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A database-driven approach for real-time prediction of crowd movement during mass events

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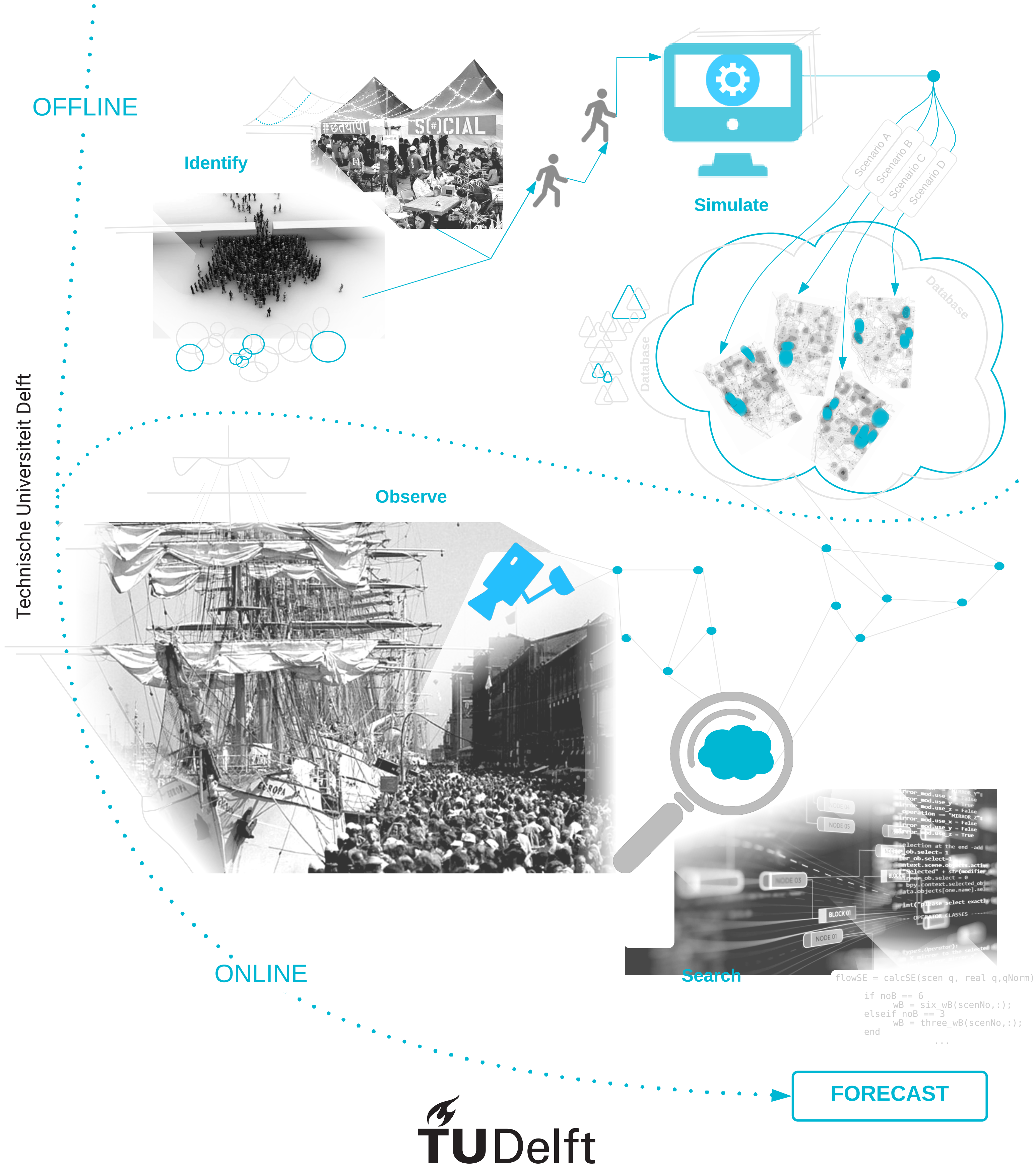

Forecasting Crowd Movements in Real-Time

A database-driven approach for real-time prediction of crowd movement during mass events

by

Paula Godoy

to obtain the degree of Master of Science

at the Delft University of Technology,

to be defended publicly on Tuesday 15^{th} of December 2020, at 11:00.

Student number:	4843002	
Project duration:	November 6^{th}, 2019 – December 15^{th}, 2020	
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This thesis has been conducted in cooperation with INCONTROL Simulation Software

Preface

This thesis is the result of my graduation project on the forecast of crowds in mass events. It marks the end of my masters in Civil Engineering, Transport & Planning, at Delft University of Technology, and it has been produced in cooperation with INCONTROL Simulation Software.

When I started this project a year ago, my interest was in developing my knowledge in pedestrian and crowd dynamics, a field that I find fascinating. Besides, I knew I wanted to do a graduation project that would also represent all that studying at TU Delft meant to me: the many challenges, the feeling of achievement when completing a tough course and of course the extraordinary learning experience. Here I want to express my gratitude for being a part of this great team of TU Delft, and to the support I have received from various incredible people.

Those who lead by example and demonstrate passion for what they do make it much easier for their followers to do the same. From TU Delft, I would first like to thank my supervisor, Martijn Sparnaaij, for leading me throughout this project. Your thorough feedback, the fruitful discussions we had and questions you asked me during our meetings have really guided me to try to develop a well-rounded project. It has been inspiring to work with you, and having your technical and personal support and encouragement were fundamental.

Instead of better glasses, you gave me better eyes. I would like to express my gratitude to the members of my committee from TU Delft - Dorine Duives, Yufei Yuan and Hans van Lint. Your valuable feedback has challenged me to rethink and be more critical about my work. Also, the lectures delivered by you during the master's program, and the opportunities for networking through for instance the CityFlows project meeting, have most certainly been key to how much I have learned and enjoyed my time at TU Delft.

You gave me your time, the most thoughtful gift of all. From INCONTROL Simulation Software, I'm deeply grateful to Nienke Valkhoff for all the technical support with the software, the much appreciated advice about my ideas and the encouraging words. My colleagues Marlies and Ignasi, I would like to thank you for the discussions and proofreading, the modelling advice and the supportive words. You have all believed in me I feel most thankful for that.

Though we may be far apart, you are always close to the heart. During this year, the (virtual) social times with friends and family were of vital importance. I want to express my gratitude to many people who I consider in many ways also part of this work. To my friends from Delft, David, Panos, Dimitri and especially to Roxani - our coffee breaks and your warm heart have made my days brighter. To my friends from Brazil, Ana, Melissa, Marilia, Paulo and Deko, who have always been there for me. To Alceu, Chico, Tiago and Gabriel, who inspired and supported me to pursue the dream of studying this masters, and have had a strong influence in my passion for transportation. Special thanks to my mom and siblings, Rosina, Johnny and Sibele for your constant love and support. I cannot wait to see you all again. To the daily support from my loving partner, Alex. Your words and love helped me believe in myself in times of doubt. To Gordon and Erna, who have made their home my second home. To the loving memory of my father, Claudio, you are and always will be with me!

Paula Godoy
Delft, December 2020

Summary

Predicting crowd movements in real-time during mass events has been shown to be a complex yet increasingly valuable task. The complexity arises from the nature of human behavior and the multiple factors known to influence this behavior. The value of a valid prediction approach has been increasing with the increasing frequency and size of these events observed in recent years. The risk of overcrowding has the potential to make such events unpleasant for visitors, who might feel uncomfortable due to experiencing high densities for extensive periods. Besides, this crowding can potentially threaten the safety of crowd. Crowd management aims at facilitating the movement and enjoyment of people by planning and preparing strategies to manage these potentially unsafe conditions. However, in order to effectively manage the crowd and avoid the appearance of too high densities, the decision of whether or not to implement certain strategies needs to be taken before the adverse conditions occur. This is where the role of prediction comes in, to provide crowd managers with an estimate of how soon an area will get overcrowded and assist them in act accordingly as early as possible.

Although technologies have been increasingly used for monitoring the crowd, the usage of these for prediction are few. Existing model-driven forecasting methods are either not able to produce real-time predictions with an adequate prediction horizon (e.g. 15 min (Duives et al., 2019)), or need a large amount of computer resources during the event to validly simulate and predict the crowd states. This is because models which are more capable of validly reproducing the different motion base cases (e.g. bidirectional movement, bottleneck behavior) and crowd phenomena observed in real life are disaggregate models (i.e. model individual pedestrian's movement) (Duives et al., 2013), which are also far more computationally expensive. Thus, the question of how to make use of these behaviorally valid models for prediction of crowd movements, which do not require a large amount of computer resources in real-time remains largely unanswered. This brings us to the objective of this research, which is to "*develop and validate a crowd movement forecasting method for mass events in which simulation is an offline step of the online (real-time) crowd forecast*". Hence, the proposed method addresses the computational burden issues of disaggregate models by assuming that simulation is a step performed prior the event. This solution is proposed as it avoids the need of super computer-like tools for the real-time prediction, as it is unlikely that any event manager would be willing to pay for such tools, but still makes use of the more behaviorally valid models. A set of scenarios is formulated and simulated, generating what is here called a database of scenarios. The online scenario selection system then searches through this database for the scenario which most closely matches the real observations and expected future conditions. This online selection system, in this research, is based on a multi-objective optimization approach, further explained below. In order to reach this objective, the main research question to be answered by this research is the following:

How to design and apply a real-time crowd movement forecasting method, which makes use of a database consisting of pre-simulated scenarios and a multi-objective optimization approach?

So, the two pillars of the forecasting method proposed in this research are the scenario database and the scenario selection system, further discussed below.

Scenario Database

The scenario database is designed with the aim of capturing the crowd dynamics of interest for prediction. From a literature study in pedestrian traffic and crowd management, it could be seen that there are specific dynamics for which the chance that the crowd can experience discomfort and unsafe conditions rise. These dynamics occur when unstable flows start appearing, as densities rise and speeds drop. Literature has shown that unstable flows are more likely to appear in specific areas, where for instance there is an obstacle obstructing the path, and at specific times, for example when there is a demand peak for a specific activity. Thus, in this thesis, these scenarios of interest are identified based on four benchmark cases for inefficiency dynamics, shown in Table 1. These four benchmark cases relate to the phenomena that can be observed which indicate the reduced throughput due to inefficient self-organization (Hoogendoorn, 2013), and these are seen as the typical dynamics relevant for prediction.

Table 1: Overview of benchmarks for inefficient dynamics

Benchmark	Short Description
Physical Bottlenecks	Specific areas of the event where the infrastructure elements can reduce the capacity and create bottlenecks.
Flow Interactions	Coexistence of distinct walking directions can hamper the throughput and create blockades.
Uneven Distribution over Network	Concentration of activities or single / main routes between specific locations creates unbalanced network by concentrating a large amount of people in specific areas.
Inefficient Route and Activity Choice Behavior	Increased attractiveness of certain areas or routes over others due to herding behavior or crowding, and can led to uneven distribution over the network or flow interactions.

For developing the scenarios, a framework is propose which consists of three steps: (1) the analyses of the event dynamics, (2) the identification of the inefficient dynamics and (3) the scenario development process in the simulation environment. The analyses of the event dynamics assesses the expected movements of the crowd at different times during the event on the multiple areas of the infrastructure, as well as the layout of the infrastructure itself. The output of this analyses is the input to the second step, which is that of identifying which inefficiencies from the four benchmarks are likely to occur and where these could appear. For instance, if a certain event has a number of activities concentrated in the same area, the uneven distribution of the network can be expected. However, the condition for this inefficiency to occur is that a high number of visitors go to this area to perform the activities. Thus, the inefficient dynamics is the situation for which a high number of visitors go to the location where the activities are concentrated.

Finally, the third step relates to building the scenarios in the simulation environment. It is clear that, for prediction, not only the conditions for which the inefficiency occurs should be predicted. If the observed dynamics are not going to lead to the appearance of the inefficiency, these insights also provide useful information to crowd managers when deciding whether or not to apply management strategies. In the process of simulating the scenarios, these conditions are incorporated by the different density levels defined for each inefficient dynamics. These density levels relate to demand pattern, that is, the total amount of agents generated per time period, which in turn defines the expected level of service of the infrastructure. While the identification of the inefficiency dictates the relative usage of the infrastructure, the density level indicates the strength of the interactions and thus whether or not the unstable flow regime occurs. The final scenario database is formed by one scenario for each inefficient dynamics identified, and the multiple variations of each of these based on the corresponding density levels. Hence, in this research, a scenario is a combination of an inefficient dynamics and a density level.

Scenario Selection System

To perform the forecast in real-time, a system is needed which is responsible for searching through the scenarios in the database for the scenario that most closely matches real observations, as well as future expectations. In this research, this system is based on a multi-objective optimization approach, illustrated in Figure 1. The goal of the multi-objective optimization part is to search through the database and select the scenario for which the differences between the outputs of the simulation and the real observations of the crowd are the minimum. For applying such system, the concept of crowd states is introduced. This concept, commonly used in system theory, refers to the metrics which contain the key information to describe the state of the crowd at a certain time instant. Examples of these metrics are flows and densities. The system proposed takes the trajectory information from the simulated scenarios and discretizes these in space and time. At each discrete locations, a number of state metrics is derived per discrete time, forming a time series of crowd state metrics.

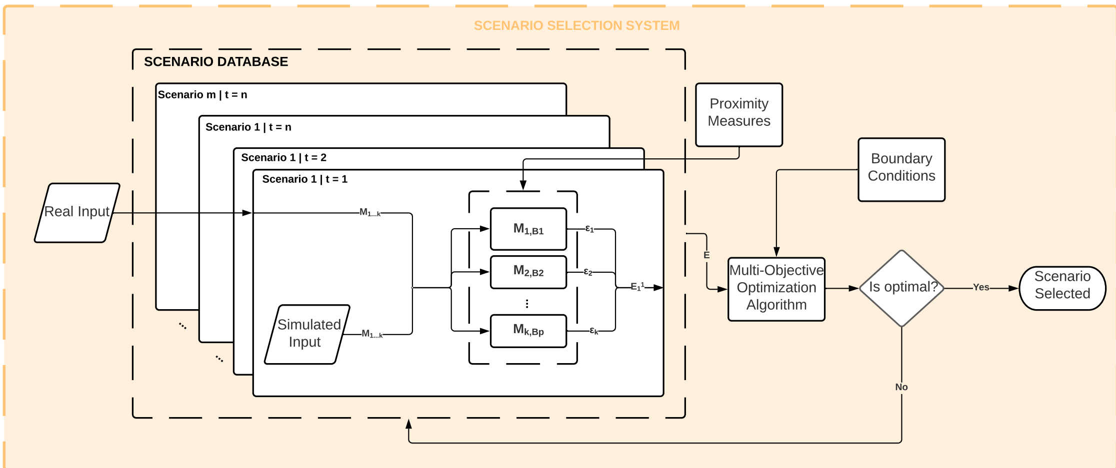

Figure 1: Multi-objective optimization for crowd movement forecast

The individual objectives which compose the multi-objective problem are then formulated when the real state metrics, derived from observing the real crowd, are compared to the simulated states in the database. For instance, an objective could be the difference between the real and simulated density of a specific area of the event terrain, while another objective could be the difference between the real and simulated travel time of a specific route. The prediction is thus the scenario and time period in the database for which the states most closely correspond to the real states.

Frameworks Application & Results

The frameworks for scenario development and scenario selection are applied to a case study based on SAIL, a nautical event which occurs every 5 years in the city of Amsterdam, The Netherlands, and attracts millions of visitors. The simulation model used to build the scenario database is Pedestrian Dynamics ®by INCONTROL Simulation Software. For SAIL, eight inefficient dynamics were identified, shown in Figure 2. The location of these inefficiencies shown in the figure are determined based on an analysis of the event dynamics, that is, by looking at the offered infrastructure and services, as well as the factors of the event environment that can influence pedestrians' choices. For instance, at the location of inefficiency number 7, there are not only activities concentrated, but it is also assumed to be an area which attracts many visitors due to the possibility of enjoying the view of the tall ships docked there.

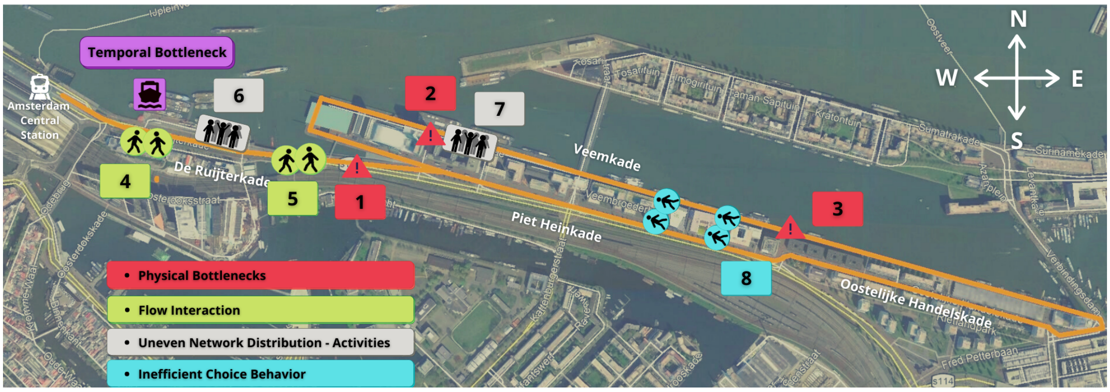

Figure 2: Inefficient self-organization phenomena and location - SAIL

The physical bottlenecks are locations where the path gets narrower or where there is an obstacles blocking the path. The flow interactions relate to an intersection (inefficiency 4 in the figure) and a path where flows are bidirectional (inefficiency 5). Following, the uneven distribution over the network inefficiencies are identified from the concentration of activities where locations 6 and 7 are shown. Lastly, inefficiency 8 indicates the expected inefficient route choice from visitors when these attempt to avoid crowding. In this research, for each of these eight inefficiencies, six density levels are simulated to form the scenario database.

The simulated scenarios are transformed into the time series of state metrics, where most of these metrics are derived at specific areas in the event terrain. These areas are called Event Blocks. For describing the current states, four state metrics are chosen, which lie on the mesoscopic and macroscopic levels. These metrics are the flow, the density, the travel time and the route shares. While the flow gives insights into the directions of movement, the density indicates the crowdedness of the different areas of the environment. As these two metrics are derived locally, the travel time and the route shares are included to give insights into the global conditions over the routes. For the flow, density and travel time, also the current state history is of interest to describe the environment conditions. The state history represents the long term movements of the state metrics, that is, how the metrics are developing over time. In this research, the state history is defined by the exponential moving average method. All aforementioned metrics are derived per Event Block, whereby a total of 13 Blocks are used to discretize the environment.

The final state metric used in this study relates to future disturbances, that is, known inputs into the system not captured by the sensor at the time of measurement. An example

of this disturbance is an upcoming train arrival which generates an inflow of people into the event terrain, and thus can influence the results of the predicted states. For the SAIL case, this disturbance relates to the arrival of the ferry, or the demand it generates. In total, 8 state metrics are derived of which 7 are given per Event Block. For the application in a real event, the real values of the state metrics are derived from the sensors by observing the real crowd. When these are compared to their corresponding metrics in the database, the individual objectives are formulated. In this research, there is a total of 92 individual objectives $(7 \times 13 + 1)$ which form the multi-objective problem. These multiple objectives are combined by the weighted-sum method, which assigns a weight to each individual objective and linearly combine these, resulting in a single objective to be minimized. The single-objective optimization algorithm is based on the Grid Search method.

To test the performance of the forecasting method, three analyses are performed. The first relates to the real crowd state data, and how the prediction is affected when this data has perturbations. The second and the third relate to the sub-selection of individual objectives, where in the second a sub-selection of areas is studied, while in the third analysis relates to a sub-selection of state metrics. The results of these analyses showed the following:

- The prediction appears to be more sensitive to an underestimation of the real states if compared to an overestimation when the densities are high. This is because the scenario selected by the scenario selection system corresponds to a lower density level than the real scenario. Meanwhile, when the sensor data is overestimated, the boundaries of the scenario space defined by the high density level scenarios limit the error.
- The increased frequency of similar states in the database can affect the quality of the prediction when the data is perturbed. This frequency relates to both the density level and the areas where inefficiencies occur. It can influence the scenario selection process by decreasing the variance of the objective function values of the scenarios best ranked by the selection algorithm. This lower variance can in turn mislead the prediction by increasing the chance of choosing a scenario for which the current state and state history is similar to the real states, but the future developments are not as these can arise from distinct inefficient dynamics.
- The sub-selection of areas and state metrics can both improve and deteriorate the performance, and the results are dependent on the uniqueness of the scenarios these sub-selected individual objectives can define. When choosing the Event Blocks, the sub-selection can most improve the results in the sense of identifying the inefficiency and density level if the dynamics of the areas selected are specific for a particular scenario. Similarly, the sub-selection of state metrics can improve the results when metrics which can be the result of multiple distinct traffic patterns are excluded.

Conclusions & Recommendations

The findings of this research highlight two aspects of the forecasting method proposed. These relate to the individual choices when designing the database and applying the scenario selection system. The first aspect relates to the choices regarding the scenario database. One should develop the database for the specific situations and dynamics that can occur on the different areas of the event environment for which prediction would be desirable. Identifying such situations and corresponding dynamics narrows down the scenario space to a representative set. The differentiation between the scenarios for which discomfort and unsafe conditions arise from those that such conditions do not occur is then simply done based on the demand pattern. Regarding the application of the scenario selection system, one should study the database before applying the method. Understanding the frequency of particular states in the different areas of the environment, and the scenarios which have similar states, can assist in adjusting the settings of system to improve the performance. This means reducing the number of conflicting objectives, by sub-selecting areas or state metrics, to a set that can be specific for a particular observed behavior on a specific location.

A number of recommendations can be given based on this research. Regarding the development of the database, not only the validity of the scenarios developed through the method proposed here could be tested, but also the statistical analysis of the final states in the database and how the frequency of particular states can affect the prediction. In relation to the scenario selection system, the state metrics and Event Blocks have large influence on the results obtained. It would be interesting to study additional or distinct metrics to describe the state of the Blocks, as well as further assess the effect of distinct combinations of Blocks and metrics.

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Glossary

Units & Variables

k density $[ped/m^2]$

$\boldsymbol{k_c}$ critical density $[ped/m^2]$

m meter

min minutes

$\boldsymbol{m_{scen}}$ simulated value of metric m

$\boldsymbol{m_{real}}$ real value of metric m

q flow $[ped/s/m]$

s seconds

tt travel time $[s]$

Definitions & Acronyms

Crowd a mass of people

Crowding / Crowdedness large number of people concentrated in an area limiting individual movement

Crowd Management preparation of measures and drawing of plans based on scenarios to facilitate the movement and enjoyment of people and avoid discomfort or threats to the safety of the crowd

Crowd State overall conditions of pedestrian spaces where there is a crowd present. In this research, this is defined by metrics that describes the past inputs into the system in order to quantify these conditions to perform prediction.

Density number of people per unit of area

Event Block discrete areas of the environment where the crowd state metrics are derived at. These can be dictated by the sensor network and location of the sensors in place.

FD Fundamental Diagram

Flow number of people per unit of time

GoF Goodness-of-Fit

Inefficient Dynamics interplay between supply (i.e. the event infrastructure and services offered) and demand (i.e. the number of visitors) which increases the chance that discomfort and unsafe conditions might arise

LOS Level of Service

Mass Event an organized gathering, attended by a large number of people (thousands) and occurring on an large-scale area (km^2)

OD / OD Matrix Origin-Destination matrix describes the movement of people between the different areas of the environment

Offline not in real-time, before the event

Online in real-time, during the event

PD Pedestrian Dynamics ®

Scenario Database a number of scenarios defined based on an analyses of the event which include the situations that can lead to the appearance of inefficient dynamics

SE Squared error

1
Introduction

Predicting crowd movements in real-time during mass events has been shown to be a complex yet increasingly valuable task. The complexity arises from the nature of human behavior and the multiple demographic, physiological and environmental factors known to influence this behavior (Duives, 2016). The value of a valid prediction approach has been growing with the increasing frequency and size of these events observed in recent years. The risk of overcrowding has the potential to make such events unpleasant for visitors, who might feel uncomfortable due to experiencing high densities for extensive periods of time. Besides, this overcrowding can potentially threaten crowd safety (Helbing & Johansson, 2010). Crowd disasters such as the Loveparade in Duisburg (2010) and the Hajj in Mina (2015) illustrate how mass gatherings can quickly turn into tragedies despite crowd management efforts (Helbing & Mukerji, 2012). Crowd management here refers to the measures prepared by the event organizer, which aim at facilitating the movement and enjoyment of people (Berlonghi, 1996). These measures are designed during the preparation phase of the event, based on expectations of what is going to happen during the event (Martella, Li, Conrado, & Vermeeren, 2017). These expectations lead to the creation of 'what-if' scenarios, based on which crowd managers develop their strategies and accompanying measures. This preparation phase typically contains 90% of the efforts of crowd management, whereas the other 10% refers to the execution of the designed measures during the event (Figure 1.1).

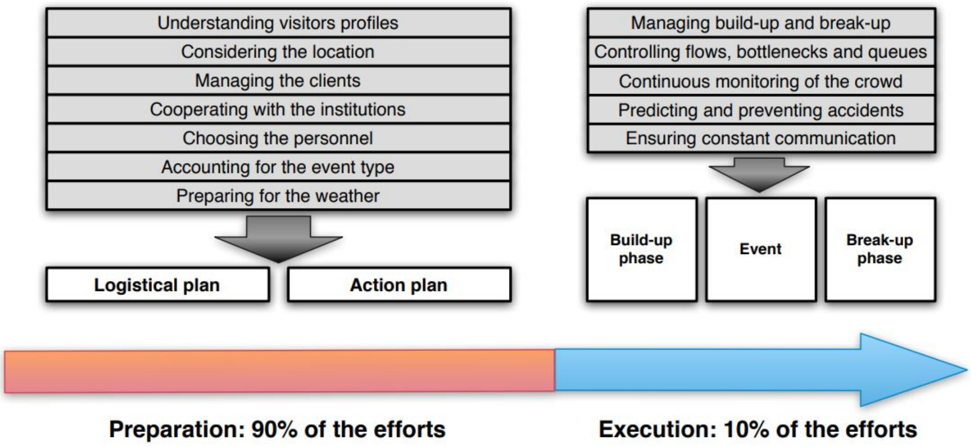


Figure 1.1: Crowd management phases (Source: Martella et al. (2017))

During the preparation phase, multiple scenarios are considered where the crowd management team takes into account factors such as the profile of visitors, location of the event and possible weather conditions. Plans are drawn up for distinct situations and corresponding desired behaviors that crowd managers want to obtain from the crowd (Martella et al., 2017). These plans are then implemented during the event whenever the crowd management team decides they are necessary. The strategies concentrate on avoiding densities reaching critical levels (Martella et al., 2017). To this end, the crowd management team evaluates possible areas where densities might become critical. Observed crowd conditions in these areas, as well as expected future developments, are then used to aid decision making. This requires constant monitoring of the crowd states, currently a human-centric task either performed by stewards in the crowd, or in a control room with the assistance of technologies like video cameras (Martella et al., 2017).

The decision of whether or not to implement management strategies can be either reactive or proactive. Taking reactive decisions means that crowd managers decide on the implementation of strategies when adverse conditions are already occurring (e.g. higher densities have been observed by the crowd monitoring systems in place). It is clear that reactive decisions are not desirable, as these increase the chance that event visitors are already experiencing discomfort, or that the safety of the crowd is at risk. Moreover, it takes time for crowd managers to deploy their measures. Consequently, means to assist crowd managers to act proactively are of interest. For proactive decisions to be made, crowd managers currently rely mostly on their own experience, and the information from crowd monitoring systems, when used, assists in such decision making by providing insights into the current crowd state. The need for improved situation awareness to assist crowd managers to act proactively instead of reactively has been highlighted in the study of Martella et al. (2017). The study shows that managers would like to have an estimate of how soon an area will get overcrowded in order to assist them to act accordingly as early as possible. For crowd managers to have time to act, that is, for them to be able to set up and deploy their strategies, a prediction horizon of at least 15 minutes should be considered (Duives et al., 2019). Although technologies have been increasingly used for monitoring purposes, the usage of these for crowd movement forecasting remains limited.

Among the attempts that have been made to develop real-time forecasting methods to be used during large-scale events, one can find both data-driven (Duives et al., 2019; Fan, Song, Shibasaki, & Adachi, 2015; Goldhammer, Doll, Brunsmann, Gensler, & Sick, 2014) and model-driven methods (Johansson, Helbing, & Shukla, 2007; Wagoum, Steffen, Seyfried, & Chraibi, 2013; Matyus, Seer, & Schrom-Feiertag, 2016). However, as will be discussed in Chapter 2, all these methods have their shortcomings. Data-driven refers to methods that use pedestrian data to design and train models, generally making use of computer vision algorithms and machine learning techniques. Most of these methods perform trajectory prediction, have a limited prediction horizon and require detailed input data. Additionally, when the objective is to predict destination sequences, most data-driven methods lack memory, that is, they assume that the future movements of visitors are independent of their previous movements (Duives et al., 2019). Data-driven methods sometimes also require the usage of historical data which either does not exist or might mislead the forecast, as for large-scale events the chances of one-off scenarios occurring are higher than those of finding a recurrent pattern (Fan et al., 2015).

Advancements in the pedestrian simulation field and developments in computer science have facilitated the construction of model-driven methods. Model-driven methods relate to the usage of pedestrian models for prediction. Examples of these models are cellular automata models (Blue & Adler, 1998), force-based models (Helbing & Molnar, 1998) and velocity-based models (Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010). More recently, aggregated models such as the model of Hughes (2002) have been also considered for this usage. Each of these models have their own shortcomings, and adaptations are often necessary for the purpose of real-time crowd movement prediction. The main disadvantage of disaggregate models is that they require a lot of computer power, thereby hindering their capability of performing real-time forecasts of a large crowd. Methods which make use of these for real-time prediction thus require many computer resources, increasing also monetary costs. Aggregated models, on the other hand, are far less computationally expensive, but also far less capable of validly reproducing the different motion base cases and crowd phenomena observed in real life (Duives et al., 2013). As stated by the study of Duives et al. (2013), for an accurate prediction to be made, these different expected situations and phenomena observed in crowds need to be captured. The reason for this being that distinct flow conditions and the phenomena observed in crowds can both improve or deteriorate the flows of pedestrians through the environment, as further discussed in Chapter 3.

To conclude, there is a need for improved situation awareness regarding the future crowd states to assist crowd managers to act proactively to guarantee the comfort and safety of the crowd. This can be done by forecasting crowd movements in real-time during the event. Currently, all methods which perform such forecasts have their own shortcomings. In general these are not able to produce real-time predictions within an adequate prediction horizon, or need a large amount of computer resources during the event to produce predictions that validly reproduce crowd behavior. Thus, methods which enable real-time forecast of large-scale crowd movements, which are capable of validly reproducing crowd behavior and provide an adequate prediction horizon are sought after.

1.1. Research Objective

The considerations above lead to the central theme of this thesis, which will focus on the real-time forecast of crowd movements from a model-driven perspective. As discussed, multiple simulation models are able to model large crowds. Models based on a higher aggregation level can produce questionable predictions given the fact that these are less capable of validly reproducing certain crowd behaviors. Meanwhile, models on a lower level of aggregation improve on this validity at the cost of increased computational resources. The question of how to make use of these behaviorally valid models for prediction of crowd movements, in ways that do not require a large amount of computer resources in real-time remains largely unanswered.

In this thesis, a method is proposed which addresses the computational burden issues of behaviorally valid models by assuming that simulation is a step performed offline (i.e. prior to the event). This solution is proposed as it avoids the need of super computer-like tools for the real-time prediction, as it is unlikely that any event manager would be willing to pay for such tools, but still makes use of the more behaviorally valid models. A set of scenarios is formulated and simulated using existing crowd simulation models, thus generating what is here called a database of scenarios. The online, real-time forecast then searches through this database for the scenario that most closely matches the real crowd states, taking into account also expected future developments. These real crowd states, as in existing methods, are derived from the real-time input data from the crowd monitoring systems. From these considerations, the objective of this research can be summarized as follows:

The objective of this research is to develop and validate a crowd movement forecasting method for mass events in which simulation is an offline step for the online (real-time) crowd forecast.

In order to apply the method, it is necessary that the user understands the event dynamics and the types of scenarios to be included in the database. Also, the system to select the appropriate scenario from the database in real-time needs to be designed, considering the types of scenarios and dynamics that need to be captured. The crowd movement forecasting method proposed in this research is thus formed by both: the scenarios which form the database, and the real-time scenario selection system. Given the aforementioned considerations regarding the crowd management needs, the objective of the forecasting method can be summarized as follows:

The objective of the forecasting method is to predict the future states of the crowd, in order to assist crowd managers in assessing the risk and discomfort of the visitors with sufficient time to take proactive measures if deemed necessary.

The two pillars of the forecasting method, namely (1) the scenario database and (2) the real-time scenario selection system are proposed with the aim of capturing the crowd dynamics of interest for prediction. To that end, two frameworks are proposed in this research, the scenario development framework (Chapter 4) and the scenario selection framework (Chapter 5). The scope considered for each of these pillars is presented below.

1.2. Research Scope

The scope of this research is described in this section. The following aspects are addressed: the focus of the scenarios which are proposed to be included in the database, the pedestrian behavior level considered for these scenarios, the focus of the scenario selection system, the case study used for application of the method (i.e. mass event and simulation model), and finally the focus of the analyses carried out in this thesis.

1.2.1. Focus of Scenario Development

During a mass event, there are multiple situations that can occur on the event terrain. One can think of the different conditions expected on the environment when most visitors are drawn to a specific activity at a specific location if compared to when visitors are performing multiple activities in different locations. In the first situation, the threat on comfort and safety is clearly much higher than in the latter, due to the probability that many visitors will accumulate in the area, increasing the density. Thus, one can use this knowledge and expectations to define which scenarios are of interest for prediction.

The focus of the development of scenarios is thus on the areas of the environment and typical behavior of visitors during the event which can lead to the comfort and safety of the crowd being at risk. However, it is considered important to highlight that this study concerns the prediction for no emergency conditions, as crowd management is mostly applied to such conditions. Beyond this, often crowd control or riot control are necessary which are not in the scope of this research. Existing knowledge in traffic flow, crowd behavior and crowd management can assist in the identification of these scenarios. For instance, based on traffic flow theory, one can identify the bottlenecks on the environment, that is, the specific locations where flows of visitors can be hampered by the interaction with the infrastructure. Similarly, there are factors which can influence the behavior of the crowd, that is, how they choose their routes and activities. These provide key inputs to the formulation of scenarios. In addition, specific crowd dynamics can provide the indication of the development of the dynamics towards unstable flow conditions and thus higher risk of discomfort and safety issues, as will be discussed in Section 3.3.

Identifying the aforementioned dynamics and representing these in a simulation environment are thus main considerations to develop the database of scenarios to be used for prediction. These dynamics and traffic states of interest are defined from the aggregate behavior of the pedestrians. The reason for this is twofold. Firstly, to have the information on the behavior in aggregate terms to assess the state of the crowd is assumed of greater interest to crowd managers. Secondly, as mentioned by Campanella et al. (2014), pedestrian models are mainly applied to assess the comfort and safety based on the aggregated flows, rather than on the individual behavior of each pedestrian. Therefore, although the simulation model used represents the behavior on the individual level (microscopic), the outputs of interest lie on the aggregated behavior obtained from these individual behaviors.

1.2.2. Pedestrian Behavior & Crowd Management Planning Levels

Pedestrians travel behavior theory is commonly defined by pedestrians' decision making process. Three distinct levels of behavior have been identified by Hoogendoorn et al. (2001), namely strategic, tactical and operational. At the strategic level individuals choose their departure time and the activities they wish to perform, resulting in a collection of activities called activity set. The schedule of these activities and the global route pedestrians will take to reach them are part of the tactical level decisions. Lastly, the decisions on the operational level guide pedestrians walking behavior, including desired velocities and deviations of this in order to avoid obstacles or other pedestrians. These decisions have in principle two dimensions: time and space. In relation to time, the decisions on the higher level change less frequently than the ones on the lower levels. The spatial dimension relates to the area considered by the pedestrian when making the decision. To illustrate these, one can think of for instance the choice of route if compared to the choice of walking speed. The choice of route spans for a longer time whereas the choice of speed is executed for the immediate next time period. Similarly, the area considered by the pedestrian when choosing his or her route is much larger than that considered when choosing the speed he or she will walk at the next time instant.

These behavior levels are linked to the levels of planning of crowd management strategies. Strategic planning focuses on influencing the behavior of pedestrians before arriving at the event. Tactical planning, on the other hand, focuses on the decisions related to the movement on the event terrain (e.g. where to perform an activity or which route to take), whereas operational planning looks at the local decisions on movement such as intersection control (Wieringa, 2015). Ideally, one would be able to consider all three behavior and planning levels when formulating the scenarios, and the accurate representation of each of these can significantly improve the prediction results and situations for which scenarios are considered relevant. However, this research will focus on the strategic and tactical levels. As previously mentioned, this is because the higher level decisions last longer and consider a larger area than the tactical level ones. Therefore, it is assumed that these decisions have a larger influence on the prediction results when the aggregate behavior is analysed.

1.2.3. Focus of Scenario Selection System

In this research, it has been defined that the method to perform the selection of a scenario within the database is by means of a multi-objective optimization approach. The application of the method for the purpose of this research requires mainly four decisions to be made. These are: (1) the choice of scenarios, (2) the choice of metrics to be used to describe the scenarios and the choice of comparison measure to form the individual objectives of these metrics, (3) the choices related to the location where the real data is derived from and finally (4) the choices regarding the optimization method, which include the decisions related to each specific method (e.g. stopping criteria).

The scenarios are developed according to the scenario development framework discussed in Chapter 4, and the choice of scenarios directly relate to the feasibility of the proposed method for real world applications. The choices of metrics and locations where the real data is derived from are made based on the capabilities of crowd monitoring systems, location of sensors in sensor network, as well as the dynamics of interest (considering the aggregate behavior of pedestrians). For the decisions regarding the optimization method, the most practical solution is considered, taking into account the time and resources available for this research. Therefore, the choices related to the optimization method are not further validated.

1.2.4. Mass Event & Simulation Model

The case study to validate the forecasting method in this thesis is defined by both, the mass event and the simulation model. The mass event chosen as the case study for this research is the SAIL event, a nautical event which happens every 5 years and attracts millions of visitors to the city of Amsterdam, The Netherlands. It is the largest public event in The Netherlands, where several tall ships moor in the IJ-port, and visitors can walk along the event terrain to watch the ships and perform other activities. One of the reasons why SAIL is the case study for this research is the crowd monitoring systems in place for the event. Data from these crowd monitoring systems has been used in previous editions of the event to monitor the state of crowd and assist crowd management. Thus, the type of event and the possibility of using real-time data from the crowd monitoring systems in place, make SAIL an interesting case study for this research. Although the edition of SAIL 2020 was cancelled due to Covid-19, the event and sensor network are still used as the main reference for the case study of this thesis. However, the analyses of the forecasting method performed is different, as it will be discussed in the following subsection.

Regarding the simulation model, the microscopic simulation model used in this thesis as a tool for modelling the scenarios is Pedestrian Dynamics ®(PD) by INCONTROL Simulation Software. This model is chosen due to the experience of the author with the model, as well as the cooperation between TU Delft and INCONTROL, which made the software available for usage. PD is a microscopic crowd simulation tool which simulates pedestrians in a continuous space. From the theory presented by Hoogendoorn et al. (2001), one can say that pedestrian models to be used in practice need to be capable of simulating all three levels, and the decisions made on higher levels are executed by those on lower levels. In PD, the higher level decisions are direct inputs, and these are executed by the embedded routing and movement modules which define the operational behavior of agents. Both the mass event and the characteristics of the model are further discussed in Section 6.1.

1.2.5. Focus of Analyses

As previously mentioned, the SAIL 2020 event was cancelled due to Covid-19 measures. Therefore, although the event is still used as the case study, it is important to define the focus of the analyses performed in this research. The analyses performed aim at assessing the sensitivity of the scenario selection system to particular inputs which could be obtained from monitoring a real crowd. This means assessing the differences in the forecasting results when for instance this 'real' input contains errors due to the detection capabilities of the sensors. Therefore, the overall goal of the analyses is to assess how the predicted states by the scenario selection system change when the real input used as reference for the search changes. Furthermore, the settings of the selection system can also be adjusted by for instance changing the number of individual objectives which form the multi-objective problem, which is likely to change the predicted states. The sensitivity of the prediction to particular settings of the system are also analysed.

1.3. Research Questions

Following from the research objective, multiple research questions are formulated, for which the main question is:

How to design and apply a real-time crowd movement forecasting method, which makes use of a database consisting of pre-simulated scenarios and a multi-objective optimization approach?

To answer the above main question, the following sub-questions are posed:

1. *What is the state-of-the-art regarding real-time crowd movement forecasting methods?*

   To answer this question a review of the literature on crowd movement forecast is performed. It is known that forecasting crowds in real-time poses many challenges such as providing behaviorally valid prediction over an adequate prediction horizon while taking into account the specifics of mass events and crowd behavior. A review of the literature illustrates how existing methods address these challenges, their main advantages and shortcomings, as well as research gaps. This question is addressed in Chapter 2.

2. *Which crowd dynamics are relevant for real-time prediction of crowd movements at mass events to guarantee the comfort and safety of the crowd?*

It is expected that prediction is necessary when certain specific crowd dynamics occur, given the crowd management strategies to manage the crowd and the objectives of this research regarding comfort and safety of event attendees. Thus, to answer this question, a review of the literature on traffic flow and pedestrian behavior theory, together with crowd management theory, aims to highlight the key dynamics to be taken into account in the formulation of scenarios. This question is addressed in Chapter 3.

3. *How to identify the scenarios that should be included in the scenario database?*

   The scenario database is formulated based on real crowd behavior, which in turn needs to be represented in the simulation environment. To this end, the relation between aspects of the real behavior of the crowd, based on the theory discussed in Chapter 3, as well as the representation of this behavior in a simulation environment are discussed in Chapter 4.

4. *How to apply a multi-objective optimization approach for crowd movement forecasting (i.e. scenario selection)?*

   In Chapter 5, the proposed scenario selection system is presented to answer the above research question. The system combines: (1) the elements necessary for real-time prediction, identified based on existing methods in Chapter 2, (2) the database of scenarios developed according to Chapter 4, and (3) the additional steps and concepts related to the multi-objective optimization approach.

5. *What is the effect of the perturbations of the sensor data on the prediction results of the forecasting system?*

   Given that the real-time data obtained from crowd monitoring sensors contains errors and noise, one can expect that these errors can affect the process of selecting a scenario from the database. Thus, this question aims to assess these effects in order to provide an analysis of the applicability of the method for real mass events. This question is addressed in Chapter 7.

6. *How are the predicted states affected by the different choices of state metrics and areas of the event terrain used for the prediction?*

   As the system makes use of distinct metrics derived from multiple areas of the event terrain, this question assesses how the prediction is affected when a sub-selection of these metrics and areas is used. The idea is to focus on the areas considered more relevant for each particular scenario, and the metrics expected to be more accurate given the monitoring sensor these are derived from. This question is also addressed in Chapter 7.

1.4. Contributions of this Research

The main contributions of this research to both science and practice are addressed in this section. A key contribution to both is that this research proposes a new way to apply behaviorally valid microscopic models for the purpose of real-time prediction. For science, this thesis also contributes by providing insights into how to identify the scenarios of mass events for which prediction would be relevant, with little or no reference data. The scenarios in this research are proposed based on the traffic flow, pedestrian behavior and crowd management theory, as well as expectations from experience. These theories are combined to form the scenario development framework, which aims to assist in the identification of the key dynamics of interest for prediction. In addition, the scenario selection system proposed, based on a multi-objective optimization approach, indicates a new way to use optimization techniques for prediction of crowd movements.

As the method proposed in this thesis focuses on mass events, the contributions to practice are related to the potential improvements to the comfort and safety of the crowd the results of the forecast can provide. The prediction results can enhance situation awareness, which can assist crowd managers in taking informed decisions of whether or not management strategies are needed in order to avoid potentially hazardous situations. Besides, the framework for scenario development and the corresponding database of simulated scenarios can improve the understanding of the crowd dynamics, and illustrate certain conditions by the visualization provided by the simulations of the scenarios. These can also be used for training personnel for the event. Lastly, this thesis contributes to practice by extending the potential usage of the data from crowd monitoring systems, as these are currently mainly used for real-time information about the crowds, and not prediction.

1.5. Research Overview

This thesis is split into three main parts: 1) Literature Review, 2) Framework Development and 3) Framework Application. Each main part contains two chapters as illustrated in Figure 1.2. The Literature Review part starts with Chapter 2. In this chapter, a review of the state-of-the-art of real-time crowd movement forecasting methods is performed, highlighting the advantages and shortcomings of these methods, as well as identifying the gaps in research. Following, Chapter 3 presents the theoretical background in traffic flow, pedestrian behavior and crowd management necessary for the development of the framework to build the scenario database. This framework is the first pillar of the method developed in this research, and is presented in Chapter 4. The second pillar is the scenario selection system, for which a framework is proposed is Chapter 5.

In order to validate the method, a case study is defined to which the forecasting method is applied. The application of the frameworks to the case study is presented in Chapter 6. The analyses performed on the developed forecasting system are then carried out in Chapter 7. Finally, Chapter 8 presents the main findings of this research. These findings and the limitations of the method are discussed, and recommendations for science and practice are made.

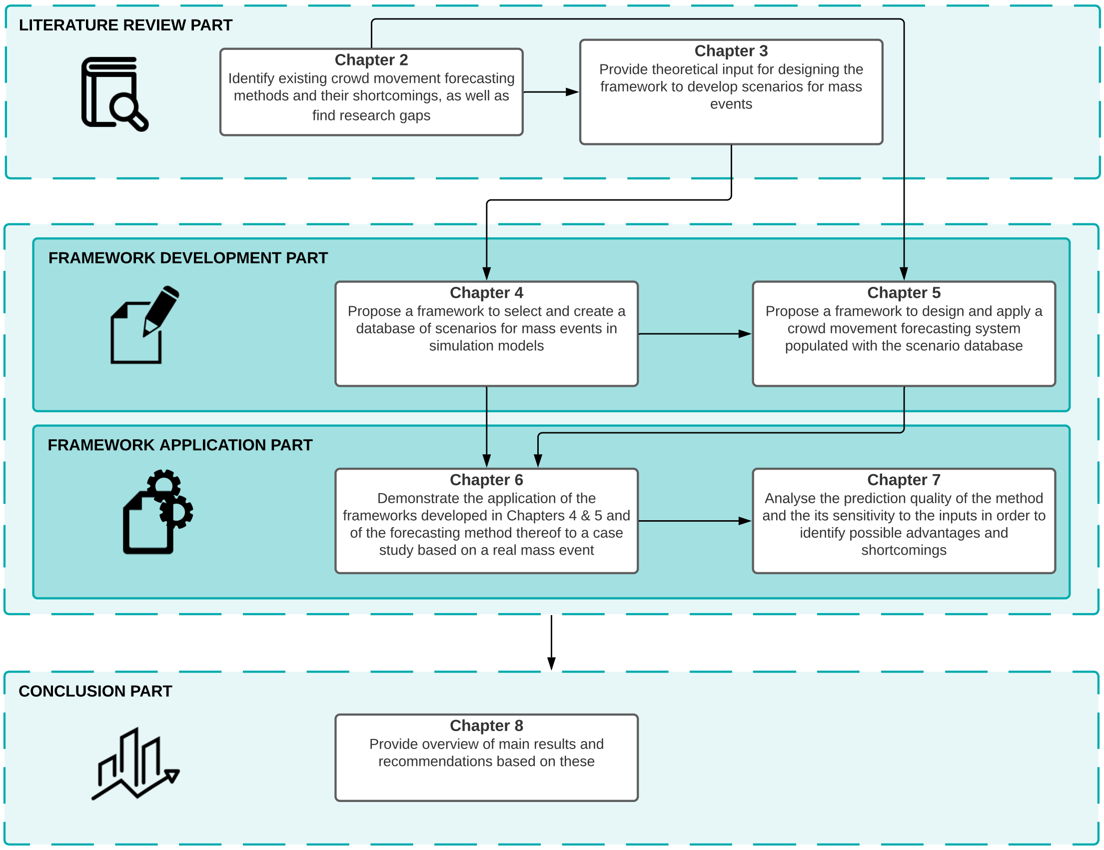


Figure 1.2: Schematic overview of this research

I

LITERATURE REVIEW

2

State-of-the-Art Forecasting Methods

A review of the literature regarding existing methods for real-time crowd movement forecast is performed in this chapter, to address the following research question:

- What is the state-of-the-art regarding real-time crowd movement forecasting methods?

The goal of the literature review presented here is twofold. Firstly, to identify which methods have been proposed so far and what their key properties are, and secondly to define the knowledge gap in order to place the present research among these. The overview of the state-of-the-art crowd movement forecasting methods given in the sections below focuses on approaches for short-term or real-time prediction for large crowds. Data- and model-driven methods can be found in literature for this real-time forecast. The former is discussed in Section 2.1, and the latter presented in Section 2.2.

2.1. Data-Driven Methods

An increasing number of studies can be found which attempt to develop a data-driven prediction scheme for pedestrian movement forecast (Duives et al., 2019; Toto et al., 2016; Asahara, Maruyama, Sato, & Seto, 2011; Goldhammer et al., 2014; Fan et al., 2015; Rudomin, Paz, & Pérez Valdez, 2016). As presented in the introduction of this thesis, data-driven refers to methods which use pedestrian movement data to design and train prediction models, generally making use of computer vision algorithms and neural networks or machine learning techniques. Meanwhile, the objective of the forecast varies from the operational level with trajectory prediction (Asahara et al., 2011; Goldhammer et al., 2014; Alahi et al., 2016; Bera, Kim, Randhavane, Pratapa, & Manocha, 2016), to the tactical level when the objective is to predict destination sequence (Danalet, Farooq, & Bierlaire, 2014; Gödel et al., 2018).

Methods which aim at predicting pedestrians' trajectories tend to consist of two main steps: 1) the derivation of patterns from the data and 2) the extrapolation of these patterns for the forecast. Consequently, proposed methods mostly predict pedestrians' short-term trajectories, which is desirable given the purpose they are created for, which include collision avoidance with autonomous vehicles (Alahi et al., 2016; Bera et al., 2016) and safety strategies at urban intersections (Goldhammer et al., 2014). Hence, the prediction horizon is often very short and scalability is limited to a few agents. This fact prevents these methods from providing an adequate prediction horizon which enables crowd managers to set up and deploy their strategies. Besides, some of these methods require historical data from past trajectories (Asahara et al., 2011). The problem with using historical data is that, for the type of event this study is concerned with, the chances of a one-off scenario are higher that of a repeated pattern (Fan et al., 2015). The event infrastructure is likely to change between occurrences of the event, or it might even be the very first time that the event is happening. Among the methods which use crowd data for trajectory prediction, the work done by Duives et al. (2019) is most closely related to this research given the forecasting horizon, event type and scale. The study discretizes the infrastructure network in cells and translates GPS traces into sequences of cells that have been visited by a pedestrian. These cell sequences are made time dependent and used to predict the next movement of the crowd with little need for historical information. The historical information of the study by Duives et al. (2019) is retrieved in real-time during the course of the event, thus using recent observations of the past few hours instead of days, months or previous editions of the event.

Destination distribution prediction is also among the data-driven approaches found in literature, although fewer studies exist on this topic. Commonly seen in these studies is the use of data from Wi-Fi or bluetooth sensors (Prasad & Agrawal, 2010; Danalet et al., 2014; Danalet, Tinguely, de Lapparent, & Bierlaire, 2016), while innovative proposals also include the derivation of heatmaps from video data to predict destinations (Gödel et al., 2018). On a citywide level, GPS data set from mobile phones were studied for the purpose of short-term prediction. Fan et al. (2015) proposes a prediction-by-clustering approach, which makes use of multiple random Markov Chains, each of which is a naive movement predictive model trained with movement of the subjects that belong to each cluster. Their algorithm learns online, as it is based on recent movement observations, and consequently has little need of historical information and can be run in real-time.

In general, the data requirements and level of detail of data-driven methods make these challenging for real-world applications. The data-driven models are also often specific to the event the data was obtained from, as mass events are naturally different (Karbovskii, Karsakov, Rybokonenko, & Voloshin, 2016). To the author's knowledge, no generalised data-driven model exists for crowd movement forecast.

2.2. Model-Driven Methods

From the existing model-driven approaches to perform real-time forecast of crowd movements for mass events, one can identify key elements for the real-time prediction. These are highlighted in Figure 2.1, based on the studies of Holl et al. (2014) and Matyus et al. (2016). It can be seen that both supply and demand elements are needed in the process. On the supply side, the event's infrastructure layout defines, amongst others, the boundaries of the walkable space and the location of activities. In real-time, the demand is derived from the data from the crowd monitoring systems, which are processed in order to indicate the current state of the crowd (e.g. number of visitors in and moving between the distinct area of the environment). Together with information about expected future conditions (e.g. given the event's schedule or known disturbances), the derived current state forms the input to the simulation core. Hence, this processing step depends on the model used in the real-time core and what input data it requires. The simulation core consists of models such as the ones presented in Chapter 1 (e.g. Helbing and Molnar (1998); Blue and Adler (1998); Moussaïd et al. (2010)). When a simulation is run combining supply and demand elements, the crowd movements are predicted and communicated to crowd managers to assist them in taking informed decisions.

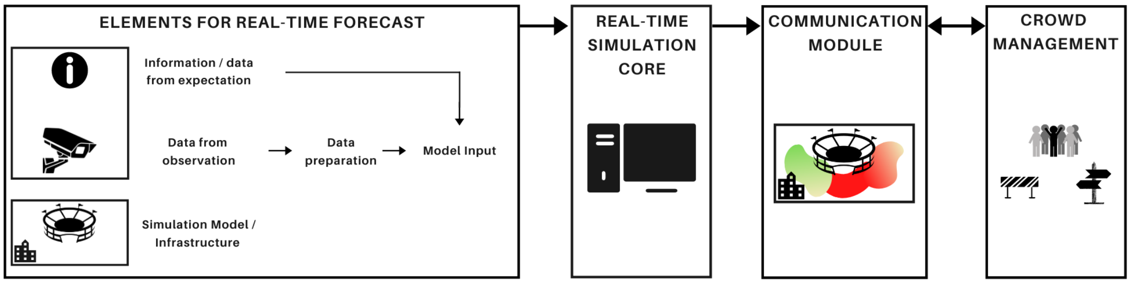


Figure 2.1: Elements identified from literature for model-driven crowd movement forecasting methods (Adapted from Holl et al. (2014))

In this section, two branches of model-driven methods for crowd movement forecast are discussed. Methods which make use of a single type of operational model are presented in subsection 2.2.1. Subsequently, subsection 2.2.2 introduces the so-called hybrid methods, which make use of two or more operational models.

2.2.1. Single Methods

Single methods, as detailed in this section, refer to approaches that make use of only one type of operational pedestrian model. Among the simulation-based methods that have been developed for real-time prediction of large crowds, optimization of well-known microscopic models such as the social-forces model (Johansson et al., 2007; Karbovskii et al., 2016), as well as algorithms for parallel computation (Wagoum et al., 2013; Holl et al., 2014; Lohner, Baqui, Haug, & Muhamad, 2016) are more commonly found. In such methods, the computational cost is dealt with at the expense of higher monetary costs for the hardware (Holl et al., 2014), or loss of detail due to the optimization processes. The focus of these approaches is to maintain, as much as possible, the behavior validity of the forecast. However, for applications for mass events, the higher monetary costs are likely to prevent these models from being considered in practice, as it is expected that event organizers would not be willing to pay for such resources. Regarding the loss of detail, the simplifications proposed might render the representation of self-organized dynamic patterns less valid. For instance, cutting off interaction forces at a certain maximum distance might mislead the forecasting results. This fact is especially relevant when the prediction is performed to identify the occurrence of critical conditions (e.g. the appearance of bottlenecks).

Approaches that propose the use of macroscopic and mesoscopic models for real-time prediction can also be found in literature. Matyus et al. (2016) presented a method able to provide a 10-minutes forecast for a crowd of 42,000 pedestrians modelled simultaneously. In their prediction, the authors used a cellular automata (CA) model and (near) real-time data from counting and bluetooth sensors. The lower spatial resolution as well as optimized motion processes of CA models allowed their method to perform 10-times faster than real-time on a typical laptop. On the macro level, Hänseler et al. (2014) designed a method for real-time crowd control, which, unlike other macroscopic models (Hughes, 2002, 2000; Treuille, Cooper, & Popoviundefined, 2006), is able to handle heterogeneous populations and interacting flows. Aggregation of agents' behavior and the simplification of the environment to a graph make macroscopic models efficient for real-time applications. Nonetheless, both CA and macroscopic models have been shown to be less capable of validly modelling crowd phenomena, thus providing poorer predictions of crowd movements (Duives et al., 2013). The environment in such models often does not create clear boundary conditions, and the interactions between agents are also simplified. The distinct movement base cases as presented by Duives (2016) are often poorly or not captured at all, making these not suitable to model every situation that can occur during mass events.

