Determining evacuation capability with biomechanical data

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Bestämning av utrymningsförmåga baserat på biomekaniska data

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Abstract
Experimental data on single file pedestrian movement has been analysed and implemented in a prototype movement model. The prototype model is developed to predict movement of persons based on a first principle approach using basic population data such as age, height, gender and response time to adapt the walking speed in a crowd. The experimental data provide the biomechanical information needed in the model. The intention with the new approach is to present a predictive capability for the future as a consequence of the identified demographical changes observed in today's society.

Illustrations/pictures:
If not specified, all illustrations and pictures belong to the authors

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Preface

In spring 2019 The Society of Fire Protection Engineering Educational and Scientific Foundation expressed an interest to support research initiative aiming at presenting new data on evacuation modelling. This was done through the proposal Research to Update Anthropometric Data and Movement Speeds.

Lund University was awarded a grant with the aim to present new data resulting from a Brandforsk research project just finished but not sufficiently analyzed. The grant from the SFPE Foundation provided means for completing most of the data analysis on single file flow and to update a prototype model for pedestrian movement. The prototype model is developed to predict movement of persons based on a first principle approach using basic population data such as age, height, gender and response time to adapt the walking speed in a crowd. The intention with the new approach is to present a predictive capability for the future as a consequence of the identified demographical changes observed in today's society.

The work presented is also part of a project performed at York University in Canada also supported by the same SFPE Foundation research proposal. The two projects are, therefore, linked and presented in a joint publication. However, the Lund University report is also available as a stand-alone publication available through the University repository.

This work has been performed during 2019 and was presented to the SFPE Foundation in March 2020.

The authors wish to express their gratitude to the Foundation for providing the means for publishing this data and for being able to further refine the prototype model for predicting pedestrian single file speed and flow.

The authors also want to thank Professor Daniel Nilsson (University of Canterbury in New Zealand) and Dr Denise McGrath (University College Dublin in Dublin, Ireland) for providing valuable feed-back on the analysis and report.

Finally, but not least, the report is based on experimental data that was collected by two students at the Fire Protection Engineering program at Lund University for their final thesis; Gabriel Larsson and Jesper Friholm. The work they did is highly appreciated.

Summary

Based on the fact that demographic changes in the population have been identified in the many countries, it has been questioned whether the documents describing the movement of people are valid. Researchers who, some thirty years ago, produced information on, for example, walking speeds in stairs, consider that their material is not suitable for use anymore.

It would be natural to conduct new experiments in order to get updated data and such efforts are also taking place. However, there might be different ways to consider the changes that have been observed, e.g. to start using basic physical factors that determine how fast a person moves. One approach could be to assume a biomechanical model linked to the individual and his or her conditions and the influence of the environment.

To that extent, the model developed by Thompson et al. (2015) has been adjusted with a new set of data on single-file pedestrian movement at different densities. The resulting model is expressed in forms of three equations that relate inter-person distance to biomechanical data such as height, foot length, and step length. Other variables included in the equations are preferred unimpeded walking speed and adaption time.

The following table presents peak flow values for single-file configuration for different cohorts.

Parameters & calculated predictions	**Lund students**	**Elderly (Cao)**	**Young (Cao)**	**Children (11 y.o.)**
Height h [m]	1.80	1.62	1.64	1.42
Preferred unimpeded walking speed v_u [m/s]	1.29	0.95	1.23	1.29
Max density [p/m]	3.28	2.58	3.40	4.34
Adaption time Ta [s]	0.37	0.68	0.37	0.37
Foot length [m]	0.29	0.28	0.28	0.22
Step extent factor A (at v_u)	0.92	0.92	0.92	0.92
Peak single-file flow [p/s]	1.03	0.71	1.06	1.23
Percentage of Lund students flow rate	100%	69%	103%	119%
Percentage difference from Lund students flow rate	0%	-31%	-3%	19%

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1 Introduction

The standard analyses of life safety in buildings and transportation systems use experimentally derived flow rates and walking speeds to calculate evacuation times. Current design guides typically use a basic flow rate for a single uniform population, which has not changed since the regulation of door and passageway sizes in the mid-20th century. In recent years, the long-established data and the relationships between speed or flow and density have been subject to scrutiny. Indeed, the authors of what are widely considered as the most relevant North American datasets (Fruin, 1971; Pauls, 1996) have stated that their data sets are no longer applicable and have asked them to be removed from future design guides (Pauls, Fruin, & Zupan, 2007).

This loss of confidence in the data is due to recognition of the ever-increasing proportions of elderly, obese and mobility impaired in society (OECD, 2017; Thompson, Nilsson, Boyce, & McGrath, 2015). These proportions have increased significantly since the original observations were made of the egress and circulation 'flows' of office workers and commuters between the 1950s and the 1980s. Mixing populations can have a dramatic effect on optimal crowd flow movement and ultimately safe escape. Despite the recognition of the potential dangers of using the original datasets, there has been no fundamental research carried out to study the effect of changing population demographics, or the nature and causes of the observed flow behaviours and associated parameters. Demographic changes have now provided the impetus and have reinforced the need to consider a first principles approach to understand pedestrian movement in populated spaces. In order to avoid increasing design and life safety implications, a fundamental change needs to be made of the approach to modelling occupant movement in populated spaces. Moreover, collecting data on modern populations only provides a temporary solution, since unavoidable demographic changes to come in the next decades would make the new data obsolete. Therefore, rather than solely updating the data, it is necessary to develop a fundamental model of pedestrian dynamics based on biomechanics that can be adapted for any set of demographic data. This new model would allow to derive the movement of a single file crowd based on the biomechanical characteristics of the people in it.

With the objective to advance this idea, an extensive literature review of movement across related fields, including fire evacuation, pedestrian movement, biomechanics and computer modelling was carried out (Thompson, Nilsson, Boyce, McGrath, & Molloy, 2015). In this review, potential parameters and their associated metrics were identified. The potential for these parameters to be modelled and measured has been considered and prototype experiments have been performed. With the aid of modern software, new analytical relationships have been deemed important to determine the metrics for future modelling and evacuation analyses. These analytical relationships are body dimensions, walking speed, inter-person distance, rate of walking steps (cadence), body sway (gait), contact vectors and spatial restrictions. Rigorous scientific analyses, the application of biomechanical principles and core aspects of physical and cognitive factors have also been utilised to lay out clear pathways for global research, regulatory and design communities. This 'roadmap' for future research and modelling activities is a result of an extensive research program recently published in Nilsson, Thompson, McGrath, Boyce and Frantzich (Nilsson, Thompson, McGrath, Boyce, & Frantzich, 2020).

The research program was initialized with the main objective of evaluating different experimental measurement techniques to identify the parameters that define pedestrian movement (Doka, 2019; Hansen, 2018; Thompson, Nilsson, Boyce, & McGrath, 2016). Experiments were run both in Lund (Larsson & Friholm, 2019) and Dublin (Thompson, Nilsson, Boyce, McGrath, et al., 2015), measuring parameters relevant to walking speed for different occupant densities and using different methods for data collection and analysis. A large body of data was collected, but only parts of the data were analysed and presented.

1.1 Objectives

The main objective of this study is to analyse and present a set of existing experimental results and to use the results to improve a current model for pedestrian movement at different densities developed by Thompson (2015). Furthermore, the improved model is used to predict flows for three different cohorts (elderly, young adults and children) based on data published by other researchers.

1.2 Delimitations

Some of the limitations of this study are due to the fact of it being a pioneering approach. Currently only single file flow has been investigated and wider flow should be considered the following step. Moreover, the study relies solely on a sample consisting of young, healthy adults (student population).

Additional limitations were due to the nature of video analysis for data collection. The transformation of the movement characteristics from the video films to data points relies on manual labour which introduces an uncertainty of the true movement patterns. However, it is judged that this uncertainty is small compared to the parameter values obtained.

2 Theoretical approach to movement

The model developed by Thompson et al. (2015) consists of the evaluation of the anthropometric parameters that govern pedestrian movement in conjunction with the boundary conditions affecting the person (i.e. proximity of other pedestrians). The model has since been refined in Nilsson, Thompson, McGrath, Boyce and Frantzich (2020).

Basically, the model consists of the preferred speed of a person and their intention to avoid collisions with other pedestrians based on their physical and cognitive abilities. It can currently be used to predict walking speeds and single file flow and is currently based on the equations, presented in the report, in a spread sheet program. The desire to avoid colliding with the person in front make you leave a space enough to that person in case there is a sudden stop or change in walking speed.

Some cognitive and physical principles of traffic flow were drawn from the Handbook of Road Technology (Lay, 2009) as a starting point. Therefore, the basic principles of human locomotion considered in this study are:

1. Unimpeded normal walking speed: also called “preferred walking speed”, refers to that the individual would choose if they were not constricted by obstacles or impediments such as other pedestrians. This parameter can be affected by age, gender and height of the individual.

2. Body dimensions: more specifically height, breadth, thigh length, shank length, ankle height, foot length, and body sway.
3. Gait parameters: step length, step extent.
4. Contact buffer: which refers to the minimum distance kept between the individual and the pedestrian in front of them, which would allow the individual to avoid a collision given a change in the movement conditions. The contact buffer can be a factor of walking speed, stress or perceived threat.
5. Visual perception time: time needed for the individual to recognize a change in the movement conditions and adjust their walking speed as needed. This parameter is closely related to contact buffer, since the change in the individual's walking speed needs to be adjusted within that space in order to avoid collisions.

Figure 1 illustrates some of these basic principles, which was used for the development of the walking speed model.

