Analysis of the capabilities of Pedestrian Dynamics for reproducing physical distancing during COVID-19 in bidirectional flows

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ANALYSIS OF THE CAPABILITIES OF PEDESTRIAN DYNAMICS FOR REPRODUCING PHYSICAL DISTANCING DURING COVID-19 IN BIDIRECTIONAL FLOWS

by

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to obtain the degree of Master of Science

at the Delft University of Technology,

to be defended publicly on Tuesday 25th of January 2022

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Preface

This thesis project marks the end of my master's degree in Civil Engineering in the track of Transport & Planning at TU Delft. This research aims at assessing the effect of a prescribed physical distance on the walking behaviour of pedestrians, and determining the capability of Pedestrian Dynamics to reproduce the walking dynamics observed during the pandemic. I hope it provides insights into future research regarding the impact of COVID-19 on the walking behaviour.

The past 10 months have been a journey that has certainly not been easy, but it has definitely been worth it. Since I started my thesis I have encountered different challenges both academically and personally, which made me feel lost and sometimes unmotivated to keep working. Fortunately, I have been surrounded by people who have always been there for me and that it is largely because of their support that I am now completing my master studies.

First, I would like to thank my daily supervisor, Dorine Duives, who has always been there to guide me through the process of doing research with her insightful comments and remarks. I really appreciate your support and words that encouraged me to keep working, but also your reminders to be proud of my work. I take with me your advice of being more pragmatic and do not overthink things too much as it will for sure be useful for my professional and personal life.

Next, I would like to thank my supervisor from InControl, Nienke Valkhoff, who provided me with the training in the use of Pedestrian Dynamics and supported me in the phase of modelling of the scenarios for this research. Moreover, I am grateful for our valuable weekly talks in which there was always something new that I learned based on your comments that steered me towards a clearer path.

I would like to thank the chair of my committee, Winnie Daamen, who provided me with feedback that allowed me to think through ideas that were not initially considered and that helped me to have a better understanding of the topic. I would also like to thank Simeon Calvert, a member of my thesis committee, whose comments always made me be aware of the contributions of my thesis to future research.

This thesis has entailed different phases and for each one of them I have counted with the support of people to whom I would like to show my gratitude. First, thanks to Martijn Sparnaaij, who provided me with insights into the calibration framework used in this research. Second, thanks to Lucia van Schaik, who helped me with the data processing for the walking behaviour assessment. Lastly, thanks to Paula Godoy, who assisted me with the usage of Pedestrian Dynamics and who always had encouraging words.

Finally, my deepest appreciation and love go to my parents who, despite of the distance, have always been there. Thank you mom and dad for your kind words and for believing in me even at times when I did not. Thanks to my friends who have helped me during this process by having long talks or hanging out when we needed a break from the thesis.

Roberto Villena Gonzales
Delft, January 2022

Summary

The COVID-19 pandemic has changed people's lives in greater or lesser degree since the outbreak back in December 2019 in Wuhan, China. Due to the high transmissibility of the virus and with the aim of preventing the virus from continue spreading, several measures have been applied during the last two years, which now have become part of people's daily life. One of these measures is physical distancing, which has been proven to be an effective way to reduce the transmission risk, since keeping a larger distance from others reduce the spread of the virus.

Several simulation models have been developed to gain insight into the transmission risk of the virus and the impact of different measures on its spread. One model is EXPOSED (Ronchi and Lovreglio, 2020), which analyses the exposure of occupants in buildings based on the microscopic movements of pedestrians, and allows comparing the impact of different crowd management solutions on the exposure of occupants. Another model is the hybrid multi-scale model developed by Bouchnita and Jebrane (2020), which represents the physical distancing by a so-called socio-psychological force (i.e. repulsive force), and provides insights into the influence of the speed and density levels on the distance kept by pedestrians and thus on the transmission risk. Although these models can provide some information regarding the compliance of the prescribed physical distance or the density levels to do so, they cannot provide insight into the changes in pedestrians' interactions during COVID-19. Thus, there is a knowledge gap regarding the influence of the measures, particularly the physical distancing, on the walking behaviour of pedestrians.

One model that has introduced the physical distancing to analyse the walking dynamics during the pandemic is Pedestrian Dynamics (PD), developed by InControl. In PD, the parameter "physical distance" has been implemented with the objective of conducting capacity analyses (i.e. aggregate level) based on the assumption that pedestrians strictly keep the prescribed physical distance from others. Therefore, another knowledge gap is with respect to the capability of the model to reproduce the underlying walking behaviour (i.e. operational level) of pedestrians during the pandemic and which changes should be done to improve its accuracy. An improvement of the model is considered to be relevant as the walking behaviour could be modelled to obtain relevant information for the implementation of crowd management solutions in situations in which a specific distance between pedestrians need to be ensured.

This research aims at understanding how the walking behaviour of pedestrians at the operational level has changed during COVID-19 because of physical distancing in situations in which pedestrians cannot comply with the prescribed physical distance. Moreover, given the time and data available for this research, the assessment of the walking behaviour is focused on bidirectional straight flows in narrow corridors. Based on the behavioural assessment and the type of movement of interest, this research also aims at determining the capability of PD to predict behaviour observed in reality by conducting a calibration of the model. Thus, the main research question to be answered by this study is the following:

Which is the optimal parameter set in Pedestrian Dynamics and its capability to accurately reproduce the walking behaviour during COVID-19 for bidirectional flows where the prescribed physical distance is not fully complied?

A review of the existing literature has provided insight into the impact that physical distancing might have on the space usage, route choice, and movement of pedestrians, and therefore in the elements of

PD that could be adjusted to replicate the walking dynamics during the pandemic. Moreover, a review of the pedestrian traffic theory and crowd movement phenomena has provided information regarding the characteristics of the walking behaviour of bidirectional flows in a normal context before the pandemic. Therefore, the previous behaviour can be compared with that observed during COVID-19 in order to identify the differences and thus the influence of physical distancing. Finally, a review of the state-of-the-art calibration methods has been conducted to determine the most suitable method to be used for the calibration of PD.

Based on the objectives of this research and the findings in literature, gaining knowledge of the walking behaviour at bidirectional straight flows during the pandemic is crucial as it provides the information of the walking dynamics that are intended to be reproduced by the calibrated model. Thus, the first step has been to formulate the following three hypotheses that describe the expected changes in the walking behaviour caused by the physical distancing:

- **Hypothesis 1:** ***Pedestrians try to keep a distance of 1.5 m from each other***
  This hypothesis states that pedestrians keep as much as possible a larger distance than they did before the pandemic to avoid close interactions and thus comply with the physical distancing rule.
- **Hypothesis 2:** ***Pedestrians show an increased awareness of their surroundings compared to the pre-corona situation***
  This hypothesis states that pedestrians look into a wider range for open spaces as they are more willing to take small detours from their most direct path in their planned route and thus being able to keep a larger distance from others.
- **Hypothesis 3:** ***The variance of pedestrian's walking velocity is greater during COVID-19 than before***
  The last hypothesis states that the velocity of pedestrians changes as a result of their willingness to move differently in order to keep the prescribed physical distance from others, and thus comply with the rule.

According to these hypotheses, the assessment of the walking behaviour at bidirectional straight flows has been carried out by analysing the trajectory data from a corridor in Utrecht Central station. The analysis of the data set has shown that the demand declined in 2020 compared to 2019 and in 2021, although it recovered, it was still at levels below 2019. The fundamental relationship flow-density has revealed that the capacity and critical density have not been reached during the pandemic in the corridor, since only the free flow branch and low-density levels were observed, which would allow a full compliance of a prescribed physical distance of 1.5 m. Therefore, the assessment of the walking behaviour and the calibration of the model was with respect to low-density scenarios. Moreover, it was concluded that the relation flow-density in free flow conditions during the pandemic has remained the same, since no significant changes were found in the gradient of the free flow branch for the three years. This was contrary to what was expected given that, as an effect of physical distancing, the speed would decrease more rapidly as the density increases.

In order to provide an answer to the hypotheses, two macroscopic metrics (spatial distribution and speed distribution over space), and three mesoscopic metrics (minimum distance headway, effort, and travel distance) have been chosen for the analysis of the walking behaviour, since they measure different aspects of the flow related to the behaviour stated in the hypotheses. The first hypothesis was not rejected given that during the pandemic the mean minimum distance headway was larger than 1.5 m, and the distribution of distance headways showed that fewer people accepted a distance lower than 1 m compared to the pre-pandemic situation. Moreover, it was concluded that the physical distancing rule has not been fully complied. The second hypothesis was not rejected when the behaviour in 2020 was analysed given that a less even distribution of speed over the space and higher effort than in 2019 indicated more changes in the speed and movement direction, respectively. Thus, these results suggested an increased awareness during the first year of the pandemic. However, the second hypothesis was rejected when the behaviour in 2021 was analysed, since results opposite to 2020's were obtained for the speed distribution over the space and the effort. Similarly, the third hypothesis was not rejected in 2020 due to a significant change in the speed distribution with respect to the pre-pandemic situation, as well as a higher effort, which indicated a larger variance of pedestrians' velocity, while the hypothesis was rejected in 2021 as the opposite results were obtained.

Regarding the assessment of PD, a sensitivity analysis has been conducted to determine how sensitive the model is to changes in parameters, and to determine the range of values of them within which the behaviour changes and remains realistic. Given that the size of the search space for the calibration is defined according to the sensitivities, only the parameters for which the model is more sensitive were chosen. A reason for this is that a good estimation of these parameters is considered more important as small changes can lead to significantly different results (Sparnaaij, 2017). Thus, based on the hypotheses and the objective of this research, the parameters have been selected such that changes in their default values could lead to an increased accuracy of the model for bidirectional straight flows in COVID-19 scenarios. These five parameters are: minimum desired speed, viewing angle, avoidance range, relaxation time, and physical distance. The qualitative analysis showed that within a range of ±25% from the default value of the parameters, the behaviour was realistic for all the parameters, except for the physical distance. Given that the latter parameter has been developed for capacity analyses assuming that pedestrians keep the same prescribed distance at any given time, it was concluded that this parameter cannot be used for reproducing the underlying behaviour in the scenarios of interest, and thus it was discarded for the remaining of the study. The quantitative analysis shed light on how significant the changes in the behaviour are and how these changes vary within the range of values of the parameters. The findings of the analysis revealed that the size of the deviations depends on the parameters and density level of the scenarios. Thus, it was concluded that PD is more sensitive to changes in the relaxation time and viewing angle in high-density scenarios, and the relaxation time in low-density scenarios. These findings show that these are the two most important parameters to calibrate.

The capabilities of PD to reproduce the walking behaviour during the pandemic have been studied by conducting a multiple objective calibration. This calibration framework allows the usage of different movement base cases, densities, and metrics such that all the relevant behaviour can be captured. Two scenarios have been considered for the calibration, which consist of the movement base case and the year (i.e. 2020 and 2021). Moreover, these years have been chosen given that the walking behaviour has changed during the pandemic and the model was intended to be improved to predict more accurately all COVID-19 situations. Regarding the comparison between the reference data and the simulation, it has been conducted by using three metrics: speed distribution over space, minimum distance headway, and effort. These metrics were selected as they best described the intended behaviour to be reproduced more accurately by the model. In addition, the selection of macroscopic and mesoscopic metrics allowed to get insights into different aspects of the flow. Lastly, seven combinations of scenarios and metrics have been evaluated, which have been selected such that insights could be obtained regarding how the calibration results were affected by the scenarios and metrics used. These combinations are: the two individual scenarios using all three metrics, the three individual metrics using all scenarios, the combination of all mesoscopic metrics and all scenarios, and the combination of all scenarios and all metrics.

Furthermore, the calibration is conducted by considering three parameters: relaxation time, viewing angle, and personal distance. The relaxation time was selected based on the results of the sensitivity analysis. The viewing angle was chosen as deviations from its default value could describe the changes in the awareness and direction of movement of pedestrians during the pandemic and thus describe the behavioural differences between 2020 and 2021. Similarly, changes in the default value of the personal distance could describe the differences in the distance headways between the same two years. Moreover, the personal distance was used instead of the physical distance parameter, since the former could provide more flexibility regarding the distance pedestrians keep from each other and thus improve the calibration of the model to reproduce the intended behaviour. Lastly, the search space is defined based on these three parameters, of which a deviation of ±24% was considered as boundaries of the search space in accordance with the maximum deviation in the sensitivity analysis, and a step size of 6% for the grid search, which is the selected optimisation method for the calibration.

The calibration results have shown that the optimal parameter set differs according to the combination that was analysed, thus the scenarios and metrics used in the analysis influenced the accuracy of the model. Moreover, although the GoF of the combinations decreased when the optimal parameter set of another combination was used, the differences between GoF were small. Therefore, regardless of the scenarios and metrics used in the calibration, the GoF's were expected not to significantly change when the optimal parameter sets of other combinations were used. Moreover, most of the optimal parameter sets within the search space included values at the boundary of the relaxation time. Thus, information could not be obtained regarding its optimal value as it could be found out of the initial search space.

Furthermore, by looking at the error space, it was concluded that the relaxation time was the most relevant parameter, since the error significantly changed based on its value regardless of the viewing angle and personal distance values. In addition, the impact of the relaxation time on the error depended on the metric used, since it was larger when analysing the speed distribution over space and effort than when analysing the minimum distance headway. Moreover, the surface shape showed that lower values of the relaxation time appeared to replicate better the behaviour during the pandemic, which suggests a faster reaction of pedestrians and more abrupt changes in their movement direction. Based on the hypotheses, these effects of low values of the relaxation time were according to the expected greater awareness and larger variability of pedestrians' velocity during the pandemic. On the contrary, when the viewing angle and personal distance were analysed together, the surface shape revealed that their values were not relevant as similar errors were yielded by any of them (i.e. flat horizontal surface).

The focus of this research lies in determining the optimal parameter set in PD to accurately reproduce the walking behaviour during COVID-19 for bidirectional flows and how capable the model is to reproduce this behaviour. The findings have shown that the parameters' values differed based on the scenarios and metrics used in the calibration. By taking into account all three parameters considered in the calibration, one could conclude that for a general usage of the model for COVID-19 scenarios the optimal parameter set would be the one corresponding to the combination of all scenarios-all metrics. However, the calibration has also shown that the relaxation time was the most relevant parameter to calibrate for as the viewing angle and personal distance did not provide relevant differences in the error. Therefore, provided that the walking behaviour has changed over the course of the pandemic, a model calibrated using a single parameter will not yield accurate results for all COVID-19 scenarios, and the model should be in principle calibrated separately for a specific situation during the pandemic. Nonetheless, in case of an unknown situation for which a calibration is not possible, lower values of the relaxation time can be expected to provide a better prediction of the behaviour during the pandemic.

The findings in this research are focused on the impact of physical distancing at the operational level, hence information cannot be provided regarding changes that might have occurred in the activity choice and route choice during the pandemic. Moreover, it is limited with respect to the type of behaviour and density level for which the model has been calibrated as bidirectional straight flows and low densities have only been considered. These factors have influenced the calibration and as such the calibrated model can provide information regarding the expected walking behaviour of pedestrians for bidirectional straight flows and low densities. Thus, it is recommended to study the influence of physical distancing on other types of behaviour and behavioural levels, and define their most important characteristics for which the model is intended to yield accurate predictions. Finally, it is advised to calibrate the model for different scenarios during the pandemic in terms of movement base cases, density levels, and periods of the pandemic that have not been analysed in this research. This could allow to obtain a model for a general usage in COVID-19 situations, since the findings in this research have shown that the walking behaviour has changed during the pandemic and that the scenarios used in the calibration affects the results obtained in the analysis.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

In December 2019, a novel coronavirus COVID-19 was identified in Wuhan, China. Since then, the virus rapidly started spreading all over the world which led to the WHO to declare it a Public Health Emergency of International Concern (World Health Organization, 2020).

After a short period of time since the outbreak, several measures were introduced to reduce the transmission risk of the virus. The risk of infection is dependent on the distance to an individual infected; therefore, one of the measures was physical distancing, which means to keep a distance from others and avoid spending time in crowded places, which resulted in a decrease of the number of relevant contacts and thus transmission (Jarvis et al., 2020; World Health Organization, 2020). In most countries a physical distance between 1 m to 2 m was introduced, given that a distance of 1m was associated with a lower risk of transmission, while greater distances were expected to be more effective in preventing the spread of the virus (Chu et al., 2020). However, some studies have shown that this range of distances might not be sufficient to minimise the risk of infection, and additional factors (e.g. ventilation) should be taken into account to minimise the risk (Setti et al., 2020; Sun and Zhai, 2020).

Regardless of the value chosen as physical distance, this measure has had and is having a great influence on pedestrians' walking behaviour, which in turn is affected by several variables such as the walking speed and density (Echeverría-Huarte et al., 2021). Moreover, the daily travel patterns and the number of out-of-home activities performed by people have also been affected, thus how they reach their destinations (i.e. transport modes) is different (De Vos, 2020). As a result, one could expect a decrease in public transport ridership and an increase in the use of car and active modes. Moreover, this might result in a change in the usage of infrastructure given the need of enforcement of physical distancing, which might yield a reduction of capacity so that people could keep a larger distance from each other. However, one has to note that other measures such as working from home and usage of public transport only when necessary have also contributed to changes in public spaces such as transport hubs.

The analysis of the effects of physical distancing can be done through pedestrian simulation models. These models may play an important role as the walking dynamics and pedestrians' behaviour could be described when the physical distancing rule is in place. However, most of the present research is concerning the improvement of existing models or the development of new ones to study the effectiveness and the impact of different measures (e.g. wearing masks, physical distancing) on the transmission of the virus. Hence, these studies do not shed light on the effect of these measures, especially of physical distancing, on the pedestrians' walking behaviour during the pandemic, which is relevant to understand in order to further study the effectiveness of the measures applied during the pandemic. Moreover, having insight into this impact would allow to predict the changes in the decisions made by pedestrians at different levels, such as activity scheduling (strategic), route choice (tactical), or route following (operational). As a result, the variation of the flow and density levels during COVID-19 can be analysed and more accurately predicted. Lastly, a model that considers the influence of these measures would give insight into the design features of an infrastructure that could restrain pedestrians from complying with the measures and thus provide designing or crowd management solutions.

One model that has introduced physical distancing to analyse the walking dynamics during the pandemic is Pedestrian Dynamics ®(PD), developed by InControl Simulation Software. In PD, a new property of an agent called "physical distance" has been introduced, which consists of modelling pedestrians as circles with a radius referred to as "body radius" and around them another circle called "private circle", which refers to the private area of each agent which has a radius of half the physical distance (INCONTROL Simulation Solutions, 2020). Nevertheless, the implementation of this new parameter aims at reproducing the changes in capacity more accurately rather than the walking behaviour at the microscopic level during COVID-19. Therefore, when the parameter "physical distance" is used in PD, the assumption is made that people strictly comply with a prescribed physical distance, and thus a realistic behaviour might not be reproduced by the model when pedestrians cannot comply with the physical distancing rule in reality. Therefore, the model needs to be locally adapted to reproduce pedestrians' behaviour under circumstances in which shorter distance headways are allowed between pedestrians. Thus, in order to gain insight into how accurate the results obtained with PD are, the walking behaviour with real data needs to be studied at different contexts during the pandemic.

Overall, the walking behaviour during the pandemic is important to be studied in order to understand how it has changed because of the different measures, particularly the physical distancing. Based on the findings and the scenarios for which the behaviour has been analysed, PD can be calibrated to reproduce the intended behaviour more accurately and thus evaluate the effects of physical distancing on the walking dynamics.

1.1 Research objective

The limitations above entail the main topic of this thesis, which will focus on defining the capability of Pedestrian Dynamics to accurately reproduce the walking behaviour observed during COVID-19 by conducting a calibration of the model. This analysis involves considering the compliance of physical distancing given that pedestrians might stop following the rules or being flexible with them in certain circumstances. Moreover, this study focuses on the analysis of the walking behaviour in narrow corridors given that it is found to be a location where pedestrians might encounter difficulties for complying with a prescribed physical distance and for which data is available. Thus, the first step is to define the scenarios during the pandemic and within the corridor in which the behaviour is studied by taking into account the desired application of the calibrated model, and compare them with respect to the pre-corona behaviour. From these considerations, the objective of this research can be summarised as follows:

The objective of this research is to understand how the walking behaviour of pedestrians has changed during COVID-19 because of physical distancing at bidirectional flows in locations where people might encounter difficulties for complying with this measure, and conduct a calibration of the pedestrian simulation model Pedestrian Dynamics to improve its accuracy for reproducing such behaviour. As a result, this research aims at determining the capability of the model to reproduce the walking behaviour during the pandemic.

A calibration of the simulation model is conducted to increase the accuracy of the predictions of PD and therefore, to find out its capability to reproduce the desired behaviour observed when physical distancing is considered. Then, the comparison between the behaviour obtained from the real data and the resulting simulated behaviour will yield how accurate the model is to reproduce the behaviour observed in the data. As a result of these considerations, the objective of the calibration can be summarised as follows:

The objective of the calibration is to determine the set(s) of values for the parameters of Pedestrian Dynamics which allow for a more accurate replication of the behaviour observed in bidirectional flows under the physical distancing rules.

The calibration is carried out by following a multiple objective framework which consists of using different scenarios and metrics based on the intended application of the model in order to capture all the relevant behaviour. Moreover, the metrics used to compare the reference data with the simulation model are aimed to be at different aggregation levels such that a better overall performance of the model can be obtained, and result in a model for general usage.

1.2 Research scope

In this section, the scope of the research is described, which entails the behavioural level that is considered, the scenarios that will be part of the analysis (i.e. movement base cases and locations), the model to be calibrated, and the focus of the analysis conducted in this project.

1.2.1 Behavioural level

The pedestrian walking behaviour can be divided into three different levels based on the choices that are made by individuals (Hoogendoorn, 2001). At the strategic level individuals choose the activities that they want to perform, which result in an activity set. At the tactical level, two main processes occur: the activity scheduling and route choice. On the one hand, the activity scheduling entails the selection of activities from the activity set to be performed, the order in which they are going to be conducted, and the area where these activities will take place. On the other hand, the route choice is the process by which individuals decide on the global route they will follow to reach the location where they will perform the selected activities. Finally, the operational level involves the decisions made by pedestrians to follow their chosen route and avoid collisions with obstacles and other pedestrians.

As has been put forward by Sparnaaij (2017), the calibration of a pedestrian simulation model should be performed at all three levels; however, this research will only focus on the operational level for the following reason. As the analysis that will be conducted in this research is in a specific location within an infrastructure, one can assume that pedestrians would only have one activity, that is walking from their origin to their destination. This assumption implies that the choice of activity (strategic level) and route (tactical level) have already been made, and therefore the analysis will focus on the walking behaviour of pedestrians who have decided to walk through the area of interest as part of their planned route. Thus, there is no need to model the activity set, scheduling nor route choice.

1.2.2 Selection of scenarios

The calibration of the simulation model and thus the analysis of its capability to replicate the walking dynamics during the pandemic will be carried out for the scenarios of interest for this study given the intended usage of the model. Therefore, the definition of the scenarios requires making decisions regarding the following: 1) the choice of behaviour to be studied, 2) the choice of movement base cases for which the intended behaviour will be analysed, 3) the choice of locations where it will be observed the walking behaviour of pedestrians, and 4) the choice of metrics for the calibration and comparison of the simulation model with the reference data.

The choice of behaviour is determined based on the hypotheses of the walking behaviour observed during COVID-19 that are of interest for this research, and which are formulated in Chapter 3. The choice of movement base cases and locations are made based on the data available and the types of interaction that are intended to be analysed given the influence of physical distancing. As explained in Chapter 3, the movement base case selected is bidirectional straight, whereas the chosen location is a narrow corridor at a transport hub. Finally, the choice of metrics is derived from the aim of this research of calibrating the simulation model for a general usage and thus finding its capability to best fit the reference data.

1.2.3 Simulation model

The microscopic simulation model aimed to be calibrated is Pedestrian Dynamics ® (PD) by InControl Simulation Software. This model is chosen due to the interest of InControl in calibrating PD to increase the accuracy of its predictions of the walking behaviour when introducing the physical distancing rule and, consequently, finding the model's capability to achieve this behaviour which will lead to future further improvements of the model.

This model has embedded modules for route choice and operational behaviour, which allows the user to influence the decisions at these levels and thus the walking behaviour by changing the values of the parameters. This is important given that, although the main goal of the model is to provide accurate information at the macroscopic level, the resulting predictions at the aggregate flow are a result of the individual behaviour observed at the microscopic level.

1.2.4 Focus of analysis

The analyses conducted in this research aim at studying the walking behaviour during COVID-19 in bidirectional flows and determine the impact of physical distancing on it. Moreover, as previously mentioned, the walking behaviour will be analysed in specific locations within an infrastructure where people are expected to encounter difficulties complying with the physical distancing rule. Thus, the analyses are mainly focused on studying the influence of the interactions between pedestrians in those situations, and the calibration is aimed at improving the predictions for those scenarios.

1.3 Research questions

In accordance with the research objective, multiple research questions are formulated, for which the main question is stated as follows:

Which is the optimal parameter set in Pedestrian Dynamics and its capability to accurately reproduce the walking behaviour during COVID-19 for bidirectional flows where the prescribed physical distance is not fully complied?

The following sub-questions are posed to assist the answering of the main question:

1. *Which are the scenarios for which the walking behaviour and compliance of physical distancing is analysed?*

The scenarios are determined based on the locations within an infrastructure where bidirectional flows are found, and in which InControl has encountered difficulties when intending to reproduce a realistic walking behaviour and a full compliance of a prescribed physical distance. Therefore, the scenarios are defined based on the movement base case (i.e. bidirectional straight), demand, density level in each year from which the data is collected given that these factors are expected to influence the walking behaviour.

2. *How does pedestrians' walking behaviour change because of physical distancing in comparison to pre-COVID-19 situation?*

It is expected that the behaviour during COVID-19 is different than before, provided that the physical distance pedestrians need to keep might be larger than the one they used to keep before the pandemic. Therefore, the comparison of the pre- and corona behaviour observed in the reference data for these different periods of time will allow to know the impact of physical distancing. This analysis, together with the sensitivity analysis, will give insight into the parameters in PD that will need to be calibrated in order to replicate such behaviour.

3. *Which are the most sensitive parameters in Pedestrian Dynamics that allow describing the intended walking behaviour?*

The parameters that can be calibrated are drawn from the mathematical formulation of the model and the reference data. Thus, the answer to this question will provide insight into the model's sensitivity to changes in these parameters, the range for these parameters within which the resulting behaviour is realistic, and thus determine the search space for the calibration.

4. *How do the parameters values in Pedestrians Dynamics change within their defined boundaries based on the scenarios and metrics used in the analysis?*

Once the parameters are selected, the calibration will provide insight into the deviation of the parameters' values with respect to their default, and how this change is related to the scenarios and metrics used in the calibration.

5. *What are the limitations of the current model for reproducing the observed behaviour in different scenarios during COVID-19?*

The answer to this question will allow to find the limitations of the calibrated model for reproducing the real behaviour observed in the data and whether it can be used in any context during the pandemic. This will be done by a comparison between the behaviour obtained with the calibrated model and the one observed in the real data.

1.4 Contribution of this research

The contributions of this research to both science and practice are described in this section. On the one hand, this research provides understanding of the walking behaviour when the physical distancing rule is applied, a situation which has not previously been analysed, and which is expected to have had a relevant impact on the interactions between pedestrians when walking. Moreover, it gives insight into the importance of calibrating microscopic simulation models according to their intended usage, since a calibration has not yet been conducted for the scenarios to be considered in this research.

On the other hand, the contributions to practice are related to the improvements that can be performed to PD, which would allow to increase the accuracy of the model to replicate the reality observed in the reference data, and thus give insight into the behaviour in future similar situations. Furthermore, the usage of a calibrated model that considers physical distancing can provide improvements to the comfort and safety when the design of an infrastructure gives more weight to them. Finally, the calibration provides the previous step to the validation of the model, in which the accuracy in reproducing different data is checked.

1.5 Research overview

As Figure 1.1 shows, this thesis is divided into three main parts: 1) Literature review, 2) Development, and 3) Model analysis.

The first step is developed in Chapter 2, in which a review is conducted about the improvement and development of crowd simulation models for COVID-19 reality, and aspects to take into account to implement the physical distancing in crowd models. Moreover, an overview is presented of pedestrian traffic theory, crowd phenomena, and the state-of-the-art calibration methods and scope of previous calibration processes. The second step is covered in Chapter 3 in which the hypotheses regarding the expected behaviour during COVID-19 are introduced, and the description of the preliminary scenarios for the sensitivity analysis as a basis of the ones that will be used in the calibration. Moreover, the simulation model, metrics, and parameters relevant for this research are also described in Chapter 3. Following, the sensitivity analysis is performed in Chapter 4.

The third step entails the analysis of the reference data (Chapter 5) which will be used to study the walking behaviour during the pandemic and for the calibration of PD. The calibration is discussed in Chapter 6.

Finally, in Chapter 7, the answer to the main research question and subquestions is provided. Moreover, the recommendations drawn from this thesis, and its limitations are described in this chapter.

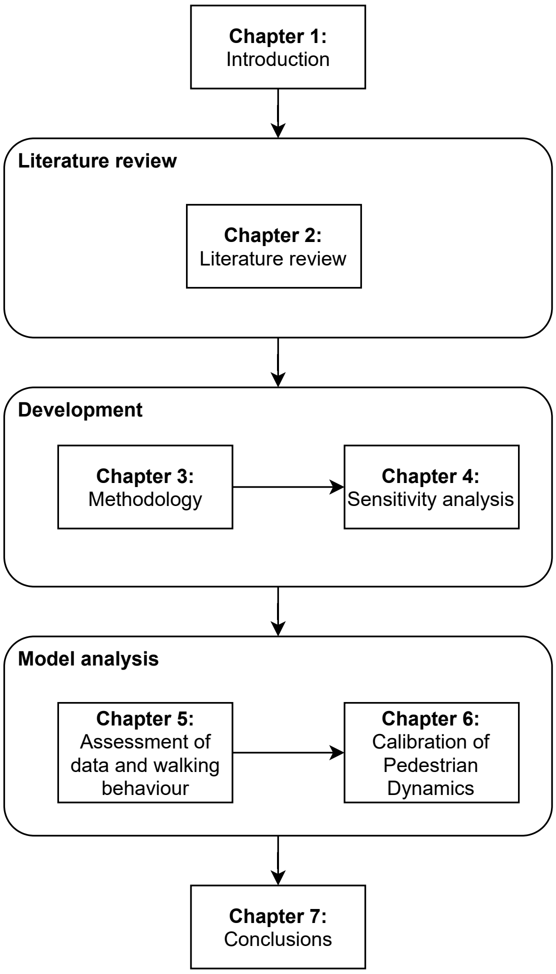


Figure 1.1: Outline of thesis

Chapter 2

Literature review

In this chapter is presented a review of the research conducted regarding the usage of crowd simulation models during COVID-19 and the factors to take into account to introduce the physical distancing in them. Furthermore, the description of pedestrian traffic theory and crowd phenomena relevant for the analysis of the walking behaviour is described, as well as a description of different calibration methods.

The aim of this review is to get an insight into different elements which are considered to be relevant for the calibration of PD to predict the walking behaviour during the pandemic. Therefore, this chapter is organised as follows. Section 2.1 covers the aspects that need to be considered to introduce the impact of measures, particularly physical distancing, on crowd simulation models, as well as the expected changes in walking behaviour resulting from the introduction of these measures. Thus, a better understanding of the walking behaviour during the pandemic and an idea of the parameters to consider for the calibration can be obtained from this section. In Section 2.2 is provided a description of pedestrians' choice behaviour, the factors which influence their choices, the characteristics of their walking behaviour at the locations of interest for this research, and the difference in their movements as an effect of the measures applied during the pandemic. Hence, an insight is provided into the factors and decisions pedestrians made which influence their movement, and also with respect to the characteristic of their movement in the locations of interest for this research. In Section 2.3 pedestrian movement phenomena are described, which are relevant to consider given their importance to determine a realistic behaviour, but also because some of them might have varied during the pandemic. In Section 2.4 contains the most relevant calibration frameworks and the important elements to be considered in the process. Finally, in Section 2.5 the conclusions of the review conducted in this chapter are presented.

2.1 Crowd simulation models and COVID-19

As mentioned earlier in Chapter 1, physical distancing was introduced as one of the main measures to reduce the transmission risk of the virus and, as a result, the walking behaviour of pedestrians has been expected to be different to how it was before the pandemic. Although, several pedestrian simulation models have been developed to analyse the transmission of the virus and the impact of the measures applied to prevent its spread (Infrastructure and Simon, 2020), there is a lack of models for the evaluation of the effects of physical distancing on the walking dynamics and the accurate replication of the reality during the pandemic. Yet, a review of these models would provide insight into the factors to consider in the implementation of physical distancing in PD, as well as some limitations that one could encounter when trying to model the behaviour observed in the reference data.

2.1.1 Development and improvement of crowd models for COVID-19 reality

There are models such as the one developed by Ronchi and Lovreglio (2020) called EXPOSED, which provides information regarding the exposure of occupants in buildings derived from the analysis of the microscopic pedestrians' movement. Moreover, the model developed in the study allows comparing the impact of different measures and crowd management solutions on the exposure of occupants in a building. Thus, one could infer about whether pedestrians are able to comply with and ensure physical distancing, particularly in confined spaces, based on the resulting levels of exposure given that this measure is considered in the occupant's exposure analysis.

Other models have been developed to assess the spread of the virus and the effectiveness of measures against coronavirus. One of them is a hybrid multi-scale model developed by Bouchnita and Jebrane (2020) in which a social force model is used to describe the movement of pedestrians. Physical distancing is thus represented by the so-called socio-psychological force, which is the sum of all repulsive forces produced by the neighbouring agents on the one analysed. Furthermore, this model provides information about the influence of the desired speed and density levels on the distance kept between agents and therefore on the transmission risk. This study shows that a speed of 1.34 m/s allows agents to keep the minimum prescribed distance in low density scenarios, whereas in panic situations ($v \geq 3$ m/s) or crowded areas ($\rho \geq 1.5$ p/m^2) they no longer comply with it. Thus, this social force-based model shows that different combinations of the desired speed and magnitude of the socio-psychological force influence differently the distance agents keep between each other, particularly in high density scenarios.

Although these models are focused on analysing the transmission risks and levels of exposure based on the applied measures, they provide relevant information regarding the compliance of them in locations where pedestrians might not be able to follow them. One could determine whether pedestrians are keeping the prescribed physical distance based on the exposure levels from the model proposed by Ronchi and Lovreglio (2020) and thus the corresponding density levels. In addition, the model developed by Bouchnita and Jebrane (2020) does not only provide information about the density levels for compliance, but also about the underlying behaviour which influences the distance kept between pedestrians, such as a high desired speeds would decrease such distance. Lastly, this information serves as a baseline when analysing the reference data so as to know which density levels might yield in a different behaviour and compliance of the physical distancing.

2.1.2 Implementation of physical distancing in crowd models

The models described above provide some insight into the compliance of physical distancing and density levels during the pandemic. Moreover, they serve as tools to assess safety in confined and open spaces, and the impact of different measures on the transmission rate of the virus. However, the impact that these measures have on the pedestrian's walking dynamics is not analysed, nor of the behavioural changes that might happen in different locations within an infrastructure.

A research by Ronchi et al. (2020) has addressed the changes needed in crowd simulation models, which involve an improvement of the representation of people movements during the pandemic in light of the effects of physical distancing on the relationship between the flow variables and the interactions between pedestrians. This study analyses the influence that the physical distancing might have on crowd models in relation to the following three aspects:

- **Space usage:** The number of people in a given area is expected to be different because of the physical distancing. This changes can be introduced in crowd models by changing the shape and size with which individuals and their corresponding personal space are represented in a model. Moreover, assumptions regarding the implementation of either static or moving crowds, the maximum local density, and the existence of groups in the model would determine the influence of the physical distancing on the area occupied by each pedestrian.

- **Route choice:** Crowd models enclose different routing methods for the route choice such as the shortest distance and the least effort; however, the distance from other people is not usually considered for choosing a route. Thus, models might need to be updated in order to introduce the willingness of people to reroute towards a less congested area and thus be able to keep a larger distance from others.

- **Movement:** There are different self-organisation phenomena in pedestrians' crowds described by Helbing et al. (2005) such as lane formation or stop-and-go waves that might not occur or occur differently during COVID-19. Hence, Ronchi et al. (2020) has proposed to modify the fundamental relationship between speed/flow and density with respect to the density range in which speed is expected to be affected by others.

As stated by Ronchi et al. (2020), the lack of experimental data entails that different assumptions are required to be made regarding the behaviour of pedestrians in order to implement in crowd models the impact of the physical distancing on the walking behaviour. Thus, this implementation in relation to the modelling of movement needs to be done by considering changes such as in the fundamental relationships (flow, density, and speed), different route choices, larger distances kept when queuing, the presence of groups which do not need to keep a physical distance, or modifying the collision avoidance which is done based on the type of model (e.g. force-based models, goal-based models).

