.02s$.

3.8 Optimisation algorithm

The calibration of complex non-linear models such as the Nomad model require an optimisation algorithm that does not get trapped in local minima solutions. Also the algorithm must be able to find a solution in reasonable computational time given the intention of performing several calibrations.

A genetic algorithm (GA) was chosen due to its simplicity and excellent qualities in dealing with non-linear models. The disadvantage of GA's is their relatively high demand of computational power. Tests with the Nomad model indicated that the GA could consistently find the correct parameter values. To improve the performance we used a hybrid optimisation procedure combining a GA and a Simplex optimiser. The Simplex is a much faster optimisation algorithm that works well in finding local minima. The idea of combining both algorithms is to apply the GA in the first part of the optimisation until the best candidate of the GA population is close enough of the optimal. Then it is send to the Simplex and the optimal parameter set θ^* is found. This hybrid procedure improved the computational performance by often taking less then 50% of the time when compared with the pure GA.

Tests were run and showed the ability of the optimisation algorithm to estimate simultaneously and accurately 12 relevant parameters from Nomad model using the synthetic trajectories.

4 Investigating the influence of flow configurations

As expected the unidirectional narrow bottleneck flow does not give enough *behaviour information* about frontal interactions between pedestrians. This can be seen by the larger errors for the a_0 when comparing with the bidirectional and the crossing flows estimations (see table 4 and figure 4). Interactions between pedestrians in a unidirectional flow occur in a leader-follower situation diminishing the amount of interactions. The leader will most of the time not perceive the follower causing a one-way interaction. This indicates that care must be taken when using unidirectional flows to calibrate parameters responsible of interactions. Behaviour in and around unidirectional bottlenecks are not enough to estimate these parameters properly and that the frontal interactions are very necessary. A similar result was obtained for τ. In the narrow bottleneck flow most of the pedestrians are in congested flow. In this condition pedestrians walk mostly at the same speed with little chance to apply path following accelerations. Given the excellent accuracy of τ in the bidirectional flow calibration, we can conclude that this parameter is very important for simulating the lane behaviour.

Table 4: The relative errors from the individual estimations. The bold values are the best results.

	Relative error			
	a_0	r_0	τ	a_W
bidi	**-0.15**	0.063	**0.08**	-0.70
cross	-0.16	0.010	0.19	-0.88
narrow	-0.28	-0.053	0.60	**-0.20**
multiple	**-0.15**	**-0.004**	0.28	**-0.20**

Parameter r_0 that is mostly useful in close range was better estimated by the crossing than the bidirectional flow (and the narrow flow). In the bidirectional pedestrians mostly walk in lanes not needing to overtake. When crossing, pedestrians perform many complex avoiding manoeuvres giving much more information to calibrate r_0.