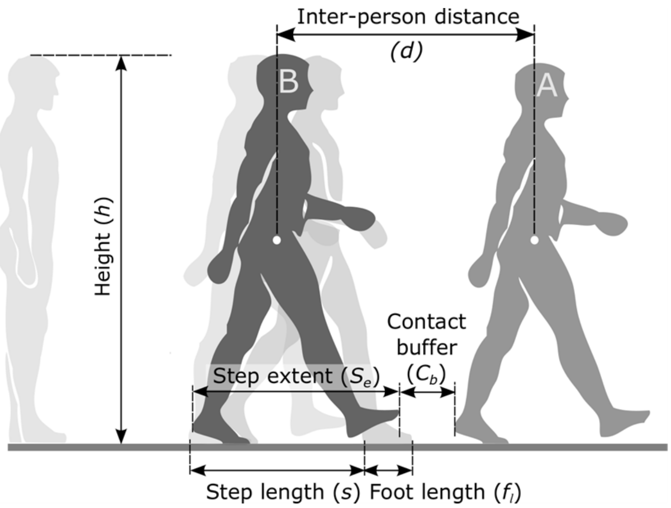

Figure 1 – Components of pedestrian movement in a congested space

As shown on Figure 1, step length (s) refers to the distance between two consecutive floor heel strikes. The step length position does not occur at any time as the two heels are not in contact with the floor simultaneously, except at stand still. Step extent (s_e) is the distance between the back heel and the tip of the toe of the forward-most foot, at any time; that is the physical space occupied by the person when taking a step. Contact buffer (C_b) is based not only on the individual but also on the nearest pedestrian in front of them. The contact buffer is measured between the instantaneous potential points of contact (heel/toe) of two consecutive pedestrians. Lastly, inter-person distance (d) is measured between the centre of the hipbone of the individual and that of the nearest pedestrian in front of them.

After a series of revisions done on the initial model by Thompson (2015), Nilsson et al. (2020) presented an improved version of the prototype model for single-file flow that considers demographics, biomechanics and visual response/adaption. This prototype model can be used as a tool for prediction of flow rates for different groups based on some key descriptive parameters of the demographics of the group. The entire development of the prototype model is detailed by Nilsson et al. (2020), and the reader is encouraged to follow the corresponding derivations there. For the purpose of this study, the initial point consists of Equations 1a, 1b and 2 presented below, which are modified versions of equations 6a, 6b and 7 by Nilsson et al. (2020). In these modified versions, the step length (s) was obtained from the analysis of the experimental data from the video recordings, after extensive regression analyses. Table 1 describes the different parameters in Equations 1a, 1b and 2. It should be noted that the two equations 1a and 1b both refers to movement conditions there the walking speed depends on the person in front, i.e. not for the case of unimpeded walking. These equations will later be applied to predict flow values for different population cohorts.

	Step extent		Contact buffer	
	Step	Foot		
Walking with contact buffer above the minimum: *where* $C_{b(min)} < v \times T_a$	$d = A(s + f_l)$		$+ (v \times T_a)$	[1a]
At standstill or low speeds where contact buffer determines personal space: $C_{b(min)} >= v \times Ta$	$d = A(s + f_l)$		$+ \left(\frac{1}{\rho} - f_l\right)$	[1b]
Relating inter-person distance to single-file flow density	$\rho = \frac{1}{d}$			[2]

Table 1 – Summary of terms and units used on Equations 1a, 1b and 1c

A	=	factor for step extent, as a proportion of step length + foot length
C_b	=	contact buffer (m)
$C_{b(min)}$	=	minimum contact buffer, at stand-still with minimum inter-person distance
d	=	inter-person distance between centroid of Person 1 and centroid of Person 2
f_l	=	foot length for people of equal demographics (m)
h	=	height of person (m)
s	=	step length - distance between successive heel-strikes to the floor of a person walking - "left heel, then right heel distance on floor" (m)
s_e	=	"step extent" of a walking person, defined as the horizontal distance between the rearmost point of the rearmost heel and the foremost point of the foremost foot (m)
s_u	=	unimpeded step length for people of equal demographics (m)
T_a	=	adaption time (time to accommodate movement adaption for a person in front) (s)
v	=	forward velocity of person at any given walking speed (m/s)
v_u	=	'unimpeded' (preferred) forward walking velocity of a person (m/s)

The factor A varies during a complete step cycle and reaches a maximum around 0.98 (0.92-0.98).

3 Method

The data collection was based on analysis of video footage of experiments done by Larsson & Friholm (Larsson & Friholm, 2019). In these laboratory experiments, participants were recorded while walking on a predefined circuit at varying densities. A total of 16 runs of single-file movement were performed, in which the movement of the participants was analysed by pinpointing the position of trackers attached to them. The analysis of the video footage generated up to 1785 usable data-points, each of them including enough information about the movement characteristics of the participant at a given point in time (e.g. step length, walking speed, inter-person distance).

The primary objective of the experiments was to investigate the relationship between walking speed and inter-person distance. The experiments were performed in 2018 and are fully described in Larsson & Friholm (Larsson & Friholm, 2019), which is also the source of all illustrations in this section (used with permission).

The walking speed and all distances deemed important were measured after the experiment using video analysis techniques.

3.1 Description of experiment

The experiments took place at the Faculty of Engineering at Lund University in 2018. The following sections describe the experiment in detail.

3.1.1 Participants

Participants were recruited at the Faculty of Engineering at Lund University during lecture hours one week before the experiments took place. Therefore, most of the participants were students. It can be assumed that many participants knew each other to certain degree. Table 2 presents demographic data of the participants. No participants had any sort of mobility impairments.

Table 2 – Participants' gender, age and height

participants	gender		age				height [m]			
total	female	male	min	max	avg	st.dev	min	max	avg	st.dev
59	22	37	17	29	20	2.0	1.60	2.02	1.80	0.103

The average height of the sample is 1.80 m, with a standard deviation of 0.10 m, and a mode and a median of 1.81 m. The average foot length of the sample is 0.287 m, with a standard deviation of 0.023 m, and a median and a mode of 0.29 m.

As a gratitude for their participation in the experiments, they received one cinema ticket.

3.1.2 Equipment

The equipment used for the experiment is detailed on Table 3, partially reproduced with permission from Larsson & Friholm (Larsson & Friholm, 2019).

Table 3 – Equipment used for the experiments run

Piece of equipment	Purpose
Measuring tape, folding ruler	Tracing the circuit; measuring the participants' height
Different kinds of tape	Outlining the circuit and the position of the cameras; creating a grid on the floor to be used as reference during the analysis
Pole of a known length	Used as point of reference in the corners of the grid.
Chairs and tables	Creating physical barriers around the circuit preventing the participants of wandering off the path
Rope	Creating a physical barrier with minimum blockage of the visibility for the cameras
Movable room partitions	Isolating the participants within the field of view of the camera from the background
Paper tags	Assigning each participant a unique number
Markers	Pinpointing specific points of interest on the participants to facilitate the video analysis
Computer	Registration of participants' tag number, age, height, scenario, etc., and for taking notes during the experiment
Video cameras with tripods	Recording of the experiment from different angles. Two models were used: SONY HDR-PJ780 and SONY HDR-CX220

The software *Farrascope* was used for the analysis of the videos. Farrascope is a custom-developed software package for frame sequences or video analysis to quantify the movement of identified points in the field of view of a fixed camera. It uses perspective reduction techniques and radial lens adjustment to remove measurement losses from the distance and lens distortion of the camera. Although the software is newly built for this project, many measurement verification tests were done, to crosscheck the screen co-ordinate values against known real-world measurements on the test poles and floor grid in the field of view of the camera. The accuracy was found to be +/-1 cm, but the greater room for error was actually due to the blur of moving feet at higher speeds, making it slightly uncertain sometimes, where the exact toe end or heel end was at that time. It should be pointed out that Farrascope is not validated except for comparing with similar data collected in Larson & Friholm (2019) which used Kinovea (Kinovea, (n.d.)).

Farrascope is developed and owned by IAScience Ltd (owner & author Bob Farrell, who is a close collaborator with one of the authors, Peter Thompson). Figure 2 shows Farrascope's user interface during the analysis of a frame. The cross-hair indicating the markers and the reference points on the floor are highlighted.

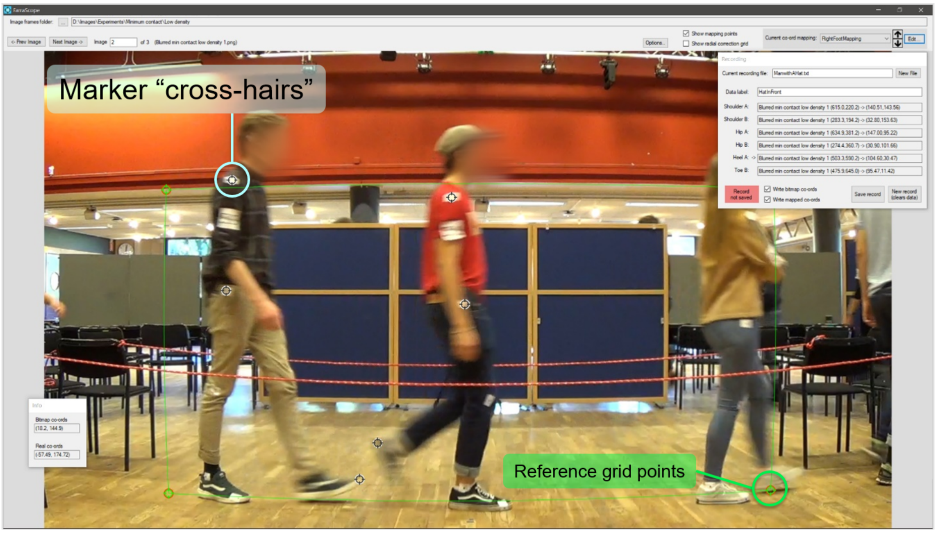

Figure 2 – Visualisation of the user interface of Farrascope showing the markers being tracked with cross-hairs and reference grid points used for establishing the position of the points of interest

3.1.3 Experimental setup

The experimental setup consisted of a circuit installed in the centre of a large room at the Faculty of Engineering, Lund University. Figure 3 presents a schematic view of the circuit and a photograph of it.

