Thèse n° 8200

Dynamic control strategies for managing pedestrian flows

Présentée le 16 septembre 2021

Faculté de l'environnement naturel, architectural et construit
Laboratoire transport et mobilité
Programme doctoral en génie civil et environnement

pour l'obtention du grade de Docteur ès Sciences

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École
polytechnique
fédérale
de Lausanne

2021

Acknowledgements

The first person I would like to thank, naturally, is my thesis supervisor Michel Bierlaire. My journey in the TRANSP-OR lab started several years before my PhD with a semester project, then continued with a couple of summer internships. The first contact concerning a PhD I had with Michel was a very informal one. On my way to lectures during my master's degree at EPFL, I walked past Michel's office and he happened to be available to talk. From then, somehow, I convinced Michel I was the right person for the job, and I'm very grateful he gave me the opportunity. Not only has Michel given me great guidance and professional support, but he also is a great person to spend time with. Although we will never agree which are the best kind of beers, the many occasions spent in less formal environments were very enriching and enjoyable.
Another person who deserves my deepest thanks is Flurin Hänseler, without whom I would not have done a PhD. Flurin was my supervisor for the first semester project I accomplished in the lab. He spent many hours helping me with the project and gave me invaluable advice which I keep applying today. Not only was Flurin a great supervisor, but he is an even greater person who hosted me during my quick visit to the Netherlands.
Besides Michel, I would like to thank the jury members who provided valuable feedback and constructive comments. Serge Hoogendoorn and Hani Mahmassani gave me insightful comments to improve my manuscript. Nikolas Geroliminis deserves my thanks for the regular comments during the five years of my PhD. Finally, I wish to thank Alexandre Alahi for occupying the role of President of the jury and for his comments over the years.
The first half of my PhD was strongly influenced by the European project "TRANS-FORM". I would like to warmly thank everybody I met thanks to this project. All the people involved positively contributed to this project and I hope I'll have the opportunity to see them again.
I would also like to thank the many colleagues with whom I shared the offices during my PhD. Some of these colleagues I met back in 2013 during my first encounter with the lab, while others have just recently joined us. I would like to thank the former PhD students of the lab for their helpful support and shared memories at various conferences and workshops: Antonin Danalet, Tomás Robenek, Marija Nikolić, Evanthia Kazagli, Iliya Markov, Stefan Binder, Anna Fernández Antolín and Meritxell Pacheco Paneque. The post-docs from the lab which also provided great support naturally deserve my thanks as well: Yousef Maknoon and Shadi Sharif Azadeh, Nikola Obrenović, Riccardo Scarinci, Matthieu de Lapparent and Virginie Lurkin. Although the COVID19 pandemic has significantly reduced the professional and social interactions with

the other lab members, I have shared great memories with them during my 5 years as a PhD student in the lab. They all deserve my gratitude: Claudia Bongiovanni, Melvin Wong, Silvia Varotto, Rico Krueger, Nour Dougui, Tim Hillel, Tom Haering, Marija Kukić, Negar Rezvany, Cloe Cortes Balcells, Nicola Ortelli, Janody Pougala, Selin Ataç, Stefano Bortolomiol and Gael Lederrey. Of all these people, one person, deserves my deepest thanks for all the exceptional moments we have shared together: Gael. My thesis would not have been the same without Gael's very useful professional advice and also the regular social and relaxing moments shared together. Finally, the lab wouldn't be the same without Mila Bender. I would like to thank her for the endless discussions we have had over the years and the countless times she's made me laugh.

Part of the job doing a PhD in the lab involves project supervision. Although all students I supervised deserve my thanks for their motivation and involvement in the projects, the two students who accomplished their master thesis were outstanding. Charles Jeanbart and Adrien Nicolet are great people and wish them all the best in their professional careers.

The many people I have met and seen during my PhD gave me motivation and energy to continue. I would like to thank all people I see regularly, and those I don't see so often, from the badminton network in the region. My current neighbours, (but also aunt and uncle) Brigitte and Adam have been a great help over the years by providing Lisa and I with a place to live (although I occasionally regretted several evenings in the pub). My parents, Alex and Wendy, naturally deserve my deepest gratitude for supporting me with the choices I made over the years, but also for pushing me when I needed a push.

The last person, but definitely not the least, who deserves my thanks is Lisa. She has always supported me during my thesis and helped me through the harder times.

Blonay, August 21, 2021 Nicholas Molyneaux

Abstract

Pedestrians, like drivers, generally dislike congestion. This is true for most pedestrian environments: trains stations, airports, or shopping malls. Furthermore, pedestrian congestion also influences the attractiveness of public transportation networks. Therefore, preventing, or at least limiting, congestion from occurring inside walkable environments is critical. Although the desire to reduce, or limit, congestion appears unquestioned, the solutions to achieve this are challenging and diverse. The range of possible measures goes from adequate design considerations during the construction phase to dynamically controlled devices for managing pedestrian flows. In this thesis we discuss, design, and evaluate several innovative dynamic control strategies dedicated to managing pedestrian flows.

Installing hardware is not sufficient, thorough understanding of the dynamics taking place inside a given infrastructure is critical. Furthermore, a framework for ensuring communication between the measurement devices, control algorithm and hardware is needed. For road traffic, this framework is called Dynamic Traffic Management Systems (DTMS). The specification of the pedestrian counterpart is discussed in this thesis: Dynamic Pedestrian Management Systems (DPMS). We compare the specificities of DTMS to DPMS and emphasize the characteristics of pedestrian dynamics. Furthermore, we propose several control strategies dedicated to pedestrian flows and evaluate their effectiveness. The first is gating, inspired from traffic lights and ramp metering in road networks. The second is the usage of flow separators to prevent bidirectional pedestrian flow from occurring. The third and final strategy we propose exploits moving walkways, by controlling their speed and direction, to influence pedestrian flows.

The different control strategies illustrate the utilisation of the DPMS by simulating different case studies. The first control strategy we propose, gating, provides only minor improvements to the pedestrian dynamics. This occurs since the strategy is not tailored to pedestrian flow characteristics. The second strategy successfully improves pedestrian travel times by dynamically allocating walking space to antagonistic flows. The third strategy, where one flavour of the control algorithm integrates short term predictions, is highly successful at reducing congestion and improving travel times. The utilisation of moving walkways by the predictive algorithm emphasizes the trade-off between decreasing travel time and reducing congestion. Nevertheless, the computational cost is high. Finally, for all control strategies and all algorithms, some users are penalized, while others benefit from the strategy.

Thanks to the different control strategies proposed in this thesis, we emphasize the need for control strategies which address pedestrian specific situations. Three specificities are identified:

user compliance, available choices, and the complexity of pedestrian motion. Addressing these aspects is critical to develop successful strategies. The strategies we discuss can be applied in any pedestrian context. Nevertheless, the potential of the strategies developed in this thesis are still underexplored. Significant improvements can be expected with further development and calibration of the control algorithms. Furthermore, practical applications could be implemented with limited cost since most of the components for using simple strategies already exist.

Keywords Pedestrian flow control, control and management strategies, pedestrian simulation, dynamic pedestrian management system, pedestrian gating, bidirectional pedestrian flow, dynamic moving walkways.

Résumé

Les piétons, comme les conducteurs, n'aiment généralement pas les embouteillages. De plus, la congestion piétonne influence l'attractivité des réseaux de transports publics. Par conséquent, il est essentiel d'empêcher, ou du moins de limiter, l'apparition de la congestion. Bien que le désir de réduire ou de limiter la congestion semble incontesté, les solutions pour y parvenir sont difficiles et diverses. L'éventail des mesures possibles va d'une conception adéquate mise en oeuvre pendant la construction, jusqu'à des dispositifs dynamiques pour gérer les flux de piétons. Dans cette thèse, nous discutons, concevons et évaluons plusieurs stratégies de contrôle dynamique innovantes dédiées à la gestion des flux de piétons.

L'installation de matériel ne suffit pas, une compréhension approfondie de la dynamique qui se déroule à l'intérieur d'une infrastructure est essentielle. En outre, un cadre permettant d'assurer la communication entre les dispositifs de mesure, l'algorithme de contrôle et le matériel est nécessaire. Pour le trafic routier, ce cadre s'appelle un "Dynamic Traffic Management System" (DTMS). La spécification de la contrepartie piétonne est abordée dans cette thèse : "Dynamic Pedestrian Management System" (DPMS). Nous comparons les deux et soulignons les caractéristiques de la dynamique des piétons. De plus, nous proposons trois stratégies de contrôle dédiées aux flux de piétons et évaluons leur efficacité. La première est l'utilisation de barrières, inspiré des feux de signalisations et de la régulation des rampes d'accès aux autoroutes. La deuxième consiste à utiliser des séparateurs de flux pour empêcher les flux bidirectionnels de piétons. La troisième exploite les tapis roulants, en contrôlant leur vitesse et leur direction, pour influencer les flux de piétons.

Les stratégies de contrôle illustrent l'utilisation du DPMS en simulant différentes études de cas. La première stratégie de contrôle que nous proposons n'apporte que des améliorations mineures à la dynamique des piétons. La deuxième stratégie améliore avec succès les temps de trajets des piétons. La troisième stratégie, où l'une des variantes de l'algorithme de contrôle intègre des prédictions à court terme, permet de réduire la congestion et d'améliorer les temps de parcours. L'utilisation des tapis roulants par l'algorithme prédictif met en évidence le compromis entre la diminution du temps de trajet et la réduction de la congestion. Enfin, pour les trois stratégies de contrôle et tous les algorithmes, certains usagers sont pénalisés alors que d'autres sont avantagés. Grâce aux différentes stratégies de contrôle proposées dans cette thèse, nous soulignons le besoin de stratégies de contrôle dédiées aux piétons. Trois spécificités sont identifiées : le respect des consignes, les choix disponibles, et la complexité des flux de piéton. Il est essentiel de prendre en compte ces aspects pour développer des stratégies efficaces. Les stratégies que

nous discutons peuvent être appliquées dans n'importe quel contexte piétonnier. Néanmoins, le potentiel des stratégies développées dans cette thèse est encore sous-exploré. De plus, des applications pratiques pourraient être mises en oeuvre avec un coût limité puisque la plupart des composants permettant d'utiliser des stratégies simples existent déjà.

Mots clés Contrôle des flux de piétons, stratégies de contrôle et gestion, simulation de piétons, système de gestion dynamique des piétons, utilisation de barrières pour les piétons, flux bidirectionnel des piétons, tapis roulants dynamiques.

Contents

List of Figures

1 Introduction

1.1 Context and motivation

Each individual has his personal preference with respect to crowding in public spaces. Nevertheless, except for some very specific contexts, individuals generally dislike and tend to avoid congested areas. This is true for drivers commuting to work, pedestrians walking inside shopping malls or passengers inside public transit vehicles. Furthermore, not only does congestion induce delays, but it also induces unpredictability in the system at hand. In the context of pedestrians, it may also generate discomfort or even safety issues. Congestion on a city road network will delay the public transit vehicles meaning the passengers might miss their connections when transferring. Drivers commuting to work need to allow for extra travel time during peak hours to account for the delay induced by congestion and the high variability of the delay. The attractiveness of pedestrian leisure infrastructure will decrease if regular congestion occurs inside. Many more examples of the negative effects of congestion can be listed, but the common aspect between them is the poor user satisfaction when congestion occurs. Interestingly, in some contexts, high density is desired. Music concerts and nightclubs are two examples referring to pedestrian situations where users seek high density.

Generally, congestion is caused when the demand is larger than the capacity of the supply serving the demand. This occurs for different reasons. Building infrastructure, be it roads, pavements, or shopping malls capable of coping with the highest demand would not be cost effective since most of the time the capacity would not be used. Furthermore, according to the UN, the world population is expected to increase by 2 billion persons in the next 30 years (United Nations, 2019). Not only is the population increasing, but the fraction of people living in urban areas is steadily increasing (United Nations, 2018). Moreover, to reduce the negative effects of the population's movements on the environment, public authorities are trying to increase the modal share of public transport. The combination of these different effects, the population increase, move to urban areas and modal shift puts pressure on the transportation networks among other areas. Therefore, it is likely that most existing infrastructure will be exceeded by the demand in the coming years if no measures are taken.

For the modal share of public transit to increase and to keep existing customers, the system must be attractive to the users. Since the congestion which occurs in public transit networks (inside vehicles or buildings) is negatively correlated to the experience passengers feel when using such networks, ensuring pedestrian infrastructure is not excessively congested is critical to have an attractive network. The attractiveness of such modes depends not only on the characteristics of the lines (frequency, capacity, speed, etc) but also on the transfer experience and the access/egress times to the networks. Managing congestion is therefore one of the critical elements for maintaining an attractive public transport system.

Whether the pedestrian infrastructure is reaching its limits because of population increase or a change in the population's living habits, eventually, the infrastructure must be adapted to cope with the increasing demand. This can be achieved with different means. The first solution which comes to mind is to increase the size of the infrastructure. Although this solution is efficient for reducing congestion since more space is available to the users, the overall experience can also decrease since the pedestrians must now navigate a larger walkable environment which takes longer. Increasing the size of the infrastructure will not improve the pedestrian dynamics if local bottlenecks remain. Furthermore, major construction work is expensive and time consuming. Physical space can also be a challenge in dense urban areas: increasing the size of a given infrastructure might not be possible without extending it in the vertical dimension, hence significantly increasing the cost. An alternative solution to increasing the capacity by extending the size is to improve the infrastructure's efficiency at handling the demand. Travel time can be reduced by using hardware that increases the moving speed of users. Providing accurate and clear information about the fastest routes to areas inside the infrastructure will improve the pedestrian's experience. Another example is dispatching demand throughout the whole infrastructure to prevent uneven congestion inside the walkable environment. Measures like the examples given here are either static or dynamics strategies for controlling and managing pedestrian flows.