2.2.2. Hybrid Methods

A specific branch of model-driven methods are the so-called hybrid models. Hybrid approaches attempt to combine two or more operational pedestrian models with distinct properties into a single model. For instance, a hybrid model can combine the lower computational needs of macro modeling (equation-based modeling) with the behavioral validity of micro modeling (agent-based modeling). This is done by assigning each model to distinct areas of the infrastructure. The reasoning behind creating such models is that in large-scale environments, not all areas have the same importance for the prediction at all times (Ngoc Anh, Zucker, Huu Du, Drogoul, & Vo, 2011). For instance, the entrance gates during the ingress phase of the event might be far more important than the areas by stages, as more people are concentrated and expected at this location. The suitability of each model for each area is dependent on the necessity to capture valid results at distinct levels of detail in a computationally efficient manner. For instance, in the simulation of a large-scale event ground, it is considered more critical to accurately capture behavioral differences at possible bottlenecks on the environment than along an open path. Applications of hybrid models found in literature exist in all possible combinations of the three different scales: macro-micro (Ngoc Anh et al., 2011; Xiong, Lees, Cai, Zhou, & Low, 2010), macro-meso (Biedermann & Borrmann, 2016) as well as meso-micro (Steffen & Chraibi, 2014).

When interfacing the different models to build the new hybrid one, some assumptions and simplifications are required and certain model specific attributes, which cannot be transformed between the spatial scales, are lost. One example is the social aspect of group behavior which is dependent on individual agents and, therefore, cannot be captured by the aggregated parameters of macroscopic models (Biedermann & Borrmann, 2016). Furthermore, most existing models are static. Being static in this case means that the areas of the environment which will be covered by each model are defined by the user before the simulation starts, and remain constant during the simulation. Defining these requires prior assumptions and expectations about the location of possible bottlenecks. This results in a loss of flexibility for the validity of the model in capturing different behaviors than the ones expected at each area of the environment.

In relation to the elements highlighted in Figure 2.1, one can say that the model-driven methods discussed above focus their efforts on modifying or proposing changes mostly to the real-time simulation core stage. The goal of these approaches, both single and hybrid methods, is clearly to improve the capabilities of the simulation core considering the tradeoffs between speed and behavior validity.

2.3. Conclusions

There is no question that, to date, there is no agreed upon model or approach for performing forecast of crowd movements in real-time, and that each of the different methods have their advantages and shortcomings. Two main gaps in research become apparent by the literature review carried out in this chapter.

Firstly, data-driven models are considered specific for the event from which the data used for the deriving the model was obtained from, and the forecasting horizon is often too short for the purpose of crowd management. Some data-driven models also require historical data which, as previously stated, for large-scale events is likely to mislead the prediction.

Secondly, methods for using microscopic models and their behavioral accuracy for crowds in large-scale events are either costly, due to the hardware needed, or, in case of existing hybrid models, they remain limited to a certain area of the event ground and to the capabilities of the models connected to it. Hence, the behavior validity of the prediction obtained with hybrid models is area-dependent and does not change over the course of the event. While a proposed solution in literature is to use simpler models such as mesoscopic and macroscopic, as these are less computationally costly, they are shown to be less able to validly predict the range of distinct situations that can occur during mass events.

One can observe an overall aim among the different model-driven methods: ensuring a high level of behavioral validity, while maintaining real-time performance by lowering computational time. The reason for this being that, for an accurate prediction to be made, the different movement base cases and crowd phenomena observed in real life need to be modelled (Duives et al., 2013). Given that most models that validly reproduce such requirements are microscopic models, which are known for being computationally expensive, methods to enable implementing these in real-time are sought after.

From the existing model-driven approaches, one can also identify key elements for the real-time prediction. On the supply side, the event's infrastructure layout defines the boundaries of the walkable space and areas where activities are located, which are necessary information to build the simulation model. Meanwhile, on the demand side, the data from the crowd monitoring systems is used to indicate the current state of the crowd and derive the model's inputs. Examples of these are the inflows from the different entrances and the number of visitors using each route available. When a simulation is run combining supply and demand inputs, the crowd states are predicted and communicated to crowd managers to assist them in taking informed decisions.

3

Crowd Dynamics Theory

The goal of this chapter is to provide understanding of the types of scenarios that occur during a mass event. To that end, the theories discussed illustrate the development of the efficient dynamics, where pedestrians are walking freely on the environment, towards the appearance of inefficient phenomena, where unstable flow conditions are expected, and the factors which can influence this transition. It is considered important to define here that the dynamics of the crowd, as referred to throughout this chapter, relates to the interplay between supply (i.e. the event infrastructure and services offered) and demand (i.e. the number of visitors) that occurs during mass events. To illustrate this interplay, one can think of a situation where the demand for an activity, for instance a commercial facility, exceeds the number of visitors that can be served per unit of time, then queues start appearing and waiting times can become exceedingly long. These theories are key inputs to the identification of scenarios to be included in the database, and to the scenario development framework which will be presented in Chapter 4. The following two research questions will be addressed in this chapter:

- Which factors influence the dynamics of crowd movements at mass events?
- Which crowd dynamics are relevant for real-time prediction of crowd movements at mass events to guarantee the comfort and safety of the crowd?

Firstly, Section 3.1 introduces the concept of crowd states, as it will be used throughout this research, which relates to the metrics to describe the aforementioned dynamics. Section 3.2 provides a theoretical background to pedestrian traffic flow theory, and the factors which influence the crowd dynamics are highlighted. The final section of this chapter (Section 3.3) discusses crowd management theory, where the focus is on the identification of the dynamics for which crowd management measures are deemed necessary, given the increased risk and discomfort these dynamics can lead to.

3.1. Crowd States

The concept of state has been commonly used in literature for describing dynamic systems. In system theory, state describes the result of all past inputs into the system enough to enable predicting the future developments of the system when no disturbances occur (Knoop et al., 2018). The state vector contains the key information to describe a system at any given time instant. In this thesis, the concept of crowd states is used with the aim of describing the crowd dynamics for different traffic conditions.

In traffic studies, the state vector can be formed by multiple distinct combinations of metrics. While Yuan et al. (2012) denoted the state vector of road segments as a vector of densities, H. Wang et al. (2016) presented an agent-based formulation consisting of the position and orientation of each individual agent (agent state). In the study of Yuan et al. (2016), the state vector is defined by multiple variables such as counts, flows, densities, velocities, travel time and route choices. The variability between metrics for different types of studies occurs because the state metrics are determined based on the output dynamics of interest. For instance, if the system aims at describing the variation between the sides preferred by pedestrians when avoiding collision with obstacles, the dynamics of interest are on a higher level of detail, and thus the state metrics needed are clearly different from those of a system that describes the evolution of flow of pedestrians through a bottleneck.

A categorization can be proposed where these dynamics of interest can be classified for a given combination of the level of aggregation of the metric over the pedestrians (i.e. metrics that describe the individual behavior of each pedestrian vs. metrics that describe the behavior of a group of pedestrians), and the applicability (i.e. metrics which are specific to a certain infrastructure element vs. metrics which are applicable to any area of the environment). Macroscopic, mesoscopic and microscopic are the three subcategories under level of aggregation, and local or global are the subcategories under applicability.

Examples of state metrics in each category are illustrated in Figure 3.1. As presented by Sparnaaij (2017), *microscopic* refers to single variables derived from the perspective of each individual. Trajectory is an example of a metric on this level, where the position of each pedestrian at each time is considered. *Mesoscopic* level metrics are also derived from a single pedestrian, but the distribution of the metric over the pedestrians is of interest. Variables on this level can give insights into how well heterogeneity in behavior is captured by the model (Sparnaaij, 2017). The distribution of the average speeds derived from the individual average speed of a group of pedestrians can be placed on this level. Aggregate and collective behavior of pedestrians are described by the *macroscopic* level metrics, for which classic examples are flows and densities. Regarding the applicability category, variables are described by *local* applicability when they are specific to a certain area or condition of the environment, whereas *global* applicability refers to variables that can describe any type of environment or condition. Bottleneck throughput is an example of the former, as it is only applicable to areas of the environment where a bottleneck exists (e.g. gates). Density, on the other hand, can describe any area of the environment in any condition.

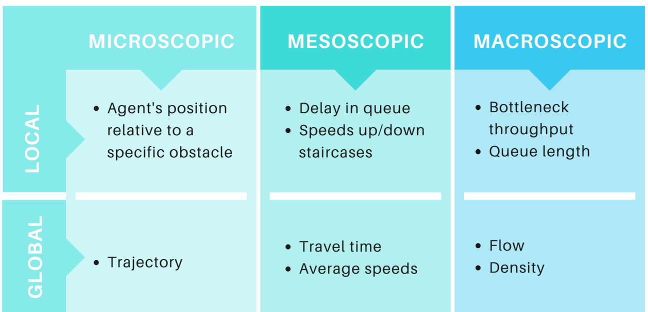


Figure 3.1: Examples of crowd state variables in each category

In this research, the dynamics of interest are described by metrics of the mesoscopic and macroscopic levels. The reason for this is the purpose of the prediction and the proposed method for performing such prediction. As defined in the scope of this research, the purpose of the prediction is to provide crowd managers with information about the future state of the crowd to help them assess the comfort and safety of the visitors. Thus, the dynamics resulting from the collective behavior are considered of far more interest. Furthermore, when representing the behavior through simulation models of large crowds, as it is done in this research, aggregate behavior is more representative given that it is more likely that such behavior is more accurately captured by simulation models. A final remark relates to a practical perspective regarding the monitoring of the crowd during the event. As will be discussed in Chapter 5, there are distinct types of sensors to monitor the state of a crowd, which collect different types of information. Most commonly used sensors often only gather data related to the aggregate behavior of pedestrians, and as the prediction method proposed in this research uses this information from the real crowd, this practical consideration also favors mesoscopic and macroscopic metrics over the microscopic ones.

3.2. Pedestrian Traffic Theory

Given the considerations made in the previous section regarding the level of aggregation of the dynamics of interest, the discussions below relate to the collective behavior of pedestrians based on the theories of traffic flow and pedestrian choice behavior. On the supply side, traffic flow theory provides a way to assess the areas of the environment and the layout of the event terrain. This assessment can give insights into the specific locations and conditions where the crowd is likely to face discomfort, or where unsafe situations might arise. On the demand side, pedestrian choice behavior theory covers the key factors which influence the choices of visitors, with the aim of assessing the infrastructure usage by the pedestrians during the event for distinct conditions. Although the supply influences the demand and vice-versa, for the purpose of structuring the discussions below, supply and demand factors are discussed separately. Figure 3.2 provides a general but not exhaustive overview of the factors that influence supply and demand in pedestrian traffic which will be further discussed below. These are derived by studying literature on pedestrian traffic and choice behavior, and are further used in Section 4.2 when a method for identifying the scenarios for a particular event is proposed.

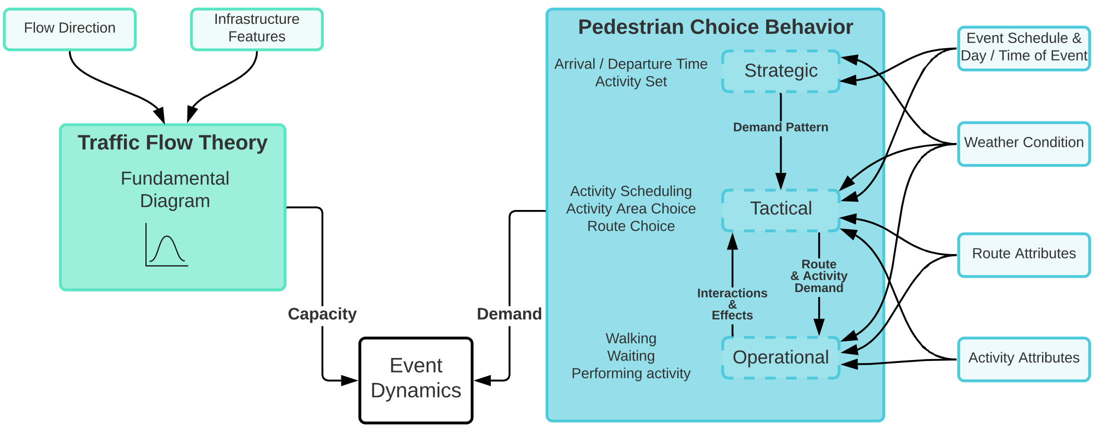


Figure 3.2: General overview of influencing factors on supply and demand

3.2.1. Supply Analysis

On the supply side, pedestrian traffic can be analysed through the lens of the fundamental diagram and factors that influence its key parameters. The fundamental relationship between flow, density and speed, where flow is given by density multiplied by speed, is a key theory which guides multiple studies in pedestrian literature. However, as one can see in Figure 3.3 by the multiple fundamental diagrams found in literature, summarized by Daamen (2004), there is no agreed upon parameters for the fundamental diagram for pedestrian traffic. The main parameters of the fundamental diagram are the capacity (q_{cap}), which indicates the maximum flow, and the critical (k_{crit}) and jam densities (k_{jam}), which represent, respectively, the densities for which the flow is maximum and that for which the flow is zero (i.e. the maximum possible density).

The lack of consensus on the parameters and shapes of the fundamental diagram for pedestrians is due to the influence of multiple factors on this relationship (Wieringa, 2015). Examples are the flow directions (i.e. uni- or multi-directional flows) and infrastructure features (e.g. stairs, flat areas). These factors are further elaborated upon.

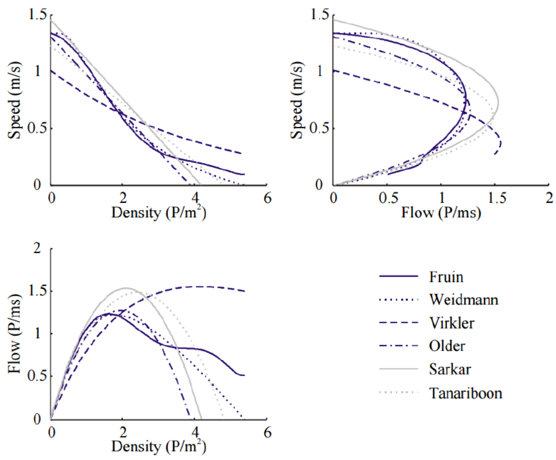


Figure 3.3: Fundamental Diagrams found in literature (Source: Daamen (2004))

Flow Direction

The movement of the pedestrians during large scale events can occur in multiple configurations. Flows along corridors can be characterized as unidirectional or bidirectional, whereas at intersections these can have multiple directions. These different configurations influence the fundamental diagram. Research has shown that for multi-directional movements, due to the different types of interactions that occur between pedestrians (e.g. face-to-face interactions which appear in multi-directional flows), the capacity of the infrastructure is reduced. Weidmann (1992) has shown that this reduction is dependent on the share per direction: the more unbalanced these are, the larger the reduction is. For instance, a 16% decrease of the capacity was observed for a share of 90%/10%. Regarding the density, while a corridor with unidirectional flows has been shown to reach densities of 7 P/m^2, in bidirectional conditions studies have generally found densities up to 4 P/m^2 (Duives, 2016).

Infrastructure Features

Even in situations where a single flow direction is expected, there are certain features of the built environment which can influence the crowd states and the development of these states over time. The distinction made in Section 3.1 between the applicability (i.e. local or global) category of the metrics to describe the crowd states highlights this fact, as local metrics can only describe certain areas of the environment. The changes in the path width along a corridor, the presence of stairs or even the gradient of the infrastructure are examples of such features which can affect the capacity.

Regarding the changes in width, several studies have shown that the maximum flow rate decreases with a decrease in width (Yanagisawa et al., 2009; Daamen & Hoogendoorn, 2012; Kretz et al., 2006). Thus, densities reach highest values directly upstream from the locations where the width changes. The presence of stairs also reduces the capacity as pedestrians' average speed have been shown to be about 50% lower on this type of infrastructure, both when ascending and descending (Buchmueller & Weidmann, 2006). Similarly, the average speed of pedestrians changes as the gradient of the path changes, and so does the capacity. However, the direction of change depends on the direction of movement in this case. For inclinations of about 20% (inclinations over this are often replaced by stairs or escalators), when walking downwards pedestrians' speed increase, while when moving upwards this speed decreases (Buchmueller & Weidmann, 2006).

3.2.2. Demand Analysis

Pedestrian choice behavior, as presented in this subsection, aims to provide an understanding of the interplay between the distinct decisions made by pedestrians when travelling, and it highlights the effect of these on the expected dynamics. For instance, identifying the demand for different routes between an origin and a destination requires understanding of the effect of certain route attributes on pedestrians' choice behavior, and thus the demand for the different routes at distinct times during the event can be assessed. The output of the demand analysis proposed in this section is thus an assessment of the usages of the infrastructure by the pedestrians, and the factors that can influence this usage according to literature.

Hoogendoorn et al. (2001) proposed the theoretical framework shown in Figure 3.4, making a distinction between three levels of pedestrian choice behavior, namely strategic, tactical and operational. At the *strategic* level individuals choose their departure time and the activities they wish to perform, resulting in a collection of activities called the activity set. The schedule of these activities and the route they will take to move between these are part of the *tactical* level decisions. These decisions are on a higher level as they change less frequently than those at the following level.

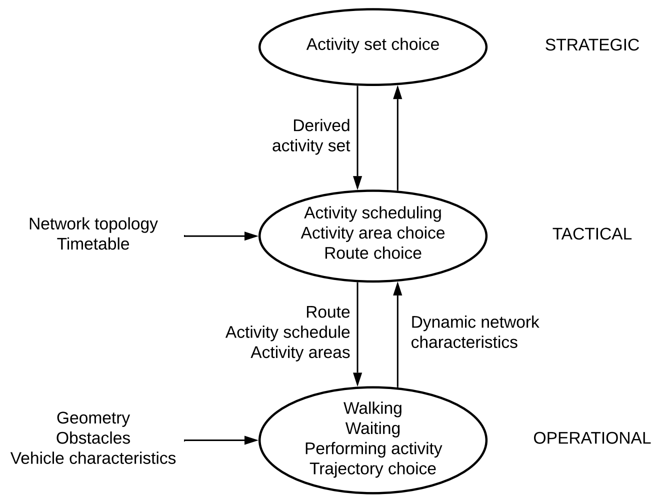


Figure 3.4: Levels of Pedestrian Choice Behavior (Source: Hoogendoorn et al. (2001))

The decisions on the *operational* level are instantaneous decisions, that is, the decision is executed for the immediate next time period. Examples are the walking speed, the decision of waiting or continuing to move, as well as the decision to perform an activity. The decisions on each level influence one another, where the higher level decisions affect the behavior of pedestrians more as these guide the following levels.

In their research, Hoogendoorn et al. (2001) used the concept of utility, where the assumption is that pedestrians aim at maximizing their utility by optimizing their choices. Based on this concepts, one can discuss the influence of distinct factors on the choices made at the different levels. These factors have been derived from literature and are detailed in Section A.1. As the section illustrates, many factors have been found to influence the behavior of pedestrians on the different levels. These can be split into personal and exogenous factors. The former relates to characteristics of the individuals, whereas the latter relates to characteristics of the event environment and event planning. Overall, it can be said that personal factors seem to influence pedestrian choice behavior on the lower levels (i.e. operational) more than on higher levels (i.e. strategic and tactical). Exogenous factors on the other hand have a greater effect on strategic and tactical choices.

In this subsection, the focus of discussion relates mostly to factors influencing the tactical level decisions. This selection is made due to the considerations that the major decisions which influence the development of the crowd states over the prediction horizon are made on this level (e.g. route and activity area choice), and the fact that decisions on this level are most often influenced by crowd management measures (Wieringa, 2015). The results of the decisions taken on the other levels are incorporated in the analyses, however less extensively.

Event Schedule & Day and Time

The schedule of the activities of the event can provide relevant indications regarding the locations where visitors are going to be at different times during the event. Furthermore, these can indicate the type of pattern of demand one can expect to arrive at the event terrain. For instance, for events that have a clear start time, the demand is expected to increase as the time gets closer to the set start time. This pattern is also influenced by other factors, such as the day of the week and time of day the event is planned to happen. These factors are even more important for events that last for an entire day or multiple days. It can be expected that visitors arrive closer to the event time for events that occur on weekdays, as they are often departing directly from their work locations. Also, for events that occur on multiple days, the Friday and weekend demand is likely to be higher than the weekday demand. This pattern is shown in the study of Iliadi (2016), where the distributions of trips on Friday, Saturday and Sunday is higher than on Thursday

Several studies have shown the influence of the day of the week and time of day on the choices of activities of pedestrians (Seneviratne, 1985; Ton, 2014; Iliadi, 2016). For instance, people usually have lunch at around midday so visitors are expected to be at locations that serve food at around that time. In the study of Iliadi (2016), the author statistically proved that there is a relationship between the time of the day of the event and tactical level choices such as route choice. In the study, the author stated that more visitors prefer to perform activities, and thus choose routes where they can perform such activities, during the morning and afternoon if compared to the evening.

Weather Conditions

As shown in Figure 3.2, this factor is expected to influence the behavior of pedestrians on all levels of behavior. On the operational level, pedestrians have been shown to increase their walking speeds as the weather becomes more uncomfortable (Knoblauch, Pietrucha, & Nitzburg, 1996). This means that in dry weather, visitors walk slower than in rainy conditions. Besides the walking speed, the weather condition also changes pedestrians' route and activity choices (Daamen, 2004; Ton, 2014; Iliadi, 2016; Bovy & Stern, 1990). Routes with weather protection, or where the surface of the terrain is safer against slipping or falling, are chosen over other routes when the weather is rainy.

Activity & Route Attributes

This subsection summarizes the influence of activities and route attributes on the choices of pedestrians. The aim is to provide an overview of multiple factors one can consider when assessing the usage of the infrastructure, thus these are combined as they are assumed to influence one another. Firstly, features of the environment, such as vegetation, presence of landmarks, canals and rivers, as well as lighting have all been shown to have a positive influence on pedestrians tactical level choices (Hill, 1982; Korthals & Steffen, 1988; Bovy & Stern, 1990). Due to the pleasantness of the routes where these elements are present, pedestrians are more likely to choose a route with these elements.

In addition to the environment features, the number of attractions along a route or within an area of the environment is highly influential on pedestrians route and activity areas choices (Bovy & Stern, 1990; Guo & Loo, 2013; Hoogendoorn & Bovy, 2004; Ton, 2014; Iliadi, 2016). These attractions can be seen as stimulation of the environment, and especially in mass events which naturally concentrate multiple attractions in distinct areas, pedestrians' choices are both triggered and influenced by such environmental stimulation.

The factors discussed so far have mainly created a positive influence to the pedestrians. However, there are also elements which provide repelling forces. An example is distance. Pedestrians have been shown to often prefer shorter routes over longer routes (Borgers & Timmermans, 1986; Daamen, 2004). Even if the progress on a shorter route is relatively slow due to crowding, the choice of a longer route is seldom made (Daamen, 2004). However, based on a state preference survey, the study of Galama (2016) has shown that crowding has a repellent influence on pedestrians route choice.

3.2.3. Sub-conclusions

In this section, based on the theories of traffic flow and pedestrian choice behavior, a selection of factors that influence the supply and the demand sides of the dynamics of mass events were presented. On the supply side, factors which affect the capacity of the infrastructure were identified. One example is the number of flow directions allowed to coexist on the environment. Studies have shown that multi-directional flows negatively affect the throughput if compared to unidirectional flows. Certain features of the infrastructure also have the same effect. It has been presented that the maximum flow decreases with the decreasing width of paths, and where stairs are present or where pedestrians are walking upward on an inclined path. The identification of the location where multiple flow directions occur, or where the infrastructure features have the aforementioned characteristics, are therefore considered important in the process of developing the scenarios. These observations can indicate the locations of the environment and under which conditions the pedestrians in the crowd could face discomfort or unsafe situations.

On the demand side, it was discussed that due to the purpose of this research the focus of the analyses of the demand relates to the tactical level decisions made by pedestrians. These relate to activity area and routes choices, and the factors that influence these. For instance, it is clear that pedestrians have preferences for routes and activities where they are triggered by the surrounding environment. This includes routes where more activities can be performed, as well as routes where there is vegetation, lighting and water present. Besides, depending on the weather condition, locations can be chosen where there is shelter, or where the walking surface is safer against slipping or falling. An implication of the discussions above for this research is the insights it provides into the demand for certain areas of the environment over others. These insights assist in identifying the scenarios which can occur during an event. For instance, one can have expectations regarding the usage of the infrastructure by simply analysing the features and characteristics of the event terrain. This in turn can indicate where visitors more visited routes or activities, or areas where can get crowded in bad weather conditions.

3.3. Crowd Management Theory

Unsafe crowd densities are more likely to occur when the crowd dynamics observed in the environment transition between efficient self-organization phenomena towards inefficient phenomena. When inefficient crowd dynamics start appearing, such as when bottlenecks become active, crowd managers need prediction to assess whether the inefficient phenomena can potentially lead to discomfort or too high densities. Understanding the development of the efficient crowd dynamics through inefficient phenomena towards turbulent flows can provide useful insights into the dynamics of interest for prediction, in relation to crowd management measures. To that end, this section discusses these flow transitions and corresponding phenomena, and their application to this research with regards to the development of scenarios to be included in the database.

3.3.1. Flow Transitions & Crowd Phenomena

Wieringa (2015) qualitatively distinguished the development of crowd disasters in terms of flow regimes by analysing Traffic Flow Theory. Five regimes were proposed by the author namely: free flow regime, unstable regime, crowd turbulence regime, crowd disaster I and crowd disaster II. The division arises from them being distinct in terms of flow dynamics, speed range and density range in the fundamental diagram. The ranges of density for each regime were proposed by Wieringa (2015) and are illustrated in Table 3.1 together with a brief explanation of each.

The regimes are presented in relation to their corresponding phenomena in the Layered Crowd Disaster Model proposed by Wieringa (2015) and shown in Figure 3.5. It can be seen in the model that not only are the phenomena related to the flow regime, but also the management of the crowd. It illustrates that preventive management can occur until turbulent flow

Table 3.1: Density ranges per flow regime and probability of crowd disaster (Derived from Wieringa (2015))

Flow Regime	Assumed Density Range	
Free Flow	$0 ped/m^2 \leq k \leq 1 ped/m^2$	Neat flow patterns, people walk at their desired speed
Unstable Flow	$1 ped/m^2 < k \leq 2 ped/m^2$	Decrease in walking speed and higher density compared to free flow, dynamic flow patterns start appearing
Turbulent Flow	$2 ped/m^2 < k \leq 3 ped/m^2$	Dynamic flow patterns, densities above critical
Crowd Disaster I	$3 ped/m^2 < k \leq 4 ped/m^2$	Congestion, density accumulates
Crowd Disaster II	$4 ped/m^2 < k \leq 5.4 ped/m^2$	Flow breakdown, maximum density

regime, even though this regime already indicates densities are above critical as seen in Table 3.1. However, it can be said that comfort and safety start being at risk when unstable flow regime appear. Beyond this regime, the probability of a disaster rises, and the effectiveness of preventive management drops.

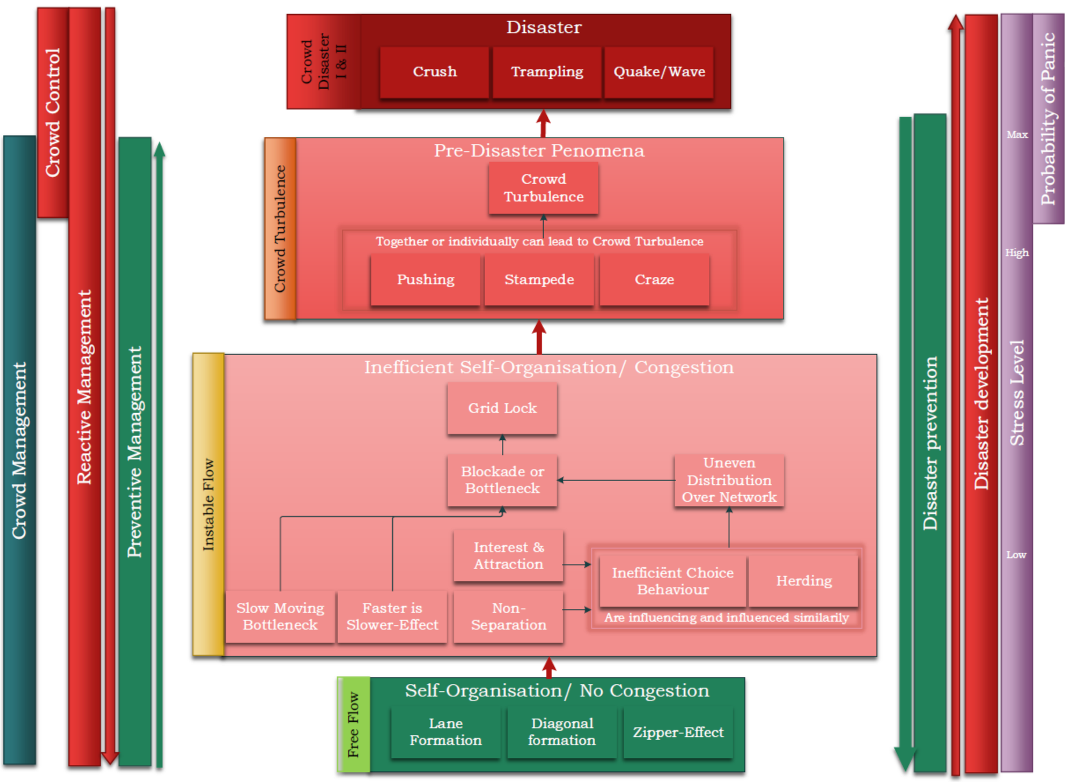


Figure 3.5: Layered Crowd Disaster Model (Source: Wieringa (2015))

In this thesis, the layer that corresponds to the unstable regime and the transitions from and to this regime are of interest and are thus further discussed. This is because, as one can see in Figure 3.5, this layer concerns the appearance of specific dynamics which can indicate that the efficient self-organization phenomena and neat flow patterns are being replaced by dynamic patterns and higher densities. Not only the probability of a disaster increases as the efficient self-organization in free flow regime starts to be suppressed (Wieringa, 2015), but also the discomfort of the pedestrians in the crowd. Besides, preventive management is assumed more effective when the phenomena under the unstable flow regime is predicted. Each of the phenomena in the figure is discussed in Section A.2. In the remainder of this section, only the phenomena related to the second layer are further explained.

Faster is Slower Effect In high densities queues by narrow bottleneck locations (e.g. gates, doors), the faster-is-slower effect occurs due to a large number of pedestrians competing for a few small gaps through the bottleneck by heading forward while the bottleneck is clogged (Duives, 2016). This slows down the total crowd motion and thus reduces the bottleneck throughput.

Grid Lock Indicate network saturation. Bottlenecks on the environment are active and demand is continuously higher than capacity, thus leading to feeder routes and mainstream routes being congested.

Herding Unclearness causing pedestrians to follow each other instead of taking optimal routes (Helbing, Buzna, Johansson, & Werner, 2005). This can occur when either only the most obvious routes or entrances are used, which can cause congestion, or when a few pedestrians start taking non-optimal routes to avoid crowding, or because they have more information to assess their optimal route, and other pedestrians follow.

Inefficient Choice Behavior Describes the phenomenon when pedestrians do not choose the optimal route between an origin to a destination. This can be caused by herding behavior or an increased interest in a different route, and it can be indicated by pedestrians taking longer routes or routes where the dominant flow direction is the opposite to the one they are moving.

Interest & Attraction Peak Refers to a peak in the demand for a certain route or activity due to an attraction or the arrival or departure of public transport.

Non-Separation This phenomenon refers to the non-separation of pedestrians flows or even the non-separation between flowing areas and queuing areas.

Slow Moving Bottleneck In pedestrian traffic, this phenomenon refers to a slow moving group of people which causes other pedestrians to attempt to overtake and can thus lead to congestion.

Uneven Distribution Over Network Occurs when there is imbalance between demand and capacity of the network, where certain areas are overcrowded while others still have a large capacity available.

3.3.2. Pedestrian Traffic Theory & Crowd Management

Crowd management entails managing both the supply and demand of pedestrian spaces. This requires not only planning the event infrastructure and location of activities and obstacles to ensure comfort and safety of the crowd, but also influencing pedestrians actions at all behavior levels. Crowd managers often think in terms of plans and scenarios, that is, if a situation occurs, which management strategy will be applied, and what to do if the strategy does not help enough. According to Hoogendoorn and Duives (2019), there are four main principles for the management of mobility. These form the basis for the principles of crowd management presented below. One can see that these are a combination of analysis of the supply (e.g. infrastructure characteristics) and demand (i.e. pedestrian behavior).

1) **Increase throughput** → This principle entails identifying the physical bottlenecks of the environment, its location and the reason why this is a bottleneck to ensure any unwanted friction in the direction of flow is removed. Examples of bottlenecks (i.e. cross-sections where the flow is hampered) are the infrastructure features discussed in subsection 3.2.1.

2) **Prevent Blockage** → As discussed in subsection 3.2.1, when multiple flow directions share the same infrastructure with non-separation, the throughput is hampered by the interactions between these. This can eventually result in blockages if the number of interactions are too high. Thus this principle aims at identifying the locations where possible interactions occur and assessing which conditions should be avoided to prevent blockages, or at least ensure that the blockages do not spill back to other parts of the infrastructure.

3) **Distribute flows over the available space** → This principle relates to avoiding the overuse of certain routes or activity areas when other routes are available, as these most used ones can get crowded which might result in discomfort and delays, or eventually lead to blockades. Optimizing the use of the available capacity by spreading the visitors on the environment can prevent these potential crowding issues. This is done by influencing people's choice behavior by informing them about other routes, or considering the site design and attributes which have attractive forces on pedestrians.

4) **Reduce the inflow of the crowd** → This principle aims at limiting the number of pedestrians simultaneously moving on the infrastructure by closing gates, routes or only allowing people into the terrain at certain time slots. Reducing the inflow aims at avoiding inefficient pedestrian behavior of having too many people at the same time on the same area, which can lead to high delays and congestion (Wieringa, 2015).

3.3.3. Benchmarks for Inefficient Dynamics

According to Hoogendoorn (2013), four cases can be identified which can indicate a reduction in throughput due to inefficient usage of the infrastructure by the pedestrians. These are (1) physical bottlenecks, (2) flow interactions, (3) uneven distribution over the network and (4) inefficient route and activity choice behavior. These dynamics can lead to discomfort and potentially unsafe conditions due to increasing densities, and therefore are considered relevant for prediction. These benchmarks are presented in Figure 3.6. From the study of the literature in crowd management presented in the previous subsections, one can see that these cases relate not only to the crowd phenomena discussed in subsection 3.3.1, but also to the crowd management principles presented in subsection 3.3.2. For instance, the non-separation of pedestrian flows relates to the appearance of flow interactions. Also, the crowd management principle of distributing flows over the available space can be applied when there is an uneven distribution over the network, as well as when physical bottlenecks appear.

Cases 1 to 3 relate to the supply characteristics. The physical bottlenecks are the infrastructure characteristics and locations where the path gets narrow, or where there is an obstacle

BENCHMARKS	REASONING
1. Physical Bottlenecks	When demand exceeds capacity, queues start forming which can potentially lead to discomfort and unsafe situations. Certain infrastructure characteristics can reduce the capacity and make these situations more likely to occur. Visitors might start choosing different routes to avoid the queues, and if the queues are not solved there might be spillbacks leading to an increased threat on safety.
2. Flow Interactions	On areas of the infrastructure where different walking directions coexist, the interactions between the pedestrians hampers the throughput. When the flows are high and the share per direction is unbalanced, there is often one direction which gets priority over the others, increasing delays for certain pedestrians and possibly leading to the appearance of blockades.
3. Uneven Distribution over Network	When activities or specific infrastructure elements (e.g. weather shelter) are concentrated in a certain area of the environment, or there are limited options of routes to move between certain locations, or even when there is a main entry location of the event, the network can become unbalanced and crowdedness can lead to discomfort and unsafe situations.
4. Inefficient Route and Activity Choice Behavior	Inefficient choices might appear even when there are multiple and sparse activities and routes on the event terrain as the interest for a particular route or activity might increase. In addition to such situation, often due to herding behavior or crowding, pedestrians might select unexpected / inefficient routes to reach their destinations. For instance longer routes or routes where the opposite flow direction is dominant. These choices might lead to undesirable flow interactions or uneven distribution over the network, which can lead to or indicate unsafe conditions.

Figure 3.6: Benchmarks for Inefficient Dynamics

obstructing the path. Flow interactions refer to the areas where flows interactions are permitted, for instance if bidirectional routes exist, or at intersections. The uneven distribution over the network occurs when there is a concentration of activities offered in a specific area, or when there are limited or even a single route between different areas.

Benchmark case 4 relates to the demand, that is, even in the case when activities are spread on the event terrain, or when there are multiple routes, the interest for a specific route or activity increases leading to crowding. Because this benchmark relates to the behavior of visitors, the inefficient route and activity choice behavior can cause or be caused by flow interactions or uneven distribution over the network. For instance, if a high share of visitors chooses a specific route over other routes, it can lead to an unbalanced network. In such case, these or the scale of these are not easily identified by simply looking at the planned infrastructure of the event, hence the distinction from the other two cases.

3.4. Conclusions

The discussion in this chapter are based on literature regarding the different metrics to describe the dynamics of the crowd, the factors influencing these dynamics, and the principles behind defining the dynamics of interest for prediction. From literature, it can be seen that multiple metrics can be used to describe the state of the crowd, and from the categorization proposed in Section 3.1 it was concluded that the dynamics of interest for this research are described by mesoscopic and macroscopic metrics. These relate to the aggregate behavior of pedestrians instead of the individual behavior given by microscopic metrics.

Based on the literature studies regarding pedestrian traffic, Section 3.2 concluded that there are multiple factors which influence the supply and demand sides, and thus the dynamics of the crowd. Reductions in the capacity, and possible conditions that could cause discomfort and safety issues, can be expected when multiple flow directions coexist, as well as when there are infrastructure features which hamper the throughput such as narrowing of paths or staircases. On the demand side, pedestrians choices and consequently the usage of the infrastructure is influenced by distinct environmental conditions, which indicate whether certain routes or activities might be more used over others. For instance, pedestrians tend to have preference for routes where more activities are located, whereas overcrowding appears to repel pedestrians.

To determine the dynamics of interest for prediction, crowd phenomena and the flow transitions between these were studied in Section 3.3. It was identified that the dynamics of interest lie in the transition between free flow to the identification of unstable flows, as in the latter case densities start increasing, inefficient phenomena start to occur, and the probability of discomfort and unsafe conditions rises. Together with the four crowd management principles, four benchmarks for identifying inefficient dynamics were derived. These are to be used as a key input for the development of scenarios as proposed in the following chapter.

II

FRAMEWORK DEVELOPMENT

4

Framework for Scenario Development

As stated in Chapter 1, this research proposes a forecasting method, where simulation is an offline step for the online forecast. Unlike the model-driven forecasting methods presented in Chapter 2, the input for the simulation core is therefore not derived from the crowd monitoring systems in real-time. The implication of this is that the inputs of the simulation core are mostly unknown, except for the supply elements such as the event infrastructure, which are planned beforehand by the event organization. In terms of the demand, a range of possible situations can occur. For instance, many pedestrians might be attracted to a specific route or activity, or most of them might choose to arrive at a similar time instead of spread out over time. These situations that can occur during the event for which prediction would be desirable thus must be simulated prior to the event. As explained in subsection 4.3.2, such situations are related to the four benchmark cases of inefficient dynamics. A database of scenarios is thus created, which is a key input for the selection algorithm proposed in Chapter 5. Hence, this chapter presents the framework for developing such scenario database. The following research questions are addressed in this chapter:

- What forms a scenario?
- How are the benchmarks for inefficient dynamics used for identifying the scenarios to be included in the database, that is, for which prediction would be desirable?
- What are the dynamics of each benchmark for building these in a simulation environment?
- How is the stochastic behavior of pedestrian models taken into account when building the scenario database?

Firstly, given the scope of this thesis with regards to the usage of simulation model for the development of the database, the processes that together form the dynamics of simulation models are discussed in Section 4.1. Following, the proposed method to identify the scenarios of interest are presented in Section 4.2, together with the overall objective of these scenarios. The formulation of the scenarios' dynamics in relation to the simulation model are then discussed Section 4.3. Finally, the framework for scenario development is proposed and discussed in Section 4.4.

4.1. Model Dynamics

In general, one can identify five modules in a typical microsimulation software as illustrated in Figure 4.1. When a simulation is run with the necessary information gathered for each of the modules used as inputs, the trajectory of each agent is obtained. The trajectory is a very detailed output which shows the location of each pedestrian at each time instant during the simulation. These are often aggregated over the pedestrians to derive the metrics of interest for the typical analyses performed (Campanella et al., 2014). These aggregate metrics are for example flows and densities, from which one can analyse the crowdedness of different areas of the infrastructure at different times, or the throughput of bottlenecks. Each of these modules, their corresponding inputs, and the output dynamics are further discussed below.

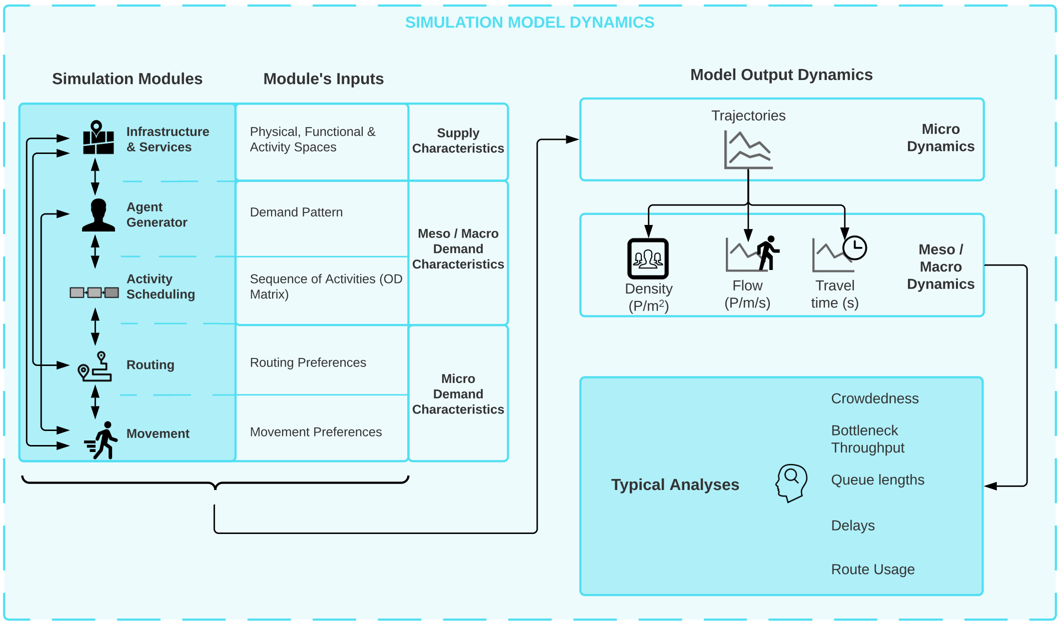


Figure 4.1: Modules, inputs and output dynamics of microsimulation models

4.1.1. Simulation Modules

The first of the five modules, here called infrastructure and services, relates to the supply side, that is, the built environment and characteristics of the facilities available on the event terrain (e.g. capacity of public transport facility or commercial activity). The following modules relate to the demand side, or more specifically the usage of the infrastructure by the agents, and the different behavior levels as proposed by Hoogendoorn et al. (2001). The first of these modules relates to the generation of agents, the location where these appear on the environment, and the assignment of properties such as the radius and maximum speed to these agents given pre-defined profiles. From their point of origin, agents then start their movement on the environment based on their assigned activity sequences, from which their next destinations and the order in which these should be visited are given. All the processes described above are direct inputs defined by the modeller.

The lower level modules, that is, the ones that are executed later in the sequence, are the routing and movement modules. These are formed by embedded route choice and operational movement models, respectively. As discussed in Section 2.2, several models have been proposed to describe the movement behavior of pedestrians. These processes guide the choice of route agents will take to move between the activities assigned to it, as well as the behavior when moving along this route regarding for instance avoiding collision with other pedestrians or the infrastructure. Because these processes can more easily be generalised, that is, are not necessarily specific for a given area or event, the routing and movement modules in simulation tools often contain underlying models to guide their processes. To adjust these models to specific conditions, if needed, the models' parameters can be modified.

The arrows in the figure indicate that the modules exchange information with one another. For instance, the infrastructure and services module send the agent generator information about the time agents should be generated given the public transport timetable, and also sends the routing and movement modules information about the boundaries of the geometry of the infrastructure. The agent generator sends information about the initial location of the agents to the activity scheduling so that the next activity in the agent's route can be defined. The routing module receives the next destination assigned to an agent from the activity scheduling module and, considering the initial position of this agent and the infrastructure boundaries, defines the global path the agent will follow. Lastly, when the movement module receives the information about this global route and starts moving the agent on this path, this module defines the local velocity deviations necessary to avoid collision due to the interaction with other agents.

4.1.2. Reflection on Model Dynamics for Prediction

To operationalize each module to build a scenario in the simulation environment, a set of inputs and parameters are necessary. The inputs related to the demand can be classified in two: (1) meso and macroscopic characteristics, and (2) microscopic characteristics. This classification relates to the influence on the different output dynamics. While the inputs of the meso and macroscopic characteristics have larger effect on the meso and macro dynamics, the inputs and parameters on the microscopic characteristics can largely influence the exact shape of the trajectory of each pedestrian. For instance, the sequence of activities can indicate which area of the environment is likely to have higher number of pedestrians due to more agents being assigned to it at a certain time. Meanwhile, the side preferred by an agent when passing an obstacle (e.g. left or right), which is a parameter of its movement preferences, can influence the shape of its trajectory when walking along this route.

In Table B.1, a comprehensive overview of these inputs and parameters is provided. As it can be seen from the table, microscopic models have multiple degrees of freedom. Each of the modules can be adjusted to the needs of the modeller at a very high level of detail, for the scenarios and dynamics one wants to reproduce. The higher the level of the detail of the behavior one wants to correctly reproduce, the larger the number of inputs and parameters one needs to get right. The question here is which of these are relevant for prediction of crowd movements during mass events. As discussed by Campanella et al. (2014), pedestrian models are mainly applied to assess the comfort and safety of pedestrian facilities based on aggregate data. Furthermore, in Section 3.1, it was discussed that the state metrics of interest for prediction of crowd states are given by aggregated metrics on the meso and macroscopic level. Therefore, the formulation of scenarios can reflect this. The aim is to make use of the underlying models on the lower level behavior (e.g. collision avoidance) to better estimate the higher level dynamics (e.g. evolution of density). As stated by Duives et al. (2013), for an accurate prediction to be made, the different motion base cases (e.g. bidirectional, merging movements) and crowd phenomena observed in crowds need to be captured. From the same study, the authors have shown that disaggregate models are often far more capable of reproducing these, as they better represent the interactions between the agents and the environment. Thus, as shown in Figure 4.1, from the trajectory data of each scenario, the metrics of interest can be derived. To that end, a selection of inputs can be made, and these are detailed in the following subsection.

4.1.3. Inputs for Output Dynamics

The following are the key inputs one needs to consider when building scenarios in a simulation model.

- *Geometry of the infrastructure* → The geometry of infrastructure defines the physical boundaries of the distinct spaces found on the event environment. This includes, among others, the position of fixed and movable obstacles as well as special infrastructure elements such as rain shelters, gates and doors. Besides obstacles, the geometry of the infrastructure also includes activity spaces, where activities are located, and functional spaces, which define areas which are not activities but that have particular function on the environment (e.g. queuing, waiting areas). The infrastructure elements are part of the factors that differentiate or separate flow directions and also define possible bottlenecks on the environment (e.g. narrowing of a path).
- *Activity time* → Activity time defines how much time each agent will spend within the boundaries of each activity space. This is part of the supply characteristics as it defined the service time, or the capacity of activities. It is based on the expected time taken by agents to perform each activities or, in the case of mass events, can also be defined by the time agents choose to spend watching a performance.
- *Demand pattern* → This input defines the amount of agents generated per time interval, as well as the location where these agents are generated. It is also an important factor due to the densities and distribution of flows on the environment defined by the pattern of the demand.
- *Schedule of Activities / OD Matrices* → Once agents are generated, the distribution of these on the distinct areas of the event environment are defined by the activities they are assigned to. OD matrices or activity schedules can be static, where the share of pedestrians out of the total number of pedestrians generated per time interval assigned to each activity does not change, or dynamic, where this share is time dependent. The flows of agents on the distinct areas of the environment over time are defined by this input.
- *Agents' profiles* → The profile of the agents often consist of two key inputs: agent's preferred speed and body radius. The former relates to the maximum speed agents will walk on when not constrained by other agents or obstacles, whereas the latter refers to the area each agent occupies in the model. As one can expect, agent's body radius have a key influence on the capacity of bottlenecks, and thus also affect densities near bottleneck locations by influencing the bottleneck's throughput.

These inputs are related to the three initial modules of the simulator namely infrastructure and services, agent generator and activity scheduling. Ideally, one would be able to define inputs which would lead to the behavior that exactly matches certain desired crowd states (Toledo & Koutsopoulos, 2004). In order to approximate this simulated states to the real ones, often a combination of inputs needs to be defined. An example is the combined effect of the demand pattern and number of agents assigned per route. By knowing the time of the peak of the demand and the route where the largest amount of agents is assigned to, one can define where the most crowded area of the environment is likely to be for the following time instants. Thus, working backwards is also possible, that is, for certain desired crowd state dynamics (output dynamics), one can define the inputs needed to create it. This principle is what defines the construction of different scenarios in simulation.

4.1.4. Sub-conclusions

The discussions made in this section have major implications for this research. A reflection was done on the dynamics of microscopic models, that is, the processes simulated (i.e. modules), their key inputs and effect on the different metrics to describe the output dynamics. It has been argued that, for the purpose of prediction of crowd states in mass events, the output dynamics related to the aggregate behavior of pedestrians are of interest. Thus, although the degrees of freedom of microscopic models enables the user to adjust many aspects of the behavior of agents at a very high level of detail, a selection of inputs for the considered output dynamics is made. The selected inputs, such as demand pattern and activity sequences, are expected to have a larger effect on the aggregate output. The usage of a microscopic model is thus considered so that the underlying models on the lower level of behavior are used to better estimate the higher level dynamics. This is because these disaggregate models are considered far more capable of reproducing the motion base cases and crowd phenomena observed in real life.

4.2. Identification of Scenarios

From the discussions in subsection 3.3.3, that led to the development of the benchmarks for inefficient dynamics, the types of scenarios for which crowd management strategies are prepared for can be identified. However, for the purpose of prediction, additional requirements regarding the scenarios' objectives need to be addressed, as it is clear that not only the scenarios for which inefficiencies occur should be included in the database. These considerations regarding the identification of the scenarios, and analyses required to develop the database are discussed in this section. First a discussion on the general objective of the scenarios is done. Subsequently, a method to analyse the event in order to capture the relevant information for the development of scenarios is proposed. The last subsection links the analyses of the event dynamics to the benchmark cases, and discusses the application of these when building the scenario database.

4.2.1. Scenarios' Objectives

For the purpose of real-time prediction to provide crowd managers with information to assist them in taking decisions, one needs to be able to predict two types of conditions. Firstly and of utmost importance, if the state dynamics occurring on the environment are going to lead to unstable flow conditions and high densities, the predicted states must provide crowd managers with this information. Secondly, if the state dynamics occurring on the environment are not going to lead to such conditions, and the densities are to remain under safe levels, the prediction should also indicate such developments. As crowd managers will decide whether or not to implement certain measures based on the prediction results, these need to be carefully considered when formulating the scenarios. Besides, crowd managers might want to assess how the crowd states will likely be if the demand in the next hour is 50% higher and the same patterns observed in the current hour are maintained.

To formulate the objective of each scenario, these conditions must be taken into account. However, it is clear that it is neither feasible nor desirable that all possible conditions are included in the scenario database. The scenarios therefore need to have a defined objective (i.e. state dynamics of interest), for which one would then use the prediction to get insights into the development of the states. Due to these considerations, the process of identifying the scenarios proposed in this research considers that the objective of each scenario, in terms of the dynamics it must reproduce, is formulated based on the states which can lead to unstable flow conditions and high densities. These in turn are based on the benchmarks of inefficient dynamics proposed in subsection 3.3.3. The condition for which the state dynamics occurring on the environment are not going to lead to inefficient phenomena and high densities are then defined by lowering the demand while the relative usage of the infrastructure remains the same. These levels of demand are further discussed in subsection 4.3.1.

An example is given to illustrate the aforementioned considerations. For a specific route where at a certain point the path gets narrow, thus creating a physical bottleneck, the objective of the scenario for this situation is to reproduce the dynamics for the case where the bottleneck becomes active and queues start forming. For instance by assigning a higher share of the agents to this route. The inflow into the environment is then changed, but the number of agents assigned to the route remains the same. Therefore, although the total number of agents on the environment is different, and so is the density, the usage of the infrastructure in relation to the number of agents on it remains the same.

4.2.2. Event Dynamics

The first step when identifying the scenarios is to analyse the event dynamics, that is, assess the layout of the infrastructure and the movement of the crowd between the different areas at different times during the event. The goal of this analyses is to indicate the locations and conditions for which the crowd could face discomfort or threats to safety. Two checklists are proposed to focus the analyses on the relevant aspects of the aforementioned goal: a supply checklist and demand checklist. The questions of the checklist are drawn based on the theory in pedestrian traffic, and the factors that influence the supply and demand, which were discussed in Section 3.2. How these are drawn is further explained below. It is highlighted that the questions below focus on the analysis of the collective behavior of pedestrians. For instance, one can think of an analysis to check 'what if' multiple pedestrians choose the same route or activity. This is due to the aforementioned considerations regarding the states of interest on the mesoscopic and macroscopic levels.

Table 4.1 illustrates the supply checklist and the reasoning behind each question proposed. The supply checklist aims at assisting in the identification of the areas of the environment where the infrastructure features or the permitted usages of this infrastructure can be problematic. From literature, it was identified that areas where for instance bidirectional flows are allowed, or where the capacity decreases due to a narrow path, are more critical. This means that it is more likely that unstable flow regimes appear at these locations. Hence, the questions below focus on highlighting these.

Table 4.1: Checklist for the supply analysis

Number	Question	Reasoning
1	Are there locations where the width of the path gets narrower due to obstacles or simply the shape of the path, or where there are infrastructure elements such as stairs or escalators?	If these locations exist, there is the possibility that flows of pedestrians get hampered by these infrastructure elements. Therefore, these locations need to be further considered in the formulation of scenarios and identification of inefficient dynamics.
2	Are there locations where multi-directional or intersecting flows exist given the planned routes?	If these locations exist, there is the possibility that capacity is reduced due to the interactions between the pedestrians. Therefore, these locations need to be further considered in the formulation of scenarios and identification of inefficient dynamics.
3	Are there activity locations positioned very close to one another? Or an area where many activities are concentrated?	If these locations exist, there is the possibility that a bottleneck might arise due the combined demand for these activities exceeding the capacity of the area where they are located. Therefore, these locations need to be further considered in the formulation of scenarios and identification of inefficient dynamics.
4	Are there areas of the environment where visitors can be sheltered from the weather? Or are there areas where the walking infrastructure remains safe and suitable for use in case of rain (e.g. asphalt, wooden platforms)?	If these locations exist, there is the possibility that, in case of bad weather conditions (e.g. rain), the demand for these areas or walking spaces can exceed capacity. Therefore, these locations need to be further considered in the formulation of scenarios and identification of inefficient dynamics.
5	Are there alternative routes from a main route which visitors are likely to take in case they feel uncomfortable or unsafe even if these routes are not optimal?	If these routes exist, they need to be identified as if there is a problem on the main route and visitors start using these alternative routes, it can be an indication that the something has happened. Besides, the use of these alternative routes can also cause unsafe situations if these are not prepared to receive these flows. Therefore, these locations need to be further considered in the formulation of scenarios and identification of inefficient dynamics.