Furthermore, these changes in crowd models can be a result of adding new parameters or adjusting the existing ones in the models. For instance, in the Optimal Steps Model (OSM), a pedestrian locomotion model, the values for the parameter personal space were modified such that the behaviour at a typical bottleneck scenario could be simulated in the model (Mayr and Koester, 2020). The implementation can also be done by modifying how pedestrians are represented in the model based on the situations that are aimed to be analysed with the model. Xu and Chraibi (2020) evaluated different control measures in supermarkets by simulating pedestrians with a velocity-based model, in which they were represented as ellipses when using shopping carts, as opposed to the ones who does not. Hence, the distance was measured differently depending on the type of agent created for the simulations.

The results from these crowd models can be assessed according to metrics such as capacity, distance headways, flow, which are selected based on the objective of the analysis and the assumed effects of physical distancing on the walking behaviour. Moreover, this assessment can be done by comparing the results against a certain acceptance criteria or by comparing different solutions against each other (Ronchi and Lovreglio, 2020).

In conclusion, calibrating PD for physical distancing implies to take into account the differences in the space usage, route choice, and movement of pedestrians compared to the pre-pandemic situation, and thus determine whether they occur when analysing the reference data. Moreover, the overview in this subsection provides insight into the changes that one needs to take into account when modelling physical distancing with respect to the movement of pedestrians. These changes in the model can be achieved in PD by modifying the default values of the existing parameters. Finally, one can conclude from this subsection the relevance of assessing the results from a model so as to verify whether the aimed behaviour is obtained and up to what extent the model is able to replicate it accurately. For this research, the resulting behaviour from PD and the one observed in the reference data will be compared based on metrics that best describe the intended behaviour.

2.2 Pedestrian traffic theory

2.2.1 Pedestrians' choice behaviour

There are three different levels of pedestrian choice behaviour distinguished by Hoogendoorn (2001):

- **Strategic level:** Pedestrians choose their departure time and the activities that they wish to perform, which result in a list of activities called the activity set.

- **Tactical level:** The activity scheduling and the location where the chosen activities are performed are part of this level. Moreover, pedestrians plan their route from their current location towards the next activity location, which result in the route choice.

- **Operational level:** At this level, the decisions made by pedestrians are related to how they follow their route and avoid collisions with other pedestrians and obstacles. These are instantaneous decisions which are performed at the next time step.

2.2.2 Influencing factors on pedestrians' choice behaviour

The decisions made by pedestrians at each of these levels are influenced by different factors, which can be divided into personal and exogenous factors (Godoy, 2020). The former is associated with the individual characteristics of pedestrians whose choices at the operational level are mainly influenced by them, whereas the latter relates to the physiological environment and its effects on pedestrians' choices, which seem to be greater at the strategic and tactical level (Duives, 2016; Godoy, 2020). The impact of these factors are important to take into account to be able to differentiate from the impact that physical distancing might have on the walking behaviour.

Personal factors

Below, the most relevant personal characteristics for this research are described:

Age is one that influences the choice behaviour of pedestrians, such as their walking speed and headways. van den Berg (2009) found that pedestrians at an age of 20-25 years walked the fastest, so as did children who were more likely to walk faster because of their enthusiasm. Moreover, it was found that the average walking velocity decreased non-linearly as the age increased (Duives, 2016).

Other factor is *gender*, which also influences the walking speed of pedestrians. Several studies have concluded that women tend to walk slower than men (Duives, 2016; Duives et al., 2014; van den Berg, 2009).

The *cultural differences* have also been found to affect the walking speed of pedestrians. Some studies have shown that on average the walking speed in African and Asian countries was lower than in Western countries (Duives, 2016). Furthermore, the cultural differences have been proved to have an impact on the density and in the relationship between speed and density (Chattaraj et al., 2009).

Furthermore, the *passenger characteristics* also have a impact on the walking behaviour and in the usage of a transport hub infrastructure (Van Den Heuvel, 2016). On weekdays, the type of passengers during peak hours are expected to be different than the ones during off-peak hours, while the passengers on weekdays are expected to be different than passengers on the weekends (Neff and Pham, 2007). Furthermore, the presence of luggage and bidirectional flows when alighting and boarding trains may affect the walking behaviour.

Exogenous factors

Similarly, the most relevant exogenous factors are described below:

The *environmental conditions* such as weather, temperature, and daytime have a direct influence on different levels of the choice behaviour of pedestrians. Precipitation might lead to higher walking speeds (i.e. operational level) (Duives, 2016), whereas the attractiveness of the surroundings might make it more likely to choose a certain route (i.e. tactical level).

The *width of paths* has an effect on the higher levels of the decision making process of pedestrians. Some studies have shown that route choice is influenced by the width of the paths (Bovy and Stern, 1990; Guo and Loo, 2013), in which wider paths were indicated as more attractive for pedestrians.

Intersections and *crossings* have been found to affect the tactical choices given that pedestrians would tend to choose routes with lower number of intersections and crossings (Bovy and Stern, 1990; Guo and Loo, 2013). This can be considered as a negative influence on pedestrians' behaviour.

The *travel distance* also affects the choices pedestrians make at the tactical level, since the shortest route is preferred by them (Borgers and Timmermans, 1986). Moreover, Godoy (2020) stated that it might influence an unplanned activity choice, since pedestrians would prefer an activity near to their current location in case this activity can be performed in several locations.

In conclusion, it is important to identify the factors that influence the walking behaviour in order to control for them when analysing the data corresponding to before and during the pandemic. Thus, one can ensure that the difference observed in the behaviour will be a result of physical distancing rather than a difference in personal and/or exogenous factors.

2.2.3 Pedestrian walking behaviour in straight corridors

The walking behaviour of pedestrians varies depending on the environment where pedestrians are moving at a specific moment in time. On the one hand, the walking behaviour has been studied for certain types of infrastructure, such as public transport facilities (Daamen, 2004), large scale events (Duives, 2016), stadiums (E. et al., 1999). On the other hand, research has been done to gain knowledge about the walking behaviour at specific locations within a facility. Some of these locations are stairs (Daamen, 2004; Köster et al., 2019; Lazi et al., 2016), bottlenecks (Daamen, 2004; Hoogendoorn and Daamen, 2005; van den Berg, 2009), corridors (Khisty, 1982; Sparnaaij, 2017), and many more which are related to the different movement base cases explained by Duives (2016).

As for this research, the main interest is to study the walking behaviour in bidirectional flows and the changes caused by physical distancing. Thus, corridors are the location of interest as this type of movement occurs within this location. Moreover, a calibration for this location has not been performed yet nor an analysis of the capability of PD, especially for the scenarios that have occurred during the pandemic. Thus, it is important to describe the behaviour that is already known to happen at this location.

The movement of pedestrians along corridors can be characterised as unidirectional and bidirectional flows. Corridors with unidirectional flows have been shown to reach densities of 7 p/m^2, whereas in bidirectional flows the maximum density have been found to be 4 p/m^2 (Duives, 2016). Furthermore, interactions of flows can occur in bidirectional flows where there is no separation between streams, but also for unidirectional flows provided different walking preferences such as different walking speeds (Godoy, 2020).

The density has also an impact on the walking behaviour of pedestrians. In low-density bidirectional flows pedestrians tend to follow the pedestrian ahead due to the idea of a reduced effort by following rather than finding a new path. However, in high density situations and a dominant flow direction there are more interactions, and pedestrians tend to move sideways to avoid collision. As a result, the lanes are expected to be shorter or fully dissolved; thus avoiding collisions is more important than following the leader (Godoy, 2020).

Moreover, studies have found that bidirectional flows are more efficient than unidirectional flows (Helbing et al., 2005), whereas a research by Kretz et al. (2006) showed that there was a decrease in the flow rate in bidirectional straight corridors. The latter study concluded that the behaviour of pedestrians was different when they encountered bidirectional flows as they accepted shorter headways and thus a more efficient use of the space.

The walking behaviour of pedestrians is also affected by the width of a corridor. The formation of more than one lane per direction can occur if the width is wide enough (Seyfried et al., 2005), which in turn, is related to the possibility of overtaking (Chattaraj et al., 2013). Furthermore, the width of a corridor can lead to self-organised behaviours (Helbing et al., 2005; Hoogendoorn and Daamen, 2004) and crowd phenomena such as the zipper effect (Daamen, 2004; Hoogendoorn and Daamen, 2005; Nicolas et al., 2017).

In conclusion, the behaviour in bidirectional flows will be analysed within a corridor, in which the characteristics described in this subsection will be compared to the ones observed in the reference data during the pandemic.

2.2.4 Walking behaviour during COVID-19

The walking behaviour of pedestrians and their interaction with each other during COVID-19 is expected to be different to the one before the pandemic. This change is mainly due to the physical distancing and directly related to the compliance of the prescribed distance.

Regarding the compliance of the physical distancing, research has shown that there are different factors which have an influence on the number of violations of the physical distancing. On the one hand, several studies have revealed a dependence between the density in an area and the contact times at a distance shorter than the prescribed physical distance. Based on the observation of trajectories at platforms at Utrecht Central train station, Pouw et al. (2020) revealed that around 80% of pedestrians at the maximum density level did not comply with the physical distancing, and that above 0.2 p/m^2 this percentage suddenly increased. This research found that around this density level the difficulty for complying with the physical distancing rule increased. Meanwhile, Echeverría-Huarte et al. (2021) conducted some experiments which showed that even at low densities (i.e. 0.16 p/m^2) 50% of the time the prescribed physical distance was violated by participants, whereas the number of violations increased up to almost 100% when the density was 0.32 p/m^2. Similarly, by applying video observation, Hoeben et al. (2021) reported that the number of people on the street would affect the ability of pedestrians of complying with the prescribed distance. This impact of density might be caused by an increased difficulty in following the rules or a reduction in attention towards physical distancing rules (Pouw et al., 2020).

On the other hand, the walking speed also influences the compliance of the physical distancing rule. The research conducted by Echeverría-Huarte et al. (2021) showed that when participants were asked to walk faster, which happened to be at a normal speed of 1.2 m/s, the number of violations of the prescribed physical distance increased in comparison to low speeds, and they also stopped less often to comply with the given physical distance, mainly in high dense scenarios. The study concluded that this behaviour is related to the increase of the required distance to stop during the reaction time when the walking speed is faster. In reality, it has been observed by Obuchi et al. (2021) a slight but consistent increase of the walking speed during the pandemic, which might suggest an increase in the number of violations of the physical distancing rule.

Another factor that affects compliance is the prescribed distance. Although people are not entirely accurate measuring their distance from obstacles and other people ahead (Hoeben et al., 2021), it has been observed by Echeverría-Huarte et al. (2021) that in the scenarios in which the given distance was 2m, more people complied with a safe distance of 1 m when compared to a given distance of 1.5 m.

The exposure time varies depending on the density and the walking speed. Pouw et al. (2020) found that the exposure time increased with the number of people, whereas it dropped when pedestrians walked faster, although this resulted in an increased number of violations of the prescribed distance.

The overview in this subsection provides insight into the walking behaviour during COVID-19 and, most importantly, which factors might affect its compliance. This information will also allow to determine which changes might be made in PD in addition to the physical distance parameter in order to describe such behaviour in relation to the aforementioned factors, and for the comparison of the behaviour observed in the reference data corresponding to before and during the pandemic.

2.3 Pedestrian movement phenomena

In this section, the findings in literature regarding crowd movement phenomena are reviewed to study its occurrence during COVID-19 and thus reproduce the observed behaviour with the simulation model.

Lane formation occurs in uni- and bidirectional flows, and has been extensively analysed in several studies (Campanella et al., 2009a,b; Daamen, 2004; Helbing et al., 2005; Hoogendoorn and Bovy, 2004;

Kretz et al., 2006). The number of formed lanes was found to depend on the density in the walking area given that this determines the overtaking opportunities (Hoogendoorn and Daamen, 2004). Furthermore, Campanella et al. (2009b) found that the heterogeneity of flows had an impact on the formation of lanes. On the one hand, homogeneous population in unidirectional flows do not overtake because all walk at the same speed and direction, thus they are distributed over the walking area in staggered layers using the space optimally. Meanwhile, in bidirectional flows pedestrians organise in lanes in such a way regions of opposing speeds are formed and pedestrians move behind others moving in the same direction. On the other hand, in heterogeneous flows lanes with different speeds are formed given that pedestrians tend to keep their speed and thus are willing to overtake by taking into account the avoidance of collisions (Campanella et al., 2009b).

The *zipper effect* described by Hoogendoorn and Daamen (2005) consists of overlapping of lanes of pedestrians which are formed in bottlenecks when the distance between these lanes is less than the effective width of pedestrians. Daamen (2004) showed that the zipper effect was due to narrow corridors where the lateral space required by a pedestrian was less than the lateral distance between lanes . It could also be observed in doorways where lanes needed to be intercalated as the width of the doorway was not wide enough to prevent interaction between pedestrians from different lanes (Nicolas et al., 2017). As a result of the zipper effect, the capacity of bottlenecks has been found to increase with the width of it gradually.

The *faster-is-slower* effects is produced when pedestrians try to move faster than normal which leads to physical interactions between them (Helbing et al., 2000). According to Parisi and Dorso (2005), the faster-is-slower effect occurs when the maximum flow is reached for a certain value of the speed, and once this speed is exceeded, the flow rate will reduce. This effect was studied by van den Berg (2009) for doorways, although it did not clearly occur in the experiments.

Another phenomenon is the so-called *stop-and-go waves* which consists of a longitudinal flow that is interrupted as a result of higher densities in unidirectional flows (Duives et al., 2013). According to Duives et al. (2013) these waves might appear in models because of the time of adaptation that agents need to change their velocity and acceleration.

Thus, crowd movement phenomena such as self-organised behaviour are important to study during the pandemic as they might not longer occur or do it differently because of changes in the pedestrians' walking behaviour. Moreover, they are relevant when defining what a realistic behaviour is for the qualitative part of the sensitivity analysis. The lane formation phenomenon is of greater interest in this research given that the behaviour in bidirectional flows will be analysed, as well as the zipper effect given that a narrow corridor will be analysed in this research. Lastly, the stop-and-go waves are of interest given the changes in speed one expects for pedestrians to have in order to keep a larger distance. However, the last two phenomena are produced at high density levels, which are unlikely to occur during the pandemic as a result of the measures applied to reduce the interactions at short distances between pedestrians.

2.4 State-of-the-art calibration methods

2.4.1 Calibration methods for pedestrian models

In this section, a review is carried out of the calibration methods for pedestrians models of interest for this research. Calibration can be described as the process by which the parameters of a model are adapted so that the model can replicate the reality more accurately (Sparnaaij, 2017). Thus, the calibration consists of finding the optimal parameter set with which the results from the simulation are approximately equal to those observed in the reference data used for the calibration.

As mentioned by Sparnaaij (2017) there has been given little attention to calibration which might be because of the lack of data. However, there are studies in which calibration has been conducted for pedestrian models, but with limited scope as these have focused in few aggregated aspects of the flows, evaluated one movement base case, used one metric, or looked at a single population composition (Campanella et al., 2009a). For a general usage of a model, it is important to consider different movement base cases in order to capture the most relevant behaviour intended to replicate with the model (Sparnaaij, 2017), since some studies have found that using different movement base cases yielded different optimal parameter sets (Campanella et al., 2012; Duives, 2016).

To deal with these limitations in the calibration of microscopic simulation models, different frameworks have been developed which can be described by using a multiple objective approach. The most relevant frameworks for calibration found in literature are described below based on their considered approach.

One objective and single metric

The framework presented by Wolinski et al. (2014) focused on finding the parameter set that best matches the results from a simulation with the reference data by defining an objective function that aimed at minimising the error between them. This framework allows the use of different metrics and models so that it is possible to analyse which model together with a single metric best replicates the behaviour observed in the reference data. Thus, an advantage of this approach is that it allows finding the best parameter set for any model based on a variety of metrics and reference data (Wolinski et al., 2014). However, it has the main limitation of not being able to generalise the optimal parameter set to different scenarios and moreover, this approach does not include a combination of metrics for the calibration.

Multi-objectives and single metric

The method proposed by Campanella et al. (2012) considered multiple objectives represented by different scenarios in order to find more generic parameter sets. Moreover, three flow configurations (bidirectional, crossing, and narrow bottleneck) were applied to analyse their influence on the accuracy of the calibrated model. This approach used parallel scenarios in which the errors of all flows were combined rather than using individual flows, thus it was achieved a more accurate calibration as the good estimations compensate for the bad ones (Campanella et al., 2012). Moreover, the quality of the estimation increased when the flows considered for the analysis were significantly different from each other as it increased the accuracy of the parameters (Campanella et al., 2012). A limitation in this approach is the use of only one metric (i.e. trajectories) for the comparison of results, thus it cannot capture the effect that different combinations of metrics might have on the calibration.

Multi-objectives and multiple metrics

In the research by Duives (2016) another calibration approach was followed to assess the capabilities of a macroscopic (MDW) and microscopic (Nomad) pedestrian simulation models for the prediction of pedestrians' dynamics in crowds at large-scale events. This method consisted of finding the optimal parameter set based on different metrics and movement base cases. An advantage is that this approach considered metrics of all three aggregation levels, although it was necessary to ensure that the chosen metrics were not influenced by the stochastic nature of the interactions (Duives, 2016). For both models, the accuracy of the results decreased when using multiple movement base cases compared with the case of just one movement base case. Furthermore, the results obtained with a model calibrated with specific movement base cases might not be able to reproduce the pedestrians' behaviour entailed by other movement base cases. Finally, the results in this study showed that the aggregation level of the metrics has an impact, since the optimal parameter sets obtained using macroscopic metrics were different from the ones obtained by mesoscopic metrics.

A research done by Sparnaaij (2017) proposed a calibration methodology using different combinations of objectives in which the effect of various scenarios (i.e. movement base cases and density levels) and metrics on the calibration of the model was analysed. The results showed that the (combination of) scenarios and chosen metrics had an impact on the resulting optimal parameter set as well as the density levels of which high density scenarios showed a larger impact on the results. Moreover, it was determined that different multiple movement base cases were required to capture all relevant behaviour of pedestrians. As a result, the model was found to be capable of reproducing with high accuracy the behaviour observed in the reference data for the scenarios for which it was calibrated (Sparnaaij, 2017). Similar, to the study conducted by Duives (2016), metrics from different aggregate levels were considered to measure different aspects of the flow, but it also showed a clear influence of the choice of metric on the results. Finally, the study showed that using multiple scenarios (i.e. movement base cases, density levels) for the calibration yielded less accurate results than if the model had been calibrated for a single scenario and for the particular movement base case to that scenario (Sparnaaij, 2017).

A multiple objective framework is depicted in Figure 2.1. This framework consists of different scenarios in which the simulation is compared with the reference data by means of a combination of metrics and their corresponding objective function. As a result, errors are obtained for each scenario and metric, which then are combined into a single error that is an input for the optimisation algorithm. In case the optimisation algorithm determines that the optimal parameter set has not yet been obtained, then a new set of parameters is created by the algorithm and the evaluation starts over until the optimal one is determined according to a stopping criteria.

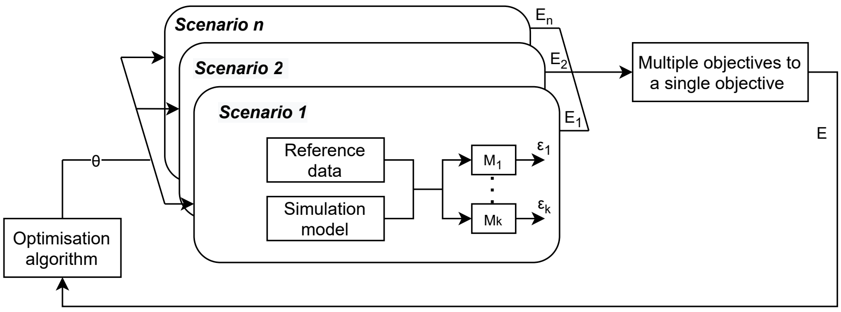


Figure 2.1: Overview of a multi-objective framework (Adapted from (Campanella et al., 2012))

2.4.2 Description and influence of movement base cases on calibration

Movement base cases are defined in such a way that one predominant action is performed by pedestrians (Duives, 2016). Moreover, Duives (2016) described eight movement base cases which can be identified in large-scale events and observed in Figure 2.2.

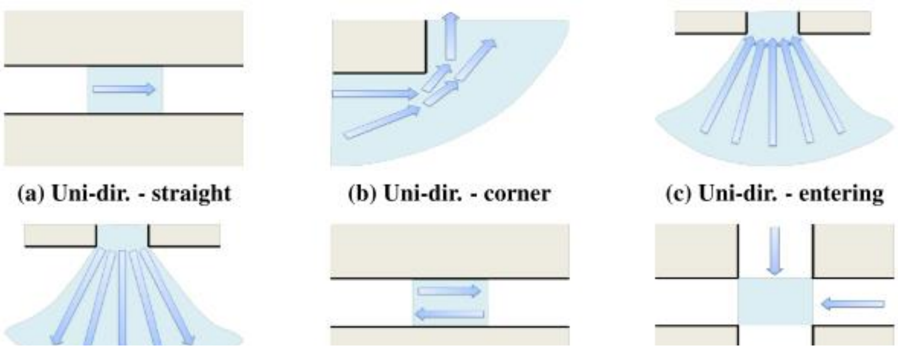


Figure 2.2: Crowd movement base cases in pedestrian flow (Figure 2.2 from (Duives, 2016))

The choice of movement base cases for the calibration of crowd simulation models leads to different optimal parameter sets. The research conducted by Duives (2016) has shown that the best parameter sets for the two models calibrated in that study were very dependent on the movement base cases used in the calibration process and, moreover, the microscopic model was found not being able to predict the movement behaviour for movement base cases for which it was not calibrated. Furthermore, Campanella et al. (2012) and Campanella et al. (2014) concluded that using different movement bases cases led to more reliable and accurate calibrations for a general usage of the model. Lastly, the findings in Sparnaaij (2017) revealed that the movement base cases influence the calibration results and that a combination of them should be included in order to capture the relevant behaviour.

2.4.3 Description and influence of density on calibration

The density of a traffic flow can be defined as the number of pedestrians who are within a specific area at a given time (Daamen, 2004). Thus, the density level is related to the number of interactions between pedestrians, which is expected to have decreased during the pandemic because of the physical distancing. Therefore, the self-organising phenomena that could arise for a specific movement base case and density level might have no longer occurred or occurred differently during COVID-19 (Ronchi et al., 2020).

The fundamental relationship between flow, density, and speed (q=ku) can be applied for pedestrian flows (Daamen, 2004). This relationship shows that the speed varies between free speed and capacity speed in the stable region, whereas in the unstable region the speed decreases with an increasing density (van den Berg, 2009).

Although the impact of density on the flow has extensively been studied (Daamen, 2004; Duives, 2016; van den Berg, 2009), its impact on the calibration results have had little attention. In this respect, the research conducted by Sparnaaij (2017) found that the effects of high density levels were more important than that of low density levels, and that high densities should be considered part of the calibration if the model is desired to be able to reproduce the behaviour observed in those. The consideration of high density scenarios is important because a model designed for low density situations might not be ideal to reproduce accurately high density crowd movements Duives et al. (2013).

2.4.4 Description and influence of metrics on calibration

Metrics are used to compare the results obtained in the simulation with the reference data, which are relevant as the accuracy of a model is determined by its capability of getting similar results as with the reference data for those specific metrics. As presented by Sparnaaij (2017), metrics can be categorised based on whether they are microscopic, mesoscopic, and macroscopic.

At the microscopic level, the behaviour of a single pedestrian is analysed and the metrics used at this level are derived from every single pedestrian. For example, the trajectory is a microscopic metric which is defined for a pedestrian based on their position at every time step. At the mesoscopic level, the metrics are also obtained from a single pedestrian, but the distribution of these variables over all pedestrians is of interest at this level. Moreover, metrics at this level can provide insight into how well the heterogeneity is captured by the model (Sparnaaij, 2017). An example of a mesoscopic metric is the distance headway distribution with which the average behaviour of all pedestrians in the simulation can be compared with the one in reference data. Finally, at the macroscopic level, the aggregate behaviour of pedestrians is described, thus metrics at this level are focused on the characteristics of the flow instead of on the individual behaviour of pedestrians (Daamen and Hoogendoorn, 2003). Moreover, the properties of the system such as self-organising phenomena are described at this level, since they are a result of the collective behaviour of pedestrians (Sparnaaij, 2017).

Similar to the movement base cases, the choice of metrics influences the optimal parameter set obtained in the calibration process. Campanella et al. (2009a) found that a model calibrated by using either a macroscopic or microscopic metric yielded unrealistic behaviour at the level not used in the calibration process. Similarly, different optimal parameter sets were found by Duives (2016) when using only macroscopic metrics than when using mesoscopic metrics, which coincided with the findings in the research by Sparnaaij (2017), in which was determined that the combination of metrics led to different optimal parameter sets.

Metrics can also be categorised based on whether they are qualitative or quantitative. The qualitative metrics are usually used to describe the self-organising patterns at the macroscopic level and for face validating the model at the microscopic level; whereas the quantitative metrics are preferred as they do not rely on the judgement of a person and are useful for the calibration process because of the large number of iterations (Sparnaaij, 2017).

Concerning the applicability of the metrics, they can also be divided into local and global variables. Local metrics are specific to a set of characteristics and scenarios, whereas global metrics can be used for any type of condition regardless of the characteristics of the scenarios (Godoy, 2020).

2.5 Conclusions

In this chapter, a review of the literature has been conducted with the objective of getting an overview of the research that has been done regarding the usage of crowd simulation models to describe the walking behaviour during the pandemic, and the factors that might influence such behaviour. Moreover, a description of pedestrians' walking behaviour, crowd movement phenomena, and a review of the different calibration frameworks has been presented in this chapter.

Firstly, the review showed that crowd simulation models have been focused on studying the transmission risk of the virus rather than the influence of COVID-19, especially the physical distancing rule, on the walking behaviour of pedestrians. However, some studies have addressed the changes that should be done in pedestrian simulation models in order to implement the physical distancing, which are related to the space usage, route choice, and movement. Moreover, the compliance of the prescribed physical distance has been found to be dependant on factors such as location within an infrastructure, speed, and density levels.

Secondly, concepts from pedestrian traffic theory relevant for this thesis have been described. The review showed that there are different levels (i.e. strategic, tactical, and operational) in which the choices made by pedestrians can be allocated, and that personal and exogenous factors influence their behaviour differently. Furthermore, the study of pedestrians' movements in straight corridors have been described provided the aim of this research for understanding the change of behaviour in bidirectional flows caused by the physical distancing that can be observed in these locations. Similarly, there are different crowd movement phenomena (lane formation, zipper effect, faster-is-slower, and stop-and-go waves) which could no longer occur or do it differently because of COVID-19, thus the behaviour and external conditions which trigger these phenomena were described in this chapter.

Finally, a review of different calibration frameworks showed that different choices regarding the metrics, movement base cases, among other things, had an influence on the resulting optimal parameter set and their choice also depended on the intended use of the model. Furthermore, the multi-objective framework was concluded to be the more complete one as different movement base cases, densities, and metrics are considered in the calibration process which yields more accurate predictions when the aim is a general usage of the model.

Chapter 3

Methodology

This chapter will focus on the description, explanation, and organisation of the elements and steps needed to follow in the remaining of this research to answer the main research question. Moreover, information to answer the first subquestion and the chosen approach to answer the following four subquestions will be provided in this chapter.

3.1 Framework of methodology

Figure 3.1 depicts an overview of the methodology. Firstly, the preliminary scenarios (Section 3.2) are defined based on the behaviour that is of interest to this research and the locations where it is aimed to understand the behaviour of pedestrians and compliance with the physical distancing rule. The hypotheses and behaviour that is expected to occur in these scenarios are defined in Section 3.3, which in turn, serve as an input together with the conclusions drawn from the literature review to define the initial metrics. Then, the most relevant parameters are chosen based on the analysis of the mathematical description of the model (Section 3.4) according to the influence they might have on the results in the preliminary scenarios to reproduce the expected behaviour during COVID-19. The initial metrics (Section 3.5) and parameters (Section 3.6) are the input to the sensitivity analysis which is described along with the approach to perform it in Chapter 4. As a result of the sensitivity analysis and walking behaviour assessment, the parameters to the change of which the model is more sensitive are determined and serve as an input for the calibration which will be discussed in Chapter 6.

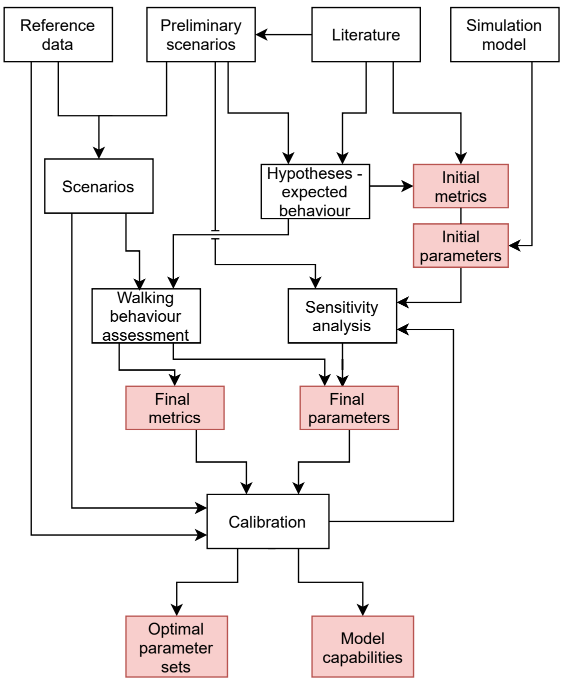


Figure 3.1: Overview of research methodology

Furthermore, the reference data (Chapter 5) together with the preliminary scenarios are used to define the final scenarios. In turn, these scenarios and the hypotheses will allow the assessment of the walking behaviour Chapter 5. Moreover, the reference data will be used for the calibration (Chapter 6) and evaluation of how well the simulation model reproduces reality. Lastly, for the calibration process, metrics at different aggregate levels drawn from the walking behaviour assessment are considered in order to compare the simulation model with the reference data, and thus determine the accuracy of the model. In principle, if the calibration results are not the expected ones, one should go back to the sensitivity analysis to analyse the impact of different or additional parameters on the walking behaviour.

3.2 Preliminary scenarios

In this section the scenarios that will be used for the sensitivity analysis are described, which in turn will serve as a basis for defining the scenarios for the calibration. The first part of this section will focus on defining the scenarios based on the movement base case of interest (i.e. bidirectional straight) given the objective of this research. The next section will focus on a further description of the chosen scenarios.

3.2.1 Description of scenarios

As mentioned in Chapter 1, InControl has included a new property in Pedestrian Dynamics ®(PD) called "physical distance" as a parameter that can be tuned in order to make more realistic the predictions of the aggregate behaviour during COVID-19 by considering a full compliance of the physical distancing rule. However, the results in projects have shown that there are certain locations where pedestrians are not able to keep the prescribed physical distance, and therefore the behaviour of agents in the model does not seem to be realistic as unusual movements can be observed in the simulations. On the one hand, this is a result of sometimes setting a value for the parameter physical distance that remains constant over the entire simulation, thus agents try to keep it at any time. As a result, agents are not able to move forward when there are limitations in terms of characteristics of the infrastructure, or high demand patterns. On the other hand, it is not possible to find an optimal value of the parameters given that the behaviour in reality with a prescribed physical distance that is intended to replicate is still not fully known. In order to address these issues, the parameter physical distance is set to lower values than the prescribed physical distance such that the expected behaviour is better reproduced and thus acceptable solutions at the aggregate level could be obtained.

Although the walking behaviour during the pandemic has not been studied in detail, one can conclude from daily observations and the reference data that pedestrians are not restricted to continue walking when the space is not enough to comply with the prescribed physical distance, but their behaviour does change such that they might stop more often or deviate from their current direction of movement with the aim of avoiding interactions as much as possible. Therefore, the scenarios are chosen such that the influence of physical distancing on the walking behaviour can be studied and also get insight into the situations that lead to a lack of the compliance of the rule. Moreover, the scenarios are defined based on the locations where InControl has encountered issues modelling the behaviour (i.e. narrow corridors, doorways, stairs) and for which there is data available.

The movement base cases observed in the locations of interest are bidirectional straight (narrow corridors), uni-directional entering and exiting (doorways), and vertical movements (stairs), of which bidirectional straight will be evaluated in this thesis given the availability of data and time to conduct this research. The type of interactions in bidirectional straight flows is head-to-head interactions and the formation of lanes occurs, thus a leader-follower behaviour can be observed in both directions. The walking behaviour in bidirectional flows is expected to be different when the physical distancing rule is introduced, since the distance headway in lanes can increase and thus the available space might not be used as efficiently as before COVID-19, while the lanes formed during the pandemic might be less stable. Moreover, the decrease of the flow rate in bidirectional straight movements stated by Kretz et al. (2006), might be steeper during the pandemic. The influence of density is investigated for this movement base case as it can be expected a difference in the walking behaviour and compliance of the physical distancing between low and high density levels. Therefore, there are two scenarios with respect to bidirectional straight flows. One is focused on low densities in which one can assume that pedestrians are able to comply with the physical distancing rule and behave accordingly; and a high density scenario where they would encounter more difficulties with following the rules and their behaviour is also analysed so as to understand the differences with respect to similar situations before the pandemic.

Furthermore, during the pandemic, the behaviour might also have changed given the relaxation of measures, less awareness of pedestrians with respect to the distance they keep, or a difference in the type of pedestrians depending on the usage of a location within an infrastructure. Therefore, a scenario is also defined based on the year in which the walking behaviour is analysed. In this research, the data used for the analysis corresponds to 2020 and 2021, and for a time in the year when the physical distancing rule was still in force.

The threshold density in a static situation for a physical distance of 1.5 m is 0.3254 p/m^2, above this value pedestrians are not able to comply with the rules, whereas at lower values there is enough space for them to follow it. Hence, density levels below and above this threshold serve as a basis of the scenarios in order to analyse its influence on the behaviour, given that according to the fundamental relations between the macroscopic characteristics, one can expect that the speed and flow are different during the pandemic and the density at which the capacity is reached is expected to be lower compared to before COVID-19. It has to be noted that the density in dynamic situations is not considered as a threshold, since it is not constant and depends on different factors (e.g. geometry, speed), which make its computation more complicated and out of the scope of this research.

As a result of the measures to stem the spread of the virus and changes in activity patterns, the demand on pedestrian infrastructure and environment has significantly dropped during the pandemic, which in turn has led to a decrease in the flow and density. Therefore, the comparison of scenarios before and during COVID-19 are made under the same conditions in terms of demand, such that the changes in behaviour before and during the pandemic can be related to the physical distance rather than to a different demand. Exogenous factors that might have an impact on the observed walking behaviour as well as the independent and dependent variables will further be discussed in Chapter 5.

3.2.2 Bidirectional straight - Low/high density

The scenarios that will initially be analysed consist of a bidirectional straight movement base case, and two density levels (i.e. high and low). These scenarios can be analysed given a bidirectional flow on a straight corridor which is depicted in Figure 3.2.

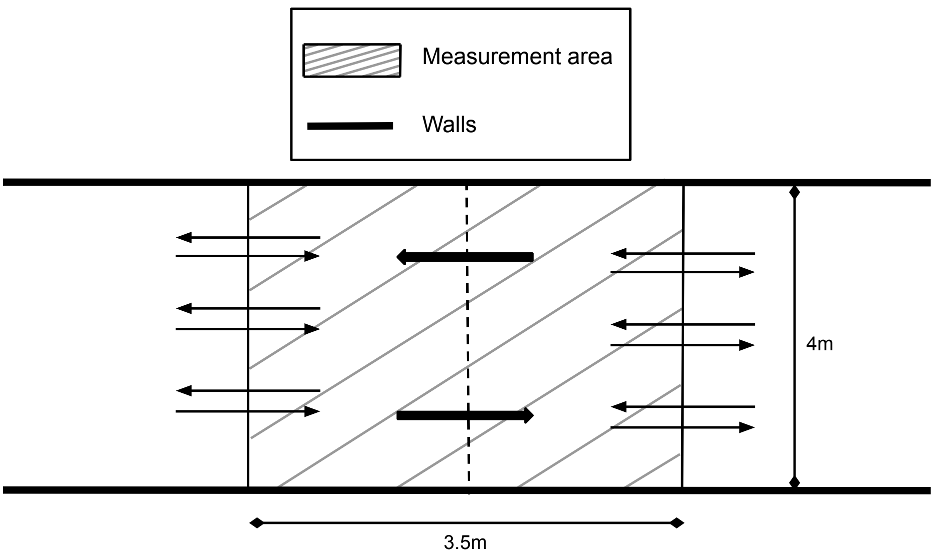


Figure 3.2: Lay-out of bidirectional straight scenario

The lay-out for these scenarios (Figure 3.2 shows the area of interest to be a corridor of 3.5 m long and 4 m wide. These dimensions are chosen given that they correspond to the length and width of the corridors located at Utrecht Central between the escalators towards the platforms and the elevators, for which there is data available. Although the dimensions of this corridor are small, they are considered to be sufficient to obtain information regarding the changes in the walking behaviour of pedestrians as bidirectional straight flows are formed within this area as well as the crowd phenomena that occur in this type of movement base case (e.g. lane formation). Thus, the behaviour observed in these scenarios can be expected to be different than the ones that could occur in longer corridors.