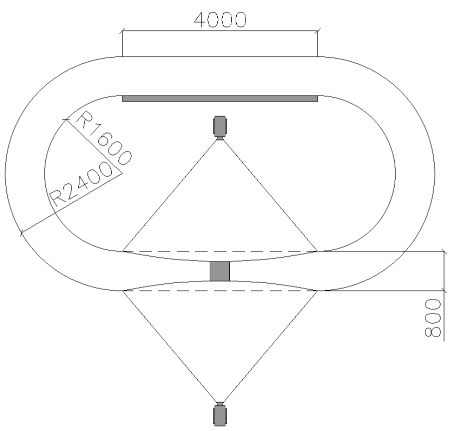

Figure 3 – a) Schematic view of the dimensions in millimetres of the circuit and the location of the camera. The third camera was filming from above. b) View of the circuit in the room

The circuit consisted of a 0.80 m wide path as shown on Figure 3, with a perimeter of 20.56 m in the centreline. The back of the chairs delimitated the path participants were walking on. Ropes were used instead to minimise clutter near the participants within the field of view of the camera, and the movable room partitions allowed doing the same in the background. All cameras were recording in HD resolution. Additional to the circuit, a workstation was placed in a corner of the room, where participants had their measures taken and their tag and markers attached. The following measurements were made: height, shoe length, thigh length (os femoris) and shank length (os tibia). The numbered tag was attached on their right arm, and markers were attached to their heels, tip of toe, knee, hip, shoulder and centre of the head. Figure 4 presents the locations of the tags and how they were used as a reference for measuring the dimensions of the body parts.

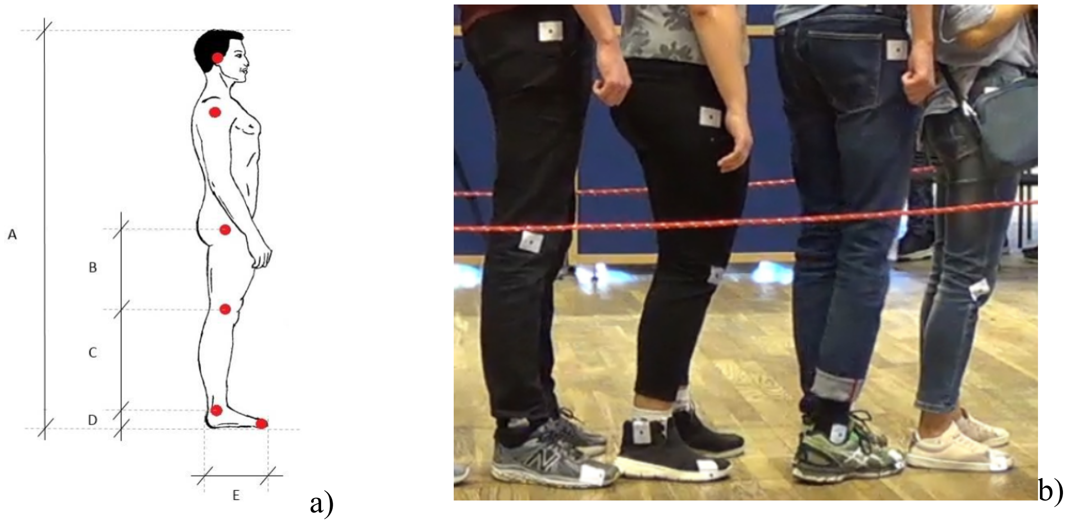

Figure 4 – a) Location of the tags attached to each participant and the dimensions measured, where A indicates the height of the participant; B is the thigh length, C is the shank length; D is the ankle height, and E is the foot length. b) Markers attached to the participants' legs

3.1.4 Procedure

Upon arrival, participants had their tag and markers attached, as well as their measurements taken. Participants were told the aim of the experiment was to study the movement of people in crowded spaces, and signed an informed consent form. However, they were not informed about which parameters were going to be analysed to avoid bias in the results. One by one, they were asked to walk alone in the circuit at their preferred walking speed, in order to measure their preferred unimpeded walking speed.

Then, they were assigned to different tests, each test consisting of a variation of the density of people per meter. In all tests, participants were asked to walk as they would do given the number of people present around them (occupant density) without overtaking. The tests had different number of participants in order to represent different occupant densities, and included participants of different heights. Table 4, partially reproduced here from (Larsson & Friholm, 2019), shows all tests performed on single-file configuration, with the number of participants, and the nominal density.

Table 4 – Number of participants and densities achieved per test on single-file configurations

Test	Participants [un]	Density [pers/m]
A2	59	2.87
A3	59	2.87
B2	49	2.38
B3	49	2.38
C2	39	1.90
C3	39	1.90
D1	29	1.41
D2	29	1.36
F	59	2.87
G	24	1.17
H	24	1.17
I	24	1.17
J	24	1.17
K	19	0.92
L	24	1.17

3.2 Data collection techniques

After finalising the experiments, the video recordings were analysed using Farrascope. The analysis consisted of following the walking cycle of each participant in each test, one at a time, on a frame-by-frame approach, in order to identify the heel strikes, points of minimum contact and position of the hip and shoulder. Only the 4 m path delimitated by the ropes was considered in the analysis. Given the different densities in each test, and the fact that each heel strike was recorded, participants in high-density tests took many short or very short steps, compared to those in low-density test. This was an expected outcome given the nature of the movement in densely packed conditions. However, it meant an imbalance in the final dataset, as high-density tests produced many more data points than the low-density ones. More specifically, walking speeds below 0.2 m/s covered approx. 1/3 of the total data points. This overrepresentation of high densities compared to the rest of the data set will be addressed in the discussion section.

During the analysis of the video footage, the coordinates of the markers on the hip, shoulder, heels and the toes were recorded, for two persons being followed along the 4 m path. With this information, the following data was derived: step length, step extent, hip position, shoulder position, inter-person distance, hip speed, and contact buffer.

3.3 Data analysis techniques

Once the data was extracted from the videos, spreadsheets were used for their analysis. Initially different plots were created consisting of a given parameter (i.e. step length and step extent) as a function of hip speed. When fitting a curve to the data points, the initial idea was to produce a power curve such as the ones used by Dean and Wang

(Dean, 1965; Wang et al., 2018). However, the fitting curve seemed to be heavily influenced by the overrepresentation of data points at lower speeds, as described before.

To counteract this effect, the data was rearranged in 0.05 m/s bands, so that each band would have the same total weight when fitting a curve to them. This adjustment produced a fitting curve that seemed more representative of the data points obtained, but at the same time, it did not allow to show the true trend of the data collected. In a third attempt, the idea of a power curve was replaced for that of a second order polynomial. The second order polynomial curve gave a better description of the data set, and there was no need for averaging any values. Therefore, second order polynomial curves were chosen to represent the data for step length and step extent. The second order polynomial equation obtained was later used in Equations 1a and 1b to predict flows for different cohorts. There is no physical reason for choosing either the power curve or polynomial regression line to describe the relation of the data. The choice was made based on how well the regression line fitted the data, i.e. using the coefficient of determination (the R^2-value).

It was also decided to present the results and their corresponding curves after normalising them to the average height of the sample. The normalisation was intended to allow others to apply the same equations to other cohorts, after being normalised to their average height as well. The method used for normalising the results consisted of applying the ratio between the average height of the sample and the height of the individual as a correction factor.

Lastly, the step length data was plotted as a function of the ratio between the instantaneous speed and the preferred speed. v/v_u. Analogously to the case of the normalisation for the height, this modification of the speed parameter allows to easily replace the experimental speed by those of other cohorts.

4 Results

Results of the analysis of the collected data are presented here. Some of the results were normalized to the average height of the participant sample, in order to allow the final model to adapt to different populations.

4.1 Normalised step length and step extent

Following the data analysis techniques described on section 3.3, Figure 5 shows the normalised step length as a function of hip speed with a fitted power curve. As it can be observed, the power curve seems to underestimate the step length at higher walking speeds. Moreover, it became apparent that the large cluster of data points at low walking speeds (which occurred at high densities) had a strong effect on the equation. That large cluster of data points between 0 and 0.20 m/s consisted of ca. 650 entries out of a total of ca. 1700 points, which means an unbalanced distribution of points along the spectrum of walking speeds covered in this study.

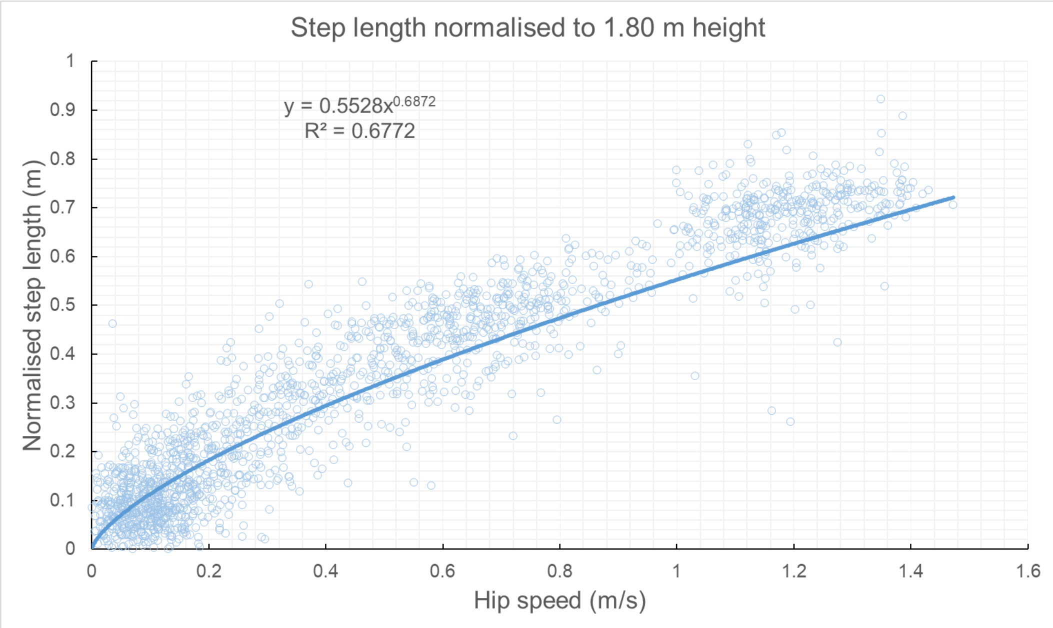

Figure 5 – Data set for step length as a function of hip speed with a fitted power curve.

As an alternative, the data points were aggregated in 0.05 m/s bands, in an attempt to counteract the overrepresentation of the movement at low walking speeds. Figure 6 shows the data set aggregated in 0.05 m/s bands. With this adjustment, the fitted power curve seems to be a better description of the trend in the data set.