Table 4.2 presents the demand checklist and the reasoning behind each question pro-

posed. This checklist aims at assessing not only the usage of the infrastructure given the factors that influence pedestrians choice behavior, but also the times and areas during the event where a large amount of visitors can be concentrated at the same time. For instance, when there is a public transport arrival, or when a performance ends, a high demand of visitors from these locations to other areas of the event terrain can be expected. Moreover, from literature, it could be seen that there might specific routes which are more attractive than others, such as routes with more activities or with specific features such as vegetation or lighting. Hence, these questions below aim at highlighting these.

Table 4.2: Checklist for the demand analysis

Number	Question	Reasoning
1	Are there times during the event when there is a demand peak, that is, where a large amount of visitors is expected to arrive in a short time frame? (e.g. the arrival of public transport or the end of a performance)	If these times exist, there is the possibility that these high demands can quickly increase densities on the environment up to unsafe levels. Therefore, the locations, times and expected demand coming from these sources need to be further considered in the formulation of scenarios and identification of inefficient dynamics.
2	Is there a main / most attractive route to or from areas where activities are planned?	If these routes exist, there is the possibility that most visitors will follow such route given its high attractiveness (e.g. presence of water, attractions along the way), and thus it can get crowded, potentially leading to discomfort and / or activating bottlenecks along the way. Therefore, the routes should be further considered in the identification of the inefficient dynamics.
3	Are there any routes between areas of the event for which the availability of alternative routes is limited?	If these routes exist, there is the possibility that if the attractiveness of these routes increases, many visitors follow them and it gets crowded, these visitors have nowhere to escape. Therefore, these routes should be further considered in the identification of the inefficient dynamics.
4	Are there any main / more attractive or popular activities (i.e. where a larger amount of visitors are expected to go to)?	If these activities exist, there is the possibility that the large number of visitors drawn by these activities lead to long waiting times, queues or crowding. Therefore, these activities should be further considered in the identification of the inefficient dynamics.
5	Are there any areas where visitors are expected to walk slower or stop more frequently (e.g. for taking pictures or observe the attractions)?	If these areas exist, there is the possibility that there will be moving bottlenecks, and it is likely more often crowded, possibly leading to discomfort and unsafe situations. Therefore, these activities should be further considered in the identification of the inefficient dynamics.

4.2.3. Identification of Inefficient Dynamics

Answering the questions in the checklists above can give insights into the dynamics of the event, the times and locations for which the crowd can potentially experience discomfort or unsafe conditions. From these analyses, and together with the benchmarks for inefficient dynamics proposed in subsection 3.3.3, the inefficiencies that can occur on the event environment can be identified. Each of the questions proposed above is connected to the benchmark cases to indicate the relationships between these, and the results are shown in Figure 4.2.

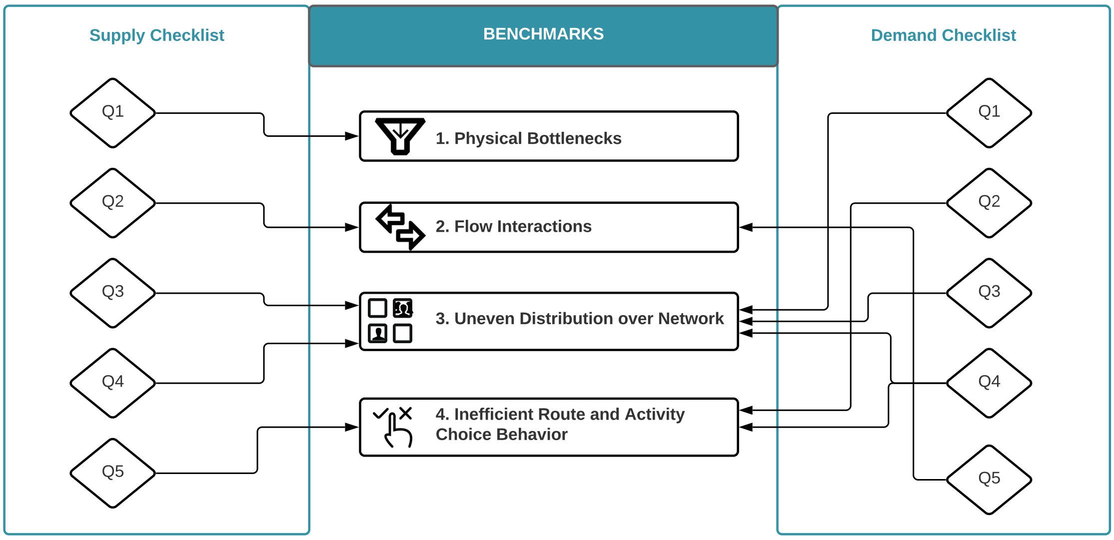


Figure 4.2: Checklists for supply and demand and relation to benchmarks of inefficient dynamics

From these links, the multiple scenarios of each benchmark case can be identified. This classification of the scenarios under each type of benchmark is proposed in order to describe the expected dynamics. For instance, for the physical bottleneck scenarios, one can expect that the dynamics of interest relate to the case when the demand for the area where the bottleneck is located exceeds the capacity of the bottleneck. When this occurs, queues start forming and visitors can start experiencing discomfort. On the other hand, for the scenarios under the uneven distribution over network, the dynamics relate to the over usage of certain areas of the environment. These can be identified by the concentration of activities at a certain location, or the availability of a single or a limited amount of routes between distinct locations. As demand for these start rising, so does the likelihood that densities might quickly increase. These dynamics which relate the key inputs to the expected outputs of each inefficient phenomena are further illustrated in subsection 4.3.2.

4.2.4. Sub-conclusions

For the purpose of prediction of crowd states, two objectives of the scenarios to be included in the database could be drawn. The first goal relates to the prediction of the occurrence of the inefficient phenomena, for which the conditions on the environment relate to unstable flow and high densities. The second relates to the prediction for which the dynamics observed are not likely to lead to inefficiencies, and densities remain under safe levels. These objectives raise the question of how to identify the scenarios for which these two goals are considered, but also taking into account that it is neither feasible nor desirable to represent all possible conditions in the scenario database. To that end, it is defined that the identification of scenarios should focus on the dynamics for which the inefficient phenomena is more likely to occur. For instance when the usage of a certain route is much larger than that of other routes, which can cause crowding and discomfort to event visitors. For this dynamics, the demand is then changed to account for the second goal of the prediction mentioned above.

The remainder of this section discussed the identification of the inefficient dynamics regarding the aforementioned focus. Based on the checklists proposed in this section, and the link between these and the benchmarks for inefficient phenomena, the areas of the environment, and times during the event to be considered for the scenario development can be identified. These aim to reduce the number of scenarios to a feasible and representative set. Also, the classification of the scenarios under each type of benchmark case aims at better describing the dynamics of interest, that is, the behavior and usage of the infrastructure which one can identify that can potentially lead to problematic situations regarding the comfort and safety of the crowd.

4.3. Scenarios' Dynamics

The processes for the development of scenarios in the simulation environment is discussed in this section. As mentioned in subsection 4.2.1, in the scenario database one must consider not only the scenarios for which the identified behavior leads to the appearance of inefficiencies, but also the ones that do not. Therefore, the concept of density levels is introduced in this section, to differentiate the scenarios for which the relative usage of the infrastructure remains the same, but the densities and consequently the safety and comfort of the crowd are distinct. Also, the dynamics of each benchmark case in relation to the simulation dynamics are presented, indicating the key inputs and expected outputs for each case. Finally, the stochastic behavior of pedestrians models is discussed, where methods to take this stochasticity into account when developing the scenario database are presented.

4.3.1. Density Levels

Density levels relate to the demand pattern, that is, the total amount of agents generated per time period. In this research, the density level is what makes the distinction between the scenarios for which the relative usage of the infrastructure remains the same, but the inefficiency does or does not occur, and when it does, how quickly uncomfortable and unsafe conditions appear. An example is given to illustrate this idea. One can think of a scenario for which there is uneven distribution of the agents over the network, and thus 80% of the agents are assigned to a single activity area. As one can imagine, depending on the total amount of agents generated per time, this 80% can lead to crowding and unsafe conditions, whereas for a different amount of agents generated this might not be problematic. Both conditions provide insights to crowd managers into the state of the environment, and thus assist them in deciding whether a strategy is necessary or not.

For each benchmark of inefficient dynamics identified, the density level indicates the strength of the interactions between agents, and between agents and the infrastructure. For instance, for higher density levels (i.e. higher number of agents generated), more interactions are expected, and the interaction forces are more likely to restrict the flows and average speeds. This concept is similar to the idea of the Levels of Service (LOS) as proposed by Fruin (1971), illustrated in Figure 4.3 and Table 4.3 for walkways. The lower the LOS (e.g. E, F), the more uncomfortable and unsafe one can expect the conditions on the environment to be. One can thus consider that the higher the density level, the lower the LOS of the infrastructure, and the faster one can expect the conditions to change towards uncomfortable and unsafe levels.

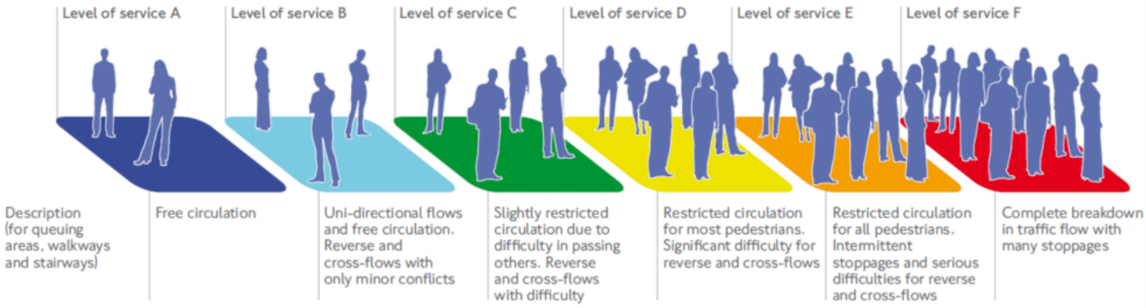


Figure 4.3: Illustration of Fruin's Level of Service concept (Source: TfL (2012))

Table 4.3: Density ranges of the distinct Levels of Service (Source: Fruin (1971))

LOS	Density Level (ped/m^2)	LOS	Density Level (ped/m^2)
A	< 0.31	D	$0.72 - 1.08$
B	$0.31 - 0.43$	E	$1.08 - 2.17$
C	$0.43 - 0.72$	F	> 2.17

The consideration of the distinct density levels result in multiple simulations being performed for each identified inefficiency. Between these simulations, only the total demand changes, while other inputs such as the share of agents per activity remains the same. It is considered important to highlight that, for the different benchmark cases, distinct levels of service might be of interest. In the uneven distribution over the network for instance, it might be of interest to include scenarios for which the density levels reach LOS F, as it can be that the uneven distribution is caused by many agents standing by a stage to watch a performance. On the other hand, for the flow interactions, such level of service might indicate a blockade or a situation that can no longer be resolved. For a given LOS, the density level also indicates how quickly an area is likely to reach that LOS. For instance, for a physical bottleneck scenario, if the bottleneck becomes active and a queue starts forming, the higher demand due to the higher density level can make the queue upstream this bottleneck grow faster.

4.3.2. Benchmarks' Simulation Dynamics

Each benchmark case has specific dynamics which one can consider for building the scenario database in a simulation model. These are indicated in Figure 4.4 and will be further discussed below.

The physical bottleneck scenarios are defined for the cases where the bottleneck becomes active, that is, when demand is higher than the capacity of the bottleneck and queues start forming. These bottlenecks are identified in different locations on the environment, for instance where there are stairs or obstacles obstructing the flows. Higher densities levels in these scenarios lead to a significant decrease in throughput of the section of the infrastructure

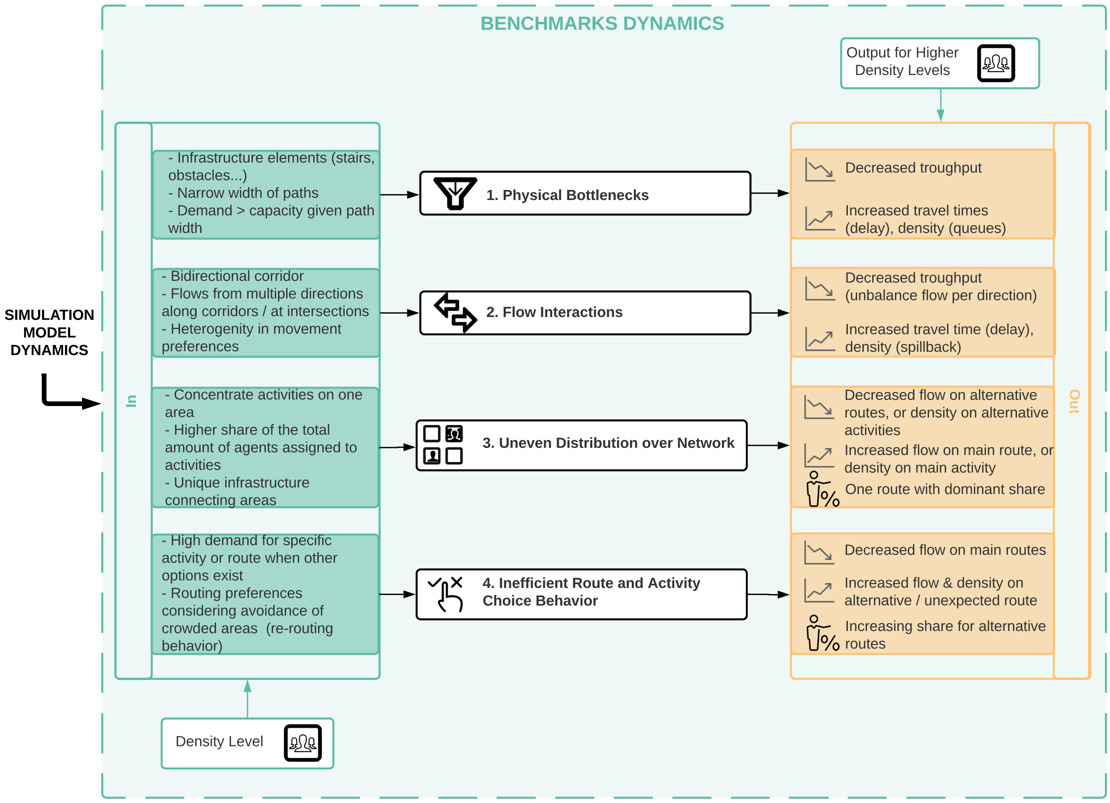


Figure 4.4: Benchmarks dynamics for modelling

where the bottleneck exists, and an increase in average travel times and densities. Depending on the density level, the queues formed can spill back to other areas of the environment.

Interactions of flows can occur due to bidirectional flows along corridors being allowed, with no separation between the different streams, as well as at intersections where multiple directions can exist. In addition, flow interactions can also occur for a single direction of movement with distinct movement preferences. For instance, when walking along a route where attractions exist, some visitors might be walking faster in order to get to their destination, while others might be entertained by the attractions and thus walk slower or stop to take pictures. The effect on the output dynamics of these conditions is the same, where the interactions between these flows decrease throughput and are likely to increase average travel times and densities.

The uneven distribution over the network arises from multiple possible conditions, as illustrated by the link between the checklist and phenomena shown in subsection 4.2.3. For instance, the concentration of activities in one area and the combined demand for these activities can lead to this uneven distribution. Similarly, the existence of a single infrastructure element (e.g. corridor) connecting certain areas of the environment can cause the network to be unbalanced as visitors move between these areas. The density levels indicate how quickly these areas are likely to get overcrowded and how densities on these areas are likely to be. The output for higher density levels is thus increasing flows on a single / main route or the density of an activity area. Also, regarding the routes, it is expected that the a single route has a dominant share of the total amount of pedestrians.

Finally, the scenarios for the inefficient route or activity choice behavior relate to the higher demand for a certain activity or route even though other options exist. Also, the scenarios related to this benchmark consider the usage of inefficient routes (e.g. longer or less attractive routes) and possibly the appearance of unexpected flow interactions due to the pedestrians re-routing to avoid crowded areas. Thus, the output dynamics when densities are higher are illustrated by a decrease in the high flows of main routes and increase in flows or densities on alternative routes, given by the increase in the share of agents who reroute via these alternative routes.

4.3.3. Stochasticity

There are different layers of uncertainty when representing pedestrian behavior in simulation. Uncertainty is first considered regarding the actual values of the inputs and parameters, which then result in the consideration of distinct scenarios for each analyses, and the usage of distributions in the inputs and parameters. An example is the assignment of a distribution of preferred speeds to determine the speed of the agents in the simulation. The usage of distributions thus adds another layer of uncertainty, as distinct replications which have the same inputs and parameters can have different results due to the values drawn from these distributions. Therefore, pedestrians models can be considered stochastic by nature (Duives, 2016), and to perform a representative analysis of the simulation results, one has to consider this stochasticity.

Within simulation models, the parameter that establishes this behavior (e.g. which values are drawn from the distributions of the inputs and parameters) is called 'random seed'. Defining the required number of replications per scenario is thus necessary to ensure that the difference in the outputs of the simulated scenarios come from the difference in the inputs and parameters set, and not from the stochasticity. The result of running these multiple simulations with the same inputs and parameters but different seeds is a distribution, and it represents the influence of these stochasticities on the model's results.

Different methods have been proposed in literature for estimating this required number of replications. A common characteristics of all proposed methods is the requirement of selecting an appropriate measure of performance, which becomes the first step in defining the required number of replications. An appropriate measure of performance can indicate the variability between the scenarios and is among the statistics produced as outputs by the model. Following, the second step is to select the appropriate method given the chosen measure of performance. Existing methods either follow a sequential approach, where one replication is done at a time until a certain stopping criteria is met (Toledo & Koutsopoulos, 2004; Ronchi, Kuligowski, Reneke, Peacock, & Nilsson, 2013), or a two-step approach (Toledo & Koutsopoulos, 2004). The latter is considered when it can be assumed that for the selected measure of performance the standard deviation does not change significantly as the number of replications increase. In this case, the minimum number of replications is determined by:

$$R_i = \left[\frac{s_{R_0}(Y_i)\, t_{\frac{\alpha}{2}}}{d_i} \right]^2 \tag{4.1}$$

where,

$s_{R_0}(Y_i)$	=	standard deviation of output sample of the selected measure of performance based on R_0 replications
$t_{\frac{\alpha}{2}}$	=	critical value of the t-distribution at significance level α
d_i	=	allowable error

The equation above can be applied to more than one measure of performance. In that case, the most critical value of R_i determines the number of replications, as it is guided by the measure with most variability.

4.3.4. Sub-conclusions

In this section, key concepts regarding the development of scenarios in the simulation model to compose the database of scenarios are addressed. The discussions regarding the density levels primarily aim at describing how the differentiation between the scenarios for which inefficient phenomena leads to problematic conditions to the ones that it does not. This is because, as previously stated, both of these provide crowd managers insights into the state of the crowd to assist them in deciding whether the application of a strategy is necessary or not. These density levels are related to the demand pattern, that is, the total amount of agents generated per time period, and not only determine the expected densities on the environment but also how quickly these densities rise. The decision regarding which density levels are of interest for each scenario is based on the dynamics of interest and acceptable levels of service for each situation.

From the simulation dynamics of each benchmarks for inefficient dynamics, the inputs for each benchmark and the outputs for higher density levels are highlighted. This is because it is based on these higher density levels and the expected dynamics for those conditions that the scenarios are formulated. The consideration of multiple density levels then results in multiple simulations for which only the demand pattern is increased or decreased. An increased number of simulations is also necessary to account for the stochasticity of the pedestrian models, as discussed in this section. However, in this case, multiple simulations are run with exactly the same input set, in order to estimate the required number of replications to ensure that the difference in the outputs for each scenario and density level come from the difference in the inputs and parameters, and not from the stochasticity. For these estimations, a metric or metrics need to be defined, as well as a method and its corresponding parameters (e.g. allowable error).

4.4. Scenario Development Framework

The discussions presented in the different sections of this chapter are combined in the form of a framework for developing the database of scenarios for the application of the method. The framework is shown in Figure 4.5, and it aims at illustrating the steps and concepts to be addressed when developing the scenario database. The analyses of the event dynamics is seen as the first step in developing the scenarios, and it concern the supply and demand checklists presented in subsection 4.2.2, considering the factors that influence supply and demand as presented in Section 3.2. Some of the output of these analyses are the different capacities of the distinct areas of the infrastructure, as well as the expected usage of the routes and activities. These are direct inputs to the identification of inefficient dynamics.

In order to identify these scenarios, the benchmark cases from crowd management theory as proposed in Section 3.3 are used as reference. The main questions to be answered in this part are related to: (1) the identification of these phenomena, (2) the areas where these are likely to occur, (3) the conditions on the environment that lead to the appearance of these and (4) the likelihood of these occurring. For instance, if a certain event has a number of activities concentrated in the same area, the uneven distribution of the network can be expected. However, the condition for this inefficiency to occur is that a high number of visitors go to this area to perform the activities, and whether this high demand is expected or not. These conditions define the dynamics of each inefficiency identified, which are the input for the development of these scenarios in the simulation.

The formulation of scenarios relates to a risk assessment of the different areas of the event. This risk assessment is performed to analyse the level of risk, measured qualitatively in terms of exposure to high densities. The idea of this level of risk is based on the study of Wieringa (2015), where the author proposes that risk could be measured by density times duration of density. However, for the application in the present research, this is a qualitative criteria defined as the exposure to high densities. Scenarios are included in the database not only if high densities are likely to occur, but in case these can be expected to last for prolonged times. For instance, based on this criteria, an area where there is a bottleneck along a main route, where all or most visitors are expected to walk on, and is thus expected to be often crowded, takes priority over an area with a bottleneck along a route where visitors are likely to use a single time.

Finally, the process to develop the scenarios combines the results of the analyses of the other two parts of the framework, with the concepts of the density levels and the demonstration of the benchmarks dynamics presented in Section 4.3. The development of the scenarios first aims at building the dynamics of the inefficient phenomena in the simulation. This means finding the inputs for which a bottleneck becomes active in a physical bottleneck inefficiency, or those for which a blockade arises when bidirectional flows interact. Once this is achieved, the additional density levels define the demand pattern variations to be simulated for each scenario. This is an iterative process as the simulation is dynamic, so it is not possible to predict beforehand its results. As previously mentioned, these define not only how quickly the high densities appear, but also the overall LOS of the area where the inefficiency occurs. For instance, one can think of the flows generated from a stage area to the other areas at the end of a performance during a music event. There is the possibility that all visitors from that stage area move quickly towards the exit, generating a high demand for the exit gates in a short period of time. However, it might also be that some visitors stay a little longer or walk slower to avoid the queues, and so the total demand for the exit gates is not as high. These two conditions represent different density levels, and their corresponding effects at the exit gate (i.e. longer queues and higher densities vs. shorter queues and lower densities) can be achieved by changing the total demand generated per time.

In order to illustrate the application of this framework, an example is created of a small-scale event and presented in Section B.2.

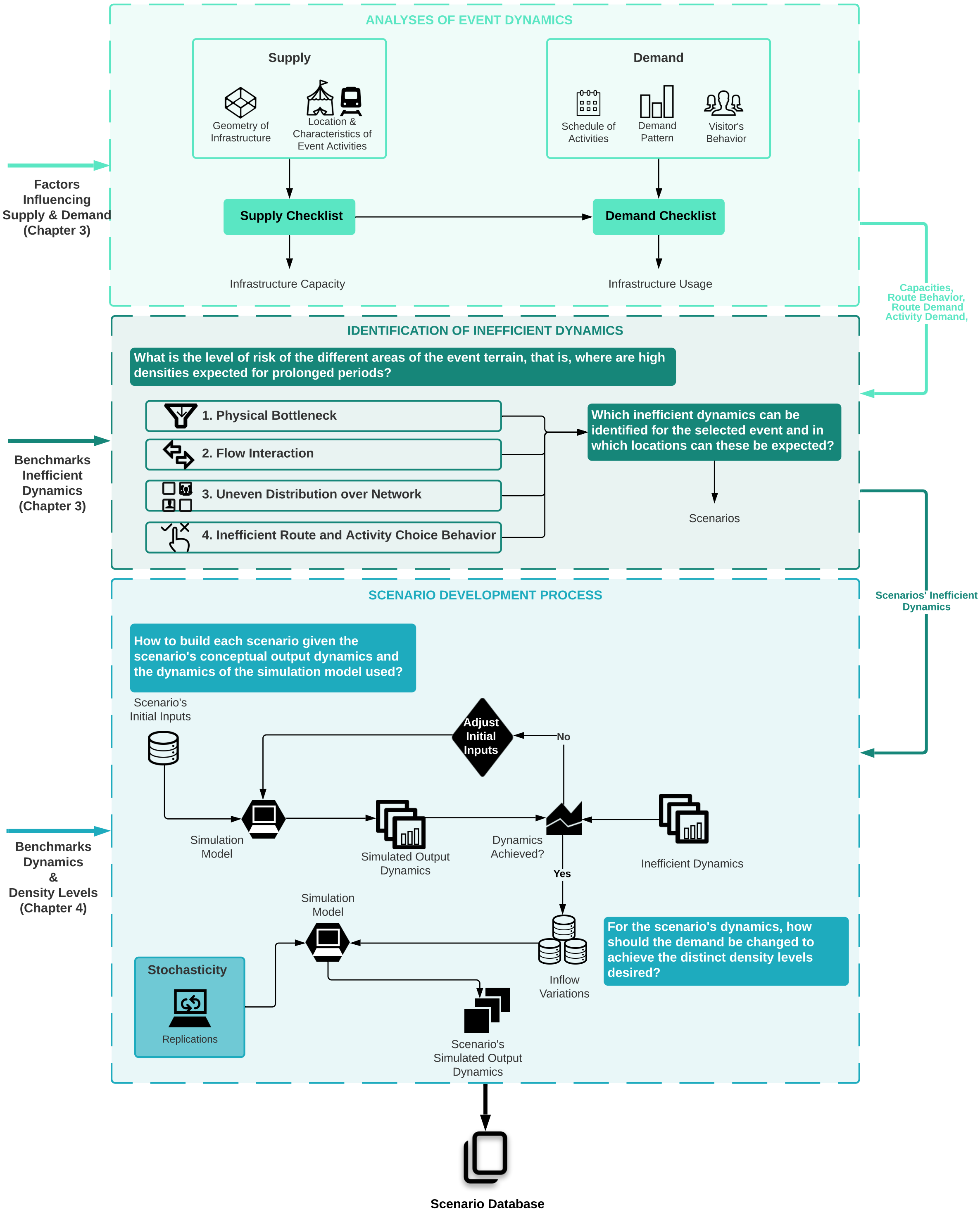


Figure 4.5: Scenario Development Framework

4.5. Conclusions

In this chapter, the framework for developing the scenario database is presented, which is one of the pillars of the forecasting method proposed in this research. To develop such framework, the discussions of this chapter focus on three main aspects. Firstly, a reflection is made regarding the multiple degrees of freedom of microscopic models and how to account for it based on the focus of the prediction. Secondly, the identification of the inefficient dynamics when considering the crowd dynamics of interest. Lastly, the formulation of these scenarios in the simulation environment is presented.

Regarding the model's degrees of freedom, it was discussed that although microscopic models can be adjusted to the needs of the modeller at a very high level of detail, for prediction, the effect of the macro/mesoscopic characteristics and corresponding inputs are of interest. This is because not only pedestrian models are mainly applied to assess the comfort and safety based on aggregate data, but also the crowd states of interest for the prediction of crowd movement lie on the aggregate metrics, such as densities. Therefore, a selection of inputs is made to account for these considerations. The main purpose of using microscopic models in this case is to make use of the underlying models on the lower level behavior to better estimate the higher level dynamics.

Following, the identification of the scenarios is discussed, where it is highlighted that the scenarios are initially formulated for the crowd states which can lead to unstable flow conditions and high densities. This is defined so that the number of scenarios can be reduced to a representative set, where the conditions that do not lead to inefficiencies are simply derived by lowering the demand for the same relative usage of the infrastructure. Two checklists are proposed to assist in the identification of the relevant areas of the environment and behavior of pedestrians which can lead to the aforementioned conditions. From answering the questions of the checklist, one can identify the inefficient phenomena and corresponding dynamics for identifying the scenarios from the benchmark of inefficient dynamics for a particular event.

Finally, for the formulation of the scenarios in the simulation environment the concept of density levels is introduced. Density levels relates to the demand pattern, or total amount of agents generated per time period, and is defined to make the distinction between the scenarios for which the inefficient phenomena occurs, and thus high densities can be expected, to the ones that it does not. Both conditions are relevant for prediction as these give insights to crowd managers when making the decision of whether or not it is necessary to apply a management strategy. For each benchmark case, the dynamics for modelling are presented, and the expected outputs when high density levels are considered are highlighted. Lastly, methods to calculate the required number of replications to account for the stochastic behavior of pedestrian models are presented, whereby the choices related to the metric and method are discussed.

5

Framework for Scenario Selection

This chapter elaborates on the real-time scenario selection system which, as stated in Section 1.1, is one of the pillars of the forecasting method proposed in this research, together with the scenario database as discussed in Chapter 4. Although certain elements from existing model-driven methods can be identified which also apply for the method proposed in this thesis (e.g. real-time data from crowd monitoring systems), additional steps and processes are necessary, which are identified in this chapter. Hence, the following research questions are addressed in this chapter:

- How to use the concept of crowd states to capture the dynamics of the scenarios for the scenario selection process?
- What proximity measures can be used to compare the scenarios with the real data and formulate the individual objectives?
- Which boundary conditions must be taken into account for the scenario selection system?

To address these questions in this chapter, an introduction is given in system theory in Section 5.1, where the elements which form existing model-driven crowd movement forecasting methods are highlighted. The scenario selection framework proposed in Section 5.2 then illustrates the components of the scenario selection system proposed in this research, and how these are connected with the concepts and information identified from the existing systems. The following sections elaborate upon the modules of the framework and the decisions that need to be made regarding each of these. Section 5.3 discusses the input module, Section 5.4 presents the search module, and Section 5.5 explains the communication module, whereby it is explained which elements are necessary to operationalize each module, and what to consider regarding the choices that need to be made for these.

5.1. Systems Theory

System theory provides the tools for describing, analysing and comparing the behavior of systems. As stated in Knoop et al. (2018), generally the considered systems are physical by nature, and although some of these systems cannot be described by a set of mathematical equations, system theory can incentivize the consideration of the relevant aspects of the system as whole in terms of its sub-systems or operative parts. For instance, the analysis of human behavior can have side effects which can be easily overlooked if only the main effect is considered (Knoop et al., 2018). For the purpose of this research, the theory of systems is used to identify the sub-systems of existing forecasting methods (subsection 5.1.2), and also to assist in the development and explanation of the scenario selection system based on these sub-systems. Below, an overview of the concepts related to the formulation of systems is provided, followed by the corresponding application to existing model-driven forecasting methods as the ones presented in Figure 2.1.

5.1.1. System Formulation

The formulation of a system is often described as a process with inputs and outputs, where the inputs contain relevant external influences that affect the process. A differentiation is made with regards to these inputs, based on whether or not these inputs can be influenced by the user. Inputs that can be influenced are called *control inputs*, and the ones that cannot be influenced are called *disturbances* (Knoop et al., 2018). Although these disturbances cannot be influenced, they can sometimes be measured. For instance, when predicting the future states of the crowd at an event, a train arrival which generates flows of pedestrians into the event terrain can be considered a measurable disturbance, as the train demand and time of arrival can provide useful information to the prediction of the states.

The *outputs* of a system contain the measurable components of this system, and these depend on the properties of the system and quantities that can be measurable. These measurable quantities are defined based on the sensors available and their capabilities. These outputs are often used for monitoring the system and determining whether control actions are necessary (Knoop et al., 2018). Regarding the crowd movement prediction system, one can think of the outputs as the key information crowd managers need to get insights into the crowd state, and define whether or not it is necessary to deploy a management strategy. For instance, the values of the density in the different areas of the environment.

These control inputs and outputs can be described by metrics to represent the evolution of the dynamics described by the system over time. Regarding the dynamics of the crowd, these metrics can be for example the values of flows, densities and travel times over time, as presented in Section 3.1. These define the state $x(t)$ of the crowd at time instant t, as well as the summary of the history of the system's state until instant t. The dynamics of the system can thus be described by a time series of state metrics (discrete-time systems). In the following section, these concepts are applied to describe the existing crowd movement forecasting systems, where it is discussed which parts of the system are of interest for this research.

5.1.2. General Model-Driven Crowd Movement Forecasting Systems

Figure 5.1 illustrates the system of current model-driven crowd movement forecasting methods, which is further detailed in this section. The crowd monitoring sensors gathers the measurable / observable data from the real pedestrian traffic in the event terrain to describe the current state of the crowd. Several monitoring sensors have been developed and updated over the years, which enabled their implementation in the complex task of monitoring crowds.

However, different types of sensors can obtain different types of measurements, and the accuracy of the measurements also varies between sensor types. An overview of some crowd monitoring methods is presented in Section C.1, where the focus of discussion is on their efficiency and capabilities for being used in the derivation of different crowd state metrics during large-scale events. From the sensors presented, and the different categories of crowd state metrics shown in Section 3.1, one can see that certain sensors only capture local data (e.g. video cameras) while others are capable of deriving global metrics (e.g. Wi-Fi sensors). Furthermore, a common characteristics of most of the existing sensors is the fact that these mostly capture meso or macroscopic metrics, and that no sensor to date provides 100% accuracy for all conditions.

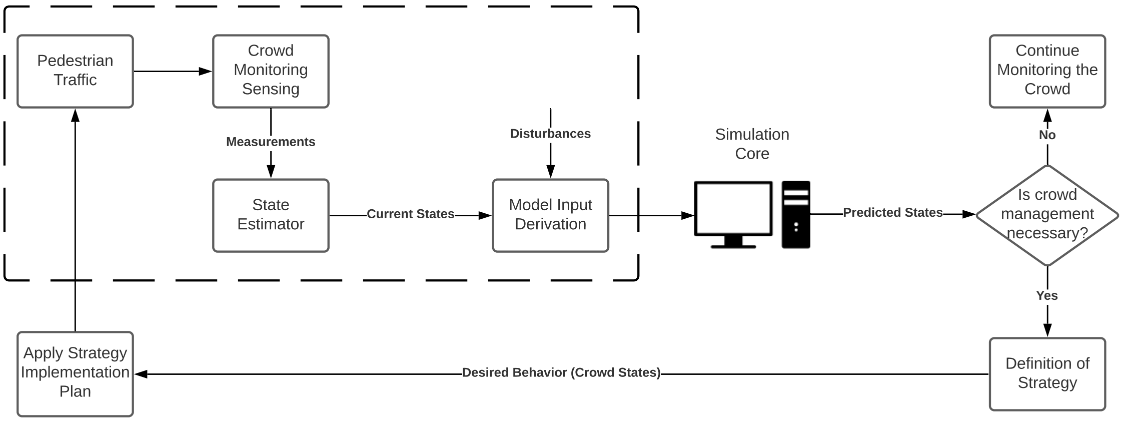


Figure 5.1: Model-driven methods for crowd prediction in system theory

Often, due to the fact that either the measurements retrieved from these sensors have errors, or the metrics of interest to describe the states cannot be directly measured by the sensors, state estimation techniques are applied. The study of Yuan et al. (2016) illustrates some of these techniques applied to the data from the SAIL event of 2015. From the three algorithms presented in the study, it can be seen that multiple state metrics can be derived. In order to derive these, the network of the event is discretized in cell, and Wi-Fi sensors and video cameras are located at the boundaries of these discrete cells. An analysis of the states estimated by the different methods, which were described by metrics such as flows, densities, travel times and speeds, illustrates that these are most often overestimated, where only travel time and speed appear to be underestimated by one of the methods. Therefore, even when state estimation techniques are used, it cannot be guaranteed that the derived real states have 100% accuracy.

As presented in the previous section, the system also has disturbances for which examples in the case of crowd movement forecasting systems are the arrival of a public transport mode, or the end of a performance which will occur over the prediction horizon. These disturbances refer to the inputs into the system which cannot be controlled (e.g. demand from the public transport vehicle). Together with the estimated states, the input to the real-time simulation core can be derived (e.g. inflows, activity sequences), and the output of the simulation yields the predicted states for the prediction horizon considered. Based on the information provided by these, crowd managers define whether management strategies are necessary or not, and if so, which strategy should be applied to the traffic of pedestrians in the event.

The area highlighted in Figure 5.1, which relates to the derivation of the real states, represents the shared elements with the scenario selection framework presented below. This is because the scenario selection system proposed also makes use of real-time information from the crowd, measured by the sensors or estimated by the state estimation techniques. How these are then used for the input of the selection system is further detailed in the following sections.

5.2. Scenario Selection Framework

The framework for scenario selection proposed in this research is shown in Figure 5.2. The point of departure of the framework, given by the scope of this research, is the utilization of a multi-objective optimization approach to select the scenario from the database which most closely corresponds to the real observations and expected future conditions of the crowd. From the system theory presented above, applied to model-driven crowd prediction methods, the real-time inputs and the theoretical concepts related to the operation of the selection system could be identified. In the scenario selection framework proposed, these relate mostly to the operationalization of the input module, which has consequences for the other modules as it will be discussed in the following sections of this chapter.

The scenario selection system proposed considers that all scenarios S_i, in the database ($S_i \in \mathbb{S}$) are discretized in space, in p sub-areas, and in time, for which n time periods exist per scenario. For discretizing the trajectory information from the simulated scenarios, the concept of crowd states as presented in Section 3.1 are used. The current state of the crowd is determined by a number of state metrics derived at each sub-area for all discrete time periods. In this research, as previously mentioned, these metrics lie on the meso and macroscopic aggregation levels. Thus, the trajectory information is transformed into a time series of k state metrics per sub-area. These sub-areas are here called Event Blocks and are further discussed in subsection 5.3.1. Besides the current state and metrics which define this state, information about known disturbances can also be included in the state vector. These can be for example the demand from a train arrival that occurs over the prediction horizon. Metrics in the state vector which provide information about these known disturbances can either be linked to a sub-area or not. The state vector to describe each scenario and time period in the database is shown according to Equation 5.1:

$$S_i^t = [M_{j,B_q}, M_{j+1,B_q}, ..., M_{j,B_{q+1}} ..., M_{k,B_p}] \quad \forall S_i \in \mathbb{S} \tag{5.1}$$

Where $i = 1,2,...m$ and $t = 1,2,...n$ relates to the scenario and time period for which the values of the state vector relate to, respectively. M_j refers to the state metric $j = 1,2,...k$, and B_q refer to the Event Block $q = 1,2,...p$, that is, the sub-area of the environment that metric M_j is derived from. Similarly, the real states are formed by a vector of state metrics. These real states are compared to the state vector of the scenarios and time periods in the database. The comparison of the individual state metrics, of the current state of each Event Block as well as disturbances, each corresponds to an individual objective. This is core of the scenario selection system, as the scenario and time period which most closely matches the real states used as input should be the selected scenario. The future states of this selected scenario are therefore the predicted states. As it can be seen in Figure 5.2, three modules are identified to form the scenario selection system. These are the input, search and communication modules, which are further detailed in Section 5.3, Section 5.4 and Section 5.5, respectively.

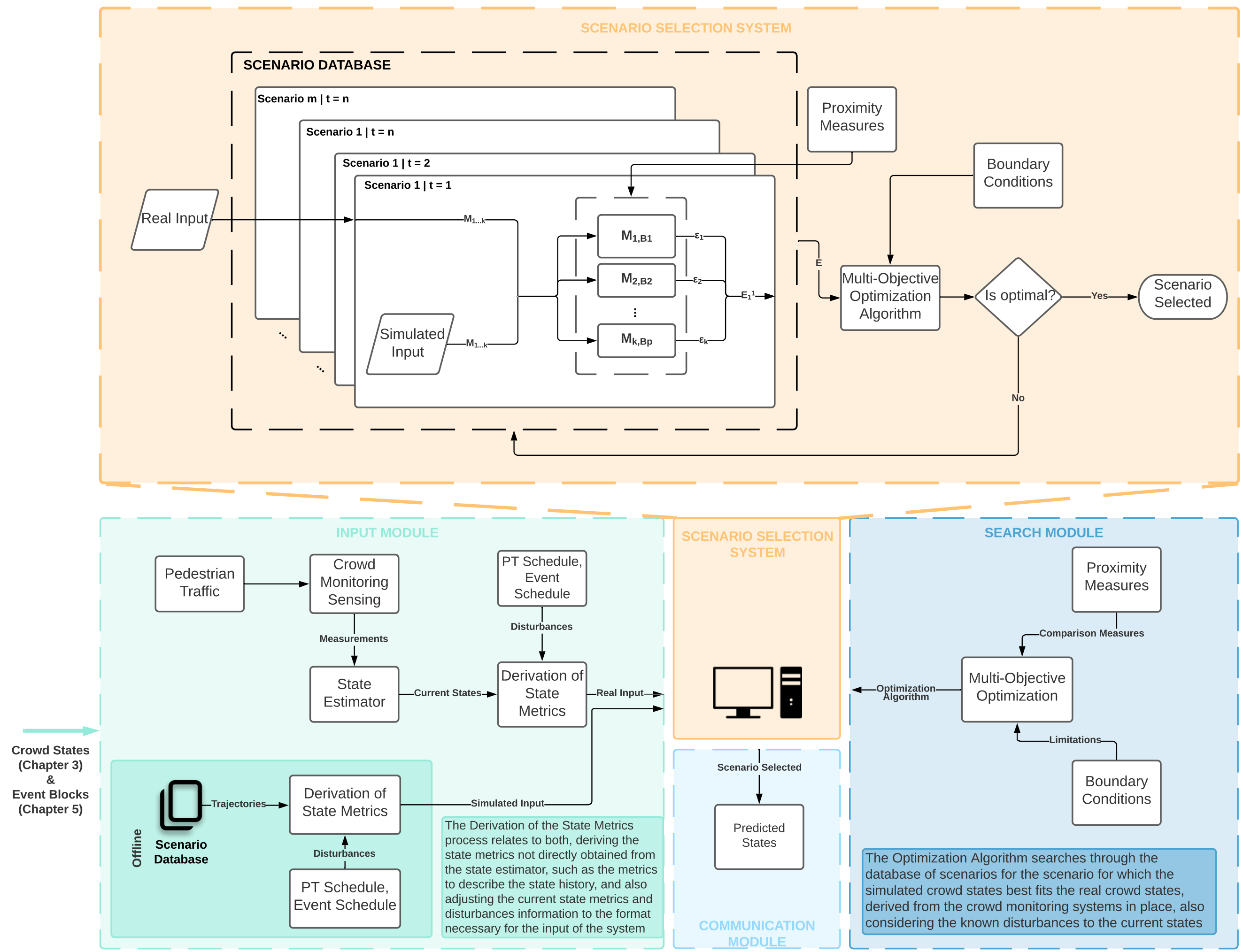


Figure 5.2: Framework for Scenario Selection

5.3. Input Module

The input module to the scenario selection framework relates to both, the real crowd states as well as the simulated states derived from the scenario database. In order to make this module operational, that is, to prepare the data to be used by the selection system, the concept of Event Blocks is introduced in subsection 5.3.1 which relate to the spatial discretization of the environment. Following, a discussion is made regarding the process of the derivation of the state metrics, as indicated in the framework, and how to account for the different parts of the system that these need to describe. For instance, the distinction between the metrics to define the current state of the crowd and the ones to account for the so-called disturbances. These are presented in subsection 5.3.2 and subsection 5.3.3.

5.3.1. State Metrics & Event Blocks

The study of Toledo and Koutsopoulos (2004) presents a set of considerations one can take into account to select the appropriate state metrics, for which examples are the context of the application and traffic dynamics. For the prediction of crowd movements in mass events, from the theories discussed in Section 3.2, one can say that the statistics that are important to the context and dynamics relate to both, the fundamental diagram as well as the choice levels of pedestrian behavior. Density for example, can indicate whether certain areas are congested or not. Regarding pedestrian choice behavior, average speeds can indicate the operational level choices, while metrics such as route shares can indicate the tactical level choices.

Another consideration from the study of Toledo and Koutsopoulos (2004) is the error source, that is, the discrepancy between observed and simulated outputs inherent from the errors due to the simplification of the behavior for simulating, as well as the capabilities of existing sensors to capture the "true" states. The errors from the simulation can only be dealt with by improving models, which is not in the scope of this research. For the errors related to sensor measurements, Toledo and Koutsopoulos (2004) discusses the decisions regarding the locations to collect these measurements. According to the authors, these should provide spatial coverage of all parts of the network. For instance, measurements close to entry locations can provide indications of errors in the travel demand flows, but not so much on route choice. Thus, the discretization of the environment based on these locations to collect these measurements is further discussed below, where the concept of Event Blocks is introduced.

Event Blocks are defined as the areas of the environment at which the state metrics are derived. Ideally, one would be able to define the location of these areas with the aim of being able to capture the dynamics of interest for prediction. The relevant locations for these Event Blocks can be defined based on the scenarios identified for the specific event, as proposed in Chapter 4, as well as the chosen metrics to define the state vector. The distinct dynamics expected during the event can also provide indications of where it is most desirable to gather information about the crowd from. For instance, an area where there are multiple activities concentrated, and thus where it is possible that many visitors will go to, is considered important to better identify how densities are developing in that area. Overall, based on the considerations above and the identified benchmarks for inefficient self-organization (subsection 3.3.3), it can be said that the following locations are considered relevant: (1) location of physical bottlenecks, (2) areas where there is constant flow interactions with no separation, (3) areas with concentration of activities and (4) entry locations.

Finally, the event area ($\mathbb{A}$) is thus assumed spatially discretized in p Event Blocks. Each Block is then given an index q ($1 \leq q \leq p$) which is used to identify the metrics that describe the state of this Block in the crowd state vector.

5.3.2. Observables

As mentioned in subsection 5.1.1, the state of the crowd can be described by the time series of state metrics. When considering the concept of the Event Blocks, a time series of each metric considered at each Event Block is thus derived. From these, one can identify both the current state of the Event Block at time t (i.e. the state at the time of measurement) as well as the summary of the history of the states until instant t. The state of the crowd on the environment is then defined when all the metrics of each Event Block and their corresponding time series are considered. The state metrics to define the current state and the state history are here called observables. This is because these relate to the inputs retrieved from the crowd monitoring sensors and state estimation techniques as discussed in subsection 5.1.2.

As previously mentioned, from the time series values of a metric of an Event Block, one can retrieve the value of the state for that metric at a certain time t, and also estimate the past variations of this metric to get to the value at time t. Figure 5.3 illustrates the time series of the average travel time between two locations. In the figure one can see not only the discrete times when the metric is measured (current state), but also the short term variations (noise) and long term movements (trend). This past long term movements are here called current state history, and together with the value of the current state these aim at uniquely define the observed behavior on the event environment. For instance, for a given value of the travel time between two locations (i.e. current state), the current state history can indicate the travel time trend, that is, whether travel times are increasing or decreasing, as well as how rapidly this value is changing.

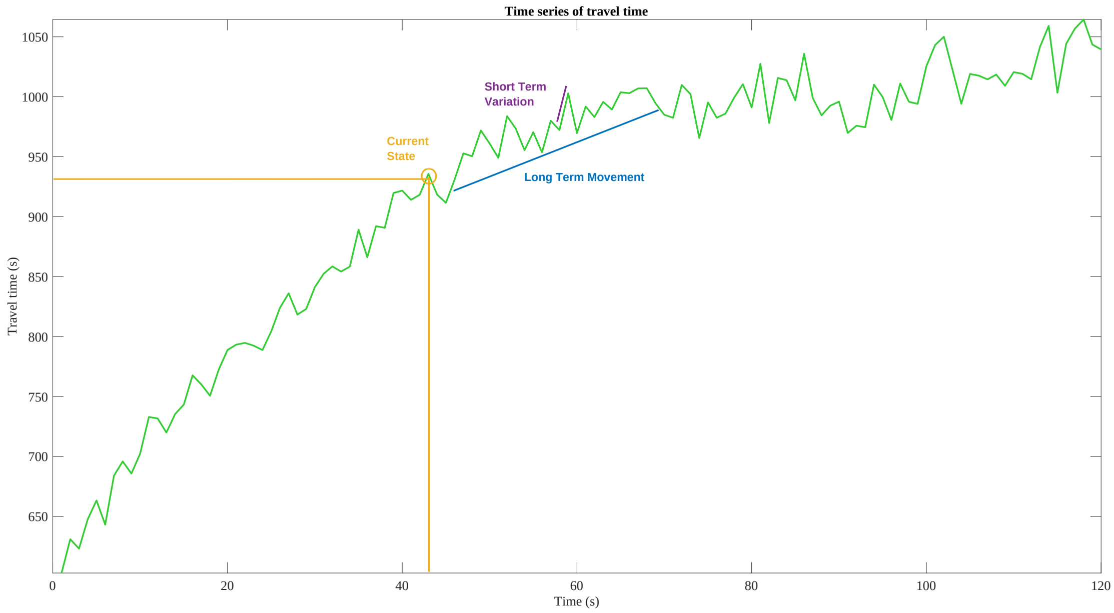


Figure 5.3: Illustration of a time series of travel time

It is clear that the history of these states is thus of interest when differentiating between the scenarios. The state history aims at describing the pattern of behavior which led to the measured values of the current state metrics. In order to define the relevant values for this trend, it is necessary to filter out the short term variations. For instance, if the travel time measured between two locations is increasing rapidly, given that a few minutes ago its values were much lower than now and slope of the trend is positive, it might be an indication that the route is congested.

Time series analysis provides multiple ways to derive these trends or long term movements from the discrete values of the time series. These refer to the smoothing of the time series data, by which the noise is filtered out or its contribution is reduced. The methods of moving average can be used to perform this smoothing (Parzen & Brown, 1964). These include simple moving averages, where all past observations have the same weight, as well as exponential moving average methods, which weight more recent observations higher assuming that these are more similar to the current state. In the latter case, the parameter α of the exponential moving average equation is what defines the degree of weighting decrease, where higher values discount older observations faster. This effect is illustrated in Figure 5.4.

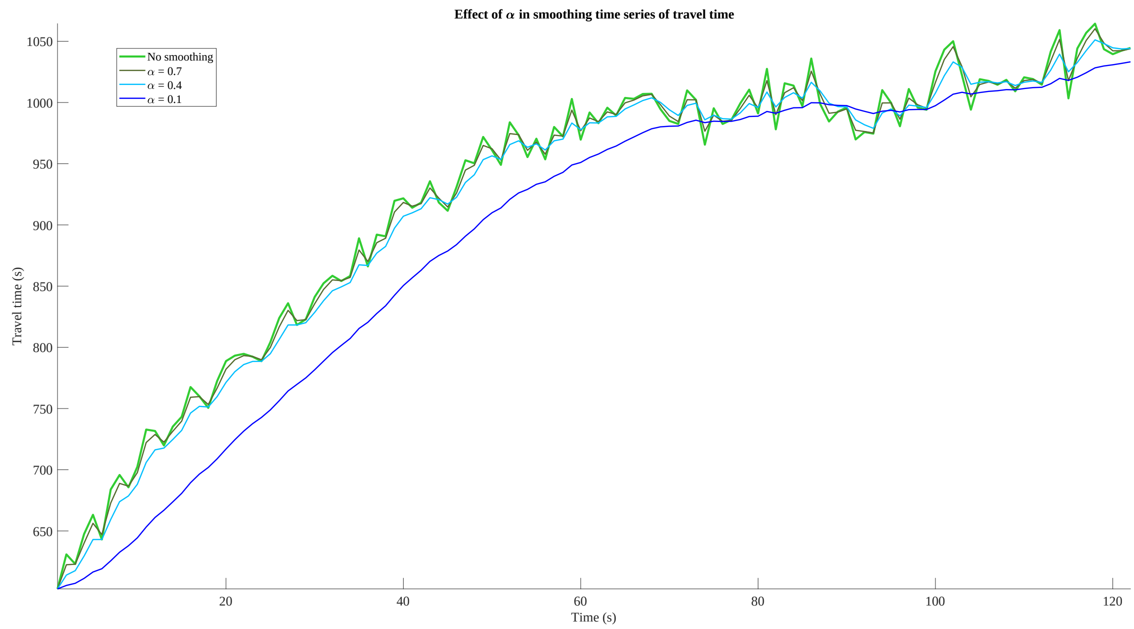


Figure 5.4: Illustration of effect of α in smoothing time series

5.3.3. Unobservables

Unobservables, as used in this research, relate to the so-called disturbances in system theory. These refer to known inputs into the system not captured by the sensor at the time of measurement. Examples of these for mass events relate to the prediction horizon of the forecast, and what disturbances to the current conditions are expected to occur between the time of measurement and the prediction horizon. For instance, in a music festival, the end of a performance within the prediction horizon will generate flows from the performance's area to the other areas of the event. These are not captured by the real-time observations but are considered relevant for the prediction due the distinct expected states these can generate, and thus also on the decision of whether or not certain management strategies are necessary.

Below, some examples of these disturbances and their expected effects on crowd states are presented. These refer to the future disturbances (i.e. between time instants t and $t+x$, where x is the prediction horizon) in relation to the current observations (i.e. at time instant t).

- *Transport Facilities* → As trains, buses, ferries, metros and other public transport modes carry a large amount of people, arrivals and departures of these within the prediction horizon, and the location of stops or stations, affect how states are likely to evolve in the different Event Blocks. If prediction is performed at time instant t and there is a public transport arrival or departure expected between t and $t+x$ this needs to be considered for prediction.
- *Weather* → The way people move through the environment, the routes they choose and the speed they walk at are all influenced by the weather condition. This factor is included under 'unobservables' for the cases that the weather condition is expected to change between t and $t+x$, as these will lead to disturbances to the observations done by the monitoring systems.
- *Event Schedule* → The end of a performance at one of the stages of the event, or if a performance is planned to start between t and $t+x$ is determined by the event schedule. The disturbance caused by this schedule is primarily for the case when the performance ends, where a large amount of visitors is expected to move from the location of the performance to the other areas of the environment.

Combining the observables and unobservables, the real crowd states to be used by the scenario selection system when searching thought the scenarios can be defined. Two state metrics can be used to describe these unobservables: (1) their expected demand and (2) the time from the current time of measurement these are expected. Besides, these can be linked to a specific Event Block. For instance, in the case of the disturbances from the event schedule, each performance location can be linked to the Event Block nearest it, and the demand from this location then would then be one of the state metrics j to describe the Block B_q at time t for scenario i (Equation 5.1).

5.3.4. Sub-conclusions

This section introduced the inputs of the scenario selection system, and decisions that need to be made to derive these for its application. For the state metrics, the decision regarding these consider the traffic dynamics based on the fundamental diagram and pedestrian choice behavior. The goal when defining these metrics is to capture the effect of these dynamics on the meso and macroscopic level metrics. For instance, density, which can provide information if the demand for a certain area exceeds capacity, and route shares, as these can indicate tactical level choices of pedestrians. These metrics are derived at discrete locations on the environment, which are here called Event Blocks. The choices related to the location of these Blocks take into account the dynamics of the inefficient self-organization phenomena as proposed in subsection 3.3.3. For the discretized environment, the discrete-time system to describe the dynamics of the crowd movement is then formulated by a time series of state metrics.

The metrics to form the state vector are separated into observables and unobservables. The former relates to the current state and state history of each metric, that is, the state at time of measurement (t) as well as the summary of the states until instant t. Considering both the value of the current state and of the state history in the state vector aims at uniquely describe the observed behavior on the environment. For instance, for a measured value of density, the state history indicates whether the density is following an increasing or decreasing trend. Smoothing methods were presented with the purpose of indicating how these trends can be derived. The choice between these methods relates to the consideration of the weight given to the observations, that is, whether or not weighting more recent observations differently than older observations, or removing the short term variations to focus on the long term movements. Methods based on moving average are presented to derive this trends. Together with the unobservables, that is, the so called 'disturbances', which refer to the inputs into the system not captured by the sensors at the time of measurement, the input to the scenario selection system is defined.

5.4. Search Module

At the core of the scenario selection method is the definition of the search approach, for which the main task identified is that of comparing real states with the multiple simulated ones stored in the database. This module has a critical role in enabling the real-time prediction to occur. For this module, decisions need to be made regarding the proximity measures used to compare the real and simulated crowd state metrics, the method to perform the multi-objective optimization, as well as the boundary conditions which must be taken into account when performing the search. The multi-objective optimization part is then formed by the individual objectives given by the combination of the different metrics and Event Blocks, which are compared based on the proximity measures, taking the boundary conditions into account. These elements identified, and decisions that need to be made, for performing this multi-objective optimization are further discussed below.

5.4.1. Proximity Measures

The first of the elements for performing the search is the definition of the proximity measures, which define how similar the simulated states are from the real states, for each scenario and time period. As shown by Toledo and Koutsopoulos (2004), among the methods to compare real and simulated values are Goodness-of-Fit (GoF) measures, hypothesis testing and confidence intervals as well as test for underlying structure.