By applying control and management strategies to pedestrian flows, the operators have the potential to significantly improve the pedestrian dynamics occurring in the infrastructure they manage. Limiting head-on collisions and preventing spontaneous flow breakdown are two examples of situations that should be prevented wherever possible. This approach has successfully been explored and applied for road traffic since the 1970s and 1980s. Nevertheless, comparatively little work has been done on pedestrian dedicated strategies. With this thesis, we aim to address the lack of pedestrian dedicated control strategies by considering the following research questions: 1) which similarities and differences between road traffic and pedestrian flows can be exploited to design a framework dedicated to pedestrian flow management? 2) how do pedestrian-focused control strategies improve pedestrian dynamics during daily operations?

No limitations are suggested regarding the applicability of either the strategies themselves or the management framework. Naturally, calibration to the local context is always necessary but the concepts are relevant for all pedestrian infrastructure. In this thesis, the case studies are inspired from an existing train station since it represents an environment that is often congested during peak hours and for which empirical data has been collected. As the literature in the following

section will emphasize, transportation hubs are popular places for the development and evaluation of control and management strategies for pedestrian flows.

1.2 Relevant literature

As stated previously, many success stories of road traffic control and management strategies can be found in the literature. The framework common in road traffic for controlling and managing traffic is the Dynamic Traffic Management System (DTMS). A dynamic traffic management system combines historical and real-time data and implements information and control strategies that improve the global performance of the traffic network. In general, the strategies are anticipating the users' responses and their impact on the system. From a methodological point of view, they combine loading models with traveller behaviour models, usually in a simulation context that accounts for the dynamic nature of the system. Multiple DTMS have been proposed in the literature for road traffic. Some examples are DynaMIT (Ben-Akiva et al., 1998), DYNASMART (Mahmassani, 2001) and METROPOLIS (Palma and Marchal, 2002).
Dynamic traffic management systems tailored for pedestrians is still an under-explored area within the literature (Dubroca-Voisin et al., 2019), although significant steps have been taken in this direction as in Abdelghany et al. (2012). The majority of elements that are required to build a pedestrian dedicated management system are listed in Kabalan et al. (2017). We will now discuss research that has been led on the components required to build the pedestrian counterpart to DTMS. We organize the discussion into three parts. First, we discuss the elements relevant for traffic modelling and data collection, then we discuss control and guidance strategies.

1.2.1 Pedestrian traffic modelling

In order to design and develop a pedestrian version of DTMS for the monitoring, prediction, and regulation of pedestrian flows, several components are needed. The following paragraphs review the state-of-the-art pedestrian motion models and demand estimation models which are needed to build a pedestrian management system.
The models used for simulating pedestrian motion are usually organized in three categories: microscopic, mesoscopic and macroscopic (Duives et al., 2013). The first group of models represent pedestrians explicitly (often called agents). These agents then interact with each other and the environment and "walk" towards their goal by avoiding obstacles. The well known "social force" model where the motion of each pedestrian is simulated by summing up forces created by attractive or repulsive effects (Helbing and Molnár, 1995) is an example of microscopic models. The "next step" model uses a discrete choice approach for computing the probability that the next step of a pedestrian lies in a given zone (Antonini et al., 2006). Finally, the cellular automaton (CA) models divide the walking area into cells within which only a single pedestrian can stay (Blue and Adler, 2001; Burstedde et al., 2001). Appealing aspects of microscopic models are the

ability to model pedestrian specific characteristics (Campanella et al., 2009) and the high level of detail which can be obtained when considering interactions with objects or other pedestrians (Teknomo, 2006). The modelling and simulation of pedestrian groups is explored in Kremyzas et al. (2016).

Mesoscopic models lie in between microscopic and macroscopic models and borrow concepts from both of them (Lemer et al., 2000). The advantage of mesoscopic models is the trade-off between computational cost and accuracy. A common modelling approach used in mesoscopic models is the notion of person groups (Tolujew and Alcalá, 2004) or packets (Hänseler, 2016).

Finally, at the other end of the scale macroscopic models are found. In these models, pedestrians are aggregated into flows. Two important modelling approaches are found. The first uses a system of PDEs to represent the flow of pedestrians (like in fluid dynamics) as in Hoogendoorn et al., 2014 or Algadhi and Mahmassani, 1990. The second class of macroscopic models does not depend directly on a system of PDEs for describing the pedestrian motion but relies on a discretization of space. They are called "cell transmission models" (CTM) (Asano et al., 2007; Hänseler et al., 2014).

A new trend in pedestrian modelling is appearing with the usage of machine learning techniques in order to improve the models. One motivation for this recent advancement is the need for reliable predictive models used by autonomous vehicles (Rudenko et al., 2019). Real-time prediction is performed in Han et al. (2019) whereas socially aware pedestrian trajectory prediction is done in Y. Sun et al. (2019).

Some studies have combined two of these modelling paradigms into one single model: these are hybrid models. The different scales can be overlaid, as in Xiong et al. (2009) and Hoogendoorn et al. (2014), or appended to each other (Xiong et al., 2010). The challenge in both cases is passing from one level to another. This is addressed in Biedermann et al., 2014, where the authors provide a framework for developing the transition between different models.

Motion models as described previously are not sufficient for pedestrians to navigate around an infrastructure. A route choice model is required to address the tactical decisions. There are multiple paradigms for modelling route choice. Graph-based and potential-based are two common approaches which can take congestion into account (Stubenschrott et al., 2014; Guo et al., 2013; Hoogendoorn and Bovy, 2004b).

By combining dynamic route choice and the motion of pedestrians, the dynamic traffic assignment (DTA) problem arises. Agents continuously reconsider their path to their destination and adjust it based on the expected travel time. An important aspect of this procedure borrows theory from economics and is strongly linked to the dynamic user equilibrium (DUE) problem (Mahmassani and Herman, 1984). Over the last couple of decades, multiple DTA models have been proposed for pedestrian traffic with different objectives in mind. For example, in Abdelghany et al. (2012), a microscopic simulator is used to model the crowding which takes place during the Hajj, the Muslim pilgrimage to Makkah (Saudi Arabia). An analytical approach is used to model the user optimal assignment problem in Hoogendoorn and Bovy (2004a) which does not rely on a graph representation of the infrastructure. This way, the authors removed the arbitrary aspects

of the infrastructure which are defined in graph representations. A tactical route choice model combined with a force-based operational model targeted at video games and pedestrian simulation is proposed in Karamouzas et al. (2009). The authors state that their model is usable in real-time and generates realistic pedestrian paths.
Finally, the choice between this wide range of models depends on the scenario under investigation. If the scenario involves a compact infrastructure and the application requires disaggregate information, then a microscopic simulator might be more appropriate. On the other hand, large infrastructures with applications impacting pedestrians at an aggregate level require faster motion models as the computational cost is larger. Nevertheless, no explicit rule can be defined. This decision relies strongly on the context.
Although the road and pedestrian traffic modelling approaches share similarities, there are some major differences. The first difference is compliance and regulations. Unlike vehicles, pedestrians do not have a set of strict rules to follow. Albeit some social rules do exist, they are still flexible and subject to interpretation. Secondly, pedestrian flow is multi-directional (Hänseler et al., 2017a). The interactions between the different pedestrians depend on the speed, direction and relative group size. For two streams of pedestrians crossing each other, the interactions will be different based on the number of people in each stream, therefore making the modelling of bidirectional pedestrian flows challenging. Bidirectional flow is studied in an experiment in Feliciani and Nishinari (2016) where the authors explored the dynamic formation phases of lanes. Even in a controlled environment lane formation is unstable. Lane formation has been reproduced in many simulation models like the social force model for example (Helbing and Molnár, 1998). Dynamic lane formation partially solves the bidirectional flow problem as dynamics are improved (Hoogendoorn and Daamen, 2005a).
Another difference lies in the existence of a fundamental diagram (FD). The existence of a FD for car traffic is clear. With pedestrian flows though, such existence is not as clear. Multiple experiments support the existence of a fundamental diagram for pedestrians. Although no global consensus exists between the authors, it is clear that higher densities reduce the speed and flow of pedestrians. This is true for flows moving in opposing directions as well as flows meeting at various angles (J. Zhang et al., 2012; J. Zhang and Seyfried, 2014; Bosina, 2018).

1.2.2 Measurement technologies

Technologies required for counting and tracking pedestrians have improved recently. Unlike for road traffic, the sensing technologies for counting pedestrians must deal with the lack of structure in the pedestrian flows: in particular, pedestrians are not constrained to lanes. Today, a common technology for counting or tracking pedestrians is computer vision. Exploiting the existing Wi-Fi network is a cost-effective way to collect data. The limitations of this technology can be addressed by combining different data sources as in Farooq et al. (2015). Another example of data fusion is the combination of video tracking with LIDAR technology (Melotti et al., 2018). Alternative methods such as mechanical counts, survey data or GPS tracking devices exist but are

either expensive or suffer from technology limitations (Danalet, 2015). The field of pedestrian tracking and detection is still evolving rapidly, partly pushed by the need for reliable algorithms for autonomous vehicles (Janai et al., 2017). These technologies allow pedestrian tracking and counting at links or at specific positions, but not only. Pedestrian tracking can also take place over large areas. Naturally, covering a whole city with millions of inhabitants is challenging and expensive, but closed places like train stations, airports or shopping malls can be completely covered (Alahi et al., 2010).

From the measurements, key performance indicators (KPIs) specific to the problem under investigation are computed. These KPIs are used to evaluate the state of the system. These KPIs can take into account different aspects of the traffic dynamics. The three fundamental variables (speed, density and flow) can be used as KPIs, but more complex KPIs can also be used like travel time or delay. The choice of the KPI depends on the control strategy or scenario being studied. Recently, different means of defining density have been investigated in the literature which aim at measuring more accurately the density experienced by pedestrians. Voronoi diagrams (or tessellations) are used where cells are built around each pedestrian. This method has the advantage of not requiring an arbitrary spatial discretization (Nikolić and Bierlaire, 2014).

As the previous paragraphs show, most of the components required to build an equivalent to DTMS for pedestrians exist in the literature. Nevertheless, their aggregation to form the management system is still underexplored. The next section discusses the other major element needed to control and manage pedestrian flows: the strategies themselves.

1.2.3 Control and information strategies

In this section, we present the different control and management strategies which can be found in the literature for pedestrian flow management. The majority of the existing control strategies propose static or offline measures to improve the flow dynamics. Albeit successful, by design they cannot adapt to the prevailing pedestrian dynamics. To emphasise the differences or similarities with road traffic strategies, the major assumptions and paradigms found in the road traffic literature are also presented.

For road traffic, control strategies using traffic signals or speed limits can rely on a high level of compliance since drivers must obey a well-defined set of rules and often full compliance is assumed (Kotsialos et al., 2002). When strategies for pedestrians are designed, the problem of compliance is central since no regulations ban pedestrians from certain movements. Therefore, control strategies must either enforce the desired behaviour by installing physical obstacles like gates or assume full compliance for elements like traffic lights or lanes. The installation of physical obstacles to direct and regulate the flows of pedestrians induces safety and emergency questions. Excessive congestion can lead to dramatic events (Ngai et al., 2009) and must be avoided at all cost by providing emergency evacuation plans. Although emergency situations must be handled correctly, during daily operations many different behaviours are observed. People have different walking speeds based on their trip purpose and socio-economic characteristics

(Weidmann, 1993). Therefore, control strategies should take into account these situations to be safe and convenient for all users. When information strategies are considered, consistency becomes central as it does for road traffic. On top of that, people undertake journeys for many different reasons. People walking for touristic reasons or passengers waiting for a connection might not be motivated by minimizing travel time. These behaviours are challenging to model as they do not follow classical utility maximization assumptions (Hoogendoorn and Bovy, 2004b). Most the attention has been guided towards reactive and offline strategies, with many applications inside transportation hubs, one area where pedestrians generally wish to move freely and reach their destination as fast as possible. Passenger flow control is therefore important to achieve this goal (Shang et al., 2019). Recently, a framework for controlling level-of-service (LOS) in a pedestrian infrastructure has been presented in Z. Zhang et al., 2016. The walkable space is represented in a bi-level way: a graph combined with cells. The same target density is enforced on each link by controlling the pedestrian's walking speed. This approach is difficult to apply in transportation hubs as the demand presents high spatial and temporal fluctuations, making uniform density or speed not desirable. Similarly to the previous study, a macroscopic pedestrian movement model was used to assess and design the strategy for controlling the opening and closing times of access gates to metro stations (Bauer et al., 2007). The scenarios were based on special events where the demand significantly exceeds the daily operation's demand. Nevertheless, although the authors use most of the components required in the design of a framework for the application of management strategies, no complete framework is proposed, indeed, each component is used independently. A feedback control scheme based upon an aggregate pedestrian motion model is proposed in Z. Zhang and Jia (2021) where the authors control pedestrian flow to prevent excessive congestion in corridors. The inflow into urban rail stations is controlled in Jiang et al. (2018) by using buffer zones in front of the doors. In Xu et al. (2016), the authors provide a general framework which can help operators decide whether local passenger flow control should be applied. Nevertheless, no system-wide short-term predictions are used to provide future state data. Passenger flow control is considered at a train network level where the trade-off between train usage and waiting passengers is explored (R. Liu et al., 2020). Although control strategies for pedestrian flows is getting more attention nowadays, most strategies rely upon a reactive scheme and the added value of short-term predictions is yet to be explored. For daily operations, Jiang et al. (2018) propose a coordinated control scheme across multiple metro (light rail) stations. The author's goal is to ensure that all passengers can get on their desired service. This objective is achieved by regulating the inflow into the stations by using a buffer zone just outside the station. Reinforcement learning is used given the large-scale network and the computational cost induced by such network. The boarding and alighting process under flow restrictions is studied in Seriani and Fernandez (2015). The authors enforce unidirectional flow through each door, hence preventing bidirectional flow. The proposed measures remain static and could be improved by dynamically defining the direction of each door based on the demand. The authors also focused on the static design of hardware like handrails near the doors. Another example of gating applied to subway networks is presented in Muñoz et al. (2018) where the authors use gates to improve