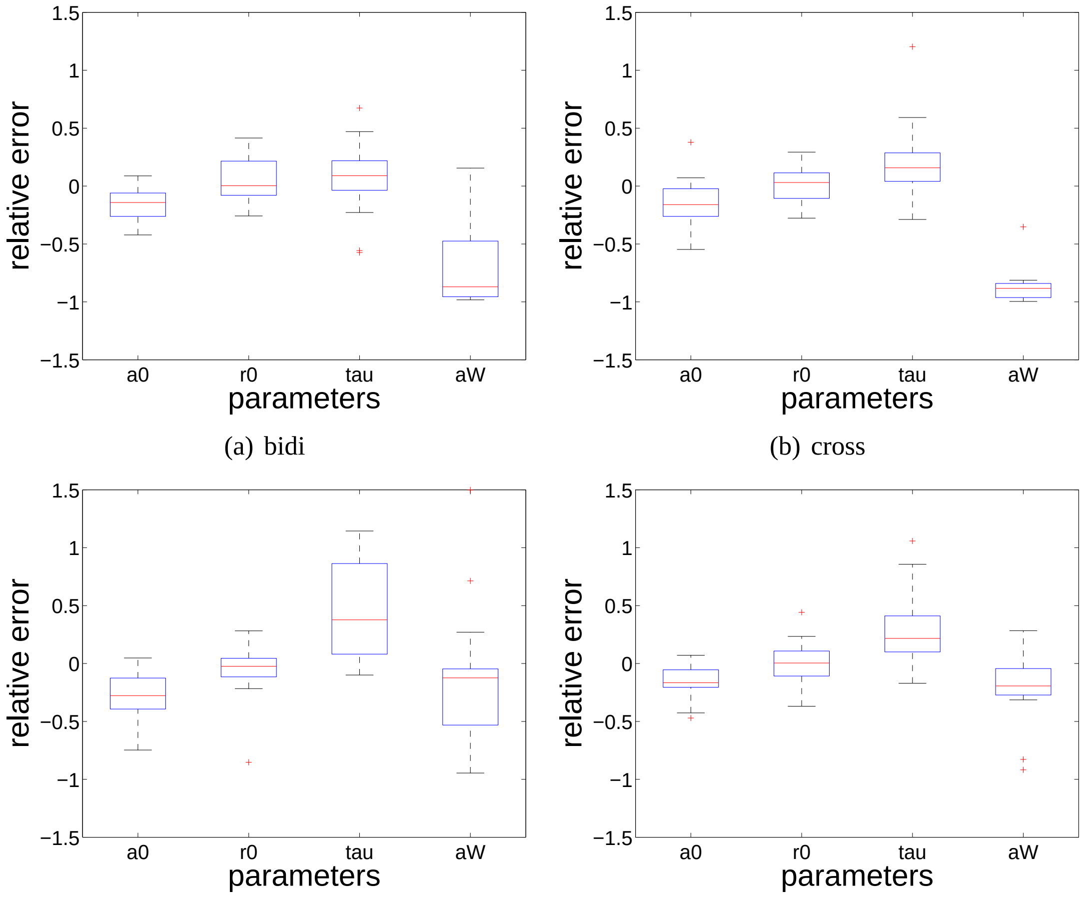
For the obstacle interaction parameter a_W the situation is inverse. Table 4 shows that this parameter was much better estimated using the narrow bottleneck flow than using other individual flows. This can be easily explained by the walking area set-up (figure 2). The narrow bottleneck is the only walking area in which large amounts of interactions between pedestrians and obstacles is occurring.

4.1 Combining flow configurations

Table 4 and Figure 4 show that combining errors of the three flows during the calibration improve the general accuracy of the estimation. Three from the four best results were obtained in the multi-objective calibration. Only the result of τ was much worse than the best result that occurred in the bidirectional flow. This was due to the very bad accuracy from the narrow bottleneck that kept the multiple objective errors high. But even so, the final error for τ is half the error from the narrow bottleneck calibration. These good results indicate that combining the errors make the good estimations compensate for the bad during the calibration.

5 Summary and conclusions

In this paper we proposed a generalised calibration methodology. The methodology is based in the definition of mappings from pedestrian states to certain values, functional



(a) bidi (b) cross (c) narrow (d) multiple

Figure 4: Box-plots for the parameters estimated

relations or distributions. These mappings are used in objective-functions that compare the results of the mappings from simulations with the same mappings from reference data and deliver an error value. This error is then given to an optimisation algorithm that finds the optimal parameter values. Such a combination of reference data, mappings, objective functions and the necessary boundary conditions to run the simulations is then called calibration scenario.

Using the fact that pedestrians are different from each other and that a model must capture this important feature we investigated the influence of flow configurations in the accuracy of calibrations.

With the results of the calibration experiments we identified some practical guidelines to improve the estimation of parameters in heterogeneous populations:

- Unidirectional flow configurations are less suited to estimate interaction parameters.
- Multiple-objectives combining different type of flow configurations give more accurate calibrations.

The next step is to apply the methodology to estimate the parameters of the Nomad Model in several trajectories from real pedestrian traffic.

These results indicate that adding flows that are significantly different from each other does increase the quality of the estimation by increasing the accuracy of the parameters.

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