GoF measures indicate the overall error of the simulated values, of which examples are squared error (SE), mean-squared error (MSE) and root-mean-squared error (RMSE). The comparison based on these measures relates to the observed and simulated measurements at each point in space and time. For instance, one can use the squared-error to compare the real density at a certain Event Block, measured with the crowd monitoring sensors, with the simulated density values of each scenario and time period in the database. The output is then an error value which indicates how close the density at that Event Block is to each scenario and time period. When the squared error of the density of the Event Block is calculated for each time period of the time series, and averaged over the number of time periods, the mean-squared error can be calculated.

When using hypothesis testing, one can check the similarity between two distributions considering a defined confidence level and assumptions dependent on the test used. An example of an application is for the case when the travel time distribution between two locations is used as one of the state metrics. Classic hypothesis tests include two-sample t-tests and Kolmogorov-Smirnov tests. The assumption of two-sample tests that both distributions (real and simulated) are independent draws from identical distributions (IDD) is an example of assumptions that need to be considered when choosing the hypothesis test to be performed (Toledo & Koutsopoulos, 2004). This is because some of these assumptions might be unrealistic in the context of pedestrian traffic simulation. For instance, two-sample t-tests assume that the real and simulated distributions are normal and share a common variance. This variance equality assumption can be considered unrealistic due to the simplifications of the behavior that are made when using a model, as these are often derived for the average or most common conditions (i.e. low variance is expected).

Finally, the test for underlying structure relates to the development of two metamodels, one for the simulated and other for the real states, which describe the structure of these. These metamodels are then compared by statistical tests for the equality of their coefficients. For instance, one could use regression models, or ARMA (auto-regressive moving average) models to describe the real and simulated time series of each metric, and compare the coefficients of these by an F-test to assess the hypothesis of the equality of these models. The metamodels can be chosen based on the nature of the application, as well as the relationship among variables which can for instance be described by traffic flow theory (Toledo & Koutsopoulos, 2004). However, deriving such models requires additional time and computer resources, as one would have to derive one metamodel per metric and Event Block, which is much more complex than using for instance the Goodness-of-Fit measures.

For the application in this research, these proximity measures discussed above determine how the individual objectives of the multi-objective optimization are formulated. These can be based on the error between the real and simulated values, in case of GoF measures, the result of the hypothesis testing to assess the equality of two distributions, or the use of hypothesis tests to assess the equality of metamodels. Each of these requires different assumptions and describe the time series data of each metric differently. In the literature in pedestrian studies which use multi-objective optimization algorithms to compare real and simulated data, only Goodness-of-Fit measures could be found (Duives, 2016; Sparnaaij, 2017).

5.4.2. Multi-Objective Optimization

In the scenario selection process, each simulated metric of each Event Block is compared to its real value, describing the different between these for each scenario and time period. The goal of the scenario selection is to select the scenario for which these differences are the minimum, that is, the scenario that best approximates to the real states. Each metric of each Event Block and its corresponding proximity measure forms an individual objective. Thus, when these are considered for the selection of a scenario from the database, a multi-objective problem arises. The multi-objective problem considers the differences between all the state metrics when searching through the database of scenarios. The search space ($\mathbb{S}$) of such problem is determined by the number of metrics in the state vector, the number of scenarios in the scenario database and the number of time periods each scenario is discretized in.

In order to find the scenario with minimum error across the considered state metrics, multi-objective optimization approaches are considered. Optimization provides a systematic way to combine these multiple and sometimes conflicting objectives in order to find the best possible scenario among the pre-simulated ones. The objectives are in conflict when an improvement in one leads to a deterioration of the other (Zak & Chong, 2013a), which can occur for instance when the state of a certain Event Block has to be prioritized over another Block during the search process. A multi-objective optimization problem to minimize the error between the simulated and real states can be mathematically defined as (Miettinen, 1998):

$$\begin{aligned} \text{minimize} \quad & \mathrm{f} = \{f_1(z), f_2(z), \ldots f_k(z)\} \\ \text{subject to} \quad & z \in \mathbb{S}^l \end{aligned} \tag{5.2}$$

Whereby the vector function of the individual objective of a state metric z is denoted by $f(z)$, and k (≥ 2) defines the number of objectives / state metrics to be optimized. The minimization goal shows that one wants to minimize all the objectives at once. Furthermore, the multi-objective function f assigns to each decision variable a multi-objective vector function value in the objective function space, that is, $\mathbf{f}: \mathbb{S}^l \rightarrow \mathbb{S}^k$.

Scalarization Methods

There exist multiple approaches to solve multi-objective optimization problems in literature. These either use *scalarization* for transforming the multiple objectives into a single objective, for which standard optimization methods can be used, or these aim at producing the set of *Pareto optimal solutions* (Miettinen, 1998). Three typical examples of scalarization of multi-objective problem are shown in Table 5.1. All of the methods below require a decision maker to consider domain knowledge for appropriate scalarization, as a preference or importance is given for the different vectors in the objective function. The weighted sum method is the only one that can guarantee that all individual objectives (i.e. state metrics) can be given equal importance in the selection process, and is thus more useful for the purpose of this research. This equal important is achieved by a combination of the weight assigned to each objective and consideration of the normalization of the objectives. The other two methods imply a preference or hierarchy between the different objectives. For instance, the minmax approach assumes that the only objective that matters is the one for which its simulated value has a larger error when compared to its real value. Meanwhile, the ϵ-Constraint method assumes that it is sufficient to find the scenario with minimum error for one objective, while the other objectives are within error bounds considered in the constraints.

Table 5.1: Overview of scalarization methods found in literature (Zak & Chong, 2013b)

Method	**Problem Re-formulation**		
Weighted-sum	Linear combination of the components of the objective function vector with weights **w**	min	$\sum_{i=1}^{k} w_i f_i(z)$
Minmax	Single objective consists of minimizing the maximum of the components	min	$max\{f_1(z), \ldots f_k(z)\}$
ϵ-Constraint	Minimize one of the components of vector subject to constraints on the other components	min s . t	$f_j(z)$ $f_i(z) \leq b_i$ for $i \in \{1, \ldots k\} \backslash \{j\}$

Optimization Algorithms

Optimization algorithms are responsible not only for finding the optimal scenario within the database, but also for the real-time performance of the search. Hence, the key properties of existing algorithms of interest for this study are their ability to find the global optimum and not get stuck in a local sub-optimal solution, their computational burden, and their ability to deal with a high-dimensional, discrete problem as the one discussed in this research. In Table 5.2, some algorithms found in literature are presented, categorized into single and multi-objective. The related studies refer to applications of the algorithms for pedestrian behavior or transportation studies, when these could be found during the literature search.

Table 5.2: Overview of optimization methods found in literature (Extended from Sparnaaij (2017))

	Method	Studies
Single Objective	Nelder-Mead	Rudloff et al. (2014)
	Genetic Algorithm (GA)	Rudloff et al. (2014); Wolinski et al. (2014)
	Greedy	Wolinski et al. (2014)
	Grid Search	Duives (2016); Sparnaaij (2017)
	Simulated Annealing	Wolinski et al. (2014)
	Covariance Matrix Adaptation (CMA)	Wolinski et al. (2014)
Multi Objective	ϵ-Domination Multi-objective Evolutionary Algorithm (ϵ-MOEA)	Deb et al. (2003)
	Nondominated Sorting GA (NSGA-II)	Deb et al. (2002); Yu et al. (2015)
	Niched Pareto GA	Horn et al. (1994)
	Strength Pareto Evolutionary (SPEA2)	Zitzler et al. (2001)

The algorithms included in the table are in principle capable of finding the global minimum, as these attempt to search through the entire feasible set for the optimal solution. Transforming the multi-objectives into a single one adds a layer of abstraction to the algorithm, and is a technique that requires the decision maker to have knowledge about the underlying problem. However, it significantly improves the speed by reducing the computational complexity. From the single-objective methods, the grid search appears to be the only one that will certainly find the global optimal for a given discretization of the search space, but it is also likely to be the slowest (Sparnaaij, 2017). Also, the grid search algorithm is able to handle the discrete problem discussed in this research, when appropriate scalarization methods are used. The other algorithms are most often used in continuous problems, although examples of use of these for mixed-discrete or discrete problems can also be found in literature (Wu & Chow, 1994; Lin & Hajela, 1992).

Among the multi-objective algorithms, the compromise between the quality of the solution, that is, the ability to find the minimum errors, and the computational time is observed when comparing these algorithms. However, the main issue regarding the application of these algorithms to the scenario selection system is the dimensionality of the problem addressed in this research. When attempting to satisfy multiple objectives, the multiobjective space needs to be mapped into a single dimension for solutions to be compared, where Pareto Dominance has been a commonly applied method to establish preferences among the Pareto optimal solutions (Garza-Fabre et al., 2009). When the number of objectives increases, the convergence ability of these is negatively affected, as the proportion of equally good solutions in the multiobjective context increases exponentially with the number of objectives. Thus, the search process becomes practically random as it is not possible to impose preference among individual solutions (Garza-Fabre et al., 2009).

Due to the aforementioned considerations, scalarization of the multi-objectives into a single-objective, and further application of a single-objective optimization algorithm, is preferable over applying multi-objective algorithms. Among the previously discussed issues regarding the dimensionality of the problem, multi-objective algorithms yield a set of Pareto optimal solutions, or, in the case of this research, a set of optimal scenarios, which can become very large for high-dimension problems. Given the objective of this thesis to assist crowd managers to have insights into the future developments of the state of the crowd, providing them with a set of scenarios to be analysed is considered problematic. It is clear that it is unlikely that there will be time to analyse these multiple scenarios prior to making decisions, and still be able to proactively manage the crowd.

Stopping Criteria

Performance of the optimization algorithm can be improved by considering an adequate stopping criterion. In this research, the selection of the stopping criterion is done depending on the optimization method and output structure (i.e. one or multiple scenarios) chosen. For instance, the stopping criteria for the grid search method of Duives (2016) is simply that all possible scenarios in the database are explored. For other methods, determining such criterion enables finding solutions deemed optimal without having to search through the entire database. The stopping criterion can be determined by convergence, whereby a scenario is selected if within n subsequent iterations of the algorithm no new optimal is found, or by stopping after a fixed number of iterations. Examples of these are the methods of Rudloff et al. (2014) and Wolinski et al. (2014). Another possible criterion that does not consider the number of iterations can be either testing if the solution satisfies some optimality condition (e.g. the distance between the real and simulated values of a state metric is lower than a certain value), or if a certain maximum computation time is reached (Sparnaaij, 2017).

5.4.3. Boundary Conditions

The boundary conditions related to the search through the scenario database considers practical implications regarding both, the state metrics and the location where these metrics are derived from, here called Event Blocks. In subsection 5.3.1, multiple considerations are made regarding both, the choice of state metrics and the choice of location to define the Event Blocks. Ideally, one would be able to have the defined metrics at the chosen locations for the application of the method in a real event. The problem is that often these metrics are limited by the capabilities of the monitoring sensors and state estimation techniques available. Also, the Event Blocks where one can derive the real states from is bounded to the location where these sensors are mounted on the environment, as mounted sensors are most commonly found in event terrains (e.g. video cameras and Wi-Fi sensors). When applying the method, the state metrics and Event Blocks which are used in the search are therefore limited by the sensor network.

5.4.4. Sub-conclusions

The core of the scenario selection system proposed in this research is the use of multi-objective optimization for finding the scenario in the database which most closely corresponds to the real state of the crowd. The search module discussed in this chapter illustrates the elements of this method. These are the proximity measures to formulate the individual objectives, the multi-objective optimization problem and corresponding algorithms, as well as the boundary conditions that one needs to consider for performing the search. It is clear that the choice between the different proximity measures relates to the assumptions that can be made with regards to the comparison between the simulated and real data, as well as the time available to derive these measures. For instance, deriving metamodels for each metric and Event Block is a highly time consuming task, and much more complex than using Goodness-of-Fit measures. Meanwhile, some hypothesis tests require assumptions that might be unrealistic in the context of pedestrian simulation.

The choice of the algorithm for the multi-objective optimization first requires the choice of whether the multi-objectives are going to be combined into a single objective through scalarization methods. The choice of algorithm is then based on this, as these are separated into single-objective algorithms and multi-objectives ones. It is argued that, due to the high-dimensional problem addressed in this research, it is preferable to perform a scalarization of the multiple objectives into a single one. Finally, the boundary conditions addressed relate to the sensor network at the event. The state metrics, and locations where these are derived from, are defined based on the location and capabilities of the sensors available. Thus, the metrics and Event Blocks used for the search are bounded to the sensor network.

5.5. Communication Module

As each scenario in the database is discretized in time periods, the output from the search module consists of a scenario at a certain time instant, when the multi-objectives are combined into one. Meanwhile, multi-objective optimization algorithms yield the *Pareto optimal* set of scenarios, and their corresponding time instants. The communication to crowd managers is thus given by the scenario for which the error is minimized for the multiple objectives considered in the optimization. As discussed in Section 4.1, the typical analyses performed relate to the crowdedness on the different areas of the environment, or the delays in these areas. These can be directly obtained from the scenario selected, where one can decide whether to show the simulation results for the given scenario, or the values of the state metrics of the scenario, considering the prediction horizon. Based on for instance the predicted development of the density in each Event Block, crowd managers can have insights into where discomfort or unsafe conditions might arise.

Not only the chosen optimization method can result in more than one scenario deemed possible, but one can also define that it is of interest to select other scenarios but the one for which the multiple objectives are minimized. Formulating the criteria for selecting scenarios for which the results should be communicated to crowd managers, means finding a way to provide the right information at the right time to facilitate decision making. Too much information might be overwhelming and not add much to the process, while too little information might not cover the relevant outcomes. Hence, the two key decisions considered at this stage are related to how many scenarios should be considered as options, and how different these should be to cover the dynamics of interest. Dealing with both of these issues requires planning how to score and rank likely scenarios, and having crowd managers analyse their outcomes. These processes of score and rank likely scenarios, and the factors that need to be considered for these are not in the scope of this research, and simply relate to recommendations for future applications of the method.

5.6. Conclusions

In this chapter the scenario selection system based on the multi-objective optimization methods was addressed. To introduce the elements and processes which are shared between the proposed system and existing model-driven crowd forecasting methods, an introduction in system theory was provided. System theory indicates how the crowd forecast system can be described by a time series of state metrics (discrete-time systems). Existing model-driven forecasting systems use these state metrics to derive the input to the simulation core. From these existing systems, it was highlighted that the real data from the crowd monitoring sensors and state estimation techniques are also key inputs of the proposed method. However, these are the used to derive the real-time input to selection system (i.e. real crowd state metrics) instead of to the simulation model. Based on these considerations, the framework for the scenario selection system is proposed, from which the point of departure is the multi-objective optimization approach which compares the time series of the real state metrics with that of the simulated scenarios.

The input to the scenario selection system is thus the real and simulated time series of state metrics. The choice of metrics and considerations regarding the different parts of the behavior these describe are part of the decisions related to the input module. These are separated into two categories which refer to the observability of these metrics. Observables relate to the metrics to describe the current state and state history, which provide information about what has happened on the event environment up to the time of measurement t, that is, the values of current state as well as the trend that led to these values. Smoothing techniques are introduced to indicate how this trend can be derived. Unobservables relate to the so-called disturbances, which indicate the inputs relevant for prediction which are not captured by the sensors at the time of measurement. Examples of these are the arrival of a public transport mode, or the end of a performance, which occur between the time of measurement and the prediction horizon, and generate additional flows of pedestrians into the event environment. From these disturbances, the demand generated by these can be included as a state metric in the state vector.

Measures to compare each state metric of each Event Block form the individual objectives which together make the search through the database a multi-objective problem. For formulating these individual objectives one thus need to define which proximity measures should be used to compare the real and simulated metrics of the crowd state vector. When considering these individual objectives for the multi-objective optimization, the decision regarding the algorithm to be used is dependent on whether or not scalarization of the objectives into a single objective is done. It is preferable to perform this scalarization due to the high-dimensional problem addressed in this research, as the performance of multi-objective optimization algorithms decreases with the increasing number of individual objectives that need to be simultaneously considered.

III

FRAMEWORK APPLICATION

6

Application of the Frameworks

This chapter discusses the application of each framework developed in the previous chapters for a specific case study based on a real mass event. The remainder of this research, and answer to the outstanding research questions thereof, is set up according to the concepts and definitions presented in this chapter.

Figure 6.1 illustrates the link between the current chapter and the other chapters of this research. Although both the current and the following chapters are under the Framework Application part of this research, a distinction is made with regards to this application. The current chapter focuses on applying the frameworks developed in Chapter 4 and Chapter 5 to the specific case study. Its outputs are the scenarios and the scenario selection system considered for the prediction analysis. Meanwhile, the specific methodologies for both, assessing the application of the forecasting method and corresponding results, and performing the sensitivity analysis of the system are discussed in more detail in Chapter 7.

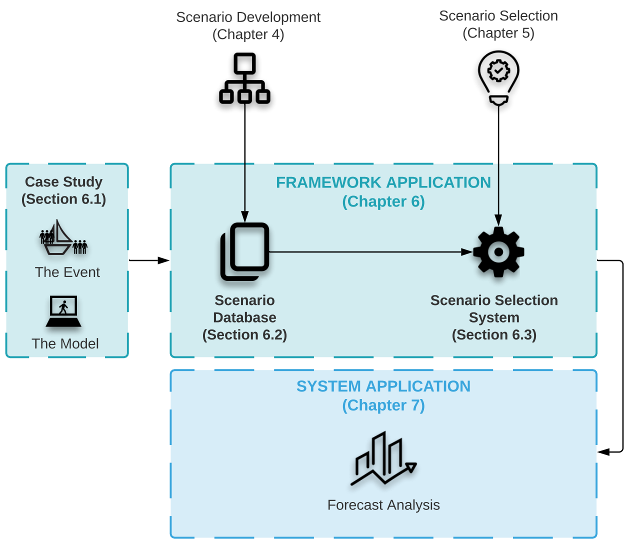


Figure 6.1: Overview of the connections between the current chapter and the other chapters of this research

This chapter is built-up as follows. Firstly, Section 6.1 introduces the case study used in this research, including both the mass event and the simulation model. Following, Section 6.2 presents the application of the scenario development framework for the case study. The output of this section is the set of scenarios which forms the database used as input for validating the selection algorithm. The application of the scenario selection framework in carried out in Section 6.3, which thus presents the scenario selection system developed for this research.

6.1. Introduction to Case Study

As stated in Chapter 1, the forecasting method proposed in this research uses a microscopic model for the prediction of crowd movements during mass events. Hence, in order to apply the frameworks and test the forecasting method, these two elements need to be defined: the simulation model and the mass event. In this section, both of these elements are discussed in detail, where the key components of each for the proposed application are highlighted.

6.1.1. The Event

Mass events which take place in urban areas are increasingly frequent in many European cities. An example of such events is SAIL, Europe's largest nautical event which occurs every 5 years in August in the city center of Amsterdam, The Netherlands. More than 600 ships moor in the IJ-port, attracting millions of visitors to the SAIL terrain to watch the ships and enjoy the atmosphere. In its previous edition in 2015, SAIL received more than 2 million national and international visitors, spread over the 5 days in which the event took place (Daamen, Yuan, Duives, & Hoogendoorn, 2016). The municipality of Amsterdam has developed a crowd monitoring dashboard which supports crowd management during the event. Information regarding the state of the crowd is derived from the data captured by the different kinds of sensors in place, namely counting cameras and Wi-Fi. These characteristics make SAIL an interesting case study for this research.

Study Area & Crowd Monitoring Network

The study area of the SAIL terrain considered for the application of the forecasting method is shown in Figure 6.2, where the location of the mounted crowd monitoring sensors are pinpointed. This study area is a sub-part of the total event area. Selecting a sub-area to test the method is necessary to limit the amount of scenarios for the application of the scenario development framework, given the time constraints of this research. The selected area is part of the so-called orange route, a walking route along the tall ships on the south bank of the IJ-port. The reason for selecting this area for application of the method is two fold. Firstly, this is expected to be the area with highest demand, as it is were most tall ships are docked, and given the fact that visitors coming from the city center of Amsterdam or from Amsterdam Central station (i.e. a main entry area of the event) use at least a part of this route to access the event terrain. Secondly, this area is where most crowd monitoring sensors are located, which makes it interesting for the proposed application.

Overview of event

This subsection presents an overview of the entry and exit points of the study area, as well as routes and activities planned for the event. There are six locations where visitors can enter and exit the study area. The main ones are located on both ends, west and east. On the west-end is not only Amsterdam Central station, but also the most used route towards the city center of Amsterdam. On the east-end is the continuation of the orange route on the Java-eiland, where more tall ships are docked, and also the connection with Amsterdam-Oost. Besides

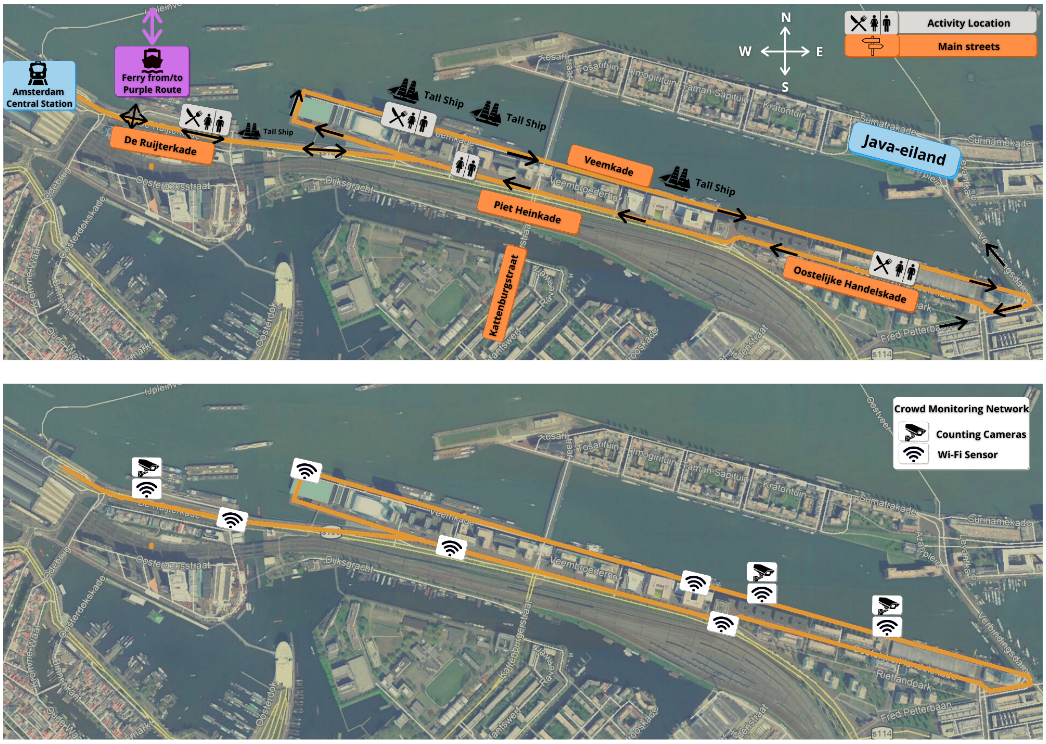


Figure 6.2: SAIL - Study area and crowd monitoring systems

these locations, visitors can also access the study area through the ferries, which arrive near the station entrance on the west-end, or from the Kattenburgstraat.

Figure 6.2 illustrates the main flow directions expected for each main street in the study area. Bidirectional flows are most often expected at De Ruijterkade, whereas on the other streets it is pre-defined that there is always a dominant flow direction. This is because the main entry location during the day is at the west-end, where visitors then continue along the orange route through the Veemkade to watch the ships, or wait for a ferry at De Ruijterkade. Besides watching the ships, visitors can also buy food or drinks at three main activity locations: (1) at the Ruijterkade, by the queue for the ferry to the purple route, and (2) (3) on both ends of the Veemkade. Every evening, a firework show is held at the Java-eiland, thus flows of visitors can be expected from east to west through the Piet Heinkade at the end of the show.

Unlike mass events which have a clear distinction between ingress, movement and egress behavior (e.g. sports events), for SAIL visitors are expected to behave differently in two situations. Firstly, when visiting the event and walking along the route to watch the tall ships, visitors' behavior can be considered more multi-purposed, typical of leisure trips, where pedestrians have lower walking speeds and perform more activities (Zomer, 2014). Secondly, at the end of the firework show in the evening, egress behavior is assumed, with higher walking speeds and more targeted goal to reach their final destination. The event occurs in August, thus during summer, so the weather conditions are expected to be good.

6.1.2. The Model

This section introduces the microscopic pedestrian simulation model Pedestrian Dynamics ®(PD) by INCONTROL Simulation Software. All three levels of behavior as proposed by

Hoogendoorn and Bovy (2004) (strategic, tactical and operational) can be modelled in PD. The higher level behavior processes (demand, activity scheduling) are direct inputs implemented by the user, whereas the behavior of the operational level (route following, collision avoidance and route choice) are based on algorithms embedded in the software, influenced by the model's parameters. In the context of this research, the inputs for the higher level processes are further discussed in Section 6.2, as these are defined by the scenarios developed for SAIL. In this section, the embedded operational models are introduced.

Overview of model

The first algorithm implemented in PD discussed in this section is the route choice algorithm. It uses the concept of an Explicit Corridor Map (ECM) (Geraerts, 2010), in combination with the A* algorithm, to determine the global route for a pedestrian. The ECM is a navigation network that defines the walkable space of an environment. There are two approaches for computing the global route: (1) shortest path and (2) least-effort. The former simply considers the path with the shortest distance between each origin and destination pair, whereas the latter takes into account a cost function based on the estimated travel time.

While following the chosen route between an origin and a destination, agents in the model need to go through the process of avoiding collisions with obstacles and other agents. Each agent uses vision to detect which obstacles, both dynamic and static, it has to avoid. The vision is modeled as a cone-shaped field of view (FoV) as illustrated in Figure 6.3. The collision-avoidance algorithm lets each agent choose a velocity that is close to its desired velocity, but that prevents them from colliding with others. The collision avoidance algorithm is based on the vision-based model developed by Moussaïd et al. (2011). fig:FOVPD also illustrates which obstacles are taken into account when determining the desired direction. These are defined by the viewing angle (ϕ) of the agent together with the viewing distance ($d_{\max}$). For more detailed information about the simulation model the reader is referred to Sparnaaij et al. (2019).

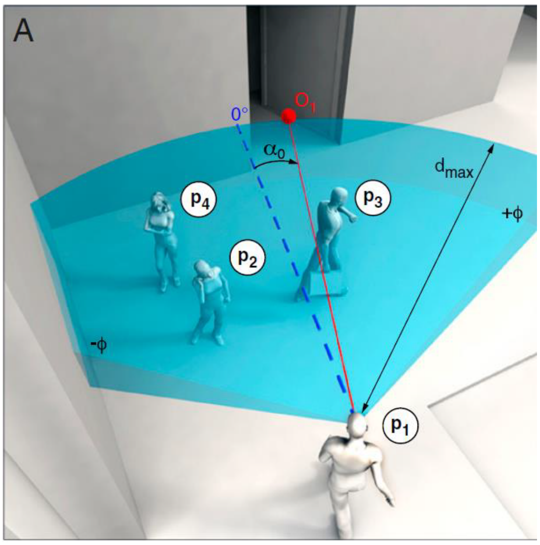


Figure 6.3: Example of the cone-shaped field of view and parameters used to determine the desired velocity (Fig. 1 (A) from (Moussaïd et al., 2011)

Section D.1 presents a discussion regarding the behavior validity of the embedded models of PD based on literature. From the discussions it is highlighted that attention needs to be paid to the validity of the prediction of bottlenecks and bidirectional flows. The throughput of the locations where these occur is expected to be lower than those in reality. This indicates that the inefficiencies related to these conditions might arise for a lower density level. This lower throughput is expected for most existing models, due to the simplification of the pedestrian movement regarding for instance rotational behavior when interacting with others and with the infrastructure. Thus, despite this lower throughput for those conditions, PD is seen as an appropriate model for the application of this research.

6.1.3. Conclusion

This section introduced SAIL and Pedestrian Dynamics ®, respectively, the mass event and the microscopic model used as case study in this research. Based on the overview of the dynamics of the event, the main access and attraction (activities and destinations) points, routes and flow directions were presented. Besides, a discussion on the expected behavior of visitors for two situations was made. The first situation is when visitors are at the event terrain watching the tall ships, where they can be expected to have lower walking speed and perform more activities. Egress behavior, where walking speeds and assumed to be higher as visitors have the main purpose of getting to their final destination, is expected for the second situation: the end of the firework show in the evening. The main routes also change between these two situations, where for the former the most popular route is from west to east through the Veemkade, and for the egress higher flows are assumed on the route through the Piet Heinkade.

Regarding the microscopic simulation model, the focus on this section was in introducing the model and discussing the capabilities of the implemented routing and operational models in representing high density crowd movements. It has been defined that, in line with research in pedestrians' route following behavior, the least-effort approach of the route choice algorithm is going to be used. Regarding the collision avoidance, the movement dynamics in multi-directional flows is selected as the main point of attention regarding the validity of the behavior. It has been discussed that the throughput expected before congestion starts appearing for the sections where flows are bidirectional is often lower than in reality. Hence, special attention needs to be paid to those sections when simulating the scenarios.

6.2. Scenario Database

Based on the overview of the event dynamics provided in the previous section, this section aims at deriving the specific scenarios to be included in the database for SAIL. These scenarios are derived by applying the steps of the Scenario Development Framework proposed in Chapter 4. Hence, subsection 6.2.1 analyses the dynamics of the study area from both perspectives, supply and demand. Following, subsection 6.2.2 identifies the types of inefficient dynamics expected in the study area, considering the benchmark cases introduced in subsection 3.3.3. The output of this subsection is the set of inefficient dynamics which, together with the corresponding density levels as presented in subsection 6.2.3, are to form the scenario database. The inefficient dynamics of each scenario are the input of subsection 6.2.4, where the simulation of the scenarios and development of the database are discussed. Finally, subsection 6.2.7 presents a discussion on the simulation process and results from Pedestrian Dynamics.

6.2.1. Analyses of Event Dynamics - SAIL

For the analyses of the event for the purpose of identifying the scenarios, as discussed in subsection 4.2.2, both the supply and the demand sides are considered, as well as the elements which can influence these. These analyses are performed based on the checklists presented in subsection 4.2.2, and they result in an overview of the areas of the environment and corresponding dynamics considered relevant for prediction. This means assessing the interaction between the supply and demand sides which can potentially lead to discomfort or unsafe conditions to the event visitors. The reason for this being that, as stated in subsection 4.2.1, the purpose of real-time prediction is to provide crowd managers with information to assist them in taking decisions. However, as it is neither feasible nor desirable that all possible conditions are included in the scenario database, the focus lies on the dynamics that can potentially lead to problematic conditions.

Supply Checklist

In order the carry out the supply analysis, information needs to be gathered regarding the the walking infrastructure, obstacles and characteristics of activities (e.g. type, size, location). The analysis is carried out based on the supply checklist (Table 6.1) for the environment of SAIL. The answer to these questions highlights the areas of the environment where inefficient dynamics are more likely to occur, or that can trigger such inefficiencies to occur.

Table 6.1: Checklist for the supply analysis of SAIL

Number	Question
1	Are there locations where the width of the path gets narrower due to obstacles or simply the shape of the path, or where there are infrastructure elements such as stairs or escalators?
2	Are there locations where multi-directional or intersecting flows exist given the planned routes?
3	Are there activity locations positioned very close to one another? Or an area where many activities are concentrated?
4	Are there areas of the environment where visitors can be sheltered from the weather? Or are there areas where the walking infrastructure remains safe and suitable for use in case of rain (e.g. asphalt, wooden platforms)?
5	Are there alternative routes from a main route which visitors are likely to take in case they feel uncomfortable or unsafe even if these routes are not optimal?

For the study area of SAIL, questions 1, 2, 3 and 5 were answered with yes, which illustrate the likely critical areas of the environment. Question 4 is not considered as there are no areas with weather protection on the SAIL route, and the walking infrastructure has the same characteristics over the entire terrain. Four key bottleneck locations are highlighted by the supply analysis and are illustrated in Figure 6.4. Location 1 presents the intersection at De Ruijterkade. This location is considered important because of the interactions between flows from multiple directions (Question 2), and also due to the proximity between the visitors waiting for the ferry and the ones watching the ships or using the commercial facility in that area (Question 3). Location 2 highlights a very narrow path at the Piet Heinkade, with an obstacle splitting the flow in two. Also, bidirectional flows are expected upstream of this bottleneck (considering the west to east movement) (Questions 1 & 2). Along the Veemkade, two locations are considered. Location 3 pinpoints the area where several tall ships are located, which is also near the main commercial activity of that route (Question 3). Hence, demand for the tall ships and for the activities can lead to inefficiencies arising there due to queuing. Besides, at that location the platform over the water which added an extra width to the path ends, so the path is narrowed. To exit the platform, visitors have two options. They either follow the route through the street, exiting the platform before it ends, or they go all the way to the end of the platform, and access the street through a gate. Both of these are narrow cross-sections. The fourth location is further down the Veemkade, where also the width of the path gets narrower (Question 1). Finally, number 5 in the figure indicates the lanes connecting the Veemkade to the Piet Heinkade, which can be used by visitors to move between these two main streets (Question 5). The average width of these lanes is about 9 meters.

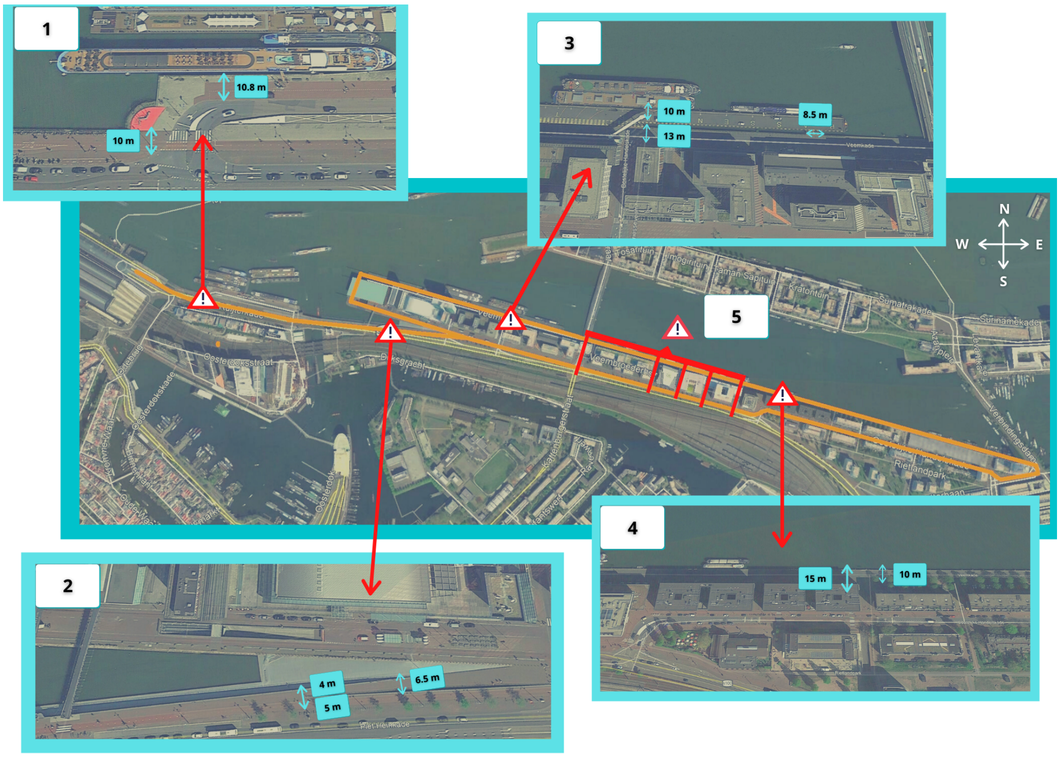


Figure 6.4: Bottleneck locations identified

Demand Checklist

The analysis of the demand has three focuses: the arrival of visitors per entry point, the route demand and the demand for activities (commercial, tall ships). The analysis is carried out based on the demand checklist (Table 6.2) applied to SAIL. Similar to the supply analysis, the answers to these questions highlight the times during the event and the areas where inefficient dynamics are likely to appear.

For the study area of SAIL, the answer to all questions in the checklist is yes. A large number of visitors is expected into the study area from the Java-eiland when the firework show ends (Question 1), and most of these visitors are expected to go towards Amsterdam Central Station. Also, as discussed in the overview of the event dynamics, there is a ferry arrival at De Ruijterkade which brings visitors from the north bank of the IJ-Port. The ferry capacity is 3300 passengers per hour, thus a single ferry arrival can bring 1100 pedestrians into the study area in a very short time window (Question 1). In relation to the routes, the study area has two main routes: (1) along the Veemkade and (2) along the Piet Heinkade. However, the route along the Veemkade is much more attractive to visitors who are going to watch the ships, as it is where most of them are docked, and also where more commercial activities are located (Question 2). At the end of the firework show, the route along the Piet Heinkade from the Java-eiland towards the Central Station is assumed to be more attractive as it is shorter and the path is

Table 6.2: Checklist for the demand analysis of SAIL

Number	Question
1	Are there times during the event when there is a demand peak, that is, where a large amount of visitors is expected to arrive in a short time frame? (e.g. the arrival of public transport or the end of a performance)
2	Is there a main / most attractive route to or from areas where activities are planned?
3	Are there any routes between areas of the event for which the availability of alternative routes is limited?
4	Are there any main / more attractive or popular activities (i.e. where a larger amount of visitors are expected to go to)?
5	Are there any areas where visitors are expected to walk slower or stop more frequently (e.g. for taking pictures or observe the attractions)?

wider. Regarding the alternative routes, although the Veemkade and the Piet Heinkade can be considered alternatives from one another as they connect the same origins and destinations, these have distinct dominant flow direction. Alternative routes connecting the west-end and east-end, with the same dominant flow conditions, is thus considered limited (Question 3).

Regarding the activity locations (e.g. tall ships and commercial), the ones along the Veemkade, especially the one at the far west, are expected to be the main activities as visitors can buy food and drinks while watching the tall ships docked there (Question 4). At the activity location near the intersection at De Ruijterkade, the demand is expected to be lower, but as highlighted in the supply analysis, there are interactions between the visitors from that activity with the demand for the ferry. The combined demand for these activities makes that area be included in the analyses of the inefficient dynamics. Lastly, the areas where visitors are expected to walk slower and stop more frequently are along the Veemkade (Question 5), as they can watch and take pictures of the tall ships.

6.2.2. Identification of Inefficient Dynamics - SAIL

From the discussions presented above, the dynamics for the SAIL event which can lead to the appearance of each type of inefficiency can be identified. As indicated in subsection 4.2.3, the questions of the checklists can be linked to the different benchmark cases. For instance, from the answer to the second question of the supply checklist, the intersection at De Ruijterkade is highlighted as an area where distinct flow directions coexist. Hence, the dynamics expected can be placed under the flow interactions inefficiency. Also, from the answer to the fourth question of the demand checklist, the route from the west-end along the Veemkade towards the east-end is highlighted as the main route of the event. As the answer to the third question of the supply checklist pinpointed a concentration of activities on the west-end of this route, the dynamics expected can be placed under the uneven distribution over the network inefficiency.

The level of risk is analysed for the different areas of the environment. From the answers to the questions of the checklist, four areas are highlighted in the study area of SAIL. Firstly, the area at the west-end of the Veemkade. This area is highlighted as high risk area due to the concentration of activities, the bottleneck and the fact that visitors are likely to walk slower and stop more frequently along this route to take pictures of the tall ships. It is thus expected that this area is likely to experience high densities for prolonged periods.

Secondly, the east-end of the Veemkade is also highlighted. The reason for including this area is due to the high demand expected for the route along the Veemkade, and how the bottleneck at the end of this route, which is its narrowest point, can obstruct the flows and often cause high densities to appear. Besides, when congestion appears along this route, visitors can start moving to the Piet Heinkade to avoid it. This in turn creates undesirable flow interactions.

Thirdly, the area at De Ruijterkade, from the intersection to the area by the ferry and activity are also highlighted. Similar to the Veemkade, the demand for that area is expected to be high as all visitors coming from the main entrance at Amsterdam Central Station walk there. This leads to the expectation of high flows constantly interacting at the intersection at De Ruijterkade. Besides, the combined demand for the ferry and the commercial activity on that area are also likely to lead to high densities for prolonged periods.

Finally, the corridor between the intersection at De Ruijterkade and the Piet Heinkade is the fourth area highlighted as a high risk area. Not only does that corridor have the narrowest bottleneck of the entire event terrain by the east-end of it, as highlighted in Figure 6.4, but also the throughput is likely to be reduce along the corridor due to the coexistence of different flow directions.

The inefficient dynamics identified for the study area of SAIL, and the location where these are expected to happen are shown in Figure 6.5. These are explained in detail in Section D.2, and summarized in Table 6.3.

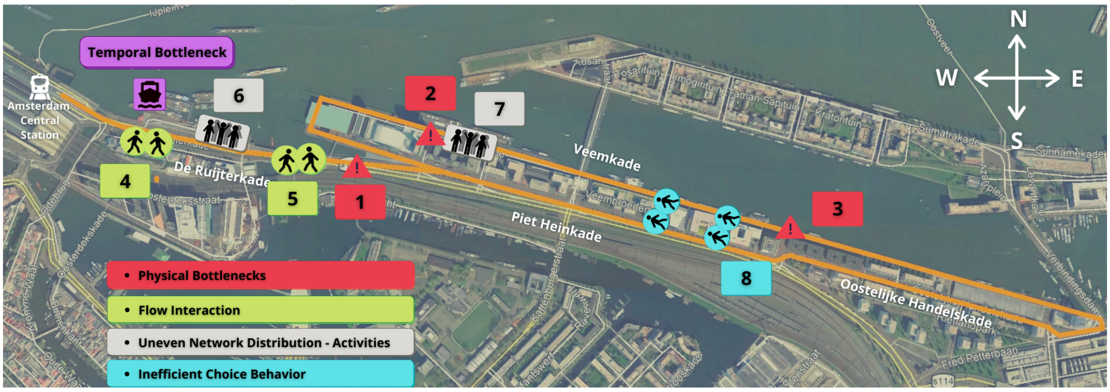


Figure 6.5: Inefficient dynamics and location - SAIL

Table 6.3: Inefficient dynamics description - SAIL

Physical Bottlenecks	
1. Piet Heinkade	Demand exceeds capacity of narrowest cross-section leading to a bottleneck becoming active and the appearance of queues upstream this bottleneck
2. Veemkade - West	(1) Demand exceeds capacity as most visitors exit platform over the water in the first exit or (2) demand exceeds capacity as most visitors exit platform through the gate. Both can lead to the activation of a bottleneck
3. Veemkade - East	Demand exceeds capacity of the narrowest cross-section leading to a bottleneck becoming active
Flow Interactions	
4. Intersection - Multidirect	Flows at the intersection at the De Ruijterkade from a dominant direction hamper the other direction(s) and interactions reduce total throughput of intersection, leading to a blockade
5. Route - Bidirect	Interactions between dominant flow direction, either coming from De Ruijtekade or from the Piet Heinkade, and secondary direction hamper the throughput of the section of the route, leading to a blockade.
Uneven Distribution over Network	
6. Activity - De Ruijterkade	Increase demand for the activities at De Ruijterkade and for the ferry lead to rising densities as visitors concentrate on that area, leading to a blockade
7. Activity - Veemkade West	Increase demand for the activity at the Veemkade - West and for the tall ships lead to rising densities as visitors concentrate on that area, leading to a blockade
Inefficient Choice Behavior	
8. Inefficient Route Choice	As densities rise along the Veemkade, higher shares of visitors going from west to east move through the connecting lanes to walk along the Piet Heinkade. This is considered inefficient as no attractions exist there and the dominant flow direction is the opposite flow. Besides, this leads to undesirable flow interactions.

6.2.3. SAIL Scenarios

This subsection discusses the implementation of the inefficient dynamics identified to formulate the scenarios to be simulated. As discussed in subsection 4.2.1, in the database of scenarios, one does not only want to include the scenarios for which inefficient dynamics occurs, but also the ones for which the dynamics that can lead to the inefficiency do not trigger its occurrence. Thus, although the identification of the phenomena described in the previous subsection focuses on the case when the dynamics lead to the the appearance of the inefficiency, variations in the demand are taken into account, for the same patterns (e.g. route usages, activity shares), by the density levels.

Density Level

As discussed in subsection 4.3.1, the concept of the distinct density levels relates to the number of interactions between agents and between agents and the infrastructure. The density level of a scenario indicates whether the inefficient dynamics described in the previous subsection occurs or not, thus also whether or not crowding and unsafe conditions might appear. Besides, it indicates how quickly densities can rise. In the scenarios developed in this research, this concept is implemented as follows. For each inefficient dynamics identified as presented in Table 6.3, 6 distinct density levels are defined for the areas each scenario focuses on. This means that for each inefficient dynamics, 6 scenarios exist where only the demand pattern is different between these. As proposed in the scenario development framework, the dynamics of reference come from the case when the inefficient phenomena leads to crowding and unsafe conditions. This is calculated based on an estimated capacity value. For instance, for a physical bottleneck, this capacity value is estimated based on the width of the narrowest cross-section. Meanwhile, for an uneven distribution over the network, this capacity can be calculated based on the service time of the activity. Variations based on this capacity are then created, for which the relative usage of the infrastructure is maintained, but the total number of agents generated is changed and thereby the density level. However, as mentioned in subsection 4.3.1, for the different benchmark cases, distinct LOS are of interest, and consequently distinct density levels. Thus, for each of the benchmark cases, the minimum and maximum density levels are defined based on the LOS of interest as presented in Table 6.4.

Table 6.4: Density level per benchmark for SAIL considering the LOS of interest

Benchmark Case	**Density Level**	
	Low	High
Physical Bottleneck	LOS B	LOS F
Flow Interaction	LOS B	LOS E
Uneven Distribution over Network	LOS B	LOS F
Inefficient Choice Behavior	LOS B	LOS E

These levels are chosen for two reasons. The lower level is defined as LOS B because it is where conflicts start appearing due to the interactions. The higher level of each scenario is chosen based on when traffic is expected to breakdown. For the inefficiencies which have bidirectional flow conditions, the highest density level is lower as traffic is expected to breakdown earlier.

Scenarios

From the inefficient dynamics identified in subsection 6.2.2, and the density levels defined above, the total amount of scenarios simulated to form the scenario database are shown in Table 6.5. The inputs to build these scenarios in the simulation are shown in the following subsections.

Table 6.5: Scenarios SAIL

Scenario	Density Levels	Benchmark Case
1. Piet Heinkade	DL 1 to DL 6	Physical Bottleneck
2. Veemkade - West	DL 1 to DL 6	Physical Bottleneck
3. Veemkade - East	DL 1 to DL 6	Physical Bottleneck
4. Intersection - Multi-direct	DL 1 to DL 6	Flow Interaction
5. Route - Bidirect	DL 1 to DL 6	Flow Interaction
6. Activity - De Ruijterkade	DL 1 to DL 6	Uneven Distribution over Network
7. Activity - Veemkade West	DL 1 to DL 6	Uneven Distribution over Network
8. Inefficient Route Choice	DL 1 to DL 6	Inefficient Choice Behavior
Total Scenarios	48	

6.2.4. Input Definition

As discussed in Section 4.3, the inputs to the model are defined in order to obtain the dynamic behavior which corresponds to the appearance of the inefficiency. For a detailed description of each scenario's inputs, the reader is referred to Section D.3. In the remainder of this subsection, the focus is to illustrate which and how the inputs are defined to obtain the desired dynamics of each scenario.

Geometry of the infrastructure

The geometry of the infrastructure is based on a CAD drawing of the study area, where the widths of the paths and main obstacles on the environment are derived from. These are illustrated in Figure 6.6. The white areas correspond to the areas available for walking, and the pink areas are near the activity locations. As correctly modelling queuing behavior can cause issues to the overall dynamics of the simulations, and it is not of interest to this research to capture such behavior realistically, only the effect on density and delay that high demand for activities can cause, queues are not modelled. Instead, the entrance to the activities are modelled by adding obstacles around the boundaries of the activity, and opening a space with a certain width through these boundaries for agents to access the activity, as if these were the locations where pedestrians would queue.

For the different scenarios, the only changes regarding the infrastructure were the movements permitted on the Veemkade, Piet Heinkade and the lanes connecting these two main streets. As mentioned in subsection 6.1.2, when modelling bidirectional flows, the interactions between the agents can reduce the throughput of cross-sections. Although in reality the appearance of blockades in such conditions can occur, in the model, these occur for lower flows than in reality. If blockades appear, the model can stop completely, and the inefficient dynamics which focus on conditions which are not even related to bidirectional flows can no be achieved. As the only scenario for which it is necessary to simulate bidirectional flows on these streets given its inefficient dynamics is the Inefficient Route Choice scenario, for all

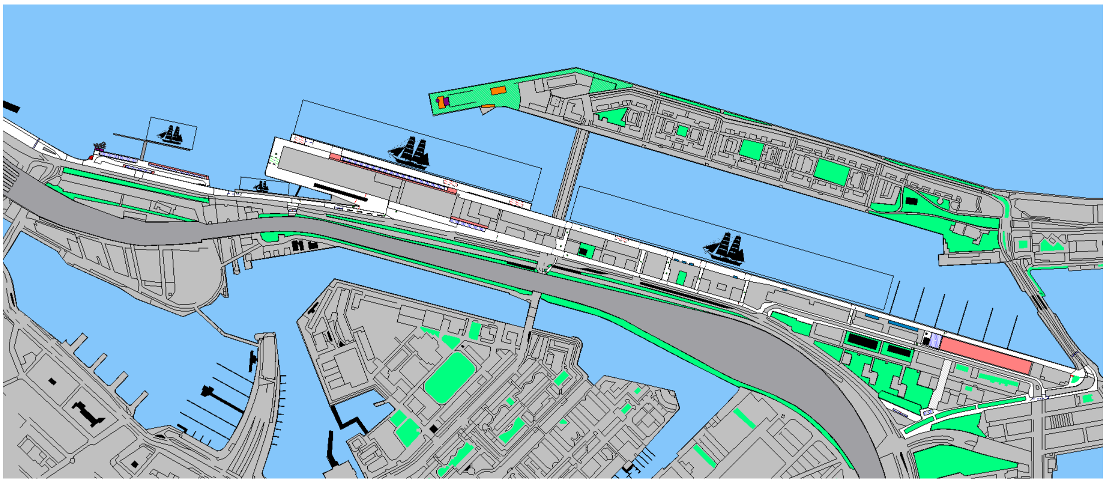


Figure 6.6: Study area in Pedestrian Dynamics ®

the other scenarios, only unidirectional movements are allowed on the Veemkade and Piet Heinkade. The lanes connecting these streets are thus excluded from the network (Figure 6.7), to avoid agents moving between these two main streets and creating bidirectional flows.

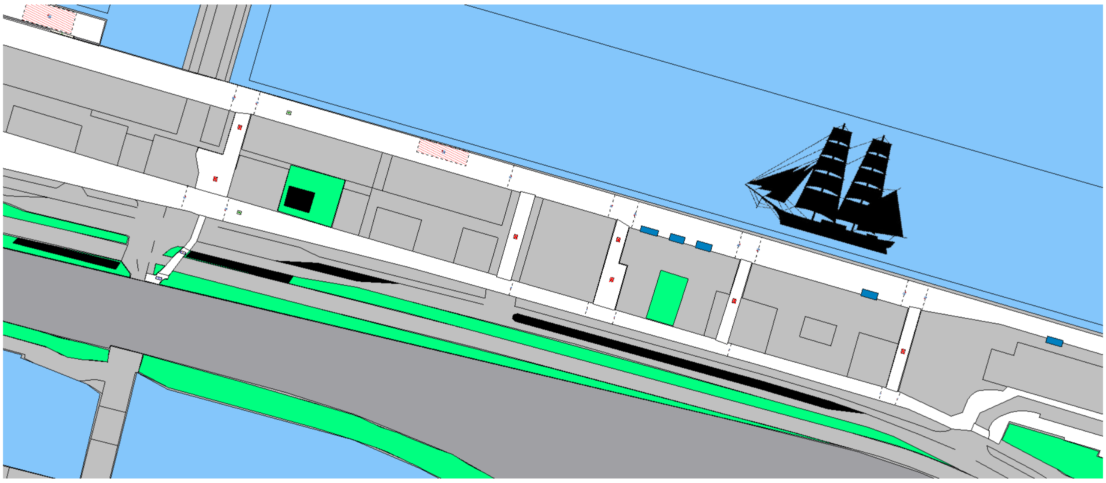


Figure 6.7: Lanes connecting the Veemkade to the Piet Heinkade

Demand Pattern

The variations of the demand pattern are derived for each conceptual scenario, as well as for the corresponding density levels considered. The inflows per scenario are summarized in Table 6.6, and the distribution of these flows per entry location are shown in Table 6.7. For all scenarios, from the minimum to the maximum inflows assumed, a step size of 10% is considered to differentiate the density levels. Two aspects are highlighted here from the aforementioned tables. Firstly, the inflows are higher on the scenarios where the focus is on the dynamics along the Veemkade, when this is unidirectional, if compared to the other locations. Also, the share per entrance changes for the scenarios for which the flows along the Veemkade have to be higher. This is because the bottleneck at the Piet Heinkade is activated when higher flows are assigned there, and so the desired states along the Veemkade do not occur if the pedestrians are generated in a location where they have to pass that bottleneck to reach the Veemkade. However, higher flows can reach the Veemkade without blocking the Piet Heinkade if pedestrians come from the different entrances. As these lead to higher densities on the Veemkade, such distribution over the entrances are used.

Table 6.6: Scenarios' demand pattern

Scenario	Max Inflow (ped/h)	Min Inflow (ped/h)	Step Size
1. Piet Heinkade	51000	34000	10%
2. Veemkade - West	57800	44200	10%
3. Veemkade - East	47600	30600	10%
4. Intersection - Multi-direct	51000	34000	10%
5. Route - Bidirect	44200	27200	10%
6. Activity - De Ruijterkade	51000	34000	10%
7. Activity - Veemkade West	47600	30600	10%
8. Inefficient Route Choice	51000	34000	10%

Table 6.7: Scenarios' share per entrance

Scenario	Share per Entrance			
	West-end	Ferry	Kattenburgstraat	East-end
1. Piet Heinkade	65%	8%	11%	16%
2. Veemkade - West	40%	6%	32%	22%
3. Veemkade - East	40%	6%	32%	22%
4. Intersection - Multi-direct	39%	6%	23%	32%
5. Route - Bidirect	65%	8%	11%	16%
6. Activity - De Ruijterkade	46%	7%	17%	30%
7. Activity - Veemkade West	40%	6%	32%	22%
8. Inefficient Route Choice	40%	6%	32%	22%

Regarding the distinct density levels, to illustrate the differences between the effect of these for a single scenario, Figure 6.8 presents the densities and flows over time at the area by the activity location on the west-end of the Veemkade. These are derived from the simulations of the different density levels for the scenario 'Activity - Veemkade West'. One can see the different density levels cover different levels of service. As the density level rises, the levels of service gets worse and the states move closer to capacity. When capacity is reached, it is possible to see the breakdown in the flow diagram for density levels 5 and 6, where, as expected, in level 6 the breakdown happens earlier than in 5.

Activity Schedules & Activity Demand

For most of the scenarios, the schedule of activities remains the same. Agents who are generated at the West-end and at the Kattenburgstraat mostly move towards the Veemkade to follow the orange route, or go to De Ruijterkade to take the ferry. The agents who arrive from the Ferry either go to the Veemkade or to the West-end. Meanwhile, the agents that are generated at the East-end mostly move towards the West-end. These routes are shown in Figure 6.9, and the share per route per scenario is presented in Table 6.8.

The main distinction between the scenarios with regards to the activities relates to the demand, that is, the share of agents from the total amount of agents generated who are assigned to an activity. In the inefficient dynamics of scenarios 6 and 7, related to the uneven distribution over the network, the share of agents from the total amount of agents assigned to an activity is higher if compared to the other scenarios. In this research, for both scenarios, this share is 80% of the total, whereas in the other scenarios it is 50%. This higher share is derived from the capacity value estimated from the average activity time assigned.