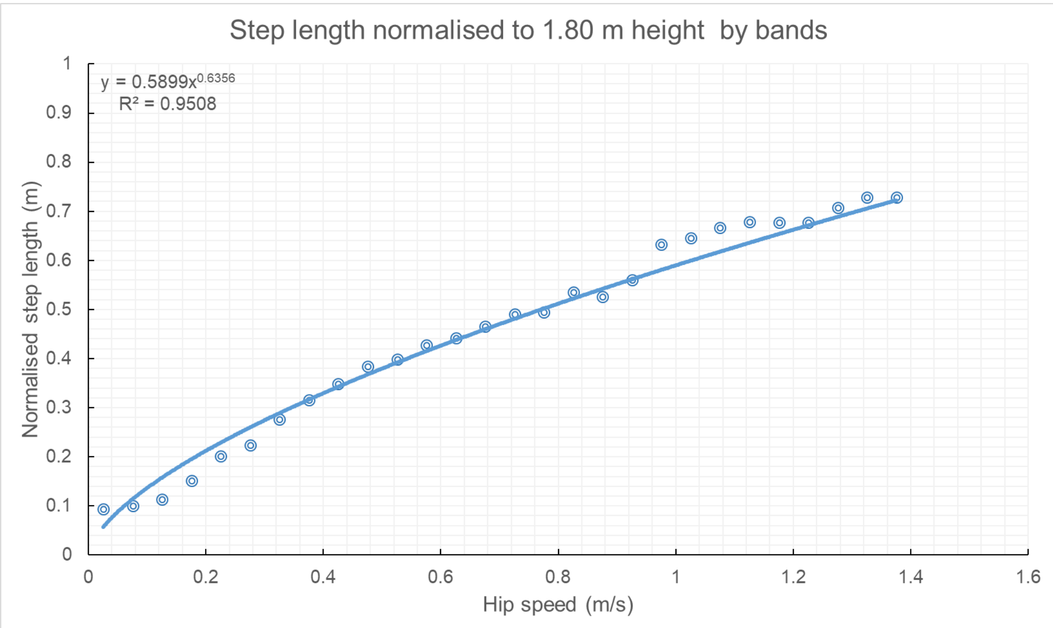

Figure 6 – Normalised step length as a function of hip speed, aggregated by bands. This simple visualisation shows how the normalized step length varies at different walking speeds

Aggregating the results in bands helped to visualise the trend better, but as in any other method used for simplification, the banding could not show the full extent of the data points collected, and its corresponding fitting curve could hardly be considered a good description of the whole data set.

Visual examination of the points on Figure 5 showed that a linear equation was by no means a good representation of the sample. Therefore, the second order polynomial seemed to be the best fitting curve for the data set. Figure 7 presents the step length normalised to the average height of the sample as a function of hip speed, with its fitting curve. This second degree polynomial curve shows a better fitting than the previous power curve and it is therefore a better description of the data set.

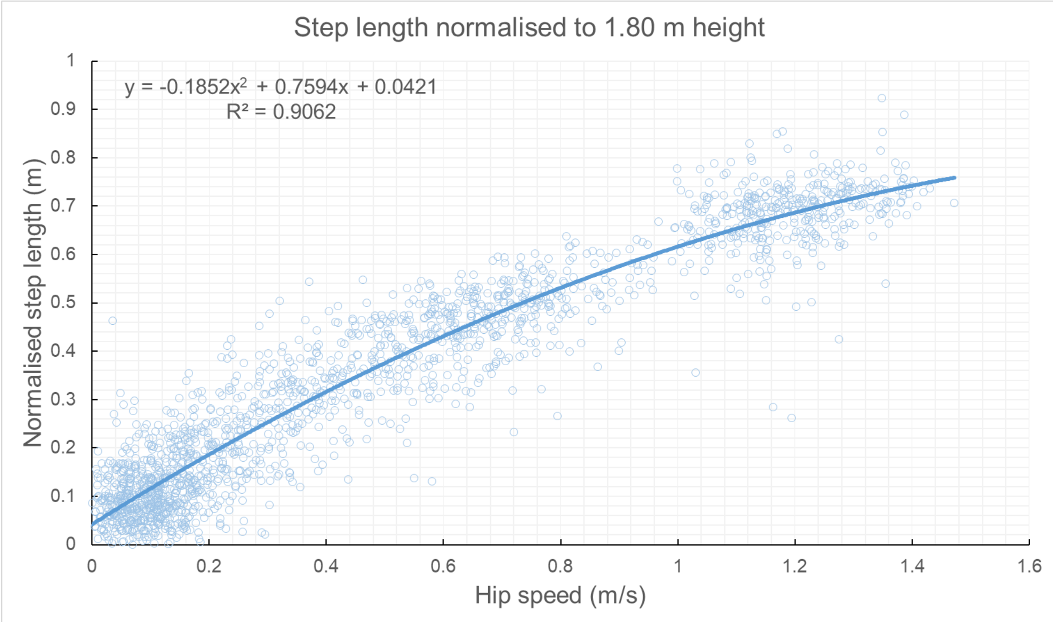

Figure 7 – Normalized step length as a function of hip speed for participants at different densities

Analogously to the steps presented for choosing Figure 7 as the best representation of the data set, Figure 8 shows the step extent normalized to the average height of the sample.

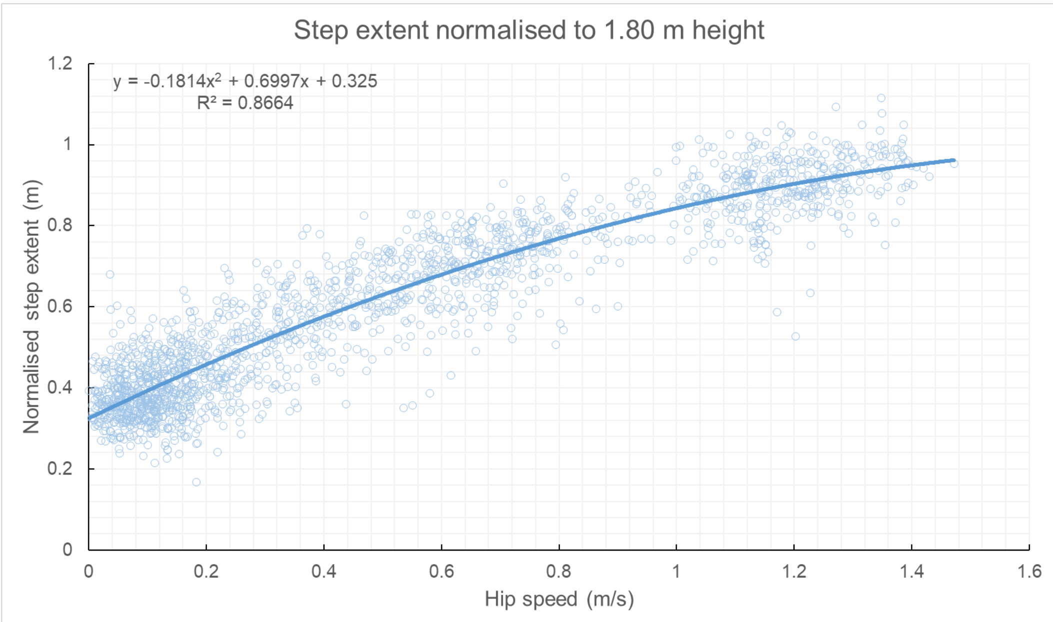

Figure 8 – Normalised step extent as a function of hip speed

4.2 Inter-person distance

Inter-person distance was measured both at the shoulder and the hip. Figure 9 shows both parameters as a function of hip speed, with the data being aggregated 0.05 m bands.

The aggregation of the data aimed to simplify the plot. Additionally, the difference between the two measurements was added to show how little they differed, which implies both parameters were equally good for describing inter-person distance.

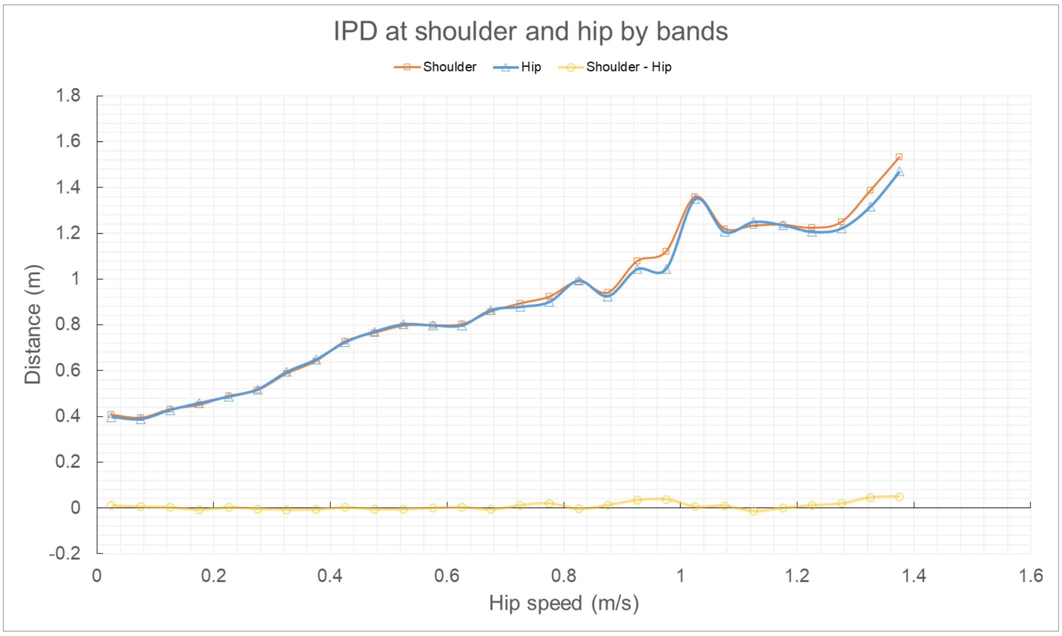

Figure 9 – Inter-person distance aggregated in 0.05 m bands, measured at shoulder and hip, and the difference between the two measurements

4.3 Contact buffer

The data collected on contact buffer is presented on Figure 10. As it can be observed, at low speeds (which occurs at high densities) the contact buffer was sometimes negative, indicating an overlap between the feet of the participants.