In addition to the different factors that may influence the behaviour of pedestrians indicated in Section 2.2, the physical distancing rule is considered to be the one with the greatest influence during the pandemic. Thus, since the objective of this research is to determine the causal relationship between physical distancing and changes in walking behaviour, other factors should remain constant among the scenarios such that they do not lead to biased results. Therefore, the demand, population composition, and external factors are considered to be constant for each scenario, which is done in the model by keeping the parameters whose impact will not be analysed in this research at their default value.

3.3 Hypotheses

The walking behaviour is expected to be different during COVID-19 than the one before the pandemic considered as normal. For this reason, in this section the hypotheses of the walking behaviour during the pandemic will be described based on the physical distancing and pedestrians' capabilities to comply with the rules, and the reason for the choice of these hypotheses.

Hypothesis 1: ***Pedestrians try to keep a distance of 1.5 m from each other***

During COVID-19, in order to reduce the transmission risk of the virus, people are asked to keep a physical distance that ranges between 1 m and 2 m, which in the Netherlands is set to 1.5 m. Therefore, it is assumed that pedestrians keep as much as possible a larger distance from each other than they did before the pandemic to avoid interactions and thus comply with the rules. Although the real distance between pedestrians might be somewhat lower than the prescribed one, since pedestrians tend to overestimate the distance they keep (Echeverría-Huarte et al., 2021), one can expect that this distance is still larger than before the pandemic.

This hypothesis is studied by analysing the distance headway that pedestrians keep from each other such that the compliance of the physical distancing rule can be determined. Moreover, the distribution of the distance headways of all pedestrians is analysed in order to shed a light on their willingness to keep a larger distance than the one they would keep before the pandemic, and on the limitations of the infrastructure's geometry that would not allow them to fully comply with the prescribed physical distance.

Hypothesis 2: ***Pedestrians show an increased awareness of their surroundings compared to the pre-corona situation***

Before COVID-19 pedestrians would follow their planned route and adhere to it as much as possible for which the avoidance of collision with obstacles and other people is taken into account. During COVID-19, one can expect that pedestrians are also more aware of their surroundings than before the pandemic, thus their distance with respect to others is an additional factor that they might now take into account when walking. Therefore, pedestrians might look into a wider range for open spaces as they might be more willing to take small detours from the most direct path in their planned route and thus be able to comply with the physical distancing.

This hypothesis focuses on analysing how the walking behaviour of pedestrians has changed due to the physical distancing rule based on changes in the awareness of their surroundings. Although the awareness is a cognitive process and cannot be fully described with physical variables, the analysis of the changes in their velocity (i.e. speed and movement direction) and effort to traverse the area of interest can provide some light on whether their awareness has increased during the pandemic. Furthermore, a change in pedestrians' awareness can also be suggested by a different distribution of pedestrians over an area, and thus the analysis their spatial distribution is relevant for this research.

Hypothesis 3: ***The variance of pedestrian's walking velocity is larger during COVID-19 than before***

In relation to the previous hypotheses, one can assume that the velocity of pedestrians changes as a result of their willingness of moving differently in order to keep a larger distance from others compared to before the pandemic, and thus comply with the physical distancing rule.

The speed (i.e. magnitude of the velocity vector) can vary depending on the decisions that a pedestrian make at the operational level which could also influence the compliance of the rules. On the one hand, pedestrians might decide to speed up and overtake the one in front which could lead to a violation of the physical distancing if there is not enough space for them when overtaking. On the other hand, pedestrians might slow down to a speed similar to that of the predecessor and thus be able to keep the prescribed physical distance.

On the other hand, the direction of the velocity is in the same direction of movement of a pedestrian, and the latter changes when they look for open spaces and decide to walk in another direction. As a result, the distribution of people over the measurement area can differ in comparison to before the pandemic and the differences in velocity can indicate this change in the spatial distribution of pedestrians.

3.4 Pedestrian Dynamics

Pedestrian Dynamics (PD) is a microscopic pedestrian simulation model by InControl Simulation Solutions, which allows to model the behaviour of pedestrians at all three levels proposed by Hoogendoorn (2001). On the one hand, the processes of activity choice (strategic level) and activity scheduling (tactical level) need to be directly implemented in the model by the user. On the other hand, the processes of route choice (tactical level), and route following and collision avoidance (operational behaviour) are already implemented in the model, which can be influenced by the model's parameters.

3.4.1 Tactical behaviour

One algorithm implemented in PD is the route choice algorithm. This algorithm employs the concept of the Explicit Corridor Method (ECM) (Geraerts, 2010), in combination with the A* algorithm, to determine the global route for an agent. Moreover, the ECM is a structure that defines the walkable area of the environment and that enables computing the shortest path by defining a minimum clearance to the obstacles, thus agents can traverse the given path. In PD, there are three approaches for computing the global route. One approach is using the shortest path, which is defined as the shortest distance for every Origin-Destination pair. A second alternative is the least-effort approach in which a cost function is considered based on the estimated travel time. Furthermore, the travel time can be calculated considering the estimated delay caused by an increasing density that yields in lower speeds. A third alternative is the physical distancing approach, which differs from the least-effort approach in the calculation of the density. In the latter approach, the density is computed by considering the private circle which results in lower speeds and thus longer expected delays.

3.4.2 Operational behaviour

Once the general route is defined, the Indicative Route Method (IRM) (Karamouzas et al., 2009) is used to calculate the indicative route that runs from the origin to the destination of every agent. Moreover, an attraction point goes along this route such that every agent is steered through its corridor while following its corresponding attraction point. An agent is able to traverse the entire route by ensuring a minimum clearance at every point of the route.

At the same time an agent follows its chosen route, it has to detect which obstacles, both static and dynamic, it has to avoid. To do so, each agent uses vision which is modelled as a cone-shaped field of view (FoV). The collision-avoidance algorithm, based on the vision-based model developed by Moussaïd et al. (2011), allows agents to determine their velocity close to their desired velocity, but at the same time the one that prevents them from colliding with others. Furthermore, the cognitive science approach proposed by Moussaïd et al. (2011) based on behavioural heuristics is used, which consist of agents applying two simple cognitive procedures guided by visual information, namely the distance of obstructions in pedestrians' lines of sight.

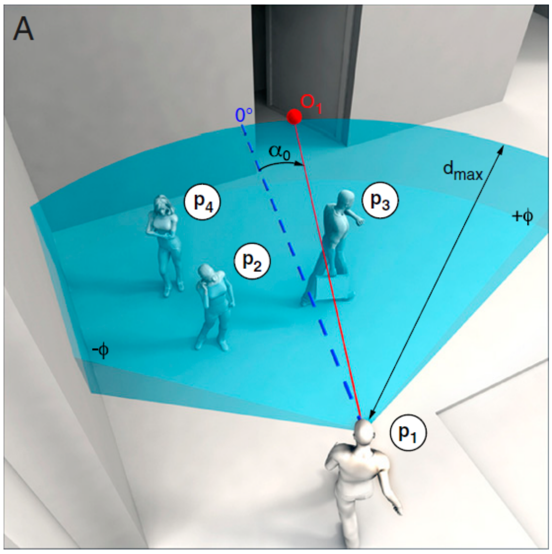


Figure 3.3: Illustration of cone-shaped FoV and parameters for determining the desired direction (Fig. 1 (A) from (Moussaïd et al., 2011))

The first heuristic concerns the walking direction for which it has to be found a trade-off between avoiding obstacles and minimising the number of detours from the most direct route. Figure 3.3 shows the cone-shaped FoV and the obstacles considered for determining the desired direction (α_{des}) based on the viewing angle of an agent (ϕ) together with the viewing distance (d_{max}) and the distance to the closest expected obstacle ($f(\alpha)$). Thus, the chosen direction is determined by minimising the distance to the destination as follows:

$$d(\alpha) = d_{max}^2 + f(\alpha)^2 - 2d_{max}f(\alpha)cos(\alpha_0 - \alpha), \quad \text{for} \quad \alpha \in [-\phi, \phi] \tag{3.4.1}$$

The second heuristic concerns the desired walking speed ($v_{des}(t)$), which takes into account the distance to the first obstacle in the chosen direction and the time to collision. This means that the desired speed is given by $v_{des}(t) = min(v_i^0, d_h/\tau)$, where v_i^0 is the desired speed of an agent, τ is the relaxation time that determines how strongly the agent reacts to deviations from its desired velocity, and d_h is the distance between the agent and the first obstacle in the desired direction (Sparnaaij, 2017). In PD, d_h is determined as follows:

$$d_h = \begin{cases} d_{i;exp:col} - d_{i;pers} & \text{When the collision is with another agent} \\ & \text{walking in the same direction.} \qquad [\text{m}] \\ d_{i;exp:col} & \text{Otherwise} \end{cases} \tag{3.4.2}$$

Where $d_{i;exp:col}$ is the distance to the first expected collision in direction α_{des} of agent i, and $d_{i;pers}$ is the personal distance that agent i keeps with another agent.

According to the method proposed by Moussaïd et al. (2011), the desired velocity ($\vec{v}_{des}$) is a combination of the desired speed and the desired direction. In PD, the change in the actual velocity ($\vec{v}_i$) at time t is determined by the following acceleration equation:

$$\frac{\partial \vec{v}_i}{\partial t} = \frac{\vec{v}_{des;i} - \vec{v}_i}{\tau} + \sum_j \vec{f}_{ij} + \sum_W \vec{f}_{iW} \qquad [\text{m/s}^2] \tag{3.4.3}$$

Where $\vec{v}_{des;i}$ and $\vec{v}_i$ are the desired and current velocity of agent i, respectively; whereas $\vec{f}_{i;j}$ and $\vec{f}_{i;W}$ describe the physical forces which occur on contact with another agent or obstacle.

Finally, the physical distancing rule is implemented in PD by a property called "physical distance". This property consists of a circle called "private circle" that surrounds an agent, which in turn is modelled as another circle whose radius is referred to as "body radius". Thus, as depicted in Figure 3.4, the radius of the private circle (pc_r) is equal to the body radius (b_r) plus half of the prescribed physical distance (pd). This property is aimed at the analysis of capacity during the pandemic rather than the study of the underlying behaviour of pedestrians. Therefore, the changes at the aggregate level (i.e. flow and density) because of a prescribed physical distance can be obtained from the analysis. Furthermore, this property assumes a full compliance of the physical distancing rule, thus the model is locally adapted in situations in which shorter distance headways need to be allowed between agents in order to reproduce an expected and more realistic behaviour under those circumstances.

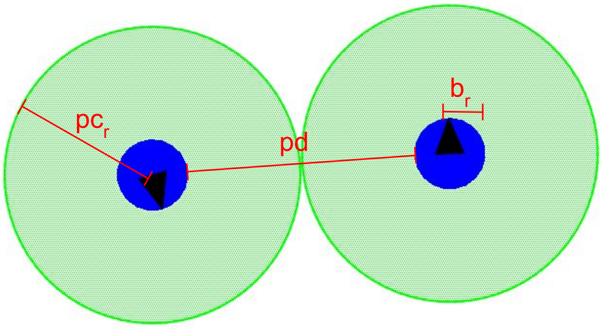


Figure 3.4: Layout of implementation of physical distancing in PD

3.5 Metrics

Findings in the literature review showed that the metrics chosen for the calibration influence the accuracy of the results obtained with the model and, moreover, the results obtained with metrics at only one aggregate level result in different outcomes than when using metrics from other aggregate level or a combination of them.

The goal of this research is to replicate with the model as accurate as possible the behaviour during COVID-19 because of the physical distancing rule. For this reason, metrics from different aggregate levels need to be used in order to analyse whether the behaviour observed is realistic at all these levels when compared to the reference data. However, by taking into account that pedestrian models are mostly used to estimate aggregate data (Campanella et al., 2014), it is considered to give more importance to macroscopic metrics over microscopic metrics. Moreover, as stated by Sparnaaij (2017), a calibration of a pedestrian model based on microscopic metrics (e.g. trajectories) does not deal with the stochastic nature of the model, thus metrics at this level are not considered in this research. So, metrics at the mesoscopic level will be used in this research as they will provide insight into the underlying behaviour and influence of the physical distancing on it.

The choice is made to use two metrics from the macroscopic level, the spatial distribution and the speed distribution over space, and three from the mesoscopic level, the effort distribution, minimum distance headway, and travel distance distribution. These are selected given that they will measure different aspects of the flow related to the expected behaviour stated in the hypotheses.

3.5.1 Spatial distribution

The spatial distribution measures how pedestrians are distributed over the measurement area. According to hypothesis 1 and 2 (Section 3.3), pedestrians would deviate more often from the most direct path to their destination to keep their distance from others as much as possible. For instance, they might walk close to the walls in case of bidirectional flows to avoid interactions with people walking in the opposite direction, and in case of bottlenecks, more pedestrians might tend to walk to the sides to get closer to the bottleneck and to prevent shorter distance headways.

The measurement is done by dividing the area of interest in a grid of 1.0 x 1.0 m and calculate the percentage of the total time that each cell is occupied by at least one pedestrian. Thus, the analysis is conducted by comparing the occupancy of each cell between the three years. This is described by the following equation:

$$SD_k = \frac{N_{occ;k}}{N_{total}} \tag{3.5.1}$$

Where N_{occ} is the number of time steps of the total number of time steps (N_{total}) considered in the simulation in which a cell k is being occupied for a pedestrian.

The spatial distribution is calculated for the different scenarios before and during the pandemic and for both the simulation and the reference data. Thus, it will be possible to determine how the distribution of pedestrians over the area of interest has changed during COVID-19 and the accuracy of the model for reproducing the spatial distribution observed in the reference data.

3.5.2 Speed distribution over space

The speed distribution over space measures the difference in speed encountered over the measurement area. From the hypotheses 2 and 3 one can expect that the speed with which pedestrians walk has changed during the pandemic and, moreover, the variance of speed over the area where it is measured is higher with respect to the variance of speed before COVID-19 as a result of trying to keep larger distance headways and reduce the number of interactions.

A grid of 1.0 x 1.0m overlays the measurement area and the distribution of the instantaneous speeds of all pedestrians over a single cell at every time step j is calculated. The velocity is determined as follows:

$$\vec{v}_{i;j} = \frac{\vec{r}_i(t_j) - \vec{r}_i(t_{j-1})}{t_j - t_{j-1}} \qquad [\mathrm{m/s}] \tag{3.5.2}$$

Where $\vec{r}_i(t_j)$ and $\vec{r}_i(t_{j-1})$ are the positions at time steps j and $j-1$ of pedestrian i. Then, the speed of each pedestrian at a cell k at time step j can be calculated based on the horizontal v_x and vertical v_y components of the velocity vector at the given time step:

$$S_{i;j;k} = \sqrt{(v_{x_i;k}^2(t_j) + v_{y_i;k}^2(t_j))} \qquad [\mathrm{m/s}] \tag{3.5.3}$$

Similarly to the spatial distribution, the speed distribution over space will allow to determine the differences in the speed encountered over the measurement area between the situations before and during the pandemic, and how accurate the model replicate this distribution in comparison to the reference data.

3.5.3 Minimum distance headway

Ideally, the minimum distance headway during the pandemic would be equal to the physical distance (e.g. 1.5m); but, as was already mentioned, this scenario does not occur as pedestrians stop complying with the rules when they are not able to keep a larger distance from each other, but also because of their tendency to overestimate the distance they actually keep. Nonetheless, during the pandemic can be expected the minimum distance headway to be larger than before.

This metric is selected so that it can be observed whether pedestrians react more strongly to the presence of others nearby as this reaction would be translated into a larger distance between them.

$$h_{p,q}(t) = min|\vec{x}_q(t) - \vec{x}_p(t)| \quad \forall \vec{x}_q(t) \in V_p(t),\ q \neq p \tag{3.5.4}$$

$$V_p(t) = \{\vec{x} \in X : \frac{\vec{v}_p(t)}{|\vec{v}_p(t)|} \cdot \frac{\vec{x} - \vec{x}_p(t)}{|\vec{x} - \vec{x}_p(t)|} \geq \cos 75^\circ \wedge (\vec{x} - \vec{x}_p(t)) \leq h_{p;max}\} \tag{3.5.5}$$

Equation 3.5.4 and Equation 3.5.5 define the minimum distance headway according to Duives (2016), where $\vec{v}_p(t)$ is the velocity of pedestrian p, $\vec{x}_p(t)$ is the location of pedestrian p, and $\vec{x}_q(t)$ the location of pedestrian q. Moreover, $h_{p;max}(t)$ is the maximum distance agent p can observe ahead from its position (i.e. the avoidance range in PD) and $V_p(t)$ is the vision field of 150° at time step t. According to these equations, the minimum distance headway of pedestrian p is computed by considering the pedestrians in front and within their viewing angle. Thus, the dot product of the normalised vectors of velocity and position should be at least equal the cosine of 75°, the angle between the direction of movement and each side of the viewing angle of pedestrian p.

The individual measurements of the minimum distance headway are combined into a single distribution for both the simulation and the reference data. Then, the mean and standard deviation can be calculated as they would indicate how different the distance headway is during the pandemic and how further and spread the distances are from the mean.

3.5.4 Effort

The effort distribution allows to measure the effort that it takes a pedestrian to traverse the measurement area (Sparnaaij, 2017). This metric provides insight into the changes in the direction of movement of pedestrians given by the direction of the velocity, which can be expected to be larger during COVID-19 as was stated in hypothesis 3. Meanwhile, the magnitude (i.e. speed) also gives insight into how often these changes occur in order to keep a larger distance as a result of being more aware of their surroundings.

This is done by calculating the average change in velocity of each pedestrian at every time step such that more changes in the velocity would imply a greater effort of a single pedestrian to traverse the measurement area. First, the speeds in x and y-direction are calculated according to Equation 3.5.2. Then, based on the definition of effort by Sparnaaij (2017), the effort is calculated as follows:

$$Eff_i = \frac{\sum_{j=2}^{n}\left(|v_{x_i}(t_j) - v_{x_i}(t_{j-1})| + |v_{y_i}(t_j) - v_{y_i}(t_{j-1})|\right)}{n-1} \qquad [\mathrm{m/s}] \tag{3.5.6}$$

Similar to the minimum distance headway, the effort is the combination of the efforts calculated for each pedestrian into a distribution for both the simulation and reference data. Moreover, the mean and standard deviation of the effort distribution would provide insight into how difficult for a pedestrian can be to traverse an area when following the physical distancing rule, since this difficulty can be drawn from higher values for both measures.

3.5.5 Travel distance

The travel distance measures the total space covered by a pedestrian within the measurement area. During the pandemic, as a result of a greater avoidance of interactions with others and keeping away from others, pedestrians are expected to deviate more often from the most direct path as they search for open spaces and therefore walk larger distances. Thus, this metric can provide insight into the impact of physical distance on the behavioural change of pedestrians.

The travel distance of a single pedestrian for both the simulation model and the reference data is calculated as follows:

$$d_{x;j} = x(t_j) - x(t_{j-1}), \quad d_{y;j} = y(t_j) - y(t_{j-1}) \qquad [\mathrm{m}] \tag{3.5.7}$$

Where $x(t_j)$ and $x(t_{j-1})$ are the x-positions of a pedestrian within the measurement area at time steps j and $j-1$, respectively. Similarly, the distance in y-direction is obtained. Then, the total distance for agent i is determined as follows:

$$D_i = \sum_{j=2}^{n} \sqrt{(d_{x_i;j}^2 + d_{y_i;j}^2)} \qquad [\mathrm{m}] \tag{3.5.8}$$

The total distance travelled by all pedestrians are combined into a single distribution in order to determine the mean, which is expected to be higher during the pandemic as well as the standard deviation.

3.6 Parameters

This study is focused on analysing the behaviour and decisions pedestrians make at the operational level as a result of physical distancing. Although physical distancing might influence the decisions at the tactical level, the route planning process is not considered given that the scenarios describe specific locations (i.e. corridors), thus the agents within the measurement area have one possible global route and the analysis will focus on how they follow their planned route. Thus, only the parameters in PD that influence the operational behaviour will be taken into account for the sensitivity analysis and calibration.

As shown in Table 3.1, the operational behaviour can be influenced in PD by 12 parameters. They can be divided into those that influence the local behaviour and those that influence the route following behaviour. These parameters are evaluated based on the mathematical description of the operational behaviour in PD (Section 3.4) in order to determine whether the expected walking behaviour during COVID-19 can be described by changing their default values. The expected walking behaviour is based on the hypotheses defined in Section 3.3. A description of the parameters and their relevance for this research are explained in more detail in the following subsections.

Table 3.1: Parameters in PD for the operational level. Parameters in orange are the chosen ones for the sensitivity analysis.

Name	Unit	Default value
Local behaviour		
Min. desired speed	m/s	0.06
Max. desired speed	m/s	mean, min., max.: [1.35, 0.8, 1.75]
Fixed-speed multiplier	-	0
Viewing angle	degree	75
FoV avoidance range	m	8
Avoidance preference	-	right
Personal distance	m	0.5
Relaxation time	s	0.5
Physical distance	m	0
Route following behaviour		
Preferred clearance	m	0.3
Max. shortcut distance	m	0
Side clearance factor	-	0
Side preference update factor	-	1

3.6.1 Parameters influencing the local behaviour

In this subsection, the parameters in PD that influence the local behaviour are described as well as whether they are considered relevant to improve the accuracy of the model to reproduce the behaviour observed during the pandemic.

Minimum desired speed: This speed is the minimum an agent would walk with given that when an agent's speed drops below this threshold it will stop walking until they can start moving again at a speed greater or equal to this threshold. Based on the expected behaviour drawn from the hypotheses, pedestrians might prefer to stop more often to avoid getting closer to others, which can be obtained by varying the default value of this parameter. Hence, this parameter is relevant for this research to describe the desired behaviour.

Maximum desired speed: This is the desired speed with which an agent will try to walk every time this is possible, and whose default value in PD is a triangular distribution with 1.35 m/s as the mean speed. It is assumed that during the pandemic this speed will remain the same as before given that one expects that in low density scenarios pedestrians will keep the same speed provided that the prescribed physical distance can be kept between them.

Fixed-speed multiplier: It is the fraction of the agent's walking speed that is used on fixed-speed surfaces. This parameter is not relevant for this study because none of the locations and scenarios on which the walking behaviour will be analysed entail fixed-speed surfaces such as escalators.

Viewing angle: It is the angle describing half of an agent's field of view. From Equation 3.4.1, the viewing angle defines, together with the avoidance range, the area where an agent looks for obstacles and other pedestrians, and from where it chooses its direction of movement for the next time step. Since pedestrians are more aware of their surroundings, according to the second hypothesis (Section 3.3), a variation of the viewing angle from its default value can influence the agents' movement towards the behaviour observed in the reference data.

FoV avoidance range: This is the distance of the field of view which is used for agent collision avoidance. Thus, an agent looks for collisions with other agents and obstacles which are within the distance defined by this parameter. Therefore, the avoidance range is relevant for this study given that its variation can influence the behaviour observed in the reference data as it might describe the intention of pedestrians of moving further away from others.

Avoidance preference: This parameter describes the bias that determines the preferred side of an agent for avoiding obstacles and other agents. This parameter is not relevant for this research as long as the same preference is set for all the agents.

Personal distance: The desired distance that an agent keeps from another agent or obstacle ahead, which is described by Equation 3.4.2. Although this parameter seems to be relevant to achieve the walking behaviour when applying physical distancing, the parameter physical distance will be used instead, since the personal distance is usually ignored such as in queues, and it only considers the distance directly in front of an agent.

Relaxation time: It is the time required by an agent to reach any desired velocity and determines how strongly agents react to deviations from their desired velocity, which implies that an agent is required to keep a certain distance from obstacles and other agents. Hence, this parameter is relevant for the analysis of two of the hypotheses given its influence on the chosen desired speed as described in Section 3.4.

Physical distance: It is the distance that an agent would like to keep between itself and other agents. Moreover, the value given to this parameter is strictly kept during the simulations, thus there is the assumption that pedestrians always comply with the physical distancing rule. Although this parameter has been introduced for determining the impact on the capacity, it is also considered for the analysis in this research to determine whether it can contribute to the replication of the underlying behaviour during the pandemic in the scenarios of interest for this study.

3.6.2 Parameters influencing the route following behaviour

This subsection provides the description and relevance for this study of the parameters in PD that influence the attraction point location.

Preferred clearance: It is the preferred minimum distance that an agent wants to keep from obstacles when planning its indicative route through a corridor. This parameter is not relevant for this research as the physical distance is focused on the distance with respect to other agents and not to static obstacles.

Maximum shortcut distance: It limits the distance that the attraction point can be from the agent and thus it can be tuned when the intention is of making an agent following the indicative route more tightly. Moreover, this parameter can be used to fix any occurrence of unrealistic local path finding behaviour Sparnaaij (2017) and it is relevant for cutting corner situations. Therefore, the value of this parameter will remain constant to its default one as it does not contribute to the aim of this study.

Side clearance factor: This parameter is used to determine how an agent plans its route from the wall, thus an agent can have a route close to the wall. The default value is set to zero which indicates that agents have theirs routes close to the walls, which is an expected behaviour during the pandemic in order to avoid others. Furthermore, it can also be used to fix an unrealistic local path finding behaviour. Given the default value of this parameters, it is not relevant for this study either and will remain constant to its default.

Side preference update factor: It is a factor used to determine how fast the indicative route of an agent converges towards its current position within the corridor. This parameter makes an agent who avoids another one to walk straight forward by updating its route rather than returning to its original route. This parameter will remain constant to its default value which would lead to an already realistic behaviour of walking straight.

3.7 Conclusions

In this chapter the most important elements for the sensitivity analysis and calibration have been described. Moreover, the definition of the hypotheses of the expected behaviour during the pandemic together with the selection of metrics, and parameters in PD that would describe such behaviour have been presented in this chapter.

Based on the literature review, the challenges found by InControl in different projects, and the available data for this research, two preliminary scenarios have been selected for the sensitivity analysis. These two scenarios include one movement base case (bidirectional straight), and two density levels (low and high). Moreover, these preliminary scenarios will in principle be associated with the reference data in order to define the scenarios which will be used in the calibration.

The hypotheses of the expected behaviour during the pandemic have been defined based on three characteristics of pedestrians and their walking behaviour which are assumed to be different: interaction distance, awareness, and velocity. The assessment of the walking behaviour in the reference data will focus on studying whether these expected changes occur and to whether these hypotheses are true.

To study the walking behaviour of interest, two macroscopic and three mesoscopic metrics have been selected. These will provide insight into the behaviour described by the hypotheses given that they measure different related aspects such as the distance headway, speed, and occupancy. Thus, the metrics considered in this research will allow the study of the changes in the walking behaviour produced by physical distancing. Moreover, these metrics will be used for the sensitivity analysis and calibration with the aim of increasing the accuracy of the model and thus its capabilities.

Finally, the analysis of PD and the parameters which influence the operational behaviour, and based on the literature and hypotheses, five parameters have resulted to be relevant for the objective of this research. These parameters will be used in the sensitivity analysis to check if the model is sensitive to changes in them. As a result, the next step will be to determine the parameters that can best describe the walking behaviour in the reference data such that they will form the search space and be used in the calibration.

Chapter 4

Sensitivity analysis

This chapter discusses the sensitivity analysis whose main objective is to assess how sensitive the model is to changes in the parameters selected in Section 3.6, and to determine the range of values of these parameters within which the behaviour is realistic. The findings will allow to answer the third subquestion stated in Section 1.3.

The parameters whose changes lead to significantly different results in the sensitivity analysis will compose the search space in order to limit the number of parameters for the calibration, given that the size of the search space is exponentially related to the number of parameters (Sparnaaij, 2017) and thus computationally more expensive. Moreover, a good estimation of those parameters is considered more important as small changes can lead to significantly different results.

Moreover, the results from the sensitivity analysis will provide some insight into the direction towards which the relevant parameters should be changed in order to describe the behaviour observed during the pandemic because of the physical distancing.

In this chapter, the methodology to conduct the sensitivity analysis is described in Section 4.1, and the qualitative and quantitative analysis described in the methodology will be discussed in Section 4.2 and Section 4.3, respectively. Section 4.4 summarises the main conclusions of this chapter.

4.1 Analysis methodology

The literature review (Chapter 2) showed that the walking behaviour varies depending on the movement base case. In view of the interest of this research, a bidirectional straight movement is chosen for the assessment of the sensitivity of PD as the calibration of the model is aimed at reproducing the observed behaviour during the pandemic at this movement base case. Moreover, in Section 3.4 and Section 3.6 the relevance of the parameters that control the operational behaviour in PD were analysed in order to determine which ones would describe the expected behaviour stated in the hypotheses (Section 3.3). Based on the selected parameters, the sensitivity analysis will assess how sensitive PD is to changes in their default values, and how the behaviour changes within a certain parameter range.

The sensitivity analysis should provide insight into the associated sensitivity of the model to changes in a single parameter (first-order effect) and the one associated to simultaneous changes in different parameters (higher-order effect) (Punzo et al., 2015). The former can be understood as the portion of the output variance which is due to the variation of one parameter, whereas the latter involves the variance due to the joint variation of several parameters. However, this analysis is computationally expensive. For this reason, and for the purpose of this research, getting insight into the first-order effects is considered to be sufficient. Therefore, a three-step methodology, which only takes into account first-order effects, is chosen for the sensitivity analysis and will be discussed in the remainder of this section. Work by Sparnaaij (2017) forms the basis of this sensitivity analysis.

4.1.1 Three-step methodology

This methodology consists of the combination of one scenario and one parameter such that the sensitivity of the model to changes in that single parameter can be determined and therefore conclude whether the resulting behaviour is significantly different from the one observed when such parameter remains at its default value.

The first step is to determine the maximum deviation from the default value for which the resulting behaviour is realistic for the scenarios considered in the analysis. As mentioned by Sparnaaij (2017), PD has already undergone a basic calibration, thus the optimal values of the parameters to replicate the intended behaviour in this research are assumed not to be very different from their default values. Therefore, a space limited by a maximum deviation of ±25% from the default value of the selected parameters is considered for the sensitivity analysis. Table 4.1 shows the values for the upper (+ 25%) and lower (-25%) boundaries, as well as the default one for the selected parameters. These five parameters, as mentioned in Section 3.6, have been chosen given that the model is expected to better replicate the walking behaviour during the pandemic by adjusting their default values. Next, a qualitative analysis (Section 4.2) is conducted to determine whether the behaviour corresponding to the boundaries is realistic for the bidirectional straight scenarios.

Table 4.1: Values of parameters at their upper and lower boundary (±25%)

	Min.	**Default**	**Max.**
Min. desired speed	0.04	0.06	0.08
Viewing angle	57	75	94
Avoidance range	6	8	10
Relaxation time	0.38	0.50	0.62
Physical distance	-	0	1.50

The second step of the process is a quantitative analysis (Section 4.3) which aims at determining whether the resulting behaviour with the upper and lower boundary values is significantly different from the one obtained with the default values. Two possible outcomes can be expected from this analysis. Firstly, neither of the boundaries is significantly different from the default, from which it can be concluded that the model is not sensitive to changes in this parameter. Secondly, only one or both of the boundaries show significant differences and thus the model is sensitive to changes in the parameter towards the upper and/or lower limit.

In case any of the boundaries yields significant different results, the following step is the analysis of the development of the sensitivity over the range between the default value and the boundary. This analysis checks how the sensitivity relates to an increasing deviation from the default value of the parameters.

4.1.2 Scenarios and parameters for analysis

In Chapter 3 the scenarios and parameters were determined based on the objective of this research. On the one hand, the sensitivity analysis will be carried out for all the scenarios of interest for the calibration, which consist of a movement base case and a density level, namely:

- Bidirectional straight flow - High density
- Bidirectional straight flow - Low density

On the other hand, the parameters used for the analysis will be the five that were previously selected, namely: minimum desired speed, viewing angle, avoidance range, relaxation time, and physical distance. Moreover, the decision on whether the analysis is performed for an increased value (upper boundary) or a decreased value (lower boundary) depends on the scenarios, particularly in the density level. Regarding the minimum desired speed, the speed at the low-density scenarios is expected to always be larger than the default value for this parameter and closer to the maximum desired speed at any given time. Thus, neither an increase nor a decrease corresponding to a maximum deviation of 25% is relevant to consider for the low-density scenario of bidirectional straight flows. With respect to the avoidance range, an increase by 25% of the default value of 8 m is expected not to make a significant change compared to the default value for high densities. The reason for this is that in PD the six most important agents within the field of view of the agent that is evaluated are considered in order to choose their preferred walking direction at every time step. Therefore, it is very likely that these six agents are within the 8 m range at high-density scenarios. Thus, only the lower boundary will be studied for the avoidance range for the high-density scenarios. Regarding the physical distance, the default value is zero and thus a maximum value of 1.5 m for this parameter is considered for all the scenarios. The remaining parameters will be analysed for both their upper and lower boundary and for all the scenarios.

Based on literature, a high density of 1.5 p/m^2 can lead to lower speeds and flows of 0.73 p/m/s (Daamen, 2004). Hence, in the bidirectional straight flows a demand of 0.80 p/m/s is set for the high density scenario and half of it for the low density scenario. This means that the high-density and low-density levels correspond, respectively, to the congested and free flow branch of the fundamental diagram in normal circumstances before the pandemic. However, it is important to note that both density levels are above the threshold described in Section 3.2, thus one can determine that a realistic behaviour would not occur if a prescribed physical distance of 1.5 m was strictly kept by pedestrians. Therefore, the assessment of the physical distance parameter is done by considering a demand (i.e. 0.20 p/m/s) that leads to a density level below the threshold of 0.3254 p/m^2. Lastly, the highest demand has been chosen such that the flow would not break down during the simulation time of 1.5 minutes, which is considered to be sufficient time to draw conclusions for the qualitative assessment. Table 4.2 shows a summary of the combination of scenarios and parameters which will be assessed in this chapter.

Table 4.2: Combination of scenarios and parameters for sensitivity analysis. "-/+" indicates the analysis is performed for a decreased and increased value from the default, "-" a decreased value, "+" an increased value, and "x" is not considered relevant

	Bidirectional Low density	**Bidirectional High density**
Min. desired speed	x	-/+
Viewing angle	-/+	-/+
Avoidance range	-/+	-
Relaxation time	-/+	-/+
Physical distance	+	+

4.2 Qualitative analysis

In this section, a description is presented of the characteristics of a realistic behaviour for bidirectional straight flows. Based on this description, the movement of agents in PD is then analysed for all the combinations shown in Table 4.2 in order to determine whether the behaviour is still realistic at the maximum upper and lower boundary. Thus, the main objective of the qualitative analysis is to determine if the initial boundaries set for each parameter (±25%) yield a realistic behaviour, on the contrary these would be changed to a lower value by the bisectional method as suggested by Sparnaaij (2017).

To do so, at least ten simulation runs are conducted per combination showed in Table 4.2, and the assessment of the behaviour is reviewed manually for each one of them to determine if it is realistic or not according to the characteristics that will be described below.

Moreover, simulations with the default value of the parameters are run as a baseline provided that it will allow to determine if any unrealistic behaviour is the result of the deviation from the default value.

In case the behaviour observed in the simulation with the default values is not realistic, the assessment of the boundaries will not be performed for that parameter in particular.

In Section 2.2 and Section 2.3 a description of the walking behaviour and crowd phenomena was given for the analysis of bidirectional flows. This description serves as a basis to determine whether the behaviour in the scenario described in Section 3.2 in PD is realistic or not. Moreover, work by Campanella et al. (2014) also provides insight into the procedure for a qualitative assessment of a model based on the characteristics of a realistic and unrealistic behaviour for different types of movement base cases.

4.2.1 Criteria to assess the walking behaviour in crowd models

The following criteria to determine whether the behaviour observed in PD is realistic are based on the assessment proposed by Campanella et al. (2014) for bidirectional flows:

- **Lack of lane formation:** One can expect that in bidirectional flows self-organised lanes are formed in both streams and that they are stable. As a result, a leader-follower behaviour can be observed in this type of flow and if it is not the case, then the behaviour is considered to be unrealistic.

- **Unusual movement:** A walking behaviour can be considered unrealistic when pedestrians suddenly change their speed or direction without any external factor triggering that deviation from their current movement.

- **High number of collisions:** A collision can be defined as the physical contact between two pedestrians which causes a sudden change in the direction and/or speed of one or both of the pedestrians (Sparnaaij, 2017). Although one can expect a higher or lower number of collisions because of different densities, the more collisions are, the more unrealistic the behaviour can be considered to be.

- **Pushing backwards:** An unrealistic behaviour entails pedestrians being pushed backwards by other pedestrians given the head-to-head interactions.