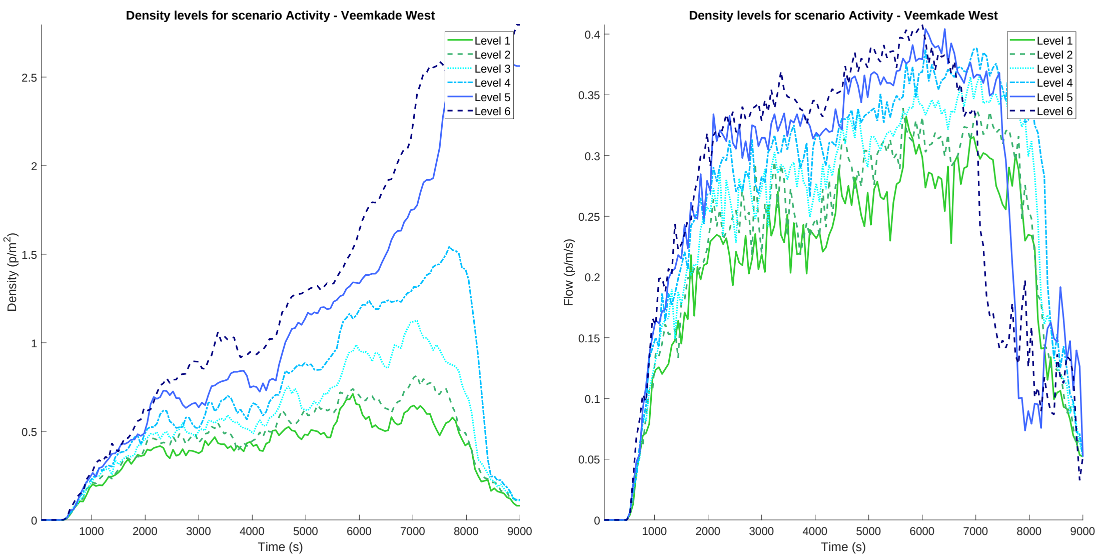


Figure 6.8: Distinct states for each density level of scenario Activity - Veemkade West

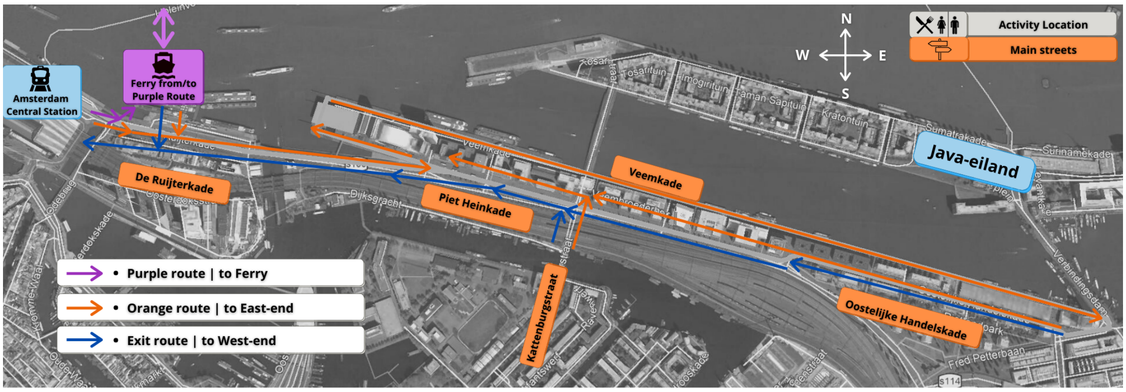


Figure 6.9: Routes of SAIL event

Routing Preferences

Regarding the routing preferences, visitors are assumed to choose their route based on the least-effort approach. This is in line with research that affirms that the least-effort approach is more representative of real pedestrian behavior (Shepherd, Clegg, & Robinson, 2010). In this approach, agents consider a cost function based on the estimated travel time, which is based on, among others, the distance and the delay caused by the density. This cost function has a parameter called 'Density delay weight' which indicates the sensitivity of the agents to delays caused by the density. For instance, if this parameter is set to zero, agents do not use the density information at all. Setting it to larger values, means that agents are more likely to choose routes or take detours to avoid the extra delay caused by densities. For scenario 8, where agents are assumed to take detours or choose distinct routes to avoid the high densities, this parameter is thus increased from its default to force agents to be more 'impatient' and more eager to change their routes.

This inefficient route choice behavior is achieved when combining the higher values of the 'Density delay weight' with another parameter called 'Viewing distance'. The latter refers to the distance from itself that agents take into account when estimating the delay caused by

Table 6.8: Origin-Destination shares per scenario

(a) 1. Piet Heinkade and 5. Route - Bidirect

O/D	West-End	Ferry	East-End
West-end	-	20%	80%
Ferry	50%	-	50%
Kattenburgstraat	30%	-	70%
East-end	60%	-	40%

(b) 2. Veemkade - West, 3. Veemkade - East, 7. Activity - Veemkade West and 8. Inefficient Route Choice

O/D	West-End	Ferry	East-End
West-end	-	30%	70%
Ferry	50%	-	50%
Kattenburgstraat	0	-	100%
East-end	40%	-	60%

(c) 4. Intersection - Multi-direct

O/D	West-End	Ferry	East-End
West-end	-	40%	60%
Ferry	80%	-	20%
Kattenburgstraat	30%	-	70%
East-end	60%	-	40%

(d) 6. Activity - De Ruijterkade

O/D	West-End	Ferry	East-End
West-end	-	20%	80%
Ferry	60%	-	40%
Kattenburgstraat	10%	-	90%
East-end	40%	-	60%

the density. For instance, for its default value of 60 meters, agents use the density information in the first 60 meters of the route to calculated the expected delay. Thus, to make agents more eager to avoid densities, this parameter is also increased for scenario 8. Agents are then forced to reconsider their route at certain locations when walking along the Veemkade, so that the current densities ahead of them is taken into account. The result of these considerations are illustrated in Figure 6.10. The figure shows the densities over time for the area by the bottleneck at the east-end of the Veemkade, where each line represents distinct density levels for the same scenario. Next to the densities over time is the share of agents that reroutes via the Piet Heinkade for the same density levels. It can be seen that, for the results of the simulation of the higher density level (Level 6), where the densities over time increase at the bottleneck, more agents choose to take the route via the Piet Heinkade. Also, the higher the density becomes, the larger the share of agents who reroute.

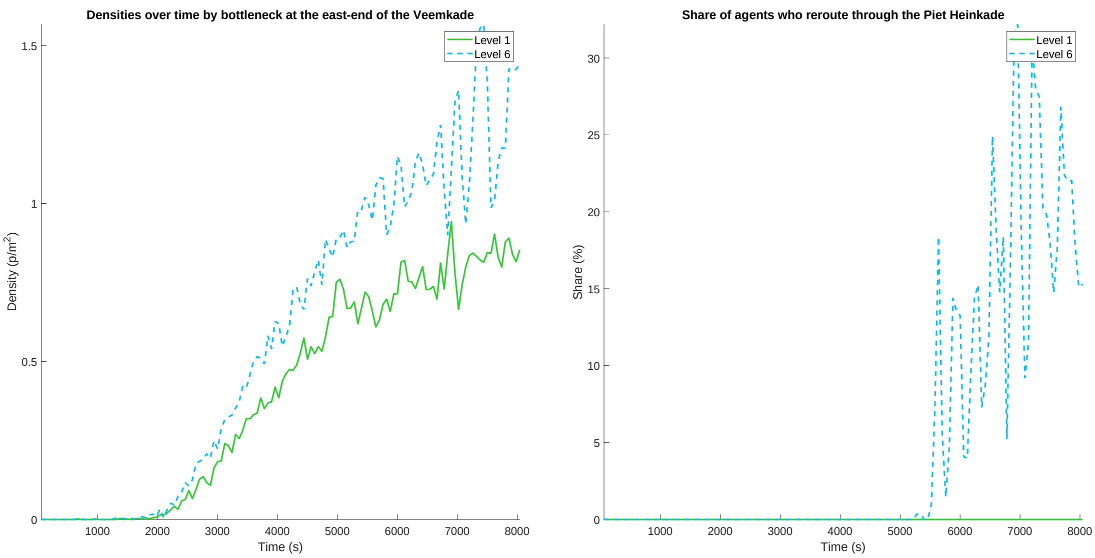


Figure 6.10: Inefficient route choice due to avoidance of high density areas

Movement Preferences

The movement preferences parameters are not modified from their default values. Also, the default preferred speed distribution of Pedestrian Dynamics ®is used. This is chosen because it is a single triangular distribution with no distinction between agent's properties such as age or gender, and the average of the distribution is 1.35 m/s which is representative of a value derived by Daamen (2004) from an average of multiple studies. The preferred speed of the agents is only modified when walking along the Veemkade. Due to the expected behavior of the visitors when walking along that route, that is, walking slower to watch the ships or to take pictures, each agent's assigned preferred speed is reduced by half of its value when walking along the Veemkade. This is chosen to maintain the initial shape of the distribution, and the distinct preferences with regards to the speed due to that, but at the same time account for the behavior of walking slower to watch the tall ships. Besides, in three locations where the most visited tall ships are expected to be, and thus were visitors are expected to stop to take pictures and walk even slower to watch the ship, the speeds are further reduced to 20% of its initial value. The value of 20% is assumed so that agents do not completely stop, as this could cause the simulated traffic to breakdown. However, this reduction only occurs while visitors walk over these locations, to simulate their behavior while taking pictures or admiring the ships. These aim to create interactions between flows with different 'purposes' along the Veemkade, as not all agents who walk over these areas are slowed down.

6.2.5. Stochasticity

Many pedestrian models are stochastic by nature (Duives, 2016). This is also the case for Pedestrian Dynamics, making it necessary to calculate the required number of replications per scenario to guarantee that the distinct states obtained arise from changes in the input instead of being caused by this stochastic nature, as state in subsection 4.3.3. In order to estimate the required number of replications, a method and a metric need to be selected. Regardless of the choice of method or metric, the underlying principle that guides the estimation of the number of replications relates to the approximation to the actual probability distribution of the metric (Sparnaaij, 2017). This means testings whether the probability distribution of the output of the n number of replications, would be considered to be a sample drawn from the same distribution of the probability distribution of the output if an *infinite* amount of replications would be considered.

Choice of Metric

The choice of the metric used for estimating the number of replications is based on two considerations. The first relates to the distinction between the density levels of each specific scenario, and the dynamics of the distinct conceptual scenarios. As a single conceptual scenario can lead to multiple simulated scenarios given the distinction between the density levels, it can be expected that the overall throughput of the network is also distinct. Hence, it is important that the metric used for the calculations captures both, the dynamics between the distinct scenarios and that of the distinct density levels of each scenario. Such metrics are derived based on the output dynamics for which examples are flow, mean speed or travel time.

The second consideration relates to the practicality in deriving the metric from the scenarios' output files. In that sense, metrics which are less computationally heavy to derive considering the amount of agents in the each scenario are preferred. Hence, the choice is made to use the travel time distribution as the metric to calculate the required number of replications. This metric is calculated based each agent's travel time, agents that did and did not complete their route, and is derived from their trajectories. The travel times of all agents simulated in one replication of one scenario form the distribution. This metric gives insights into both, the flow condition for distinct density levels, as higher travel times indicate that flow is less efficient, and also the distinct dynamics of distinct scenarios (e.g. scenarios where higher share of visitors performs activities, travel times can also expect to be higher).

Choice of Method

From the two methods presented in subsection 4.3.3, the sequential method is chosen for the application in this research. The reason for this is two-fold. Firstly, it it expected that it reduces the amount of simulations that need to be run, as additional replications are only performed if the estimated number of replications exceed the initially defined one. Secondly, due to the large number of pedestrians simulated in the scenarios of SAIL, and the number of observations to derive the distribution of the travel time from the output thereof, it is considered likely that the scenario's distribution will be a good approximation to the actual probability distribution of the travel times. Therefore, the necessary number of replications per scenario is anticipated to be low. To calculate the number of replications, Equation 4.1 is used, which was shown in subsection 4.3.3. The parameters used in the application of this equation and of the method are presented in Table 6.9.

Table 6.9: Parameters for calculating the required number of replications

Parameter	Value
Initial number of replications (R)	5
$t_{\frac{\alpha}{2}}$	1.96
d_i	0.02

Five replications are used as the initial number of replications in order to calculated the standard deviation of the distribution of the metric. For all scenarios, using the parameters presented in Table 6.9, the number of replications obtained was smaller than 1. Therefore, a single replication per scenario and density level is considered for the analyses performed in the remainder of this research.

6.2.6. Simulation Process

From the discussions presented above, one can see that for each of the 8 scenarios, 6 variations are considered for the distinct density levels. For each of these variations, 5 replications are run to estimate the required number of replications. As the results of the stochasticity calculations for all scenarios was below 1, no additional replications had to be run. Therefore, a total of 240 simulations were run. Each scenario is simulated for 2.5 hours, where the first hour loads the environment, and the other one a half hours corresponds to the measurement time. The average number of agents simulated per scenario is 75000 agents. The trajectory information of each of these scenarios is then used for the derivation of the metrics and formulation of the individual objectives, as it will be discussed in the following section.

A remark is made regarding the simulation process for the scale of the model and number of agents per scenario developed in this research. As the demand is increased to account for the different density levels, the interaction between the agents and between these with the infrastructure can lead to the appearance of unexpected issues. For instance, some agents might get stuck at a location due to being 'pushed' by other agents or infrastructure elements when avoiding collision with these. In such cases, these agents might accumulate and end up creating a bottleneck where in reality there wouldn't be one, and result in an unrealistic scenario.

The creation of small-scale models of the different areas of the event is expected to positively contribute to resolving these issues. As the scale of the model is reduced, it then becomes easier to have more control over the scenarios and inefficiencies that appear, and shorten the simulation process. However, for the application of the method in this way, additional requirements are necessary. For instance one needs to address the question of how to sub-divide the environment to build these multiple models. Hence, the usage of the method when the scenarios are built based on multiple small-scale simulation models is posed as a question for future research.

6.2.7. Assessment of Simulated Behavior

As mentioned in Chapter 1, the choice to develop a set of scenarios offline for the real-time forecast is proposed to address the computational burden issues of models considered behaviorally valid. Hence, the behavior validity of the model used in this research is assessed in this subsection based on crowd phenomena to be represented in the model for the SAIL scenarios. For instance, for the flow interaction scenarios, the behavior can be assessed in terms of lane formation in bidirectional flows through corridors. The study of Duives (2016) shows from the analysis of empirical data that the occurrence of crowd phenomena is dependent on the movement base case. Hence, this subsection assesses the behavior of three movement base cases, namely:

- Uni-directional bottleneck flow: this movement base case relates to the physical bottleneck inefficiency, and is focused on bottlenecks which appear from the narrowing of a path or obstacles which reduce the capacity of cross-sections.
- Bidirectional flow in straight corridor: this movement base case relates to the flow interactions inefficiency, and is focused on the situation where only two flows interact when these share the same corridor, thus creating face-to-face interactions.
- Intersecting flow: this movement base case also relates to the flow interactions inefficiency, and is focused on the situation where two or more flow interact while the angle of the interaction can be any angle between 10° and 170°.

For the above cases, a qualitative analyses of the behavior simulated by PD is performed. This is because, from a study of the literature, it could be seen that no clear quantitative rules could be determined to identify crowd phenomena (Duives et al., 2014c; Moussaïd et al., 2012). However, qualitative criteria to assess the realism of the behavior can be determined. To assess the behavior validity of the model for the three selected cases, scenarios from the database are manually reviewed through face validation of the trajectories and simulations. For all scenarios, the criteria is developed on the basis of the comparison between the development of the inefficiency when the density level is increased, that is, the development of high-density regions, as well as the appearance of the specific phenomena related to each case. These are further explained per case below.

Uni-directional bottleneck flow

In uni-directional bottleneck situations, the assessment of the behavior can be discussed separately between the entering and exiting flows through the bottleneck. This is because research has given indications that the behavior in these two conditions is distinct (Daamen & Hoogendoorn, 2010; Duives, Daamen, & Hoogendoorn, 2014a). The high density and low velocity regions appear upstream the bottleneck, where the interactions between the pedestrians cause small sideways movements to avoid collision. These can be observed through the trajectories, which transition from smooth to irregular when densities rise (Duives, 2016; Duives et al., 2014a). Downstream the bottleneck, high density and high velocities are observed due to pedestrians fanning out and occupying the larger width available. The lack of this behavior upstream and downstream of the bottleneck location is considered unrealistic and so the trajectories are assessed based on these expected behavior.

Figure 6.11 illustrates 100 trajectories just upstream the physical bottleneck scenario Veemkade - East. From these trajectories, it can be seen that when the densities are higher in the busy period the trajectories become more irregular. This irregularity appears from the interactions between the agents, which combined with the goal to move forward seem to make these agents have lateral movement more often in an attempt to overtake. These are also observed in trajectories obtained from observing real pedestrians.

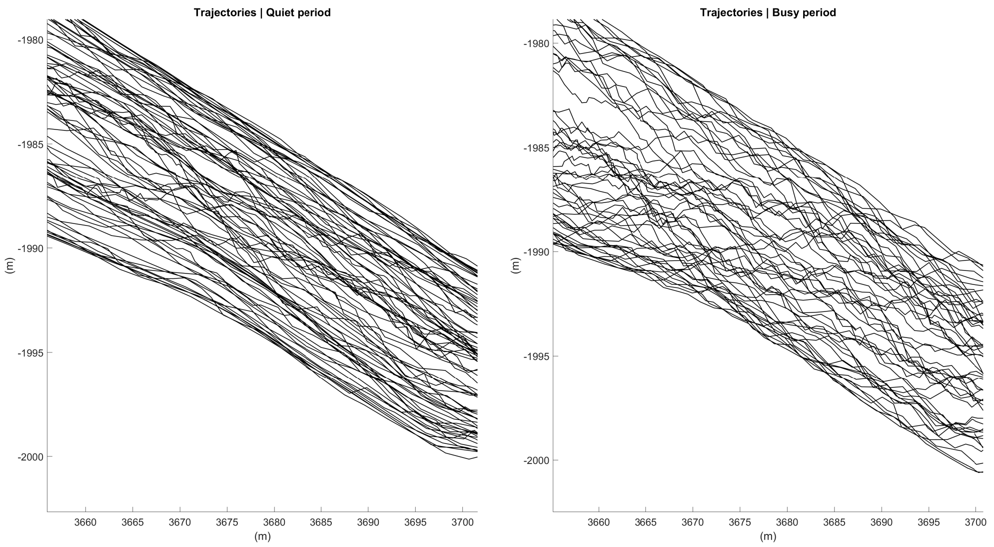
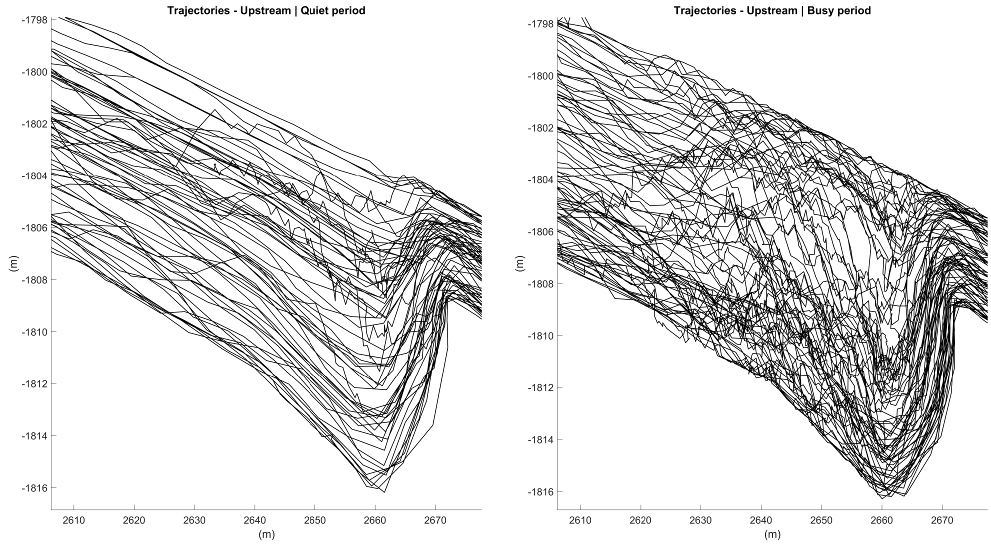
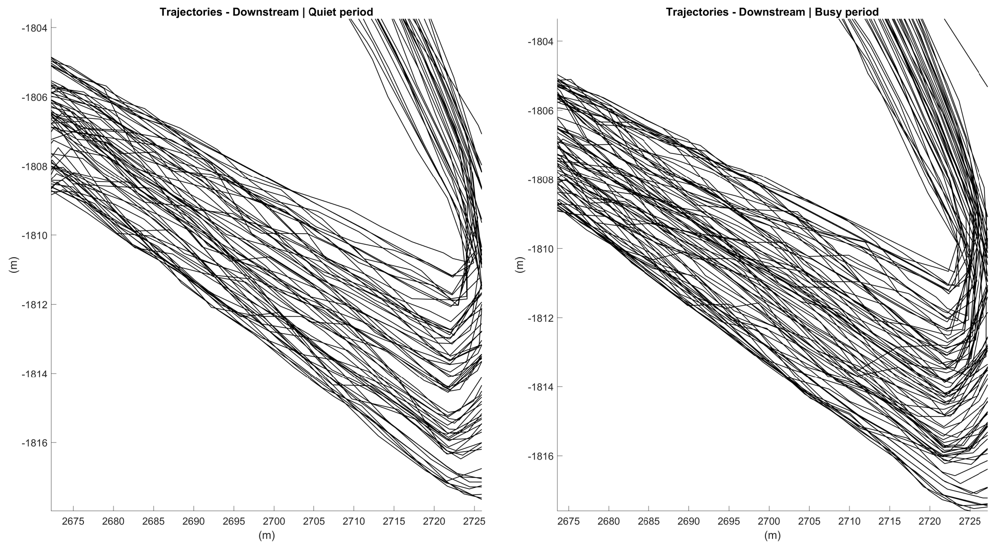


Figure 6.11: Visualization of trajectories of the Veemkade - East scenario for a quiet (left) and busy (right) period

The bottleneck in the Veemkade - East scenario is distinct from the bottleneck in the Piet Heinkade scenario. The Veemkade - East bottleneck corresponds to the entrance to a narrow corridor and thus the fanning out behavior after that bottleneck is not observed in this scenario, but it can be seen in the Piet Heinkade bottleneck. Figure 6.12a and Figure 6.12b illustrate the trajectories upstream and downstream the Piet Heinkade bottleneck, respectively, in a quiet and busy period. While the busy and quiet periods upstream can be easily distinguished due to the irregularity of the trajectories, downstream the bottleneck this does not happen. This is expected to be because downstream the bottleneck the flows are steady. One can say that these two locations capture distinct areas of the FD, where only upstream the bottleneck the congested branch is reached, as it is illustrated in Figure 6.13. The flow and the density downstream appear to stay near capacity for most of the time, while upstream the flows decrease as the density rises beyond capacity.



(a) Upstream Bottleneck in quiet (left) and busy (right) periods



(b) Downstream Bottleneck in quiet (left) and busy (right) periods

Figure 6.12: Visualization of trajectories of the Piet Heinkade scenario

From the discussion above, one can say that PD reproduces the behavior at bottlenecks for the criteria presented regarding the interactions and areas of the FD covered at each side of the bottleneck. Hence, the model is considered adequate for the purpose of the application in this research. It is however important to highlight that based on the criteria used the model is not quantitatively validated. For instance, it is not possible to say whether the flow through the bottleneck or the densities reached at the bottleneck locations are representative.

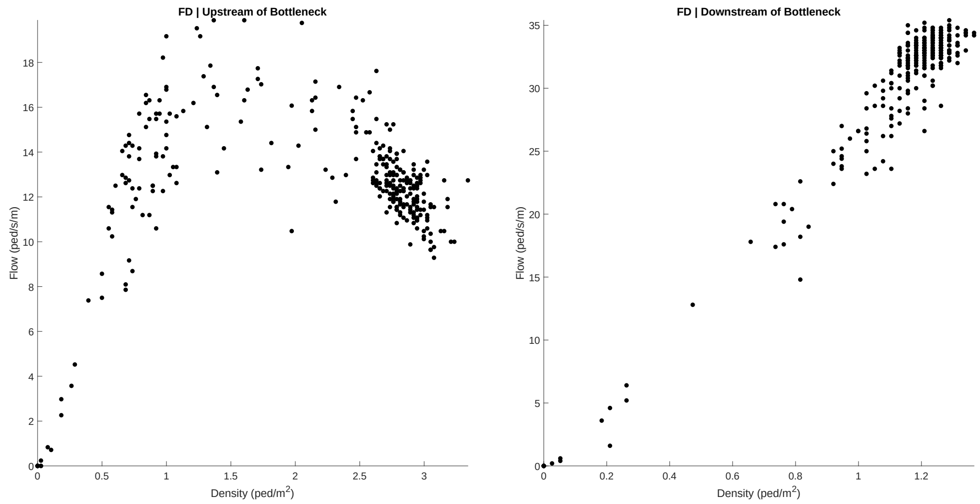
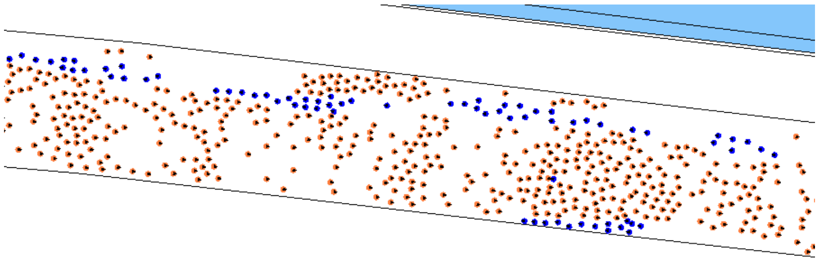


Figure 6.13: FD's derived upstream (left) and downstream (right) of Piet Heinkade bottleneck

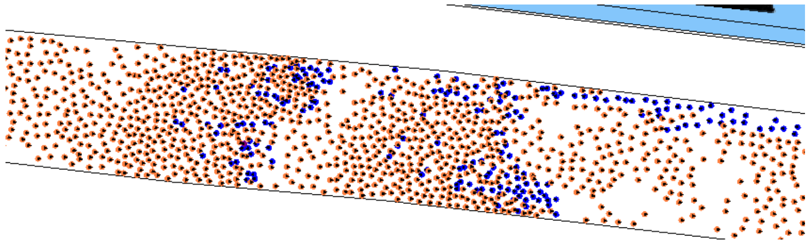
Bidirectional flow in straight corridor

In the case bidirectional flows in straight corridors, the development of the lane formations to blockades when densities increase is analysed. This formation of lanes appears to arise from some leader-follower behavior when bidirectional streams exist (Sparnaaij, 2017), which makes the pedestrians walking in the same direction follow one another. In the study of (Duives, 2016), the author mentions that pedestrians in low density bidirectional situations are observed to have mainly front-to-back interactions, and that this might be due to the idea of a reduced effort in following rather than finding a new path through the crowd. However, as densities rise in bidirectional streams with a dominant flow direction, pedestrians are faced with more interactions, and to avoid collision these move sideways. These lanes are then expected to be shorter or even fully dissolved, as in such conditions, pedestrians are forced to finding their path through the crowd. One can think of a situation where the first pedestrian in a lane moves to one side, and the following pedestrian is not be able to follow as this pedestrian might be interacting with other due to the high densities and be pushed to a different side. Avoiding collision with the opposite flow is thus assumed more important than following its leader. When such conditions occur, it is more likely that a blockade occurs. The lack of this formation of lanes in low density bidirectional streams, and the break up of these lanes when densities rise, is thus considered unrealistic and so the analysis is done based on these expected behavior.

The behavior in bidirectional streams is better visualized in snapshots of the simulation in the model, so these are shown below. Figure 6.14 illustrates the behavior of agents in the model in low and high density when bidirectional flows interact in a straight corridor. The formation of lanes can be seen in Figure 6.14a, where these lanes appear to be stable as long as the densities are low, and thus there is space for pedestrians to avoid collision while still following their respective leaders. In high densities these lanes break up as the interactions force pedestrians in the same lane to move sideways or reduce their speeds at different rates. This behavior can in turn separate the leaders and followers, as illustrated in Figure 6.14b. Given these simulation results, one can say that PD reproduces the behavior of bidirectional flow in straight corridors adequately for the given criteria.



(a) Bidirectional streams in low density



(b) Bidirectional streams in high density

Figure 6.14: Visualization of the simulations of bidirectional flows

Intersecting flow

Intersecting flow appear to be less understood than the other two movement base cases discussed above. From literature, qualitative criteria can be derived from the studies of Versluis (2010), S. Wang et al. (2010) and Duives (2016). Versluis (2010) discusses that for intersecting flows crossing at 90° angle, pedestrians tend to stop and wait to avoid collision, rather than moving laterally. S. Wang et al. (2010) has shown that the major stream of the intersecting flows has higher walking velocities if compared to the minor stream. From the results of these two studies, it can be expected that agents in intersecting situations stop more frequently, especially the ones in the minor stream. The lack of this behavior is thus considered unrealistic.

The simulated behavior in PD of intersecting flows does indicate that pedestrians tend to stop, or significantly reduce their speeds, and wait to avoid collision, especially the ones on the minor stream. These form temporary clogs at the intersection, and reduce the total throughput. The lateral movement is rarely noticed at the intersection at De Ruijterkade in all simulations assessed for the pedestrians on the minor stream. However, the pedestrians in the major stream do move laterally. This seems to occur when pedestrians follow others on their same direction of movement. Because of that, the pedestrians of the major stream do not stop as often, which can lead to higher average speeds for this stream if compared to the minor stream. Based on these results, it can be said that PD reproduces the behavior of intersecting flows adequately for the given criteria.

6.3. Scenario Selection System

In this section, the scenario selection system based on the multi-objective optimization approach of this research is developed. Based on the Scenario Selection Framework proposed in Chapter 5, the elements which form the system are presented. First the choice of state metrics is discussed in subsection 6.3.1, followed by the formulation of the individual objectives based on the selected proximity measures (subsection 6.3.2). The optimization method and the considered boundary conditions are also discussed in this section in subsection 6.3.3 and subsection 6.3.4, respectively.

6.3.1. State Metrics

The multi-objective optimization is formed by the usage of multiple metrics to describe each scenario's dynamics. The choice of the metrics is based on both theoretical and practical implications. Firstly, as stated in Section 3.1, the preferred metrics are on the meso and macroscopic aggregation level due to the fact that the dynamics of the crowd considered relevant for prediction in the development of scenarios are also based on these levels. For instance, it is of far more interest given the scope of this research to capture the development of the density rather than the exact trajectories of each pedestrian in the crowd. From a practical perspective, metrics on the meso and macroscopic level are also more commonly obtained from the sensor data of crowd monitoring systems such as video cameras and Wi-Fi sensors. Given these considerations, the selected metrics are at the meso and macroscopic level of aggregation.

For each scenario in the database, the discrete locations (i.e. Event Blocks) where each of the selected metrics is derived at are presented in subsection 6.3.4. In this section, only the general formulation of the metrics are described. Below, the metrics chosen to describe the current state, the state history and the disturbances are further explained.

Current State

Four metrics are chosen as the baseline to describe the current state of the crowd. On the macroscopic level, the flow and the density are chosen, whereas on the mesoscopic level the travel time distribution and the route shares are used. The flow, the density are included as these are commonly used indicators given their direct link to the dimensions of the fundamental equation. Although presuming a certain FD, one could argue that the density can already describe the conditions on the environment, both metrics are included as the value of the density along does not provide any indication about the flow directions occurring. The travel time distribution aims at capturing the conditions on the route, in between sensors. Route shares are also added as these provide insights the tactical level choices of pedestrians with regards to the usage of the infrastructure, which is important given the scale of the environment of mass events. Furthermore, according to the study of Daamen et al. (2016), these metrics were retrieved from the crowd monitoring dashboard of the SAIL event in 2015, thus it is assumed that these can be obtained from sensors and state estimation techniques. Each scenario in the database is discretized based on an aggregation period of 1 minute, converting the trajectory database into multiple time series of crowd state metrics.

Flow

The flow describes the number of people per direction of movement that crossed a certain measurement line, located in the center of each Event Block, during a defined aggregation period. It is calculated by Equation 6.1.

$$\overrightarrow{q}_{d_i,B_x} = \frac{N_{d_i}}{\Delta t \times l_{B_x}} \quad \text{[ped/s/m]} \tag{6.1}$$

Where N_{d_i} is the total number of pedestrians with travel direction d_i that crossed the measurement line of Event Block B_x during the aggregation period Δt. As the Event Blocks have different widths and lengths, the flow is normalized to a flow per meter by the length of the measurement line of each Event Block (l_{B_x}). This metric provides insights into the main direction of movement of the pedestrians along the different routes of the event terrain, as well as the magnitude of the values.

Density

Density is an instantaneous metric (i.e. which does not have a time component) describing the number of pedestrians in an Event Block per unit area according to Equation 6.2.

$$k_{B_x} = \frac{N_{B_x}}{A_{B_x}} \quad \text{[ped/m}^2\text{]} \tag{6.2}$$

Where N_{B_x} is the number of pedestrians inside Event Block B_x, normalized by the area of the corresponding block (A_{B_x}). This metric provides insights into the crowdedness of the areas in the environment, and is a key indicator of the comfort and safety of visitors in the event. Thus, it is not only considered relevant for the application in the multi-objective optimization, but also in the analysis of the forecasting results. Since this metric is instantaneous, it is a snapshot of the last instant of the measurement period.

Travel Time (1st & 3rd Quartiles)

In order to explain the decision to use the 1st and the 3rd quartiles of the travel time distribution, the derivation of the travel time of each pedestrian is explained first. The travel time as used in this research is the time taken for each pedestrian to move between each pair of Event Blocks. The value of each pedestrian's travel time is derived when the pedestrian is identified at a certain Event Block B_y, where only its last visited Event Block (B_x) is then considered for the travel time calculations, according to Equation 6.3.

$$tt_{i,B_y \to B_x} = t_{i,B_x} - t_{i,B_y} \quad \text{[s]} \tag{6.3}$$

Where $tt_{i,B_y \to B_x}$ is the travel time of pedestrian i between B_y and B_x, calculated by subtracting from the time pedestrian i is identified at Event Block B_x, the time it left Event Block B_y. The same measurement line used to derive the flow is considered for the estimation of the travel time, that is, a pedestrian is identified at a certain Event Block when it crosses the referred measurement line. Unlike the previous measures, this metric is not normalized at this stage, this is only done when deriving the individual objectives for the optimization algorithm as it is discussed in subsection 6.3.2. For a detailed explanation of this metric and the decision not to normalize it the reader is referred to Section D.4.

Considering the travel time of each individual pedestrian who arrived at B_x coming from B_y, between the current and the previous time aggregation period, a travel time distribution can be drawn. The purpose of including the statistical measures of the travel time distribution as a metric is two-fold. Firstly, to get insights into the crowdedness of the route between each pair $B_y \rightarrow B_x$. Secondly, to get insights into the demand for activities along this route. Given these purposes, a choice is made to use the 1^{st} and the 3^{rd} quartiles of the travel time distribution. This choice is further explained in the following paragraph. The 1^{st} and the 3^{rd} quartiles of the travel time distribution are defined in this research as stated below, based on the method of Siegel and Morgan (1996):

Q1	The 1^{st} quartile is the median of the bottom half of the dataset, derived after the dataset is ordered in ascending order and divided into two halves by the median, which results in a value which at least 25% of the data will be less than or equal to.
Q3	The 3^{rd} quartile is the median of the top half of the dataset, derived after the dataset is ordered in ascending order and divided into two halves by the median, which results in a value which at least 25% of the data will be larger than.

An example is given to illustrate the reason for choosing the quartiles to describe the travel time distribution given the aforementioned purposes. One can think of two situations that can occur on a route between a pair $B_y \rightarrow B_x$. The first is the demand for this route exceeding capacity, which results in congestion. The second situation is that there is an activity location along this route, which is not congested, where most pedestrians walking along the route stop for some time to perform the activity. Both situations result is higher expected travel times if compared to free-flow, low activity demand conditions. Congestion is likely to shift the distribution to the right and make it more narrow. Meanwhile, the demand for activities is also likely to skew the distribution to the right, but the lower values of travel time are not as affected as in the first situation, as visitors who are not performing activities are able to walk freely on the environment. The distribution in this case is not only expected to be skewed but also more spread. Given these considerations, the quartiles are considered a better statistical measure to capture the difference between these two dynamics than the mean or the standard deviation, as these takes into account the extremes of the distribution.

The travel time distribution is also affected by the locations between which the travel time of a pedestrian is measured. As stated above, the measurement lines used to derive the flow is also considered for estimating the travel time, and this measurement line is positioned in the center of the Block. Thus, the travel time of a pedestrian from B_y to B_x encompasses the condition along the route between these two locations, and also part of the conditions within the Event Blocks. This can be problematic if the Event Block covers an area where an activity is located. For instance, taking as an example the case when a destination Block B_x covers the area of an activity location. If a pedestrians crosses the center line of B_y at time t_{B_y}, moving towards B_x, and it stops at the activity in B_x before crossing the center line, based on its travel time this pedestrian has not yet 'arrived' in B_x, where actually it has arrived. If this happens for many pedestrians, the travel time distribution between $B_y \rightarrow B_x$ can indicate larger travel times which might lead to the idea that the route is congested. Thus, two options are given to deal with this consideration. First, one can define two lines to derive the travel time based on the boundaries of the Event Block. Secondly, one can simply ensure that the location of the Event Blocks only covers areas where people are expected to be moving. In the first case, an additional state metric would then have to be defined which would be the time spent in the Block. Thus, the second option is chosen in this research. As it is shown in subsection 6.3.4, the location of the Event Blocks are all where pedestrians are expected to be moving.

Route Shares

Similar to the travel time, the route shares considers the sequence of Event Blocks visited by each pedestrian, and is derived per pair of Event Blocks. From the total number of pedestrians that arrive in an Event Block B_x, the share that departed from B_y is estimated according to Equation 6.4.

$$s_{B_y \to B_x} = \frac{N_{B_y \to B_x}}{N_{B_x}} \quad [-] \tag{6.4}$$

Where $s_{B_y \to B_x}$ is the share of pedestrians who travelled from B_y to B_x, $N_{B_y \to B_x}$ is the total amount of pedestrians who were identified at B_x coming from B_y, and N_{B_x} is the total amount of pedestrians who were identified at B_x. This metric provides insights into both, the routes used by the pedestrians and the direction of movement along these routes.

Current State History

As stated in subsection 5.3.2, not only the current states are of interest for describing the conditions in the environment but also the state history. The state history represents the long term movements of the state metrics, that is, how the metrics are developing over time. For a certain value of the density in an Event Block (i.e. current state), the state history can indicate the trend of this density, that is, whether it is increasing or decreasing, as well as how rapidly this value is changing.

Three of the four baseline state metrics presented above are considered for the derivation of the state history: the flow, the density and the travel time. As the objective of the history metrics are to indicate the trend of the metrics, the short term fluctuations have to be smoothed out. In this research, the time series are smoothed using the exponential moving average. This method is chosen over simple moving averages because it can account for the fact that more recent observations have higher weight than older observations. It is desirable to have such behavior in order to identify the most critical conditions, which are when the state metrics are increasing rapidly (e.g. densities quickly moving to beyond critical indicating unsafe conditions). The exponential moving average is calculated recursively according to Equation 6.5.

$$S_t = \begin{cases} x_1 & t = 1 \\ \alpha \times x_t + (1-\alpha) \times S_{t-1} & \text{t} > 1 \end{cases} \tag{6.5}$$

Where S_t is the value of the exponential moving average at any time t, x_t is the value of the observed metric at time t, and α is the smoothing factor coefficient which ranges from 0 to 1. As discussed in subsection 5.3.2, the higher the value of α, the faster older observations are discounted. Given the objective of smoothing the data, which is exactly to reduce the effect of the 'peaks' or noise, a smoothing factor of 0.25 is chosen for the derivation of the state history. Figure 6.15 illustrates the effect of this smoothing for the flow and density metrics of a scenario.

Disturbances

Finally, the last metrics to compose the crowd states vector relate to the known disturbances. As stated in subsection 5.3.3, these metrics refer to known inputs into the system not cap-

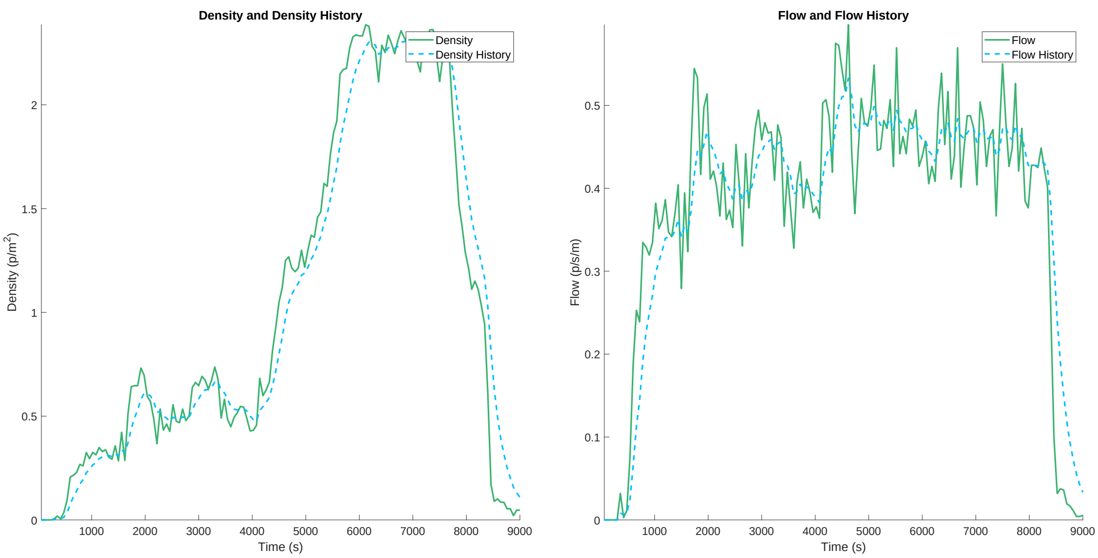


Figure 6.15: State history results

tured by the sensor at the time of measurement. In the study area of SAIL, the main disturbance source considered is the arrival of the ferry from the purple route, and the additional demand into the environment it generates over the prediction horizon. The ferry load (i.e. ferry demand divided by the capacity) is added as a metric to state vector. This metric relates to the future demand, that is, the demand generated by the next ferry from the current time of measurement. Thus, in each scenario, the ferry load is included in the state vector of the time instants prior to its arrival time. That is, if the next ferry arrives at 1:20h, and the ferry frequency is 20 minutes, the load value of this ferry is added to the state vector of all time instants between 1:01h and 1:20h. This metric is the only metric which is not bounded to any Event Blocks, as there is only one location where ferries arrive in the study area.

Overview of Crowd State Vector

An overview of the metrics presented above, and how these compose the crowd state vector is given in Table 6.10. The trajectory data retrieved from the simulation of the scenarios is transformed in the time series of the metrics presented in this table. The resulting database is thus formed by the values of the metrics for each scenario i at time period t, and the state vector is thus formed by all metrics m of scenario i at time t. The combination of the metrics and the Event Blocks is also illustrated in the table. One can see that while there is a single value of density to describe an Event Block B_x, there are two values of flow due to the consideration of the distinct directions of this metric. For the travel time and route splits, there are n values to describe each Event Block, where n is the total amount of Event Blocks which are the origin of pedestrians whose destination is Event Block B_x. For instance, if an Event Block B_x is the destination of 3 origin-Blocks, $n = 3$ and the route shares are derived from total amount of pedestrians who arrive at Event Block B_x between $[t-1, t]$, coming from each $B_{1,2,3}$.

Table 6.10: Overview of Crowd State Vector Metrics - SAIL

	Metric (Scenario$_i^t$)	Event Block(s)
1	**Density**	Bx
2	**Density History**	Bx
3	**Flow**	$[B_x \overrightarrow{d}, B_x \overleftarrow{d}]$
4	**Flow History**	$[B_x \overrightarrow{d}, B_x \overleftarrow{d}]$
5	**Travel Time (Q1 & Q3)**	$[B_{(1...n)} \to B_x]$
6	**Travel Time History (Q1 & Q3)**	$[B_{(1...n)} \to B_x]$
7	**Route Shares**	$[B_{(1...n)} \to B_x]$
8	**Ferry Load**	$[Demand_{nextferry} \div Capacity_{ferry}]$

6.3.2. Individual Objectives & Proximity Measures

In this study, each objective consists of a combination of a scenario i, at time period t, and a metric of an Event Block m_{B_x}. Only the ferry load is given per scenario, time period and metric as it is not linked to a specific Block. Thus, two questions need to be answered: (1) for the metrics which have multiple values per Event Block, how to combine these in order to have one value per Block so that these are normalized across the metrics and (2) how to formulate the objective function of each of these metrics.

In order to obtain a single metric per Event Block, the metrics for which multiple values per Block exist need to be combined in a meaningful way. For instance, one can define whether the flow of an Event Block is an equally weighted combination of the two directions, or if the direction with highest flow should be weighted higher. Similarly, combining the values of the travel time of all origins to destination-Block B_x can be done by considering all the origins with the same importance, or origins with highest route share (i.e. where most visitors are coming from) with higher weight. As considering different weights for combining these values requires additional assumptions regarding the relative importance of the values of each direction (flow) or pair of Blocks (travel time & route splits), in this research it is decided to combine the values considering equal weights.

The question regarding the formulation of the individual objective functions of each metric requires two additional decisions. Firstly, the proximity measure to compare the real and simulated values of each metric needs to be chosen, and secondly, if necessary, a way to normalize the objectives which have different units and orders of magnitude needs to be defined. Regarding the proximity measure, in line with other studies which compare real and simulated pedestrian behavior through multiple metrics (e.g. Duives (2016); Sparnaaij (2017), and due to practical reasons regarding the time available for this research, the objective function of each metric and scenario is defined by the Square Error (SE), according to Equation 6.6, where m_{scen} is the simulated value of metric m, and m_{real} is the real value of the same metric. These are then normalized for the metrics that require normalization, as discussed below.

$$SE_i^t = (m_{scen} - m_{real})^2 \tag{6.6}$$

From the metrics presented in Table 6.10, the only metrics which are already normalized are the route shares and the ferry load, which vary from 0 to 1. Therefore, a normalization method needs to be defined for the other metrics. In this research, this normalization is defined based on the maximum possible variation of each metric, so that, similarly to the route shares and ferry load, the other metrics also vary between 0 and 1. For a detailed explanation of this method and the reasoning behind the choice of using it, the reader is referred to Section D.5. The normalization values are summarized in Table 6.11. The maximum value of the density and the flow are derived from the critical density and capacity of the FD proposed by Weidmann (1992), as these are the maximum value of these metrics on the FD. The travel time is the maximum travel time in the scenario database between each pair of Event Blocks. A more detailed explanation of how the squared error and the normalization values are applied to each metric is presented below.

Table 6.11: Normalization of State Metrics

	Metric	Norm
1	**Density**	$k_{Norm} = 5.4\ [ped/m^2]$
2	**Density History**	$k_{Norm} = 5.4\ [ped/m^2]$
3	**Flow**	$q_{Norm} = 1.225\ [ped/s/m]$
4	**Flow History**	$q_{Norm} = 1.225\ [ped/s/m]$
5	**Travel Time (Q1 & Q3)**	$tt_{Q1,B_y \to B_x,Norm} = \max_{s \in S} B_y \to B_x\ [s]$
6	**Travel Time History (Q1 & Q3)**	$tt_{Q1,B_y \to B_x,Norm} = \max_{s \in S} B_y \to B_x\ [s]$

Flow - Current & History

The objectives of the current state and state history of the flow are all derived according to Equation 6.7:

$$SE_{q,B_x} = \frac{1}{2}\left(\frac{q_{d_1,scen} - q_{d_1,real}}{q_{Norm}}\right)^2 + \frac{1}{2}\left(\frac{q_{d_2,scen} - q_{d_2,real}}{q_{Norm}}\right)^2 \tag{6.7}$$

Where q_{d_1} and q_{d_2} are the flows in the two directions measured. It is considered important to highlight that not all Event Blocks are bidirectional at all times. As mentioned in the scenario development, certain types of scenario have bidirectional flows in different areas of the infrastructure while others do not. Nevertheless, Equation 6.7 is applied in all cases as it provides an additional way to differentiate between these two situations. For instance, if the real scenario has bidirectional flows in a certain Event Block, then $q_{d_j,real}$ is different then zero in both directions j. When compared to two different scenarios, where in one only $q_{d_1,scen}$ is different than zero, and in the other both $q_{d_1,scen}$ and $q_{d_2,scen}$ are different than zero, there is a higher chance that the error is larger in the first case, as the deviation computed by the second term of the equation (i.e. $q_{d_2,scen} - q_{d_2,real}$) is maximum.

Density - Current & History

The objectives of the current state and state history of the density are defined according to Equation 6.8:

$$SE_{k,B_x} = \left(\frac{k_{scen} - k_{real}}{k_{Norm}}\right)^2 \tag{6.8}$$

As each Event Block already has a single value of density, the squared error is simply given by the density of the scenario for Event Block B_x (k_{scen}) and the real density of the same Event Block (k_{real}).

Travel Time (1^{st} & 3^{rd} Quartiles) - Current & History

The travel time objective is a combination of both travel time metrics from the travel time distribution, that is, the 1^{st} (Q1) and 3^{rd} (Q3) quartiles. The objectives of the current state and state history of the travel time are all derived based on the same equation, and this equation is described for each destination-Block B_x based on all n pairs $B_y \rightarrow B_x$, where $y = [1, n]$ according to Equation 6.9:

$$SE_{tt,\rightarrow B_x} = \frac{1}{n}\sum_{y=1}^{n}\left(\frac{1}{2}\left(\frac{tt_{Q1,B_y\rightarrow B_x,scen} - tt_{Q1,B_y\rightarrow B_x,real}}{tt_{Q1,B_y\rightarrow B_x,Norm}}\right)^2 + \frac{1}{2}\left(\frac{tt_{Q3,B_y\rightarrow B_x,scen} - tt_{Q3,B_y\rightarrow B_x,,real}}{tt_{Q3,B_y\rightarrow B_x,Norm}}\right)^2\right) \tag{6.9}$$

Where $SE_{tt,\rightarrow B_x}$ is the square error of the travel time towards Event Block B_x. The first term of the equation refers to $tt_{Q1,B_y\rightarrow B_x,scen}$ and $tt_{Q1,B_y\rightarrow B_x,real}$, which are the scenario and real values of the first quartile of the travel time of pair $B_y \rightarrow B_x$, respectively, divided by the normalization term of first quartile of the travel time for the same pair. This is combined with the second term of the equation that refers to $tt_{Q3,B_y\rightarrow B_x,scen}$ and $tt_{Q3,B_y\rightarrow B_x,real}$, which are the scenario and real values of the third quartile of the travel time of pair $B_y \rightarrow B_x$, respectively, divided by the normalization term of the third quartile of the travel time for the same pair. In order to obtain a single error value per Event Block, the average over all the origin-Blocks to Block B_x is calculated.

Route Shares

Similarly to the travel time objective, the route shares objective is derived based on each destination-Block B_x, given all n pairs $B_y \rightarrow B_x$, where $y = [1, n]$ according to Equation 6.10:

$$SE_{s,\rightarrow B_x} = \frac{1}{n}\sum_{y=1}^{n}\left(s_{B_y\rightarrow B_x,scen} - s_{B_y\rightarrow B_x,real}\right)^2 \tag{6.10}$$

As the route share values of each pair $B_y \rightarrow B_x$ are already on a scale of zero to 1, no normalization is necessary and thus the squared error is simply given by the scenario value of the route share $B_y \rightarrow B_x$ ($s_{B_y\rightarrow B_x,scen}$) and the real value of the route share of the same pair ($s_{B_y\rightarrow B_x,real}$). In order to obtain a single error value per Event Block, the average over all the origin-Blocks to Block B_x is calculated.

Ferry Load

The last metric included in the state vector is the ferry load, for which the objective is formulated according to Equation 6.11:

$$SE_{load_{ferry}} = (load_{scen} - load_{real})^2 \tag{6.11}$$

As this metric is not bounded to an Event Block, the objective is given only by the comparison of the scenario load of the next ferry ($load_{scen}$) and the real load of the next ferry ($load_{scen}$).

6.3.3. Combined Objectives & Optimization Method

The choice of the optimization method to be used in this research is guided by the tasks it needs to be capable of performing. For instance, the method needs to be able to find the scenario which mostly closely approximates to the real conditions observed. Also, the dimensionality of the problem, that is, the number of individual objectives given the number of metrics and Event Block is taken into account. Furthermore, practical considerations for the purpose of this research are also taken into account in the selection of the method. This includes how easy it is to implement the method within the time available for this research.

The individual objectives formulated in the previous section all add a piece of information to describe the scenarios and the real crowd states. From these, the question to be answered in this subsection relates to how to combine these individual pieces of information in order to select the scenario from the database which most closely matches the real one. As discussed in subsection 5.4.2, scalarization of the multi-objectives into a single-objective, and further application of a single-objective optimization algorithm, is preferable over applying multi-objective algorithms, given the dimensionality of the problem addressed in this research. Therefore, the first choice that needs to be made relates to the scalarization method.

The scalarization method used in this research is the weighted sum method (Marler & Arora, 2010). The choice is made due to the practicality of the method, the considerations made in subsection 5.4.2 regarding the application of the other methods and the implicit weight those give to certain objectives over others. Given this choice, the following decision is how to define the weights. As the individual objectives of each metric as proposed in the previous section are normalized, and apart from the ferry load all individual objectives correspond to a combination of a single metric and a single Event Block, equal weights are assigned to these when combining them to form the single-objective function. Although one could make choices to prioritize certain Event Blocks (e.g. where densities are higher), and also certain metrics over others (e.g. flows over travel time), in this research it has been decided that all Blocks and metrics have equal weights. The objective function for comparing the state metrics of a scenario i at time t with the real crowd states for all metrics m and Event Blocks B combined is given by Equation 6.12:

$$O = \frac{1}{N_m \times N_B + 1}\left(\sum_m \sum_B SE_{m,B} + SE_{load_{ferry}}\right) \tag{6.12}$$

The value of the objective function O is thus given by the summation of the objective functions of all metrics m and Event Blocks B, and the ferry load, divided by the total number of metrics which are given per Event Block (N_m) in the state vector, multiplied by the total number of Event Blocks (N_B) on the environment, plus 1 for the ferry load. As the proximity measure used is the Squared Error, no negative values for the objectives exist, and these can thus be summed over with no concerns about one cancelling the other out. Also due to the choice of using the Squared Error, which is a dissimilarity measure, the objective function is minimized as smaller values of O mean a closer match of the scenario to the real data.

Following the definition of the objective function is the decision regarding which algorithm to use to search through the database. In this research, the Grid Search is used to find the scenario. As presented by Sparnaaij (2017), when using the grid search algorithm, one can guarantee that the global minimum is found as the entire set of possible options is considered.

Furthermore, from the algorithms presented in Table 5.2, this is the most straightforward algorithm to be applied to a discrete problem as the one addressed in this research. The grid is defined by each metric of each Event Block of each scenario and time instant, so no lower or upper bounds are manually determined. This method is more flexible as it does not require prior definition of the metrics and objective functions to be considered in the search, and no stopping criteria is needed. A drawback of this algorithm is that it is potentially slower as it searches over the entire database.

6.3.4. Boundary Conditions

As previously mentioned, most of the objectives which form the optimization are composed by a combination of a metric and an Event Block. The Event Blocks used for the prediction, as discussed in subsection 5.4.3, are the locations where the real crowd states are derived from. These are discussed under the boundary conditions as these locations and types of sensors at each location are often defined by the event organization. For the study area of SAIL, the location of the crowd monitoring systems were shown in Figure 6.2.

In this research, as the application of the method is for a case study based on the SAIL event instead of the event itself, there is flexibility in the choice of Event Blocks for testing the method. Thus, the boundary conditions defined by the sensor network of the event are adjusted to consider an optimized sensor network based on the inefficiencies identified. The purpose of this is to take the considerations made in subsection 5.3.1 into account for deciding the locations where more sensors are needed. Although the original sensor network is still used, this is theoretically extended to cover certain areas deemed relevant given the scenarios presented in subsection 6.2.2. Besides, it is assumed that all sensor locations have both, counting cameras and Wi-Fi sensors. Therefore, all state metrics which are defined per Event Block can be captured at all locations.