the clearing time of the platforms.
Information provision to pedestrians is studied in Feliciani et al. (2018). The authors investigate how information about walking speeds influences system performance. The case study is a two-lane closed loop where pedestrians can change lane in only two positions. They show that providing information about the walking speed of both lanes to pedestrians is beneficial to the overall system. The effectiveness of some crowd management actions was observed in a real-life situation in Campanella et al. (2015), where a Brazilian metro stop offered very poor LOS and possibly dangerous situations during the new-year celebrations. Some management strategies had been planned and used to prevent critical situations while some reactive actions were also used. Qualitative observations were done and compared to operations from the previous years. The authors emphasize the need for an integrative framework including pedestrian simulations for evaluating various crowd management strategies. The optimal configuration of traffic lights for signalized crosswalks has been studied for example in Y. Zhang et al. (2017). The authors propose a mixed integer-linear program to optimize the configuration of the green, orange and red phases to minimize the pedestrian's delay while satisfying vehicular traffic constraints.
One area which has been more thoroughly investigated is controlling pedestrian dynamics in emergency situations. The goal is to measure and minimize the time required for all pedestrians to leave an infrastructure. The difference with daily operations lies in the pedestrian behaviour and the final objective. For example, the optimal placement of exits and furniture inside rooms is analysed in Hassan et al. (2014) using a cellular automata model and simulated annealing for the optimization. Similarly, flow is regulated in order to maximize discharge in a corridor during an evacuation in Shende et al. (2011). A potential-based pedestrian assignment model is used to optimize pedestrian evacuation in Guo (2018). Many evacuation scenarios take place in schools or office-type buildings where people must weave between tables and other obstacles to leave the building. Larger buildings like stadiums and train stations are also analysed in terms of evacuation time. Few control strategies are designed to be multi-purpose and are applicable to different infrastructure categories.
Pedestrian safety during large events is obviously critical. Demand management is performed in Abdelghany et al. (2012). The demand pattern of pilgrims heading to the Mecca (Saudi Arabia) is regulated thanks to a booking system. Although the congestion levels are successfully reduced, this information strategy does not include a dynamic component to regulate real-time traffic. That was addressed with further research in Abdelghany et al. (2016) where pedestrian flow control is applied in the Mecca during pilgrimage. A reactive policy is applied to reduce inflow to prevent excessive congestion and hazardous situations. No online predictive control policy is applied. The design of static checkpoints for large events is explored in Aros-Vera et al. (2020). Pedestrian flow is controlled in a reactive way in Z. Zhang et al. (2016) where the authors use a macroscopic model to simulate the movements of pedestrians. The assumptions about homogeneity on the links are hard to satisfy in practice. In L. Wang et al. (2013), the authors show that simulation tools can be used to prevent high congestion and hazardous situations during special events. They simulated congestion inside a train station under exceptionally high demand.

Guidelines for practitioners to manage crowds during major events are discussed in Still et al. (2020) where the DIM-ICE risk model is applied to several case studies. The authors emphasize that management issues and infrastructure configuration is often the cause of casualties, and not the users themselves. In Martella et al. (2017), the authors interviewed ten senior individuals who where responsible for crowd management in various Dutch events. The outcome from their work emphasized how important adequate planning is and the need for further development of measurement solutions.
The state-of-practice regarding control and information strategies focuses on safety. The evaluation of platform measurement devices to capture platform safety is done using sensors in Heuvel et al. (2017) for several Swiss and Dutch train stations. Similar safety considerations are explored in Van den Heuvel et al. (2012) where the authors discuss the "Station Transfer Model" used by the Netherlands Railway manager (NS). State-of-practice crowd management measures and issues are discussed in Wijermans et al. (2016). The authors propose a framework for supporting crowd management: the planning, monitoring, and decision-making phases are discussed. A practical example considering a festival in the Dutch city of Arnhem is discussed. The crowd management measures involve video-based monitoring and the assignment of agents to address any hazardous situations. Finally, the authors conclude that effort must be invested to bridge the gap between research and practice.
Through the various flow management strategies presented above, we see that the development and evaluation of control and management strategies dedicated to pedestrian flows is becoming a popular field of research. Nevertheless, most strategies are either offline or reactive. Furthermore, most of them focus on intra-hub pedestrian dynamics. Predictive control strategies focusing on daily operations and applicable to any environment are underexplored. Many case studies focus on transportation hubs, special events or emergency situations.

1.3 Contributions and thesis structure

Considering the literature presented in the previous paragraphs, two conclusions can be made. Firstly, no comprehensive discussion about all the elements required to apply control strategies for pedestrians can be found in the literature. Secondly, few dynamic control or management strategies dedicated to everyday pedestrian life have been proposed. Therefore, this thesis aims to address these gaps by answering the two research questions presented in the introduction with the following contributions:

(a) the exploration of pedestrian transfer dynamics inside transportation hubs and the relationship with urban public transport networks, developed in Chapter 2,

(b) the discussion and formalization of all the elements required to apply control strategies for managing pedestrian flows through the development of a Dynamic Pedestrian Management System (DPMS), developed in Chapter 3,

(c) the evaluation of the impact of different control strategies on the pedestrian dynamics taking place inside pedestrian infrastructure, developed in Chapters 3, 4 and 5,

(d) the development of pedestrian flow control and management strategies which exploit characteristics of pedestrian dynamics, developed in Chapters 4 and 5,

(e) the cost-benefit analysis of including short term predictions in the control algorithms, developed in Chapter 5.

The structure of this thesis is described in the following paragraphs and aims to emphasize the contributions presented above. The core of the thesis is composed of four chapters, followed by the concluding chapter.
Based upon the work performed during the European project "TRANS-FORM", Chapter 2 serves two objectives. First, to present in detail the data used as inspiration for the case studies discussed in later chapters. Second, to motivate the need for pedestrian control strategies and multi-modal passenger modelling. The TRANS-FORM project aimed at developing synergies between urban public transport modelling (bus, light rail), regional public transport modelling (train) and intra-hub pedestrian motion modelling. Particular attention was given towards management in case of disturbances. In this chapter, we present the main lessons learned and outcomes which can be extracted from the analysis of the intra-hub pedestrian dynamics. This chapter has been published as a technical report:

> N. Molyneaux and M. Bierlaire (2021a). *Analysis and modelling of intra-hub pedestrian dynamics*. Technical Report TRANSP-OR 20210526. Lausanne, Switzerland.

In Chapter 3, we propose the design of Dynamic Pedestrian Management Systems (DPMS), and identify the elements that are needed to build the system. This chapter formalizes the pedestrian counterpart to road traffic DTMS. Three key challenges are identified regarding pedestrian management systems: compliance to information, a large and unregulated set of choices available to pedestrians and the complexity of pedestrian assignment models. A first control strategy inspired by road traffic is presented to illustrate the DPMS framework. We tested this control strategy on a single intersection to evaluate its potential at improving pedestrian dynamics.
Chapter 4 presents a control strategy tailored to pedestrian dynamics. The usage of flow separators is proposed to prevent bidirectional pedestrian flow along a corridor. Two applications are discussed. The first is a proof-of-concept installation. One single device installed in a straight corridor. The second case study is inspired from an existing infrastructure: the train station in Lausanne, Switzerland. The content of Chapter 3 and Chapter 4 has been published together in the journal "Transportation":

> N. Molyneaux, R. Scarinci, and M. Bierlaire (Aug. 2021). "Design and analysis of control strategies for pedestrian flows". In: *Transportation* 48.4, pp. 1767–1807. ISSN: 1572-9435. DOI: 10.1007/s11116-020-10111-1. URL: https://doi.org/10.1007/s11116-020-10111-1.

The third and final control strategy which is proposed exploits existing pedestrian dedicated hardware: moving walkways. The control algorithm dynamically chooses the speed and direction of the moving walkways. Different flavours of the control algorithm are proposed and tested in two case studies. The single corridor setup used for the flow separator strategy is considered. The other case study is a simplification of the whole train station in Lausanne. This control strategy is presented in Chapter 5. The content of this chapter has been published as a technical report:

> N. Molyneaux and M. Bierlaire (2021b). *Controlling pedestrian flows with moving walkways*. Technical Report TRANSP-OR 210218. Lausanne, Switzerland.

Finally, this thesis is concluded by Chapter 6 where practical considerations and potential next steps are discussed. The simulation code used for this thesis is available on github:

https://github.com/NicholasMolyneaux/hub-simulator

This piece of software has evolved over the course of my PhD, therefore exactly reproducing the numerical results might not be possible. Nevertheless, the numerical differences should only be minor and will not affect the conclusions drawn from the results.

2 Analysis and modelling of intra-hub pedestrian dynamics

This chapter is based upon the work we performed in the context of the European project TRANS-FORM. At EPFL, our tasks mostly focused on intra-hub data analysis and modelling. Several members of the TRANSP-OR lab collaborated on the TRANS-FORM project: Riccardo Scarinci, Yuki Oyama, Nikola Obrenovic and Shadi Sharif Azadeh. The following academic and industrial partners were involved in the project:

- Delft University of Technology (Netherlands)
- Blekinge Institute of Technology (Sweden)
- Linköping University (Sweden)
- École Polytechnique Fédérale de Lausanne (Switzerland)
- IBM Research (Switzerland)
- ETRA (Spain)

The content of this chapter is available as a technical report:

> N. Molyneaux and M. Bierlaire (2021a). *Analysis and modelling of intra-hub pedestrian dynamics*. Technical Report TRANSP-OR 20210526. Lausanne, Switzerland.

2.1 Introduction

The TRANS-FORM project, carried out by a European consortium mixing research partners, industrial partners and stakeholders, was devoted to analysing and managing passenger transfer experience in public transport networks. It is common for passengers to transfer between different services when commuting to their work locations. Each time an individual leaves one public transport (PT) vehicle and gets on another, he uses a transfer location to change service. Transfer locations range in size from small bus stops to multi-story train stations. The larger transfer locations are called "hubs". Hubs can typically include light rail and bus stops, regional train connections and even international train lines. Such hubs therefore act as connecting links between the different public transport modes and lines. Public transport networks can be divided into two levels. On one hand, urban networks provide public transport services inside a densely populated area. On the other hand, regional networks provide such services in between different densely populated areas. Nevertheless, in some cases a clear demarcation cannot be made and public transport services belong to both levels.

While the exchange hub lies in between the urban and regional levels when a passenger's trip is considered, when dynamics are considered, the hub level boasts the fastest changing dynamics. The level-of-service inside a hub can significantly change within a matter of minutes. High spatial and temporal variations are observed in normal operating conditions. In case of disruptions or disturbances in the public transport network, consider an interruption of most of the trains inside a large station for example, negative effects like high congestion or missed connections can occur. In extreme cases, dangerous situations can occur if pedestrians enter the hub but cannot leave on their scheduled service. Inside transportation hubs, maybe the most critical areas regarding crowding are the platforms. To prevent severe health hazards, platforms must never be overcrowded otherwise passengers could get pushed onto the train track or road. Therefore, measures must be taken to prevent such hazardous situations and poor level-of-service from occurring. Since the intra-hub conditions can be problematic, control and management strategies to mitigate the negative effects of both pedestrian congestion and PT disturbances/disruptions which consider both the public transport network and the intra-hub dynamics should be considered.

Prior to developing such risk mitigation strategies, the pedestrian dynamics taking place inside the hub must be understood. The flow dynamics and the structure of the demand are two critical topics to explore to understand the operating conditions of any infrastructure. Furthermore, the interactions between the intra-hub pedestrian flows and the public transport services must also be explored. Therefore, regarding the hub level, the TRANS-FORM project aims at improving our understanding of pedestrian dynamics inside hubs and investigating the connections between public transport networks and hub pedestrian dynamics. With this chapter, we address thesis contribution *(a)* by considering whether the inclusion of pedestrian dynamics in the decision process of scheduling or disturbance/disruption management has the potential to improve passenger welfare. This is achieved by analysing pedestrian tracking data collected inside an existing infrastructure and by developing an integrated modelling scheme for hub dynamics and urban

public transport networks. The outcome of this procedure is twofold. Firstly, in-depth knowledge of an existing infrastructure is acquired to use as case studies in the following chapters of this thesis. Secondly, we emphasize the challenges associated with multi-model integration and motivate the need for pedestrian dedicated measures to improve flow dynamics.
This chapter is structured as follows. After this introduction, we present the relevant literature on multi-modal coordination in public transport networks. After that, we present some metrics dedicated to the monitoring of pedestrian dynamics. Following the theoretical considerations, we present the results from the analysis of the pedestrian tracking data. Next, the modelling assumptions and considerations are discussed and the results from the urban and hub integrated modelling are shown. Finally, we conclude this chapter and discuss some ideas for future research.