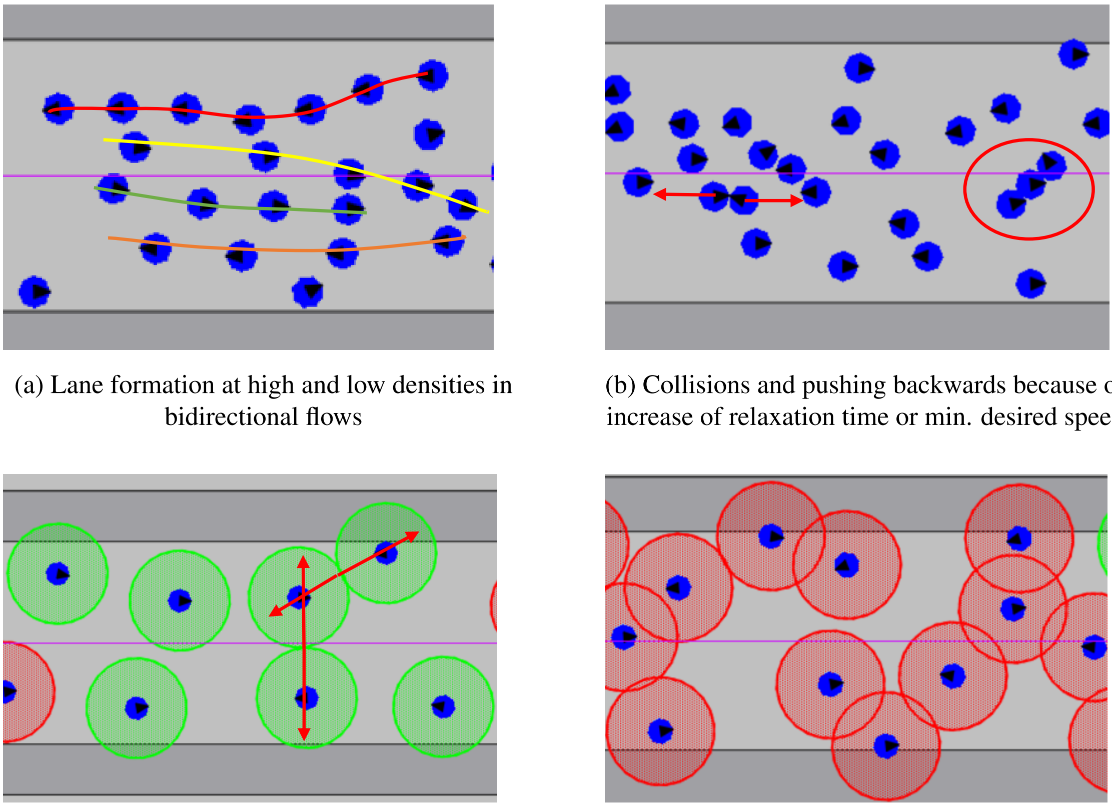
- **Walking outside the simulated area:** The more pedestrians walk outside the simulated area, the more unrealistic the behaviour can be considered to be.

4.2.2 Bidirectional straight flow - High density

The simulation with the default values of the parameters showed that lanes were formed in both directions which were stable as they lasted for long periods and no pushing backwards was noticed, as can be observed in Figure 4.1a. As the density was increasing by the end of the simulation, more collisions were observed from people walking in opposite directions as well as more agents leaving the measurement area. Thus, some lack of realism is observed in the analysed high density scenarios with respect to head-to-head collisions and staying in the measurement area.

The simulations for the deviations of each parameter showed some differences with respect to the default, especially for the upper boundary of the relaxation time and minimum desired speed, since more collisions and pushing backwards were observed. It can be noted in Figure 4.1b that when the occupancy level increases in a corridor, the agents are hindered by others, which leads to more collisions and pushing backwards. Nonetheless, this behaviour only occurs a few times more compared to the default.

Regarding the physical distance parameter, the simulations showed that, as expected, the walking behaviour is not realistic at high-density levels, since agents are not able to keep a strict distance of 1.5 m. As depicted in Figure 4.1c and Figure 4.1d, agents collided between each other, which resulted in them bouncing to the sides and the flow going into a gridlock situation. Moreover, although a reduction of the physical distance value resulted in fewer number of collisions, by the end of the simulations agents started showing sudden changes in their movement of direction, which is not considered a realistic behaviour. Therefore, the physical distance parameter that assumes a strict distance kept by agents, is not considered for the improvement of the model to reproduce the underlying behaviour in bidirectional scenarios at high-density levels, which could occur during the pandemic.



(a) Lane formation at high and low densities in bidirectional flows

(b) Collisions and pushing backwards because of increase of relaxation time or min. desired speed

(c) Pushing to the sides and backwards caused by a 1.5m value of physical distance (High density)

(d) Gridlock caused by a value greater than default for the physical distance (High density)

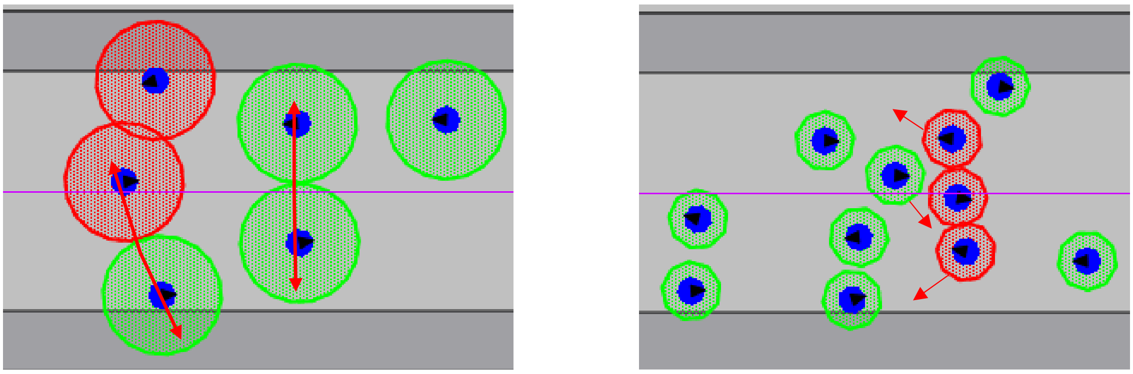
Figure 4.1: Results of realistic and unrealistic behaviour in PD in bidirectional flows with boundary values of parameters

4.2.3 Bidirectional straight flow - Low density

At density levels produced by a demand of 0.4 p/ms/s, the behaviour for the default values was somewhat similar to the one observed for the high density. Agents did not push each other backwards during the head-to-head interactions and there were no collisions observed with the default values. Moreover, lane formation also occurred during the simulations as showed in Figure 4.1a. This was according to the expectations for low demands given that agents would have more available space to adjust their walking behaviour and avoid getting closer to others. Finally, agents did not show any unusual movement and overall they stayed within the measurement area.

The deviations of the parameters, particularly the upper values, showed a few collisions more than the default ones (Figure 4.1b), but fewer than in the high density scenarios. Yet, this behaviour can be considered to be realistic.

The qualitative assessment of the physical distance parameter was conducted with a demand of 0.20 p/m/s that leads to a density below 0.3254 p/m^2. As shown in Figure 4.2a, a strict distance of 1.5 m also led to an unrealistic behaviour in bidirectional flows in narrow corridors, since agents tended to push to the sides and the flow went into a gridlock. Furthermore, a decrease of the value of the physical distance parameter led to fewer collisions, but sudden changes in the direction of movement were observed when the density reached its highest values during the simulation (Figure 4.2b). Although one could expect that in reality pedestrians might block each other when trying to keep a 1.5 m distance, it is also expected that in order to keep walking they would accept shorter distances than the prescribed one. Thus, the physical distance parameter is not taken into account for the intended improvement of the model to reproduce the underlying behaviour in bidirectional flows at low densities as the usage of this parameter assumes a full compliance of the prescribed physical distance at any given time during the simulation.



(a) Collisions and pushing to the sides with a physical distance of 1.5m

(b) Sudden changes in direction of movement with a physical distance of 0.5m

Figure 4.2: Results of walking behaviour in bidirectional flows at low densities

4.2.4 Conclusions

Overall, the behaviour observed in all scenarios with the boundary values of the parameters is considered to be realistic, although some lack of it could be noticed in the high density scenarios as there were more collisions and pushing backwards between agents. The deviation of the default values did not yield an unrealistic behaviour and therefore the maximum upper and lower boundaries remain at ±25% for the quantitative analysis.

One important outcome of the qualitative analysis is that when the parameter physical distance is set to a value greater than its default, an unrealistic behaviour is yielded for the bidirectional straight scenarios, which are of interest for this research. Therefore, it can be concluded that pedestrians encounter difficulties in keeping a strict distance of 1.5 m in bidirectional flows, even at low densities. Furthermore, provided that the parameter physical distance aims to analyse the capacity assuming that pedestrians keep the same prescribed physical distance at any given time during the simulation, it is concluded that this parameter will not be used for the improvement of the model to reproduce the underlying behaviour at circumstances in which the compliance of the physical distancing rule is not possible.

4.3 Quantitative analysis

In this section, the second and third steps of the three-step methodology are conducted. First, the behaviour obtained with the upper and lower boundary is analysed to determine whether they are significantly different from the default. Second, the development of the sensitivity over the whole range between the boundaries is performed, which aims at determining how the sensitivity relates to the deviation. These two steps are conducted separately for the bidirectional straight with high densities (Subsection 4.3.1) and low densities (Subsection 4.3.2).

In the quantitative analysis the metrics that will be used are the speed distribution over space, minimum distance headway, and effort given that they are considered to provide the required insight into different aspects of the walking behaviour and at different aggregate levels. Similarly to the qualitative analysis, the duration of simulations will be of 1.5min as it is considered to be sufficient to capture the intended behaviour and for which the flow does not break down.

The significance of the results with the maximum deviation from the default is determined by conducting a two-sample AD test (Pettitt, 1976), in which it is defined whether the sample corresponding to the boundary value and the one to the default are drawn from the same distribution. Both samples are considered to differ significantly if the AD value is greater than the AD_{crit} at a significance level of 0.05. The AD test is chosen given its advantage of being a more powerful test than others (e.g. Kolmogorov-Smirnov) as it detects better the differences between two distributions (Cousineau and Engmann, 2011).

Sparnaaij (2017) conducted an analysis of PD which revealed the stochastic nature of the model. Moreover, the study showed that there is an influence of the order of the seeds and that a higher number of replications yields a smaller influence of the exact order. Therefore, the difference between the two samples (i.e. boundary and default value) should also be studied to see whether it is greater than the difference which could exist only as an effect of the stochastic nature.

In this research, the difference in the mean and standard deviation between the samples with the boundary values and the default values is compared with the difference produced by the order of the seeds and number of replications. In case the latter difference is higher, the deviation is expected to occur as a result of the stochasticities rather than by the change in the parameters' values. The findings of Sparnaaij (2017) with respect to the relationship between the number of replications and the effect of the order of the seeds is used as similar scenarios (i.e. bidirectional straight) were considered and because a further analysis in the stochastic nature of the model is considered to be out of the scope of this research. Moreover, the number of replications for the sensitivity analysis is set to 25 due to time constraints, since the level of precision is considered to be sufficient for the quantitative analysis conducted in this research given that the aim of the assessment is to get an idea about the behaviour reproduced by the model and the impact of the changes in the parameters, instead of determining accurate results by reducing the influence of the stochasticities.

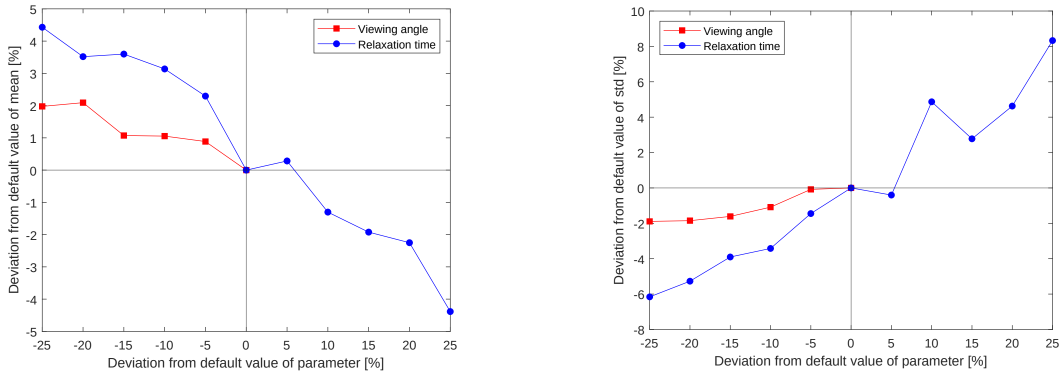
Finally, the development of the sensitivity will be conducted for those boundaries that differs significantly from the default values and for all five metrics.

4.3.1 Bidirectional straight - High

The analysis of the boundaries and the two-sample AD test showed that for most of the metrics, the upper and lower boundaries of the minimum desired speed, the lower boundary of the avoidance range, and the upper boundary of the viewing angle yield a not significant difference from the default. Thus, one can assume that the model is not sensitive to changes in these parameters for a bidirectional straight and high density scenario. Therefore, these parameters are not considered for the third step of the three-step methodology.

By looking at the size of the deviations of the mean and standard deviation of each parameter, and comparing them with the expected deviation because of the stochastic nature of the model, two parameters resulted in deviations larger than expected as a result of the stochasticities, the relaxation time (upper and lower boundaries) and the viewing angle (lower boundary). Hence, the development of the sensitivity over the range between the upper and lower boundary of these two parameters is analysed.

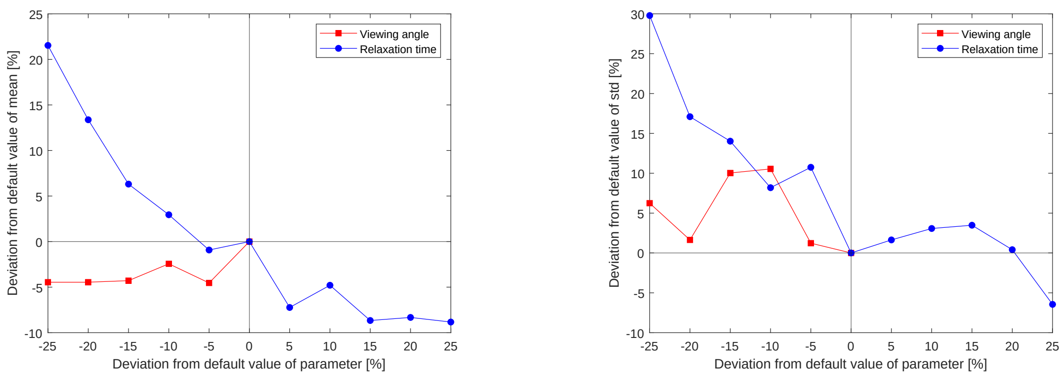
Figure 4.3 depicts the sensitivity of the model for the speed distribution over space. Among the two macroscopic metrics, this one provides more insights into the sensitivity of the model and the changes in behaviour. The figure shows the deviation (%) of the mean and standard deviation from the values corresponding to the default. It can be noted that the model is more sensitive to changes in the relaxation time than in the viewing angle. Overall, with respect to the relaxation time, the deviation clearly increases at each increment of 5%, whereas for the viewing angle the deviation at the upper boundary is not very different than the one for a deviation of 5%. Moreover, one can observe that an increase of the relaxation time would lead to a reduction of the overall speed, which is in line with the mathematical formulation of the speed in PD (Section 3.4) as a higher value for the relaxation time leads to a lower preferred speed. Furthermore, a decrease of the viewing angle yields a higher speed distribution over the measurement area, which can be as a result of the agents having more possible directions from which they can choose their preferred direction and therefore they do not need to reduce their speed.



(a) Mean (b) Standard deviation

Figure 4.3: Sensitivity - Bidirectional high density - Speed distribution over space
Deviation: Viewing angle [-25%, 0], Relaxation time [-25%, +25%]

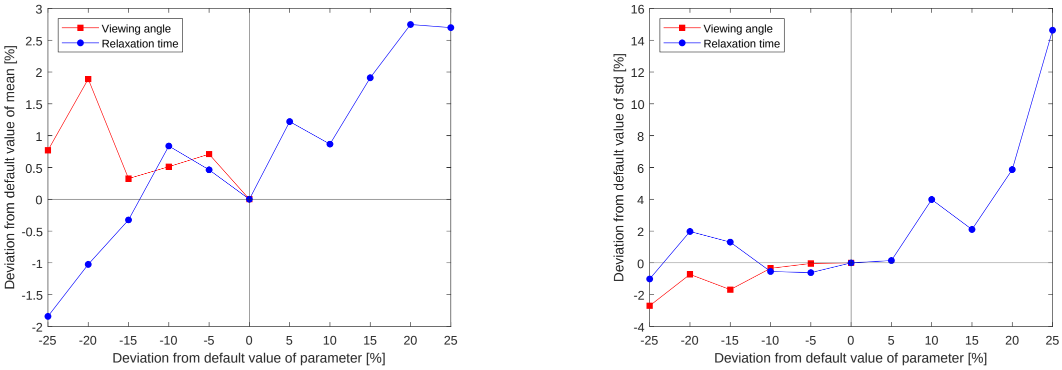
Figure 4.4 shows the results regarding the sensitivity of the model to changes in the effort distribution. Similar to the results for speed distribution over space, the model can be observed to be more sensitive to the relaxation time, and the viewing angle does not vary much among different deviations from the default. Moreover, a decrease of the relaxation time leads to a higher mean of the effort, which indicates that agents change more often their velocity while traversing the measurement area, whereas an increase in the relaxation time leads to a lower effort and thus less changes in velocity (i.e. speed and direction). Regarding the viewing angle, a decrease from its default value leads to a lower effort, which can be expected given that their field of view decreases and this leads to fewer possible directions of movement and thus less changes in direction. Moreover, a large standard deviation observed for the effort indicates that agents very often try to change their velocity, particularly at the end of the simulation when the density is higher.



(a) Mean (b) Standard deviation

Figure 4.4: Sensitivity - Bidirectional high density - Effort
Deviation: Viewing angle [-25%, 0], Relaxation time [-25%, +25%]

From Figure 4.5 one can draw similar conclusions as for the speed distribution over space and effort with respect to the sensitivity of the model to changes in the parameters. However, in this case an increase of the relaxation time yields a higher mean of the minimum distance headway, whereas a decrease of the relaxation time leads to a decrease of the mean. Moreover, a reduction of the viewing angle leads to a small increase of the mean. Large standard deviations can be a result of the differences in the density at the end of the simulation when capacity is closed to be reached. During COVID-19, larger distance headways can be expected, thus the sensitivity analysis provides an insight into which direction the parameters should vary to achieve the expected behaviour.



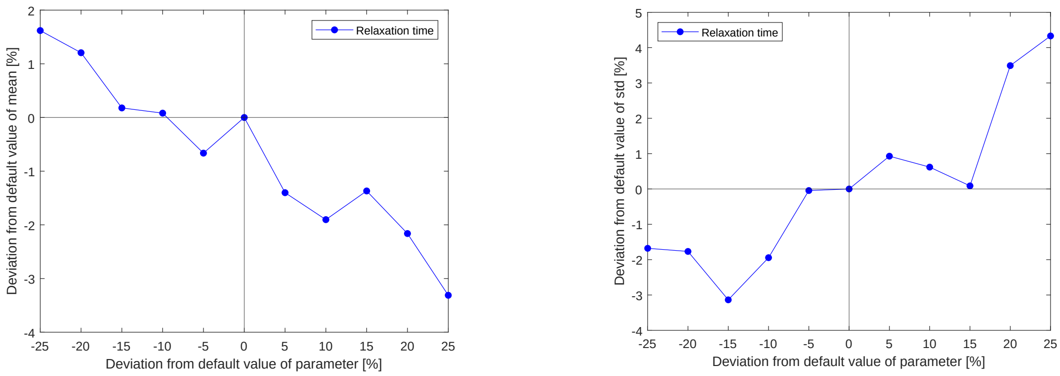
(a) Mean (b) Standard deviation

Figure 4.5: Sensitivity - Bidirectional high density - Minimum distance headway
Deviation: Viewing angle [-25%, 0], Relaxation time [-25%, +25%]

In case of bidirectional straight flows at high densities, the model is more sensitive to both boundaries of the relaxation time at and to the lower boundary of the viewing angle. Moreover, changes in the relaxation time lead to larger deviations than the viewing angle. Finally, an erratic behaviour is observed in some combinations of scenarios and metrics (e.g. Figure 4.5a) as small deviations from the default of the parameters yield deviations of the metric larger than the one produced by the boundary values. This suggests that the model is unstable as a solid trend cannot be provided for the evaluated combination.

4.3.2 Bidirectional straight - Low

Similar to the bidirectional straight flows for high densities, the two-sample AD test showed that the upper and lower boundaries for most of the parameters are significantly different, except for the viewing angle. Furthermore, the deviation of the relaxation time is greater than the difference expected because of stochasticities for 25 replications of 2.2% and 5% (Sparnaaij, 2017) for the mean and standard deviation, respectively.

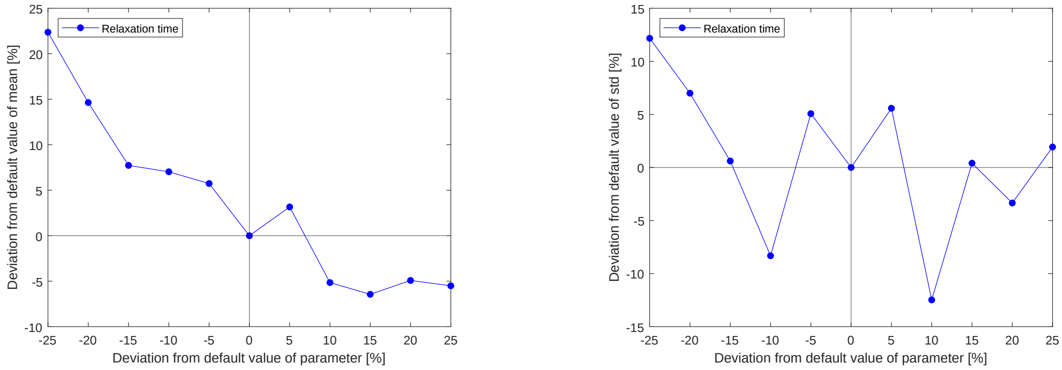


(a) Mean (b) Standard deviation

Figure 4.6: Sensitivity - Bidirectional low density - Speed distribution over space
Deviation: Relaxation time [-25%, +25%]

Figure 4.6 shows the sensitivity of the model to changes in the relaxation time for the speed distribution over space. Similar to the high-density scenario, a decreased value of the relaxation time leads to an increase of the mean of the speed over the area and an increase of the parameter's value yields a reduction of the mean. However, the deviations of the standard deviation are lower in this scenario, which suggests that, regardless of the location of the agents within the measurement area, the speed does not vary greatly as they do not need to because of the low density.

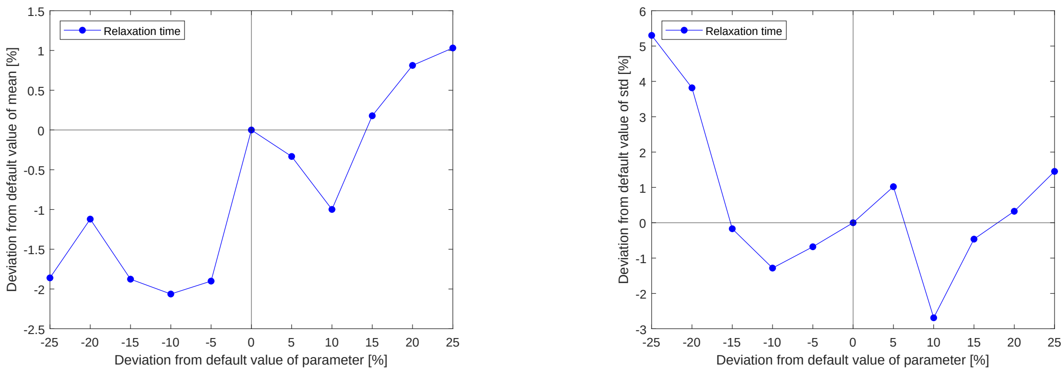
Figure 4.7 shows similar results for the effort distribution as for the high-density scenario, although the standard deviation is also lower in this scenario given the same reason as for the speed distribution over space.



(a) Mean (b) Standard deviation

Figure 4.7: Sensitivity - Bidirectional low density - Effort
Deviation: Relaxation time [-25%, +25%]

Figure 4.8 shows that an increased value of the relaxation time leads to a higher mean of the minimum distance headway, and a decreased value of the relaxation time yields an opposite effect. Furthermore, one can also observe that both the mean and the standard deviation are smaller than for the high-density scenario, which can be expected as a result of lower densities that allow agents to move at the same speed and thus maintain a more constant distance from each other.



(a) Mean (b) Standard deviation

Figure 4.8: Sensitivity - Bidirectional low density - Minimum distance headway
Deviation: Relaxation time [-25%, +25%]

For this scenario, the model is more sensitive to changes in the relaxation time than for any other parameter. Furthermore, lower deviations of the standard deviations in this scenario suggest that the density level does influence the behaviour of agents in the model. Finally, an erratic behaviour is also observed for a low-density scenario, since small deviations from the default of the parameters result in a greater deviation of some metrics (e.g. Figure 4.8a) in comparison with the deviation produced by the boundary values of the parameters.

4.3.3 Conclusions

The results from the quantitative analysis showed that the maximum deviation from the default of some parameters yields a significantly different behaviour than the one obtained with their default values, for which it is important to take into account the impact of the stochastic nature of the model.

Furthermore, the quantitative analysis revealed that the sensitivity of the model depends on the density level of the analysed scenario. While the model did not show sensitivity to changes in the minimum desired speed, the avoidance range, and the upper boundary of the viewing angle in the high-density scenario, the model showed not to be sensitive to any of them in the low-density scenario.

Finally, the relaxation time is the parameter to which the model is sensitive in the two scenarios and for which higher deviations have been observed. The viewing angle also shows to have an impact on both bidirectional straight flows, although only the lower boundary for the high density scenario shows to have an significant influence on the model.

4.4 Conclusions

This chapter analysed the sensitivity of the model to changes in the parameters selected in Chapter 3 and thus provide insights to answer the third subquestion in Section 1.3.

The qualitative analysis showed that an upper and lower deviation of 25% yields a realistic behaviour for the minimum desired speed, viewing angle, avoidance range, and relaxation time. As for the parameter physical distance, the assessment showed that any value greater than the default led to an unrealistic behaviour for bidirectional flows in narrow corridors, even at very low densities, given that the usage of this parameter assumes a strict compliance of the prescribed physical distance at any given time. Thus, the parameter physical distance will not be used for the improvement of the model to reproduce the underlying behaviour during the pandemic, since pedestrians are expected to be flexible with the distance they keep from each other when they are not able to comply with the physical distancing rule.

The qualitative analysis showed that the parameters to which the model is sensitive depend on the scenarios. The relaxation time showed to be a common parameter for all the scenarios, and for which the highest deviations have been achieved. Moreover, a -25% deviation of the viewing angle leads to significant differences in the bidirectional straight with high densities. Furthermore, the quantitative analysis showed that the sensitivity of the model to changes in the parameters depends on the density level of the scenario that is analysed.

Overall, one can conclude that the relaxation time and the viewing angle are the parameters to which PD is most sensitive based on the analysis conducted in this chapter. The remaining parameters are ruled out because either they lead to insignificant deviations from the default or the resulting deviation is lower than the one expected by the stochasticities.

By taking into account the objective of reproducing the behaviour when the physical distancing rule is introduced, the sensitivity analysis provides some insight into what changes should be conducted in the parameters. For instance, a larger distance headway is in line with the expected behaviour stated in the hypotheses and this could be obtained by increasing the relaxation time and viewing angle as observed in the results of the quantitative assessment. However, it is important to consider the erratic behaviour observed for some metrics and scenarios which suggests an instability of the model.

Finally, the outcome of the sensitivity analysis will serve as a basis to define the search space for the calibration, since the more sensitive the model is to changes in a parameter, the greater the impact on the model of small deviations in that parameter will be.

Chapter 5

Assessment of data and walking behaviour

In this chapter the data sets available for this research will be described and analysed in order to obtain the relevant information that will give insight into the walking behaviour during the pandemic and the compliance of the physical distancing rule. Moreover, the analysis of the walking behaviour will also be discussed in this chapter.

This chapter is organised as follows. Section 5.1 covers the description of the characteristics and information that is needed to get from the data in order to analyse the walking behaviour. In Section 5.2, the analysis of the data available for this research is presented in order to define the data set that will then be used to analyse the walking behaviour before and during COVID-19 (Section 5.3). Lastly, the main conclusions are presented in Section 5.4.

5.1 Data set requirements

In Section 3.3 the hypotheses related to changes in the walking behaviour due to physical distancing were proposed, and given that the study of them implies the analysis of the walking dynamics, the type of data needs to provide relevant information that will allow the analysis of pedestrians' movement before and during the pandemic and determine the changes it has experienced.

In this research, it is important to understand the behaviour at the aggregate and operational level given that the impact of physical distancing on the pedestrian flow is at both levels. Moreover, the calibration that will be performed in Chapter 6 needs to consider both aggregate levels in order to ensure a realistic behaviour and more accurate results for both of them. Thus, while the macroscopic metrics provide information regarding the aggregate behaviour of pedestrians, the mesoscopic and microscopic metrics give information with respect to the underlying behaviour, the interactions between pedestrians, and the decisions at the operational level which cause the aggregate behaviour.

Therefore, the data needed for this project should allow to obtain sufficient information to understand the behaviour of pedestrians based on their location within the study area at any given time. Thus, the most suitable type of data for this research is trajectory data as it records the location of every individual pedestrian continuously through time, and thus provides the required information to describe their walking behaviour at different aggregate levels according to the metrics described in Section 3.5.

Furthermore, the type of data depends on the objective of the research. As mentioned by Duives (2016), these types of information are defined by the measurement location, the specificity of the information, the production process, the availability of the information, and the possibility of identification.

Firstly, the measurement locations of interest for this research are the ones described in Section 3.2. Therefore, an area-bound technique (e.g. video system) should be used in order to generate information about those specific locations. Secondly, with respect to the specificity of the information, the technique used to collect the required data should be able to capture the location of pedestrians (location-specific).

Thirdly, regarding the availability of information, the information of the location of pedestrians should be continuous in time and space so that analysing the underlying behaviour of pedestrians is possible. Fourthly, the selected system should be one that pulls information given that the information is required at a high frequency. Finally, the system used to collect data should be capable of identifying pedestrians once they are detected by sensors and track them based on an assigned id, thus information regarding their walking behaviour (e.g. speed, flows) can be determined.

Finally, the time when the data is collected is also important for this research given the objective of understanding how the walking behaviour of pedestrians has changed during the pandemic because of the physical distancing rule. Therefore, data from before and during the pandemic is required for the assessment of the walking behaviour.

5.2 Analysis of data

A data set needs to be chosen based on the data set requirements described in the previous section and the objective of gaining insight into the walking behaviour in bidirectional straight flows. Thus, the data set should consist of trajectory data that corresponds to a location where bidirectional straight movements occur, and with which is possible to retrieve the location of pedestrians at any given time. Moreover, the method used to provide the data set should also identify pedestrians, so the required information with respect to their walking behaviour can be obtained. Therefore, from the available data sets, the one from Utrecht Central station and provided by Dutch Railways (NS) was chosen given that meets all the requirements.

5.2.1 Description of data sets

The data sets consist of trajectories described by the position (i.e. x and y coordinates) of each pedestrians at every time step of 0.1 seconds. Thus, information is provided regarding the location of pedestrians continuously through time and, moreover, given that pedestrians are tracked and are given an id, the specific location of each pedestrian is possible to retrieve; therefore, the computation of metrics and the analysis of the walking dynamics of pedestrians are possible to be conducted.

These data sets are collected by sensors embedded with a new technology developed by the Swiss company ASE, which allows tracking pedestrians anonymously within a predefined area (van den Heuvel et al., 2019). Therefore, as mentioned by van den Heuvel et al. (2019), these sensors allow the assessment of the walking speeds and densities in different circumstances in the area of interest.

At Utrecht Central stations, there are several sensors which record the trajectories from different locations, thus according to the scenarios of interest in Section 3.2, the data set that will be used for the analysis in this project corresponds to sensor 24, which is installed right above the corridor located next to the northern escalator of platform 18/19. Figure 5.1 depicts the area of the scope of sensor 24 in which the sensor captures and tracks pedestrians walking through the corridor between the escalator on the left-hand side and the elevator on the right-hand side. Moreover, pedestrians using the escalators, the elevator and the area above and below the corridor are also detected by the sensor.

The trajectories of the pedestrians tracked by the sensor for a weekday during the peak hour are depicted in Figure 5.2, in which the area of interest for this research (i.e. corridor) is indicated by a red frame. Thus, the information collected is specific to the location of interest, which entails that pedestrians who might have taken other routes are not taken into account, that is the decisions at the operational level are only considered in the analysis. Furthermore, it can be observed in Figure 5.2 that the flow within the corridor is not entirely bidirectional as pedestrians are coming in and out the escalators; however, the main movement base case is still considered to be bidirectional straight given that the biggest share of the total demand comes from the north-east and south-west part of the station (Figure 5.1, particularly during the pandemic.

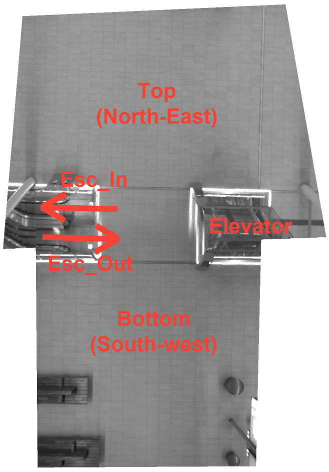


Figure 5.1: Area of scope of sensor 24 (Source: NS)

Figure 5.2: Trajectories in corridor at Utrecht Central at platform 18/19 of 100 pedestrians

According to the objective of the research of studying the impact of physical distancing on the walking behaviour at bidirectional flows, the data set used will correspond to 2019, 2020, and 2021 corresponding to the same sensor. On the one hand, the data set from 2019 will be used to describe the behaviour which was considered to be "normal" before COVID-19 and as the reference for comparison with the following years. On the other hand, the data set from 2020 and 2021 will allow to describe the behaviour of pedestrians when the physical distancing was implemented and when there was the steepest drop of the usage of public transport.

5.2.2 Selection of observations and sample sizes

In order to study the influence of physical distancing (independent variable) on pedestrians' walking behaviour (dependent variable), one needs to control for exogenous factors given that they can affect the causal relationship and thus yield biased results (Van Den Heuvel, 2016). Therefore, exogenous factors need to be identified so that it is possible to control for its impact on the walking behaviour and ensure that the observed changes are caused mainly by the physical distancing.

The characteristics and type of passengers that make use of the train station are different through the day and years. Furthermore, during the weekdays the type of passengers are different depending on the time of the day, particularly between peak and non-peak hours; whereas the type of passengers during the weekend are assumed to be somewhat similar through the day. Therefore, the walking behaviour is expected to be different depending on the day and time chosen for the analysis. Thus, a data set for a Saturday can be selected given that, based on the findings of Agarwal (2004), the type of passenger can be assumed to be the same during the day and regardless of the time of the day. Therefore, one can control for the impact that different types of passengers can have on the walking behaviour.

The demand and density levels are also factors that might affect the walking behaviour. During the pandemic, public transport experienced a steep decrease in demand as a result of the measures imposed to prevent the spread of the virus and, once there was a relaxation of them, the demand increased to values still below the ones reached before COVID-19. Figure 5.3 shows the demand through the third Saturday of June in each year, in which one can observe that the demand in the corridor before the pandemic was larger than in 2020, during which most of measures were applied, whereas in 2021 the demand increased mainly because of the relaxation of some measures such as the reopening of locations and more people going back to work at the office. Thus, one can expect that the demand, density level and therefore the walking behaviour would vary according to the period selected in each year for analysis.