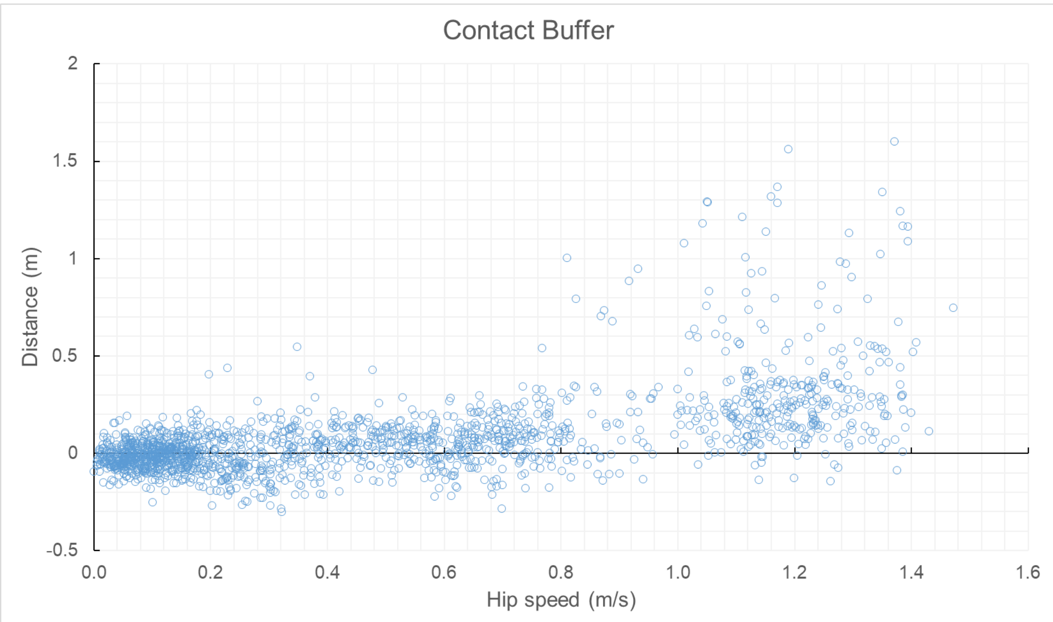

Figure 10 – Contact buffer data collected. Negative values indicate overlapping of the feet between two participants

In order to reduce the impact of overrepresentation of certain flow characteristics, the data on contact buffer was aggregated in 0.05 m bands as a function of hip speed. The result is presented on Figure 11. It can be seen that the contact buffer remains negative on average at lower speeds. Polynomial fitting curves are provided for the negative and positive sections independently. The yellow line represents a model for estimation of the contact buffer, which becomes independent of the walking speed once the average preferred unimpeded walking speed for the sample (1.28 m/s) is reached.

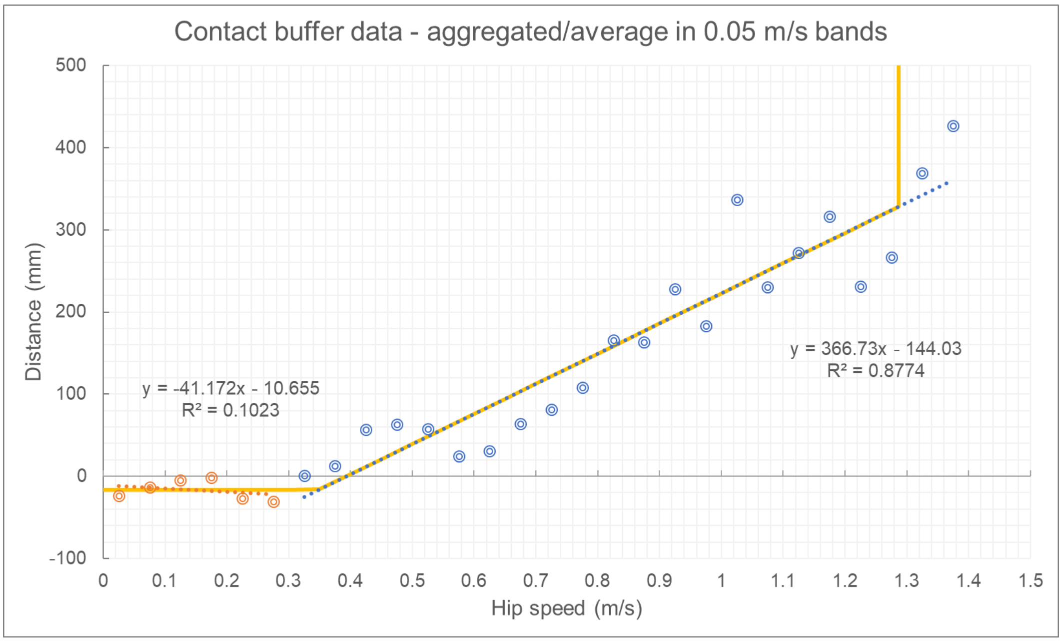

Figure 11 – Contact buffer as a function of hip speed, aggregated by 0.05 bands. Dotted lines mark the fitted curves respectively to the negative and positive sections. The yellow curve is the representation of a model for estimating contact buffer based on the walking speed.

4.4 Deriving step extent from step length

As indicated on section 2, step extent is proportional to the sum of step length and foot length, with the proportion reducing linearly from nearly 100% at standstill to around 92% at the preferred walking speed. Figure 12 shows the fitted curve to the experimental values for step extent compared to the model expectation of step extent being equal to step length plus foot length. The difference between the two values corresponds to the proportional factor *A* shown on Equations 1a and 1b.

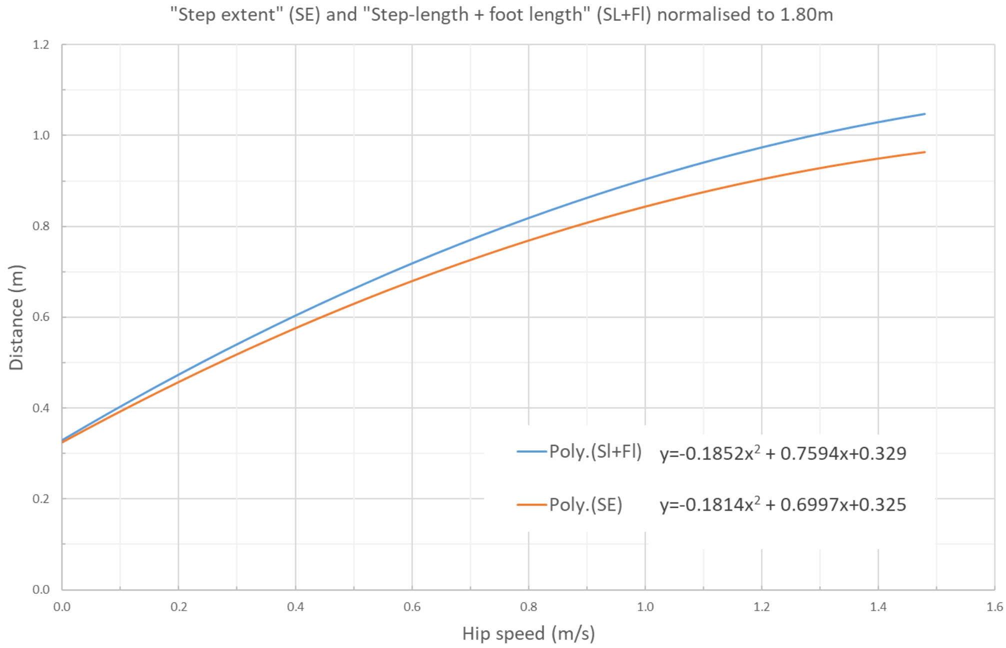

Figure 12 – Fitted second order polynomial curves to the measured value of step extent and the sum of the measured values for step length plus the average foot length for the sample

4.5 Deriving step extent from preferred speed and height

Figure 13 shows the step length data as a function of the reduction in walking speed, as a proportion of the sample average preferred unimpeded speed (i.e. the relationship between the instantaneous walking speed v and the preferred walking speed for the individual v_u).

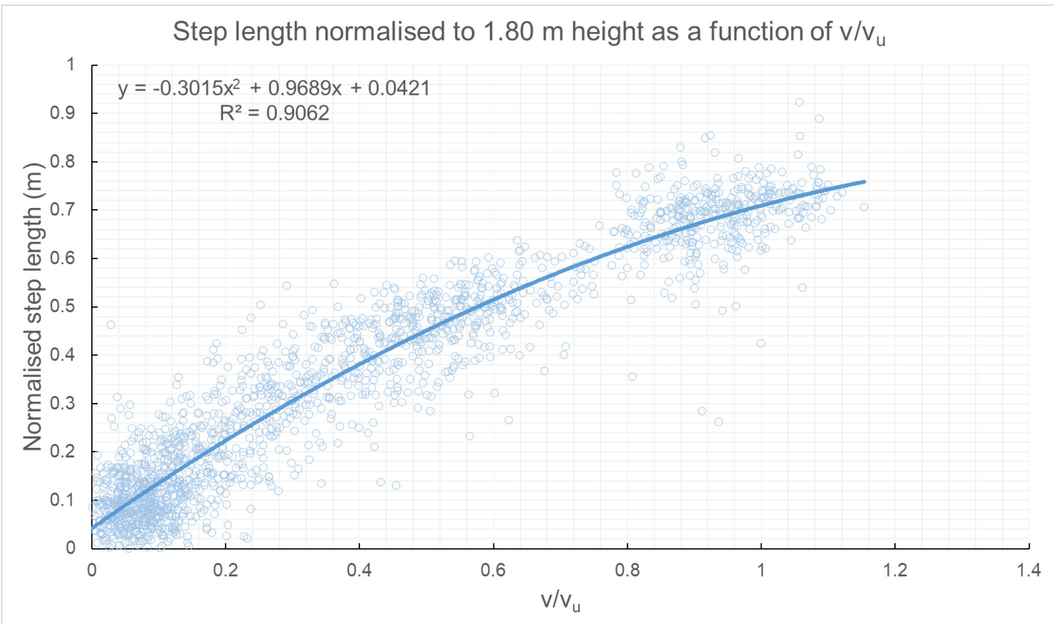

Figure 13 – Normalised step length as a function or the relationship between the individuals walking speed and their preferred walking speed.