2.2 Literature review

As already presented in section 1.2.1, the literature on intra-hub pedestrian modelling is vast. Many different modelling schemes (microscopic, mesoscopic and macroscopic) exist and have been applied to a large variety of cases studies. Nevertheless, such models are scarcely used to include intra-hub dynamics into PT scheduling schemes. The following literature review presents the methods for including intra-hub dynamics in public transit models. This is done both for regular operations and in the case of disruptions or disturbances.
Transfer time is generally considered in railway scheduling and timetable synchronization problems. The coordinated railway scheduling problem is addressed in Cao et al. (2019). The authors propose a methodology for including variable transfer times in large scale problems. Although they relax the constraint where the transfer times are considered constant, the walking transfer time interval is considered independent from the pedestrian dynamics.
In Yap et al. (2019), the authors propose a methodology for reducing the complexity of the timetable synchronization problem by identifying which hubs should be prioritized when synchronization must be applied. The walking transfer time is integrated into the problem by using a low percentile of the walking speed and the walking distance as cut-off criteria. Although this approach improves the realism in the expected transfer time computation, extra travel caused by congestion is not considered.
A methodology for proposing public transit routes considering crowdedness inside hubs is proposed in Du et al. (2018). Nevertheless, the authors consider the median travel time per demand period. Although different demand periods are considered, a scalar is still used to report the walking transfer time and distance.
In the case of disruptions, transfer walking times are rarely considered. A review of metro (subway) disruption management strategies is presented in S. Zhang et al. (2021). Except from estimating the demand change when disruptions occur, the authors never mention any explicit consideration of walking transfer times inside the management strategies. They conclude that little research has been led on a multi-modal approach to public transport disruption management. Many disturbance and disruption management strategies aim at minimizing passenger waiting

time, but don't consider realistic transfer walking times. Strong assumptions are made regarding time required by passengers to transfer on foot (Qu et al., 2015; Corman et al., 2014).
Identification of passenger transfers from smart card data provides valuable insight into the choices passengers make. Nevertheless, this is challenging since the operator has no a priori knowledge on the passenger's origin or destination or trip purpose. Multiple methodologies exist for inferring these transfers based upon the data (Yap et al., 2017; Hofmann and O'Mahony, 2005). In general, the modelling assumptions made to propose a solvable formulation to the timetable synchronization problem include a fixed and static scalar value for the transfer walking time. Although the solution algorithms consider this walking transfer time, such an assumption is unrealistic in practice. The transfer time depends on the socio-economic characteristics of each passenger, the prevailing pedestrian traffic conditions inside the hub and other exogenous aspects like the weather for example (Wu et al., 2015).
Maybe the most advanced methodology for considering passenger assignment in public transit networks and intra-hub dynamics can be found in Hänseler et al. (2020). The authors include mesoscopic intra-hub models for each station in the network. The focus of this work is the description of in-vehicle congestion and platform usage. The authors emphasize that their methodology is tailored towards high-demand scenarios.
Without being exhaustive in the literature review, we see that strong assumptions regarding the transfer times are generally made when solving the timetable synchronization problem or considering walking transfer times. The benefits for users of relaxing the assumptions by considering more realistic transfer times is yet underexplored. Before presenting the integration considerations between the hub and urban models, we discuss metrics for monitoring pedestrian dynamics and the results of the data analysis. By doing so, we expect to gain further understanding of the dynamics taking place inside transfer hubs.

2.3 Pedestrian centric indicators

A prerequisite to modelling and understanding the pedestrian dynamics which take place inside walkable environments is having metrics to measure such dynamics. The existing methodologies for measuring service characteristics are evaluated in terms of their ability to reflect the actual (provided) level-of-service from a passenger's perspective at the hub level. When considering the variability and reliability of the performance of a hub, many different metrics and indicators of different complexity can be defined. The challenge lies in the identification of meaningful indicators which can be consistently evaluated and for which data is available. The following indicators are put forward.

Travel time The time pedestrians take to perform the origin-destination trip inside the hub is maybe the most critical indicator which can be identified when passengers must change connections. As an individual plans ahead the time required for reaching the platform from

the entrance of the hub (for example), the variability of travel time is critical in assessing the performance of a hub. The distribution of travel times can change depending on different factors like congestion, construction work or even the users themselves.

Travel distance Similarly to travel time, the distance travelled by pedestrians inside the hub can provide valuable information on the variability of the system. If many individuals dwell in the highly used areas of the hub, then the passengers must extend their walking distance to avoid these "obstacles". Likewise, many different situations can make a user divert from his ideal path to his objective, therefore inducing variability in his trip.

Pedestrian mean velocity Combining both previous quantities can be done to calculate mean velocity. The division of travel distance by travel time is defined as the pedestrian mean velocity. Pedestrians can be classified into different groups based on variables like age or trip purpose and these different behaviours will imply different free flow velocities (Vanumu et al., 2017).

Transfer reliability Missing a connecting train often leads to long travel time extensions. The transfer time between two platforms is critical when considering this aspect and any extra walking time between platforms can be problematic for pedestrians with short connection times (Shi et al., 2012). The transfer reliability can be computed by counting the fraction of people who managed to catch their connection. This approach allows a definition of transfer reliability for different spatial and temporal aggregations.

Pedestrian density Different methods for computing density exist in the literature. As discussed in section 1.2.1, pedestrian centric measures can be obtained by using Voronoi tessellations (Nikolić and Bierlaire, 2018). Classical average values can be obtained by counting the number of people inside a given area. Regardless of the method used to compute pedestrian density, it is critical to prevent excessive congestion from recurrently taking place since this can lead to dangerous situations. Furthermore, density is the most common method used to measure level-of-service (LOS) inside pedestrian infrastructure (Fruin, 1971). Density is also critical when considering pedestrian and crowd safety (Still et al., 2020).

These different metrics, travel time, travel distance or velocity for example, can be used to gain insight about daily or hourly variations of level-of-service inside the hub. Moreover, bottlenecks can be identified for a specific geographical place and a specific time inside the hub. This information can help planners to come up with better resolutions in case of a disruption or disturbance which may cause problems in the hub. Naturally, these indicators depend on the availability of the data. In some cases, all the indicators discussed previously cannot be evaluated as sufficient information is lacking.

Travel time, travelled distance and mean speed are properties of the pedestrians, while transfer reliability focuses more on the level of service of the infrastructure. Pedestrian density can be computed either per pedestrian, or per area. One common element to all indicators is the existence of variability, induced either by pedestrian specific factors (walking speed for example) or by external elements like the PT arrival times, weather, demand level, etc. In order to grasp this variability, distributions of the indicators need to be considered.
The different indicators presented above are now considered in light of the case study selected for the data analysis. The variability of the indicators is represented using histograms and other considerations relative to demand are presented.

2.4 Pedestrian tracking data analysis

Transportation hubs play an important role in modern cities, both for linking different public transport services but also as important infrastructures in the heart of cities. This is particularly true for the city of Lausanne (Switzerland) as the main train station serves as a link between the northern and southern parts of the city. Understanding the dynamics which take place inside a transportation hub is therefore a critical preliminary step towards integrated modelling. Many different aspects of the pedestrian dynamics can be considered. The current analysis focuses around three axes. First, the analysis of pedestrian demand and the identification of the critical areas inside the hub is done. The critical areas can be entrances/exits, the junction between multiple corridors or the areas around service points. Secondly, the pedestrian flows inside the hub are explored. “Origin-destination” demand is analysed by using historical data and considering the flow’s source. Finally, pedestrian walking speed and travel time are summarized. The walking time distribution is critical when individuals transfer between different public transport services. The analysis is carried out on pedestrian tracking data which has been collected inside both pedestrian underpasses of the station in Lausanne in 2013. Figure 2.1 shows the geographical representation of a zone in the hub. In this case, the zone is a pedestrian underpass (PU) connecting platforms and station exits in Lausanne train station. The areas marked in green indicate the field of view of the tracking sensors.

The overall demand in Lausanne’s train station during the morning peak hour is summarized in Figure 2.2. The available dataset includes ten days of tracking data. Systematic differences are visible when comparing the demand in both underpasses. The western underpass is used by more individuals than the eastern underpass. The significant drop in pedestrian demand for the 9th and 10th April 2013 is certainly due to the Easter school holidays which covered that week. Naturally, daily variations take place. Further analysis considering socio-economic characteristics was done in Lavadinho et al. (2013).

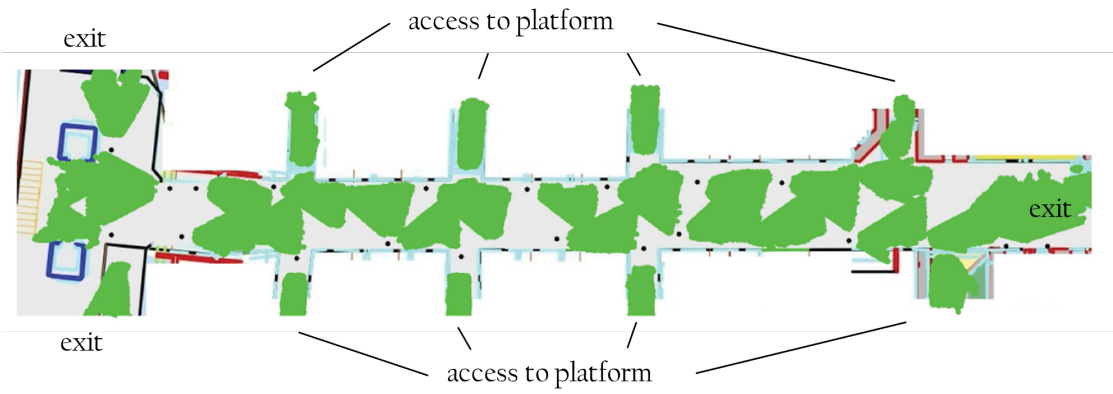


Figure 2.1: Geographical representation of a hub zone with tracking coverage from cameras, taken from Lavadinho et al. (2013).

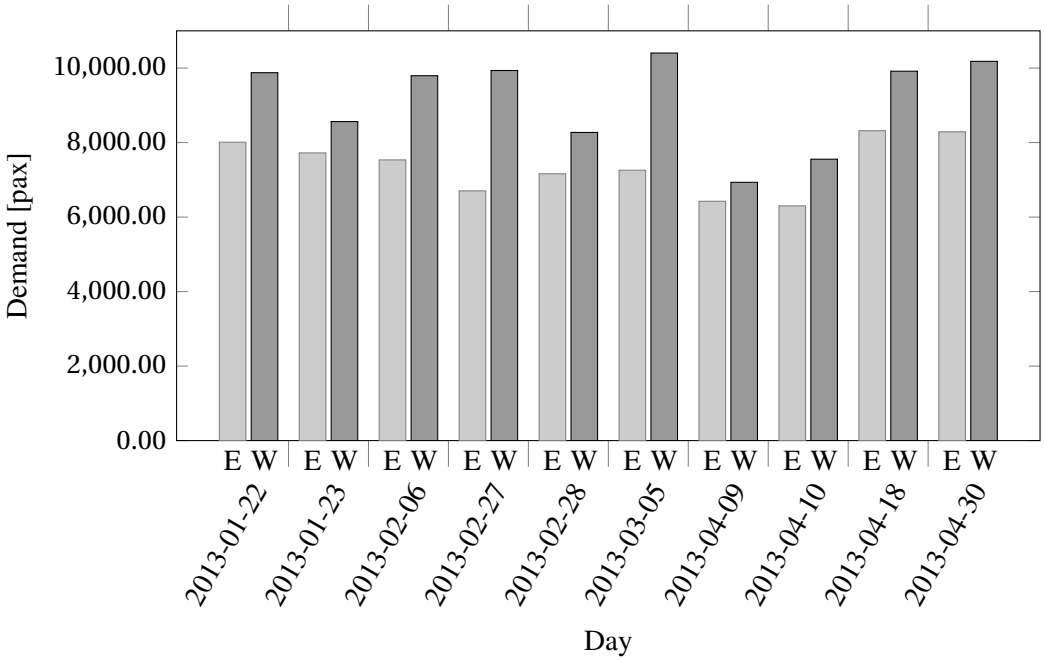


Figure 2.2: Daily demand in both pedestrian underpasses (East and West) during the morning peak hour (7:00 to 8:30).

Flows To visualize the importance of the "transit" aspect of the station, Figure 2.3 presents a chord diagram (Hänseler et al., 2016). A chord diagram shows the distribution of pedestrian flows between different OD pairs in the station. Naturally, the train platforms attract most of the pedestrians, but people do come to the station for shopping (red bands) or simply traversing the station (North to South and vice-versa).

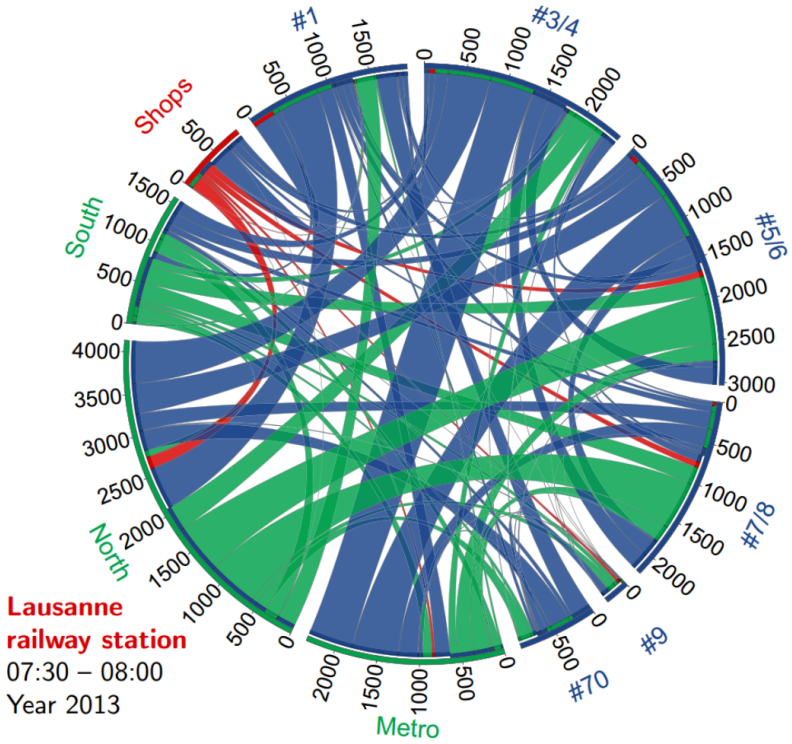


Figure 2.3: Chord diagram representing the flows at an origin/destination level inside the station.

Another possibility for visualizing the pedestrian flows in the underpasses is by plotting each individual trajectory such that higher occupied zones become darker, as in a heat map. The exercise is done in Figure 2.4, where both underpasses are visible. With this trajectory heat map, it is possible to locate the areas of the underpasses which are most used, and qualitatively estimate which platforms attract the most passengers. When comparing both underpasses, the eastern underpass (bottom) appears to suffer less from high densities than the western underpass. This goes in the same direction as a socio-economic qualitative survey (Lavadinho et al., 2013), which indicates higher utilization of the western underpass. Furthermore, the fact that the northern exit (right in images) is more heavily used than the southern one is also visible. Finally, some artificial high density zones are created from the network of cameras. In PUE (bottom image), some polygonal areas appear through high density areas.