In total, five sensors are added to the existing network, and the proposed network is shown in Figure 6.16. The reason for adding sensors B1, B8 and B13 is so that the main entry and exit locations which were not yet covered by the existing sensor network are now included. Adding sensors to this locations aims at identifying the demand into the event terrain, rather than having a large inflow of visitors coming from for instance the east-end (B13), which would then only be identified by the sensors once these arrive in B10. Regarding sensor B4, as shown in subsection 6.2.1, this is the narrowest bottleneck on the event terrain, thus monitoring the trend of the density over this location is considered relevant to identify rapidly increasing trends earlier and thus take proactive measures. Lastly, sensor B6 is included due to the already mentioned importance of that area along the Veemkade for the scenarios. The concentration of activities (tall ships, commercial) and the expected high demand along that route were the reasons for adding sensor B6, as in the original network there is a large gap between B5 and B9.

The locations are represented by a circle due to the detection range of these sensors, which can vary between different manufacturers and types of sensors. In this thesis, a radius of 25 meter is assumed for all sensors. As it can be seen in the figure, there are in total 13 Event Blocks defined by sensors, for which all 7 Block-dependent metrics given in Table 6.10 are derived. The final set of metrics is the total number of metrics per Block and the ferry load. The final crowd state vector thus has 92 metrics, and thus there are 92 individual objectives which form the multi-objective optimization problem for the study case used in this research.

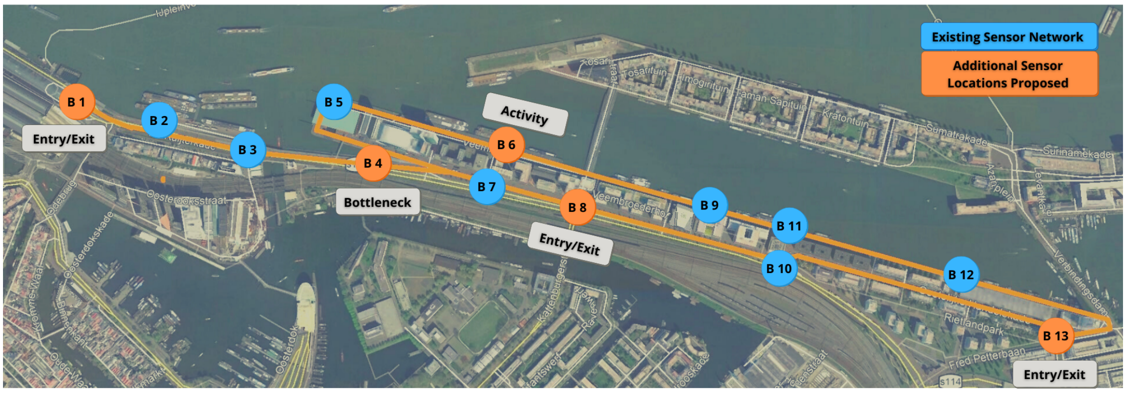


Figure 6.16: SAIL - Proposed sensor network

6.4. Conclusions

This chapter introduced the mass event and simulation model used as tools for validating the method proposed in this research. The selected mass event is based on the SAIL event, and the microscopic model used for developing the scenario database is Pedestrian Dynamics by INCONTROL Simulation Software. Based on the analysis of the event dynamics of SAIL, considering the checklist for supply and demand analysis proposed in subsection 4.2.2, the scenarios for which the inefficient dynamics can be identified were derived. These scenarios form the main conceptual scenarios to be included in the database, that is, the scenarios for which the usage of the infrastructure can potentially lead to discomfort and unsafe conditions for the crowd. Eight scenarios were identified, and for each of these, six density levels are considered to differentiate between the scenarios for which the dynamics result in the appearance of inefficient phenomena to the ones that do not.

To take the stochastic behavior of the simulation model into account when developing these scenarios, the required number of replications is calculated for each scenario and density level. The sequential method proposed by Toledo and Koutsopoulos (2004) is chosen and the metric used as reference for the calculations is the average travel time, as it takes the dynamics of the simulation into account given that it is derived from the trajectory information of each agent. For all scenarios and density levels considered, the resulting required number of replications was smaller than 1, and therefore a single replication of each scenario and density level is considered for the database.

Regarding the scenario selection system, the eight scenarios and corresponding six density levels are discretized in space in 13 Event Blocks, for which 7 metrics per Block exist to describe its state. Each of the metrics of each Event Block, as well as the ferry load metric which is not linked to any Blocks, forms a single objective for the multi-objective optimization problem. Thus, 92 objective spaces exist, 1 for each metric of each Block, which are scaled per scenario and time period into a single objective by the weighted sum method. A single-objective optimization algorithm is thus chosen, which in this research the choice is made to use the Grid Search approach. The analyses performed in Chapter 7 to validate the method make use of the system developed according to the discussions presented in this chapter, and the scenarios developed for the SAIL event.

7

Forecasting Analysis

The main goal of this chapter is to get insights into the sensitivity of the forecasting results to particular inputs from the real crowd states, and settings of the selection system. Three different objectives are used for the analyses. The research questions presented below illustrate these objectives, which are further explained in the following paragraph.

- How are the predicted states affected by changes to the accuracy of the sensor data and state estimation techniques?
- How are the predicted states affected by the choice of Event Blocks used for the search process?
- How are the predicted states affected by the choice of state metric used for the search process?

As presented in subsection 5.1.2, no sensor to date provides 100% accuracy for all conditions. Thus, the first analysis performed in this chapter relates to the changes in the forecasting results when the input data from the sensors contain errors. The second analysis relates to the selection of the areas of the environment used by the selection algorithm when searching through the database. The idea in this analysis is to assess whether all areas are needed for the forecast, or if with a limited set of areas one can also perform the prediction.

As discussed in subsection 5.4.2, within the multiple objectives used by the optimization algorithm, there might be conflicting individual objectives. Thus, trade-offs are often necessary between the optimal solution for each individual objective, and so with larger number of objectives it is more likely that the individual errors of each objective are less optimal. The idea of having a sub-selection of Event Blocks aims at reducing the number of conflicting individual objectives, where the focus is then on the areas considered of relevance for a particular scenario.

Finally, an analysis related to the selection of the metrics of the state vector used by the selection system is performed. The reason for including this analysis relates to the considerations made regarding the two aforementioned analyses. Given that some metrics are likely to be more accurate than others, and the expectation that reducing the number of conflicting objectives can improve the prediction, it is decided to also assess the effect of using a sub-selection of metrics.

This chapter is build-up as follows. Firstly, the methodology for performing the aforementioned analyses is presented in Section 7.1, where the scenarios and the measure to compare the results are introduced. Following, the first analysis performed in this chapter, in Section 7.2, relates to the changes in the forecasting results when the input data from the sensors contains errors. Section 7.3 discusses the results of the second analysis, which relates to the sub-selection of the Event Blocks used by the selection algorithm. Section 7.4 presents the analysis which relates to the sub-selection of the state metrics used by selection system. Finally, a discussion on the findings of the analyses is carried out in Section 7.5, where practical considerations regarding the resources for the application of the method are also presented.

7.1. Methodology

This section introduces the general methodology for performing the analyses of the sensitivity of the system to each of the presented objectives. For performing the analyses, three choices need to be made. Firstly, one needs to define the set up of the analysis, that is, the particular inputs, settings and variations of these which are going to be tested. These are distinct for each of the three analysis objectives, and are thus further discussed in the section which concerns the objective's results. Secondly, a metric needs to be defined to quantitatively compare the predicted states for the different inputs and settings tested. Lastly, the indicators to qualitatively describe the prediction, that is, to assess whether the predicted behavior is representative of the real behavior (i.e. of the real scenario) also need to be determined. As the latter two are applicable to all the three analyses objectives, these are further detailed in this section.

7.1.1. Test Scenarios

Due to time constraints of this research, a selection of the scenarios included in the database is used for the analyses. From the 8 scenarios presented in Table 6.3, one of each benchmark of inefficient dynamics is chosen. These are listed in Table 7.1. It is decided to use one scenario of each benchmark because it is expected that these have different sensitivities to the objectives analysed in this research. For instance, regarding the state metrics, in order to identify whether a physical bottleneck is becoming active, the density and density history of the area where the bottleneck is located are key indicators. On the other hand, for identifying the flow interaction scenarios correctly, the density alone does not provide the required information as a high density on an area might arise independently of the flow direction. Two density levels of each scenario are used in the analyses, a high and an intermediate level, where the high level relates to the appearance of the inefficiency.

7.1.2. Methodology Overview

Figure 7.1 illustrates the methodology used for the analyses. The steps and decisions regarding the development of this method are detailed below.

Table 7.1: Overview of test scenarios used for validating the algorithm

	Test Scenario	Density Level	Inefficient Benchmark Case
1	**Veemkade - East**	High - LOS F	Physical Bottleneck
2	**Veemkade - East**	Inter - LOS D	Physical Bottleneck
3	**Route - Bidirect**	High - LOS E	Flow Interaction
4	**Route - Bidirect**	Inter - LOS D	Flow Interaction
5	**Activity - Veemkade West**	High - LOS F	Uneven Distribution over Network
6	**Activity - Veemkade West**	Inter - LOS D	Uneven Distribution over Network
7	**Inefficient Route Choice**	High - LOS E	Inefficient Choice Behavior
8	**Inefficient Route Choice**	Inter - LOS D	Inefficient Choice Behavior

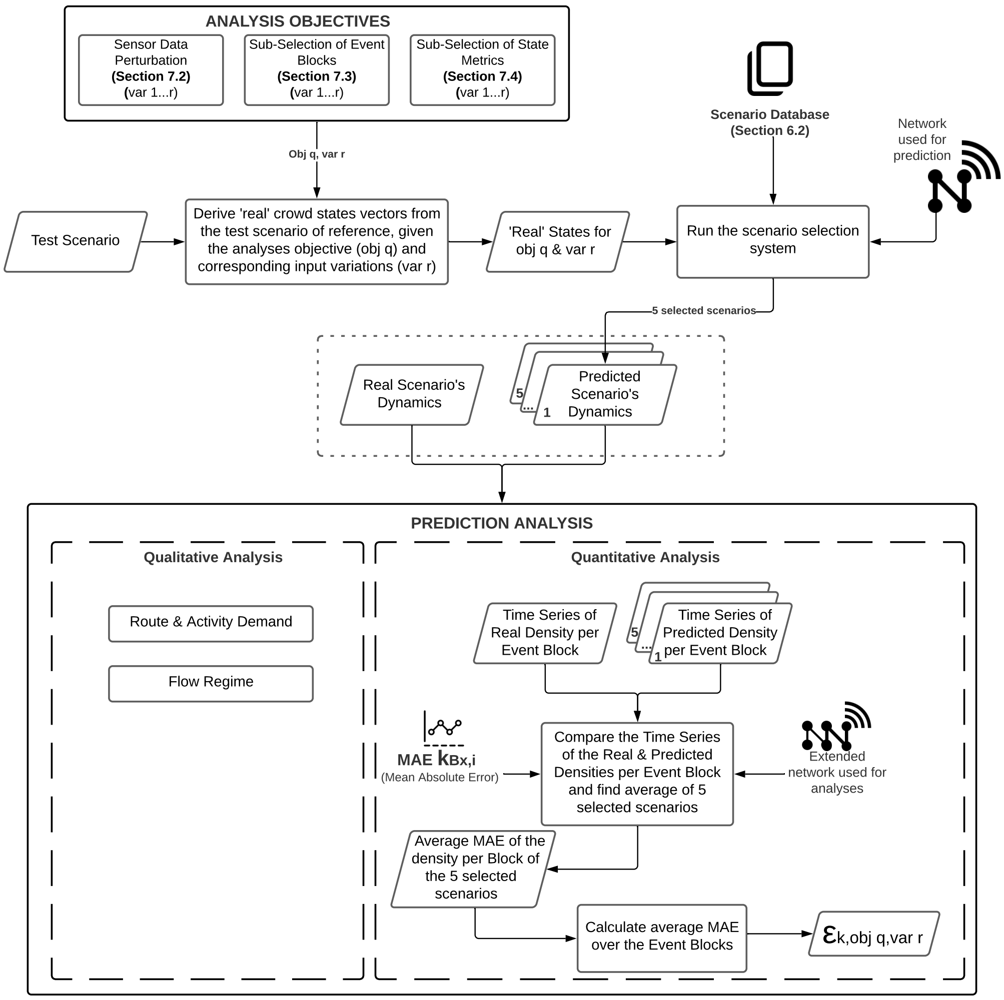


Figure 7.1: Overview of the Analyses Methodology

The first step of the analysis relates to the derivation of the 'real' crowd state vector. In this research, this 'real' state vector is derived from the test scenario being analysed, at a certain time instant. This time instant is chosen based on the time when the inefficiency starts occurring for each scenario of the high density level (i.e. DL 6). For instance, in the physical bottleneck scenario, this time instant is the time when queues start forming at the bottleneck location. The same time instant is then used for the intermediate density level.

Each simulation has in total 150 time instants (2.5 hours discretized in minutes), and the time instant of each scenario are presented in Table 7.2.

Table 7.2: Time instant of each test scenario

	Test Scenario	Time (min)
1 & 2	**Veemkade - East**	105
3 & 4	**Route - Bidirect**	70
5 & 6	**Activity - Veemkade West**	90
7 & 8	**Inefficient Route Choice**	110

The scenario selection system is run for each real state vector, where the real states are compared to each state vector of all scenarios and time instants in the scenario database. These correspond to all scenarios presented in Table 6.3 and their corresponding six density levels. For the scenario selection process, the sensor network used is the one shown in Figure 6.16, which consists of 13 Event Blocks, except for the sub-selection of Event Blocks objectives, where the number of Blocks used is reduced as further explained in subsection 7.3.1. It has been decided in this research that the 5 optimal scenarios and corresponding time instants (i.e. the 5 scenarios with lowest objective function value) are used in the analyses. This is because, since the 'real' crowd states are retrieved from a time instant of the scenario being analysed, there is a scenario in the database for which the objective function value can be zero. Thus, only analysing the sensitivity of the selection system based on the optimal scenario might falsely indicate low sensitivity, as it might often select the correct scenario. On the other hand, analysing the results of the 5 scenarios most likely to be chosen can provide better insights into the sensitivity of the system to changes in the 'real' input and choices regarding the settings of the method (e.g. number of individual objectives used).

In the remainder of this section, the discussion is on the choice of metric to compare the real and predicted states, as well as the indicators to qualitatively assess the predicted dynamics.

7.1.3. Qualitative & Quantitative Analysis

The prediction analysis is performed both qualitatively and quantitatively. In the qualitative analysis, the real scenario's dynamics are compared to the dynamics of the selected scenarios. Two indicators are used in this comparison: (1) the route and activity demand and (2) the flow regime.

The first indicator assesses whether or not the areas and routes that have higher demand in the real scenario are the same areas as the ones in the selected scenarios. This is considered important as one can then identify whether the relative usage of the infrastructure is comparable between the real and selected scenarios. The second indicator assesses whether or not the scenarios selected correctly represent the condition of the real scenario in relation to the appearance of inefficiency. As discussed in subsection 3.3.1, when the flow conditions are at the unstable regime, or when these are transitioning to this regime, it is more likely that the crowd is or starts experiencing discomfort, or that their safety is at risk. This unstable flow regime is characterized by increasing densities, and reduced throughput.

For the quantitative analysis, the chosen metric to compare the real and predicted states is the density. Unlike the flow, for which low values can indicate both free-flow conditions as well as congestion, each value of the density provides unique insights into the crowd state. Thus, this metric is considered appropriate to compare the realized and predicted states of each Event Block. This comparison relates to the states over the prediction horizon, that is, whether or not the realized time series of the density are comparable to the predicted time series for the next 15 minutes. Hence, a method to compare these density time series needs to be defined.

There are multiple ways to compare two time series. As discussed in subsection 5.4.1, not only Goodness-of-Fit measures such as the MAE (mean absolute error) and RMSE (root-mean-squared error) can be used, but also test for underlying structure through the development of metamodels such as ARMA (auto-regressive moving average). Deriving such models requires additional time and computer resources, as one would have to derive one metamodel per Event Block for the realized and predicted densities, and only then compare these for assessing the prediction. Therefore, it is decided to use a GoF measure, more specifically the mean absolute error to compare the real and predicted time series of the density of each Event Block. The MAE is calculated based on Equation 7.1:

$$MAE_{i;k_{Bx,s}} = \frac{1}{n}\sum_{j=1}^{n}\left|k_j - \hat{k}_j\right| \tag{7.1}$$

Where $MAE_{i;k_{Bx,s}}$ is the mean absolute error of test scenario i, derived from the time series of the density of Event Block B_x and scenario selected s, over the prediction horizon, n is the number of data points being compared, and k_j and $\hat{k}_j$ are the densities of the selected scenario and the real density at time period j, respectively. The MAE is chosen over the RMSE because it has a clearer interpretation of its values for the purpose of comparison between the prediction results, given that it doesn't assign higher weight to possible outliers. As discussed in subsection 7.1.2, the 5 optimal scenarios selected by the system are used for the analyses. Therefore, the final value of the mean absolute error of Event Block B_x is given by Equation 7.2, where $n_s = 5$.

$$MAE_{i;k_{Bx}} = \sum_{i=1}^{n_s}\frac{MAE_{i;k_{Bx,s}}}{n_s} \tag{7.2}$$

In order to analyse the prediction validity of the system for the entire study area, including the areas not used for the prediction step (i.e. in between sensors), an extended network of Event Blocks is used. A total of 20 Event Blocks are defined, seven more than those used for prediction, and these are spread on the event environment. Thus, for each test scenario i, a total of 20 $MAE_{i;k_{Bx}}$ values exist. In order to have a single metric of comparison per analysis objective and variation (obj_q, var_r), the average error of the density over all Event Blocks $(\varepsilon_{i;k,objq,varr})$ is estimated according to Equation 7.3, where $n_B = 20$.

$$\varepsilon_{i;k,objq,varr} = \sum_{x=1}^{n_B}\frac{MAE_{i;k_{Bx}}}{n_B} \tag{7.3}$$

In the following sections, the results of the different objectives and variations are analysed for each test scenario. For these analyses, the $\varepsilon_{i;k,objq,varr}$ of each test scenario is compared to a reference value based on the corresponding test scenario and analysis objective. This reference is presented in the set up subsections of each analysis objective. The reason for comparing against this reference is to assess the extent to which an improvement or a decrease in the performance of the prediction from the reference are observed for each variation. The change is determined according to Equation 7.4.

$$\Delta\varepsilon_{i;var r;ref} = -(\varepsilon_{i;k,objq,var r} - \varepsilon_{i;k,objq,ref}) \tag{7.4}$$

Where $\varepsilon_{i;k,objq,var r}$ is the error of the density of test scenario i over all Event Blocks for analysis objective q and variation r, and $\varepsilon_{i;k,objq,ref}$ is the reference error of the density of test scenario i over all Event Blocks for analysis objective q. As the values of ε represent an error, an increase in ε means a decrease in performance. Therefore, a negative sign in front of the equation is applied.

7.2. Analysis of Sensor Data Perturbations

In this section, the results of the different analysis objectives related to the accuracy of the sensor data and state estimation techniques are discussed. The main goal is to assess how an overestimation or underestimation of the state metrics of the real state vector affect the predicted states. Firstly, the set up of the analysis is defined, where the variations of the real input to be tested are presented. Secondly, the results are shown and discussed.

7.2.1. Set up of sensor data perturbation analysis

From the eight metrics that form the state vector, presented in Table 6.10, a selection is made for testing the sensitivity to the sensor data accuracy. The selected metrics are the density, the flow and travel time, and their corresponding state history. Route shares are not tested because of the complexity of applying under or overestimation errors to these given the way they are defined. That is, one needs to determine which OD pairs would be the ones for which the under or overestimation would be applied, and how the other OD pairs would be reduced accordingly. As the results are dependent on these choices, route shares data remains unchanged. Below, the assumptions to derive the perturbations of each metric are presented.

Regarding the sensors, as both macroscopic metrics (i.e. flows and densities) are derived locally, that is, for a specific area or cross-section, the type of sensor commonly used to derive these are video cameras. These sensors are one of the most accurate methods for counting pedestrians, as discussed in Section C.1. However, tracking is not possible with video cameras. Most commonly used sensors for tracking pedestrians, and thus deriving travel times and route shares, are Wi-Fi and bluetooth. These are less accurate as they detect a low share of the total amount of pedestrians.

In this research, it is of interest to assess the sensitivity of the prediction to an over and underestimation of the selected state metrics for the different test scenarios. While the underestimation might be caused by the detection of less pedestrians than there actually are on the environment, the overestimation can be the result of the state estimation techniques applied. In the case of the travel time, the under or overestimation might be caused by the identification of a non-representative set of the population. This can occur when for instance most pedestrians identified are performing activities (thus having longer travel times), while in reality most pedestrians of the total amount in the crowd are not performing activities. Hence, also due to the aforementioned considerations regarding the type of sensor each metric is derived from, the travel time estimation errors are assumed to be higher than those of the flows and densities. The input variations of each state metric to be tested are shown in Table 7.3. The percentage of under or overestimation are applied to the time series of the current state metrics (i.e. flow, density and travel time), then the corresponding state history metrics are estimated from these time series.

Table 7.3: Input variations for sensor data analysis

Variation	Percentage of estimation variation		Direction & Metrics	Level
	Travel Time	Flow & Density		
Reference	All metrics correctly estimated			
Sensor Var 1	+25%	+10%	Over | All	Low
Sensor Var 2	+50%	+20%	Over | All	High
Sensor Var 3	-25%	-10%	Under | All	Low
Sensor Var 4	-50%	-20%	Under | All	High
Sensor Var 5	-25%	+10%	Over | Macro	Low
Sensor Var 6	-50%	+20%	Over | Macro	High
Sensor Var 7	+25%	-10%	Under | Macro	Low
Sensor Var 8	+50%	-20%	Under | Macro	High

The reference values of each scenario for this analysis are the $\varepsilon_{i;k,objq,ref}$ when all metrics are 100% accurate (i.e. neither over nor under estimated). To exclude the possibility that the differences analysed are caused by a reduction in the number of objectives, the selection algorithm is set to use all state metrics and Event Blocks during the search through the database. Regarding the variations shown in Table 7.3, variations 1 to 4 aim at assessing whether there is a difference between the estimation directions (i.e. over or underestimation) of the metrics for the different test scenarios. The two variations between the percentage of each direction are included to analyse if even low under/over estimations (i.e. 25% and 10%) can result in significant errors in the output. Following, variations 5 to 8 aim at analysing whether distinct directions of variation for the different metrics can have distinct effects on the prediction. For instance, when all metrics are under or overestimated (as in variations 1 to 4), it is expected that the selected scenarios are simply distinct density levels of the test scenario used as input. However, when there is a difference between the estimation errors of the different metrics, that is, when travel times are higher and densities lower, the dynamics of a distinct scenario might be identified instead. This can be exemplified for the case where travel times are overestimated and densities underestimated, from a physical bottleneck scenario. The state vector might be then become more similar to the scenarios where a higher share of visitors is performing activities, over the real scenarios where there is congestion due to bottlenecks.

7.2.2. Results & Analysis

Table 7.4 and Table 7.5 present the $\Delta\varepsilon_{i;varr;ref}$ for each test scenario i, and input variation r of the sensor data perturbations' objectives, derived according to the methodology described in subsection 7.1.2. The values in the table indicate how much the error of each test scenario i changes from its reference for each variation. The larger the increase in the error (i.e. the more negative it is), the darker the shade of red of the cell, while the darker shades of green represent larger decrease in the error (i.e. positive values). These results are discussed below.

Table 7.4: Results of Sensor Data Perturbation Analysis - Sensor Var 1 to 4. The combinations are shown by their variation number, direction, metric and level as shown in Table 7.3. Every column of each row represents the change in the error from the reference. The more negative the value (the darker the shade of red), the higher the decrease in the performance when compared to its reference.

	Test Scenario	$\Delta\varepsilon_{i;varr;ref}$			
		Over | All		Under | All	
		1 - Low	2 - High	3 - Low	4 - High
1	**Veemkade - East | High**	0.00	0.00	-0.01	-0.11
2	**Veemkade - East | Inter**	-0.01	-0.07	-0.04	-0.10
3	**Route - Bidirect | High**	-0.03	-0.05	-0.04	-0.09
4	**Route - Bidirect | Inter**	-0.02	-0.06	-0.02	-0.06
5	**Activity - Veemkade West | High**	-0.03	-0.15	-0.06	-0.11
6	**Activity - Veemkade West | Inter**	-0.03	-0.09	-0.04	-0.07
7	**Inefficient Route Choice | High**	-0.01	-0.01	0.00	-0.11
8	**Inefficient Route Choice | Inter**	0.00	-0.03	-0.03	-0.10

Table 7.5: Results of Sensor Data Perturbation Analysis - Sensor Var 5 to 8. The combinations are shown by their variation number, direction, metric and level as shown in Table 7.3. Every column of each row represents the change in the error from the reference. The more negative the value (the darker the shade of red), the higher the decrease in the performance when compared to its reference.

	Test Scenario	$\Delta\varepsilon_{i;varr;ref}$			
		Over | Macro		Under | Macro	
		5 - Low	6 - High	7 - Low	8 - High
1	**Veemkade - East | High**	0.01	0.00	-0.02	-0.13
2	**Veemkade - East | Inter**	0.01	0.00	-0.06	-0.07
3	**Route - Bidirect | High**	-0.01	-0.04	-0.01	-0.02
4	**Route - Bidirect | Inter**	0.00	-0.01	-0.01	-0.02
5	**Activity - Veemkade West | High**	-0.04	-0.04	0.02	-0.02
6	**Activity - Veemkade West | Inter**	-0.02	-0.05	-0.01	-0.05
7	**Inefficient Route Choice | High**	0.00	-0.01	-0.01	-0.01
8	**Inefficient Route Choice | Inter**	0.00	-0.02	-0.01	-0.02

Underestimation vs. Overestimation

From the results shown in Table 7.4, it can be seen that the sensitivity of the system to an underestimation appears to be larger than that of the overestimation for most of the test scenarios. For instance, comparing the second and fourth columns of test scenarios 1 to 3, as well as 7 and 8, a larger increase in the error is seen in the latter column. To further discuss these differences, the 5 scenarios selected and used to calculate the error changes shown in Table 7.4 are presented in Figure E.2. It is possible to see that the scenarios selected for variation 4 (Under|All, High) are often lower density levels of the same conceptual scenario from its test scenario, or are a previous time instant of the same conceptual scenario. However, as the time period of the test scenario is when the inefficiency starts occurring, selecting a time period before that in the same scenario indicates a similar behavior as selecting a distinct density level. This is because the patterns or the relative usage of the infrastructure remain, but the flow regime is distinct.

Another aspect highlighted by the results shown in Table 7.4 is the difference between the sensitivity of the high and intermediate density level scenarios to variation 2 (Over|All, High). When looking at the second column of Table 7.4, where the metrics are highly overestimated, the following can be observed. The increase in the error of test scenario 2 (second row, second column) is larger than in test scenario 1 (first row, second column). Similar remark is made for test scenarios 3 and 4, as well as 7 and 8. From this, it can be seen that the intermediate density levels are often more sensitive to this variation than the higher levels of the same conceptual scenario. The reason for this can be expected to be due to the boundaries of the states defined by the higher density level scenarios. As the observations apply for most of the test scenario, except for test scenarios 5 and 6, remarks can be made regarding these observations. As defined in subsection 7.1.1, the test scenarios on the high density level relate to the scenario for which the highest densities are observed for each conceptual dynamics. That is, the high density level corresponds to the boundary of the prediction, or where the maximum possible density that can be predicted for a certain inefficiency are. Thus, the larger sensitivity for the underestimation for most test scenarios is expected to be due the lower frequency of higher densities, as the ones in the overestimation variations, for the same dynamics in the database. This expectation is based on the comparison between the distinct density levels, as the intermediate density levels present a larger sensitivity to an overestimation if compared to its high density level counterpart.

These errors are further illustrated through the time series of the densities shown in Figure 7.2 and Figure 7.3. The time series correspond to the Event Blocks where the highest densities appear in the different test scenarios. The larger errors obtained for the underestimation are highlighted in the time series of the densities shown in Figure 7.2. In this scenario, it can be seen that the overestimation variations do not significantly affect the prediction if compared to the results of the high underestimation variation. This is because of the aforementioned boundaries of the states defined by the high density level scenarios. When analysing the predicted time series of test scenario 3 for the different variations (Figure 7.3), it can be seen that the overestimation variations affects the prediction more than in test scenario 1. However, the underestimation variations still more negatively influence the prediction given that not even the pattern of the time series is captured. While the real development of the density rises, the predicted time series of the underestimation variations remain almost flat.

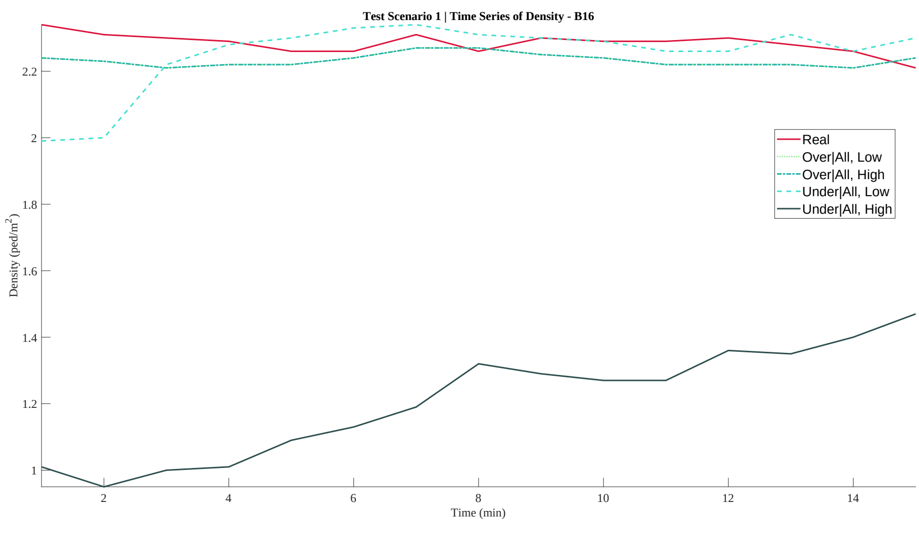


Figure 7.2: Test Scenario 1 | Resulting time series of density in Block 16

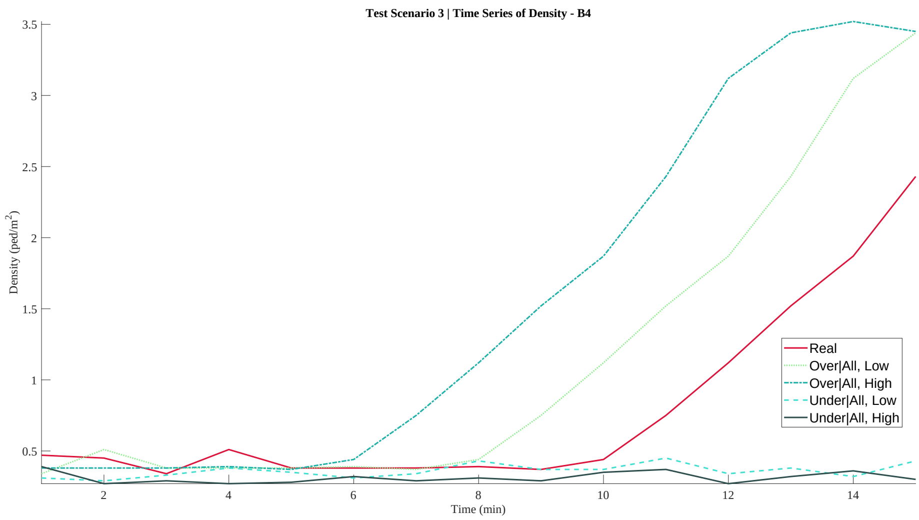


Figure 7.3: Test Scenario 3 | Resulting time series of density in Block 4

When illustrating the time series of the densities of the test scenarios on the intermediate density level, the larger sensitivity to the overestimation of these if compared to the high density level scenarios is observed. Figure 7.4 and Figure 7.5 illustrate how the prediction is overestimated from the start, that is, from the first minute of the prediction horizon. Comparing these patterns to the one from Figure 7.3, a key distinction is that in the latter the predicted states diverge from the real ones over time. Overall, for both high and low density level scenarios, the prediction for the area where the the densities rise seems to be highly sensitive to the perturbations of the sensor data.

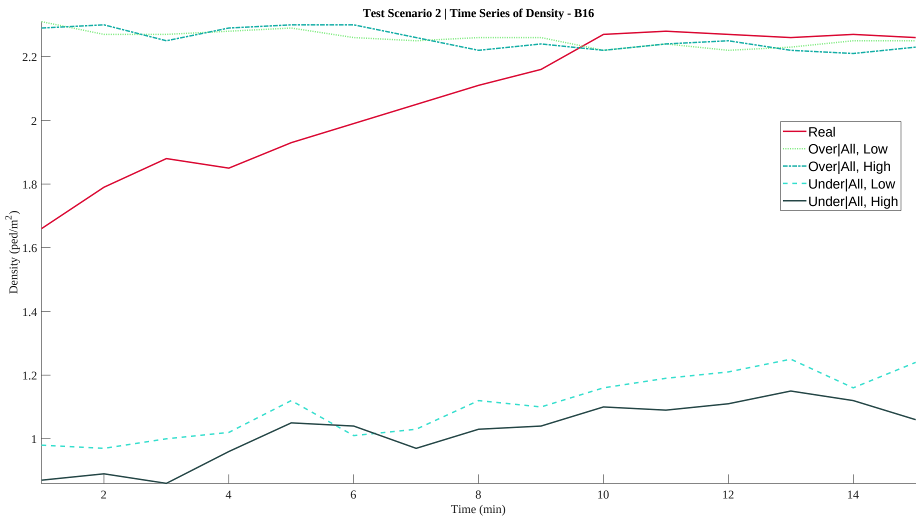


Figure 7.4: Test Scenario 2 | Resulting time series of density in Block 16

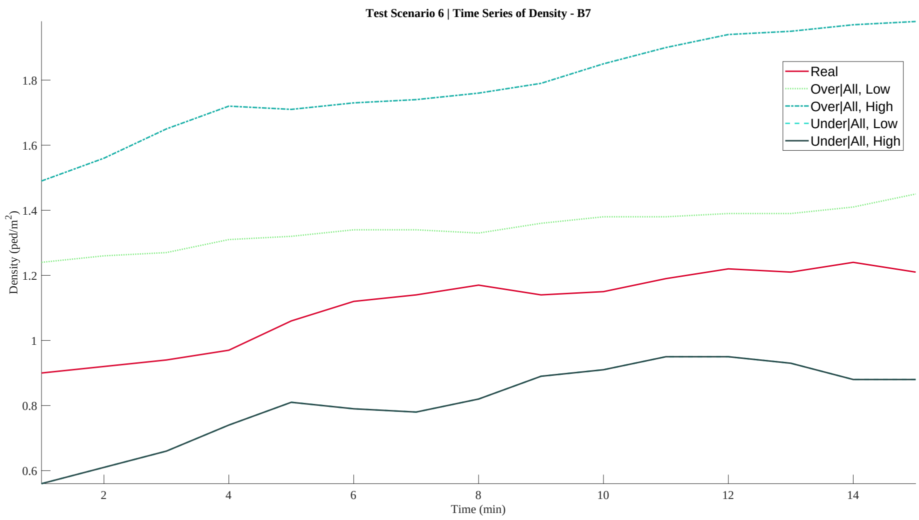


Figure 7.5: Test Scenario 6 | Resulting time series of density in Block 7

When analysing the results of test scenario 5, a distinct aspect of the dependence of the prediction on the database is highlighted, which could explain the different results. For this scenario, the aspect highlighted relates to the areas of focus of each conceptual scenario instead of the density levels. As presented in subsection 6.2.2, the Veemkade is an area where several inefficient dynamics are expected. Therefore, the frequency of scenarios and time instants in the database for which certain dynamics are observed on the Veemkade increases. For example, the scenarios for the 'Activity - Veemkade West' and 'Veemkade - West' are distinct in the share of agents assigned to perform an activity. However, the areas where densities and travel times increase, and flows decrease, when each of these inefficiencies occur relate either to the same, or to very closely located Event Blocks. This increases the number of scenarios and time periods in the database for which closely related states can be found. Hence, when the algorithm searches through the database, there is likely a wider range of options for distinct conceptual dynamics for which the objective function values have relatively low variance. This is not only due to the metrics used to describe the dynamics, but also the Event Blocks taken into account by the scenario selection system when searching through the database. For this same reason, test scenario 5 has the highest increase in error for the low underestimation variation (column 3 - Under|All, Low).

The sensitivity of test scenario 5 for variation 2 (Over|All, High) is thus larger than the other scenarios because of scenario 'Veemkade - West'. The demand for the west-end of the Veemkade to activate the physical bottleneck on that location is higher than that for the 'Activity - Veemkade West' inefficiency. Hence the selection of the high density levels of the 'Veemkade - West' scenario, as the crowd states of test scenario 5 in variation 2 (Over|All, High) are overestimated across all Event Blocks.

Distinct Estimation Directions

The results shown in Table 7.5 indicate that, overall, the prediction error is not significantly sensitive to the case when the perturbations of the distinct sensors occur in different directions. If compared to the $\Delta\varepsilon_{i;varr;ref}$ values of Table 7.4, the error changes are lower. Surprisingly, there are even some variations for which the error decreases if compared to the reference, as it can be seen by the cells colored in green. This is because this error is derived from the 5 scenarios selected by the system, and further compared to the reference case. As it can be seen in Figure E.2 and Figure E.3, even in the reference case, where the data has no perturbations, some of the five scenarios selected by the system are not from the dynamics of the test scenario used as input. One can see this by looking at scenario selected 3, of test scenario 2, in Figure E.2. Due to the previously mentioned dependencies of the prediction on the database, similar states might occur in these different conceptual scenarios. The sensitivity of the system to the perturbations on the input is thus assumed to be larger for similar conceptual scenarios, as even short variations can change the scenario selected.

Unlike what was initially expected, the results shown in Table 7.5 and Figure E.3, indicate that the perturbations in distinct directions do not significantly misidentify the test scenario's conceptual dynamics. Instead, the scenarios selected are commonly distinct density levels of the same conceptual dynamics, or similar dynamics in terms of the route and activity demand as well as flow regime. The reason for this might be two-fold. Firstly, the results are dependent on not only the direction of the perturbation (under or overestimation), but also on the scale. In this research, the data is perturbed by translating each data point in the defined direction and scale, where the scale is given by the percentage change value (e.g. 50%). From the results, it seems like that even when the data is highly perturbed, the state vector of the other scenarios in the database are still further away from these perturbed states for most test scenarios. This might be due to the perturbed pattern not existing in the database, or simply because the scale of the perturbation was not too large. The results might be different if different scales where used, or if the prediction did not take all Event Blocks into account. Which leads to the second reason for the observed results, the areas of the environment used for the prediction. If only a sub-selection of Blocks were used, for instance in the west-end of the Veemkade, the perturbed patterns could be more representative of a distinct scenario.

Sub-conclusions

Overall, the prediction appears to be highly sensitive to the perturbation from the sensor data, especially the underestimation of the state metrics. This is because the underestimation of the state metrics might lead to the selection of a scenario at a time where flows are stable, and so the high density areas which arise in reality are not correctly predicted. The frequency of particular states in the database in terms of the density level as well as areas where inefficiencies occur can influence the prediction when the data is perturbed. This could be seen by the low error changes for variation 2 (Over|All, High), when the overestimated metrics are beyond the boundaries of the states that exist on the database for some scenarios, and so the predicted states are commonly the highest density level ones. Regarding the areas, when the range of options from distinct scenarios which have similar patterns increases, the variance of the lower bound of the objective function values decreases, and so small variations in the real states can lead to the selection of distinct scenarios. This is observed specifically for test scenario 5, and it occurs not only due to the metrics used to describe the dynamics, but also the Event Blocks taken into account by the selection system. For instance, several scenarios focus on inefficiencies on the west-end of the Veemkade, and even the ones on the east-end influence the states that can be found on the west-end. This increases the chance that the similar spatial and temporal patterns of the state metrics exist in the database. Meanwhile, the conceptual dynamics of the inefficient route choice is always identified, despite the sensor perturbations, due to its unique patterns regarding the pairs of Event Blocks used by the pedestrians. Finally, the distinct estimation directions do not appear to identify distinct dynamics as initially expected. These might be due to the scale of the perturbations tested, which lead to spatial patterns that do not exist in the database when the entire area is taken into account.

7.3. Analysis of Sub-Selection of Event Blocks

In this section, the results of the different analysis objectives related to the sub-selection of Event Blocks is discussed. The main goal is to assess how the reduction in the number of objectives considered by the scenario selection system influences the predicted states, where this reduction is derived from excluding all state metrics of certain Event Blocks. The set up of the analysis is presented in subsection 7.3.1, where the Event Blocks considered by the scenario selection system for the prediction are illustrated for each test scenario. The results of each input variation are shown in subsection 7.3.2, and a general analysis of these results is performed.

7.3.1. Set up of sensitivity for choice of Event Blocks

As presented in subsection 6.2.2, each scenario has a specific area where the inefficient dynamics is expected to appear. For instance, scenario ’Activity - Veemkade West’, of the uneven distribution over the network dynamics, focuses on the increase in demand for the activity location at the west-end of the Veemkade. Thus, one can say it is important to more accurately predict the dynamics of that particular area when the density starts rising at that location. In order to assess whether or not this can be achieved with the scenario selection system, one can decide to only take into account the Event Blocks relevant for the particular area of interest for the prediction. Also, another aspect of the analysis through the sub-selection of Event Blocks relates to not including the relevant Blocks to assess what the effect on the predicted states is. This can give insights into how the scenario selection system performs in case sensors are malfunctioning at critical locations and time. In this analysis, four sub-selections are used, according to Table 7.6, and the selection system is run for each one of the test scenarios presented in Table 7.1 for these sub-selections. The chosen six Event Blocks are shown in Figure E.4 to Figure E.7. The first sub-selection uses six Event Blocks, chosen based on not only the area of interest but also the areas which generate flows towards this main area, and that are assumed to influence the relevant areas within the 15 minutes time horizon. The second sub-selection uses three of the six Event Blocks of the first sub-selection, to further reduce the number of objectives considered by the search algorithm and focus on the areas where densities are rising more rapidly. The third sub-selection relates to excluding the most relevant Block (i.e. the one nearer the area where densities start rising). Finally, the fourth considers the same three Blocks as the second sub-selection variation, however in this sub-selection these Blocks are excluded.

Table 7.6: Input variations for choice of Event Blocks

Variation	Number of Event Blocks
Reference	All 13 Blocks
Blocks Var 1	6 Blocks
Blocks Var 2	3 Blocks
Blocks Var 3	12 Blocks (All - most relevant)
Blocks Var 4	10 Blocks (All - Blocks Var 2)

The reference values of each scenario for this analysis are the $\varepsilon_{i;k,objq,ref}$ when all 13 Event Blocks are used. To exclude the possibility that the differences analysed are caused by errors from the sensor data perturbations, all metrics of the real state input for all variations tested are 100% accurate. That is, no over or underestimation is applied. Also, for each Event Block, all state metrics which define its state according to Table 6.10 are used. Therefore, for variation 1, the total number of individual objectives is reduced from 92, in the reference case, to 42, as for each of the six Event Block, all 7 metrics are taken into account. For variations 2, 3 and 4 the number of individual objectives is 21, 84 and 70, respectively.

7.3.2. Results & Analysis

Table 7.7 shows the prediction error results for the input variations of the sub-selection of Event Blocks. From the results shown in the table, the sub-selection of only the relevant Event Blocks does not seem to significantly influence the predicted states of the test scenarios analysed. As it can be seen in columns 1 and 2, for a larger part of the scenarios, both the 6 and 3 Blocks variations yield either a slight increase in the error, given the negative $\Delta\varepsilon_{i;varr;ref}$, or no apparent change. Regarding the sub-selections which exclude the relevant Blocks, only the 10 Blocks variation appears to more significantly influence the prediction. This can be seen by the values in the first and second rows of column 4, where the highest increase in the error appears when the three relevant Blocks are excluded. Meanwhile, the results of column 3 indicate that if a single Block fails, the error in the prediction does not significantly rise for any of the scenarios. To better understand these results, the five scenarios selected and used to calculate the error changes shown in Table 7.7 are presented in Figure E.9 and further discussed below.

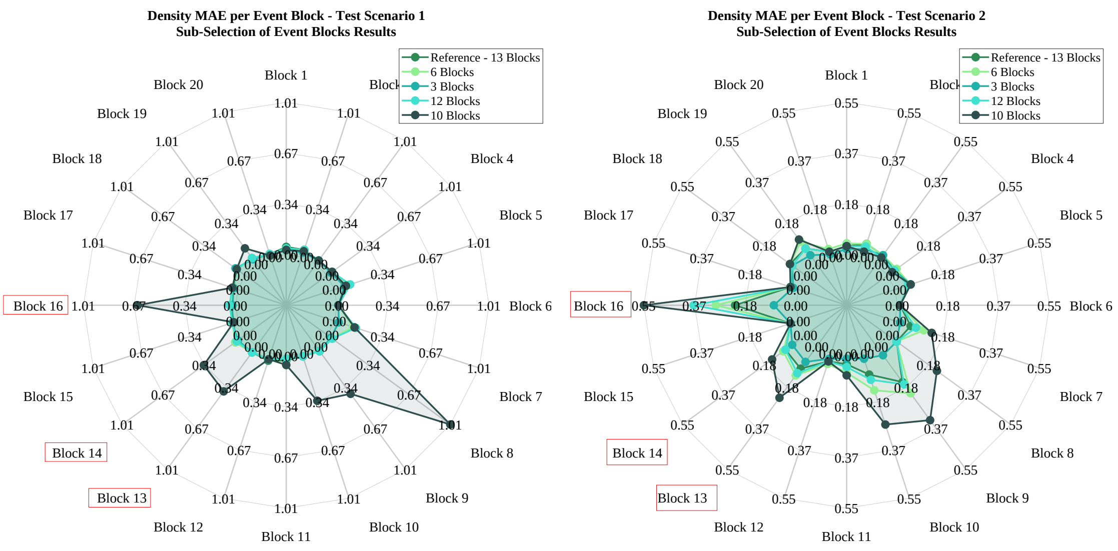
Table 7.7: Results of Sub-Selection of Event Blocks Analysis. The combinations are shown by their variation number, direction, metric and level as shown in Table 7.6. Every column of each row represents the change in the error from the reference. The more negative the value (the darker the shade of red), the higher the decrease in the performance when compared to its reference.

	Test Scenario	$\Delta\varepsilon_{i;varr;ref}$			
		6 Blocks	3 Blocks	12 Blocks	10 Blocks
1	**Veemkade - East | High**	0.00	0.01	0.00	-0.14
2	**Veemkade - East | Inter**	-0.02	0.03	-0.01	-0.06
3	**Route - Bidirect | High**	-0.01	-0.01	0.00	-0.01
4	**Route - Bidirect | Inter**	-0.01	-0.01	0.00	-0.01
5	**Activity - Veemkade West | High**	0.01	0.01	-0.01	0.00
6	**Activity - Veemkade West | Inter**	-0.01	0.00	0.00	0.00
7	**Inefficient Route Choice | High**	0.00	-0.01	0.00	0.01
8	**Inefficient Route Choice | Inter**	0.00	-0.01	0.00	0.00

The results of Table 7.7 and Figure E.9 indicate distinct behavior for the different test scenarios. The sub-selection of the three relevant Blocks improves the prediction of test scenarios 1, 2 and 5 only, as it can be seen in the values of column 2. Similarly, the results shown in column 4 indicate that the sub-selection which excludes these three relevant Blocks mostly deteriorates the prediction of test scenarios 1 and 2. These results can be explained by the Event Blocks selected for these analyses. For test scenarios 1 and 2, when 3 Blocks are sub-selected, these exclude the Blocks at the west-end of the Veemkade, only focusing on the Blocks on the east-end of that route. This in turn can assist in making the distinction between the scenarios in the database which focus on each end of that route. When 6 Blocks are used, however, this distinction does not occur, as the areas on the west-end are also taken into account. Thus, the selection algorithm searches for a scenario in the database for which both ends of the Veemkade have less error. The results of test scenario 5 support this reasoning as both the sub-selection of 6 and 3 Blocks improve the results, given that both exclude the east-end of the route, thus enabling the distinction to be made. For the same reason, when the three relevant Blocks on east-end of the Veemkade are excluded in the 10 Blocks variation, the selection system identifies the scenarios based on the information obtained from the Blocks on the west-end. Hence, the scenarios selected correspond to the Activity - Veemkade West.

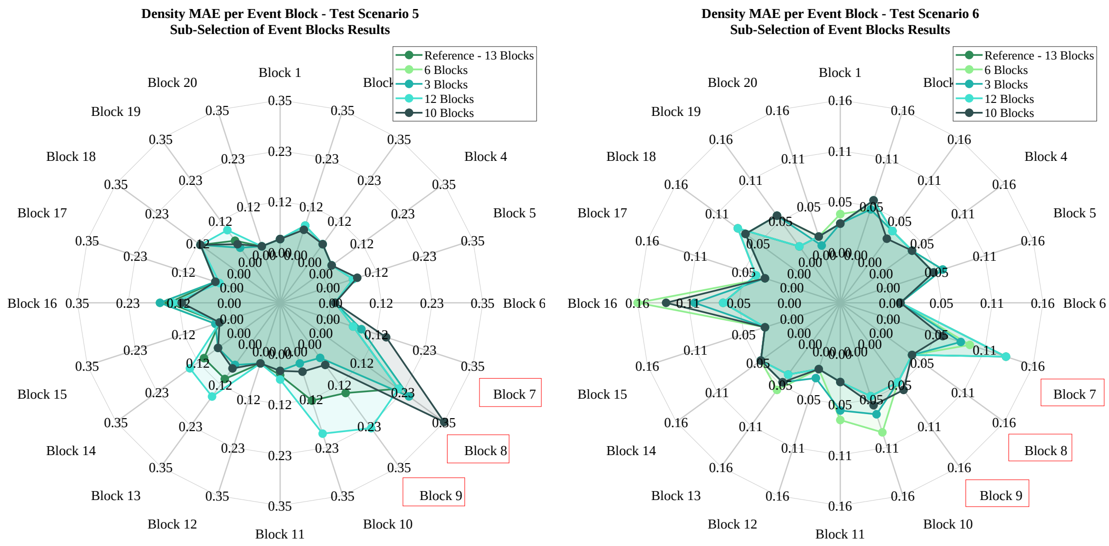
To illustrate the results discussed above, Figure 7.6 to Figure 7.7 show the mean absolute error per Event Block, where the Event Blocks nearest to the location where the inefficiency occurs are highlighted in red. From the figures, it is possible to see that, for test scenarios 1 and 2, the errors in the prediction rise at both ends of the Veemkade when only 10 Blocks are used. The main Blocks that represent the east-end and Blocks 16 and 14, while the west-end are 9 and 8, which are the Blocks with higher errors in Figure 7.6. This is because of the aforementioned fact that the selection system is unable to differentiated between the scenarios of the two ends of the Veemakde when the relevant Blocks which enable the differentiation are excluded.

For test scenarios 2 and 5 shown in Figure 7.6b and Figure 7.7a, respectively, the sub-selection of 3 Blocks improved the prediction exactly on the areas near the inefficiency location. Similarly, the results for the variation when 6 Blocks are used for test scenario 2 (Figure 7.6b) illustrate that the larger errors are on the Blocks on the west-end of the Veemkade (Blocks 9 and 10), as well as Block 16. These results illustrate the trade-offs when a larger number of individual objectives is used for the selection, as less optimal individual solutions are found when more objectives are considered.



(a) Resulting MAE for test scenario 1 *(b)* Resulting MAE for test scenario 2

Figure 7.6: Mean absolute error per Event Block | Sub-selection of Event Blocks - Test scenarios 1 & 2



(a) Resulting MAE for test scenario 5

(b) Resulting MAE for test scenario 6

Figure 7.7: Mean absolute error per Event Block | Sub-selection of Event Blocks - Test scenarios 5 & 6

Sub-conclusions

Overall, the effect of the sub-selection of Event Blocks when only the most relevant Blocks are considered can improve the prediction. This is because it reduces the effect of the trade-offs by focusing on the relevant areas, where densities are rising. This finding supports the idea that building smaller-scale scenarios, with a focus on a certain area can be beneficial for the performance of the prediction. This is because by having an area of focus, less overlap between the crowd states obtained from different scenarios and inefficient dynamics can be expected. This in turn facilitates the process of selecting a scenario from the database in which the densities are rising in the correct location.

Regarding the sub-selection which excluded the most relevant Blocks, the prediction is not significantly affected when a single sensor fails as the other sensors provide enough information for identifying the correct scenario. However, another conclusion can be drawn given the results of the analysis when 3 relevant Blocks are excluded. The prediction can be negatively influenced when the Blocks used over the ones that are excluded relate to the area of a different inefficiency, for which similar states occur. Following the discussion above regarding the smaller-scale models, the reduction in the overlap between the states that occur in different areas, but that relate to different scenarios, can be obtained. However, even if small-scale models are used, the misidentification issue can remain when two inefficiencies occur in areas very close to one another. This is because the Event Blocks used for by the selection system for these might not able to make the differentiation alone. The importance of the state metrics chosen to describe the scenarios when small-scale models are used is then highlighted, as these can provide the additional layer of differentiation.

7.4. Analysis of Sub-Selection of State Metrics

In this section, the results of the different analysis objectives related to the sub-selection of state metrics are discussed. The main goal is to assess how the reduction in the number of objectives considered by the selection system influences the predicted states, where this reduction is derived from excluding certain state metrics of all Event Blocks. The set up of the analysis is presented in subsection 7.4.1, where the state metrics and combinations of metrics used for the input variations are illustrated. The results of each input variation are shown in subsection 7.4.2, and a general analysis of these results is performed.

7.4.1. Set up of sensitivity for choice of State Metrics

In subsection 7.2.1, it was presented how different real state metrics can have distinct accuracy depending on the sensor these are derived from. For instance, flows and densities are often more accurate metrics than travel time, as they are derived from video cameras. Thus, performing the prediction based on a selection of state metrics assumed more accurate can be expected to improve the results. Similar to the considerations regarding the sub-selection of Event Blocks, the sub-selection of State Metrics can reduce the number of conflicting objectives used by the optimization algorithm.

The sensitivity of the predicted states to five sub-selections of state metrics is tested in this subsection. These input variations are shown in Table 7.8. While variations 1 to 3 test the sensitivity of the output to each metric individually, where variation 1 (q) corresponds to only flows, variation 2 (k) to only density and variation 3 (tt) to only travel times, variations 4 (k&q) and 5 (k&tt) combine two metrics. For the k&q variation, only macroscopic metrics are taken into account (i.e. density and flow). Meanwhile, the k&tt combines the density with the travel time. The density is used in both combinations because, as mentioned in subsection 7.1.3, each value of the density provides unique insights into the state of the crowd, and is also the metric used for assessing the performance of the prediction.

Table 7.8: Input variations for choice of State Metrics

Variation	State Metrics (current & history)
Reference	All 8 metrics
Metric Var 1	Flow (q)
Metric Var 2	Density (k)
Metric Var 3	Travel Time (tt)
Metric Var 4	Density & Flow (k&q)
Metric Var 5	Density & Travel Time (k&tt)

The reference values of each scenario for this analysis are the $\varepsilon_{i;k,objq,ref}$ when all state metrics defined in Table 6.10 are used. To exclude the possibility that the differences analysed are caused by errors from the sensor data perturbations, all metrics of the real state input for all variations tested are 100% accurate. That is, no over or underestimation is applied. Also, all 13 Event Blocks are used for all variations defined in Table 7.8, where only the metrics used for describing each Block's state are reduced. For q, k and tt variations, the total number of individual objectives decreases from 92 to 26 (e.g. flow and flow history of each one of the 13 Event Blocks). For k&q and k&tt variations, the number of individual objectives is 52.

7.4.2. Results & Analysis

Table 7.9 shows the prediction error results for the input variations of the sub-selection of State Metrics. Overall, it can be seen that the use of the travel time metric, by itself or in combination with the density, seems to cause most significant increase in the prediction error. This can be seen by comparing the results of columns 3 and 5, where travel time is used, with the other columns. These results are confirmed by the scenarios selected shown in Figure E.11. The highlights of this analysis are further discussed below.

Table 7.9: Results of Sub-Selection of State Metrics Analysis. The combinations are shown by their variation number, direction, metric and level as shown in Table 7.8. Every column of each row represents the change in the error from the reference. The more negative the value (the darker the shade of red), the higher the decrease in the performance when compared to its reference.