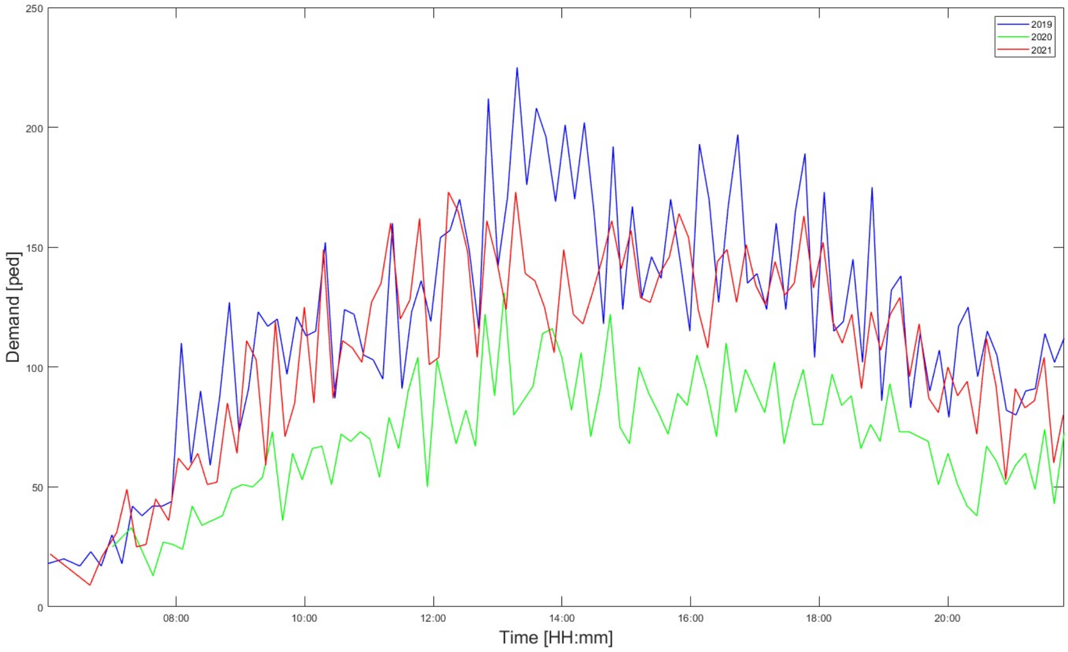
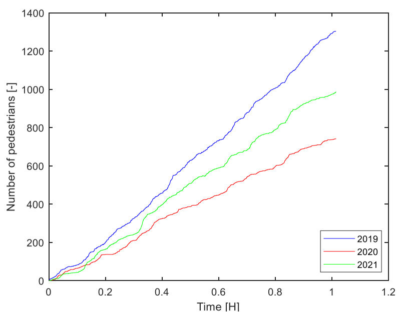
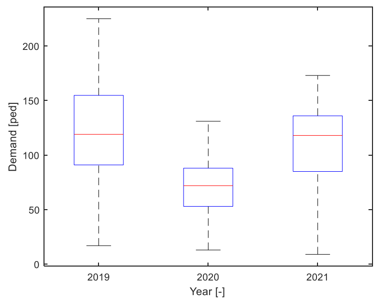


Figure 5.3: Saturday's demand in the corridor in June of 2019, 2020, and 2021

Moreover, in Figure 5.4a one can observe that the total number of pedestrians walking through the corridor reduced to almost half in 2020 compared to 2019, whereas by June 2021 the number of pedestrians was around 75% of the demand in 2019. This can also be observed in Figure 5.4b, in which one can note the difference in the average demand between the three years. Thus, the demand has changed over the years of interest and therefore different density levels can be expected during a day, which can yield changes in the walking behaviour.



(a) Cumulative curves during the hour with highest demand in each year



(b) Average demand in the corridor during a Saturday (Time step: 15min)

Figure 5.4: Variation of demand in the corridor between 2019, 2020, and 2021 in a Saturday

Therefore, a different time of the day for each year is chosen such that a similar demand and density level is obtained. Thus, by controlling for this factor, the differences observed in the walking behaviour because of a different demand can be disregarded. From the demand through an entire day (Figure 5.3) the periods with similar demands can be chosen in each year. The time of the day selected to study in 2020 corresponds to the one with the highest demand given that one can expect a more distinct change in the walking behaviour, as well as in the compliance of the physical distancing. The time of the day in 2019 and 2021 are chosen such that their demand coincides to the one in 2020 as for the latter, the demand is the lowest among all three years. Thus, the periods of the day selected in each year are the following:

- 2019: 09:30h - 10:30h
- 2020: 13:30h - 14:30h
- 2021: 09:30h - 10:30h

The highest demand in 2020 occurred at midday, whereas a similar demand in 2019 and 2021 was found early in the morning. By choosing these periods, one can control for the impact of a different demand and density level on the walking behaviour.

As a conclusion of this section, the type of data chosen for this research is trajectory data as it provides sufficient information to conduct an analysis of the walking dynamics of pedestrians within the corridor where the physical distancing impact will be analysed. Moreover, the main factors that may affect the behaviour observed in the data are the passenger type and the density level, and for which it is necessary to control so that any difference in the walking behaviour can be mainly attributed to the physical distancing. Lastly, the periods of the day for each year in which the enforcement of measures is different, and in which a similar demand can be found have been drawn from the data sets.

5.3 Analysis of walking behaviour

The aim of this analysis is to describe and understand the differences in walking behaviour of pedestrians before and during the pandemic. In Section 5.3.1, the aggregate behaviour of pedestrians is studied by looking at the relationship between the flow variables (i.e. flow, density, speed) and thus determining whether changes occurred at the macroscopic level. In Section 5.3.2 the underlying behaviour that causes the aggregate behaviour is studied by computing the metrics at the mesoscopic level described in Section 3.5, in which the changes in the interaction between pedestrians and their walking behaviour as an effect of physical distancing can be determined.

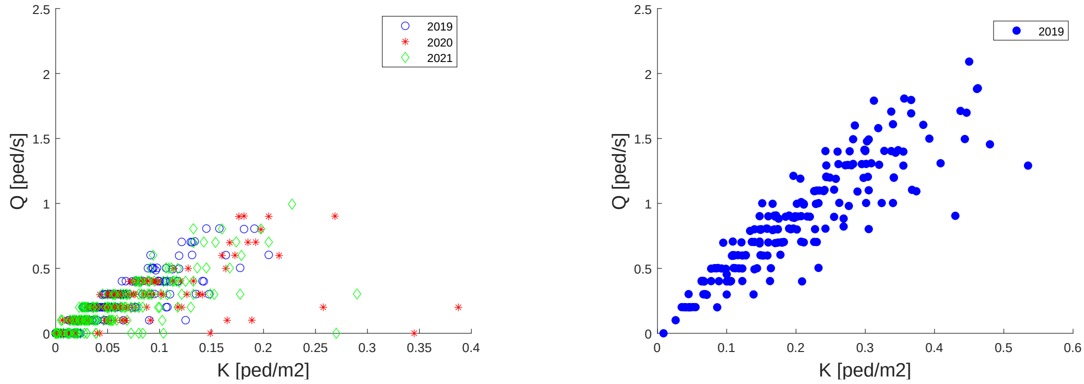
The analysis by means of the flow variables (flow, density, speed), and the metrics described in Section 3.5 will be conducted by considering three periods of 10 minutes each per year which are drawn from the periods of the day listed in Section 5.2.2. By considering 10-minute periods, one can ensure a more constant flow through the corridor within this time than with 60-minute periods, in which there is more variation given the arrivals and departures of trains. Thus, these periods are chosen such that a similar flow crosses the middle section of the corridor within each of them.

5.3.1 Analysis of the fundamental relationship Flow - Density

The analysis of the aggregate behaviour can be conducted by constructing the fundamental diagrams from the data of the corridor, particularly the flow-density relationship. As a result, any differences that might be caused by the measures applied during COVID-19 at this level can be distinguished. Moreover, the values for the flow and density found at this step will serve as a basis to which the results from the calibration need to be checked.

Figure 5.5a shows the flow-density relation for the three years in which one can observe that congestion does not occur at the scenario with the highest demand in 2020. Similarly, in 2019 and 2021, all data points fall within the free flow region for a similar demand as for 2020. Therefore, these results suggest that during the weekends the maximum flow (i.e. capacity) was not reached neither before nor during the pandemic and thus the critical density was not reached either.

Furthermore, even in free flow conditions, a difference one would expect as an effect of physical distancing is that pedestrians would react differently to an increasing density by moving with a lower speed so as to maintain a larger distance. This impact would be expressed in the fundamental diagram by a less steep free flow branch, which would yield in a decreased capacity and critical density than the one reached in normal circumstances before COVID-19. However, Figure 5.5a shows that the slope of the free flow branch is similar among the three years and thus no conclusion can be drawn on the impact of physical distancing on the speed.



(a) Flow-density plot on Saturday

(b) Flow-density plot for 2019 in a weekday

Figure 5.5: Fundamental relationships

In order to analyse whether the capacity of the corridor is reached, the fundamental diagram flow-density has been constructed for data available for a weekday in 2019. This relation is shown in Figure 5.5b, in which one can observe that a maximum flow (2.1 ped/s) is reached at a density of approximately 0.45 p/m^2. On the one hand, although the capacity and critical density might be different during the weekend because of the factors explained in Section 5.2, the obtained values serve to get an idea of the rather low values for the flow and density during the weekends and for which the impact of physical distancing will be analysed in this project. On the other hand, the capacity and critical density during the pandemic can be expected to be lower than the ones shown in Figure 5.5b; however, this cannot be determined given the available data and because it has probably not been reached during the pandemic provided the decrease in public transport usage.

Finally, to know whether the small difference observed in the flow-density relationship between the years is statistically significant, an AD test has been conducted to determine if the samples of each year are drawn from the same distribution. With a 95% level of confidence, the results of the test showed that they differ significantly. However, they are considered not to be meaningful to draw conclusions on the impact that physical distancing might have at the macroscopic level. Thus, more detail should be paid to the underlying behaviour.

In conclusion, the analysis of the fundamental relationship flow-density has shown that their relation still remains the same for free flow conditions given the same gradient of the uncongested branch in the three years. This is contrary to what was expected given that, as an effect of the physical distancing, one would expect for the speed to decrease as the density increases. Finally, one can conclude that during the pandemic the demand has decreased as the capacity and critical density have not been reached, which has yielded low-density levels that would allow pedestrians to comply with a prescribed physical distance of 1.5 m.

5.3.2 Analysis of behaviour at the macroscopic and mesoscopic level

In this subsection, the computation and analysis of the behaviour by means of macroscopic and mesoscopic metrics described in Section 3.5 are conducted in order to get insight into the changes in the walking behaviour and caused by physical distancing, and thus prove whether the hypotheses stated in Section 3.3 are rejected or not.

Spatial distribution

The analysis of the spatial distribution provides information on the usage of the of the corridor and whether there has been any variation during the pandemic. As mentioned in Section 3.5.1, one could expect that pedestrians would walk close to the walls more often in bidirectional flows in order to avoid interaction with others at a distance shorter than 1.5 m. Moreover, a variation in occupancy would indicate a change in the awareness of pedestrians.

The corridor has been divided into a grid of 1.0 x 1.0 m cells to be able to analyse how the occupancy varies at different areas within the corridor. Moreover, the analysis is conducted by taking into account all pedestrians that walk within the grid, including its edges, which is determined by the position of pedestrians at any given time. Table 5.1 shows the share of the total number of time steps considered in the analysis that each cell was occupied by at least one pedestrian in each year. This is in accordance with the definition of the spatial distribution provided in Section 3.5.1.

Table 5.1: Spatial distribution of pedestrians within the corridor in each year

2019	**Top of corridor**			
Escalator	0.08	0.06	0.05	0.03
	0.05	0.08	0.05	0.03
	0.03	0.07	0.05	0.04
	0.04	0.07	0.05	0.05
	Bottom of corridor			

2020	**Top of corridor**			
Escalator	0.06	0.06	0.05	0.03
	0.06	0.06	0.05	0.05
	0.06	0.05	0.05	0.05
	0.05	0.05	0.06	0.04
	Bottom of corridor			

2021	**Top of corridor**			
Escalator	0.06	0.06	0.06	0.01
	0.11	0.08	0.05	0.02
	0.05	0.05	0.04	0.04
	0.04	0.05	0.04	0.04
	Bottom of corridor			

Furthermore, in Table 5.2 it can be observed the difference in the spatial distribution during the pandemic with respect to the one observed in 2019 given the occupancy in each cell. This difference is described by the following equation:

$$\delta_{i,19/Y} = Occ_{i,Y} - Occ_{i,19} \qquad [\%] \tag{5.3.1}$$

Where $Occ_{i,Y}$ is the occupancy of cell i in year Y (i.e. 2020 and 2021), while $Occ_{i,19}$ is the occupancy of cell i in year 2019.

Table 5.2: Difference as a percentage of the spatial distribution in 2020 and 2021 with respect to 2019: Green indicates greater values than in 2019 and yellow lower values than in 2019

2019/2020	**Top of corridor**			
Escalator	-2%	0%	0%	0%
	1%	-2%	0%	2%
	3%	-1%	0%	0%
	1%	-2%	1%	-1%
	Bottom of corridor			

2019/2021	**Top of corridor**			
Escalator	-2%	0%	1%	-1%
	6%	0%	0%	-1%
	2%	-2%	-1%	0%
	1%	-2%	-1%	-1%
	Bottom of corridor			

On the one hand, the difference in the cells next to the escalators has increased between 1% and 3%, whereas in 2021 it varied between 1% and 6%. On the other hand, the occupancy of cells close to the elevator (i.e. wall) in general decreased during the pandemic, as well as for the cells in the middle of the corridor. These differences seem rather small and a conclusion cannot be drawn with respect to a change in the spatial distribution during the pandemic because of physical distancing. However, the results in Table 5.2 could suggest a variation in the types of passengers who walk through the corridor, whereby most of them need to use the escalators rather than only crossing from one side to the other one.

Furthermore, the difference between the mean occupancy in each year and the occupancy of each cell is investigated. This difference is described by the following equation:

$$\delta_{i/\mu,Y} = Occ_{i,Y} - Occ_{\mu,Y} \qquad [\%] \tag{5.3.2}$$

Where $Occ_{i,Y}$ is the occupancy of cell i in year Y (i.e. 2019, 2020 and 2021), while $Occ_{\mu,Y}$ is the mean occupancy in year Y. The results are shown in Table 5.3, in which it can be observed that the occupancy of the cells next to the escalators has increased, whereas a decrease in the cells next to the elevator is observed. These findings are similar to the one shown in Table 5.2 and thus also suggest a change in the types of passengers. Nonetheless, the differences are rather small and it cannot be concluded whether there is a change in the spatial distribution caused by different types of passengers.

Table 5.3: Difference as a percentage of the spatial distribution in each year with respect to their corresponding mean: Green indicates greater values than the mean and yellow lower values than the mean

2019	**Top of corridor**			
Escalator	3%	1%	-1%	-3%
	0%	3%	0%	-2%
	-3%	1%	0%	-1%
	-1%	2%	0%	0%
	Bottom of corridor			

2020	**Top of corridor**			
Escalator	1%	1%	0%	-2%
	1%	1%	0%	0%
	1%	0%	0%	-1%
	0%	0%	0%	-2%
	Bottom of corridor			

2021	**Top of corridor**			
Escalator	1%	1%	1%	-4%
	6%	3%	0%	-3%
	0%	0%	-1%	-1%
	-1%	0%	-1%	-1%
	Bottom of corridor			

Based on these results, changes in the awareness of pedestrians cannot be concluded given the small variations in the spatial distribution between the three years. Taking this into account, the results might suggest that given the reduction in the occupancy of the cells in the middle of the corridor, pedestrians would prefer walking on the sides of the corridor to avoid close interactions with others. Moreover, one can also observe that there has been an increase in the occupancy of the cells next to the escalators and a reduction of the remaining, which suggests that most of the pedestrians using the corridor are only doing so to use the escalators. This variation in the types of passengers can indicate that there is a change in the route choice (tactical level) as a greater share of pedestrians walking through the corridor would correspond to the ones choosing the escalators.

Speed distribution over space

The speed distribution over space provides information of the aggregate behaviour of pedestrians walking through the corridor. The mean speed is calculated for each of the cells considering all the pedestrians who occupy them at a given time step. A different speed distribution over space during the pandemic will provide insight into the changes in the awareness of pedestrians, since a less even distribution of speed would indicate that pedestrians change more often their speed with the objective of keeping a larger distance from each other. Table 5.4 shows the resulting speed distribution within the corridor.

Table 5.4: Speed in each cell within the corridor and for each each year [m/s]

2019	**Top of corridor**			
Escalator	1.38	1.48	1.42	1.30
	1.50	1.62	1.63	1.40
	1.44	1.51	1.32	1.38
	1.27	1.34	1.34	1.37
	Bottom of corridor			

2020	**Top of corridor**			
Escalator	1.52	1.40	1.46	1.29
	1.56	1.74	1.77	1.41
	1.23	1.35	1.45	1.31
	1.18	1.23	1.35	1.35
	Bottom of corridor			

2021	**Top of corridor**			
Escalator	1.13	1.20	1.32	1.19
	1.19	1.26	1.21	0.99
	1.24	1.27	1.33	1.28
	1.20	1.28	1.27	1.31
	Bottom of corridor			

Furthermore, Table 5.5 shows the difference in the percentage of the speed in each cell with respect to the mean speed over all the cells. Whereas in 2020 the speed differs significantly in most of the cells with respect to the mean (μ= 1.41 m/s), in 2021 the speed is more evenly distributed over the corridor given that the speed in them is close to the mean (μ= 1.23 m/s). Moreover, the mean speed over all the cells in 2020 has not changed with respect to 2019 (μ= 1.41 m/s), whereas in 2021 the mean speed has experienced a decrease. Therefore, on the one hand, there is a less even distribution of the speed in 2020 with respect to 2019, and this might indicate that pedestrians vary their speed more often in order to keep a larger distance from each other. On the other hand, the large deviation of the mean speed in 2021, compared to the mean of 2019, suggests a different walking behaviour as a result of different types of passengers using the corridor. In particular, these pedestrians are the ones who choose using the escalators, since the cells next to them are the ones with the lowest speed, which might imply that the density in them is high enough that people would need to reduce their walking speed. Lastly, the differences found between the three years with respect to this metric are significant given that an AD test (Table A.1) showed that the speed distribution over space of a year is significantly different from the other two years.

Table 5.5: Difference as a percentage of the speed in each cell with respect to the mean speed in each year: Green indicates a greater speed than the mean and yellow a lower speed than the mean

2019	**Top of corridor**			
	-3%	5%	0%	-9%
Escalator	6%	14%	15%	-2%
	1%	6%	-7%	-3%
	-10%	-6%	-5%	-3%
	Bottom of corridor			

2020	**Top of corridor**			
	8%	-1%	3%	-9%
Escalator	11%	23%	25%	0%
	-13%	-4%	2%	-7%
	-17%	-13%	-5%	-4%
	Bottom of corridor			

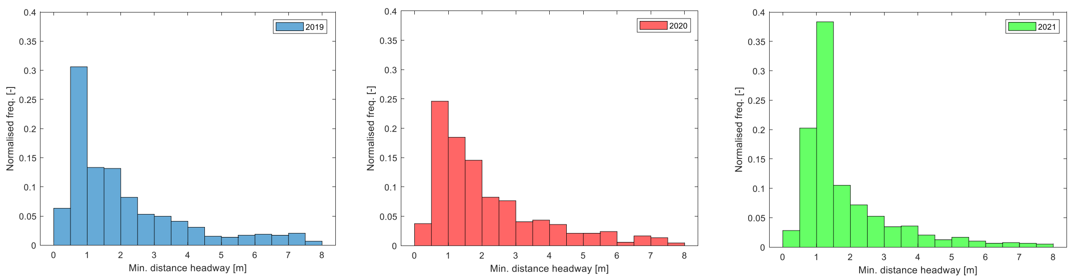
2021	**Top of corridor**			
	-8%	-3%	8%	-3%
Escalator	-3%	3%	-1%	-19%
	0%	3%	8%	4%
	-2%	4%	4%	7%
	Bottom of corridor			

In conclusion, an increased awareness of pedestrians can be inferred because of the larger variation of speed in 2020 compared to 2019, as stated in the second hypothesis (Section 3.3). Similarly, a large variance of the speed, as expected according to the third hypothesis, is true in 2020 given the deviation between the speed of each cell and the mean speed. However, in 2021 this variation decreased and a more evenly distribution of the speed over the corridor was observed. Therefore, these unexpected changes might be a result of different types of pasengers, mainly pedestrians with the intention of using the escalators, rather than less awareness to their surroundings.

Minimum distance headway

The study of the first hypothesis which states that pedestrians keep a larger distance during COVID-19 than before is carried out by looking at the minimum distance headway between pedestrians within the corridor. This metric is computed according to the description made in Section 3.5.3, thus it involves the viewing angle and viewing range of the pedestrians under analysis. According to the first hypothesis, the average minimum distance headway computed with the data of 2020 and 2021 will be larger than the one corresponding to 2019 and , moreover, the distribution of this metric will provide insight into the compliance of a prescribed physical distance of 1.5 m.

Figure 5.6 shows the histograms of the distribution of the 5th percentile of the minimum distance headway of pedestrians in each year for which a similar demand has been considered. In 2019 (Figure 5.6a) half of pedestrians in the corridor would keep a distance lower than 1.5m, in 2020 it was around 45% (Figure 5.6b), whereas in 2021 it increased up to 62%. On the one hand, this shows that pedestrians did not fully comply with the physical distancing rule when all measures were in force in 2020, as well as in 2021 when there was a relaxation of some measures except for the physical distancing. On the other hand, one can observe that fewer pedestrians accepted a distance shorter than 1 m during the pandemic, while the distance between 1m and 1.5m increased during the last two years, particularly in 2021 when this range of distance headway had the largest share.



(a) MD in 2019 (b) MD in 2020 (c) MD in 2021

Figure 5.6: Minimum distance headway (MD) in corridor

By looking at the mean of the minimum distance headway in Table 5.6, one can note that the minimum distance headway slightly increased in 2020 with respect to 2019. However, contrary to what was expected, the minimum distance headway in 2021 was lower than in previous years. Moreover, an AD test (Table A.2) was conducted in order to know whether there is a significant difference among the years, which showed that the samples are drawn from different distributions and thus they are significantly different. However, one can argue that the difference between 2019 and 2020 is not meaningful as there is a small difference in the mean and their standard deviations are relatively high. Thus, it can be concluded that the minimum distance headway has not changed as stated in the first hypothesis.

Table 5.6: Mean and Std of minimum distance headway

	Mean [m]	**Std [m]**
2019	2.09	1.77
2020	2.15	1.65
2021	1.83	1.39

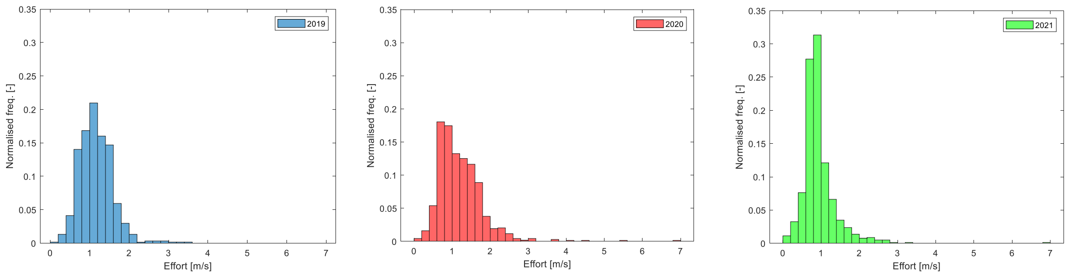
Even though the average minimum distance headway in 2020 is similar than before the pandemic, the results suggest that pedestrians were more conservative with respect to the distance between each other as fewer people walked with a distance shorter than 1.5 m. Moreover, the number of pedestrians with a minimum distance headway between 1 m and 1.5 m has increased during the pandemic, which can be observed for 2021 (Figure 5.6c) in particular. This might imply that pedestrians have in fact intended to comply with the prescribed distance. However, being aware of the distance with respect to others might have led to shorter distances than they intended to keep. As a result, one could argue that pedestrians tend to overestimate the interpersonal distance between themselves and any other individual. Furthermore, the shorter average minimum distance headway in 2021 in comparison to the previous years might also be as a result of an adjustment of the distance kept between pedestrians in order to be closer to the prescribed one. This change in their behaviour might have been triggered by the relaxation of more measures during the last year.

In conclusion, the results suggests that the first hypothesis is not rejected, since the mean minimum distance headway was above the prescribed physical distance of 1.5 m. Moreover, a full compliance of a prescribed physical distance of 1.5 m has not occurred, although a decrease in the share of people with a distance shorter than 1.5 m suggests that pedestrians were willing to do so. The reasons for a lack of full compliance and the difference observed between 2020 and 2021 might be various. Firstly, the relaxation of measures and tiredness might have resulted in less attention to keeping the prescribed distance. Secondly, the type of pedestrians using the train station might have varied through the years leading to a different walking behaviour. Thirdly, pedestrians might have preferred to walk at a short distance for a short period of time to overtake others rather than queuing and respecting a 1.5 m distance, particularly given the short length of the corridor. Lastly, more groups of people from the same household might have used the corridor in 2021 with respect to the previous years given that they do not need to keep the prescribed physical distance and therefore its impact can be observed in a lower mean for the minimum distance headway.

Effort

The study of the second and third hypotheses is done by the computation of the effort as it provides information regarding the direction of movement as a consequence of the presence of others within the corridor and get insight into the change of speed. As a result, conclusions can be drawn regarding the awareness and variance in velocity of pedestrians.

In Figure 5.7 the effort distribution for the three years of interest is shown. These distributions show that the frequency of values around 1 m/s is greater in 2021 than in 2019 and 2020. Moreover, by observing the mean and standard deviation in Table 5.7, the effort in 2020 is higher than before the pandemic, but lower than in 2021. According to the second and third hypotheses, pedestrians change more often their velocity (third hypothesis) provided that they are more aware of their surroundings (second hypothesis) and thus continuously look for open spaces with the aim at keeping a larger distance headway. The results for the effort in 2020 are in accordance with these hypotheses as pedestrians were changing their velocity more often while traversing the corridor. However, the effort in 2021 decreased to a value lower than the one of 2019, which is opposite to what was expected, given that it reveals that pedestrians had a more constant and linear movement within the corridor. The latter behaviour in 2021 can be related with less awareness of pedestrians and a shorter minimum distance headway kept in that year, since one can assume that shorter distance headways occurred as a result of fewer changes in the direction of movement (i.e. low effort) compared to 2019 because they paid less attention to their surroundings.



(a) Effort distribution in 2019 (b) Effort distribution in 2020 (c) Effort distribution in 2021

Figure 5.7: Effort distribution in corridor

Similar to the minimum distance headway, the difference between the effort in 2019 and 2020 is small. However, the AD test (Table A.3) showed that the differences between the samples with which the effort has been obtained are not drawn from the same distribution and thus they are significantly different.

As for effort, the unexpected result for 2021 can be explained by a reduced attention to the distance headway and an adjustment of the distance headway in order to be closer to 1.5 m. Hence, during 2020 one could conclude that pedestrians were more aware of their surroundings and as a result they kept a larger distance, whereas in 2021 their awareness might have decreased which resulted in less changes in their speed and direction of movement. Similarly, the third hypothesis would be accepted in 2020, but rejected in the scenario of 2021 in which the velocity is shown to be more constant. Furthermore, although this metric provides information regarding the change in velocity, a conclusion of whether there is a greater effect of the change of direction rather than speed (or vice-versa) cannot be drawn.

Table 5.7: Mean and Std of effort

	Mean [m/s]	**Std [m/s]**
2019	1.16	0.43
2020	1.21	0.61
2021	0.94	0.46

In conclusion, the effort is observed to slightly increase in 2020 with respect to 2019, but in 2021 the effort decreased to even lower values. As a result, with respect to the second hypothesis, these results would suggest that pedestrians through the pandemic have reduced their awareness regarding the distance kept from others, provided that their direction of movement did not change much in 2021 when compared to 2020. Moreover, regarding the third hypothesis, a higher effort in 2020 and lower effort in 2021 suggest that the velocity variance was higher than in 2019 in the former and lower in the latter. However, one cannot conclude on the reasons that lead to the opposite behaviour observed in 2020 and 2021. Some factors such as the lack of willingness to comply with the prescribed physical distance, different types of passengers, or a greater number of groups can result in the behaviour observed by means of the effort.

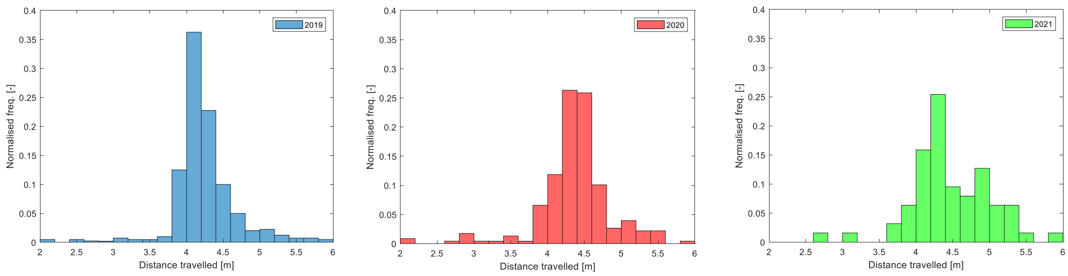
Travel distance

The distance travelled by pedestrians is a metric that can provide information on whether they keep a larger distance between them as a larger walking distance would suggest that pedestrians deviate more often from the most direct path and that physical distancing would be the cause of this change. Furthermore, this metric can provide further information to answer the second hypothesis.

Table 5.8: Mean and Std of travel distance

	Mean [m]	Std [m]
2019	4.24	0.59
2020	4.44	0.58
2021	4.46	0.55

As shown in Table 5.8, the mean travel distance has increased during the pandemic, this being similar in 2020 and 2021. Moreover, Figure 5.8 shows the distribution of the travel distance in each year, in which one can observe that the frequency of walking distance larger than 4.5 m has increased during the pandemic, as well as distances larger than 5 m have been more frequent, particularly in 2021 (Figure 5.8c).



(a) Travel distance in 2019 (b) Travel distance in 2020 (c) Travel distance in 2021

Figure 5.8: Travel distance in corridor

The results of the AD test (Table A.4) showed that the distribution of the travel distance in 2019 differ significantly from the ones during the pandemic, whereas the difference between 2020 and 2021 does not, which might suggest that the physical distancing is in fact leading to longer distances walked by pedestrians within the corridor.

In conclusion, the distance travelled by pedestrians within the corridor has significantly changed and increased during the pandemic. Such increase would indicate that physical distancing has influenced the walking behaviour of pedestrians given that more deviations from their most direct path occurred. Therefore, this provides insight into the awareness of pedestrians during the pandemic which would result to be larger than in 2019. Moreover, a larger distance travelled suggests that pedestrians might be willing to reduce their interaction at short distances with others. This would indicate that an impact of the physical distancing on the route choice (tactical level) is possible, since pedestrians might prefer taking longer routes with the aim of reducing interactions and distances shorter than 1.5 m.

5.4 Conclusions

In this chapter, an analysis of the trajectory data from a corridor at Utrecht Central station was conducted to study the walking behaviour of pedestrians in bidirectional straight flows and its changes because of the physical distancing. To do so, metrics at the macroscopic and mesoscopic levels have been chosen such that information can be retrieved concerning the aggregate and underlying behaviour of pedestrians.

The analysis of the data showed that the demand has clearly decreased during the pandemic and, although the demand in 2021 experienced an increase, this was still lower than precorona levels. Moreover, given the expected impact of the demand on density and thus on the walking behaviour, the decision was made to analyse a different time of the day for each year in which a similar demand was found. Moreover, the impact of the type of passengers was taken into account by choosing data from a Saturday as a similar type of passengers is assumed to use the station during the day.

The relationship between density and flows appeared to be similar among all three years, and in none of which the capacity was reached. Thus, pedestrians walked in free flow conditions during the time of the day with the highest demand in 2020. A similar demand to 2020's was considered for the other years to analyse and compare the walking behaviour.

Regarding the first hypothesis, the analysis of the minimum distance headway indicates that it cannot be rejected, given that the mean minimum distance headways in both years have been greater than 1.5 m. Moreover, the distribution of this metric showed that the physical distancing was not fully complied during the pandemic, but there was a decrease in the share of pedestrians walking at a distance shorter than 1.5m from others and an increase of pedestrians walking at a distance similar to the prescribed one. This implies that pedestrians tried to keep the prescribed physical distance.

With respect to the second hypothesis, the answer varies based on the year in which the behaviour is analysed. In 2020, the hypothesis is not rejected given that a higher awareness is suggested by a less even distribution of speed and a higher effort, which implies that more changes in the direction of movement occurred. However, the hypothesis is rejected when the behaviour in 2021 is analysed given that the speed was more evenly distributed over the space and the effort was lower than the one observed before the pandemic. Thus, these results imply a decrease of the awareness of pedestrians.

Concerning the third hypothesis, the answer is the same as for the second hypothesis. In 2020, the hypothesis is not rejected given that the results for the speed distribution over space and effort showed a larger variance of the speed and direction of movement, while in 2021 the hypothesis is rejected, since the speed was more evenly distributed over the space and the effort was lower than in 2019 which indicates a less variability of the velocity.

Furthermore, the results obtained with the spatial distribution showed that this metric did not provide relevant information to answer the hypotheses, since the differences between the years were very small and thus insignificant. Nonetheless, the results might suggest a change in the route choice as a greater share of pedestrians walking through the corridor would correspond to the ones choosing the escalators. Similarly, a longer travel distance during the pandemic would indicate a different route choice to avoid interactions at short distances.

The information provided by the walking behaviour analysis has provided insight into the impact of physical distancing and thus it will form the basis for defining the scenarios and determining the metrics for the calibration according to the behaviour that is of interest to reproduce more accurately with the model.

Chapter 6

Calibration

This chapter discusses the calibration of Pedestrian Dynamics using individual and multiple objectives in order to analyse the influence of the scenarios and metrics used for the calibration. Moreover, the results aim at providing insight into the capability of the model to reproduce the walking behaviour observed in the reference data which was studied in Chapter 5.

The chapter covers the following elements: Section 6.1 describes the methodology, in which the elements of the calibration framework and the procedure to perform the calibration are explained. In Section 6.2 the analysis of individual objectives is conducted to determine how well the model can reproduce the reference data for a specific scenario and metric. Section 6.3 discusses the calibration with combined objectives to determine the optimal parameter sets for each combination of scenarios and metrics. Finally, in Section 6.4 the calibrations results and their implications with respect to the capabilities of the model to reproduce the reference data are discussed.

6.1 Calibration methodology

In this section, the methodology to conduct the calibration is described. This entails a description of each of the elements that are part of the multiple objective calibration shown in Figure 6.1.

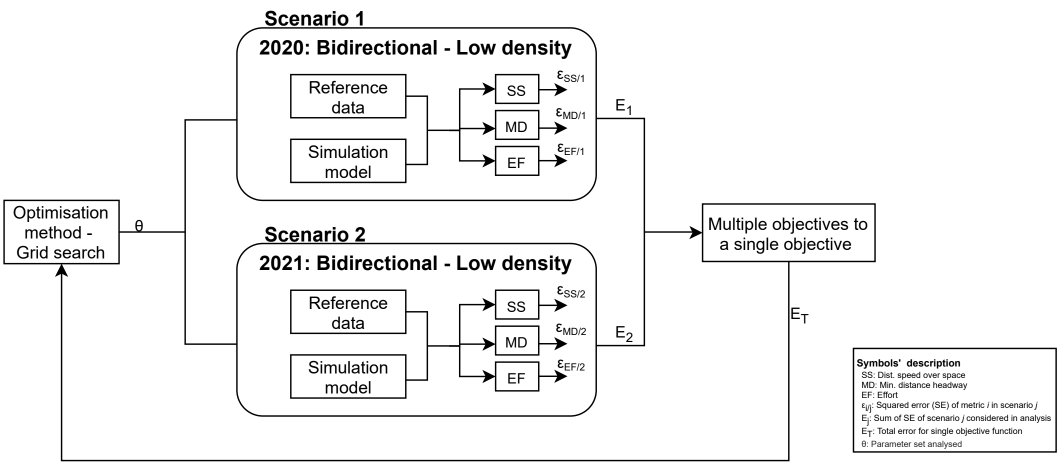


Figure 6.1: Multiple objective calibration framework with elements to consider in this research

Some of these have already been discussed in previous chapters, thus a description of the aspects which are specific for the calibration will be discussed in this section. In Section 6.1.1 the scenarios, reference data and simulation models used for the calibration are described, while the selected metrics are explained in Section 6.1.2. Moreover, the objective functions are discussed in Section 6.1.3, the optimisation methods and stopping criteria in Section 6.1.4, and the hypotheses to define the parameters that form the search space in Section 6.1.5.

6.1.1 Scenarios, reference data and simulation

Based on the data available for this research, the calibration will be performed for the corridor for which the walking behaviour was assessed in Chapter 5. This corresponds to the corridor within the elevator and escalator towards the platforms 18/19 at Utrecht Central, and the movement base case of interest in this corridor will be the bidirectional straight.

Scenarios

According to the results found in Chapter 5 the demand during the pandemic has been very low (0.20 p/m/s) and thus only free flow conditions have occurred. Therefore, only low density scenarios will be considered for the calibration, which implies that the optimal parameter sets of the calibrated model will not be suitable for high-density scenarios. Moreover, although the walking behaviour was assessed for a similar demand in each year, the decision has been made to consider the year as a specific element of each scenario, since significantly opposite results have been obtained for the metrics in each year with respect to 2019. Thus, two scenarios are defined, which consist of bidirectional flows with low density levels for the years 2020 and 2021. These scenarios are summarised in Table 6.1.