The last analysis focusing on the flows of pedestrians through the station is the location of the entrance and exit "stamps" for each individual. This is important in assessing the reliability of the data. In Figure 2.5 the blue dots represent entrance points while green dots represent exits. Not only are no points found far from the physical entrance locations (this could be the result of some filtering), but very few exit stamps are located in the middle of the underpasses (indicating the tracking system lost someone). This is encouraging as the available data set appears robust, or has been filtered.

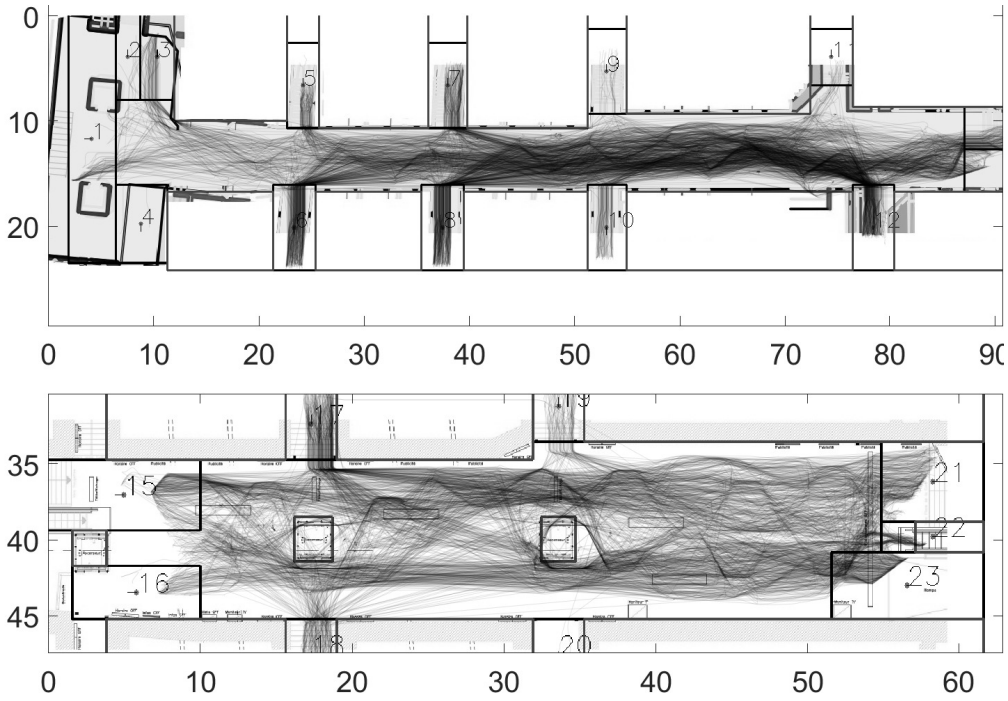
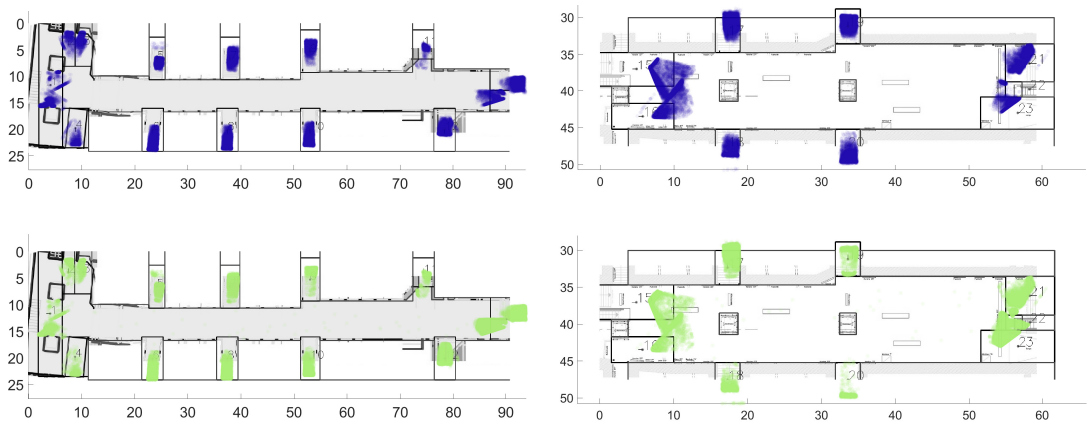


Figure 2.4: Subset of all trajectories for the main station in Lausanne. Only 1000 trajectories are shown and they have been smoothed using a moving-average algorithm of width 5. The axis labels are distance references in meters.

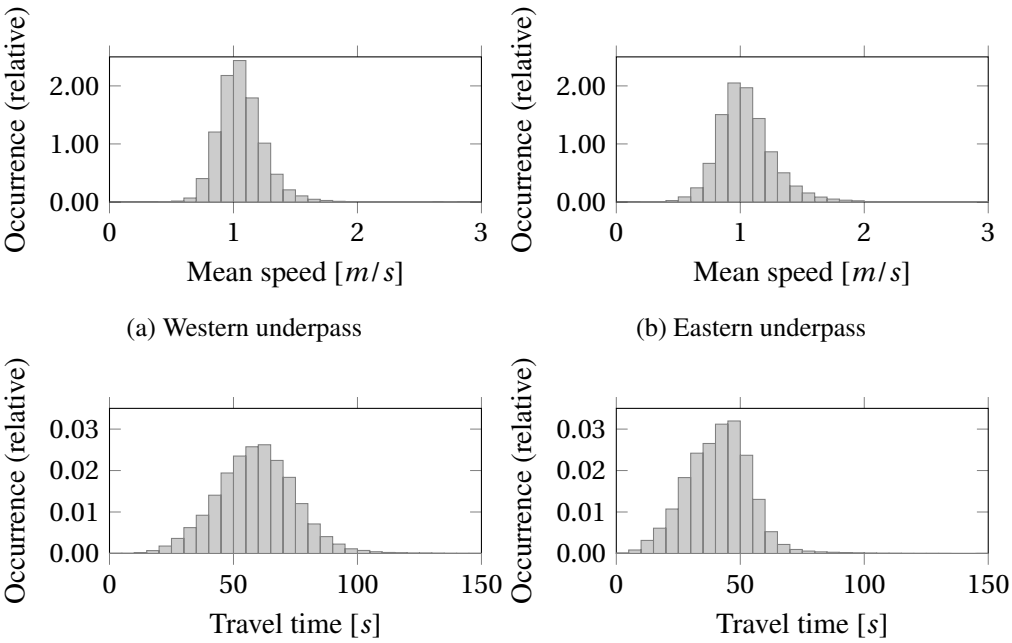


(a) Western underpass

(b) Eastern underpass

Figure 2.5: The entrance (top row) and exit (bottom row) points of each individual for all ten days are represented with dots.

Velocities & travel time Using finite difference approximations, the velocity of each pedestrian can be calculated throughout his trip in the underpasses. The distribution of the mean speed of each pedestrian is shown in Figures 2.6a and 2.6b, for both underpasses. Although a small difference in the distributions is visible, they both have the same mean and globally share the same shape. The mean is located at approximately 1.1m/s.



(a) Western underpass

(b) Eastern underpass

(c) Western underpass

(d) Eastern underpass

Figure 2.6: The distribution of mean velocities and travel times for both pedestrian underpasses.

On the other hand, when considering the distributions of travel times in both underpasses, one significant difference stands out (Figures 2.6c and 2.6d). For the western underpass, the travel time follows a normal-like distribution, while the eastern underpass yields a truncated distribution. Although the left tail seems to be normal-like, the right tail appears truncated at travel times of 60 seconds. The cause for this behaviour is not known for sure, one possible explanation would be the variety of length of all possible trips. In PUW, there is enough diversity in the trip lengths to create a full distribution, while PUE does not contain longer trips.

Velocity & accumulation When combining the velocity of each individual with an estimation (approximation) of density in the underpasses, an aggregate speed-density diagram can be created. To simplify the computation and obtain an aggregate estimate of density, the accumulation of pedestrians inside an underpass is used. This is simply the count of the number of pedestrians inside an underpass at a given moment. In Figure 2.7, the accumulation of pedestrians inside

PUW is plotted for the 22nd of January 2013. It is clear that very large variations induced by trains arriving in the station occur and one can easily imagine congestion taking place. In only a couple of minutes it varies from less than 50 to over 300 people.

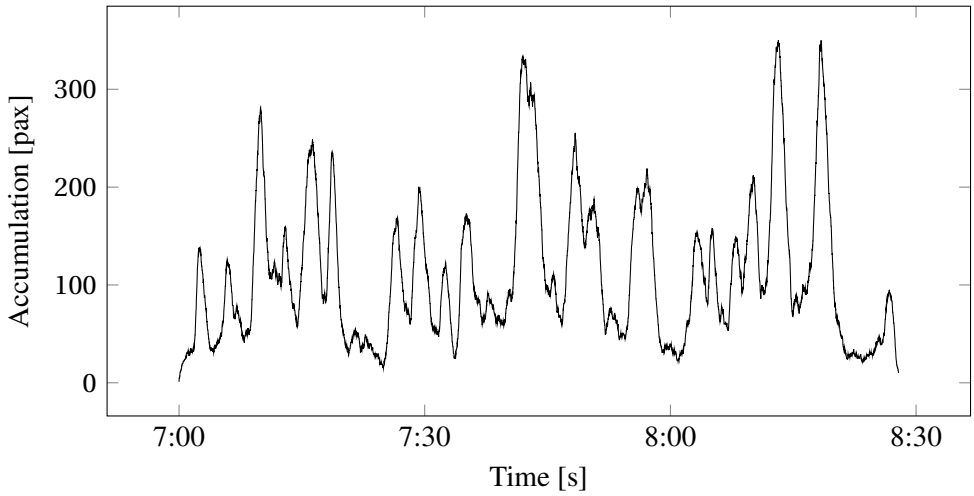


Figure 2.7: The accumulation of pedestrians in each underpass is highly variable.

When considering the link between velocity and accumulation as in Figure 2.8, an interesting pattern appears. As the accumulation increases, the variability of mean pedestrian speed decreases. We observe that for high accumulations (high density), the velocity values converge towards 1m/s. This converging velocity phenomenon has two potential sources. The first is the pressure of the surrounding people. Individuals wishing to walk slower or faster than the average speed of the crowd cannot and are forced to follow everyone else. The dynamics are not yet congested, but there are many pedestrians inside the corridors reducing the freedom of choice regarding the walking speed. The second source can be a statistical effect. The mean speed values for points where many pedestrians (high accumulation values) are considered are more representative of the general population. Considering the available data, distinguishing between the two origins is challenging. Finally, this figure also highlights the absence of severe congestion inside the corridors since the mean speed of the users does not decrease as accumulation increases.

The different indicators analysed in this section emphasized the variability in the pedestrian dynamics. The demand shows significant spatial and temporal variations. Understanding the source of these variations is important in the context of disruption management and rescheduling strategies. For example, the significant variations in pedestrian accumulation inside the station is strongly linked to the arrival of trains. The integrated modelling approach will exploit this connection.

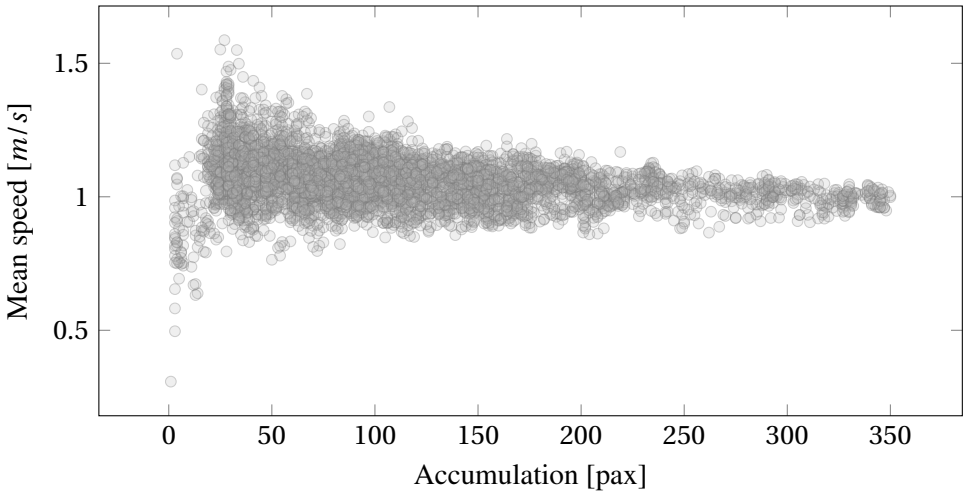


Figure 2.8: Each point represents the mean velocity of all pedestrians inside the infrastructure for a given interval and the corresponding accumulation in the station at that time.

2.5 Hub and urban integrated modelling

As previously stated, the modelling objective of the TRANS-FORM project is to propose an integrated approach which considers both urban public transport dynamics and intra-hub dynamics. To achieve this, we first discuss the interactions which take place between these two levels. Then, we discuss some modelling assumptions which must be made at the pedestrian level.

Naturally, the pedestrian dynamics taking place inside a hub are strongly influenced by the public transport services which are alighting passengers into the infrastructure. Such pedestrian demand is endogenous to the public transport network. The demand can also be exogenous if the pedestrians arrive on foot to the hub. A pedestrian inside a hub can either take a PT service or leave the infrastructure on foot.

Although embarking pedestrians must board a PT vehicle, the PT services are not constrained by the pedestrian dynamics in the same way as passengers are constrained by the services. The vehicles can leave the hub according to the schedule regardless of the dynamics taking place inside the hub. Although on platform congestion significantly impacts the vehicle dwell times through the boarding and alighting process (Heuvel et al., 2015), pedestrian congestion elsewhere inside the station does not directly impact the services. For example, transferring passengers could be blocked or delayed inside a corridor due to congestion even though the boarding process has completed. This is an example where the operator ignores the excess walking time of passengers induced by congestion inside the hub. Such a decision can lead to the passenger missing his connection. Therefore, passengers could benefit if the PT operators consider the prevailing intra-hub dynamics. Indeed, if the operator integrates prevailing conditions into the decision process, then measures can be taken to allow the passengers to catch their connection.