It should be noted that the equation of the fitted curve is based on experimental values normalised to the average height of the sample (1.80 m/s) and the average preferred unimpeded walking speed. To apply the curve to cohorts of different demographics, the normalisation process needs to be reversed first and then redone using the average height of the target cohort (to derive step length), and the value of "v/vu" should be multiplied by the cohort average preferred walking speed (to derive walking speed).

4.6 Application of the model to the experimental data

The model can now be applied using input form the experimental data. In order to do that, Equations 1a, 1b and 2 are used with input parameters based on the demographics of the experimental sample. Table 5 presents the parameters used as input and the results produced. All input parameters are based on the experimental results used for developing the model. The adaption time was not directly measured in the experiment but derived from the gradient of the linear fit curve on the contact buffer for all the positive contact buffer points, cf. Figure 11.

Table 5 – Input parameters used in the model and the results produced. The input parameters are marked in gray.

Parameters & calculated predictions	Lund students
Height h [m]	1.80
Preferred unimpeded walking speed v_u [m/s]	1.29
Max density [p/m]	3.28
Adaption time Ta [s]	0.37
Foot length [m]	0.29
Step extent factor A (at Vu)	0.92
Peak single-file flow [p/s]	1.03

To contrast those results to the experimental data, Figure 14 superimposes the output of the model (full line) in the form of walking speed as a function of inter-person distance to the spread of experimental data points. The values for step extent at points of minimum contact are shown in a dashed line. The crossing between the inter-person distance and the step extent indicate negative contact buffer, i.e. situations where the toe of the person behind is located in front of the heel for the person in front, see Figure 4.

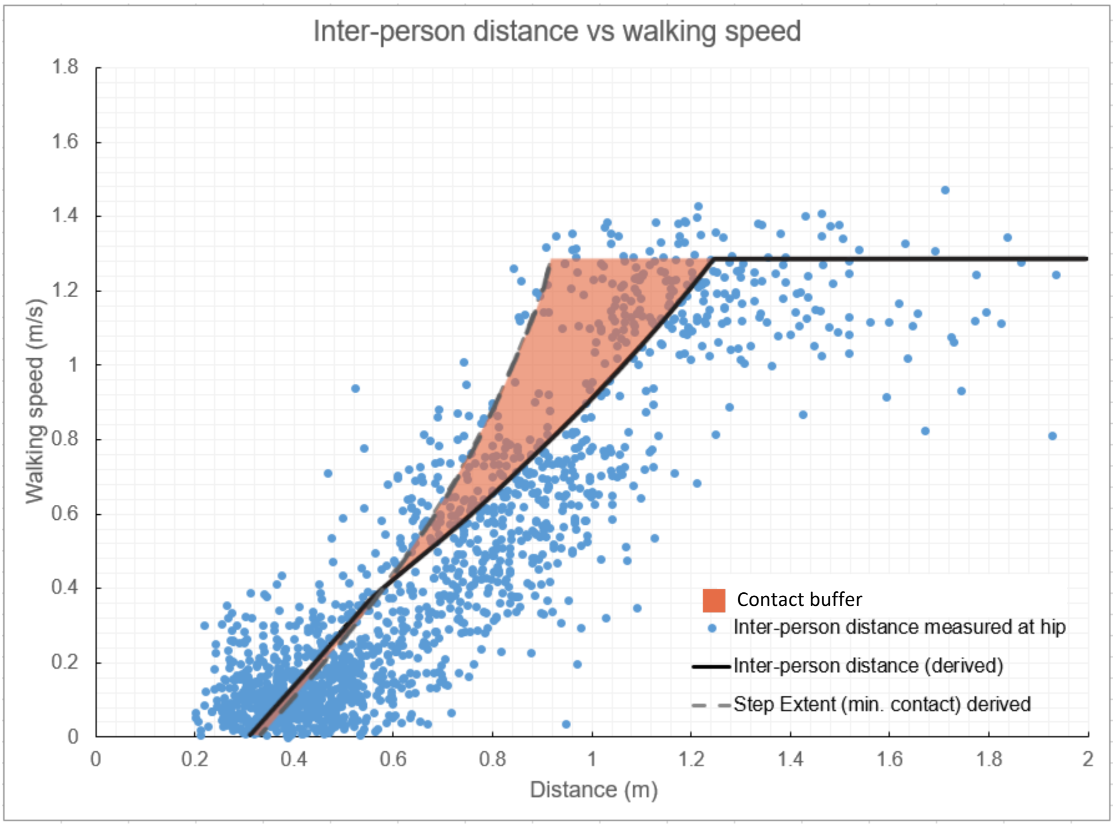

Figure 14 – Model for walking speed as a function of inter-person distance contrasted with the experimental data. Negative contact buffer can be seen at low densities.

4.7 Application of the model to other cohorts

Similar to the previous section, the model was applied in order to compare its predictions to other available experimental data. For prediction of flow values for both elderly and young adults, the data produced by Cao (Cao et al., 2016) was used. In the case of children, the data produced by Wang (Wang et al., 2018) was used. The input needed from both sources was average height, walking speed and foot length. An assumption was made for adaption time for the elderly sample, given the lack of available data. For this cohort, the adaption time was considered to be that of the young population with an added value of 0.309 ms based on the results of a laboratory experiment made using a treadmill (Nilsson et al., 2020). Table 6 presents a summary of the input values for indicative predictions of flow for each cohort. As the predictive model and the experiments performed are part of a pilot study, additional experiments are needed to validate the results.

Table 6 – Summary of predictions from the movement adaption model based on parameters from Cao (2016) and Wang (2018).

Parameters & calculated predictions	Lund students	Elderly (Cao)	Young (Cao)	Children (11 y.o.)
Height h [m]	1.80	1.62	1.64	1.42
Preferred unimpeded walking speed v_u [m/s]	1.29	0.95	1.23	1.29
Max density [p/m]	3.28	2.58	3.40	4.34
Adaption time Ta [s]	0.37	0.68	0.37	0.37
Foot length [m]	0.29	0.28	0.28	0.22
Step extent factor A (at v_u)	0.92	0.92	0.92	0.92
Peak single-file flow [p/s]	1.03	0.71	1.06	1.23
Percentage of Lund students flow rate	100%	69%	103%	119%
Difference from Lund students flow rate	0%	-31%	-3%	19%

4.7.1 Elderly

Figure 15 presents the prediction of the model for walking speed as a function of inter-person distance. As shown in the figure, the model does not predict negative inter-person distance even at high densities. Negative inter-person distances were found in the experimental data from the Lund experiments, but the lack of it could be due to the longer adaption time used as input for the elderly population.

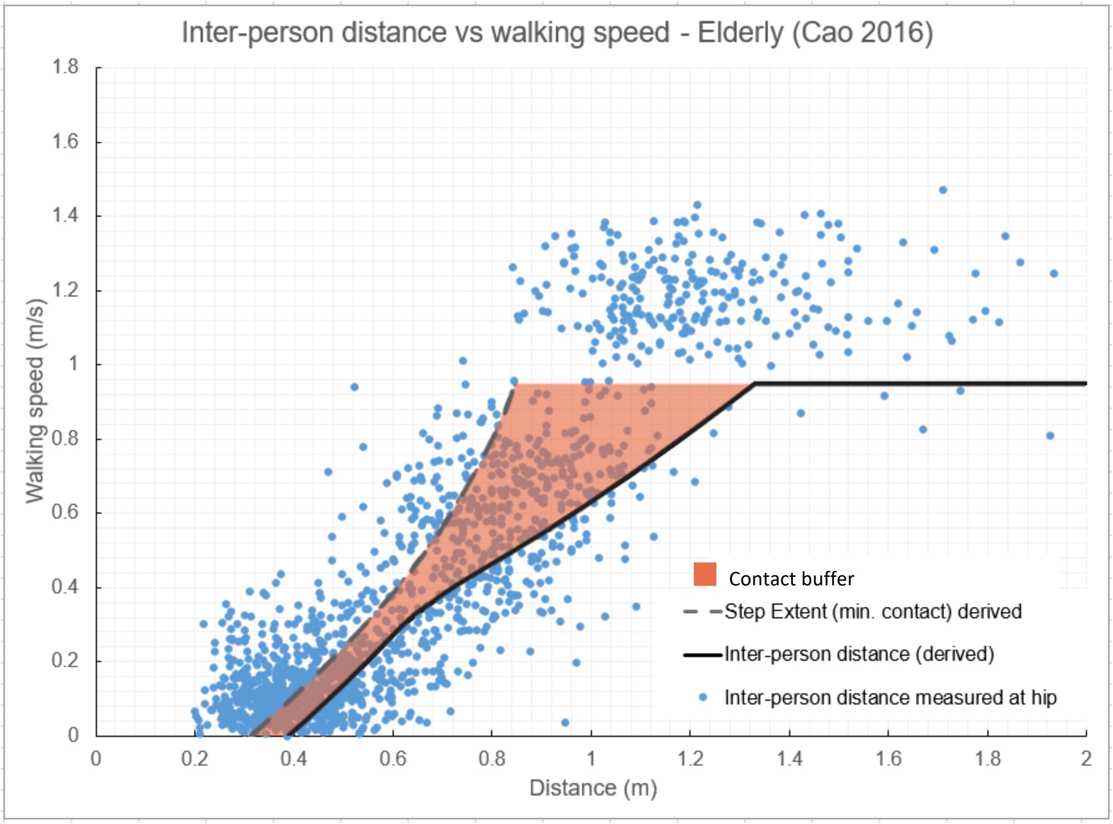

Figure 15 – Step extent and inter-person distance predicted by the model for an elderly cohort based on Cao (2016) sample, contrasted to the experimental data from the Lund experiments.

4.7.2 Young

Figure 16 presents the expected walking speed for a young cohort based on the input from Cao (Cao et al., 2016). The negative contact buffer at high densities (notice crossing of the full line and the dashed line) matches the observed behaviour in the Lund experiments.