Table 6.1: Scenarios for calibration based on movement base case, year of data, and density level

Movement base case	**2020**	**2021**	**Density level**
Bidirectional straight flow	x		Low
Bidirectional straight flow		x	Low

Reference data

The reference data that will be used to calculate the metrics explained in Section 6.1.2 consists of three periods of ten minutes each, which are drawn from the one-hour period discussed in Section 5.3. Within each of these periods, the demand and density is approximately the same in 2020 and 2021, so that one can control for these factors and hence limit their impact on the observed pedestrian's walking behaviour. Furthermore, the presence of escalators yields the outflow to be different than the inflow in the corridor. In order to ensure a uniform outflow from the escalators, the analysed periods have been selected such that the outflow from them is constant over the three years. Thus, OD pairs have been obtained from the reference data for each 10-minute period in order to obtain the mean OD pair for each year, which are shown in Table 6.2.

Table 6.2: OD pairs (number of pedestrians) of each route in reference data for a 10-min period according to Figure 5.1

	2020				**2021**			
	Bottom	**Top**	**Esc_In**	**TOTAL**	**Bottom**	**Top**	**Esc_In**	**TOTAL**
Bottom	-	76	5	**81**	-	73	12	**85**
Top	55	-	23	**78**	57	-	7	**64**
Esc_Out	10	7	-	**17**	5	14	-	**19**

Simulation model

The geometry of the infrastructure observed in the reference data is reproduced in PD such that it represents the walkable area within the corridor and the location of the escalators and elevator on the sides of the corridor. The representation in PD is shown in Figure 6.2, in which the action area (i.e. green area) represents the corridor where the trajectories are evaluated and for which the calibration will be conducted.

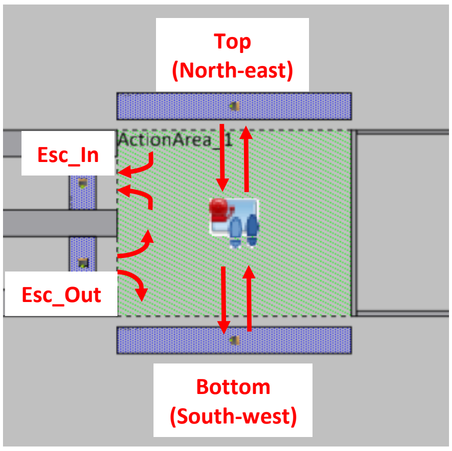
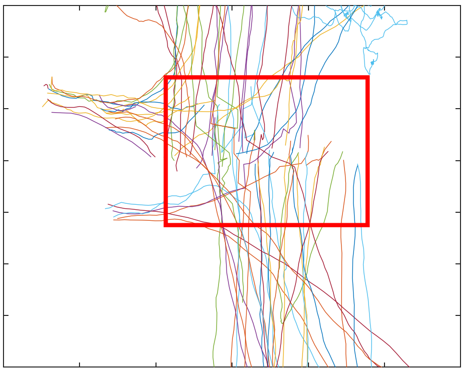
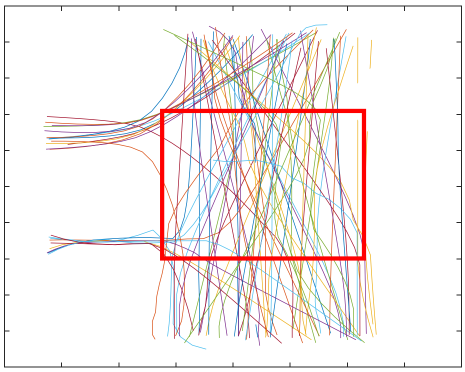


Figure 6.2: Design of corridor in PD

Moreover, in Figure 6.3 the trajectories obtained with the reference data (Figure 6.3a) and PD (Figure 6.3b) are depicted. Note that there is an offset to the right in the trajectories captured by the sensor, whose impact on the trajectories considered within the corridor has been controlled by increasing the measurement area in its horizontal axis.



(a) Trajectories in reference data



(b) Trajectories in PD

Figure 6.3: Trajectories within a corridor in the reference data and the model

Regarding the demand, this is determined based on the OD pairs obtained with the reference data, which are used as an input to the model for running the simulation of each of the parameter sets explained in Section 6.1.5 and shown in Appendix B. Thus, the demand for the simulation is obtained by modifying the OD pairs in Table 6.2 proportionally to the duration of the simulation so that to ensure the same flow though the corridor as in the reference data. For practical reasons, the simulation time chosen is 1.5 minutes such that the running time is reduced, which otherwise would be ten minutes as the period from which the trajectories have been collected. In Table 6.3 the resulting OD pairs for the simulation can be observed.

Table 6.3: OD pairs of each route in PD for a 1.5-min simulation time according to Figure 6.2

	2020				2021			
	Bottom	**Top**	**Esc_In**	**TOTAL**	**Bottom**	**Top**	**Esc_In**	**TOTAL**
Bottom	-	11	1	**12**	-	10	2	**12**
Top	8	-	4	**12**	8	-	1	**9**
Esc_Out	2	1	-	**3**	1	2	-	**3**

Regarding the route choice, as mentioned in Section 1.2, the assumption was made that the route choice is already made and therefore the analysis is focused on the behaviour at the operational level. Moreover, the global route choice is not considered in this research given that there is only one possible global route for each OD pair and factors that increase the cost of taking a particular route, such as the distance travelled or the travel time are not taken into account. For this reason, the route choice in PD is set to the shortest path as it is the least computationally heavy option.

Finally, in order to deal with the effect of the stochasticities, several replications need to be run for each of the parameter sets in the search space which is described in Section 6.1.5. Sparnaaij (2017) considered a fixed order of the seeds to deal with the stochasticity of the model, which yield in 100 replications for bidirectional scenarios; however, since in this research a fixed order is not considered, a higher number of replications will be taken into account. Thus, 300 replications are set to each parameter set.

6.1.2 Metrics

In Chapter 5 the analysis of the walking behaviour was performed by means of two macroscopic metrics (spatial distribution and speed distribution over space) and three mesoscopic metrics (minimum distance headway, effort, and travel distance). Among all these metrics, the speed distribution over space, minimum distance headway, and effort are selected for the calibration given that it was concluded from the walking behaviour analysis in Chapter 5 that these three provide relevant information regarding the behavioural changes because of physical distancing. Thus, they are considered the most relevant for the calibrated model to reproduce. Moreover, metrics that provide information about the pedestrians' flow at different aggregate levels are considered given that a simulation model calibrated based on a metric at one level provides unrealistic results at the other levels (Duives, 2016). The selected metrics for the calibration are described below:

Speed distribution over space

A macroscopic metric is important to be used in the calibration of PD given that the model is mostly used to obtain information of the aggregate behaviour of pedestrians. Furthermore, this metric aims at controlling for the behaviour at the macroscopic level to be realistic when calibrating the model.

This metric is calculated according to Equation 3.5.2 and Equation 3.5.3. However, while the time step of the reference data is 0.1s, the time step of the simulation is 0.2s; therefore, they need to match such data the results for this metric can be compared. This is done by interpolating the reference data rather than the simulation given that there are less points to be interpolated by doing so and, moreover, a loss of accuracy is considered to be better than artificially gaining it.

Once the time steps are the same in the reference data and simulation, the speed distribution over the space is computed as described in Section 3.5. It is important to note that in case of the simulation, the mean speed in each cell is calculated considering the speed distribution of all the replications.

Minimum distance headway

The minimum distance headway provides information at the mesoscopic level and it is relevant for the calibration as it provides the best insight into the distance that pedestrians have kept during the pandemic and the compliance of the prescribed physical distance.

This metric will be calculated according to Equation 3.5.4 and Equation 3.5.5. For both the reference data and simulation data, the 5th percentile of the minimum distance headway of each pedestrian/agent is combined into a single distribution for which the mean and standard deviation are calculated. Moreover, for the simulation data the distribution includes the measurements from all the replications.

Effort

The effort also provides relevant information regarding the variance of the velocity during the pandemic. This metric is calculated according to Equation 3.5.6. Similar to the speed distribution over the space, the size of the time step influences the results for this metric, thus the reference data is interpolated instead of the simulation. This will allow to compare the measurements obtained with the reference data and the simulation.

Furthermore, the effort is calculated for each pedestrian/agent according to Equation 3.5.6 and then all the individual results are combined into a distribution, which includes all the measurements from all replications in case of the simulation data.

For the simulation, given how the corridor is represented in PD (Figure 6.2), the period for the measurement of all metrics is considered from the start of the simulation provided that agents are always within the intended measurement area (i.e. corridor).

6.1.3 Single and multiple objective functions

This subsection describes the objective functions which will be used to determine the most optimal parameter set for each of the combinations to be considered in the calibration of PD.

The most optimal parameter set is obtained by choosing the one that yields the minimum objective function, since the smaller its value, the smaller the error. Thus, the best fit of the model to the reference data is obtained by using the parameter set that results in the smaller error for a specific combination of scenarios and metrics. Moreover, the study of several combinations in this research implies that multiple objective functions are considered and which need to be combined into a single objective function, as Duives (2016) and Sparnaaij (2017) did for the calibration of Nomad and PD, respectively. The combination into a single objective is performed according to the weighted sum method.

The combination of multiple objective functions entails the normalisation of the results of each metric given the difference in units, but also in the order of magnitude. In Duives (2016) and Sparnaaij (2017) two methods are presented for the normalisation. Whereas the former is based on the maximum error for a combination of scenario and metric, the latter is based on the ratio between the values of the metrics from the reference data. In this research the choice for the method presented by Sparnaaij (2017) is made as it deals with the assumption that the maximum error of a single combination of a scenario and a metric is equally wrong than the maximum error of another combination. Table 6.4 shows the normalised values of each metric and scenario, where the speed distribution over space is set to one and the ratio of the remaining metrics is set accordingly. However, given that different ratios are obtained per scenario, the choice is made to use as normalised values the mean ratio of the two scenarios per metric.

Table 6.4: Ratio between metrics per scenario and normalised mean values

	$\mathbf{M_{norm;20}}$	$\mathbf{M_{norm;21}}$	$\mathbf{M_{norm;mean}}$
Speed distr. over space	1	1	1
Effort - Mean	0.751	0.683	0.717
Effort - Std	0.420	0.353	0.387
Min. dist. headway - Mean	1.615	1.427	1.521
Min. dist. headway - Std	1.239	1.082	1.161

Hence, the objective function is the normalised squared error (SE) as shown in Equation 6.1.1 and Equation 6.1.2 for the macroscopic and microscopic metrics, respectively.

$$SE(\theta)_{macro} = \frac{1}{16}\sum_{i=1}^{16}\left(\frac{\frac{\sum_{r=1}^{r}(M(\theta)_{sim;i;r})}{r} - M_{ref;j}}{M_{norm}}\right)^2 \qquad (6.1.1)$$

$$SE(\theta)_{meso} = \frac{1}{2}\left(\frac{M_{sim;\mu} - M_{ref;\mu}}{M_{norm}}\right)^2 + \frac{1}{2}\left(\frac{M_{sim;\sigma} - M_{ref;\sigma}}{M_{norm}}\right)^2 \tag{6.1.2}$$

Where M_{sim} is the value of the metric from the simulation, M_{ref} is the value obtained from the reference data, M_{norm} is the normalised value of each metric, and θ is the parameter set.

In case of the speed distribution over the space (Equation 6.1.1), the speed per cell is the mean of a distribution which consists of the speed of all pedestrians within this cell in all the replications r. Moreover, given that the corridor is split into 16 cells, i in Equation 6.1.1 is the cell for which the mean for all replications is calculated, while 1/16 represents the contribution (i.e. error) of each cell to the total error. For this metric, the standard deviation is discarded as it is not considered to be relevant at the macroscopic level.

Regarding the mesoscopic metrics, SE is calculated based on the mean and standard deviation of the minimum distance headway and the effort. The mean and standard deviation each contribute half of the total error, thus 1/2 is assigned for each one of them in Equation 6.1.2.

Lastly, the multiple objectives are combined into a single objective according to the following equation:

$$OF(\theta) = \frac{1}{N_s * N_m}\sum_{1}^{s}\sum_{1}^{m} SE(\theta)_{s;m} \tag{6.1.3}$$

Where N_s and N_m correspond to the number of scenarios and metrics used in the analysis. Moreover, different weights are not assigned to the macroscopic and mesoscopic metrics as the aim is to calibrate the model equally for all of them. The parameter set that yields the smallest value for this objective function is the one with which the model best replicates the reference data. Thus, one could conclude that the Goodness of Fit of the model is the best to the data.

6.1.4 Optimisation method and stopping criteria

The optimisation method is the element of the calibration framework (Figure 6.1 responsible for defining a new parameter set to be tested and finding the most optimal parameters given the search space, where the parameter sets are defined.

There are several optimisation methods found in literature such as the following:

- Genetic algorithm, Greedy approach, Simulated annealing, Covariance matrix adaptation (Wolinski et al., 2014).
- Genetic algorithm + Simplex (Campanella, 2016).
- Grid search (Duives, 2016; Sparnaaij, 2017).

For the calibration conducted in this research the grid search is selected as the optimisation method because of the following reasons. Firstly, this method provides the global optimum given that it covers all the search space in order to find the parameter set that yields the minimum value for the objective function. Secondly, the grid search allows getting insight into the shape of the surface of the error space as a result of the metrics used in the calibration. This provides insight into how the error varies depending on the parameters and metrics used and how stable the solutions are. Lastly, this method is the most practical one given the available time for this research as it is easy to implement and the reliability provided by this method is considered sufficient for the intended calibration.

However, the disadvantages are also important to take into account as they result in some limitations when finding an optimal parameter set. On the one hand, the grid search has a great influence on the resulting optimal parameter set as only the points in the grid search are considered (Duives, 2016), thus it is not known how the solution might change in the space in between the analysed points. Thus, the accuracy of the results depends on the level of precision of the grid. On the other hand, this method is the slowest method among all as it explores all the points in the search space.

The stopping criteria determine if the optimal parameter set has been obtained or not, and it goes in hand with the optimisation method selected for the calibration. While some methods seem to use a criterion based on convergence after running subsequent iterations without finding a new optimal parameter (Wolinski et al., 2014), Sparnaaij (2017) describes other possibilities such as stopping when a minimum criterion is fulfilled or after a specific number of iterations is defined beforehand. However, provided that the grid search method will be used, a search space criterion is not necessary.

6.1.5 Hypotheses and search space

In Chapter 4 the model was concluded to be sensitive to changes in the relaxation time and the viewing angle as significant deviations were achieved for high-density scenarios, whereas for low-density scenarios, only the relaxation time was found to be relevant. Moreover, in Chapter 5 was found that the density levels below its critical value occurred during the pandemic and for which the assessment of the behaviour was conducted, as well as the following calibration will be.

Therefore, in principle, the search space should only consist of the relaxation time. However, as the behavioural analysis showed, an opposite behaviour was observed with respect to pre-corona behaviour in 2020 and 2021. For instance, the minimum distance headway and effort were higher in 2020 than in 2019, whereas in 2021 the values for the same metrics were lower than in 2019. Thus, additional metrics need to be considered provided that by tuning the value of one parameter will not be possible to reproduce the opposite behaviour described by the speed distribution over space, minimum distance headway, and effort in 2020 and 2021.

Hypotheses

The following hypotheses are formulated with the aim of describing the reasons for the difference in the walking behaviour during COVID-19, and hence determine the additional parameters that would allow replicating the aforementioned behaviour:

Hypothesis 1: ***The types of pedestrians during the pandemic in 2020 are different than in 2021***

In Section 5.3 the results for the spatial distribution and the speed distribution over space suggested that more people using the escalators chose to walk through the corridor in 2021 than in 2019 and 2020, whereas a shorter minimum distance headway in 2021 could indicate that more groups of people from the same household walk through it. Therefore, one could conclude that the type of pedestrians walking through the corridor might have changed during the pandemic.

Hypothesis 2: ***Pedestrians adjusted their measured physical distance to be closer to 1.5 m in 2021 than at the beginning of the pandemic***

The distribution of the minimum distance headway (Section 5.3) showed that the share of a distance headway between 1 m and 1.5 m increased up to 39% in 2021, while in 2019 and 2020 it was 13% and 18%, respectively. Therefore, one can assume that pedestrians adjusted their distance to be closer to the prescribed one, which has resulted in somewhat shorter distances as they tend to overestimate their measured distance.

Hypothesis 3: ***The awareness of pedestrians to the distance kept from each other decreased in 2021 with respect to 2020***

Another reason for the increase of the share of a minimum distance headway below 1.5 m can also be a decrease in the awareness of pedestrians in 2021. As a result, the interaction of pedestrians at short distances might have increased resulting in a lower mean for the minimum distance headway, as well as for the effort given that the results showed less deviation from the most direct path in 2021 with respect to the previous years.

Provided the factors stated in these hypotheses that might have led to the difference in the behaviour during the pandemic, two additional parameters are selected for the calibration in addition to the relaxation time.

The first one is the viewing angle, since a deviation from its default value could describe the changes in the awareness and direction of movement that pedestrians might have experienced during the pandemic as a result of the relaxation of measures, walking in groups, or differences in the type of passenger who used the station during COVID-19.

The second parameter needs to be selected such that changes in its value could allow to describe short distance headways either as a result of an adjustment of the prescribed physical distance or because of a decrease in the awareness. On the one hand, the parameter physical distance was chosen to describe the distance kept by pedestrians in the sensitivity analysis (Chapter 4); however, the results of the qualitative assessment (Section 4.2 showed that the assumption of a strict distance between pedestrians provided by this parameter does not yield a realistic behaviour for bidirectional straight flows in narrow corridors. On the other hand, the parameter personal distance was initially not considered given its limitations such as it only takes into account pedestrians ahead and is ignored in queues. Nonetheless, the personal distance provides more flexibility regarding the distance pedestrians can keep from each other and changes in its default value can describe the distance headways observed during the pandemic. Therefore, personal distance is chosen as one of the parameters for which the calibration will be conducted in this chapter.

Search space

Based on the relaxation time, viewing angle, and personal distance, the search space is defined as follows:

- For all three parameters, an upper and lower deviation from the default value is considered. This will provide a bigger search space in which it will be more likely to find the optimal parameter values for the opposite behaviour observed during the pandemic.
- The upper and lower boundaries for all three parameters correspond to a deviation of ±24% from their default. These boundaries are in accordance with the maximum deviation considered in the sensitivity analysis. The results of the calibration would allow determining whether the optimal parameter set falls inside this range or not.
- The size of the step from the default value is set to 6%. Although similar studies consider smaller step sizes (Sparnaaij, 2017), in this research is opted for 6% because of time constraints, since the smaller the deviations, the greater number of simulations would be needed to run during the grid search.

In Table 6.5 the default values, and the upper and lower boundaries of the parameters that define the search space are shown.

Table 6.5: Search space

	Lower value	**Default value**	**Upper value**	**Step size**
Relaxation time [s]	0.38	0.50	0.62	6%
Viewing angle [°]	57	75	93	6%
Personal distance [m]	0.38	0.50	0.62	6%

6.2 Analysis of individual objectives

This section discusses the findings of the individual objectives, which correspond to a single combination of one scenario and one metric to get insight into the accuracy of the model to reproduce the behaviour observed in the reference data given a certain metric and search space. Moreover, the results in this section can provide insight into how each metric shapes the error space and draw conclusions on the stability of the calibration and on whether the optimal parameter set falls within the search space.

6.2.1 Analysis of error variability per metric

In this subsection, the variance of the error of the simulation with respect to the reference data is analysed to gain insight into the impact of the parameter set on the error. Moreover, the overestimation or underestimation of the results obtained with the model is evaluated by considering the non-squared and non-normalised error (M_{sim} - M_{ref}). The distribution of the errors are shown as box plots consisting of 729 points each (i.e. number of parameter sets) in order to analyse the error's variance.

Speed distribution over space

Provided that the corridor is split into 16 cells, each of them with their corresponding speed, the error per parameter set is obtained by computing the error of each cell in the simulation with respect to the same cell in the reference data, and then taking the average of the absolute error over all the cells. The results are shown in Figure 6.4. Moreover, given that the average absolute error is considered for this metric, all values are positive, thus the overestimation or underestimation of the model cannot be observed.

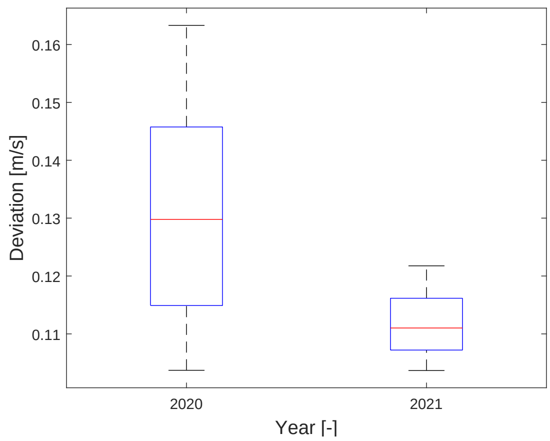


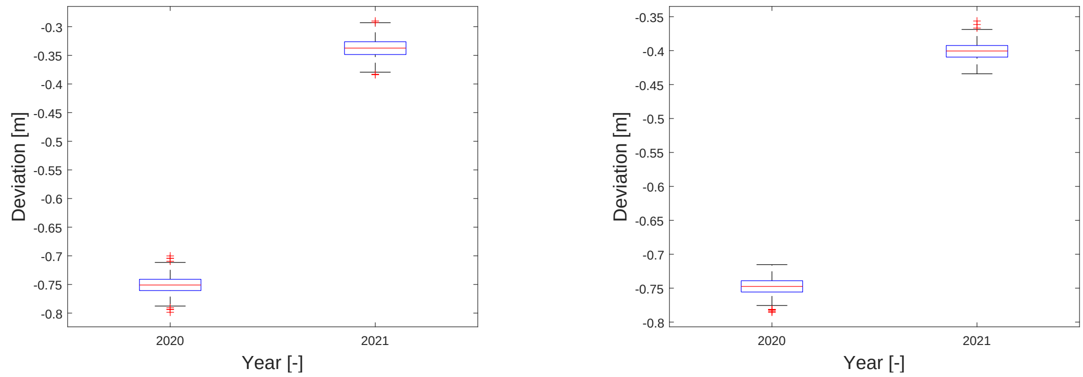
Figure 6.4: Box plots of the non-squared and non-normalised errors for the mean of the speed distribution over space

The results show that the errors are in general larger in 2020 than in 2021 and, moreover, there is a larger variation of the error in 2020 computed with each parameter set compared to 2021. As a result of this variation between the scenarios, one could expect that the error space surface is less flat in 2020.

Minimum distance headway

Figure 6.5 shows the error distribution of the mean and standard deviation of the minimum distance headway. The results show that both the mean and standard deviation of the two years are underestimated by the model. Moreover, one can observe that the difference between the maximum and minimum error is approximately 0.1 in both years, thus the error space surface can be expected to be equally flat in both years.

Similar to the speed distribution over space, the model appeared to fit more closely to the data of 2021 ($\mu_{sim_{21}}$ - $\mu_{ref_{21}}$ = - 0.35) than of 2020 ($\mu_{sim_{20}}$ - $\mu_{ref_{20}}$ = - 0.75). Moreover, by computing the relative error (M_{sim}/M_{ref} - 1), the minimum distance headway in 2021 is underestimated by around 19%, whereas in 2020 it is by 33%. These differences suggest that the model best reproduces short distance headways, since the walking behaviour assessment in Chapter 5 showed that the minimum distance headway in 2021 was the shortest of all three years.

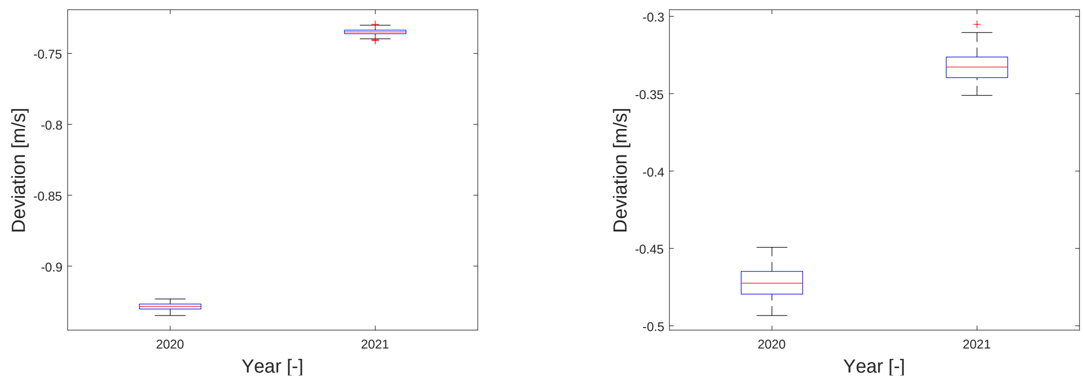


(a) Mean (b) Standard deviation

Figure 6.5: Box plots of the non-squared and non-normalised errors for the mean and standard deviation of the minimum distance headway

Effort

In Figure 6.6 the absolute error for the effort is depicted. The results show that the model underestimates the mean effort and the standard deviation in 2020 and 2021, being the former year with the largest deviation with respect to the reference data. Thus, the simulation of the effort distribution fits more closely to the data of 2021 ($\mu_{sim_{21}}$ - $\mu_{ref_{21}}$ = - 0.70) than 2020 ($\mu_{sim_{21}}$ - $\mu_{ref_{21}}$ = - 1.0). However, the relative error of the mean effort in 2021 (85%) shows a large deviation with respect to the reference data, and given the standard deviation, it is unlikely that the model could fit the reference data.



(a) Mean (b) Standard deviation

Figure 6.6: Box plots of the non-squared and non-normalised errors for the mean and standard deviation of the effort

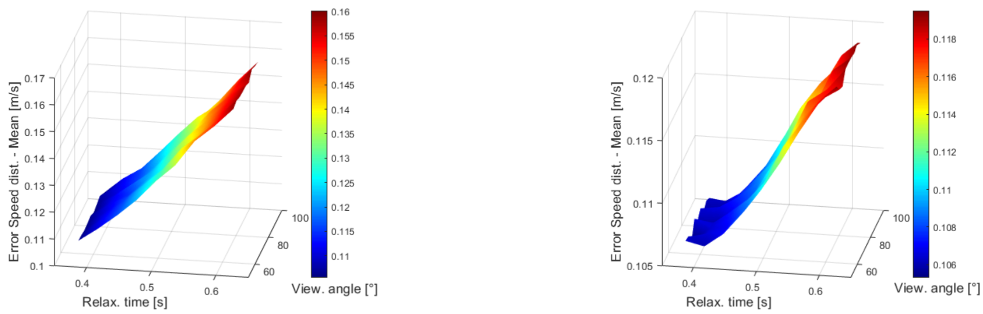
Furthermore, the difference between the maximum and minimum error is approximately the same in both years (i.e. 0.02), which occur for both the mean and standard deviation, thus one can expect that the error space surface is equally flat in both years.

6.2.2 Analysis of the error space

The results from the previous subsection can be used to get insight into how the metrics used for the calibration shape the error space and its variability as a consequence of the parameter set used for the scenarios in the model. In this subsection, the analysis of the error space shape is studied to determine whether the size of the search space is large enough such that the most optimal solution can be found in it, and how relevant the parameters are to reproduce the behaviour observed in each of the scenarios.

Relaxation time - Viewing angle

Regarding the speed distribution over the space, the surfaces obtained for both years (Figure 6.7) result in a decreasing plane in which the smallest error and thus better fit to the data corresponds to values of the relaxation time below the default, regardless of the value of the viewing angle. Small errors for low values of the relaxation time imply a higher acceleration rate and thus faster reactions of agents. Furthermore, the optimal parameter sets correspond to the lower boundary in both years.



(a) 2020 (b) 2021

Figure 6.7: Error of the mean speed distribution over space in relation with the relaxation time and viewing angle

With respect to the minimum distance headway, small changes in behaviour are observed in both years given the rather flat plane observed in Figure 6.8. Thus, a clear direction in which to look for the lower error is not possible, although in 2021 (Figure 6.8b) the error seems to be lower for values near the lower boundary of the relaxation time and the default of the viewing angle. Furthermore, there is a small difference (4 cm) between the smallest and largest error in both years, which suggests that regardless of the values given for these parameters, the model yields similar results.

(a) 2020 (b) 2021

Figure 6.8: Error of the mean minimum distance headway in relation with the relaxation time and viewing angle

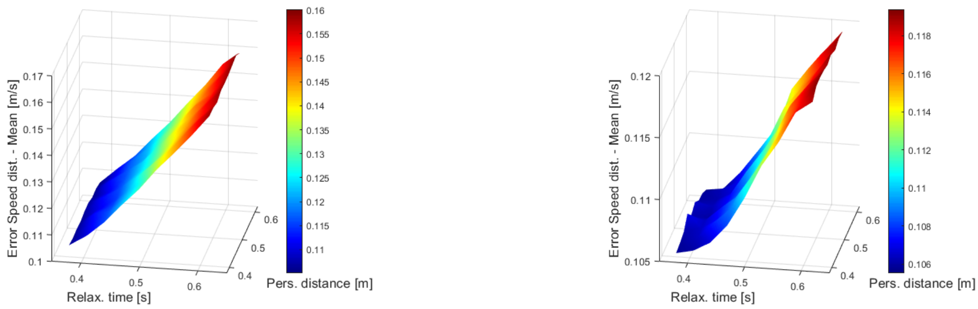
The results of the effort in Figure 6.9 also show a decreasing plane as for the speed distribution over space. Similarly, the lowest error are found at the lower boundary of the relaxation time irrespective of the viewing angle. Moreover, the surface of 2021 (Figure 6.9b) is nearly horizontal for values below the default of the relaxation time, which indicates that the error computed with these values are approximately the same within this range for the relaxation time and any given value for the viewing angle. Lastly, regarding the viewing angle, in Figure 6.9a one can observe a rather constant gradient of the plane for any given value of the viewing angle, whereas in Figure 6.9b the gradient reduces as the relaxation time approaches to its lower boundary. Note that the error is negative given that the mean effort of the reference data is greater than the mean effort of the simulation data.

(a) 2020 (b) 2021

Figure 6.9: Error of the mean effort in relation with the relaxation time and viewing angle

Relaxation time - Personal distance

The surface of the speed distribution in 2020 (Figure 6.10a) and 2021 (Figure 6.10b) is a decreasing plane in which the smallest error can be observed for small values of the relaxation time regardless of the personal distance. Thus, the best fit correspond to values lower than the default of the relaxation time. Moreover, the gradient of the plane is rather constant, which indicates that the error uniformly increases/decreases for any given value of personal distance.

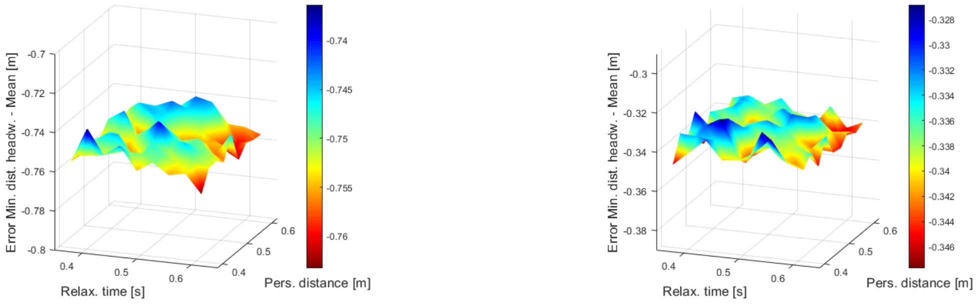


(a) 2020 (b) 2021

Figure 6.10: Error of the mean speed distribution over space in relation with the relaxation time and personal distance

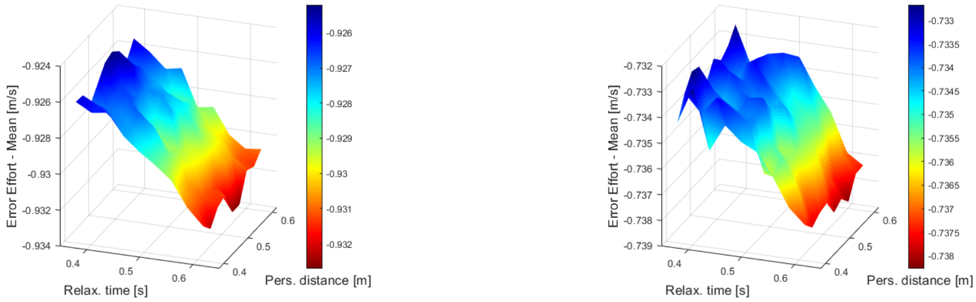
The results for the minimum distance headway (Figure 6.11) show that a conclusion cannot be drawn regarding the values for the relaxation time and personal distance that lead to the lowest error. Moreover, a difference of 3 cm is found between the smallest and largest error (i.e. flat surface), which suggest that similar results are found for different values of the relaxation time and personal distance within the search space.

Based on the shape of the error space for the effort (Figure 6.12) one can observe similar results as for the speed distribution over space with respect to the relaxation time (i.e. decreasing plane). However, in both years the gradient of the plane is not constant and thus the error does not increase/decrease very uniformly if one looks at a specific value of the personal distance. Moreover, in 2021 (Figure 6.12b) the slope between the lower boundary and the default of the relaxation time is less steep and thus similar errors are encountered within this range in comparison to the slope observed in 2020 (Figure 6.12a).



(a) 2020 (b) 2021

Figure 6.11: Error of the mean minimum distance headway in relation with the relaxation time and personal distance

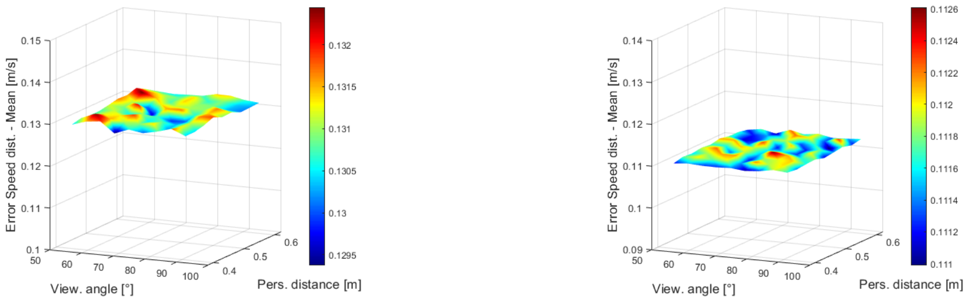


(a) 2020 (b) 2021

Figure 6.12: Error of the mean effort in relation with the relaxation time and personal distance

Viewing angle - Personal distance

Regarding the speed distribution over space, Figure 6.13 shows a rather flat surface in which similar errors are found over the space irrespective of the values of the viewing angle and the personal distance. Moreover, a difference of less than 0.01 m/s is observed in both years, which is not relevant to determine the best combination of values of these two parameters.

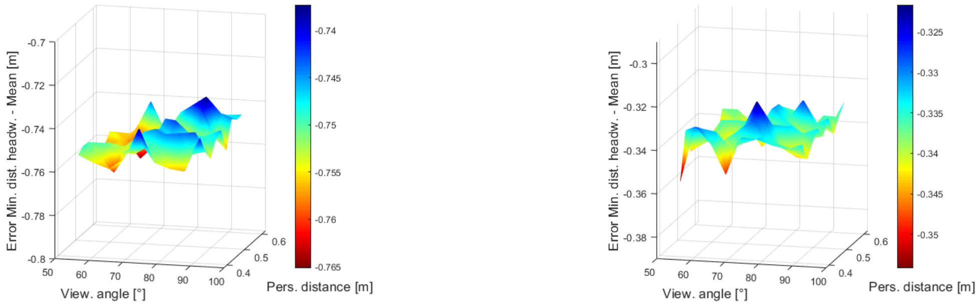


(a) 2020 (b) 2021

Figure 6.13: Error of the mean speed distribution over space in relation with the viewing angle and personal distance

The results for the minimum distance headway (Figure 6.14) shows an irregular surface in which the best solution can be found in different directions as for the speed distribution over the space. In 2020 (Figure 6.14a) a value close to the upper boundary of the viewing angle and personal distance yields lower errors than in the opposite direction, while the peaks observed on the sides indicate that the two boundaries of the personal distance yield similar errors for the default value of the viewing angle (i.e.

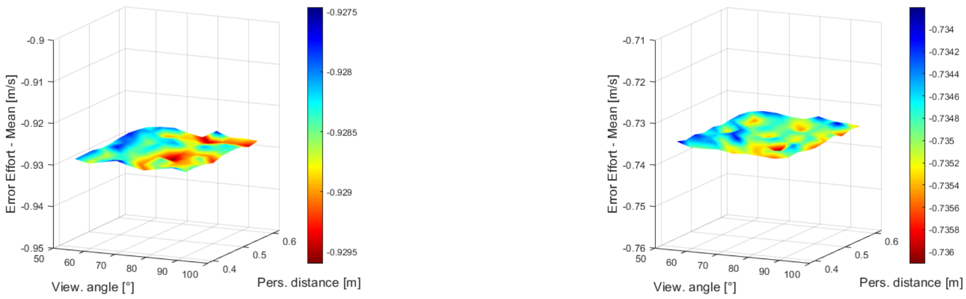
75). Regarding the year 2021 (Figure 6.14b), the lowest error is found with the default value of these parameters. Nonetheless, both years there is a difference of 3 cm between the smallest and largest error and thus the value of each parameter is not relevant to obtain a significant increase of the accuracy of the model.