The relationship between the hub dynamics and the PT services is therefore asymmetrical. Although the intra-hub demand and PT demand influence each other, PT operators can take actions

which directly impact the transfer experience of passengers. Nevertheless, the measures which can be considered depend on the type of service. High frequency buses and international trains cannot be managed the same way. When passengers use a high frequency service, they don't systematically check the schedule before going to the stop. Therefore, if a passenger misses a connection, he will need to wait only a short time until another vehicle from the same service arrives. On the other hand, for low frequency services, passengers take care to plan their trips such as to reduce the chance of missing the connection. In this case, a passenger who has missed his connection will suffer from a significantly longer journey time since he must wait a long time until the next service arrives (Luethi et al., 2007).

The passenger's welfare is therefore significantly impacted by the prevailing pedestrian dynamics and the PT operator's decisions. Hence, we see the importance of understanding and integrating the intra-hub dynamics into the PT operator decision making process, but also the importance of ensuring good level-of-service inside the pedestrian environment as well. Next, we discuss how an intra-hub model can provide insight about the prevailing dynamics to the PT network and some of the modelling choices for the pedestrian simulation model.

Within the TRANS-FORM project, the objective of the exchange hub modelling is to provide insight to the other levels (urban and regional) about the pedestrian dynamics taking place inside the walkable environment. Therefore, a pedestrian simulator which can accurately model pedestrian congestion and route choice is required. The pedestrian demand comes from two sources: public transport vehicles and on-foot individuals. Therefore, the model must be able to accommodate this. Considering the different constraints and wishing to have flexibility, we choose to use a microscopic pedestrian simulator based upon the NOMAD pedestrian model (Campanella, 2016). The operational model is taken from the NOMAD package. The default simulation parameters for the operational model are used. The tactical decisions (route choice) are modelled using the shortest path algorithm where the cost is walking distance. A graph is used to model the paths pedestrians can follow. Many aspects such as what information is available to the pedestrians and the subsequent user-optimal choice equilibrium are discussed in Hoogendoorn and Bovy (2004b). In practice, pedestrians can dynamically update their route based upon the prevailing traffic conditions but generally choose the shortest path (Heuvel et al., 2015). Inside a simulation environment, this behaviour generates a fixed-point problem which must be solved. This is usually called the traffic assignment problem. The PT-induced demand is provided by the urban public transit model.

Although the computational cost is higher for disaggregate simulators compared to mesoscopic or macroscopic simulators, the ability to model pedestrians individually outweighs the excessive calculation time. For example, this flexibility allows us to accurately compute OD specific statistics even for OD pairs with few users. Another advantage of using a microscopic simulator is the coherence with the urban PT model which is used. The urban PT model is BusMezzo (Cats et al., 2010) which is an agent-based model. For details regarding the urban public transport model we refer the reader to the reports of the TRANS-FORM project (*TRANS-FORM* 2019).

Maybe the most critical information which is useful for the PT operators concerning the internal

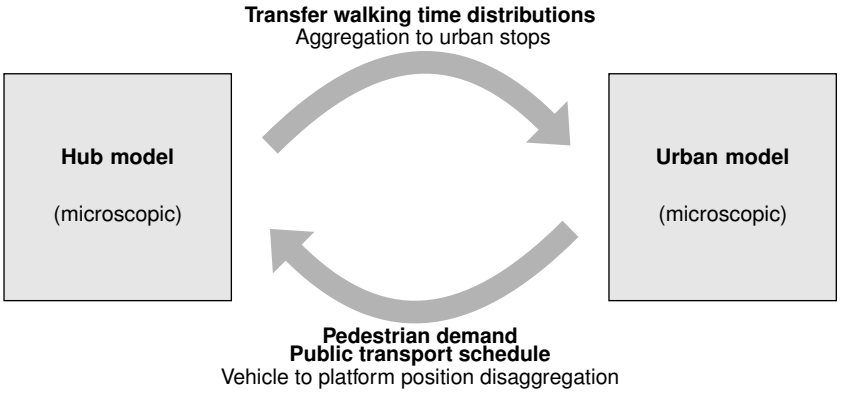


Figure 2.9: Hub model and urban model data exchange.

hub dynamics is the time required for passengers, which become pedestrians inside the infrastructure, to reach their connecting service. This transfer walking time is not a deterministic quantity since individuals walk at different speeds or have different aversion to congestion for example. The prevailing dynamics also impact the time taken to reach a given destination. In order to take into account such stochasticity of the transfer time, the walking times are provided to the PT services as distributions. The walking times between all origin and destinations are given to the PT network model. By doing so, the PT operator has quantifiable information about the prevailing dynamics inside the hub. Figure 2.9 summarizes the data exchange between both models. The hub model provides travel time distributions for all origin-destination pairs inside the infrastructure to the PT model. The urban PT model provides the arrival times of each vehicle with the passenger demand data (destination vehicle or station exit) to the pedestrian simulation model.

The pedestrian assignment isn't the only fixed-point problem which takes place inside the simulation environment. Recall that the pedestrian demand originates partly from public transport vehicles. On one hand, transferring passengers leave one vehicle and must walk to catch their destination vehicle. On the other hand, the number of passengers which are able to catch their connection depends on the pedestrian demand inside the infrastructure. Therefore, the demand of the public transport services depends on the pedestrian dynamics taking place inside the hub, and the pedestrian demand depends on the public transport network. This induces a second equilibrium problem between the PT networks and the pedestrian dynamics. To address this fixed-point problem, we choose to perform several sequential runs of each model. The runs of the hub model and urban model are alternated, and the data transferred between them updated at each iteration. The equilibrium is reached once the exchanged data is the same between iterations.
Only a partial view of all the elements required to build an intra-hub pedestrian simulator have been discussed here. More aspects must be considered to design a functional model (Campanella, 2016). Next, we present the numerical results from the integrated modelling.

2.6 Hub and urban integration results

The scenario analysed for exploring the mutual influence of the hub model and the urban PT model is presented here. The scenario is the following successive runs of each model: Urban -> Hub -> Urban -> Hub -> Urban. With this setup, the influence of the hub model on the transfer location choice can be analysed. The sensitivity of the pedestrian travel times inside the hub as a function of the PT demand can also be considered. The first iteration of the urban model uses physical distance to infer transfer times. The subsequent iterations include walking time distributions from the hub model, as discussed in the previous section. The urban network of Den Haag (Netherlands) is used as a case study. The urban network covers the city and the hub considered is Den Haag central station. The pedestrian infrastructure is visible in Figure 2.10. The morning peak hour between 6 AM and 9 AM is considered.

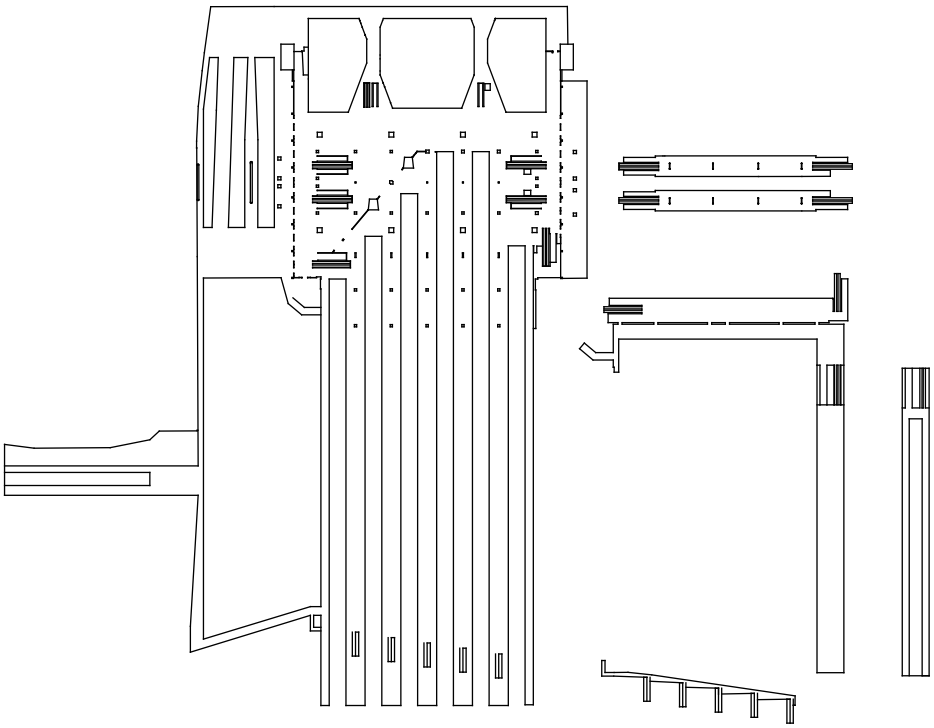


Figure 2.10: Den Haag pedestrian infrastructure.

Figure 2.11 presents the change in median walking time between the two hub model iterations. The first observation is the absence of significant changes in demand for any given OD pair. This is visible since all points are located along the diagonal of the figure. The changes are relatively more important for OD pairs with low demand, which is expected considering the stochastic nature of the hub model. The change in median travel time is significant for OD pairs with very low demand. This is caused by the little number of pedestrians taken into account for computing this indicator. The statistical validity is questionable for these cases. On the other hand, when hundreds or thousands of pedestrians use a specific OD, then the results have stronger statistical

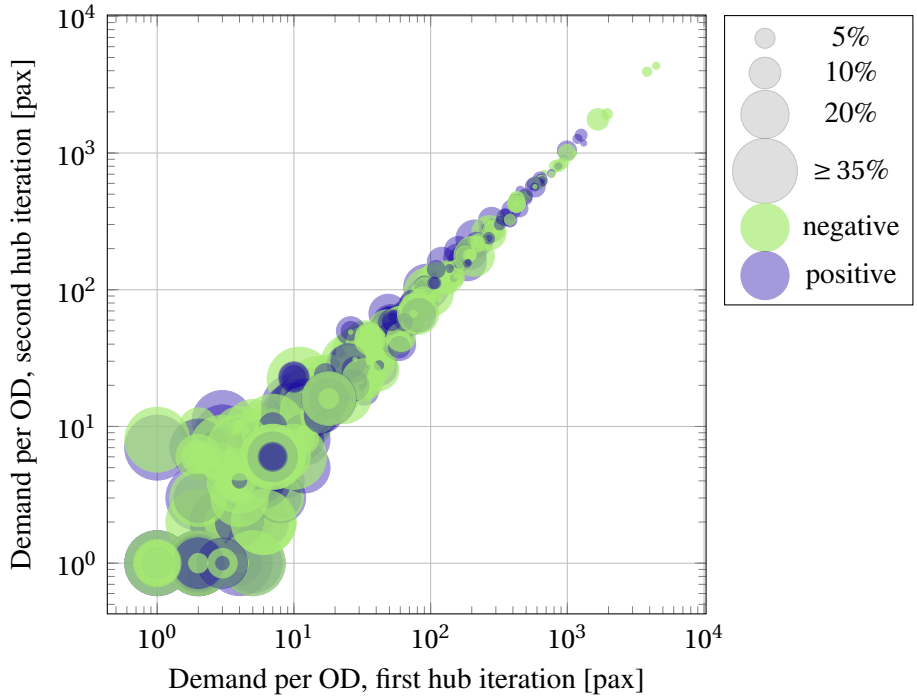


Figure 2.11: Change in median travel time for each origin-destination pair in the hub for two successive iterations of the hub and urban network simulations.

significance. For the higher demand cases, the changes in travel time are between 0% and 10%. No systematic pattern is visible regarding an increase or decrease as a function of the demand levels. Considering these results, we can assume that most of the variations are induced from the stochasticity of the simulator.

The effect of including the distributions of transfer times in the urban model provided limited added value. There are 52 public transit lines considered in the case study. Out of these 52 lines, only 4 of them show a change larger than 10% in the number of boardings occurring. Furthermore, these 4 lines are used by less than 20 passengers. On the other hand, lines with many boarding passengers show very little change (less than 2%) in relative boardings. The change in number of passengers using Den Haag as a transfer location is small (approx. 1%), hence few passengers are affected by the inclusion of transfer time distributions.
One possible explanation for the limited influence of incorporating a walking time distribution can be found in the relative limited crowding levels at this particular station. Combined with the lack of narrow spaces at this specific station, this results in limited differences when using a walking time distribution compared to assuming an average walking speed. However, it can be hypothesized that more substantial differences might be found if demand levels would increase and/or this method would be applied to a station having more confined spaces.

2.7 Discussion & practical recommendations

The analysis of the empirical tracking data emphasized the pedestrian dynamics variability. Such results highlight the strong assumptions which are made when operators consider a fixed time for the passenger's transfer between services. Therefore, PT operators should invest effort in developing methodologies which consider transfer time variability. Considering the mean or median transfer time cannot be considered acceptable since 50% of the users would miss their connection under such assumption. A first step would be developing time dependant transfer times. During the peak hours, travel time is generally increased due to congestion. Therefore, pre-computing transfer times for different periods of the day is a manageable approach to introduce more realistic walking transfer times. Developing real-time solutions requires more complex modelling techniques and real-time data collection hardware. Regardless of whether online or offline solutions are used, exploiting transfer time distributions should ideally become the norm for PT operators when considering intra-hubs transfer times.

Integrating the urban PT model with the intra-hub pedestrian model increased the realism of each model by improving the quality of the input data. On one hand, the hub model had access to reliable and precise data regarding the origins, destinations and alighting times of each pedestrian. On the other hand, the urban model received detailed transfer time distributions for each origin-destination pair. This iterative process emphasized the low levels of congestion that take place inside the hub, hence most passengers experience free flow travel times inside the infrastructure. Therefore, the walking transfer times do not depend on the urban network. For the case study presented here, the integrated modelling provided benefit in terms of realism and detail, but the iterative process presented no benefit.