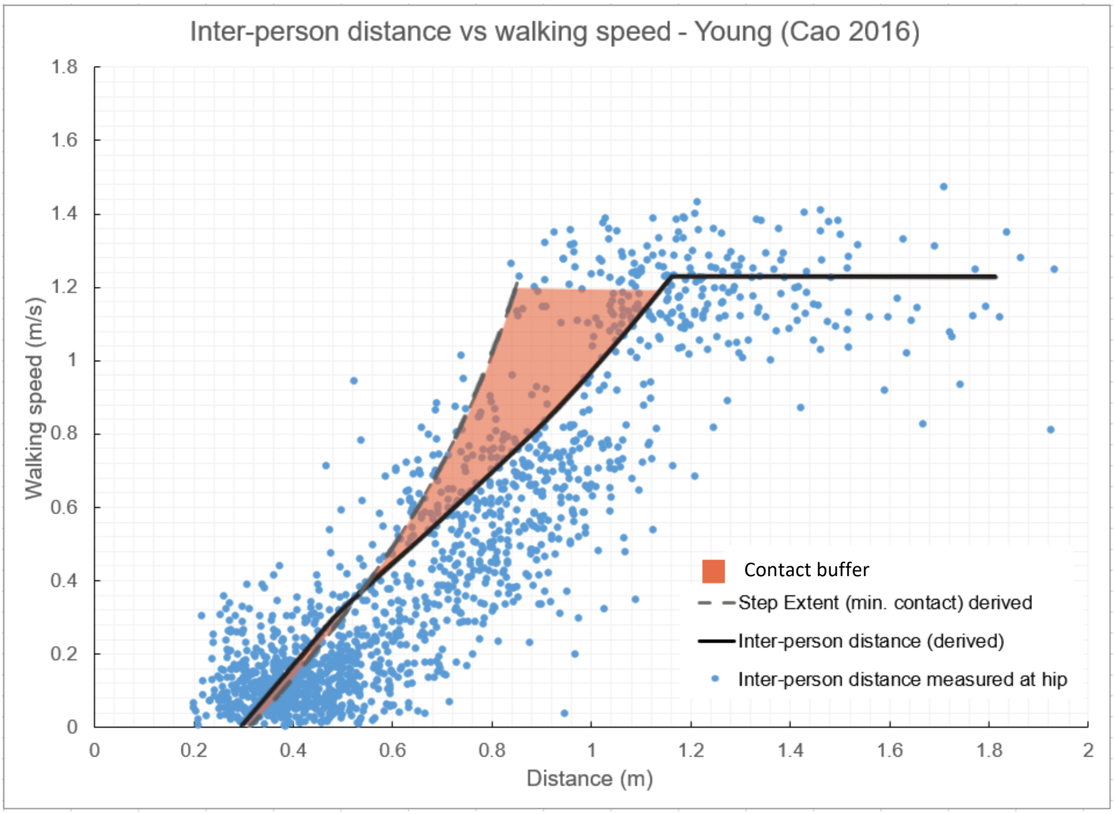

Figure 16 - Step extent and inter-person distance predicted by the model for a young cohort based on Cao (2016) sample, contrasted to the experimental data from the Lund experiments.

4.7.3 Children

Figure 17 presents the model's prediction of walking speeds for children based on the input form Wang (Wang et al., 2018). The results fall in the lines of other studies performed on walking speed of children. Results are not unexpected based on other studies (Hankin & Wrigth, 1958).

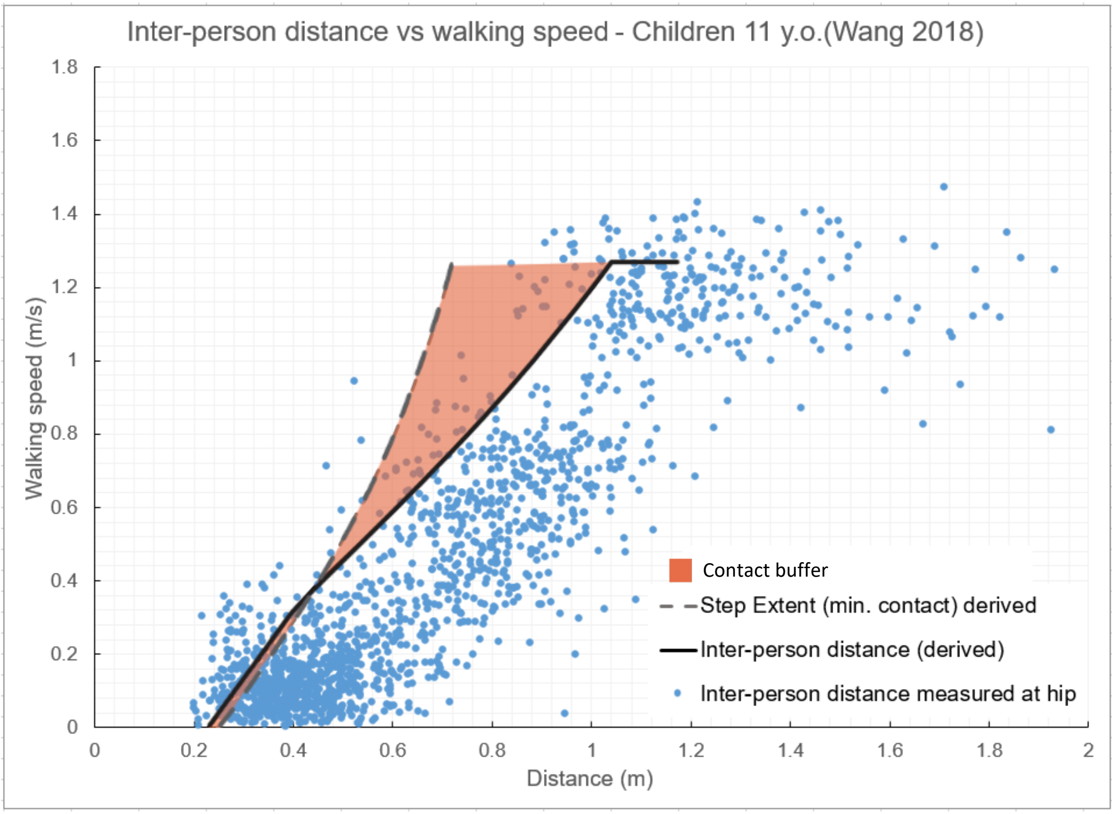

Figure 17 – Step extent and inter-person distance predicted by the model for a cohort of 11 year old children according to the data set from Wang (2018) contrasted to the experimental data from the Lund experiments.

4.7.4 Summary of model predictions

With the results obtained from the application of the model to different cohorts, it was possible to present the data in a more practical term for its use. Figure 18 shows the predicted flow as a function of density for the cohorts presented in Table 6. The predicted curves are superimposed with the experimental data obtained by Cao (Cao et al., 2016), which consists of three cohorts: young adults, old adults, and a mixed group of both in a 1:1 proportion.

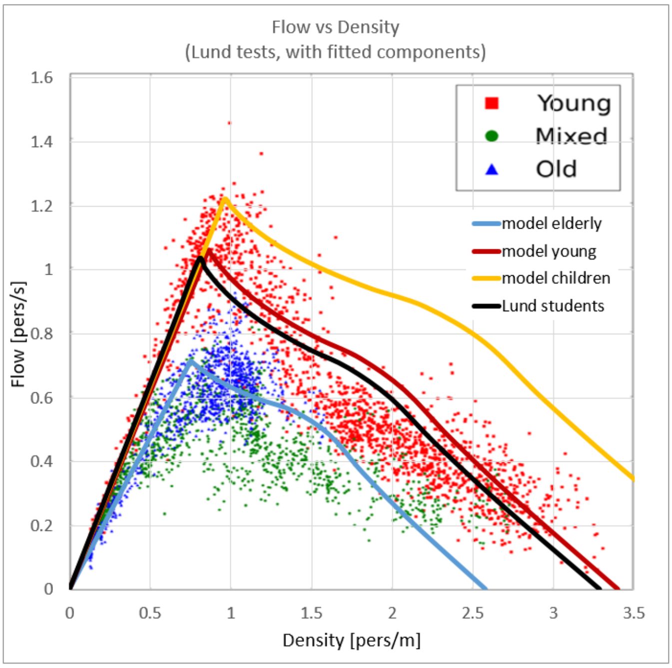

Figure 18 – Predicted single file flows based on different cohorts compared to the experimental values obtained for young, mixed and old samples by Cao (2016).

Similarly, the data is also presented in terms of walking speed as a function of density on Figure 19, also superimposed with experimental data from Cao (Cao et al., 2016).

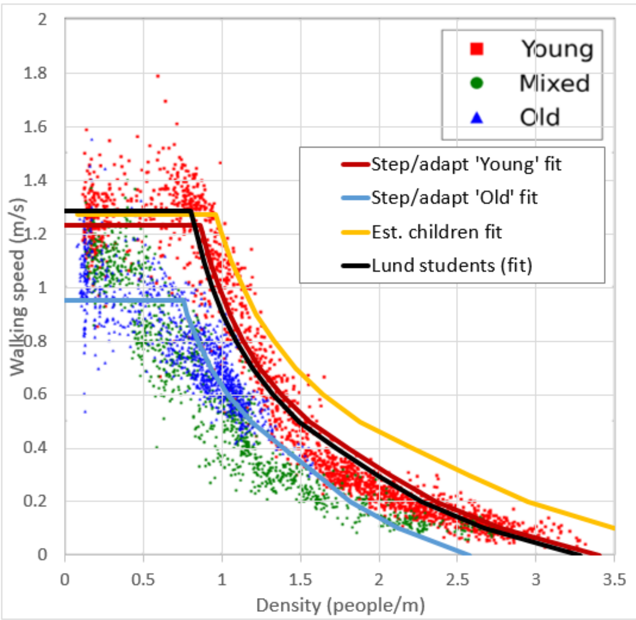

Figure 19 – Predicted walking speed as a function of density compared to the experimental values obtained for young, mixed and old samples by Cao (2016).