	Test Scenario	$\Delta\varepsilon_{i;varr;ref}$				
		Only q	Only k	Only tt	k, q	k, tt
1	**Veemkade - East | High**	-0.02	0.01	-0.13	0.01	0.00
2	**Veemkade - East | Inter**	0.01	0.03	-0.06	0.03	-0.01
3	**Route - Bidirect | High**	-0.01	-0.01	-0.01	-0.01	0.00
4	**Route - Bidirect | Inter**	-0.02	0.00	-0.05	-0.02	0.00
5	**Activity - Veemkade West | High**	0.01	0.02	-0.01	0.01	0.01
6	**Activity - Veemkade West | Inter**	0.00	0.01	0.00	0.01	0.00
7	**Inefficient Route Choice | High**	0.01	0.03	-0.04	0.03	-0.04
8	**Inefficient Route Choice | Inter**	0.01	0.01	-0.01	0.01	-0.01

The improved results when only the density is used as a metric can be explained due to the aforementioned considerations about the uniqueness of the states that the values of the density describe. Besides, as defined in subsection 7.1.3, the metric used to assess the performance of the prediction is the density. This can partially explain the increase in performance for the variation when only the density is used. On the other hand, the negative results of the travel time are due to the opposite behavior of this metric if compared to the density, as the values of the travel time can be the result of multiple distinct traffic patterns. In this research, as presented in subsection 6.3.1, it was decided that the the travel time metric would be defined by the first and third quartiles of the travel time distribution. This choice aimed at providing an additional layer of differentiation of the values of this metric for the different scenarios. However, it appears that this is not fully achieved by these chosen metrics. The question is thus whether the travel time as it is defined in this research is an appropriate metric to be included in this method, or if other metrics could be used to quantify the conditions along the routes. It is possible that adding more parameters related to the travel time distribution could improve the differentiation between the scenarios, for instance the standard deviation.

From the results of the combination between the density and the other metrics, the following can be observed. Although adding the travel time to the density negatively influences fewer scenarios than only using the travel time, when compared to the case when only the densities are used, the decrease in performance is still significant. For instance, for test scenario 2 the prediction error when only using the density decreases, while when densities and travel times are used it increases. These indicate the travel time can actually hinder the ability of the system in identifying the scenarios. However, without the travel time, so for instance when only the macroscopic metrics are used, no information about the conditions over the routes are included in the prediction. If there are more Event Blocks to describe the conditions of certain areas, this might not be a problem as the local density and flow information might be enough to differentiate between the scenarios. In case the Event Blocks are spread on the environment, which is more often the case in mass events, having no information about the condition on the routes between these Blocks can be problematic. The chance of an inefficiency appearing in a location not covered by an Event Block increases as these Blocks get further apart. Hence, although the results shown in Table 7.9 and Figure E.11 indicate that only using densities and flows improves the prediction, these results might be different for distinct sensor networks.

Sub-conclusions

So, it is clear that the sensitivity of the system is different per metric. The results show that, for the state metrics used in this research, removing certain metrics can improve the prediction. However, this improvement depends on the metrics which are excluded and how well the remaining ones can uniquely identify the scenarios in the database. For instance, when only the density is used, the scenarios and density levels can be identified due to the unique states the density values defined. On the other hand, the travel time metric can be the result of multiple distinct traffic patterns. Although the results appear to be negatively influenced by the usage of the travel time metric, this is the only metric which describes the conditions over the routes between the sensors. When the sensor network has sensors positioned spread on the environment, having information about the conditions in between these sensors is clearly important. Thus, instead of completely excluding this metric, it is preferable to define ways to improve the information one wants to obtain from this metric. One can think of for example adding more parameters related to the distribution of the travel time, which could provide the differentiation between the scenarios.

7.5. Discussions & Practical Considerations

The previous sections present a number of findings regarding the sensitivity of the forecast for particular inputs from the real crowd states and settings of the selection system. In this section, these findings are discussed for the application of the forecasting method. Two aspects of the results are discussed, as these appear to be more influential on the performance of the system. The first aspect relates to the dependence of the prediction on the states found in the database, discussed in subsection 7.5.1, while the second aspects relates to choices of the individual objectives used by the selection system, presented in subsection 7.5.2. Finally, some practical considerations regarding the development and application of the method, in light of the objective of real-time crowd movement forecast, are discussed in subsection 7.5.3.

7.5.1. Dependence on Crowd States Database

From the analyses performed in the previous sections, the dependence of the results on the states included in the database is highlighted. Particularly the frequency of certain state vectors with similar values on the different areas of the environment can significantly change the scenarios which are selected. When certain areas are the focus of multiple conceptual scenarios, the chance that there are particular states in the state vector with similar values increases, thus making it more difficult to differentiate between the scenarios. This can be problematic when the scenario selected does not indicate the correct flow regime and appearance or not of the inefficiencies over the prediction horizon. For instance, in the case study used in this research, two inefficient dynamics were identified on the west-end of the Veemkade. One relates to the activation of a physical bottleneck while the other relates to the increased demand for the activities on that area. In order to activate the bottleneck, the total demand on the environment for which the flow regime becomes unstable is higher than that for the inefficiency regarding the increased activity demand. As the dynamics are described by the state metrics derived at the discrete locations of the Event Blocks, similar states are derived from these two scenarios. However, the future development of these can be significantly different.

The limitations in terms of differentiating between these similar state arises from a combination of the metrics and areas used for describing the scenarios. Thus, one possible way to address this issue would be to change the way the scenarios are developed for instance by narrowing down the simulation space. Instead of developing the scenarios simulating all the different areas, the scenarios could be developed specifically for the areas where the inefficiency is occurs. This could also assist in enabling better control over the scenarios and how these can be differentiated.

Another aspect of the dependence on the database relates to the boundaries of the states that exist in the database. The highest and lowest density levels of each conceptual scenario define the maximum and minimum states that can be found on the different Event Blocks. One observation regarding such boundaries is that when the state metrics are overestimated, the prediction would tend towards the scenario which shows the appearance of the inefficiency. This would be on the 'safe side' if compared to the effect of having underestimated metrics, which would lead to the opposite effect. The problem appears when there is overlap between the different scenarios in terms of their area of focus, as in such case these boundaries can be poorly defined. This means that the overestimation of the state metrics can induce the prediction towards distinct scenarios, for which the states are closer to these overestimated states. These distinct scenarios might illustrate the appearance of the a distinct inefficiency, which might induce crowd managers to wrongly define which strategy to apply. Using the same example of the inefficiencies on the west-end of the Veemkade, if the higher densities are occurring due to the increased demand for the activity, a strategy could be to redirect visitors to other activities. In case the higher densities are occurring due to the activation of the bottleneck, it might be better to limit the inflow into the area.

So, for the method to be robust against the similarities of the scenarios in the database, and over or under estimation of the real states, one would have to first test the frequency of certain states in the database which are within some similarity bounds. Identifying these could provide guidance on how these similar states with distinct developments could be differentiated.

7.5.2. Choices regarding the sub-selection of Individual Objectives

The analyses of the sub-selection of Event Blocks and state metrics both relate to the question of which individual objectives to use for the prediction. In many ways this question also relates to the weight assigned to each individual objective when combining these into a single objective. It is clear from the results that both an improvement and a decrease in the performance of the prediction can occur from the choices regarding these objectives. Both choices, that is, which Event Blocks and which state metrics should be used, relate to the uniqueness of the states and scenarios these can define.

When choosing the Event Blocks, the sub-selection can most improve the results in the sense of identifying the inefficiency and density level if the dynamics of the areas selected are specific for a particular scenario. The areas chosen should correspond to the Blocks where unique states related to a specific inefficiency occur. For instance, if it is known that a bottleneck is becoming active, the Blocks should be chosen such that the areas near that bottleneck capture the dynamics of the bottleneck only. This means excluding the Blocks that relate to a different inefficiency and which generate similar states to the ones observed when the bottleneck is becoming active. This might not be straightforward, as depending on how the environment is discretized by the Blocks, it might be the case that certain inefficiencies are related to same Blocks. In such case, combining the sub-selection of Blocks with the sub-selection of state metrics can assist in making this differentiation.

Similar to the choice of Event Blocks, when choosing the sub-selection of state metrics to be used, the ability of the individual metrics to uniquely identify certain scenarios must be taken into account. Based on the results of subsection 7.4.2, the sub-selection of metrics can most improve the identification of the scenarios when the metrics that can be the result of multiple distinct scenarios are excluded. In the case study and test scenarios of this research such metric is the travel time, as the individual and combination of metrics which do not include travel time can better identify the scenarios.

So, the insights into the influence of distinct choices of Event Blocks and state metrics can be combined for improving the prediction. By understanding the effect of the different metrics, and the uniqueness of certain states in specific Blocks, one can define specific metrics for each Event Block which could improve the robustness of the system in terms of making distinctions between the scenarios. Further research is needed into these combined choices and the effect of these on the scenarios which are selected. For these further studies, one can investigate the database, that is, the frequency of certain values of the metrics of each Event Block, identify the scenarios for which similar states occur, and use such knowledge for defining the settings of the selection system.

7.5.3. Practical Considerations

The practical considerations addressed below relate to the resources used to build the database (offline step) and run the selection algorithm (online step). The computer available for this research is a Windows 10 laptop, Intel core i7 - 4800MQ CPU @ 2.70 GHz, 16 GB RAM, 64-bit Operating system. Regarding the offline development of the database, as mentioned in subsection 6.2.3, 240 simulations are run to account for the 8 scenarios and corresponding 6 density levels, as well as the 5 replications per scenario and density level to estimate the required number of replications. Pedestrian Dynamics ®3.2 is the version of the microscopic model used for running the simulations. All scenarios have a duration of 2.5 hours, which on average corresponded to 2 hours of simulation time in the computer available for this research. The average amount of agents simulated per scenario is 75,000, where the maximum is about 100,000. The size of the output files from Pedestrian Dynamics for all scenarios together is 67 GB. This refers to the 8 scenarios and corresponding 6 density levels, as a single replication is enough for each scenario and density level to account for the stochasticity.

The output files from Pedestrian Dynamics of these 48 simulations are used to derive the crowd states and generate the crowd states database, which is the input of the online scenario selection system. The size of the final database is 10.2 MB, which is a significant reduction from the original output files. The scenario selection algorithm is developed and run in MATLAB R2020a version, installed in the same laptop described in the previous paragraph. In such laptop, the algorithm takes an average of 2.24 seconds to run and return the selected scenarios.

IV

CONCLUSIONS

8

Conclusions, Discussions & Recommendations

In this chapter, the main conclusions of the research presented in this report are drawn. These conclusions are presented in relation to the research questions in Section 8.1. From the findings and analyses done in this research, Section 8.2 discusses the limitations of the method. Finally, Section 8.3 presents the recommendations that can be made based on the results and limitations identified from the application of the proposed method.

8.1. Conclusions

The objective of this research is to develop and validate a real-time crowd movement forecasting method in which simulation is an offline step for the online forecast. The main research question identified in this research is the following:

How to design and apply a real-time crowd movement forecasting method, which is populated with a database of pre-simulated scenarios and uses a multi-objective optimization approach?

From a review of the literature in existing crowd movement forecasting methods, it is noticed that, for simulating in real-time, most model-driven methods make a trade-off between behavioral validity and computational burden. Models which validly reproduce the different movement base cases and crowd phenomena observed in real life, and are thus expected to yield more accurate predictions, are disaggregate models, known for being computationally expensive. Thus, literature suggests that methods to enable implementing these behaviorally valid models for real-time prediction are sought after.

As the main research question presented above states, a database of pre-simulated scenarios must be built. To understand the types of scenarios that occur during a mass event for which prediction would be desirable, theory in pedestrian traffic and crowd management is studied in Chapter 3. From this literature study, four benchmark cases of inefficient dynamics, shown in Figure 3.6, were identified, which indicate the typical conditions for the appearance of unstable flow regime. When the flow regime is unstable, densities increase and walking speeds decrease. Hence, when such flow regime occurs, the probability that the crowd experiences discomfort and potentially unsafe conditions rises. Thus, these benchmark cases are seen as relevant for prediction.

The scenario database is the first pillar of the method proposed in this research. To identify and build the scenarios, the framework proposed, shown in Chapter 4, includes three main stages. Firstly, through an analysis of the supply and the demand of the event, the specific areas and times at which the crowd could face discomfort or threats to their safety are pinpointed. Secondly, the inefficient dynamics of the event are identified based on the known dynamics of the benchmark cases and supply and demand analysis performed. In Chapter 4, it was also argued that the conditions for which the observed dynamics do not lead to the appearance of inefficiencies must be included in the database. Hence, for the third step, to build the scenarios in the simulation environment, the concept of density levels is introduced. Density levels relate to the demand pattern, that is, the total amount of agents generated per time period, and is responsible for making the distinction between the scenarios for which the relative usage of the infrastructure remains the same, but the higher demand induces the unstable flow regimes to occur. Together, these inefficiencies and their corresponding density levels form the scenario database to be used for the prediction.

The second pillar of the method is the real-time scenario selection system, which in this research is based on a multi-objective optimization approach. As discussed in Chapter 5, to apply the multi-objective optimization for prediction, the concept of crowd states as introduced in Section 3.1 is used. This concept, commonly used in system theory, refers to the the metrics which contain the key information expected to describe the state of the crowd at a certain time instant. For formulating the multi-objective problem of this research, the trajectory data from the simulation of the scenarios is converted into the time series of crowd state metrics, derived at discrete locations on the event terrain. This enables the application of the multi-objective optimization approach. Each individual objective that composes the multi-objective problem is formulated when the real state metrics are compared to its corresponding field of the state vector of each scenario and time period in the database. This real states are derived from observing the real crowd and from knowledge about future disturbances into the system over the prediction horizon. The prediction is thus the scenario and time period in the database for which the states most closely correspond to the real states.

The proposed method is validated in the analyses performed in Chapter 7. The first analysis, related to the sensor data perturbations, indicated that the system is more sensitive to an underestimation of the state metrics than an overestimation, due to the boundaries created by the scenarios on the high density level. Also, the analysis showed the importance of assessing the frequency of particular states in the database. This frequency relates to both the density level and the areas where inefficiencies occur. It can influence the scenario selection process by decreasing the variance of the objective function values of scenarios best ranked by the selection algorithm. This lower variance can in turn mislead the prediction by increasing the chance that a distinct scenario for which the current state is similar to the real states is chosen, but for which the future developments are not as these can arise from distinct conceptual scenarios. Especially when the data is perturbed, the likelihood that distinct scenarios would be selected increases.

In Chapter 7, the influence of the choices regarding the individual objectives used by selection algorithm were also analysed. It was found that the sub-selection of areas and state metrics can both improve and deteriorate the performance, and the results are dependent on the uniqueness of the scenarios these individual objectives can define. The sub-selection of

Blocks to focus on the areas where the high densities arise indicate that if smaller-scale models for the different areas of the infrastructure where built, the prediction could still be performed through this method. This would not only save time and effort in building the scenarios, but also provide more control over the simulation process.

To conclude, the discussions above highlight two aspects of the forecasting method proposed in this research. These relate to the individual choices when designing the database and applying the scenario selection system. The first aspect relates to the choices regarding the scenario database. One should develop the database for the specific situations and dynamics that can occur on the different areas of the event environment for which prediction would be desirable. Identifying such situations and corresponding dynamics narrows down the scenario space to a representative set. The differentiation between the scenarios for which discomfort and unsafe conditions arise from those that such conditions do not occur is then simply done based on the demand pattern.

Regarding the application of the scenario selection system, the frequency of particular states in the different areas of the environment is highlighted. The overlap between similar states in these different areas arising from different scenarios can influence the prediction by reducing the variance of the lower-bound of the objective function values. This in turn facilitates that, if the data is perturbed, the scenario selected is incorrect. Building small-scale models of the different areas of the environment could assist differentiating between these. Also, reducing the number of conflicting objectives, by sub-selecting areas or state metrics, to a set that can be specific for a particular observed behavior can also improve the prediction.

8.2. Discussions

This section discusses the limitations identified for this research. Firstly, aspects of the development of the scenario database are discussed in subsection 8.2.1. Regarding the scenario selection system, the discussions of subsection 8.2.2 focus on the state metrics and formulation of individual objectives. Finally, subsection 8.2.3 discusses the results obtained from the analyses performed.

8.2.1. Discussion on Scenario Database

From the steps of the scenario development framework, multiple decisions need to be made for the application of these steps. The limitations regarding the choices for the identification of the inefficient dynamics, the density levels and the simulation of the scenarios are discussed in this section.

Inefficient Dynamics

This research assumes that the scenarios to be included in the database are based on the four benchmark cases of inefficient dynamics. This limits the prediction to the situations defined by these four cases. As the benchmark cases are derived from literature, it is expected that these are able to capture a relevant set of scenarios that can occur for which prediction might be needed. However, as the set of scenarios developed is not compared to real data from the event, this research cannot determine the realism of the scenarios developed based on this method. Also, it is not possible to determine whether the method can be generalized for mass events. This would required applying it for different cases and identifying the cases for which it is applicable, but especially for the ones that it fails.

Density Levels

The concept of density levels as introduced in this research is key for differentiating the scenarios for which the inefficiency occurs from those that it does not. In this research, the step size to increase the density level from the minimum to maximum of each scenario is constant, that is, the density levels are equally distant. Based on the analysis of the results, the density level can play a significant role when the real data is perturbed. For instance, if the real data from the sensors is underestimated, the scenario selection is often a lower density level than it is actually observed in the environment. Given this finding, one could argue that, the larger the density, the more relevant it is to perform accurate predictions. This would mean that the step size between density levels on high density conditions should be smaller than those on the lower density conditions. This wider range of options of higher densities on the environment could improve the prediction if one considers that the real data from the sensors has perturbations.

Simulation

One aspect of the development of the scenarios is the fact that many simulations are run prior to the event for developing the scenario database. For very large and complex event areas, or for events that occur in multiple days in which different infrastructure and activities occur on these days, the scenario database can be significantly large. Hence, the influence of the size of the event area, and complexity of the environment, on the feasibility of the application of the method needs to be further studied. One topic to be addressed is the size of the model used for the development of the scenarios. In this research, the computation time of the simulation increases as the entire environment is simulated for all scenarios. However, given that the scenarios focus on specific areas, one could argue that only simulating those areas would be sufficient for performing the prediction. This can be supported by the insights from the results that show that improvements on the performance of the system can be achieved when a subselection of areas is used. These insights, however, are limited, and more research is needed to get a better picture of the application of the method when the scenarios have different sizes.

8.2.2. Discussion on Scenario Selection System

The metrics and areas where these metrics are derived are some of the key decisions regarding the development of the scenario selection system. Following, the formulation of the individual objectives also plays a major role in the performance of the system. Hence, the limitations regarding these choices are discussed in this section.

Crowd State Metrics & Event Blocks

The choice of state metrics in this research focuses on the mesoscopic and macroscopic metrics, specifically on metrics which can be derived by sensors commonly used in crowd monitoring of mass events. The results have shown that the performance of the prediction can be highly sensitivity to the metrics used, and the uniqueness of the states these can define. This raises the question if the results of the prediction would be different if additional or distinct metrics were used. These could be metrics from sensors, or even domain knowledge added by crowd managers. From the sensors, these could include for instance other parameters of the travel time distribution, or even metrics on a distinct level of aggregation. Currently, GPS trackers can provide data on microscopic level. However, one has to keep in mind the issues with penetration rate as well as the ability of simulation models to capture the behavior on this levels.

The Event Blocks, or the areas of the environment where the state metrics are derived from, are also seen as a topic for further study. In this research, these study of these Blocks is limited to the sub-selection of areas, that is the number of areas used for the prediction, and to a lesser extent to the location of these Blocks. However, one could argue that these specific locations could be chosen such that the performance of the selection system is improved. As stated in subsection 5.3.1, measurements close to entry locations can provide indications of the travel demand flows, but not so much on route choice. Thus, further insights into the effect of the specific locations in which the environment is discretized could provide valuable information for the application of the method, and choice of state metrics to be derived for these.

Individual Objectives

The individual objectives used in this research are formulated by the comparison of the metrics based on the GoF measures, specifically the Squared Error. The choice of this measure implies that the comparison is done based on the individual data points of the time series of the state metrics. Hence, the information from the time series is only retrieved for the metrics for which the current state history is derived. This raises the question if the results would change if the time series of the metrics were compared, instead of the discrete data points. As discussed in subsection 5.4.1, this can be done by using GoF measures such as the RMSE, or metamodels for describing the time series, which can be further compared by statistical tests for the equality of their coefficients. Testing the differences obtained from using these more sophisticated measures can be fruitful to understanding the robustness of the method further.

8.2.3. Discussion on Forecasting Analyses

The results of the application of the method obtained in this research are not focus on the realism of the prediction, as no real data from SAIL is used for the analysis. Hence, it is not yet possible to say the validity of the prediction through this method for real-world application. However, the analyses provide useful insights into the strengths and weaknesses of the method. These can be further explored with real data, to assess whether the results would remain the same, or if differences occur. For instance, studying the effect of selecting a set of state metrics for the prediction, and the specific influence of each individual metric.

8.3. Recommendations

Recommendations for future research and practical applications of the method are discussed in this section. These are based on the knowledge acquired during the development of this research, the findings obtained, and the limitations identified. The recommendations for practice are presented in subsection 8.3.1, while the recommendations for science are shown in subsection 8.3.2.

8.3.1. Recommendations to Practice

Based on the knowledge acquired while developing this research, the following recommendations can be made for practice:

- From identifying the scenarios based on the scenario development framework, and simulating these for developing the database, improved insights are obtained about the potentially dangerous conditions prior to the event. This can assist in the preparation of plans for managing the crowd, as well as in the study of the environment.
- In this research, it was assumed that the sensor network and the types of sensor are defined beforehand, by the event organization. However, the sensor network can be defined by the scenarios identified instead, as the scenarios highlight the specific areas and times where high densities can potentially occur. This can improve the performance of the scenario selection system as well as the optimize the usage of the sensors for monitoring purposes.
- Studying the crowd state database prior to applying the method can assist in defining the settings of the scenario selection system which can best differentiate between specific scenarios in real-time. By understanding the database, the sub-selection of metrics and Event Blocks can be done to optimize the operation of system, using also critical knowledge about the crowd which might not be obtained from the sensors.

8.3.2. Recommendations to Science

Based on the knowledge acquired while developing this research, the following recommendations can be made for science:

- Recommendations regarding scenario database:
  - The scenario database in this research is developed based on the concept of the benchmark cases of inefficient dynamics. An interesting research topic would be to test the validity of the scenarios developed through this method with actual data from mass events. This can be done by developing the scenarios for specific events through this method, and comparing these to the scenarios that actually occurred. The analyses relate to the specific dynamics that occur, as well as how well these are represented by the simulation model's outputs.
  - Another interesting topic for research relates to the statistical analyses of the final states in the database, when the trajectory data from the simulations is converted

into the time series of state metrics. Research could assess the frequency of particular states, the sources of these similarities and the specific metrics, and quantify the effect of this frequency on the prediction.
  - The development of the database in this research uses all areas for all scenarios. The simulation model of the event is therefore very large and takes more time to run each scenario. An alternative to this approach could be to study how to develop smaller models, which focus on the areas of the environment which are specific for each particular scenario, and how to apply the system for such database.

- Recommendations regarding scenario selection system:
  - The state metrics and the Event Blocks have large influence on the results obtained. It would be interesting to study additional or distinct metrics to describe the state of the Blocks. For instance, distinct statistical measures which relate to the travel time distribution could facilitate the distinction between the scenarios, or other metrics which could be developed to describe the conditions over the routes.
  - Following from the recommendation above, it would also be interesting to research the effect of distinct combinations of Blocks and metrics on the prediction results. From the understanding of the states that occur in the database for the distinct scenarios, one could identify the specific combinations of metrics and Blocks which could facilitate the differentiation between particular scenarios.
  - A key aspect of the scenario selection system is the use of the real states derived from the sensors. In this research, these are only used as direct input for the prediction. It would be interesting to also measure these real states after the prediction, and compare them to the states predicted by the system. This data assimilation process could create a feedback loop to adapt the settings of the system. An adaptive system could for instance dynamically update the weights assigned to each metric given the measured error of these state metrics.

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V

APPENDICES

A

Discussions on Crowd Dynamics Theory

A.1 Influencing factors on pedestrians' choice behavior

The factors that influence pedestrians' choice behavior are more extensively discussed below. As it will be seen, some factors have been more widely discussed in literature than others. For instance, as route choice behavior of pedestrians has been more researched over the years, multiple elements have been identified which influence this behavior. On the other hand, there is a large gap in literature concerning choices such as arrival time and activity time. The factors discussed below aim at illustrating how distinct dynamics can occur on the event environment by simply considering the effect of these factors on the behavior of pedestrians.

A.1.1. Personal Factors

- *Age* → Age is factor proven to influence different aspects of the choice behavior of pedestrians. Regarding choices on the strategic level, Chang and Lu (2013) has shown that for the event studied by the authors, middle-aged (25-35) people prefer to arrive at least one hour before the event starts. In general, it can be expected that older people prefer to arrive closer to the time the event starts, as younger people often spend more time socializing with friends or doing other activities. Most studies on the effect of age on the choice behavior of pedestrians are related to the choice of route and walking speed. Regarding the former, it was found that seniors place a higher value on the safety of the route (Seneviratne, 1985). For the latter, it was found that average walking speeds decrease non-linearly as age increases (Duives, 2016).
- *Gender* → Similar to age, gender is a fact associated with changes on operational level decisions. Walking speeds of women are found to be lower than those of men (Duives, Daamen, & Hoogendoorn, 2014b).
- *Culture* → Although walking speeds have been found to be influenced by this factor, where on average Western countries have higher speeds than African and Asian countries (Duives, 2016), this factor is also expected to affect other levels of behavior. For instance, access mode choice is expected to be affected as people from different countries have been shown to have distinct mobility cultures (Buehler, 2011; Geis, 2019).

- *Familiarity* → This factor is mainly found in literature to be correlated to tactical level decisions (Bovy & Stern, 1990; Golledge, 1999). Route choice, unplanned activities as well as activity scheduling are all influenced by the familiarity of the visitors with the event environment. Familiar pedestrians tend to choose routes and activities that they know (Golledge, 1999). In the case of events which might occur in city centres, one can expect that, if a large amount of the event visitors are familiar with the area, the demand for different routes and activities can be estimated based on daily patterns.
- *Time spent* → This factor refers to the time a visitor spends at the event, and it can be related to both the time assigned to perform activities and the number of activities performed. A visitor who spends more time at the event can be expected not only to perform more activities (Iliadi, 2016), but also to spend more time performing activities due to a more relaxed behavior.
- *Group size* → The last personal influencing factor considered in this section relates to the groups. Several authors have highlighted that a considerable amount of pedestrians in events do not walk alone but in groups (Aveni, 1977; Coleman & James, 1961; Moussaïd et al., 2010). This percentage is up to 70% according to Moussaïd et al. (2010), where most frequent groups are composed of two to four members. Walking speeds of pedestrians were observed by the study to decrease linearly as group size increases.

A.1.2. Exogenous Factors

- *Surrounding environment* → Features of the environment, such as vegetation, presence of landmarks, canals and rivers, as well as lighting have all been shown to have attractive influence on pedestrians tactical level choices (Hill, 1982; Korthals & Steffen, 1988; Bovy & Stern, 1990). Due to the pleasantness of the routes where these elements are present, pedestrians are more likely to choose route with these elements, even when these are longer than other possible routes.
- *Width of paths* → Tactical level choices, especially route choice, are also influenced by the width of the paths as shown by different studies (Korthals & Steffen, 1988; Bovy & Stern, 1990; Guo & Loo, 2013). These studies state that wider paths have been shown to be attractive to pedestrians. The width referred to in this section might be of a corridor on the environment or even to a sidewalk, for events which occur in the city center for example.
- *Intersections or crossings* → The number of intersections or crossings also affects tactical level choices. However, unlike the two elements previously mentioned, this factor has been shown to influence pedestrians negatively. This means that pedestrians tend to avoid routes with a higher the number of intersections or crossings (Bovy & Stern, 1990; Guo & Loo, 2013).
- *Travel distance* → Although travel distance has been shown to influence pedestrians route choice, where pedestrians choose the shortest route between two activities (Borgers & Timmermans, 1986), this factor is also expected to influence unplanned activity choice. This is because a pedestrian can be considered to select an activity near its position if that activity can be performed in more than one location.
- *Number of attractions* → The number of attractions along a route or within an area of the environment is highly influential on pedestrians route and unplanned activities choice as shown by several studies (Bovy & Stern, 1990; Guo & Loo, 2013; Hoogendoorn & Bovy, 2004; Ton, 2014; Iliadi, 2016). These attractions can be seen as stimulation of the envi-

ronment, and especially in large-scale events which naturally concentrate multiple attractions in distinct areas, pedestrians can be considered triggered by the environment in their choices influenced by this factor.

- *Weather condition* → As many large-scale events happen outdoors, it is expected that the weather condition affects their behavior on different levels. On the operational level, pedestrians have been shown to increase their walking speeds as the weather becomes more uncomfortable (Knoblauch et al., 1996). This means that in dry weather, visitors walk slower than in rainy weather conditions. Besides the walking speed, the weather condition also changes pedestrians' route and activity choices (Daamen, 2004; Ton, 2014; Iliadi, 2016; Bovy & Stern, 1990). Routes with weather protection are chosen over other routes when the weather is rainy. Also, in uncomfortable weather conditions, visitors strategic level behavior might change. Visitors might decide to spend less time at the event and thus their arrival time changes, but they might also decide not to go to the event at all, leading to less demand. The choice of mode of transport to access the event might be different as visitors are likely to prefer private modes due to the weather conditions. Regarding temperature, the effect varies as it seems to be dependent on the amount of time pedestrians are exposed to such temperature (Duives, 2016). It can be expected that, if the weather is too warm, visitors that are exposed to it for longer are more likely to start preferring routes with weather protection.
- *Day & time* → The day of the week and time of the day has been shown to influence tactical level pedestrian behavior (Seneviratne, 1985; Ton, 2014; Iliadi, 2016). The activities that pedestrians choose might be different depending on the day of the week and time of day of the event. For instance, people usually have lunch at around midday so visitors are expected to be at locations that serve food at around that time. In the case of events, this factor can influence not only tactical level but also strategic level decisions. For instance, it can be expected that the visitors arrive closer to the event time for events that occur on weekdays, as they are often departing directly from their work locations. Also, for events that occur on multiple days, the weekend demand is likely to be higher than the weekday demand. This pattern is shown in the study of Iliadi (2016), where the distributions of trips on Friday, Saturday and Sunday is higher than on Thursday. The author also statistically proves that there is a relationship between the time of the day of the event and tactical level choices such as route choice.
- *Access / Egress facilities* → This factor influences the strategic level choices of pedestrians (i.e. arrival time and access mode). For events located in central areas, where access is facilitated by many modes of transport available, pedestrians are likely to choose based on their personal preferences (e.g. cultural aspects), or simply based on the mode's capacity and service frequency. This in turn influences their arrival time since it is conditioned to the mode's timetable.
- *Event schedule* → The key decisions affected by this element are the arrival time and planned activities. As shown by Zomer (2014), the type of performance (e.g. spectacular, nice) and the usage of information before the event can highly influence the activities visitors plan to perform. This in turn influences how visitors schedule their activities, thus by influencing the planned activities, the event schedule can indirectly define likely sequences of activities visitors are going to perform during the event.
- *Event's land use* → Events can occur in multiple locations. Although these can be fully dedicated for the event organization, large-scale events often make use of existing infrastructure of cities' public areas. Hence, there might be areas of the environment that event visitors might interact with pedestrians which are not visiting the event, and thus

might have different trip purposes and therefore distinct behavior. Visitors might try to avoid such areas due to the conflicts, thus the land use of the event is expected to influence visitors' route choices and unplanned activities.

- *Crowd management* → During an event, crowd management measures aim at providing information to visitors regarding, among others, the event's main attractions, locations of these attractions, route crowdedness and sometimes even travel times areas of the event environment. As shown by (Zomer, 2014), such information might highly influence route choice of pedestrians during events. The goals of these measures can be to distributed flows over the network or also to limit the inflow into certain areas if necessary (Galama, 2016). The effect of these measures on the development of scenarios are many, as not only different measures might be considered for distinct scenarios, but also the compliance with the information given might change.

A.2 Crowd Phenomena Description

The Layered Crowd Disaster Model proposed by Wieringa (2015) illustrates multiple phenomena which were observed in real crowds. In the model, these are connected to the different flow conditions these phenomena are expected to appear. Although prediction of crowd disaster is not in the scope of this research, the phenomena which relate to development of the states (e.g. flow conditions) towards a crowd disaster can provide key insights for dynamics of interest for prediction. Therefore, these are detailed in this section.

A.2.1. Phenomena Description

The phenomena in the Crowd Disaster Model are referred to as self-organization phenomena due to the spontaneous occurrence of these, which arise simply from the interactions between the pedestrians with other pedestrians and the environment, with no external influence (Helbing & Johansson, 2010). The first three phenomena relate to the free flow conditions, and these are still considered efficient phenomena as they can improve the throughput as it will be discussed below.

Lane Formation Diagonal Formation In free flow state, these two phenomena relate to the appearance of lanes for different directions of movement. While lane formation occurs in bidirectional corridors, diagonal formation has been observed at crossing flows (Helbing et al., 2001). These lanes appear due to frequent interactions between the pedestrians in mixed streams, which move pedestrians a little aside every time an interaction occurs in order to pass each other. This side-wards movement tends to separate oppositely moving pedestrians, and as pedestrians in uniform lanes have rare and weak interactions, these lanes tend to not break easily (Helbing et al., 2001). The formation of these lanes can reduce the capacity loss in bidirectional flows (Hoogendoorn & Bovy, 2003).

Zipper-Effect This phenomena relates to the behavior observed when pedestrians walk diagonally in front of each other, that is, when they show a lateral displacement, so that the space directly in front of their feet is still empty (Hoogendoorn & Daamen, 2005). This can improve the capacity as the lanes formed can become narrower, thus allowing for more pedestrians to cross per time (Hoogendoorn & Daamen, 2005). While the formation of lanes is a phenomena already established in literature, the existence of the zipper-effect phenomena is still a topic for further research.

When the efficient self-organization develops to inefficient self-organization, the neat flow patterns become dynamic, and the phenomena presented in subsection 3.3.1 start appearing. As it can be seen in Figure 3.5, the appearance of these phenomena can lead to a blockade or the activation of a bottleneck. When this occurs, the decreasing throughput and increasing density levels can lead to the phenomena described under the crowd turbulence flow regime. Due to increased stress and discomfort, the behavior of the pedestrians can become more aggressive. However, due to the limited possibility to move, the following phenomena can be occur:

Pushing As the name suggests, this phenomena relates to the intentional pushing behavior of pedestrians when these experience long waiting times with no clear reason for these delays, and the discomfort for being in too high density conditions (Helbing & Mukerji, 2012). Although it is argued that this pushing behavior is intentional, Helbing and Mukerji (2012) state that in fact the situation the pedestrians are in when these start pushing happens unintentionally, simply due to the physical interaction forces whenever density increases.

Stampede Relates to the situation when many people move uncontrollably and quickly towards the same direction at the same time (Wieringa, 2015). Similar to herding, stampede can be caused by pedestrians presenting a following behavior. However, the time frame when this happens when considering the stampede is much shorter, and so the increase in the density can be expected to be much quicker, putting the crowd at a higher risk of unsafe conditions.

Craze A craze relates to the competition for scarce places (Wieringa, 2015). This can be for situations when the pedestrians at a concert attempt to be closer to the stage, or in evacuation conditions when pedestrians compete for the exit doors. This competing behavior and high densities can generate turbulent flows.

All of the above phenomena can lead to crowd turbulence. The turbulence state has been illustrated by Helbing et al. (2007) and is shown in Figure A.1. The blue line is fundamental diagram proposed by Weidmann (1992), and the red line indicates the observed flow density relations derived from an event when crowd turbulence occurred. As stated by Helbing et al. (2007), this turbulence results from a sequence of instabilities in the flow pattern, and is identified when people are so densely packed that they move involuntarily. It can seen in the figure that the stage when crowd turbulence could start occurring would be around critical densities, but unlike the fundamental diagram of Weidmann (1992), the density appears

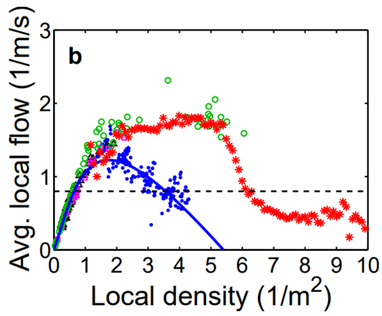

Figure A.1: Fundamental Diagram illustrating Crowd Turbulence (Source: Helbing et al. (2007))

to increase much further, and flows only start decreasing later, possibly due to this involuntarily movement of the crowd in turbulent state.

When a crowd disaster occurs, that is, when the conditions on the environment can cause injuries or death of pedestrians, the accumulation and high densities thereof lead to the appearance of the following phenomena:

Crush Helbing and Mukerji (2012) refers to crush as the phenomena where people are crushed by a physical bottleneck at its narrowest point.

Trampling Trampling refers to the situation when falling pedestrians are being walked over (Helbing & Mukerji, 2012).

Quake/Wave Wieringa (2015) defines quake as the situation when the pedestrians are experiencing pushing behavior which are not intentional but arise from the fluctuating forces in the crowd.

A.2.2. Reflection on the application for this research

The identification of the inefficient self-organization on the event environment leads to the assumption that unstable flow conditions can start appearing. As previously mentioned, for such flow conditions the likelihood that the crowd might experience discomfort or that unsafe density levels might arise increases. Given the objective of the prediction method developed in this research, which is that of providing insights to crowd managers regarding the comfort and safety of the crowd, the identification of these phenomena can provide key inputs to the scenarios that can occur for which crowd management would be necessary.

The chronological order of the layered crowd disaster model indicates also that the early identification of inefficient self-organization can allow for the avoidance of grid lock situations. As it is clear that not all possible conditions and dynamics can be captured in the scenario database, the phenomena which indicate the unstable flow conditions can provide key insights into which dynamics are relevant for prediction. For instance, from identifying the increasing interest and attraction for a specific activity, one can anticipate higher densities in the area where the activity is located, and possibly higher flows in the routes towards this activity.

Although the phenomena in the unstable flow layer can all represent the dynamics for which prediction would be desirable, it is considered that in event terrain, the faster is slower effect can be rarely expected. This is because of the locations where this phenomena occurs (narrow bottlenecks such as doors or gates). In event terrains, the either do not exist, for instance in events in the urban areas, or, in the case of gates, are used mainly for coordinating the entrance of pedestrians into the terrain, thus no competing behavior is expected. Similarly, slow moving bottlenecks which significantly hamper the flows are not often expected in event terrains. This is not only due to the size of these terrains, and therefore space for overtaking, but also because often group compositions are small, of two to four members according to Moussaïd et al. (2010).

B

Discussions on Scenario Development Framework

B.1 Inputs and Parameters of Simulation Models

The table below contains an overview of typical inputs and parameters required to build a simulation model. The description of each input and parameter is provided as it can be known by other names in different simulation tools. Also, the description aims at giving insights into how each input affects the model's operations and thus the crowd dynamics.

Table B.1: Overview of inputs and parameters of the different simulation modules

Module	Input	Parameter	Description
Infrastructure & Services	Geometry of infrastructure		Defines the physical boundaries / dimensions of activity and functional spaces, obstacles, walls, walkable areas as well as special infrastructure elements such as rain shelters, gates and doors.
	Movable infrastructure		Defines the location of obstacles that can change position (e.g. barriers).
	Functional spaces		Assigns physical elements that are not activities a function (e.g. queuing areas)
	Activity spaces		Defines the type of activity performed in each physical location for which the boundaries where drawn when building the geometry. Also, considers the behavior in each type of activity (e.g. standing, sitting).
	Activity time		Time an agent takes to perform an activity.
	Transport facilities		Defines which physical elements correspond to facilities for access and egress transport modes. The location and capacity of these is considered.
	PT timetable		Defines the time each public transport facility will generate or terminate agents.
	No. of queues per activity		Defines which queues are to be considered for an agent that wants to go to an activity that requires queuing.
Agent Generator	Demand pattern		Defines the number of agents generated by the model per time interval.
	No. of agents per route		Proportion of the total number of agents generated per interval assigned to each route.
	Max. number of agents		Maximum number of agents created by a generator.
	Transport generator		Connects a certain generator with a transport mode (e.g. agents are created according to the timetable of a public transport service)
	Max. desired speed		Maximum speed an agent will walk on when its walking freely.
	Agent radius		Parameter that defines the area an agent occupies in the model.
	Activity group		For a certain activity type, this input defines the sub-group of that type to be considered (e.g. from the ’commercial activities’ type, sub-groups can be food places or shopping areas).

Table B.1 – continued on next page

Table B.1: Overview of inputs and parameters of the different simulation modules

Module	Input	Parameter	Description
Activity Scheduling	Activity conditioning		Conditions that agents need to meet to be assigned to an activity (pre-), or conditions checked when an agent arrives at an activity (post-condition).
	Location distribution		For a certain activity group, it is possible that multiple locations can be used to perform it. The location distribution determines how agents are distributed between these.
	Revising allowed		Determines whether an agent is allowed to revisit certain activities.
	No. of activities per route		Defines the maximum number of activities to be performed by an agent assigned to a certain route.
	Sequence of activities		Determines the order in which activities must be performed.
Routing		Routing method	Method used by an agent when planning its route from its origin to its destination (e.g. least effort, shortest distance).
		Use densities for routing	When the least effort routing method is used, if this parameter is switched on it indicates that an agent will try to avoid crowded areas.
		Preferred clearance	The minimum distance an agent prefers to keep between itself and obstacles when determining a path through a corridor (in meters).
		Max. shortcut distance	Maximum distance from the current position of the agent that an attraction point can be, whereby $\leq= 0$ means no restriction (in meters).
		Side clearance factor	Factor an agent uses to plan its route in relation to the corridor's wall.
		Side pref. update factor	Determines how fast the indicative route of an agent converges towards its current position.
Movement		Min. desired speed	Minimum desired speed of an agent. This functions as a threshold as agents stop walking if their speeds are below this minimum and only start walking again when they can move at speeds higher than or equal to this threshold.
		Relaxation time	Parameter that defines how strongly an agent reacts to deviations from its desired velocity.
		Viewing angle	Angle that defines agent's field of view.

Table B.1 – continued on next page

Table B.1: Overview of inputs and parameters of the different simulation modules

Module	Input	Parameter	Description
		FoV avoidance range	Maximum distance in the FoV used by agent's when finding possible collisions with obstacles and other agents.
		Avoidance preference	Bias that determines the preferred side of passing an obstacle (e.g. left or right).
		Personal distance	Desired distance an agent wants to keep between itself and other agents.

B.2 Example Scenario Development Framework Application

This section introduces a small-scale example of the application of the development of the scenarios through the scenario development framework shown in Figure 4.5. The fictitious event terrain created for illustrative purposes is shown in Figure B.1. It can be seen that there is a music stage, illustrated in blue in the figure, five commercial facilities, shown in orange, and one toilet area. The arrows on the corridors indicate that there is one entry located on the right, and one exit located on the left. Thus, only unidirectional flows are expected along the entry and exit corridors.

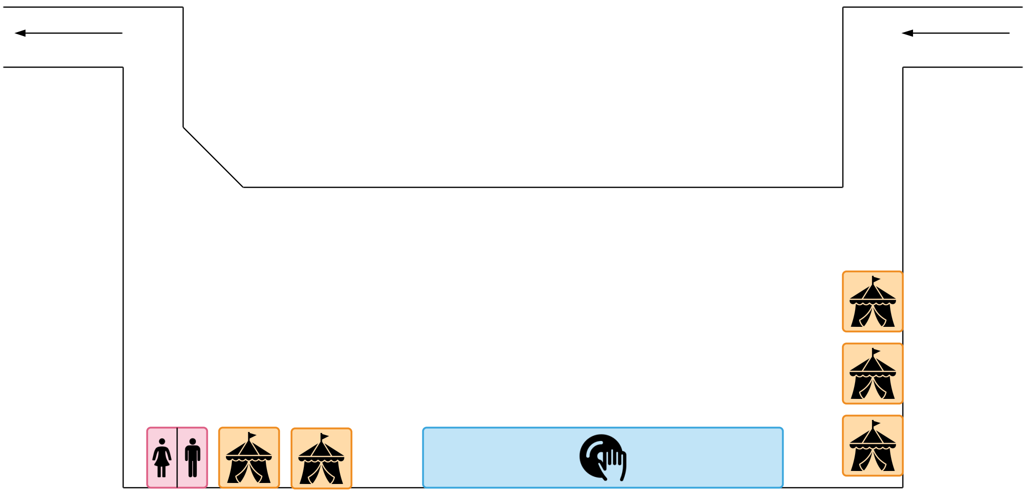

Figure B.1: Small Scale Example - Terrain

The event dynamics is analysed for this terrain based on the supply and demand checklists presented in subsection 4.2.2. From the supply checklist, only questions 1 and 3 are answered with yes for the above terrain. Question 1 relates to the locations where the width of the path gets narrow, which occurs by the entrance to the exit corridor. Meanwhile, question 3 relates to the concentration of activities in the same area. In the event terrain shown in Figure B.1, there are two areas which concentrate activities, on the right-hand side, where three commercial facilities exit, and on the left-hand side, where there are two commercial facilities and one toilet. From the demand checklist, questions 1 and 4 are answered with yes. A demand peak can be expected at the end of a performance, where there might be a large amount of visitors moving towards the exit, clogging the bottleneck near the exit. Further, based on question 4, one can expect that the most attractive activities are the ones near the stage. As the main attraction of that event is to watch the music concert, visitors are more likely to perform activities on the commercial facilities on the right-hand side, as they can also watch the performances from there. Hence, the three areas highlighted by the questions of the checklists are shown in Figure B.2.

The level of risk of these different areas is estimated qualitatively based on the exposure to high densities. From the three areas, only the physical bottleneck at the exit, and the area by the stage and commercial activities on the right-hand side are expected to have high densities for extensive periods. This is because, as previously mentioned, the commercial facilities on

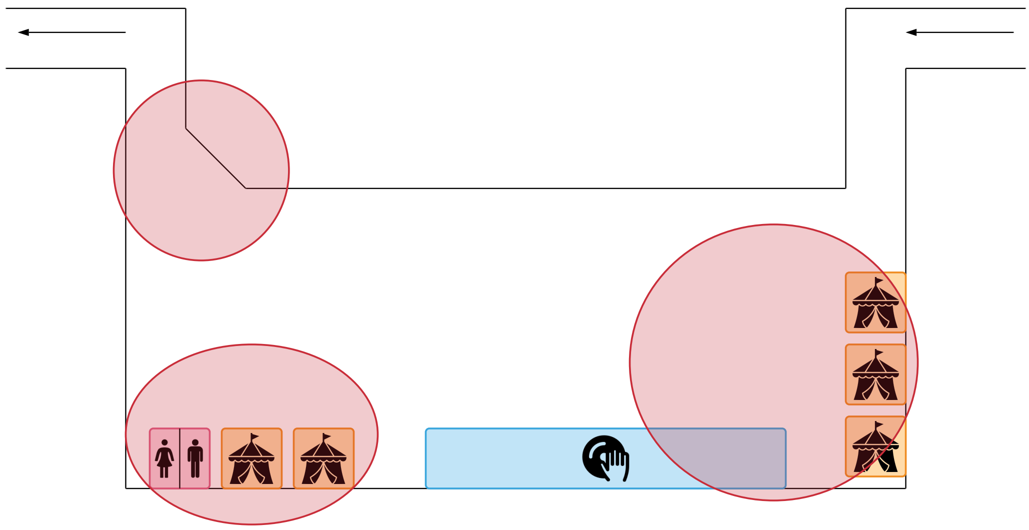

Figure B.2: Small Scale Example - Checklist highlights

the left-hand side are likely to receive lower demand than the ones on the right-hand side. Besides, there is more available space for the visitors who go to those activities. On the other hand, as the activities on the right-hand side are near the stage, visitors are more likely to stop at the area to watch the concert, reducing the space available for walking and queuing for the commercial activities. Hence, two inefficient dynamics are identified: (1) a physical bottleneck scenario by the exit, and (2) an uneven distribution over the network at the area by the stage and commercial facilities on the right-hand side. These are illustrated in Figure B.3.

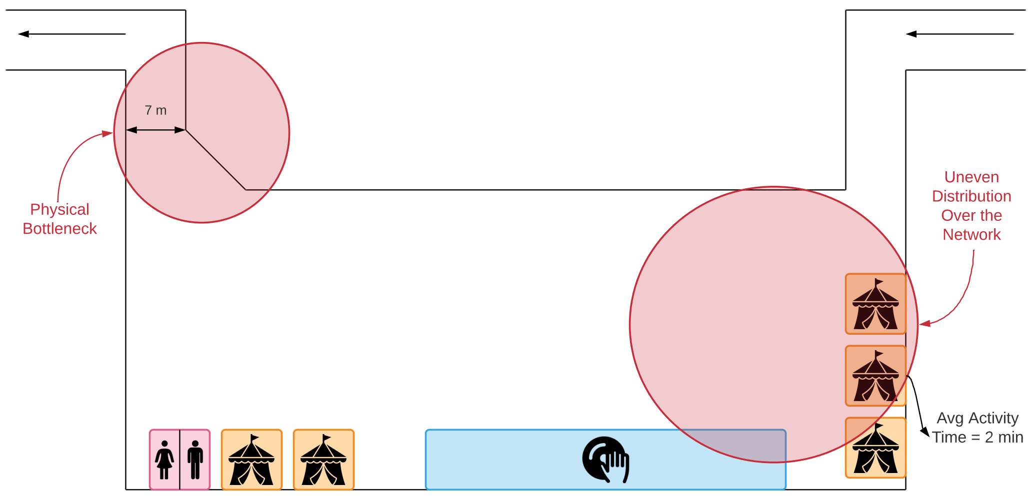

Figure B.3: Small Scale Example - Risk Assessment & Inefficiency Identification

For these two inefficient dynamics, the start point for estimating the density levels is defined from a static capacity calculation. For the physical bottleneck, the width of the narrowest point of the path is used for this calculation, as well as the capacity value of a fundamental diagram. The maximum flow of pedestrians according to the FD proposed by Weidmann (1992) is $1.225 Ped/m/s$. Hence, the point of departure of the density level for the physical bottleneck scenario is a total demand of $30870 Ped/h$ $((1.225 \times 7) \times 60 \times 60)$.

Regarding the uneven distribution over the network scenario, the point of departure for the density level relates to the capacity of the activities, which can indicate when queues might start arising. The capacity of activities can be calculated based on the activity time. Given that the activity time of each facility is $2min/Ped$, the capacity of each commercial activity is $30Ped/h$. In total, the capacity of the activities on the right-hand side is thus $90Ped/h$. These capacity values are calculated so that there is a starting point for the simulations, an initial reference input to start up the model. As the simulation is dynamic, the process to define the additional density levels is interactive, that is, by adjusting the demand and observing the development of the high density regions.

C

Discussions on Scenario Selection Framework

C.1 Crowd monitoring systems and capabilities

In the scenario selection framework, a key element is the real pedestrian traffic data retrieved from crowd monitoring sensors. From these, the key inputs to the scenario selection system proposed in this thesis are derived. Below, different types of sensors are presented and their capabilities in retrieving distinct crowd state metrics are discussed.

- *Video Imaging/CCTV* → Cameras mounted over the environment areas provide video imaging of the crowd. The system itself is relatively expensive, but is one of the most commonly seen and most accurate methods for counting pedestrians. By applying image processing techniques, these system can achieve an accuracy up to 98% on flows up to 2200 ped/h (Baelde, 2016). From these systems, local measurements can be captured, which is important to assist in getting more detailed information on the condition of bottlenecks and heterogeneity between pedestrians (Daamen et al., 2016). Studies have derived pedestrians' flows patterns from these sensors, and they can also assist in the derivation of densities and other state variables. As these are not able to identify the identity of pedestrians, tracking is not possible with these type of sensors (Duives, 2016).
- *Infrared Sensor* → Similarly to the video imaging, infrared sensors need to be mounted and are thus also less flexible. The state variables this sensor collects is also similar to the video cameras (e.g. flows), as these also are not able to identify pedestrians' identities. However, the accuracy and coverage of these sensors is lower than the cameras, especially in high density situations where, as shown by (Kerridge et al., 2004), the detection rate decreases if compared to low density situations. Both infrared and counting cameras' performances are dependent on the environment, light and weather conditions (Duives, 2016).
- *Wi-Fi & Bluetooth* → Although these sensors also need to be mounted, given that they can be simply attached to existing infrastructure elements they are more flexible than the two previously discussed ones. From Wi-Fi and bluetooth sensors, densities, travel times and route splits can be obtained (Daamen et al., 2016). However, in order to have meaningful values of the measurements for the entire crowd, the penetration rate of

these systems needs to be defined, often estimated from other sensors such as video cameras. The range of these sensors should not overlap, as this would mislead the results given that the same device could be detected in multiple sensors without necessarily moving (Baelde, 2016). Also, as these sensor detect the personal mobile devices of the pedestrians, the raw data collected need to be anonymised before sending to the server (Daamen et al., 2016).

- *GPS* → GPS trackers are portable devices which track the position of its carriers while they walk through the environment. Similar to Wi-Fi and bluetooth sensors, these trackers can be used to derive route splits, however the level of detail in the route information is higher for these trackers (Daamen et al., 2016). The penetration rate is also a required parameter for using the GPS data. This rate is often much lower than that of Wi-Fi and bluetooth sensors, as visitors to the event must be willing to carry the trackers, and since a tracker needs to be provided per visitor, to achieve a high penetration rate in a crowd many trackers would be necessary. Also, as discussed in the study of Daamen et al. (2016), real-time data synchronization from trackers can be problematic given the dependence on good communication between the trackers and the server.
- *Stewards* → Stewards are either responsible for counting people manually or for working at the event area, sometimes walking in the middle of the crowd to evaluate the states. Problems might arise due to the dependence on people's perception of the environment. Different perceptions might lead to different qualitative state estimates by different stewards for the same crowd conditions. Also, as a long-term solution having stewards performing the counts can be particularly expensive, and quantitative data from these counts might contain errors caused by cases of missed or duplicated counting (Baelde, 2016).
- *Airborne system (UAV)* → The cameras attached to airborne systems collects similar data to those captured by video cameras, with the advantage that these systems are not spatially-fixed. However, these systems give less information about each individual within a frame (Duives, 2012). Besides, due to the risk of this equipment falling and hurting visitors, these are often prohibited or only allowed within a minimum distance of the event boundaries.
- *Social Media* → Social media applications such as Twitter and Instagram have been shown to also contribute to the monitoring of crowds during large-scale events. From these applications, it is possible to estimate the number of people or even evaluate the emotion of the crowd on different areas of the environment. Also, these systems can be used to communicate with the crowd during the event by informing visitors of changes in schedule or crowding in areas (Duives, 2016). Often, only qualitative and incomplete data can be retrieved for crowd management usage. This is either because only a sub-sample of the population uses social media at the event, or because the information from these comes from inside the crowd, thus not fully capturing the crowd states around the area.

D

Discussions on Application of the Frameworks

D.1 Discussion on Simulation Model's Behavior Validity

The first point of discussion is regarding the route choice algorithm. From the two options available in PD (i.e. shortest path and least-effort), studies in pedestrians' route following behavior affirm that the least-effort approach is more representative of real pedestrian behavior (Shepherd et al., 2010). The following discussions on this section are regarding the collision avoidance algorithm.

In the study of Duives et al. (2013), a review of crowd simulation models and their capabilities in representing crowd movements is performed. Multiple aspects are addressed by the authors for the distinct models they assess, such as the applicability of the model in terms of computational burden, or even the possibility to model self-organizing movement. Of these, the aspect discussed in this research relate to the motions that frequently occur during crowd movements. This is considered more relevant than the other aspects for the proposed application given that its valid representation can most considerably affect the prediction results, as discussed in Chapter 4. For instance, models that do not validly reproduce the interaction forces between agents and the boundaries of the environment, are more likely to yield unrealistic throughput, either by under or overestimation. This can be critical if one considers that, in the case of a overestimation, it can result in the model not predicting the appearance of possible bottlenecks.

The selected motions from the ones proposed by Duives et al. (2013), given the application for the study area of SAIL, are the unidirectional, bidirectional and crossing flows, as well as the entering and exiting movements, typical of bottlenecks. Based on the criteria developed by the authors, the entering and exiting movement can be partially modelled by the velocity-based model developed by Moussaïd et al. (2011) implemented in PD. Similar to most of the models reviewed by the authors in their study (Duives et al., 2013), exiting behavior is considered poorly modelled by this velocity-based model. This is because interpersonal repulsive forces are not included, so the widening of the wedge at the exit is not realistically simulated. Regarding the unidirectional, bidirectional and crossing flow cases, these can be modelled by the velocity-based model implemented in PD. However, a remark is made here regarding the validity for multi-directional movements. Although the model is able to represent that behavior, similar to other microscopic models which represent the interaction forces between agents, the throughput achieved before congestion starts appearing is often lower than in reality. This is also highlighted by the study of Sparnaaij et al. (2019), which compared the model's output in bidirectional scenarios under high-density conditions with empirical data and found that, although the model is able to reproduce the throughput, a specific set of parameters is needed. One example is the reduction of the agent's radius if compared to the value considered valid for other types of movement.