In environments with significant congestion, the results would certainly be different. In cases where the fastest route changes depending on the demand levels, the transfer times will also change. Therefore, in such conditions, integrating the intra-hub dynamics into the decision process of the urban network would significantly improve the passenger's transfer experience. The benefit comes from the accurate representation of the walking transfer times.

The approach of integrating the urban and intra-hub models was limited to developing an exchange interface for the data. The effect of the intra-hub congestion on the user's route planning at the PT network level was addressed by the iterative procedure previously described. Nevertheless, this aspect should be improved by building a comprehensive model including all aspects. This direction has been explored recently in Hänseler et al. (2020).

2.8 Conclusion

Thanks to the analysis of the pedestrian tracking data, we were able to understand some of the dynamics taking place inside the train station of Lausanne (Switzerland). In general, pedestrians experience very low levels of congestion, if any congestion at all. This is supported by the absence of walking speed decrease as a function of pedestrian accumulation inside the corridors.

The integration of the urban and intra-hub models gave us insight towards understanding the interactions which take place between the different levels. This process provided more accurate walking transfer times and detailed demand data for the intra-hub model. The near absence of congestion inside the Den Haag train station explains the lack of reciprocal influence between the hub and urban levels. Although the integrated modelling did not provide the expected benefits in the current case study, we expect the results would be different for case studies suffering from higher congestion.

In the future, case study selection should depend not only on the size or complexity of the hub, but also on the congestion experienced by users. The development of multi-modal models should also be pursued. When integrating different models, taking into account aspects like route choice across several PT lines and hubs is often impossible since the models do not allow for this. Therefore, by developing models which simultaneously consider the hub dynamics and the PT networks, the user's strategical and tactical decisions can be modelled.

The TRANS-FORM project has emphasized the need for more elaborate multi-modal decision processes. Although the benefit for the passengers is clear when disruptions or disturbances occur in the PT networks, during daily operations, the integrated approach did not provide the expected added value for the selected case study. Therefore, another approach is recommended for improving the transfer experience of passengers during daily operations: intra-hub pedestrian flow management and control. During daily operations, operators can influence the intra-hub dynamics by using control and information strategies. Moreover, the spatial and temporal consistency of the dynamics can also be addressed by using intra-hub measures. This can be achieved by providing the pedestrians with information or by guiding them using control strategies. This topic will be explored in the coming chapters of this thesis.

3 Design of dynamic pedestrian management systems

This chapter is based upon several sections from the following publication:

N. Molyneaux, R. Scarinci, and M. Bierlaire (Aug. 2021). "Design and analysis of control strategies for pedestrian flows". In: *Transportation* 48.4, pp. 1767–1807. ISSN: 1572-9435. DOI: 10.1007/s11116-020-10111-1. URL: https://doi.org/10.1007/s11116-020-10111-1.

3.1 Introduction

As highlighted in the previous chapter, transferring passengers could significantly benefit from intra-hub management and control strategies. They are not the only users who would benefit from such measures. Users of airports, shopping malls, or city centres could also benefit. Therefore, the design and application of control strategies to mitigate the negative effects of congestion in any infrastructure should be explored. Nevertheless, the utilization of control and management strategies to manage pedestrian flows inside pedestrian infrastructure cannot be reduced to the installation of hardware. Two examples of the other elements required to make a strategy operational are measurement devices to collect real-time data or a centralized brain to decide which actions should be applied. Therefore, a framework which encompasses all these elements such that they can communicate with each other must exist. This chapter discusses such framework in the context of pedestrian flow management. This framework is common when road traffic control strategies are used: dynamic traffic management systems (DTMS). Amongst other elements, two fundamental components must be combined to build a DTMS: traffic models and control or information strategies. The role of traffic models is to predict and evaluate the performance of the network given some scenario. Control and information strategies are designed to optimize the network performance.

Although the high-level concepts are similar between road and pedestrian traffic, in practice

many constraints are different. These differences arise from the major discrepancies between the different users. Road users must follow a set of well-defined rules whereas pedestrians can choose to stop or change direction inside the infrastructure as they wish, hence pedestrian dedicated solutions are needed. As emphasized in the literature review presented in section 1.2.3, relatively little attention has been given to dynamic traffic management systems for pedestrians. No comprehensive traffic management system integrating pedestrian specificities is available. One possible reason for this resides in the lower social or political pressure on decision-makers to reduce pedestrian congestion compared to road congestion.
This chapter addresses the underexplored pedestrian dedicated management systems which we identified as contribution *(b)*. We start by investigating a general framework for dynamic traffic management for pedestrians which can be applied to any infrastructure. The first hypothesis which we investigate is the applicability of general DTMS literature to pedestrian traffic. We address this by emphasizing the pedestrian-specific elements needed to design Dynamic Pedestrian Management Systems (DPMS). The specificities of pedestrian flows compared to road traffic are discussed. Next, we evaluate whether a control strategy inspired by road traffic is efficient for regulating pedestrian flows. This strategy is tested in a simple case study.
Before discussing in detail the components of the DPMS, we overview the literature on DTMS and highlight the major contributions in road traffic control strategies. After that, a detailed discussion of the DPMS components is presented. Finally, we apply the DPMS with a gating strategy, after which we conclude this chapter.

3.2 Literature review

Like the literature review from section 1.2.1 emphasized, no complete framework akin to road DTMS is available for pedestrian traffic. Furthermore, few dynamic control strategies have been proposed which focus on daily operations. The situation for road traffic is very different. Many different DTMS frameworks can be found in the literature and dozens of control strategies have been successfully applied in practice. This vast literature is summarized in the present section where some of the major contributions are discussed. The topics relevant for DTMS like traffic flow models, measurement methods, or control and guidance strategies are reviewed.
Modelling the motion of vehicles has been an active area of research over the last decades. Microscopic, mesoscopic and macroscopic models are widespread in the literature. Many macroscopic models are based on the LWR model (Lighthill and Whitham, 1955). This model has been extended to include different components to try and improve the realism and accuracy when compared to empirical data. More recently, models like METANET (Papageorgiou et al., 2010; Frejo et al., 2019) or the cell transmission model (Daganzo, 1995a; Z. Zhang et al., 2015) have proven accurate at reproducing many different phenomena observed in real traffic. These models rely on the fundamental diagram of road traffic to reproduce observed phenomenon. At the other end of the spectrum, microscopic models like the car-following model (Newell, 2002), MATSIM (Horni et al., 2016) or DYNAMIT (Lu et al., 2015) model agents individually. The

advantage of this group of models lies in the detail of the interactions between the different agents and objects in the system. Somewhere in between these macroscopic and microscopic models lie link-based models. Links in the system are modelled individually as in Daganzo (1995b). One last category of models which has been investigated more recently relies upon the macroscopic fundamental diagrams (Daganzo, 2007; Geroliminis and Daganzo, 2008; Loder et al., 2017). They build on the assumption that the network can be partitioned into blocks in which uniform congestion holds. Although the theoretical implications are convenient, in practice the assumptions are hard to respect as different congestion levels can be found in very close links. Drivers are usually considered utility maximizers which means they try to minimize their travel time. Discrete choice models can be used to model route choice through the network (Fosgerau et al., 2013). An extensive discussion about dynamic traffic assignment (DTA) is performed in Peeta and Ziliaskopoulos (2001). Many different frameworks for predicting traffic conditions or evaluating control strategies have been proposed over the years (Papageorgiou et al., 2010; Mahmassani, 2001; Janson, 1991; Ben-Akiva et al., 2001). They rely on different motion models to predict the state of the traffic. As exposed previously, the different types of motion models induce different levels of accuracy and computational time. Given the assumptions on which they rely, the DTA frameworks can be either analytical or simulation-based. Analytical models can be deterministic or probabilistic while simulation-based models are usually stochastic.

As technology has evolved, so have the technologies available to measure vehicular traffic. Today the range of sensing technologies is wide and addresses many scenarios. From in-road inductive sensors to networks of cameras, all these technologies are used to measure traffic congestion (or lack thereof) and are critical to any traffic management system (Klein et al., 2006). In general, sensing technologies for road traffic track speed, flow, or density at a given location on the network. The common technique for estimating average link speed is via license plate recognition. This technology allows travel time (and average speed) estimation over network segments (Jenelius and Koutsopoulos, 2013). Recent progress in machine learning and computer vision allows fast improvements in real-time detection and have opened the way for autonomous vehicles (Janai et al., 2017).

Similarly to pedestrian traffic, KPIs are computed from the measurement data. Flow, density and speed are common examples but more complex ones like travel time, waiting time or delay (Ben-Akiva et al., 2001) can also be used. In the context of highway traffic, Y. Wang and Papageorgiou (2005) use extended Kalman filtering to estimate the state of a highway section thanks to measurements taken at discrete locations. Not only can the state be estimated based on the measurements from the system (density, flow, speed, etc) but predictions can also be incorporated to include information about the future state of the system. When state prediction is used with control strategies it is known as model predictive control (MPC). This scheme has been applied to different vehicle control strategies, for example with ramp metering (Hegyi et al., 2005) and urban signalized intersection control (de Oliveira and Camponogara, 2010).

Control and information strategies The literature on traffic control is vast and many examples exist to show how beneficial on the traffic dynamics control and information strategies are. The ALINEA ramp metering strategy and its many adaptations show how important it is to regulate traffic (Papageorgiou et al., 1991; Papageorgiou et al., 1997; Chi et al., 2013). Comparison of centralised, distributed and decentralised ramp metering with or without MPC is done in Frejo and Camacho (2012). The authors conclude that a fully centralised control approach is the best at improving the traffic dynamics but is not feasible in practice for large networks. The utilisation of distributed solutions is put forward since they produce more improvements than fully decentralised solutions without significantly increasing computational time. Another strategy which aims at regulating the flow of vehicles is signalized intersections. Not only are lights necessary for allowing antagonistic streams of traffic to safely cross intersections, but they are also used to maximize the throughput of the junction (Lämmer and Helbing, 2008; Varaiya, 2013). Signalized intersections can use fixed (static) phases or adaptive phases. Many examples of adaptive algorithms can be found in the literature: fuzzy logic (Collotta et al., 2015), dynamic programming (Chen and D. J. Sun, 2016), or scenario-based (Louati et al., 2016). Coordinated versions of signalized intersections allow the optimization at a network level of the dedicated KPI (Gartner et al., 2001). Variable speed limits are also an effective way for mitigating congestion (Frejo et al., 2019). Online toll pricing is presented in Y. Zhang et al. (2019), where the authors use a DTA framework to control in real-time the pricing scheme. Many different flavours of these strategies exist, for further reading we refer to Papageorgiou et al. (2003) and Ng et al. (2013).
The second important group of methods for influencing traffic is information. Unlike control strategies which enforce some actions, information about the state of the system provided to the users can influence how they choose their route or speed for example. Often called advanced traveller information systems (ATIS), these guidance schemes can provide different types of information such as expected travel time, average speed, expected delay, incident location, etc (Levinson, 2003). Before smartphones and personal navigation systems where available, variable message signs (VMS) and radio where the usual means of informing drivers. Today many drivers can receive real-time updates about the expected congestion and react to it. One of the most challenging aspects linked to guidance is the prediction of the driver's reactions. On the one hand, when expected travel times are provided to individuals, these predictions should be as close as possible to the actually realized journeys. Ensuring the accuracy of the predictions is vital for users to trust the information but requires modelling the compliance to the guidance (Ben-Akiva et al., 2001). On the other hand, when real-time information is provided to drivers, they might choose to change route hoping to find a shorter one (Dia, 2002). Modelling these phenomena requires either real-time data or surveys to collect data in order to estimate discrete choice models which are then used to simulate the driver's responses.
For car traffic, many different combinations of traffic models and control strategies have been tested. DTMS became popular in the 90' during which different frameworks where proposed. With DYNAMIT (Ben-Akiva et al., 1998), the authors propose a DTMS which is used to generate route guidance or control and focuses on the consistency of the information provided to the

users. DYNASMART is another framework which generates control strategies as well as route guidance (Mahmassani, 2001). Unlike DYNAMIT which focuses on consistency, DYNASMART focuses on a system optimal solution. The advantages and inconveniences of mesoscopic and microscopic simulators for DTMS are discussed in Palma and Marchal (2002) where the authors propose METROPOLIS as a framework for evaluating route guidance.

As the previous paragraphs have emphasized, research on car traffic management systems is fairly advanced. The vast literature on control strategies can be classified into various groups. Some examples are the kind of data which is used (real-time, estimated, predicted, etc.), the complexity of the algorithm (rule-based, static, reactive, MPC, etc.), or the spatial management of the devices (centralised or distributed/decentralised). This list of various control approaches is far from exhaustive. Furthermore, many practical applications have been successfully applied in practice using DTMS. On the contrary, as presented in the main literature review, no comprehensive framework which discusses and integrates all blocks of a pedestrian dedicated traffic management system for dynamic control strategies is currently available. This is true despite the growing interest for strategies to control and regulate pedestrian flows. Although many different assignment models exist, control and guidance strategies are still underexplored. This is also true about pedestrian management systems. In the next section, we address this by describing the components of a DTMS with pedestrian specific characteristics in mind.

3.3 Dynamic pedestrian management system

Although the general idea of DTMS for pedestrian traffic is similar to road traffic, it is worth presenting in detail the components and emphasize where differences lie. As the literature review highlights, few dynamic control strategies for pedestrians exist and no comprehensive framework for managing pedestrian flows can be found. Therefore, in the following paragraphs, we present each component which plays a role in a dynamic pedestrian management system. Figure 3.1 schematically presents all the components and their interactions. Demand, supply, data collection, state estimation and state prediction are only some of the important elements inside a DPMS. These components influence the pedestrian traffic as they provide different, but mandatory, data needed by the control strategy. Before talking about these components, we discuss the spatial and temporal representation of the walkable environment.