(a) 2020 (b) 2021

Figure 6.14: Error of the mean minimum distance headway in relation with the viewing angle and personal distance

Similar to the speed distribution over space, a flat surface is obtained for the effort as it is observed in Figure 6.15. Moreover, the error is less than 0.01 m/s and thus the value of the viewing angle and personal distance are not relevant to increase the accuracy of the model.



(a) 2020 (b) 2021

Figure 6.15: Error of the mean effort in relation with the viewing angle and personal distance

6.2.3 Conclusions

Regarding the non-squared and non-normalised error for each metric, one can conclude that the model seems to be capable of replicating the speed distribution observed in the data, especially for the one of 2021. Moreover, the model encounter difficulties when reproducing the underlying behaviour given the large deviations of the error for both mesoscopic metrics, being the effort the one with the largest deviation.

Furthermore, a specific combination of parameters with respect to the studied metric shapes the space differently. On the one hand, an increasing and decreasing plane, such as for the effort, shows that the optimal parameter sets include the lower boundary of the relaxation time even though the optimal parameter values could be found outside the search space if this is increased. On the other hand, horizontal surfaces are found, such as for the minimum distance headway, which indicates that there is no clear direction in which the optimal parameter set can be found. However, there is a small difference found between the smallest and largest error for most of these surfaces which makes them rather flat. Lastly, the analysis shows that the relaxation time is the most relevant parameter to be changed as the error size significantly changes based on its value in comparison to the viewing angle and personal distance, whose values do not provide relevant changes in the error size and thus in the accuracy of the model.

6.3 Analysis of multiple objectives

In this section the calibration of the model is conducted using different combinations of scenarios and metrics as previous research found that the calibration results depend on them Duives (2016); Sparnaaij (2017). On the one hand, this will allow to determine the optimal parameter set of each combination depending on the scenario and metric considered for the calibration (Section 6.3.1). On the other hand, the variation of the goodness of fit (GoF) of each combination will be analysed by comparing the error when their most optimal parameter set is used with the one obtained when the optimal parameter set of another combination is used (Section 6.3.2).

The tested combinations are presented in Table 6.6, for which the optimal parameter set will be determined, and thus the influence of each scenario and metric on the accuracy of the model to fit the reference data. Then, these combinations will be compared based on the variation of their GoF given the optimal parameter used.

Table 6.6: Tested combinations of scenarios and metrics. B-LD stands for bidirectional flows at low densities

Combinations	**Scenarios**		**Metrics**		
	B-LD 2020	**B-LD 2021**	**Effort**	**Min. distance headway**	**Speed distr. over space**
Individual scenarios - all metrics					
B-LD 2020	x		x	x	x
B-LD 2021		x	x	x	x
Individual metrics - all scenarios					
Effort	x	x	x		
Min. distance headway	x	x		x	
Speed distr. over space	x	x			x
Combination of metrics - all scenarios					
Mesoscopic	x	x	x	x	
Combination all metrics - all scenarios					
All	x	x	x	x	x

6.3.1 Analysis of overall results

In Table 6.7 the optimal parameter sets obtained for each combination are shown together with their corresponding objective function, which is the minimum one found in the search space.

An important finding is that the lower boundary value of the relaxation time leads to the minimum objective function in all the combinations except for the minimum distance headway - all scenarios. This suggests that there is a change of the desired speed of agents given that the relaxation time influence the acceleration rate based on the distance to the first expected collision. Moreover, these results also indicate an increase of the acceleration of agents, according to Equation 3.4.3, which might suggest a faster reaction of agents than when the default value is used. However, this value of the relaxation time raises the question whether a bigger search space would yield different results and thus a lower value would be the most optimal for this parameter.

Regarding the viewing angle, its lowest optimal value correspond to the default for two combinations of scenarios and metrics, whereas for the remaining of the combinations its most optimal values are greater than its default. PD takes into account the six closest agents to determine the desired direction regardless of the maximum distance they can look ahead, thus a wider angle might suggest that agents on the sides are more important to consider for the scenarios and metrics used in the calibration. As a result, this gives insight into the awareness of agents which might have increased during the pandemic as stated in the second hypothesis in Section 3.3.

With respect to the personal distance parameter, a specific direction from its default value is not observed in comparison with the other two parameters, since its optimal value per combination is either below or above the default, being the upper boundary in one of them. Moreover, the optimal parameter sets of the first two combinations only differ in the personal distance value, which suggests that the model deals with the different behaviour observed in 2020 and 2021 by means of this parameter.

Finally, the minimum objective function (OF(θ)) indicates the accuracy with which the model is able to reproduce the reference data corresponding to each combination. The model seems to encounter more difficulties to reproduce more accurately the effort observed in the reference data in comparison with the other metrics, which is in line with the findings of the analysis of individual objectives. Similarly, the model fits best the reference data for the speed distribution over space. Nonetheless, one cannot conclude on how good the fit of the model is based on the objective function values, since this depends on the intended usage of the model.

Table 6.7: Optimal parameter sets and corresponding objective functions of combinations. Yellow indicates a parameter with a value at its lower boundary and green at its upper boundary

Combinations	**OF(θ)**	**Relaxation time [s]**	**Viewing angle [°]**	**Personal distance [m]**
Individual scenarios - all metrics				
B-LD 2020	0.617	0.38	88.5	0.53
B-LD 2021	0.311	0.38	88.5	0.41
Individual metrics - all scenarios				
Effort	1.184	0.38	84	0.53
Min. distance headway	0.189	0.5	84	0.62
Speed distr. over space	0.02	0.38	79.5	0.41
Combination of metrics - all scenarios				
Mesoscopic	0.694	0.38	75	0.53
Combination all metrics - all scenarios				
All	0.469	0.38	75	0.53

6.3.2 Influence of scenarios and metrics

The results in Table 6.7 showed the parameter sets that results in the minimum objective function and thus the best fit for each combination. However, the influence of the scenarios and metrics on the calibration results cannot be derived from it. Thus, the changes in the GoF of a combination when using the optimal parameter set of another combination are analysed in this section with the aim of determining how the selection of scenarios and metrics impact the calibration results. The difference in the GoF is determined as follows:

$$\Delta GoF_{i,j} = -(OF_i(\theta_j) - OF_i(\theta_i)) \tag{6.3.1}$$

Where $OF_i(\theta_i)$ is the objective function of combination i when using its optimal parameter set θi, whereas $OF_i(\theta_j)$ is the objective function of combination i when using the optimal parameter set of combination j. This equation states that if the latter objective function is greater than the former one, it means that the GoF decreases, which indicates that the fitness of the model to the data is worse than when using the optimal parameter set for that specific combination.

Scenarios

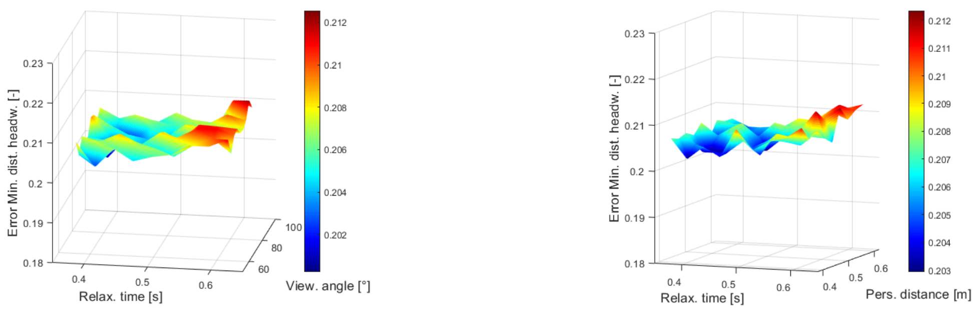
The difference between the two scenarios is the year from which the reference data has been collected, since the movement base case (i.e. bidirectional straight) and density level (i.e. low) are the same for both of them. Thus, the difference of the GoF shows how well the model fits to the data of a certain year when using the optimal parameter set corresponding to the other year.

The first two rows and columns of Table 6.8 show the variation of the GoF when the model is calibrated using one of the scenarios and all metrics. The results show that the GoF decreases when using the optimal parameter set of the other scenario; however, this difference is very small and thus a calibration based on one scenario would yield a similar accuracy for the other scenario.

Table 6.8: Variation of GoF for the comparison between different scenarios. Yellow and green indicate the smallest and largest decrease in GoF, respectively. The abbreviations are listed in Table 6.6

		Resulted parameter set	
		B-LD 2020	**B-LD 2021**
Used parameter set	**B-LD 2020**	-	-0.01539
	B-LD 2021	-0.01751	-

Furthermore, a calibration of the model using both scenarios yields similar shapes of the parameter space with respect to individual objectives. These planes are shown in Appendix C. However, there is a difference when the minimum distance headway is analysed given that its surfaces (Figure 6.16a and Figure 6.16b) are tilted towards lower values of the relaxation time irrespective of the values of the viewing angle and personal distance in contrast to the rather horizontal surface found in Figure 6.11 and Figure 6.8.



(a) Relaxation time - Viewing angle

(b) Relaxation time - Personal distance

Figure 6.16: Variation of objective function for combination minimum distance headway - all scenarios

Metrics

Table 6.9 reveals that there is overall a decrease of the GoF when the optimal parameter set of a different combination of scenarios and metrics is used. Thus, the metric chosen for the calibration affects negatively the accuracy of the model for reproducing the other metrics. However, the decrease of the GoF is very small, and thus similar errors could be expected if the optimal parameter set of any of the combinations of scenarios and metrics were used.

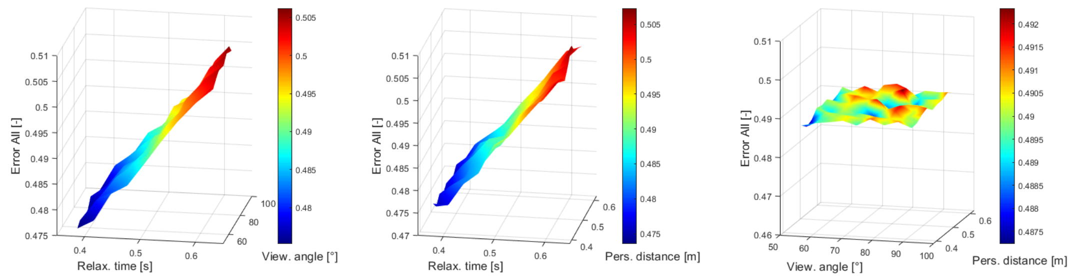
Furthermore, the GoF varies according to the metric used to calculate the objective function of a combination. On the one hand, one can observe that when the parameter set of the combination of the minimum distance headway is used, the largest decrease of the GoF is found in all the other combinations. On the other hand, the parameter set of the mesoscopic and all combinations lead to the lowest decrease of GoF for the effort and minimum distance headway, whereas the effort yields the lowest error for the speed distribution over space. Thus, although the use of multiple scenarios and metrics leads to a decrease of the GoF, its influence on the other combinations is lower than when the optimal parameter sets of the other combinations are used.

Table 6.9: Variation of GoF for the comparison between different metrics where the parameter set of a combination (rows) are used instead of the optimal parameter set for each combination (columns). Yellow and green indicate the smallest and largest decrease in GoF, respectively. The abbreviations correspond to the metrics: EF - effort, MD - min. distance headway, SS - speed distribution over space.

		Resulted parameter set		
		EF	**MD**	**SS**
Used parameter set	**EF**	-	-0.02075	-0.000533
	MD	-0.05698	-	-0.00320
	SS	-0.00826	-0.02433	-
	Meso.	-0.00218	-0.01160	-0.000629
	All	-0.00218	-0.01160	-0.000629

When looking at the error per combination, the speed distribution over space experiences the lowest decrease of its GoF regardless of the metric used in the calibration in comparison with the effort and minimum distance headway and, moreover, the error is also very small. On the contrary, the minimum distance headway experiences the highest decrease of its GoF. Thus, the model calibrated using one or all the metrics will fit better to the speed distribution over the space of the reference data, whereas it will encounter more difficulties to do so for the minimum distance headway.

Finally, an equal decrease of the GoF of each metric when the mesoscopic and all combinations are used suggests that the calibration using only the mesoscopic metric would yield the same variation of the GoF and thus the same results as when all the metrics (i.e. macroscopic and mesoscopic) are used.



(a) Relaxation time - Viewing angle (b) Relaxation time - Personal distance (c) Viewing angle - Personal distance

Figure 6.17: Variation of objective function for combination all metrics - all scenarios

Furthermore, the calibration of the model using all scenarios and metrics results in similar shapes of the parameter space in comparison with the ones obtained with the individual objectives. While the surface formed by the relaxation time together with the viewing angle (Figure C.7a) and personal distance (Figure C.7b) is tilted towards the lowest boundary of the relaxation time, the surface formed by the viewing angle and the personal distance (Figure C.7c) is a horizontal plane in which the values given to these parameters seem not to be relevant to increase the accuracy of the model.

6.3.3 Conclusions

The multiple objective calibration shows that the optimal parameter set is different for each of the combinations analysed in this section as one would expect. Thus, it can be concluded that the calibration results depend on the scenarios and metrics used in the analysis. Moreover, most of the optimal parameter sets include the boundary values of either the relaxation time or personal distance, which does not provide information regarding their optimal values as they could be found if the search space was increased. However, with respect to the relaxation time, one can conclude that lower values would yield the most accurate predictions, and thus the optimal value of the relaxation time could be found at values below its default.

The comparison of combinations shows a decrease of the GoF of all the combinations. However, the errors are very small when different optimal parameter sets of the combinations are used to calculate their objective functions. Thus, regardless of the scenarios and metrics used in the calibration, the results are expected not to vary much when the optimal parameter sets of other combinations are used.

6.4 Conclusions

In this chapter an analysis of individual objectives and a multiple objective calibration are performed to find the optimal parameter sets that best fit the model to the reference data and thus gaining insight into the capability of the model to reproduce the walking behaviour observed during the pandemic. Moreover, the analyses conducted aims at determining how the selected scenarios and metrics affects the calibration results.

The analysis of individual objectives revealed small deviations regarding the macroscopic metric and thus suggests a better fit of the model to the reference data at this aggregate level. On the contrary, the model underestimates the mesoscopic metrics and a good fit to the reference data seems unlikely given the large deviations. Moreover, in Chapter 5 a larger difference was found between the mean of the mesoscopic metrics in 2019 and 2021 than between 2019 and 2020. However, the model shows to replicate more accurately the behaviour in 2021, and thus raises the question whether the model is able to reproduce the behaviour described by those metrics before the pandemic.

Regarding the parameter space, the selected metric and a pair of parameters were found to shape differently the error space. On the one hand, when the relaxation time is considered, the error space shape is a steep plane, in which values closer to its lower boundary yield the smallest errors for the speed distribution over space and the effort irrespective of the value of the viewing angle and personal distance. On the other hand, a rather horizontal plane was found for the minimum distance headway and all pair of metrics, and for all the metrics when compared to the viewing angle and personal distance pair. Although this plane is irregular, the difference between the highest and lowest error is very small, which suggests that the model would yield similar results for any parameter set, and thus different values for the pair of parameters would not lead to significant changes in the accuracy of the model.

The multiple objective calibration revealed that values at the lower boundary of the relaxation time lead to the best fit for 6 out of 7 combinations of scenarios and metrics to the reference data, whereas values above the default of the viewing angle provides the best solution for all combinations. However, values above and below the default of personal distance are found, being the upper boundary for one of the combinations (minimum distance headway and all scenarios). Low values of the relaxation time suggest a faster reaction during the pandemic, whereas higher values of the viewing angle suggest a greater awareness of pedestrians of their surroundings. Regarding the personal distance, the values obtained in the calibration does not suggest a characteristic of the walking behaviour during the pandemic by itself given that its values do not point towards a clear direction from its default. However, the only difference between the optimal parameter set of 2020-all metrics and 2021-all metrics is the personal distance, since for the former and latter combination its value is respectively lower and higher than the default. This is in accordance with the opposite behaviour observed in the reference data of both years.

The comparison of combinations showed a decrease of their GoF when the optimal parameter set of another combination is used in the calibration. Nonetheless, the difference is very small and thus using all scenarios and metrics in the calibration would lead to similar results as if individual scenarios and metrics were used.

The error space using all scenarios showed a similar shape as for single combinations (i.e. one scenario and one metric) except for the minimum distance headway, for which a slightly steep plane towards low values of the relaxation time was obtained. Hence, when different scenarios are used, the value of the relaxation time gets more relevance to determine the best solution with respect to the minimum distance headway.

Overall, the results obtained in this chapter show that indeed the optimal parameter set that best fit the model to the reference data depend on the scenarios and metrics used in the calibration. In this respect, if the model is intended for general usage, the parameter set for the combination of all scenarios and all metrics should provide a good fit to the data given that when this set is used, the GoF of the other combinations experiences a small decrease. Moreover, the model is observed to be more capable of reproducing the behaviour at the macroscopic level during the pandemic given the small error in the speed distribution over space, and is less precise with respect to the underlying behaviour described by the mesoscopic metrics. Regarding the shape of the error space, one can conclude that the relaxation time is the most relevant parameter, since the error significantly changes based on its value, whereas the allocated values to the viewing angle and personal distance do not have a great influence on the resulting error. Thus, the calibration should be conducted more carefully for the relaxation time than for the viewing angle and personal distance as it is the most important parameter to describe the behaviour during the pandemic. However, the viewing angle and personal distance could have a bigger role in more complex scenarios such as bottlenecks, T-junctions, corners, and high densities. Finally, the optimal parameter sets include values at the boundary of the search space, thus one cannot conclude on whether the best solution is within this space. Therefore, the search space should be increased and gain more insight into the optimal values, especially for the relaxation time. It is important to note that the calibration of the model has been carried out based on the walking behaviour observed at a specific period of each year. Therefore, if periods of the year with a different walking behaviour were assessed, the calibration results would also be expected to be different.

Chapter 7

Conclusions

In this chapter the answer to the main research question and subquestions is provided in Section 7.1. Moreover, the limitations of this research are presented in Section 7.2, and recommendations for practice and further research are discussed in Section 7.3.

7.1 Conclusions

An analysis of the walking behaviour of pedestrians has been conducted in this research to get insight into how it has changed given the physical distancing. Then, a calibration of PD has been carried out with the aim of making the model more suitable for reproducing the behaviour of interest during the pandemic, and thus determine the capabilities of the model to replicate such behaviour.

The results obtained from this study provide answers to the main research question and subquestions stated in Chapter 1. First, the subquestions will be answered and finally the main research question.

1. Which are the scenarios for which the walking behaviour and compliance of physical distancing is analysed?

The scenarios were defined in this research based on the movement base case, density level, and the year from which the data was available to analyse the walking behaviour during COVID-19.

The movement base case was determined according to the interest of InControl in getting insights into the walking behaviour of pedestrians during the pandemic and the difficulties encountered when modelling pedestrians' movements in locations within an infrastructure where the referred movement could be observed. Thus, the movement base cases of interest were bidirectional straight and bottleneck, of which bidirectional straight has been chosen given that a more complete data set of trajectories within a corridor was available for the analysis of this type of movement, which would allowed the comparison of the behaviour before and during the pandemic, and subsequently the calibration of the model.

After reviewing the current literature, the density level was found to have a great influence on the calibration results of crowd models. However, the analysis of the data revealed that only low densities (0.20 p/m^2) occurred during the pandemic in the analysed corridor irrespective of the day of the week and the time of the day. Thus, although the density level is expected to influence the pedestrians' movements and the compliance of physical distancing during the pandemic, the decision has been made to only analyse the walking dynamics in low-density scenarios given the available data for this research.

The data analysis revealed that the walking behaviour has changed during the pandemic as different results were found in the analysed year and for the chosen metrics. Thus, the studied year and period of the year have been included as relevant characteristics of the scenarios included in the calibration.

In conclusion, this research focuses on the analysis of the walking behaviour and compliance of the physical distancing at bidirectional straight flows and low densities in June 2020 and 2021.

2. How does pedestrians' walking behaviour change because of physical distancing in comparison to pre-COVID-19 situation?

The change in pedestrians' walking behaviour as a consequence of the implementation of physical distancing has been studied in this research based on three main hypotheses.

The first hypothesis formulated in this research states that pedestrians try to keep a distance of 1.5 m from each other. In order to determine whether this hypothesis is rejected or not, the minimum distance headway was calculated as it would shed light on the distance kept by pedestrians and on the compliance of a prescribed distance. The results revealed that the mean minimum distance headway was greater than 1.5 m during COVID-19, and the share of pedestrians with a distance shorter than 1.5 m decreased during the pandemic, while the share of distances around 1.5m increased. The latter finding suggests that, although pedestrians did not fully comply with the prescribed physical distance, they tried to keep a distance of 1.5 m as less people accepted distances smaller than 1 m in comparison to the pre-pandemic situation.

Overall, one can conclude that the first hypothesis is not rejected given that a mean minimum distance above 1.5 m was found during the pandemic and because more people were observed to keep a distance close to 1.5 m than before COVID-19. Moreover, how the distance headway and its distribution have changed during the pandemic provides relevant insight into the walking behaviour over the course of the pandemic. Firstly, provided the greater mean distance headway in 2020 compared to other years, pedestrians were more conservative of the distance they kept during the first year of the pandemic when most of the measures were tightened. Secondly, after a year since the pandemic started, pedestrians decreased their distance between them, which might have been as a result of the adjustment of their distance in order for it to be closer to the prescribed one as suggested by the higher share of the range of distances around 1.5 m. However, other factors whose influence was not evaluated in this research might have led to these changes. For instance, the lower mean distance headway observed in 2021 might have been caused by an increased number of groups of people from the same household walking through the corridor or changes in the population composition in that year.

The second hypothesis formulated states that pedestrians show an increased awareness of their surroundings compared to the pre-corona situation. The influence of physical distancing on the awareness was studied by means of the speed distribution over space, effort, and spatial distribution.

The results for the speed distribution over space showed that the speed was distributed less evenly in 2020 compared to 2019, while in 2021 the speed was more evenly distributed over the corridor than in 2020. Thus, the greater variation of speed between cells in 2020 suggests an increased awareness of pedestrians, whereas a decreased of the awareness is inferred for the last year as similar speeds were found in each cell. Regarding the effort, a higher value in 2020 revealed that more changes in movement direction and speed occurred, thus an increased awareness could be inferred. In 2021, the effort resulted to be lower than before the pandemic which would point to a decrease of the awareness. Finally, the spatial distribution showed that the overall occupancy of the side cells of the corridor increased during the pandemic, whereas a reduction was observed in the middle of the corridor. However, the changes in the occupancy of cell over the three years were very small and thus relevant insights into the awareness cannot be derived from the results for this metric.

In conclusion, the speed distribution over space and the effort suggest that the awareness has varied during the pandemic. Thus, in 2020, the second hypothesis is not rejected as the findings point to an increased awareness of pedestrians, while in 2021, the second hypothesis is rejected as the findings suggests that the awareness has decreased. Finally, it is important to note that the awareness of pedestrians is a cognitive process and as such the findings obtained in this research can only suggest how it might have changed based on the walking dynamics observed during the pandemic.

The third hypothesis formulated states that the variance of pedestrians' walking velocity is greater during COVID-19 than before. To determine whether the velocity was different during the pandemic, the speed distribution and the effort were studied. On the one hand, the increase of the effort in 2020 indicates that pedestrians changed more frequently their velocity, which is complemented by the findings regarding the speed distribution over space as there is a greater variation of speed between cells than before the pandemic. On the other hand, the reduction of the effort in 2021 to values lower than before the pandemic, and a more even distribution of the speed over the corridor show a less variation of the velocity. Therefore, the speed and direction of movement during the last year changed less than in 2020.

Hence, the answer to the third hypothesis depends on the year in which the walking behaviour is analysed. In 2020, the hypothesis is not rejected given the greater speed difference between the cells in comparison to the pre-pandemic situation, and the increased effort that indicates more changes of speed and direction of movement. In 2021, the third hypothesis is rejected, since the speed is more uniformly distributed and effort is lower than in the previous years. Nonetheless, some factors such as a different population composition might have influenced the obtained results, and thus this should be taken into account for further research.

Overall, the findings show that the walking behaviour has indeed changed during the pandemic when compared to how it was before, but also over the course of the pandemic changes have been observed in pedestrians' movements. Moreover, it can be concluded that the physical distancing has had an influence on the walking behaviour and that, based on the evidence provided by the results of this research, possible changes in their awareness might have occurred, which in turn might have led to how pedestrians responded to a prescribed physical distance during the pandemic.

3. Which are the most sensitive parameters in Pedestrian Dynamics that allow describing the intended walking behaviour?

A sensitivity analysis was conducted in this research to determine how sensitive the model is to changes in five parameters. Moreover, the study focused on whether the walking behaviour changes within a certain range of values for these parameters and, if so, whether the observed behaviour is realistic or not.

The qualitative analysis revealed that the walking behaviour is realistic for any given value of the relaxation time, viewing angle, minimum desired speed, and avoidance range within a range of 25% from their default value. Regarding the parameter physical distance, the assessment showed that any value greater than the default led to an unrealistic behaviour for bidirectional flows in narrow corridors, even at very low densities, given that the usage of this parameter assumes a strict compliance of the prescribed physical distance at any given time. Thus, it was concluded that this parameter would not be used for the improvement of the model to reproduce the underlying behaviour and that it could only be used to determine the capacity during the pandemic, which was the objective for its inclusion in PD.

The quantitative analysis showed that the model is sensitive to changes in the relaxation time regardless of the density level, and to the viewing angle in high-density scenarios. Although, changes were also observed when different values were used for the minimum desired speed and avoidance range, this variation was concluded to be lower than the one produced by the stochastic nature of the model rather than by different parameter values.

Provided that the scenarios consist of bidirectional straight movements at a low density level, one can conclude that the model is most sensitive to the relaxation time, and thus it is the most important parameter for which the model should be calibrated. However, the sensitivity of model might be different if more complex scenarios (e.g. bottlenecks, T-junctions) were studied. Moreover, it can be concluded that the size of the deviations depends on the parameters and density level of the scenarios.

4. How do the parameters values in Pedestrians Dynamics change within their defined boundaries based on the scenarios and metrics used in the analysis?

A multiple objective calibration of PD has been conducted in this research to determine the most optimal parameter sets. To do so, the relaxation time found in the sensitivity analysis was considered together with the viewing angle and the personal distance, as the different behaviour during the pandemic could not be reproduced by tuning one parameter. Therefore, these three parameters are the ones whose change and influence on the behaviour have been studied in this research.

The multiple objective calibration showed that the values of the parameters depend on the combination of scenarios and metrics considered in the analysis. However, conclusions can be derived from their most optimal values within the search space.

Some similarities can be observed regarding the values of the parameters. On the one hand, the value of the relaxation time corresponds to its lower boundary (0.38 s) irrespective of the scenario and metric used in the calibration, except when the minimum distance headway is used and for which the default value yields the best fit to the data. A lower relaxation time suggests a greater reaction and more abrupt changes in the direction of movement than before the pandemic. On the other hand, values of the viewing angle greater than its default lead to the a better fit in all combinations. Higher values of the viewing angle increases the field of view from which agents choose their desired direction and thus it could suggest more changes in their movement direction. Regarding the personal distance, the optimal values are either below or above its default value, and thus there is no specific direction into which one can look for the optimal values of the parameter sets considered in the analysis.

Finally, it is important to highlight that the optimal parameter sets found in the calibration represent the best solution found within the search space and from the parameter sets defined by the step size of the grid. Thus, the most optimal solution might be outside the search space, particularly for the relaxation time, or within the same search space if the step size of the grid is smaller. Nonetheless, the answer to this question provides insight into which direction one can look for the optimal values of the analysed parameters.

5. What are the limitations of the current model for reproducing the observed behaviour in different scenarios during COVID-19?

The calibration results shed light on the limitations of the model for reproducing the behaviour during the pandemic. By looking at the individual objectives analysed in this research, the results revealed that the model tends to underestimate the mesoscopic metrics. Therefore, the effort obtained with the model would show that the variance of pedestrians' walking velocity is lower than it is in reality, and thus the impact of physical distancing on the effort provided by the model would be lower. Moreover, shorter minimum distance headways obtained with the model would show closer interactions between agents, thus the compliance of the physical distancing provided by the model would be smaller.

Regarding the multiple objective calibration results, the model also showed to be more limited for reproducing the mesoscopic metrics given their higher objective function compared to the macroscopic metric. This suggests that the model encountered more difficulties when reproducing the underlying behaviour compared to the aggregate level. Moreover, the usage of different combinations of scenarios and metrics did not improve the accuracy of the model with respect to these metrics, thus the limitations of the model were not overcome. This is in line with the findings in literature that revealed a decrease in the accuracy of the model when several movement base cases and metrics are used in the calibration of the model.

Furthermore, the model has been calibrated for bidirectional straight movements and low densities, hence other types of behaviour described by different movement base cases (e.g. bottlenecks, intersecting flows) and density levels are not captured by the calibrated model in this research. Thus, the limitations of the model to describe other types of behaviour during the pandemic are unknown and the model should be calibrated for those. However, the findings in this research can provide insight into similar scenarios with respect to the changes that should be conducted to the parameters and how relevant they are to increase the accuracy of the predictions by the model.

Finally, the analysis of the error space showed that the relaxation time is the most important parameter to calibrate, since the error changed significantly according to its value regardless of the value given for the viewing angle and personal distance (i.e. steep plane), while the error difference between any pair of values for the viewing angle and personal distance was very small (i.e. flat horizontal plane). Thus, the relaxation time is the most important parameter to calibrate and, given the different behaviour observed during the pandemic, the model would be limited to reproduce those behaviours with the calibration of a single parameter.

Based on the answers to the subquestions, the main research question of this research can be answered.

Which is the optimal parameter set in Pedestrian Dynamics and its capability to accurately reproduce the walking behaviour during COVID-19 for bidirectional flows where the prescribed physical distance is not fully complied?

The parameters selected for the calibration were the relaxation time, viewing angle, and personal distance. While the relaxation time was chosen given the sensitivity of the model to changes from its default value, the selection of the viewing angle and personal distance was based on the need of additional parameters that would allow to describe the different behaviour observed during the pandemic and thus aim for a model that could be used for reproducing all COVID-19 scenarios accurately.

Based on the multiple objective calibration, the optimal parameters were defined for different combinations of scenarios and metrics. Regarding the relaxation time (RT), the minimum objective function of most of the combinations corresponded to a value of 0.38 s, including the one with all the scenarios and metrics. Low values of the relaxation time would describe higher acceleration rates and more abrupt changes of movement direction during COVID-19, and thus an increased reaction of pedestrians.

Regarding the viewing angle (VA), although the same value has not been found for most of the combinations, it can be concluded that values above its default (75°) provides the best fit of the model to the reference data and for most of the combinations. However, if the calibration includes all the scenarios and metrics, the most optimal value of the viewing angle will correspond to the default. Values of the viewing angle above its default indicate a wider field of view of pedestrians which might suggest an increase awareness of their surroundings.

With respect to the personal distance (PeDi), the optimal values have been found either below or above its default (0.50 m) depending on the analysed combination in contrast to the relaxation time and viewing angle, for which the optimal values remained on one side of their default. Moreover, the combinations in which a single scenario was analysed showed that the personal distance increased to 0.53 m and decreased to 0.41 m for 2020 and 2021, respectively, while the relaxation time and viewing angle remained at 0.38 s and 88.5° for both scenarios. Thus, one could infer that the model responds to the different behaviour observed in these two years by means of the personal distance, whose values are in accordance to the larger minimum distance headway in 2020 and shorter distance headway in 2021 compared to 2019.

Furthermore, by looking at the error space shape, it can be concluded that some parameters are more important to calibrate than others. On the one hand, the value given for the relaxation time affects significantly the obtained error regardless of the given value for the viewing angle and personal distance. That is, for a specific value of the relaxation time, the error did not significantly change when different values of the other two parameters are chosen (i.e. flat decreasing surface). On the other hand, the relationship between the viewing angle and personal distance showed that the error was similar irrespective of the values of these parameters (i.e. flat horizontal surface) and thus their values were not relevant to significantly improve the accuracy of the model. Hence, it can be concluded that the relaxation time is the only parameter for which the model should be calibrated and therefore improve the accuracy of its results.

The characteristics of the walking behaviour that are intended to be reproduced with the model also provide insight into how relevant changes in the parameters are. These characteristics are described by the metrics used in the calibration. Regarding the speed distribution over space and the effort, one can conclude that the relaxation time is the most important parameter as significant changes in the error are obtained when values lower and higher than its default are used, whereas changes in the viewing angle and personal distance do not significantly affect the accuracy of the predictions. Regarding the minimum distance headway, one can conclude that errors are smaller when low values of the relaxation time are used. However, the errors do not significantly change when higher values than its default are used. Similarly, different values of the viewing angle and personal distance do not have a significant impact on the accuracy. Therefore, the importance of changes in the parameters' values depends on the characteristic of the walking behaviour for which accurate predictions are intended.

Provided that the behaviour during the pandemic is different depending on the year and the period of the year on which it is analysed, a single model for all COVID-19 scenarios will not be capable of reproducing accurate results for both of them. Thus, the model should be calibrated for a specific behaviour for which it is intended to reproduce accurate results.

Overall, the parameter values differ based on the scenarios and metrics used in the calibration and therefore the optimal parameter set is different for each combination analysed. By taking into account all three parameters, one could conclude that the optimal parameter set corresponding to the combination All scenarios-All metrics (RT: 0.38 s, VA: 75°, PeDi: 0.53 m) would provide an overall best fit assuming a general usage of the model for COVID-19 scenarios. However, the relaxation time is the most relevant parameter to calibrate, since the viewing angle and personal distance do not lead to significant improvements of the model. Thus, a model calibrated with a single parameter would not be capable of reproducing the different walking behaviour observed during the pandemic. Finally, as mentioned in the limitations, the capability of the model has been analysed with respect to bidirectional straight flows and low densities, for which the walking behaviour during the pandemic was analysed. Thus, it cannot be concluded with respect to the model's capability to reproduce other types of behaviour that have not been considered in this research, although insights into how parameters should change (e.g. low values of RT) can be derived from the results.

7.2 Limitations

In order to provide insights for recommendations to practice and future research, the limitations of the present study are discussed in this subsection.

This research has mainly focused on the influence of physical distancing on pedestrians' behaviour at the operational level (route following and collision avoidance). Thus, information is not provided with respect to the impact on their behaviour at the strategic level (activity choice) and tactical level (activity scheduling and route choice), which might have also changed during the pandemic. For instance, the larger distance travelled by pedestrians within the corridor during the pandemic suggests that they might have been willing to choose different routes to avoid close interactions with others in spite of the distance they needed to walk.

The walking behaviour assessment and calibration have been conducted for bidirectional straight flows and low densities. Therefore, insights cannot be provided regarding the impact of physical distancing on other types of scenarios nor in the capability of PD to reproduce them accurately.

The walking behaviour assessment conducted in this research corresponded to two specific periods during the pandemic (i.e. June 2020 and June 2021), between which differences in the behaviour were found. However, insights cannot be obtained regarding how the behaviour was at other periods during the pandemic, in which the time since the outbreak and the measures in place by then might have had a different impact on the walking behaviour. Thus, the calibrated model might not provide accurate results for the still unknown behaviour during those periods.

Furthermore, the location where the walking behaviour has been analysed and for which PD has been calibrated is a corridor of short length. Therefore, the walking behaviour and the compliance of the physical distancing described in this research might not correspond to longer corridors where, for instance, pedestrians might spend more time at closer distances and thus might behave differently.

In this research, the same type of passengers has been considered in order to control for its impact on the behaviour observed in the data. However, the influence of other factors such as population composition or presence of groups from the same household have not been taken into account. Thus, the differences observed in the walking behaviour might not only be a result of physical distancing.

With respect to the calibration process, the results showed the boundary value of the relaxation time as the best solution for most of the combinations studied in this research. Although the lower boundary of the relaxation time leads to more accurate results, it is not possible to conclude on the optimal value from the search space defined for the calibration, nor how much lower it is needed to look for the most optimal value. Furthermore, as a result of the step size for the grid search, insights cannot be obtained regarding the changes in the solution if the space between the analysed points was considered.

Lastly, provided that the awareness is a cognitive process, the changes in the physical variables considered in this research can only suggest an effect of physical distancing on the awareness of pedestrians. Thus, insights into whether the awareness of pedestrians has changed or not, and how it has changed, cannot be obtained from this research.

7.3 Recommendations

This section presents recommendations based on the results and limitations of this research. First, the recommendations for practice with respect to the usage of PD for COVID-19 scenarios are presented in Section 7.3.1. This is followed by the recommendations for future research building on this thesis in Section 7.3.2.