4.7.5 Comparison with other studies

Lastly, Figure 20 compares the measured step length as a function of walking speed to that obtained by other studies. The curve obtained falls along the lines of the models proposed by the other studies.

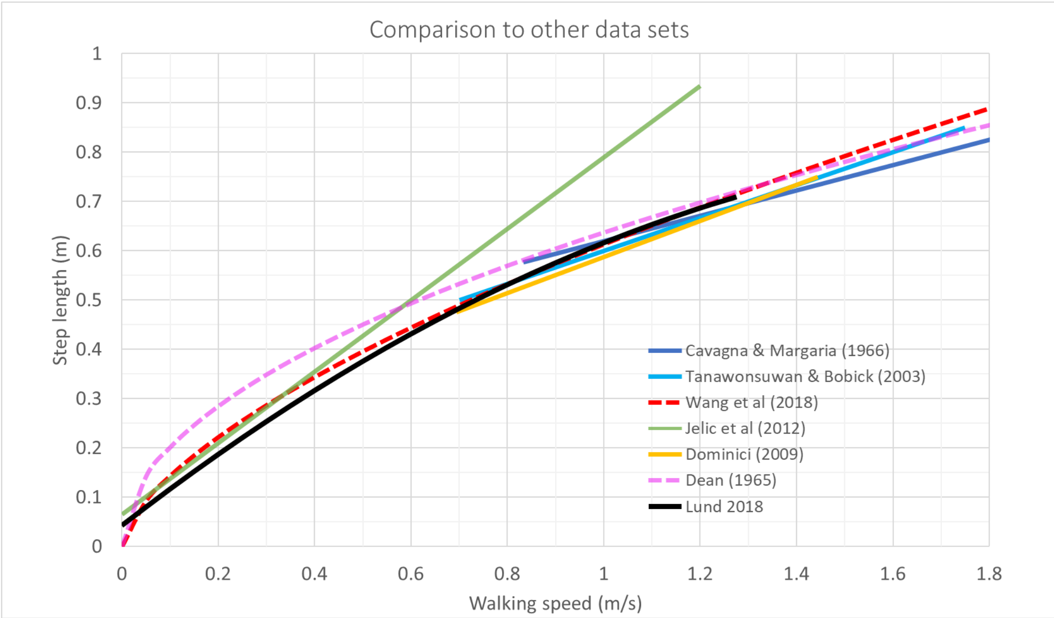

Figure 20 – Comparison of the obtained fitted curve for the Lund experiment and those from other studies

5 Discussion

The experimental results are on themselves an important contribution to the existing available data on walking speeds on a young adult cohort, as it is based on a modern sample of people. Moreover, the way the data was collected and presented (i.e. not only walking speeds but also biomechanical information) would potentially allow designers to know to a better degree whether this data set is representative of the population they expect in their buildings.

Much can be discussed about the best choice for a fitting curve for the large set of data presented in terms of step length and step extent (see Figure 7 and Figure 8). As it can be seen on Figure 20, different groups of researchers opted for different kinds of fitting curves: linear equation, power curve, second degree polynomial. As explained on section 4.1, the second degree polynomial proved to be a better description of the complete data set, and therefore more representative of the trends measured in the experiment.

The data obtained allowed improving the prototype model (Nilsson et al., 2020) for estimating walking speeds at different densities on single-file configurations. This improved model can be applied to reflect different flow conditions and some demographic characteristics of the occupants. The equations behind the model aim for a higher level of detail in the description of the movement, and represent a contribution to the improvement of previous models produced by other studies. Currently the model is described in a spreadsheet program but has also been implemented in a computer simulation model, Simulex (Thompson, 1994), for testing.

The flows predicted by the model show similarities with the experimental data (Cao et al., 2016) available for contrast, especially in the prediction for peak flow rate.

The model developed by Thompson et al. (Nilsson et al., 2020; Thompson et al., 2016; Thompson, Nilsson, Boyce, McGrath, et al., 2015) has the advantage of being thought out not just as a description of the experimental data set but also as a versatile tool that can be used for different cohorts. This approach is especially useful given the natural variation in cohorts around the world but also in the decades to come.

Input on adaption time needed to be estimated for the elderly cohort as there was only little available data on it. The adaption time can be expected to vary between different cohorts so it needs to be collected together with other biomechanical data for each cohort. This is something needing more attention in future studies.

With the increasing challenges to securing funding for research on pedestrian dynamics, it is important that the scientific community develops basic standards for data collection, so that the same experimental measurements can be used in different models. This means a change in the way of designing studies: from collecting data for a unique study or set of studies, to a global approach in which fundamental variables are measured across different studies in a standardised way. New data sets would enrich any existing models and their ability to be fed into different models would make them a more efficient use of the available resources.

Although custom-developed software was used to collect and process the data, the data collection technique used to extract the information from the video recordings proved to be highly time-consuming. Moreover, despite the high resolution of the videos, blurred images were unavoidable and lead to a lower level of precision in the measurements. Additionally, in the case of high densities, overlapping between the feet of two consecutive participants (i.e. negative contact buffer) did not always allow for a precise location of the corresponding markers, as one might have been behind the other person's foot. It is therefore considered that the technique of markers and video recordings may imply some subjectivity in the identification of the position of each marker.

A different technique, such as optical motion capture, could improve the accuracy of the measurements. However, such a technique can only be applied in laboratory conditions and mostly on single-file configurations only.

Despite of the possible imprecision of the analysis of video recordings, the technique has the advantage of providing a detailed sequence of events (such as identifying particular responses by the test participants), not just the coordinates, which may be beneficial when collecting data on pedestrian movement more complex scenarios (e.g. doorway passage, stairs, different cohorts, etc.). Additionally, the relatively low cost of video recordings compared to that of motion capture systems allow for larger samples in the experiments.

The overrepresentation of data points at high-density (and therefore low speed) levels may have an influence on the fitted curve. Producing a separated chart for the high-density section only was not possible due to the high variation between the data points (a densely packed cluster), and it was not possible to identify a trend.

6 Conclusions

The data set of walking speeds produced by this study is a valuable contribution to the current effort of SFPE to update anthropometric data for modelling of egress and pedestrian movement in an attempt to keep up with changes in demographic. The data is also hereby made publicly available.

Moreover, the improvements made to the model for estimating flows at different densities is a versatile tool possibly to be used in the future to model pedestrian movement that can easily be adapted for different cohorts. This versatility is especially beneficial when dealing with buildings or spaces used by people of different ages. Nevertheless, the model still requires data on certain specific parameters relative to each cohort for it to be useful. Therefore, a collaboration within the research community is needed in order to collect data on those specific parameters.

References

Cao, S. C., Zhang, J., Salden, D., Ma, J., Shi, C., & Zhang, R. (2016). Pedestrian dynamics in single-file movement of crowd with different age compositions. *Phyiscal Review E, 94*(1). doi:doi:10.1103/PhysRevE.94.012312

Dean, G. A. (1965). An analysis of the energy expenditure in level and grade walking. *Ergonomics, 8*(1), 31-47. doi:https://doi.org/10.1080/00140136508930772

Doka, K. (2019). *Advanced parametric testing of evacuation modelling for different population groups using BIM generated geometries.* (Master), Ghent University, Ghent.

Fruin, J. J. (1971). *Pedestrian Planning and Design*. New York: Metropolitan Association of Urban Designers and Environmental Planners.

Hankin, B. D., & Wrigth, R. A. (1958). Passenger flow in subways. *Operational Research Quarterly, 9*(2), 81-88. doi:https://doi.org/10.1057/jors.1958.9

Hansen, A. (2018). *A Scoping Review for the Parameters of Crowd Movement.* (Bachelor), Lund University, Lund. (5565)

Kinovea. ((n.d.)). Features: Kinovea. Retrieved 12 10 2018 https://www.kinovea.org/features.html

Larsson, G., & Friholm, J. (2019). *Evaluation of measurement methods for determining individual movement in crowds* (5585). Retrieved from Lund, Sweden:

Lay, M. G. (2009). *Handbook of road technology* (4th edition ed.). United Kingdom: Spon Press.

Nilsson, D., Thompson, P. A., McGrath, D., Boyce, K. E., & Frantzich, H. (2020). *Crowd safety: prototyping for the future*. Retrieved from

OECD. (2017). Obesity Update 2017. Retrieved 19-FEB-2020

Pauls, J. L. (1996). Movement of people. In P. J. DiNenno, C. L. Beyler, R. L. P. Custer, W. D. Walton, J. M. Watts Jr., D. Drysdale, & J. R. Hall Jr. (Eds.), *The SFPE Handbook of fire protection engineering* (2nd Edition ed., pp. 3263-3285). Quincy, MA: National Fire Protection Association.

Pauls, J. L., Fruin, J. J., & Zupan, J. M. (2007). Minimum Stair Width for Evacuation, Overtaking Movement and Counterflow — Technical Bases and Suggestions for the Past, Present and Future. In N. Waldau, P. Gattermann, H. Knoflacher, & M.

Schreckenberg (Eds.), *Pedestrian and Evacuation Dynamics 2005* (pp. 57-69). Berlin, Heidelberg: Springer Berlin Heidelberg.

Thompson, P. A. (1994). *Developing new techniques for modelling crowd movement.* (PhD), University of Edinburgh,

Thompson, P. A., Nilsson, D., Boyce, K. E., & McGrath, D. (2015). Evacuation models are running out of time. *Fire Safety Journal, 78*, 251-261.

Thompson, P. A., Nilsson, D., Boyce, K. E., & McGrath, D. (2016). Crowd safety: prototyping for the future showing how the science for "pedestrian flow" can keep up with demographic change. In. Sweden: Brandforsk.

Thompson, P. A., Nilsson, D., Boyce, K. E., McGrath, D., & Molloy, M. (2015). *Exploring the biomechanics of walking and crowd flow*. Paper presented at the Sixth International Sumposium for Human Behaviour in Fires, University of Cambridge, UK.

Wang, J., Boltes, M., Seyfried, A., Zhang, J., Ziemer, V., & Weng, W. (2018). Linking pedestrian flow charactersitics with stepping locomotion. *Physica A: Statistical Mechanics and its Applications, 500*, 106-120. doi:https://doi.org/10.1016/j.physa.2018.02.021