When avoiding obstacles in high-density conditions, pedestrians are observed to rotate their bodies or even walk sideways (Yamamoto et al., 2019), thus providing more space for a larger number of pedestrians to cross the same width. As more research is needed in this rotational behavior of pedestrians, to the author's knowledge, this not yet implemented in any commercial simulation tools. Thus, when formulating the scenarios for the application of the method, attention needs to be paid to the validity of the prediction in bidirectional sections of the infrastructure. Furthermore, in the sections of the infrastructure where bidirectional flows are expected to play a minor role on the development of the states of interest, these need to be avoided in the simulation.

D.2 Identification of Inefficient Dynamics - SAIL

This section presents the reasoning behind the identification of each scenario under each benchmark of inefficient dynamics. These scenarios are briefly described in Table 6.3 and further explained below.

D.2.1. Physical Bottlenecks Inefficient Dynamics

The first physical bottleneck identified is located at the Piet Heinkade, where the total width of the path (about 9 meters) is split into two narrow lanes by an obstacle obstructing the movement in that location. Upstream the bottleneck (from west to east), the flows are bidirectional, whereas downstream of it it is expected that the two lanes are used for different directions. The lane on the right (closer to the water) is anticipated to be used by the flows going towards the Veemkade, and the left lane for the opposite flows. If the flow towards the Veemkade exceeds the capacity of that bottleneck, and queues start forming upstream, the flow from the other direction is also likely to get hampered.

The second physical bottleneck is at the west-end of the Veemkade. There are two distinct dynamics of this bottleneck which are likely to cause the appearance of inefficient phenomena. Firstly, if the flows along the Veemkade are higher than the capacity of the path considering only the width without the platform (see Figure 6.4 - 13 m width), and a higher share of visitors uses that path. Secondly, if a higher share of visitors decides to go all the way to the end of the platform, the capacity of the gate (8.5 m width) to go back the route along the Veemkade can be exceeded and queues start appearing.

Finally, the narrowing of the path on the east-end of the Veemkade is the third physical bottleneck location identified. If the capacity of the narrower part of the path is exceeded, queues also start forming and can propagate upstream.

From the width of the paths indicated in Figure 6.4, a static analysis can be performed and an indication of the demand to activate these bottlenecks can be estimated based on traffic flow theory (fundamental diagram). The aim of the static capacity estimated here is only to give insights into the difference in maximum demand to be assigned to each section of the infrastructure before congestion starts appearing, it is thus considered sufficient to calculate this value based on the fundamental diagram proposed by Weidmann (1992). This is the chosen fundamental diagram because it is derived based on the average value found by plotting the fundamental diagram found in 25 different papers, and the flow characteristics are for a non-pushy crowd. Besides, this fundamental diagram is widely used in research. For unidirectional conditions, the maximum flow of pedestrians according to Weidmann (1992) is $1.225 Ped/m/s$, and from these the capacity values for each of physical bottlenecks identified are indicated in Table D.1.

Table D.1: Capacity values of the physical bottlenecks identified for the study area

Location	Narrowest Point (m)	Static Capacity - Unidirect (Ped/h)
Piet Heinkade	4	17640
Veemkade - West	8.5	37485
Veemkade - East	10	44100

D.2.2. Flow Interaction Inefficient Dynamics

As indicated in subsection 3.2.1, the capacity of the infrastructure decreases when flows are multi-directional if compared to when these a unidirectional. At certain times during the event these flow interactions can occur with higher or lower intensity, that is, where a higher share of visitors from one direction can hamper the flow of the other directions, and thus also the total throughput of cross-sections. In the study area, the main locations where these can occur are at the intersection at De Ruijterkade, as well as along the path between that intersection and the Piet Heinkade. For the former, the key dynamics consider each of the possible movement directions being dominant over the others, and thus queues extending in distinct directions. For the route, one can consider the dynamics based on the distinct shares per direction, where the dominant flow direction can either be west-east or east-west.

In bidirectional conditions, the maximum flow as proposed by Weidmann (1992) is reduced by a percentage dependent on the share of flows per direction, where a maximum reduction of about 16% can be observed for direction shares of 90%/10%. Table D.2 indicates the capacity values for each of the locations identified for bidirectional conditions (at the critical 90%/10% share).

Table D.2: Capacity of sections for bidirectional flows

Location	Narrowest Point (m)	Static Capacity - Bidirect (Ped/h)
Intersection - De Ruijterkade	10	37044
Route - De Ruijterkade to Piet Heinkade	9	33340

D.2.3. Uneven Distribution over Network Inefficient Dynamics

The dynamics of interest for this phenomena relate to the increased interest and attraction of visitors for specific activity locations as well as for specific routes. Regarding the activities, one can expect that the activity location on the west-end of the Veemkade attracts most visitors. As previously mentioned, this location is also were many tall ships are located, thus the combined demand for these attractions can create high densities on that area as the capacity can be exceed. Besides, the activities concentrated at De Ruijterkade, where not only commercial facilities are located but also the entrance to the ferry towards the purple route, can present the same dynamics. The combined demand for these two activities can lead to discomfort and possibly unsafe density levels.

The route along the Veemkade is the only route to watch the tall ships and the demand for it besides being very high, the behavior of visitors along this route also causes the uneven distribution as visitors are likely to walk slower and stop more frequently for pictures. Thus, it is most likely that the network will be unbalanced as the capacity for that route is overused while the Piet Heinkade is likely to be significantly less crowded. This consideration leads to the, expected dynamics for the following phenomena (inefficient choice behavior) discussed below.

D.2.4. Inefficient Choice Behavior Inefficient Dynamics

As the route along the Veemkade gets crowded due to bottlenecks being activated or the attraction for activities along that route increases, visitors moving from west to east might start choosing less efficient routes to avoid this crowding. The less efficient route in this case is to move along the Piet Heinkade, as this route is less attractive, and the dominant flow direction is the opposite direction. This inefficient choice behavior can lead to undesirable flow interactions and, if the share of visitors who choose this route increases, can also indicate discomfort as visitors try to avoid the Veemkade.

D.3 Scenarios' Setup in Pedestrian Dynamics - SAIL

This section presents the inputs to build each scenario considered for the SAIL event in Pedestrian Dynamics. These inputs are defined based on the capacity calculations mentioned in the previous section, as well as the dynamics that need to be reproduced, as indicated in Figure 4.4.

D.3.1. Scenarios

Similarly to how it is done in subsection 6.2.3, the sections below describe each input considered for the development of the scenarios. However, below these inputs are shown in more detail.

Demand Pattern

The inflows per scenario are summarized in Table D.3, and the distribution of these flows per entry location are shown in Table D.4. For all scenarios, this demand is assumed to be uniformly distributed over the hour, except for the demand coming from the ferry, which then follows the ferry schedule (i.e. 20 minutes frequency) and generates a maximum of 1100 pedestrians per arrival. The definition of these demand patterns and shares per entrance was based on an visual analysis of the conditions on the areas where the inefficient dynamics were defined. Also the difference between the capacities of the physical bottlenecks, especially the identification of the capacity at the Piet Heinkade bottleneck as shown in Table D.1, indicate that that bottleneck would always be congested if most of the demand would be generated from the West-end. Thus, the dynamics on the other areas (e.g. demand exceeding capacity of the Veemkade-West) would never occur as pedestrians would get stuck at the Piet Heinkade. To account for that, even thought it can be expected that most demand comes from the West-end, the distribution over the entrances is spread for the scenarios for which the dynamics focus on the Veemkade and Piet Heinkade.

Table D.3: Scenarios' demand pattern

Scenario	Max Inflow (ped/h)	Min Inflow (ped/h)	Step Size
1. Piet Heinkade	51000	34000	10%
2. Veemkade - West	57800	44200	10%
3. Veemkade - East	47600	30600	10%
4. Intersection - Multi-direct	51000	34000	10%
5. Route - Bidirect	44200	27200	10%
6. Activity - De Ruijterkade	51000	34000	10%
7. Activity - Veemkade West	47600	30600	10%
8. Inefficient Route Choice	51000	34000	10%

Table D.4: Scenarios' share per entrance

Scenario	Share per Entrance			
	West-end	Ferry	Kattenburgstraat	East-end
1. Piet Heinkade	65%	8%	11%	16%
2. Veemkade - West	40%	6%	32%	22%
3. Veemkade - East	40%	6%	32%	22%
4. Intersection - Multi-direct	39%	6%	23%	32%
5. Route - Bidirect	65%	8%	11%	16%
6. Activity - De Ruijterkade	46%	7%	17%	30%
7. Activity - Veemkade West	40%	6%	32%	22%
8. Inefficient Route Choice	40%	6%	32%	22%

Activity Schedules & Activity Demand

In the SAIL terrain, the schedule of the activities is what mostly guides the usage of the infrastructure, as the route options are limited. Three main routes are defined for the study are of SAIL, based on the exit location of the pedestrians who follow these routes. The first is for the pedestrians who follow the Orange route, that is, the route to visit the tall ships along the Veemkade, exiting on the east-end. The second route relates to the pedestrians who take the ferry to the Purple route, and the third route is for the ones who go to Amsterdam Central, or exit at the west-end. The corresponding points of origin considered for each of these destination locations are shown in Table D.5, where the existing origin and destination pairs are the ones indicated with an x.

Besides their entry and exit locations, a share of pedestrians is also assigned to perform

Table D.5: Origin-destination pairs

Origin/Destinations	West-End	Ferry	East-End
West-end	-	x	x
Ferry	x	-	x
Kattenburgstraat	x	-	x
East-end	x	-	x

an activity along their route. The commercial activity locations are mainly three, at De Ruijterkade, Veemkade-West and Veemkade-East, as illustrated in Figure 6.5. Due to the location of these activities, it is expected that the first two will have higher demand than the Veemkade-East, whereby the Veemkade-West is assumed to have the highest demand of all. The assignment of the activities is based on the pedestrians exit location. For instance, pedestrians who exit at the east-end are the ones assumed to be at the event to watch the tall ships along the Veemkade. Thus, these are mostly assigned to activities along the Veemkade, where a higher share is assigned to the activities at the Veemkade-West. On the other hand, pedestrians who exit the study area through the ferry are only assigned to activities at De Ruijterkade.

For most of the scenarios, the share of agents from the total amount generated per hour who are assigned to perform an activity along their route is 50%. However, for the uneven distribution over the network scenarios, given the dynamics of these scenarios, the share of agents assigned to an activity is increased to 80%.

Routing & Movement Preferences

The routing and movement preferences are mostly controlled by parameters of the embedded algorithms of Pedestrian Dynamics. For most of the scenarios, as discussed in subsection 4.1.3, the macro/meso behavior characteristics defined through the inputs are of interest for the scenarios this study is concerned with. However, for scenario 8 - Inefficient Route Choice - a specific set of parameter of Pedestrian Dynamics is used to simulate the dynamics of this scenario. These are further detailed below.

The route planning behavior of agents in Pedestrian Dynamics can be influenced by the routing method chosen. As previously stated, the method chosen in this research is the least-effort approach. Unlike the shortest-path method which simply considers the route with shortest distance, the least-effort also takes the density along the route into account when planning the route for each agent. The densities are considered based on a cost function which considers both, the total travel time along the route when the route is free, as well as the delay expected considering the density along the route. The exact equation to calculate this cost is shown in Equation D.1.

$$totalCost = normalTime + weightedDensityDelay + \left(normalTime \times E_{dis} \times W_{dis}\right) \tag{D.1}$$

Where,

$$normalTime = \frac{D}{S \times E_{sm} + E_{fs}} \tag{D.2}$$

$$weightedDensityDelay = \left(\frac{D}{S_L \times E_{sm} + E_{fs}} - normalTime \right) \times D_w \quad \text{(D.3)}$$

The elements which form the $normalTime$ equation relate to the distance (D) from itself the agent takes into account to estimate the delay caused by density, the maximum speed (S) of an agent, the speed multiplier of an edge (E_{sm}) and fixed speed of an edge (E_{fs}). For the $weightedDensityDelay$, the S_L refers to the local sped depending on the density at the edge, and D_w is the delay weight of an agent. Finally, E_{dis} and W_{dis} relate to the discomfort factor of an edge and discomfort weight of an agent.

For the application for this research, two items of this equation are highlighted. These are the distance (D) and the the delay weight of an agent (D_w). As one can see by the equations, these two values have a large influence on the totalCost estimated by an agent when defining its route. For the delay weight, this value indicates how sensitive an agent is to encountering delays along its route. These delays are calculated based on the density, and for instance if an agent would need 20 seconds to transverse a certain edge at its desired speed, but due to high densities it is expected that this agent can only walk at half of its speed, the total time expected is then 40 seconds due to the 20 second delay caused by density.If the delay weight is high, this extra time to transfer (i.e. delay) is considered more important the regular time, and so agents are more likely to avoid these crowded areas. For scenario 8, by making agents reconsider their route by the locations where these can move between the two routes (i.e. the lanes connecting the Veemkade to the Piet Heinkade), this rerouting due to the desire to avoid crowded areas can be considered. For the simulations of scenario 8, for all density levels, the value considered for the distance was 100 meter, and for the delay weight a uniform distribution between 1.5 and 5. These values are assumed based on analysis of the equations above and the effect expected for these values thereof, as well as from a discussion with simulation experts who had experience with this parameters from previous simulations.

D.4 Derivation of Travel Time

One of the state metrics used for the application of the case study, as presented in subsection 6.3.1 are the first and third quartiles of the travel time distribution between each pair of Event Blocks. In this section, the derivation of the travel time and the rational behind the choices made regarding this metric are discussed.

As presented in the same subsection aforementioned, the travel time as used in this research is the time taken for each pedestrian to move between each pair of Event Blocks. The value of each pedestrians' travel time is derived when the pedestrian is identified at a certain Event Block B_x, where only its last visited Event Block (B_y) is then considered for the travel time calculations. These calculations are according to Equation D.4, where $tt_{i,B_y \to B_x}$ is the travel time of pedestrian i between B_y and B_x, estimated by subtracting the time pedestrian i is identified at Event Block B_x coming from Event Block B_y.

$$tt_{i,B_y \to B_x} = t_{i,B_x} - t_{i,B_y} \quad [\text{s}] \quad \text{(D.4)}$$

The first decision discussed regarding this metric is that of considering only the travel time between each pair of Event Block. This approach is chosen because the travel time then also gives insights into the usage of the infrastructure and routes. For instance, if there are two routes to go from Event Blocks B_i to B_j, where one is direct and the other passes through B_k, the value of the travel time between B_i to B_j only considers the direct route, as the travel time of pedestrians who are identified at B_j from the other route are then considered in the $B_k \rightarrow B_j$ pair.

As stated in subsection 6.3.1, the normalization of this metric can be done by dividing the travel time by the length of the route between each pair $B_y \rightarrow B_x$. However, as it happens in SAIL and likely in other mass event given the scale of the environment, there might be distinct routes between each pair $B_y \rightarrow B_x$, with no other Event Block in between to differentiate which route was used by visitors who arrive at B_x coming from B_y. This leads to the problem that a larger number of Event Blocks is needed in order to ensure that there is only one possible route between each pair of Event Blocks. As in reality these Event Blocks for the application of the method for prediction are derived based on the sensor network of the event, adding sensors in all locations necessary to make the distinction between all possible routes would likely be unfeasible. Another factor which one must take into account is that there are activity locations between certain pairs of $B_y \rightarrow B_x$ and which do not exist between others. The travel time distribution between these pairs with activities is thus expected to be higher as visitors stop to perform the activity.

The considerations above highlight the fact that normalizing the travel time simply based on the length of the route between each pair $B_y \rightarrow B_x$ does not make the values of this metric more comparable, as there are other route attributes which influence its value. Therefore, no normalization is done for the travel time at this stage, only when formulating the individual objectives for the optimization as it is discussed in subsection 6.3.2.

D.5 Normalization Method

As stated in subsection 6.3.2, the state metrics require normalization because the metrics have different units and orders of magnitude. To explain in more detail, without normalization the variation of the orders of magnitudes for the various metrics leads to those with a larger order of magnitude being more influential on the optimization process. For instance, based on the fundamental diagram proposed by Weidmann (1992), one can say that the density in an Event Block can vary from 0 to 5.4 ped/m^2, while the flow ranges from 0 to 1.225 $ped/m/s$. It is thus clear that, when comparing the real and simulated values of the flow of an Event Block, the order of magnitude of the difference is much lower than that of the density. Assuming that both, the real flow and the real density are on the upper bound of their respective values (i.e. 1.225 and 5.4), and these are being compared to a scenario for which their corresponding values are both 0, the resulting Square Error of the flow is 1.5 $ped/m/s$ while for the density it reaches 29.16 ped/m^2. The density has implicitly more impact on determining which scenario is chosen by the optimization algorithm, that is, a scenario for which the density error is lower has higher chances of being selected over a scenario for which the flow error is lower.

In order to define a method to normalize the metrics a set of assumptions need to be taken into account, as discussed by Sparnaaij (2017), which relate to two error metrics to compare the real and simulated data. These are the absolute ($M_{scen} - M_{real}$) and relative ($\frac{M_{scen}-M_{real}}{M_{real}}$) errors. In this thesis, the choice to use the absolute error is made due to two reasons. Firstly, it avoids the problem of having an infinite error when the real value of the metric is zero. Secondly, as stated by Sparnaaij (2017), one of the assumptions of the relative error is that, for the magnitude of deviation, the error is smaller if the real value of the metric is larger, if compared to a smaller real value. For instance, a deviation of the density of 0.5 ped/m^2 between the real and the scenario's value is five times more wrong when the real density is 1 ped/m^2 over when it is 5 ped/m^2. This behavior is not desirable given that it is considered more important to get more accurate predictions when the values are higher (e.g. near or over capacity) given the impact of smaller deviations from these.

Given the choice of using the absolute error, two examples of normalization methods can be found in the pedestrian literature, both related to calibration of a pedestrian model. While Duives (2016) performs a normalization based on the maximum error for a given type of scenario and metric, Sparnaaij (2017) normalizes each metric based on the ratio between the values of the metrics from his reference (i.e. real) data, which is retrieved per type of scenario considered by the author. Unlike these studies, the scale of the environment and the number of pedestrians in the simulations is much larger in the present study, and so is the variation between the values of each metric both within a scenario (due to the distinct areas of the environment) and between scenarios (given the different dynamics and density levels). Besides, the metrics considered in the current study are also different. Therefore, although concepts discussed by both aforementioned authors are used as reference, a new method for normalization is proposed in this research.

As done by Duives (2016), the normalization method proposed in this research is based on the maximum deviation of each metric. However, Duives (2016) assumes that there are no differences between the maximum error of metric m in scenario i and the maximum error of the same metric in scenario j. This is considered problematic as there is no normalization across scenarios, so an equally large deviation of the normalized error can be considered different depending on the size of the deviation for a particular scenario. Therefore, in this thesis, the assumed maximum deviation of each metric is based on its order of magnitude considered across all scenarios according to Equation D.5.

$$Norm_m = \max_{s \in S} E_m \tag{D.5}$$

Where $Norm_m$ is the normalization value of metric m, and E_m is the maximum error of metric m across the set of all scenarios (S) in the scenario database. However, a distinction is made regarding the value assumed as to be the maximum error (E_m) given the distinct nature of the metrics used in this research for which normalization is necessary which were presented in subsection 6.3.2. As already discussed in subsection 6.3.1, unlike the flow and density metrics which in themselves are normalized across the different areas of the environment, the travel time metric is dependent on the route attributes (e.g. length, existence of activities). Furthermore, through the fundamental diagram, one can say that the flow and density have reference values which one can use for defining the maximum error, which are valid across all Event Blocks and scenarios. For the travel time, although one can derive a value valid across the scenarios, it is not desirable to consider a single value for all pairs of Event Blocks, as this would not consider the aforementioned route attributes and distinct dynamics between these pairs. For instance, as one can imagine, the maximum travel time between $B_x \rightarrow B_y$ can be very large if the route between these is long, and it also has an activity in between. Therefore, it is considered problematic to use this value to normalize the travel time between $B_p \rightarrow B_q$, where the route is much shorter, no activities or bottlenecks exist in between, and maximum possible observed travel times are therefore much smaller.

Based on these considerations, it is decided that in this thesis, the flow and density are normalized based on their maximum values in the fundamental diagram, for which the fundamental diagram of reference is that of Weidmann (1992). The first and third quartiles of travel time, on the other hand, are normalized based on their maximum value per pair $B_y \rightarrow B_x$ over all scenarios in the database. Finally, the trend metrics also need to be normalized. As these relate to the angle of the line that describes the trend over the past 15 time instants, it is considered that the maximum error occurs when the real and simulated trends of a metric are on opposite ends of the possible range of gradients. This range is given by $(-\frac{\pi}{2}, \frac{\pi}{2})$, thus the maximum error is π, which is the normalization value used for all the trend metrics (flow, density, first and third quartiles of travel time). Table D.6 summarizes these considerations.

Table D.6: Normalization of State Metrics

Metric		Norm
1	**Density**	5.4
2	**Density History**	5.4
3	**Density Trend**	π
4	**Flow**	1.225
5	**Flow History**	1.225
6	**Flow Trend**	π
7	**Q1 - Travel Time**	$\max_{s \in S} B_y \rightarrow B_x$
8	**Q1 - Travel Time History**	$\max_{s \in S} B_y \rightarrow B_x$
9	**Q1 - Travel Time Trend**	π
10	**Q3 - Travel Time**	$\max_{s \in S} B_y \rightarrow B_x$
11	**Q3 - Travel Time History**	$\max_{s \in S} B_y \rightarrow B_x$
12	**Q3 - Travel Time Trend**	π

E

Discussions on Forecasting Analysis

E.1 Sensor Data Perturbations

The discussions of this section relate to the analysis of the sensor data perturbations described in Section 7.2.

E.1.1. Selected Scenarios

As presented in subsection 7.1.2, it has been decided that in this research the 5 optimal scenarios (i.e. the 5 scenarios with lowest objective function value) are used for the analyses. Therefore, when calculating the values shown in Table 7.4 and Table 7.5, these 5 scenarios are used according to Equation 7.1 to Equation 7.4. For the analyses, however, it is important to identify which specific scenarios and time instants these correspond to, as well as the order in which these are selected. Hence, these results are shown in Figure E.2 and Figure E.3. Each scenario selected is shown by its conceptual, name according to Table 6.3 (e.g. Veemkade - East), and density level (e.g. DL 1, DL 6). The cells of the tables are colored based on the comparison between the scenario selected and time instant against its corresponding real scenario and time instant, according to Figure E.1.

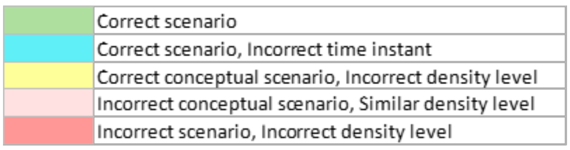

Figure E.1: Cell color code for Figure E.2 and Figure E.3

1	Physical Bottleneck - High Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	100	Veemkade - East DL 4	86
Scen Selected 2	Veemkade - East DL 6	100	Veemkade - West DL 5	112	Veemkade - West DL 5	112	Veemkade - East DL 6	99	Veemkade - East DL 5	80
Scen Selected 3	Veemkade - East DL 6	109	Veemkade - East DL 6	111	Veemkade - East DL 6	111	Veemkade - East DL 5	104	Veemkade - East DL 4	90
Scen Selected 4	Veemkade - East DL 5	110	Veemkade - East DL 6	109	Veemkade - East DL 6	110	Veemkade - East DL 4	108	Veemkade - East DL 4	89
Scen Selected 5	Veemkade - East DL 6	111	Veemkade - East DL 6	110	Veemkade - East DL 6	109	Veemkade - East DL 6	105	Veemkade - East DL 4	87
2	Physical Bottleneck - Intermediate Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 6	120	Veemkade - East DL 4	105	Veemkade - East DL 4	73
Scen Selected 2	Veemkade - East DL 4	109	Veemkade - East DL 5	115	Veemkade - West DL 6	105	Activity - Veemkade West DL 4	85	Veemkade - East DL 3	80
Scen Selected 3	Activity - Veemkade West DL 4	107	Veemkade - East DL 5	105	Veemkade - East DL 6	115	Veemkade - East DL 3	84	Veemkade - East DL 3	73
Scen Selected 4	Veemkade - East DL 5	101	Veemkade - East DL 5	104	Veemkade - West DL 5	107	Veemkade - East DL 3	86	Veemkade - East DL 2	88
Scen Selected 5	Veemkade - East DL 4	99	Veemkade - East DL 5	118	Veemkade - East DL 6	119	Veemkade - East DL 3	93	Veemkade - East DL 2	84
3	Flow Interaction - High Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Route - Bidirect DL 6	70	Route - Bidirect DL 6	74	Route - Bidirect DL 6	75	Route - Bidirect DL 4	71	Route - Bidirect DL 1	63
Scen Selected 2	Route - Bidirect DL 6	69	Route - Bidirect DL 6	72	Route - Bidirect DL 6	74	Route - Bidirect DL 5	69	Route - Bidirect DL 1	67
Scen Selected 3	Route - Bidirect DL 6	72	Route - Bidirect DL 6	73	Route - Bidirect DL 6	73	Route - Bidirect DL 5	68	Route - Bidirect DL 1	68
Scen Selected 4	Route - Bidirect DL 6	68	Route - Bidirect DL 6	70	Route - Bidirect DL 6	72	Route - Bidirect DL 4	67	Route - Bidirect DL 1	69
Scen Selected 5	Route - Bidirect DL 6	71	Route - Bidirect DL 6	75	Route - Bidirect DL 5	83	Route - Bidirect DL 5	69	Route - Bidirect DL 4	57
4	Flow Interaction - Intermediate Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Route - Bidirect DL 4	70	Route - Bidirect DL 5	72	Route - Bidirect DL 5	83	Route - Bidirect DL 1	69	Route - Bidirect DL 1	63
Scen Selected 2	Route - Bidirect DL 4	73	Route - Bidirect DL 5	73	Route - Bidirect DL 5	74	Route - Bidirect DL 4	68	Route - Bidirect DL 4	57
Scen Selected 3	Route - Bidirect DL 4	71	Route - Bidirect DL 4	73	Route - Bidirect DL 5	72	Route - Bidirect DL 1	63	Route - Bidirect DL 1	67
Scen Selected 4	Route - Bidirect DL 4	68	Route - Bidirect DL 5	75	Route - Bidirect DL 5	80	Route - Bidirect DL 4	70	Route - Bidirect DL 1	63
Scen Selected 5	Route - Bidirect DL 4	72	Route - Bidirect DL 4	70	Route - Bidirect DL 5	73	Route - Bidirect DL 1	67	Route - Bidirect DL 1	62
5	Uneven Distribution - High Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Veemkade - West DL 5	96	Veemkade - East DL 5	78	Activity - Veemkade West DL 4	72
Scen Selected 2	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	91	Veemkade - West DL 6	94	Activity - Veemkade West DL 4	78	Veemkade - East DL 5	67
Scen Selected 3	Veemkade - East DL 6	87	Activity - Veemkade West DL 6	92	Veemkade - West DL 6	99	Veemkade - East DL 6	71	Activity - Veemkade West DL 4	78
Scen Selected 4	Activity - Veemkade West DL 6	92	Veemkade - West DL 5	89	Veemkade - West DL 6	100	Veemkade - East DL 6	78	Activity - Veemkade West DL 5	70
Scen Selected 5	Activity - Veemkade West DL 5	93	Veemkade - East DL 6	95	Veemkade - West DL 6	96	Activity - Veemkade West DL 6	90	Veemkade - East DL 5	69
6	Uneven Distribution - Intermediate Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	111	Activity - Veemkade West DL 3	83	Veemkade - East DL 2	73
Scen Selected 2	Activity - Veemkade West DL 3	92	Activity - Veemkade West DL 5	93	Veemkade - East DL 6	95	Veemkade - East DL 4	71	Veemkade - East DL 4	71
Scen Selected 3	Activity - Veemkade West DL 4	93	Activity - Veemkade West DL 4	111	Activity - Veemkade West DL 4	104	Activity - Veemkade West DL 3	78	Activity - Veemkade West DL 4	72
Scen Selected 4	Activity - Veemkade West DL 3	94	Activity - Veemkade West DL 4	93	Veemkade - East DL 5	101	Activity - Veemkade West DL 5	73	Veemkade - East DL 2	76
Scen Selected 5	Activity - Veemkade West DL 3	95	Activity - Veemkade West DL 4	104	Activity - Veemkade West DL 6	91	Veemkade - East DL 4	77	Veemkade - East DL 4	68
7	Inefficient Choice - High Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 4	76
Scen Selected 2	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 5	65
Scen Selected 3	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 4	105	Inefficient Route Choice DL 5	67
Scen Selected 4	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	116	Inefficient Route Choice DL 5	93	Inefficient Route Choice DL 4	71
Scen Selected 5	Inefficient Route Choice DL 6	108	Inefficient Route Choice DL 6	116	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	89	Inefficient Route Choice DL 4	77
8	Inefficient Choice - Intermediate Density									
	Ref		Sensor Var 1		Sensor Var 2		Sensor Var 3		Sensor Var 4	
Scen Selected 1	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	117	Inefficient Route Choice DL 3	84	Inefficient Route Choice DL 3	68
Scen Selected 2	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 4	117	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 1	79
Scen Selected 3	Inefficient Route Choice DL 4	100	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 3	109	Inefficient Route Choice DL 1	78
Scen Selected 4	Inefficient Route Choice DL 4	112	Inefficient Route Choice DL 4	112	Inefficient Route Choice DL 6	112	Inefficient Route Choice DL 2	116	Inefficient Route Choice DL 3	84
Scen Selected 5	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	105	Inefficient Route Choice DL 5	117	Inefficient Route Choice DL 4	87	Inefficient Route Choice DL 1	95

Figure E.2: Name and order of scenarios selected by the system per sensor variation for reference and variations 1 to 4

1	Physical Bottleneck - High Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Veemkade - East DL 6	105	Veemkade - East DL 6	107	Veemkade - East DL 6	105	Activity - Veemkade West DL 5	118
Scen Selected 2	Veemkade - East DL 6	106	Veemkade - East DL 6	106	Veemkade - East DL 5	110	Veemkade - East DL 6	105
Scen Selected 3	Veemkade - East DL 6	100	Veemkade - West DL 5	106	Veemkade - East DL 6	111	Activity - Veemkade West DL 6	108
Scen Selected 4	Veemkade - East DL 6	102	Veemkade - West DL 5	104	Veemkade - East DL 5	120	Veemkade - East DL 5	110
Scen Selected 5	Veemkade - East DL 6	99	Veemkade - West DL 5	105	Veemkade - East DL 5	102	Veemkade - East DL 5	120
2	Physical Bottleneck - Intermediate Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	107
Scen Selected 2	Veemkade - East DL 5	101	Veemkade - East DL 6	85	Activity - Veemkade West DL 4	107	Veemkade - East DL 3	103
Scen Selected 3	Veemkade - East DL 4	111	Veemkade - East DL 5	101	Activity - Veemkade West DL 4	104	Veemkade - East DL 2	118
Scen Selected 4	Veemkade - East DL 5	89	Veemkade - East DL 6	95	Activity - Veemkade West DL 5	105	Veemkade - East DL 3	104
Scen Selected 5	Veemkade - East DL 4	109	Veemkade - East DL 6	93	Activity - Veemkade West DL 3	104	Veemkade - East DL 3	108
3	Flow Interaction - High Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Route - Bidirect DL 6	70	Route - Bidirect DL 5	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70
Scen Selected 2	Route - Bidirect DL 6	69	Route - Bidirect DL 5	72	Route - Bidirect DL 6	69	Route - Bidirect DL 5	76
Scen Selected 3	Route - Bidirect DL 5	70	Route - Bidirect DL 5	73	Route - Bidirect DL 5	76	Route - Bidirect DL 6	64
Scen Selected 4	Route - Bidirect DL 6	68	Route - Bidirect DL 6	69	Route - Bidirect DL 6	72	Route - Bidirect DL 6	66
Scen Selected 5	Route - Bidirect DL 5	72	Route - Bidirect DL 5	71	Route - Bidirect DL 6	66	Route - Bidirect DL 5	75
4	Flow Interaction - Intermediate Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Route - Bidirect DL 4	70	Route - Bidirect DL 4	71	Route - Bidirect DL 4	70	Route - Bidirect DL 4	72
Scen Selected 2	Route - Bidirect DL 4	71	Route - Bidirect DL 5	68	Route - Bidirect DL 4	72	Route - Bidirect DL 4	70
Scen Selected 3	Route - Bidirect DL 5	68	Route - Bidirect DL 5	69	Route - Bidirect DL 4	68	Route - Bidirect DL 1	75
Scen Selected 4	Route - Bidirect DL 5	69	Route - Bidirect DL 4	70	Route - Bidirect DL 4	73	Route - Bidirect DL 1	77
Scen Selected 5	Route - Bidirect DL 4	69	Route - Bidirect DL 5	68	Route - Bidirect DL 1	71	Route - Bidirect DL 1	74
5	Uneven Distribution - High Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Activity - Veemkade West DL 6	90	Veemkade - West DL 6	77	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90
Scen Selected 2	Activity - Veemkade West DL 6	91	Veemkade - West DL 6	76	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 5	104
Scen Selected 3	Veemkade - West DL 6	76	Veemkade - West DL 5	81	Activity - Veemkade West DL 5	93	Activity - Veemkade West DL 4	93
Scen Selected 4	Veemkade - West DL 6	77	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 5	93
Scen Selected 5	Veemkade - West DL 5	81	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 5	96	Activity - Veemkade West DL 4	107
6	Uneven Distribution - Intermediate Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Activity - Veemkade West DL 4	90	Veemkade - East DL 5	89	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 1	108
Scen Selected 2	Veemkade - East DL 4	94	Veemkade - East DL 4	94	Activity - Veemkade West DL 3	88	Activity - Veemkade West DL 2	108
Scen Selected 3	Veemkade - East DL 5	89	Veemkade - East DL 6	81	Activity - Veemkade West DL 2	108	Activity - Veemkade West DL 2	109
Scen Selected 4	Veemkade - East DL 5	78	Veemkade - East DL 6	85	Activity - Veemkade West DL 3	95	Activity - Veemkade West DL 1	107
Scen Selected 5	Activity - Veemkade West DL 5	86	Veemkade - East DL 6	80	Activity - Veemkade West DL 2	109	Activity - Veemkade West DL 2	106
7	Inefficient Choice - High Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	89	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110
Scen Selected 2	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	87	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	115
Scen Selected 3	Inefficient Route Choice DL 6	108	Inefficient Route Choice DL 6	77	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	116
Scen Selected 4	Inefficient Route Choice DL 6	89	Inefficient Route Choice DL 5	93	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	120
Scen Selected 5	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	116	Inefficient Route Choice DL 6	107
8	Inefficient Choice - Intermediate Density							
	Sensor Var 5		Sensor Var 6		Sensor Var 7		Sensor Var 8	
Scen Selected 1	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 3	84	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	117
Scen Selected 2	Inefficient Route Choice DL 3	109	Inefficient Route Choice DL 5	80	Inefficient Route Choice DL 4	117	Inefficient Route Choice DL 4	110
Scen Selected 3	Inefficient Route Choice DL 4	92	Inefficient Route Choice DL 4	88	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	108
Scen Selected 4	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	87	Inefficient Route Choice DL 3	118	Inefficient Route Choice DL 3	118
Scen Selected 5	Inefficient Route Choice DL 4	100	Inefficient Route Choice DL 4	92	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 3	119

Figure E.3: Name and order of scenarios selected by the system per sensor variation for variations 5 to 8

E.2 Sub-Selection of Event Blocks

The discussions of this section relate to the analysis of sub-selection of Event Blocks described in Section 7.3.

E.2.1. Sub-selected Blocks

The figures presented below illustrate the selected Event Blocks per test scenario presented in Table 7.1. For test scenarios 1 and 2, which relate to the physical bottleneck at the east-end of the Veemkade, the six and the three Event Blocks selected are highlighted in Figure E.4. As the inefficient dynamics are expected to occur by Event Block B11, the areas which generate large flows towards this Block are chosen.

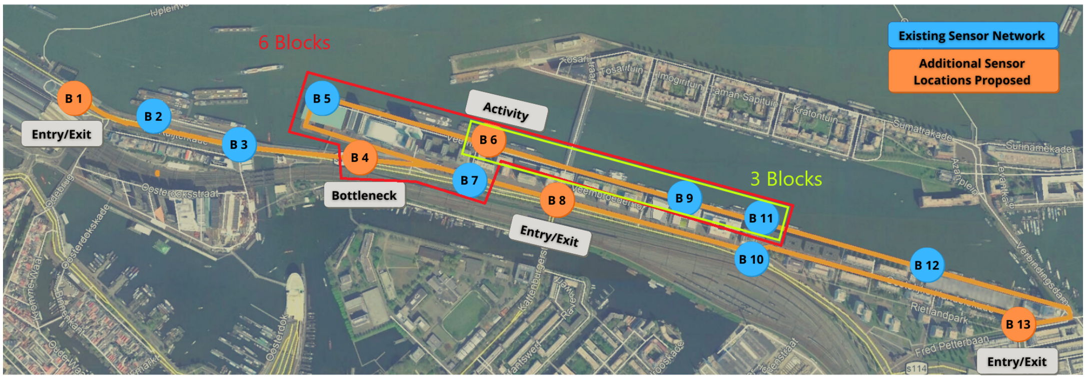

Figure E.4: Six Event Blocks sub-selected for test scenarios 1 and 2

For test scenarios 3 and 4, which relate to the flow interactions between pedestrians coming from and to Amsterdam Central Station, the six and three Event Blocks selected are highlighted in Figure E.5. As the inefficient dynamics are expected to occur between B2 and B4, the areas relevant for the dynamics of the movement along this stretch are chosen.

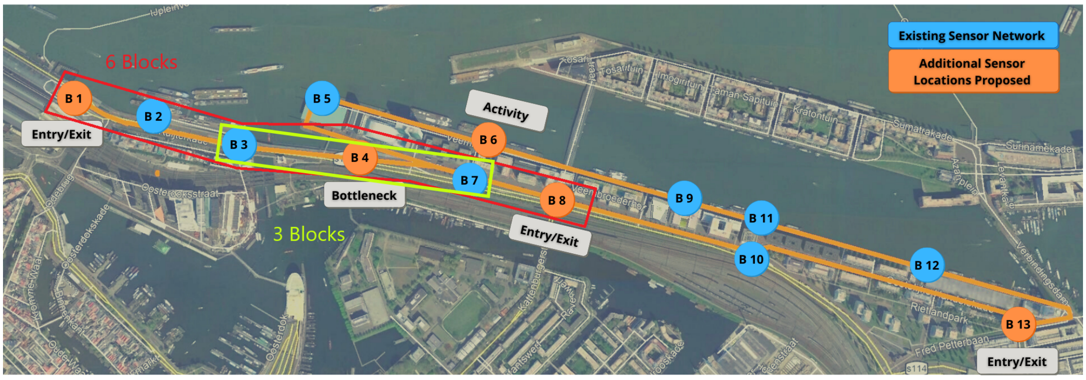

Figure E.5: Six Event Blocks sub-selected for test scenarios 3 and 4

For test scenarios 5 and 6, which relate to the uneven distribution over the network due to the combined demand for the activities on the west-end of the Veemkade, the six and three Event Blocks selected are highlighted in Figure E.6. As the inefficient dynamics are expected to occur between B5 and B9, the areas relevant for the dynamics of the movement along this stretch are chosen.

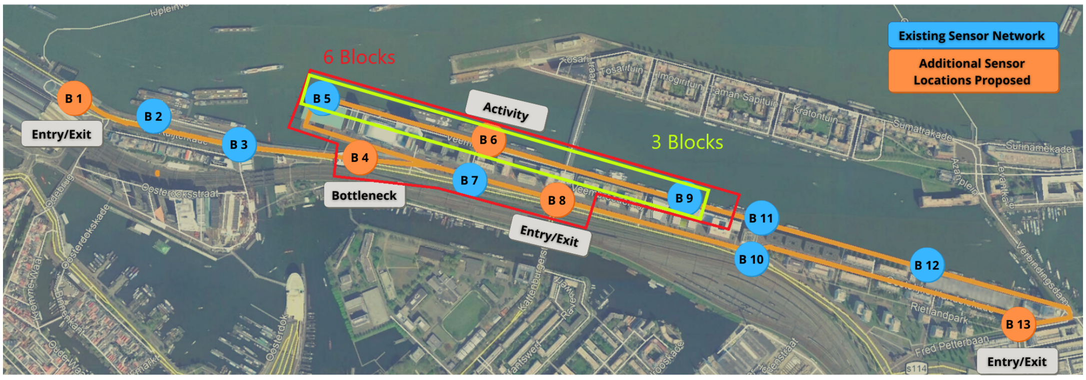

Figure E.6: Six Event Blocks sub-selected for test scenarios 5 and 6

Finally, for test scenarios 7 and 8, which relate to the inefficient choice of route of pedestrians trying to avoid the high densities along the Veemkade by re-routing to the Piet Heinkade, the six and three Event Blocks selected are highlighted in Figure E.7. As the inefficient dynamics are identified by the pedestrians rerouting through the lanes that connect these two main streetds, the areas relevant for capturing this re-routing behavior are chosen.

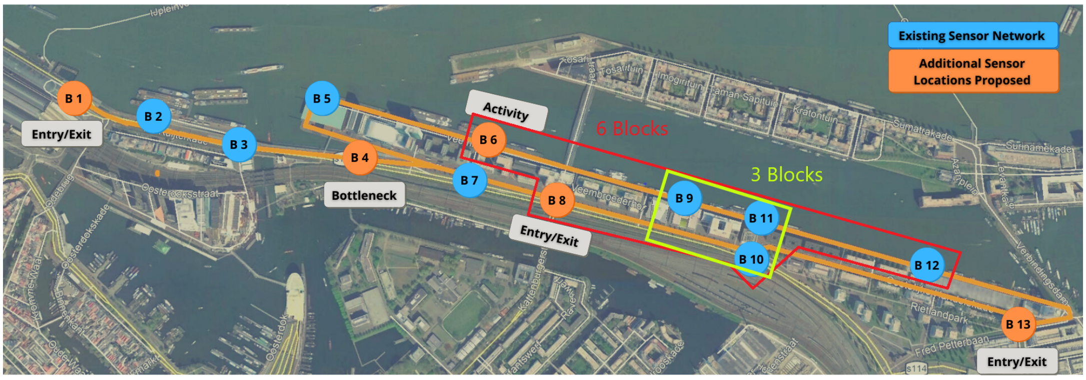

Figure E.7: Six Event Blocks sub-selected for test scenarios 7 and 8

E.2.2. Selected Scenarios

As shown in Section E.1, for the analyses of the results, the specific scenarios and time instants, as well as the order in which these are selected, used for calculating the error changes shown in Table 7.7 are presented. Figure E.9 shows these scenarios for the reference case, as well as setting variations according to Table 7.6. Each scenario selected is shown by its conceptual name according to Table 6.3 (e.g. Veemkade - East), and density level (e.g. DL 1, DL 6). The cells of the tables are colored based on the comparison between the scenario selected and time instant against its corresponding real scenario and time instant, according to Figure E.8.

	Correct scenario
	Correct scenario, Incorrect time instant
	Correct conceptual scenario, Incorrect density level
	Incorrect conceptual scenario, Similar density level
	Incorrect scenario, Incorrect density level

Figure E.8: Cell color code for Figure E.9

	Ref		Block Var 1		Block Var 2	
1	**Physical Bottleneck - High Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105
Scen Selected 2	Veemkade - East DL 6	100	Veemkade - East DL 5	110	Veemkade - East DL 6	107
Scen Selected 3	Veemkade - East DL 6	109	Veemkade - East DL 6	100	Veemkade - East DL 6	108
Scen Selected 4	Veemkade - East DL 5	110	Veemkade - East DL 6	109	Veemkade - East DL 6	103
Scen Selected 5	Veemkade - East DL 6	111	Veemkade - East DL 6	102	Veemkade - East DL 6	106
2	**Physical Bottleneck - Intermediate Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105
Scen Selected 2	Veemkade - East DL 4	109	Activity - Veemkade West DL 4	107	Veemkade - East DL 4	104
Scen Selected 3	Activity - Veemkade West DL 4	107	Veemkade - East DL 5	101	Veemkade - East DL 4	102
Scen Selected 4	Veemkade - East DL 5	101	Veemkade - East DL 3	117	Veemkade - East DL 4	107
Scen Selected 5	Veemkade - East DL 4	99	Activity - Veemkade West DL 4	104	Veemkade - East DL 4	101
3	**Flow Interaction - High Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70
Scen Selected 2	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69
Scen Selected 3	Route - Bidirect DL 6	72	Route - Bidirect DL 6	72	Route - Bidirect DL 6	72
Scen Selected 4	Route - Bidirect DL 6	68	Route - Bidirect DL 6	68	Route - Bidirect DL 6	68
Scen Selected 5	Route - Bidirect DL 6	71	Route - Bidirect DL 6	73	Route - Bidirect DL 6	73
4	**Flow Interaction - Intermediate Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70
Scen Selected 2	Route - Bidirect DL 4	73	Route - Bidirect DL 4	73	Route - Bidirect DL 4	71
Scen Selected 3	Route - Bidirect DL 4	71	Route - Bidirect DL 4	72	Route - Bidirect DL 5	68
Scen Selected 4	Route - Bidirect DL 4	68	Route - Bidirect DL 4	71	Route - Bidirect DL 4	73
Scen Selected 5	Route - Bidirect DL 4	72	Route - Bidirect DL 3	71	Route - Bidirect DL 5	70
5	**Uneven Distribution - High Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90
Scen Selected 2	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	91
Scen Selected 3	Veemkade - East DL 6	87	Activity - Veemkade West DL 5	93	Activity - Veemkade West DL 5	93
Scen Selected 4	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 5	104	Activity - Veemkade West DL 5	96
Scen Selected 5	Activity - Veemkade West DL 5	93	Activity - Veemkade West DL 5	96	Activity - Veemkade West DL 5	104
6	**Uneven Distribution - Intermediate Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90
Scen Selected 2	Activity - Veemkade West DL 3	92	Activity - Veemkade West DL 4	93	Activity - Veemkade West DL 3	101
Scen Selected 3	Activity - Veemkade West DL 4	93	Veemkade - East DL 3	109	Activity - Veemkade West DL 4	93
Scen Selected 4	Activity - Veemkade West DL 3	94	Veemkade - East DL 4	93	Veemkade - East DL 4	85
Scen Selected 5	Activity - Veemkade West DL 3	95	Veemkade - East DL 3	90	Veemkade - East DL 3	106
7	**Inefficient Choice - High Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110
Scen Selected 2	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 5	120	Inefficient Route Choice DL 6	118
Scen Selected 3	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 5	113	Inefficient Route Choice DL 5	106
Scen Selected 4	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 5	105	Inefficient Route Choice DL 5	109
Scen Selected 5	Inefficient Route Choice DL 6	108	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 5	120
8	**Inefficient Choice - Intermediate Density**					
	Ref		**Block Var 1**		**Block Var 2**	
Scen Selected 1	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110
Scen Selected 2	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 3	117
Scen Selected 3	Inefficient Route Choice DL 4	100	Inefficient Route Choice DL 4	105	Inefficient Route Choice DL 4	105
Scen Selected 4	Inefficient Route Choice DL 4	112	Inefficient Route Choice DL 5	105	Inefficient Route Choice DL 4	116
Scen Selected 5	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	113	Inefficient Route Choice DL 4	119

Figure E.9: Name and order of scenarios selected by the system per sub-selection of Event Block variation for reference and variations 1 and 2

E.3 Sub-Selection of State Metrics

The discussions of this section relate to the analysis of sub-selection of State Metrics described in Section 7.4.

E.3.1. Selected Scenarios

As shown in the above sections, for the analyses of the results, the specific scenarios and time instants, as well as the order in which these are selected, used for calculating the error changes shown in Table 7.9 are presented. Figure E.11 shows these scenarios for the reference case, as well as setting variations according to Table 7.8. Each scenario selected is shown by its conceptual name according to Table 6.3 (e.g. Veemkade - East), and density level (e.g. DL 1, DL 6). The cells of the tables are colored based on the comparison between the scenario selected and time instant against its corresponding real scenario and time instant, according to Figure E.10.

	Correct scenario
	Correct scenario, Incorrect time instant
	Correct conceptual scenario, Incorrect density level
	Incorrect conceptual scenario, Similar density level
	Incorrect scenario, Incorrect density level

Figure E.10: Cell color code for Figure E.11

1	Physical Bottleneck - High Density											
	Ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105	Veemkade - East DL 6	105
Scen Selected 2	Veemkade - East DL 6	100	Veemkade - East DL 6	85	Veemkade - East DL 6	104	Veemkade - East DL 5	110	Veemkade - East DL 6	107	Veemkade - East DL 5	110
Scen Selected 3	Veemkade - East DL 6	109	Veemkade - East DL 5	105	Veemkade - East DL 6	106	Activity - Veemkade West DL 5	109	Veemkade - East DL 6	104	Veemkade - East DL 6	100
Scen Selected 4	Veemkade - East DL 5	110	Veemkade - East DL 6	88	Veemkade - East DL 6	108	Activity - Veemkade West DL 6	104	Veemkade - East DL 6	106	Veemkade - East DL 6	109
Scen Selected 5	Veemkade - East DL 6	111	Veemkade - East DL 6	107	Veemkade - East DL 6	107	Activity - Veemkade West DL 5	101	Veemkade - East DL 6	109	Veemkade - East DL 6	113
2	Physical Bottleneck - Intermediate Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105	Veemkade - East DL 4	105
Scen Selected 2	Veemkade - East DL 4	109	Veemkade - East DL 4	104	Veemkade - East DL 4	106	Veemkade - East DL 6	93	Veemkade - East DL 4	104	Veemkade - East DL 6	93
Scen Selected 3	Activity - Veemkade West DL 4	107	Veemkade - East DL 5	105	Veemkade - East DL 4	104	Veemkade - West DL 5	91	Veemkade - East DL 4	107	Veemkade - East DL 5	101
Scen Selected 4	Veemkade - East DL 5	101	Veemkade - East DL 3	105	Veemkade - East DL 4	103	Activity - Veemkade West DL 6	99	Veemkade - East DL 4	106	Activity - Veemkade West DL 4	107
Scen Selected 5	Veemkade - East DL 4	99	Veemkade - East DL 4	107	Veemkade - East DL 5	99	Veemkade - West DL 5	96	Veemkade - East DL 5	100	Veemkade - East DL 4	99
3	Flow Interaction - High Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70	Route - Bidirect DL 6	70
Scen Selected 2	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69	Route - Bidirect DL 6	69
Scen Selected 3	Route - Bidirect DL 6	72	Route - Bidirect DL 5	71	Route - Bidirect DL 6	68	Route - Bidirect DL 6	71	Route - Bidirect DL 5	71	Route - Bidirect DL 6	71
Scen Selected 4	Route - Bidirect DL 6	68	Route - Bidirect DL 5	72	Route - Bidirect DL 5	69	Route - Bidirect DL 6	65	Route - Bidirect DL 5	70	Route - Bidirect DL 6	65
Scen Selected 5	Route - Bidirect DL 6	71	Route - Bidirect DL 5	70	Route - Bidirect DL 5	70	Route - Bidirect DL 6	73	Route - Bidirect DL 5	69	Route - Bidirect DL 6	67
4	Flow Interaction - Intermediate Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70	Route - Bidirect DL 4	70
Scen Selected 2	Route - Bidirect DL 4	73	Route - Bidirect DL 3	69	Route - Bidirect DL 4	69	Route - Bidirect DL 2	72	Route - Bidirect DL 4	71	Route - Bidirect DL 4	69
Scen Selected 3	Route - Bidirect DL 4	71	Route - Bidirect DL 3	73	Route - Bidirect DL 4	71	Route - Bidirect DL 1	71	Route - Bidirect DL 3	73	Route - Bidirect DL 4	68
Scen Selected 4	Route - Bidirect DL 4	68	Route - Bidirect DL 4	71	Route - Bidirect DL 4	72	Piet Heinkade DL 3	72	Route - Bidirect DL 3	79	Route - Bidirect DL 4	72
Scen Selected 5	Route - Bidirect DL 4	72	Route - Bidirect DL 3	74	Route - Bidirect DL 3	79	Piet Heinkade DL 1	75	Route - Bidirect DL 3	69	Route - Bidirect DL 3	71
5	Uneven Distribution - High Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90	Activity - Veemkade West DL 6	90
Scen Selected 2	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	98	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 6	91
Scen Selected 3	Veemkade - East DL 6	87	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 4	94	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 5	96
Scen Selected 4	Activity - Veemkade West DL 6	92	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	93	Activity - Veemkade West DL 6	91	Activity - Veemkade West DL 6	93	Activity - Veemkade West DL 5	86
Scen Selected 5	Activity - Veemkade West DL 5	93	Activity - Veemkade West DL 6	93	Activity - Veemkade West DL 6	87	Activity - Veemkade West DL 5	86	Activity - Veemkade West DL 6	98	Activity - Veemkade West DL 5	93
6	Uneven Distribution - Intermediate Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90	Activity - Veemkade West DL 4	90
Scen Selected 2	Activity - Veemkade West DL 3	92	Activity - Veemkade West DL 4	91	Activity - Veemkade West DL 4	91	Activity - Veemkade West DL 4	94	Activity - Veemkade West DL 4	91	Activity - Veemkade West DL 4	93
Scen Selected 3	Activity - Veemkade West DL 4	93	Veemkade - East DL 5	80	Activity - Veemkade West DL 4	88	Activity - Veemkade West DL 3	94	Activity - Veemkade West DL 4	92	Activity - Veemkade West DL 4	94
Scen Selected 4	Activity - Veemkade West DL 3	94	Activity - Veemkade West DL 4	94	Activity - Veemkade West DL 4	92	Activity - Veemkade West DL 4	93	Activity - Veemkade West DL 4	89	Activity - Veemkade West DL 3	94
Scen Selected 5	Activity - Veemkade West DL 3	95	Veemkade - East DL 4	89	Activity - Veemkade West DL 4	89	Activity - Veemkade West DL 3	88	Activity - Veemkade West DL 4	88	Activity - Veemkade West DL 3	93
7	Inefficient Choice - High Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110	Inefficient Route Choice DL 6	110
Scen Selected 2	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	112	Inefficient Route Choice DL 6	109	Inefficient Route Choice DL 5	124	Inefficient Route Choice DL 6	112	Inefficient Route Choice DL 5	124
Scen Selected 3	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	92	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	122	Inefficient Route Choice DL 6	111	Inefficient Route Choice DL 6	107
Scen Selected 4	Inefficient Route Choice DL 6	115	Inefficient Route Choice DL 6	94	Inefficient Route Choice DL 6	111	Inefficient Route Choice DL 6	107	Inefficient Route Choice DL 6	113	Inefficient Route Choice DL 6	122
Scen Selected 5	Inefficient Route Choice DL 6	108	Inefficient Route Choice DL 6	101	Inefficient Route Choice DL 6	113	Inefficient Route Choice DL 6	120	Inefficient Route Choice DL 6	108	Inefficient Route Choice DL 6	120
8	Inefficient Choice - Intermediate Density											
	ref		Metric Var 1		Metric Var 2		Metric Var 3		Metric Var 4		Metric Var 5	
Scen Selected 1	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110	Inefficient Route Choice DL 4	110
Scen Selected 2	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 4	116	Inefficient Route Choice DL 4	111	Inefficient Route Choice DL 5	105	Inefficient Route Choice DL 4	109	Inefficient Route Choice DL 5	105
Scen Selected 3	Inefficient Route Choice DL 4	100	Inefficient Route Choice DL 4	109	Inefficient Route Choice DL 4	109	Inefficient Route Choice DL 3	113	Inefficient Route Choice DL 4	116	Inefficient Route Choice DL 3	113
Scen Selected 4	Inefficient Route Choice DL 4	112	Inefficient Route Choice DL 4	111	Inefficient Route Choice DL 4	116	Inefficient Route Choice DL 4	126	Inefficient Route Choice DL 4	111	Inefficient Route Choice DL 4	126
Scen Selected 5	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	94	Inefficient Route Choice DL 4	108	Inefficient Route Choice DL 5	108	Inefficient Route Choice DL 5	94	Inefficient Route Choice DL 5	108

Figure E.11: Name and order of scenarios selected by the system per sub-selection of State Metric variation for reference and variations 1 to 5

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