7.3.1 Recommendations for practice

The analysis of the walking behaviour shows that pedestrians' movements during the pandemic are different depending on the year and period of the year analysed. Moreover, the calibration results show that the accuracy of the model depends mainly on the relaxation time than on the viewing angle and personal distance. Thus, it is not possible to have a calibrated model that can be applied for all COVID-19 scenarios. Therefore, it is advised to calibrate the model based on the specific scenario during the pandemic for which the model is intended to yield more accurate predictions.

The calibration results show that low values of the relaxation time provide the best fit of the model to the reference data irrespective of the chosen scenarios during the pandemic. Therefore, when calibrating the model for its intended usage, it is advised to look for values of the relaxation time lower than its default, which replicates a faster reaction of pedestrians and sudden changes of movement direction given the increased acceleration rate.

Based on literature and the findings in this research, the movement base case, density level, and metrics influence the accuracy of the calibration results. Thus, it is recommended to only consider for the calibration of the model the types of movement and density level that describe the type of behaviour that is likely to occur, as well as the metrics which describe the characteristics of interest of the walking behaviour, otherwise the accuracy of the model is likely to decrease. This entails that the calibrated model in this research for bidirectional straight movements and low densities is advised to be used to get insight into similar scenarios.

The sensitivity analysis showed that the physical distance parameter did not yield a realistic behaviour in narrow corridors and that the flow went quickly into a gridlock. Although this parameter was introduced in the model for capacity analysis, it is recommended to evaluate its impact on similar scenarios for which the walking behaviour has been assessed in this research in order to determine how accurate the obtained results are for its intended usage.

Finally, before implementing the calibrated model, it is advised to evaluate whether the obtained errors are permissible, followed up by a validation using different data than the one used in the calibration. This should be done based on the intended usage of the model and based on the aggregate level of pedestrian flows from which it is desired to get insights. If unsatisfactory results are obtained, the proposed calibrated model should be revised and further changes should be carried out to reduce the error.

7.3.2 Recommendations for future research

The recommendations for future research can be divided into recommendations for research focused on the walking behaviour analysis (Section 7.3.2) and research focused on the calibration of Pedestrian Dynamics (Section 7.3.2).

Recommendations regarding the walking behaviour analysis

This research has focused on the walking behaviour at the operational level and the influence of physical distancing on this behaviour. However, results obtained for the travel distance metric suggests that pedestrians have been more willing to walk longer distances during the pandemic than what they did before. Although these results are for short distances within a corridor, they raise the question whether pedestrians have chosen longer routes or activities that imply walking longer distances in order to avoid crowded areas or areas where they cannot keep 1.5 m from others. Thus, future research is recommended to analyse the behavioural changes at the strategic level (activity choice) and tactical level (activity scheduling and route choice) as more insights into the willingness of pedestrians to comply with the physical distancing and the capability of PD to reproduce this behaviour at different levels could be obtained.

Another recommendation for future research is to consider additional factors to the ones considered in this thesis that might influence the walking behaviour and control for them in order to determine more accurately which changes in behaviour are produced by physical distancing. In this research, the influence of different types of pedestrians and demand has been controlled by considering a weekend and a time of the day with a similar demand for all the evaluated years. However, factors such as the population composition or presence of groups from the same household are also expected to influence the walking behaviour observed in the data and thus the results obtained with the metrics.

This research provides information regarding the impact of physical distancing on the walking behaviour and its compliance for bidirectional straight flows and low densities. Thus, further research should be conducted for different movement base cases and densities, since pedestrians are expected to behave differently, which would show that their movements during the pandemic can be dependant on the layout of the infrastructure and the number of people in the area where they are walking.

Recommendations regarding the calibration of Pedestrian Dynamics

The calibration results show that the optimal parameter sets of several combinations of scenarios and metrics include parameters which are at their boundaries, thus information regarding the most optimal values of these parameters cannot be provided. Therefore, future research is recommended to conduct an analysis considering a larger search space such that additional parameter values are included, particularly for the relaxation time, whose value in most of the optimal parameter sets is its lower boundary and for which it is more important to calibrate given its greater influence on the accuracy of the model with respect to the other parameters.

Furthermore, provided that the grid search method has been used in this research, the space between the points of the grid cannot be evaluated and thus it is not possible to determine whether there would be a change in the minimum objective function and optimal parameter set. Therefore, to gain insights into whether the solution might change, further research should be carried out considering either a small step size of the grid or other optimisation methods that would allow the evaluation of this space.

As the literature review showed, the movement base cases and density levels included in the calibration influence the accuracy and the intended usage of the model. Thus, provided that in this research the model has only been calibrated for a bidirectional straight movement and low densities, future research is recommended to conduct a calibration of the model with different movement base cases and densities in order to determine how the accuracy of the model changes when more than one movement and density level is considered and, moreover, to obtain a calibrated model intended for a general usage.

Finally, the parameters in PD and metrics used for the calibration have been chosen based on the characteristics of the walking behaviour during the pandemic, for which more accurate results were intended to obtain with the model. Thus, future research with the aim of analysing the behaviour at any behavioural level should take into account different parameters and metrics that best describe the desired behaviour.

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Appendix A

Anderson-Darling test results of metrics for walking behaviour assessment

Table A.1: AD test results between years for speed distribution over space. Significantly different if AD-stat is greater than AD-crit (2.492)

Years	**AD-stat**	**Significance**
2019/2020	6.28	Significant
2019/2021	116.41	Significant
2020/2021	80.04	Significant

Table A.2: AD test results between years for minimum distance headway. Significantly different if AD-stat is greater than AD-crit (2.492)

Years	**AD-stat**	**Significance**
2019/2020	13752	Significant
2019/2021	12655	Significant
2020/2021	15802	Significant

Table A.3: AD test results between years for effort distribution. Significantly different if AD-stat is greater than AD-crit (2.492)

Years	**AD-stat**	**Significance**
2019/2020	4.83	Significant
2019/2021	75.46	Significant
2020/2021	60.81	Significant

Table A.4: AD test results between years for travel distance. Significantly different if AD-stat is greater than AD-crit (2.492)

Years	**AD-stat**	**Significance**
2019/2020	23.7	Significant
2019/2021	9.34	Significant
2020/2021	1.87	Not significant

Appendix B

Search space: Parameter sets

Table B.1: Parameter Sets - Part 1

Combination	Relaxation time [1/s]	Viewing angle [°]	Personal distance [m]
1	0.38	57	0.38
2	0.38	57	0.41
3	0.38	57	0.44
4	0.38	57	0.47
5	0.38	57	0.5
6	0.38	57	0.53
7	0.38	57	0.56
8	0.38	57	0.59
9	0.38	57	0.62
10	0.38	61.5	0.38
11	0.38	61.5	0.41
12	0.38	61.5	0.44
13	0.38	61.5	0.47
14	0.38	61.5	0.5
15	0.38	61.5	0.53
16	0.38	61.5	0.56
17	0.38	61.5	0.59
18	0.38	61.5	0.62
19	0.38	66	0.38
20	0.38	66	0.41
21	0.38	66	0.44
22	0.38	66	0.47
23	0.38	66	0.5
24	0.38	66	0.53
25	0.38	66	0.56
26	0.38	66	0.59
27	0.38	66	0.62
28	0.38	70.5	0.38
29	0.38	70.5	0.41
30	0.38	70.5	0.44
31	0.38	70.5	0.47
32	0.38	70.5	0.5
33	0.38	70.5	0.53
34	0.38	70.5	0.56
35	0.38	70.5	0.59
36	0.38	70.5	0.62
37	0.38	75	0.38
38	0.38	75	0.41
39	0.38	75	0.44
40	0.38	75	0.47
41	0.38	75	0.5
42	0.38	75	0.53
43	0.38	75	0.56
44	0.38	75	0.59
45	0.38	75	0.62
46	0.38	79.5	0.38
47	0.38	79.5	0.41
48	0.38	79.5	0.44
49	0.38	79.5	0.47
50	0.38	79.5	0.5
51	0.38	79.5	0.53
52	0.38	79.5	0.56
53	0.38	79.5	0.59
54	0.38	79.5	0.62
55	0.38	84	0.38
56	0.38	84	0.41
57	0.38	84	0.44
58	0.38	84	0.47
59	0.38	84	0.5
60	0.38	84	0.53
61	0.38	84	0.56
62	0.38	84	0.59
63	0.38	84	0.62
64	0.38	88.5	0.38
65	0.38	88.5	0.41
66	0.38	88.5	0.44
67	0.38	88.5	0.47
68	0.38	88.5	0.5
69	0.38	88.5	0.53
70	0.38	88.5	0.56
71	0.38	88.5	0.59
72	0.38	88.5	0.62
73	0.38	93	0.38
74	0.38	93	0.41
75	0.38	93	0.44
76	0.38	93	0.47
77	0.38	93	0.5
78	0.38	93	0.53
79	0.38	93	0.56
80	0.38	93	0.59
81	0.38	93	0.62
82	0.41	57	0.38
83	0.41	57	0.41
84	0.41	57	0.44
85	0.41	57	0.47
86	0.41	57	0.5
87	0.41	57	0.53
88	0.41	57	0.56
89	0.41	57	0.59
90	0.41	57	0.62
91	0.41	61.5	0.38
92	0.41	61.5	0.41
93	0.41	61.5	0.44
94	0.41	61.5	0.47
95	0.41	61.5	0.5
96	0.41	61.5	0.53
97	0.41	61.5	0.56
98	0.41	61.5	0.59
99	0.41	61.5	0.62
100	0.41	66	0.38
101	0.41	66	0.41
102	0.41	66	0.44
103	0.41	66	0.47
104	0.41	66	0.5
105	0.41	66	0.53
106	0.41	66	0.56
107	0.41	66	0.59
108	0.41	66	0.62
109	0.41	70.5	0.38
110	0.41	70.5	0.41
111	0.41	70.5	0.44
112	0.41	70.5	0.47
113	0.41	70.5	0.5
114	0.41	70.5	0.53
115	0.41	70.5	0.56
116	0.41	70.5	0.59
117	0.41	70.5	0.62
118	0.41	75	0.38
119	0.41	75	0.41
120	0.41	75	0.44
121	0.41	75	0.47
122	0.41	75	0.5
123	0.41	75	0.53
124	0.41	75	0.56
125	0.41	75	0.59
126	0.41	75	0.62
127	0.41	79.5	0.38
128	0.41	79.5	0.41
129	0.41	79.5	0.44
130	0.41	79.5	0.47
131	0.41	79.5	0.5
132	0.41	79.5	0.53
133	0.41	79.5	0.56
134	0.41	79.5	0.59
135	0.41	79.5	0.62
136	0.41	84	0.38
137	0.41	84	0.41
138	0.41	84	0.44
139	0.41	84	0.47
140	0.41	84	0.5
141	0.41	84	0.53
142	0.41	84	0.56
143	0.41	84	0.59
144	0.41	84	0.62
145	0.41	88.5	0.38
146	0.41	88.5	0.41
147	0.41	88.5	0.44
148	0.41	88.5	0.47
149	0.41	88.5	0.5
150	0.41	88.5	0.53
151	0.41	88.5	0.56
152	0.41	88.5	0.59
153	0.41	88.5	0.62
154	0.41	93	0.38
155	0.41	93	0.41
156	0.41	93	0.44
157	0.41	93	0.47
158	0.41	93	0.5
159	0.41	93	0.53
160	0.41	93	0.56
161	0.41	93	0.59
162	0.41	93	0.62
163	0.44	57	0.38
164	0.44	57	0.41
165	0.44	57	0.44
166	0.44	57	0.47
167	0.44	57	0.5
168	0.44	57	0.53
169	0.44	57	0.56
170	0.44	57	0.59
171	0.44	57	0.62
172	0.44	61.5	0.38
173	0.44	61.5	0.41
174	0.44	61.5	0.44
175	0.44	61.5	0.47
176	0.44	61.5	0.5
177	0.44	61.5	0.53
178	0.44	61.5	0.56
179	0.44	61.5	0.59
180	0.44	61.5	0.62
181	0.44	66	0.38
182	0.44	66	0.41
183	0.44	66	0.44
184	0.44	66	0.47
185	0.44	66	0.5
186	0.44	66	0.53
187	0.44	66	0.56
188	0.44	66	0.59
189	0.44	66	0.62
190	0.44	70.5	0.38
191	0.44	70.5	0.41
192	0.44	70.5	0.44
193	0.44	70.5	0.47
194	0.44	70.5	0.5
195	0.44	70.5	0.53

Table B.2: Parameter Sets - Part 2

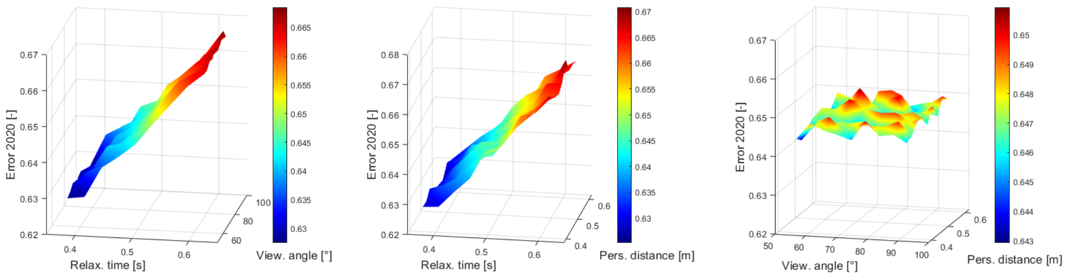
Combination	Relaxation time [1/s]	Viewing angle [°]	Personal distance [m]
196	0.44	70.5	0.56
197	0.44	70.5	0.59
198	0.44	70.5	0.62
199	0.44	75	0.38
200	0.44	75	0.41
201	0.44	75	0.44
202	0.44	75	0.47
203	0.44	75	0.5
204	0.44	75	0.53
205	0.44	75	0.56
206	0.44	75	0.59
207	0.44	75	0.62
208	0.44	79.5	0.38
209	0.44	79.5	0.41
210	0.44	79.5	0.44
211	0.44	79.5	0.47
212	0.44	79.5	0.5
213	0.44	79.5	0.53
214	0.44	79.5	0.56
215	0.44	79.5	0.59
216	0.44	79.5	0.62
217	0.44	84	0.38
218	0.44	84	0.41
219	0.44	84	0.44
220	0.44	84	0.47
221	0.44	84	0.5
222	0.44	84	0.53
223	0.44	84	0.56
224	0.44	84	0.59
225	0.44	84	0.62
226	0.44	88.5	0.38
227	0.44	88.5	0.41
228	0.44	88.5	0.44
229	0.44	88.5	0.47
230	0.44	88.5	0.5
231	0.44	88.5	0.53
232	0.44	88.5	0.56
233	0.44	88.5	0.59
234	0.44	88.5	0.62
235	0.44	93	0.38
236	0.44	93	0.41
237	0.44	93	0.44
238	0.44	93	0.47
239	0.44	93	0.5
240	0.44	93	0.53
241	0.44	93	0.56
242	0.44	93	0.59
243	0.44	93	0.62
244	0.47	57	0.38
245	0.47	57	0.41
246	0.47	57	0.44
247	0.47	57	0.47
248	0.47	57	0.5
249	0.47	57	0.53
250	0.47	57	0.56
251	0.47	57	0.59
252	0.47	57	0.62
253	0.47	61.5	0.38
254	0.47	61.5	0.41
255	0.47	61.5	0.44
256	0.47	61.5	0.47
257	0.47	61.5	0.5
258	0.47	61.5	0.53
259	0.47	61.5	0.56
260	0.47	61.5	0.59
261	0.47	61.5	0.62
262	0.47	66	0.38
263	0.47	66	0.41
264	0.47	66	0.44
265	0.47	66	0.47
266	0.47	66	0.5
267	0.47	66	0.53
268	0.47	66	0.56
269	0.47	66	0.59
270	0.47	66	0.62
271	0.47	70.5	0.38
272	0.47	70.5	0.41
273	0.47	70.5	0.44
274	0.47	70.5	0.47
275	0.47	70.5	0.5
276	0.47	70.5	0.53
277	0.47	70.5	0.56
278	0.47	70.5	0.59
279	0.47	70.5	0.62
280	0.47	75	0.38
281	0.47	75	0.41
282	0.47	75	0.44
283	0.47	75	0.47
284	0.47	75	0.5
285	0.47	75	0.53
286	0.47	75	0.56
287	0.47	75	0.59
288	0.47	75	0.62
289	0.47	79.5	0.38
290	0.47	79.5	0.41
291	0.47	79.5	0.44
292	0.47	79.5	0.47
293	0.47	79.5	0.5
294	0.47	79.5	0.53
295	0.47	79.5	0.56
296	0.47	79.5	0.59
297	0.47	79.5	0.62
298	0.47	84	0.38
299	0.47	84	0.41
300	0.47	84	0.44
301	0.47	84	0.47
302	0.47	84	0.5
303	0.47	84	0.53
304	0.47	84	0.56
305	0.47	84	0.59
306	0.47	84	0.62
307	0.47	88.5	0.38
308	0.47	88.5	0.41
309	0.47	88.5	0.44
310	0.47	88.5	0.47
311	0.47	88.5	0.5
312	0.47	88.5	0.53
313	0.47	88.5	0.56
314	0.47	88.5	0.59
315	0.47	88.5	0.62
316	0.47	93	0.38
317	0.47	93	0.41
318	0.47	93	0.44
319	0.47	93	0.47
320	0.47	93	0.5
321	0.47	93	0.53
322	0.47	93	0.56
323	0.47	93	0.59
324	0.47	93	0.62
325	0.5	57	0.38
326	0.5	57	0.41
327	0.5	57	0.44
328	0.5	57	0.47
329	0.5	57	0.5
330	0.5	57	0.53
331	0.5	57	0.56
332	0.5	57	0.59
333	0.5	57	0.62
334	0.5	61.5	0.38
335	0.5	61.5	0.41
336	0.5	61.5	0.44
337	0.5	61.5	0.47
338	0.5	61.5	0.5
339	0.5	61.5	0.53
340	0.5	61.5	0.56
341	0.5	61.5	0.59
342	0.5	61.5	0.62
343	0.5	66	0.38
344	0.5	66	0.41
345	0.5	66	0.44
346	0.5	66	0.47
347	0.5	66	0.5
348	0.5	66	0.53
349	0.5	66	0.56
350	0.5	66	0.59
351	0.5	66	0.62
352	0.5	70.5	0.38
353	0.5	70.5	0.41
354	0.5	70.5	0.44
355	0.5	70.5	0.47
356	0.5	70.5	0.5
357	0.5	70.5	0.53
358	0.5	70.5	0.56
359	0.5	70.5	0.59
360	0.5	70.5	0.62
361	0.5	75	0.38
362	0.5	75	0.41
363	0.5	75	0.44
364	0.5	75	0.47
365	0.5	75	0.5
366	0.5	75	0.53
367	0.5	75	0.56
368	0.5	75	0.59
369	0.5	75	0.62
370	0.5	79.5	0.38
371	0.5	79.5	0.41
372	0.5	79.5	0.44
373	0.5	79.5	0.47
374	0.5	79.5	0.5
375	0.5	79.5	0.53
376	0.5	79.5	0.56
377	0.5	79.5	0.59
378	0.5	79.5	0.62
379	0.5	84	0.38
380	0.5	84	0.41
381	0.5	84	0.44
382	0.5	84	0.47
383	0.5	84	0.5
384	0.5	84	0.53
385	0.5	84	0.56
386	0.5	84	0.59
387	0.5	84	0.62
388	0.5	88.5	0.38
389	0.5	88.5	0.41
390	0.5	88.5	0.44
391	0.5	88.5	0.47
392	0.5	88.5	0.5
393	0.5	88.5	0.53
394	0.5	88.5	0.56
395	0.5	88.5	0.59
396	0.5	88.5	0.62
397	0.5	93	0.38
398	0.5	93	0.41
399	0.5	93	0.44
400	0.5	93	0.47
401	0.5	93	0.5
402	0.5	93	0.53
403	0.5	93	0.56
404	0.5	93	0.59
405	0.5	93	0.62
406	0.53	57	0.38
407	0.53	57	0.41
408	0.53	57	0.44
409	0.53	57	0.47
410	0.53	57	0.5
411	0.53	57	0.53
412	0.53	57	0.56
413	0.53	57	0.59
414	0.53	57	0.62
415	0.53	61.5	0.38
416	0.53	61.5	0.41
417	0.53	61.5	0.44
418	0.53	61.5	0.47
419	0.53	61.5	0.5
420	0.53	61.5	0.53
421	0.53	61.5	0.56
422	0.53	61.5	0.59
423	0.53	61.5	0.62
424	0.53	66	0.38
425	0.53	66	0.41
426	0.53	66	0.44
427	0.53	66	0.47
428	0.53	66	0.5
429	0.53	66	0.53
430	0.53	66	0.56
431	0.53	66	0.59
432	0.53	66	0.62
433	0.53	70.5	0.38
434	0.53	70.5	0.41
435	0.53	70.5	0.44
436	0.53	70.5	0.47
437	0.53	70.5	0.5
438	0.53	70.5	0.53
439	0.53	70.5	0.56
440	0.53	70.5	0.59
441	0.53	70.5	0.62
442	0.53	75	0.38
443	0.53	75	0.41
444	0.53	75	0.44
445	0.53	75	0.47
446	0.53	75	0.5
447	0.53	75	0.53
448	0.53	75	0.56
449	0.53	75	0.59
450	0.53	75	0.62
451	0.53	79.5	0.38
452	0.53	79.5	0.41
453	0.53	79.5	0.44
454	0.53	79.5	0.47
455	0.53	79.5	0.5
456	0.53	79.5	0.53
457	0.53	79.5	0.56
458	0.53	79.5	0.59
459	0.53	79.5	0.62
460	0.53	84	0.38
461	0.53	84	0.41
462	0.53	84	0.44
463	0.53	84	0.47
464	0.53	84	0.5
465	0.53	84	0.53
466	0.53	84	0.56
467	0.53	84	0.59
468	0.53	84	0.62
469	0.53	88.5	0.38
470	0.53	88.5	0.41
471	0.53	88.5	0.44
472	0.53	88.5	0.47
473	0.53	88.5	0.5
474	0.53	88.5	0.53
475	0.53	88.5	0.56
476	0.53	88.5	0.59
477	0.53	88.5	0.62
478	0.53	93	0.38
479	0.53	93	0.41
480	0.53	93	0.44
481	0.53	93	0.47
482	0.53	93	0.5
483	0.53	93	0.53
484	0.53	93	0.56
485	0.53	93	0.59
486	0.53	93	0.62
487	0.56	57	0.38
488	0.56	57	0.41
489	0.56	57	0.44
490	0.56	57	0.47
491	0.56	57	0.5
492	0.56	57	0.53
493	0.56	57	0.56
494	0.56	57	0.59
495	0.56	57	0.62

Table B.3: Parameter Sets - Part 3

Combination	Relaxation time [1/s]	Viewing angle [°]	Personal distance [m]
496	0.56	61.5	0.38
497	0.56	61.5	0.41
498	0.56	61.5	0.44
499	0.56	61.5	0.47
500	0.56	61.5	0.5
501	0.56	61.5	0.53
502	0.56	61.5	0.56
503	0.56	61.5	0.59
504	0.56	61.5	0.62
505	0.56	66	0.38
506	0.56	66	0.41
507	0.56	66	0.44
508	0.56	66	0.47
509	0.56	66	0.5
510	0.56	66	0.53
511	0.56	66	0.56
512	0.56	66	0.59
513	0.56	66	0.62
514	0.56	70.5	0.38
515	0.56	70.5	0.41
516	0.56	70.5	0.44
517	0.56	70.5	0.47
518	0.56	70.5	0.5
519	0.56	70.5	0.53
520	0.56	70.5	0.56
521	0.56	70.5	0.59
522	0.56	70.5	0.62
523	0.56	75	0.38
524	0.56	75	0.41
525	0.56	75	0.44
526	0.56	75	0.47
527	0.56	75	0.5
528	0.56	75	0.53
529	0.56	75	0.56
530	0.56	75	0.59
531	0.56	75	0.62
532	0.56	79.5	0.38
533	0.56	79.5	0.41
534	0.56	79.5	0.44
535	0.56	79.5	0.47
536	0.56	79.5	0.5
537	0.56	79.5	0.53
538	0.56	79.5	0.56
539	0.56	79.5	0.59
540	0.56	79.5	0.62
541	0.56	84	0.38
542	0.56	84	0.41
543	0.56	84	0.44
544	0.56	84	0.47
545	0.56	84	0.5
546	0.56	84	0.53
547	0.56	84	0.56
548	0.56	84	0.59
549	0.56	84	0.62
550	0.56	88.5	0.38
551	0.56	88.5	0.41
552	0.56	88.5	0.44
553	0.56	88.5	0.47
554	0.56	88.5	0.5
555	0.56	88.5	0.53
556	0.56	88.5	0.56
557	0.56	88.5	0.59
558	0.56	88.5	0.62
559	0.56	93	0.38
560	0.56	93	0.41
561	0.56	93	0.44
562	0.56	93	0.47
563	0.56	93	0.5
564	0.56	93	0.53
565	0.56	93	0.56
566	0.56	93	0.59
567	0.56	93	0.62
568	0.59	57	0.38
569	0.59	57	0.41
570	0.59	57	0.44
571	0.59	57	0.47
572	0.59	57	0.5
573	0.59	57	0.53
574	0.59	57	0.56
575	0.59	57	0.59
576	0.59	57	0.62
577	0.59	61.5	0.38
578	0.59	61.5	0.41
579	0.59	61.5	0.44
580	0.59	61.5	0.47
581	0.59	61.5	0.5
582	0.59	61.5	0.53
583	0.59	61.5	0.56
584	0.59	61.5	0.59
585	0.59	61.5	0.62
586	0.59	66	0.38
587	0.59	66	0.41
588	0.59	66	0.44
589	0.59	66	0.47
590	0.59	66	0.5
591	0.59	66	0.53
592	0.59	66	0.56
593	0.59	66	0.59
594	0.59	66	0.62
595	0.59	70.5	0.38
596	0.59	70.5	0.41
597	0.59	70.5	0.44
598	0.59	70.5	0.47
599	0.59	70.5	0.5
600	0.59	70.5	0.53
601	0.59	70.5	0.56
602	0.59	70.5	0.59
603	0.59	70.5	0.62
604	0.59	75	0.38
605	0.59	75	0.41
606	0.59	75	0.44
607	0.59	75	0.47
608	0.59	75	0.5
609	0.59	75	0.53
610	0.59	75	0.56
611	0.59	75	0.59
612	0.59	75	0.62
613	0.59	79.5	0.38
614	0.59	79.5	0.41
615	0.59	79.5	0.44
616	0.59	79.5	0.47
617	0.59	79.5	0.5
618	0.59	79.5	0.53
619	0.59	79.5	0.56
620	0.59	79.5	0.59
621	0.59	79.5	0.62
622	0.59	84	0.38
623	0.59	84	0.41
624	0.59	84	0.44
625	0.59	84	0.47
626	0.59	84	0.5
627	0.59	84	0.53
628	0.59	84	0.56
629	0.59	84	0.59
630	0.59	84	0.62
631	0.59	88.5	0.38
632	0.59	88.5	0.41
633	0.59	88.5	0.44
634	0.59	88.5	0.47
635	0.59	88.5	0.5
636	0.59	88.5	0.53
637	0.59	88.5	0.56
638	0.59	88.5	0.59
639	0.59	88.5	0.62
640	0.59	93	0.38
641	0.59	93	0.41
642	0.59	93	0.44
643	0.59	93	0.47
644	0.59	93	0.5
645	0.59	93	0.53
646	0.59	93	0.56
647	0.59	93	0.59
648	0.59	93	0.62
649	0.62	57	0.38
650	0.62	57	0.41
651	0.62	57	0.44
652	0.62	57	0.47
653	0.62	57	0.5
654	0.62	57	0.53
655	0.62	57	0.56
656	0.62	57	0.59
657	0.62	57	0.62
658	0.62	61.5	0.38
659	0.62	61.5	0.41
660	0.62	61.5	0.44
661	0.62	61.5	0.47
662	0.62	61.5	0.5
663	0.62	61.5	0.53
664	0.62	61.5	0.56
665	0.62	61.5	0.59
666	0.62	61.5	0.62
667	0.62	66	0.38
668	0.62	66	0.41
669	0.62	66	0.44
670	0.62	66	0.47
671	0.62	66	0.5
672	0.62	66	0.53
673	0.62	66	0.56
674	0.62	66	0.59
675	0.62	66	0.62
676	0.62	70.5	0.38
677	0.62	70.5	0.41
678	0.62	70.5	0.44
679	0.62	70.5	0.47
680	0.62	70.5	0.5
681	0.62	70.5	0.53
682	0.62	70.5	0.56
683	0.62	70.5	0.59
684	0.62	70.5	0.62
685	0.62	75	0.38
686	0.62	75	0.41
687	0.62	75	0.44
688	0.62	75	0.47
689	0.62	75	0.5
690	0.62	75	0.53
691	0.62	75	0.56
692	0.62	75	0.59
693	0.62	75	0.62
694	0.62	79.5	0.38
695	0.62	79.5	0.41
696	0.62	79.5	0.44
697	0.62	79.5	0.47
698	0.62	79.5	0.5
699	0.62	79.5	0.53
700	0.62	79.5	0.56
701	0.62	79.5	0.59
702	0.62	79.5	0.62
703	0.62	84	0.38
704	0.62	84	0.41
705	0.62	84	0.44
706	0.62	84	0.47
707	0.62	84	0.5
708	0.62	84	0.53
709	0.62	84	0.56
710	0.62	84	0.59
711	0.62	84	0.62
712	0.62	88.5	0.38
713	0.62	88.5	0.41
714	0.62	88.5	0.44
715	0.62	88.5	0.47
716	0.62	88.5	0.5
717	0.62	88.5	0.53
718	0.62	88.5	0.56
719	0.62	88.5	0.59
720	0.62	88.5	0.62
721	0.62	93	0.38
722	0.62	93	0.41
723	0.62	93	0.44
724	0.62	93	0.47
725	0.62	93	0.5
726	0.62	93	0.53
727	0.62	93	0.56
728	0.62	93	0.59
729	0.62	93	0.62

Appendix C

Error space of combination of scenarios and metrics

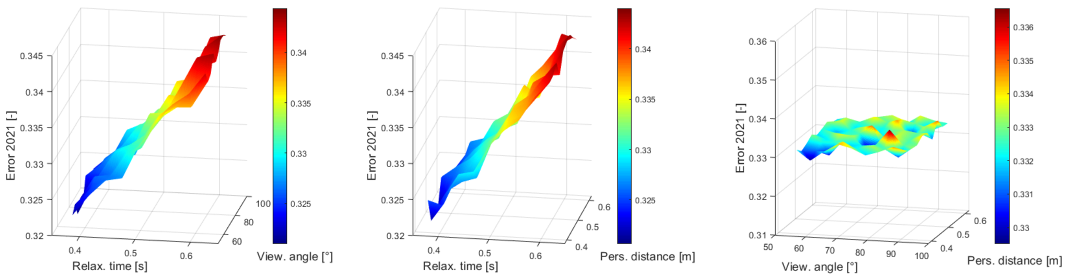


(a) Relaxation time - Viewing angle

(b) Relaxation time - Personal distance

(c) Viewing angle - Personal distance

Figure C.1: Variation of objective function for combination B-LD 2020 - all metrics

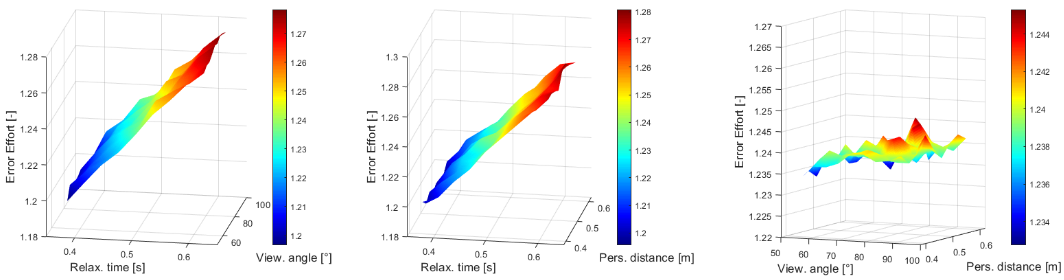


(a) Relaxation time - Viewing angle

(b) Relaxation time - Personal distance

(c) Viewing angle - Personal distance

Figure C.2: Variation of objective function for combination B-LD 2021 - all metrics

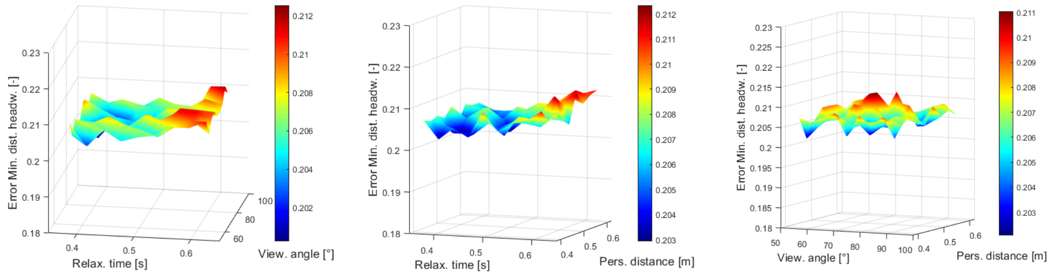


(a) Relaxation time - Viewing angle

(b) Relaxation time - Personal distance

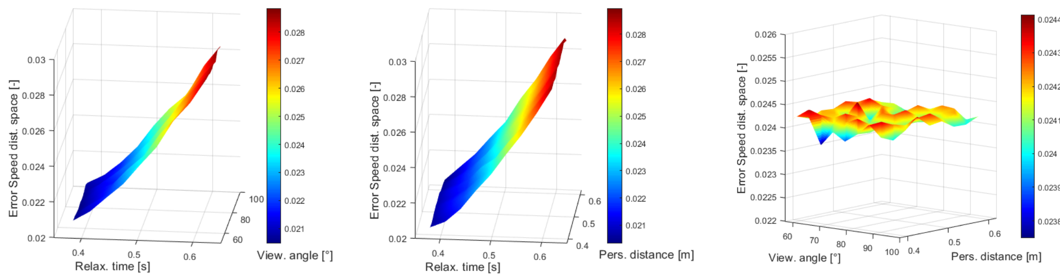
(c) Viewing angle - Personal distance

Figure C.3: Variation of objective function for combination effort - all scenarios



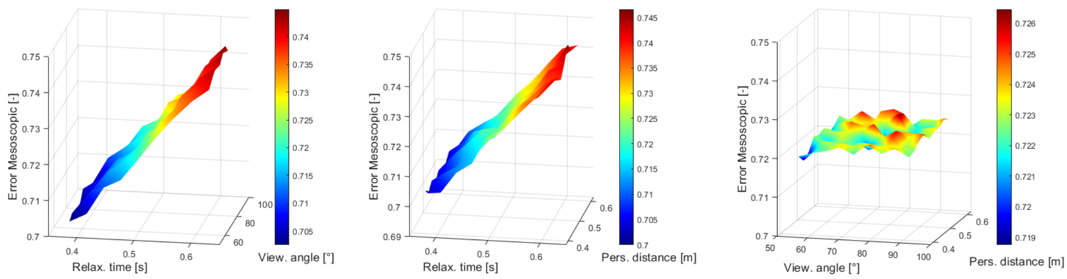
(a) Relaxation time - Viewing angle
(b) Relaxation time - Personal distance
(c) Viewing angle - Personal distance

Figure C.4: Variation of objective function for combination minimum distance headway - all scenarios



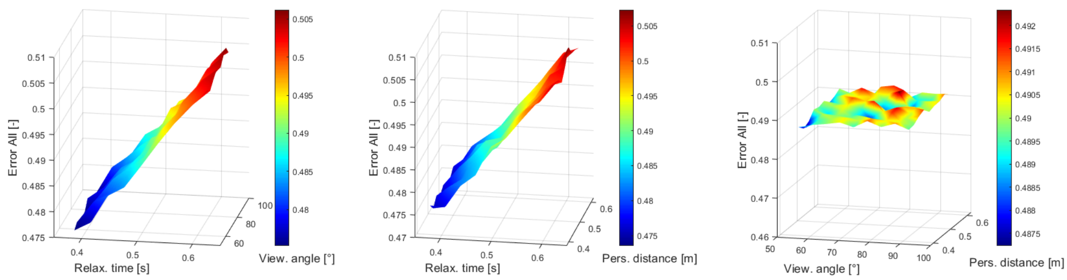
(a) Relaxation time - Viewing angle
(b) Relaxation time - Personal distance
(c) Viewing angle - Personal distance

Figure C.5: Variation of objective function for combination speed distribution over space - all scenarios



(a) Relaxation time - Viewing angle
(b) Relaxation time - Personal distance
(c) Viewing angle - Personal distance

Figure C.6: Variation of objective function for combination speed distribution over space - all scenarios



(a) Relaxation time - Viewing angle
(b) Relaxation time - Personal distance
(c) Viewing angle - Personal distance

Figure C.7: Variation of objective function for combination all metrics - all scenarios