Spatial & temporal representations The spatial context in which pedestrians can move around is represented as an object L. This object can be a grid, a tessellation, a graph, a continuous space, etc. Each element composing the object L like cells, nodes, links, areas, coordinates, etc. are indexed by e. The spatial context can include many different obstacles, points of interest and features which can influence the pedestrian's behaviour. Benches, trash bins, ticket machines are examples of static obstacles which pedestrians must walk around. Therefore, to be accurate,

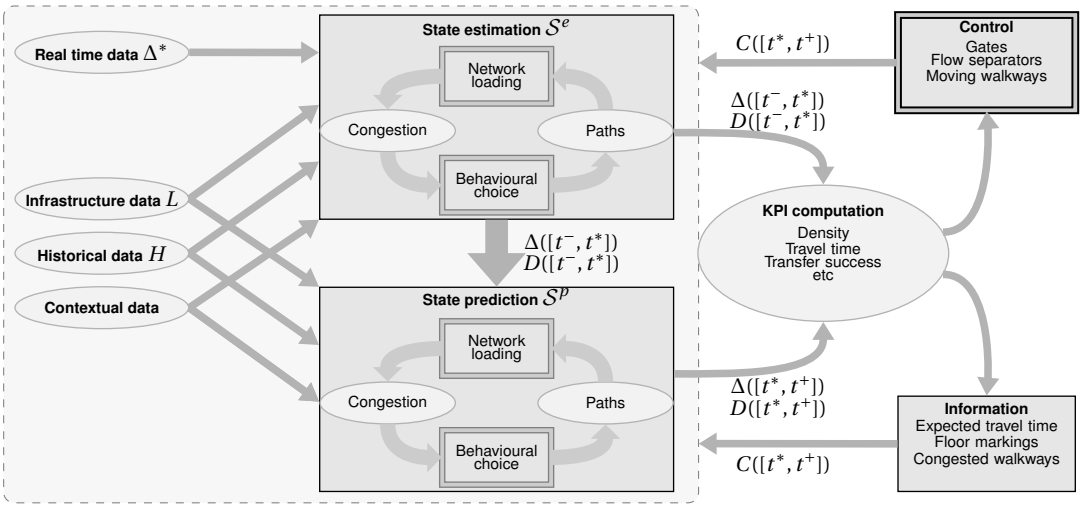


Figure 3.1: Dynamic Pedestrian Management System (DPMS). Three elements are significantly impacted by pedestrian flow specificities: network loading, behavioural choices and control algorithms.

any representation of the infrastructure must be able to take into account these features. The way obstacles are handled differs based on the representation. When cells are used, the cells which are covered by obstacles are either truncated or simply removed from the set. For graph-based representations, the network can be designed to avoid obstacles making pedestrians navigate around them. Finally, if the space is modelled as a continuum, then the walkable area must exclude any obstacles which creates holes in the space.

The spatial representation of car traffic networks is usually based on graphs. The wider range of spatial representations for pedestrian traffic likely finds its origin in the two-dimensional dynamics which take place. Since pedestrians can move around freely in a two-dimensional space, the representation must deal with this.

The time horizon of interest is $T = [t_{start}, t_{end}]$ and can be discrete or continuous. The present time is t^*. Although time is continuous by nature, individuals take decisions in a discrete fashion based on the surrounding environment. When a pedestrian sees important congestion inside a corridor, she might choose to change path (Heuvel et al., 2015). Another example can be the effect of advertising: when a pedestrian sees a coffee shop, she might suddenly decide to stop to buy a drink.

Based on the level of detail which is required and the type of spatial representation which is chosen, time can be modelled differently. Hänseler et al. (2017a) use a discrete temporal representation combined with a cell-based spatial representation. In Hoogendoorn and Bovy (2004a), space is modelled as a continuum with a continuous representation of time.

Supply The supply is the combination of the spatial and temporal objects which allow the pedestrians to accomplish their trips. The supply data can be static or dynamic. For the sake of

generality, we denote by $Y(L', T')$ the supply associated with a spatial context $L' \subseteq L$ and temporal horizon $T' \subseteq T$. In the following equations, when the spatial dimension is omitted, it means that it applies to the entire object L. Hence $Y(L, T)$ is equal to $Y(T)$, and $Y(L, T)$ is also equal to Y.
Dynamic elements extend beyond obstacles. Construction work on a subset of the infrastructure makes some elements of the supply dynamic. Another reason for dynamic supply is contextual elements like the opening hours of restaurants and shops or train timetables. Such elements are two examples of activity-focused dynamic supply elements. Another example can be an unexpected change in track assignment forcing passengers to walk to a new platform. Finally, even the weather can be considered as contextual data since pedestrians are more likely to seek sheltered paths when it is raining (Aultman-Hall et al., 2009).

Demand We consider a population of N pedestrians, or agents, indexed by n. As already hinted in the previous section, pedestrians can take decisions at multiple points in space and time. These decisions are taken at time t and create the demand $D_n(t)$ for each pedestrian $n \in N$ with $t \in T'$. For simplicity, we denote by $D(T')$ the demand induced by all pedestrians during the interval T'.
As the pedestrian walks along her path, she will continuously adapt her path as to maximize her utility. Some examples of choices to make include which corridor to use, a choice between stairs and lifts or whether to stop at some point of interest. As a passenger is walking to catch her train, suddenly she might be confronted with a highly congested corridor forcing her to adapt her original path to avoid this congestion. A few moments later, when the pedestrian was hoping to take the lift to change floors, she might discover that repair work is happening and she needs to use the stairs to change floor. In a different context, a pedestrian might suddenly choose to stop to watch a screen showing some sporting event. When a pedestrian decides to go through the security screening in an airport, she might see that there is a large queue and choose to go for lunch while waiting for the queue to shorten. All these decisions individuals must take mean that their path, destination, etc. are dynamic and very likely to change over time.
The decisions regarding the path to take, like turning left or right at junctions are the same for pedestrians and drivers. The difference between pedestrians and drivers resides in the freedom for pedestrians to stop at any point in space or time to perform an activity. For further discussions about the choices pedestrians take, see Bierlaire and Robin (2009).

Fundamental quantities & data There are different types of quantities of interest Δ, each indexed by γ. The main quantities of interest are pedestrian density, speed, flow and paths (Nikolić et al., 2016). From these quantities, we define two different categories of data: real time data $\Delta^* \left(L', T'\right)$ and historical data $\Delta^H \left(L', T'\right)$, associated with the spatial context L' and temporal context T'.
The real time data of a given type γ is collected thanks to measurements devices. These devices collect data with a spatial and temporal discretization and aggregation which is not guaranteed to match the spatial and temporal characteristics of the models. Another challenge when collecting

pedestrian data resides in the high temporal and spatial variability of the dynamics. Furthermore, the discretization and aggregation across different quantities γ might not be consistent. In practice, the data collection usually takes place in two situations. Firstly, quantities like speed or flow are measured across lines. Secondly, data collection takes place inside areas where speed, flow, density and paths can be measured. Note that the data collection might not be available for all spatial and temporal elements inside L' and T'.
The measurement devices collect the data with some inherent errors and bias. A lack of recognition of these particularities can potentially lead to important errors in the management system. In Hänseler (2016) for example, the author had to take into account the saturation of the link flow counts and correct the measurement values.
The second category of data is the historical data $\Delta^H(L', T')$. The quantities of interest are the same as for the real time data. The archiving procedure can use aggregation and discretization to change the spatial or temporal context. One example could be link flow counts. The real time version of this quantity $\Delta^*_\gamma(L', T')$ could be flows discretised into one-minute intervals. The historical version of this quantity $\Delta^H_\gamma(L', T')$ could be average hourly flows. Results from models and simulations can also be archived. An important data type is the origin-destination matrix of all pedestrians. These matrices can be estimated using models as in Hänseler et al. (2017b) and then archived to be used at later stages.

Control & information Before presenting some examples of control and information strategies for pedestrians, we will clarify the different parts of a control/information strategy. Firstly, the control *devices* V are the physical objects (hardware, technology) used to apply the control/information strategy. The control *algorithm* $\mathcal{A}$ exploits a set of key performance indicators (KPIs) to "decide" how the *device* should act. This sequence of decisions makes the *configuration* $C_v(T')$ of a particular device v. The algorithm could be considered as the brain of the *control strategy* which encompasses all these components. The case of information is analogous to control. The main differences concern the way the information is passed to the pedestrians and the question of compliance. The information *devices* can be smartphones, information boards or signs for example. The control/information algorithm uses the quantities of interest to compute the KPIs. These KPIs reflect the goal of the strategy. The KPIs can be the same as the measured quantities. Nevertheless, they can also be more complex and specific to the application and control strategy. Some examples of more advanced KPIs are average travel time or transfer success (the number of passengers who are able to catch their connection).
The specification of the *algorithm* is a critical and challenging step in the conception of control and information strategies. In some cases intuition and expertise are sufficient for this task, but for other situations more advanced tools are required. One possibility for this is the usage of optimization frameworks. The specification of the control algorithm or the specification of the control configuration are the decision variables of the optimization problem, and the objective function is an indicator measuring the quality of the pedestrian dynamics.
The dimensions of pedestrian movement which can be controlled are walking speed and walking

direction at an operational level and route at tactical level (Robin et al., 2009). Controlling these aspects will generally have short term and local impacts as the influence of the steps taken by pedestrians hardly extend further than a few meters. Regarding information, operators can provide expected travel time, path states, (un)congested areas and more. This will impact the paths pedestrians choose. Influencing the path can also extend further to mode choice or departure time choice.

Control and information strategies aim at improving pedestrian dynamics by preventing problematic situations. Multi-directional pedestrian flow is one example. If head-on collisions can be reduced, then pedestrians can generally walk faster (Feliciani and Nishinari, 2016). Another effect which occurs as pedestrian density increases is flow breakdown (Yang et al., 2014) and the stop-and-go behaviour (Seyfried et al., 2010). Bottlenecks inside pedestrian infrastructure are also issues which should be prevented if possible (Hoogendoorn and Daamen, 2005b). All these phenomena induce extra travel-time for the pedestrians and can be mitigated with adequate control or information strategies.

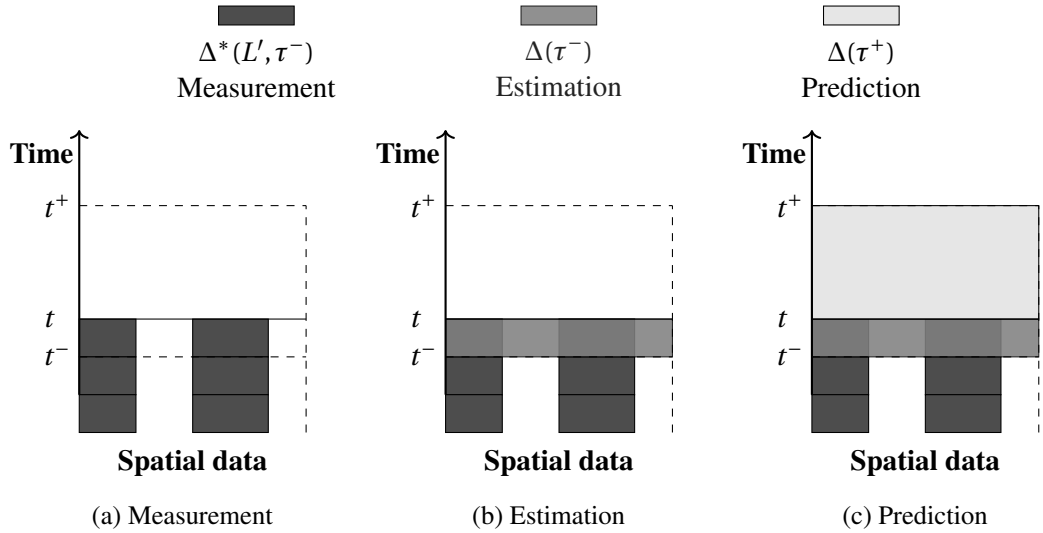
Without going into details, we will briefly mention some ideas of control strategies for pedestrians. Regulating the flow of pedestrians with gates or traffic lights can be used to prevent high congestion in specific areas. This could be achieved by monitoring density, flow or walking speed for example. Separating antagonistic pedestrian flows, thanks to accelerated moving walkways (Scarinci et al., 2017) for example, has the potential to improve the dynamics. On a more tactical level, the management of pedestrians at a city level during important sports events for example could be interesting. After a football match, thousands of people leave the stadium. This sudden peak in demand can lead to excessive congestion in the closest public transport stops. Therefore, by informing the spectators that the fastest way to their destination is not by using the closest stop but maybe by walking a little further to another stop which isn't crowded could decrease travel time.

Compliance becomes a significant problem with strategies like floor markings, lights or information regarding the fastest route home since nothing forces the pedestrians to follow the guidelines. Allowing pedestrians to choose whether they wish to follow the "rules" makes the application of information strategies challenging. If travel time is provided to users for example, then the strategy must take into account the pedestrians' reactions to that information. This problem of consistency is central to any rolling horizon strategy. The question of compliance is one way to categorize measures which influence the flow dynamics. Control is built upon full compliance, whilst information gives the individuals a choice: follow or not follow.

State estimation The role of the state estimation $\mathcal{S}^e$ is to use the data sources and fill in the gaps regarding the quantities of interest $\Delta(\tau^-)$ and the demand $D(\tau^-)$ for a given interval $\tau^- = [t^-, t^*]$. Recall that the current time is t^*:

$$\Delta(\tau^-), D(\tau^-) = \mathcal{S}^e\left(Y(\tau^-), C(\tau^-), \Delta(t^-), \Delta^*(L', \tau^-), \Delta^H(L', \tau^-)\right), \tag{3.1}$$

where t^- is the start of the interval where the estimation is performed, L' the spatial context where the data is collected for the real time data Δ^* or where it exists for the historical data Δ^H. Figure 3.2 presents this procedure schematically.



(a) Measurement (b) Estimation (c) Prediction

Figure 3.2: State estimation and prediction procedure. The horizontal axis represents quantities of interest in space.

Measurement devices which produce the real-time data $\Delta^*(\tau^-)$ generally do so with some bias and errors. Furthermore, the measurement areas usually don't cover the full infrastructure L and/or don't measure all quantities. In this case, models are necessary to complete the real-time data. Different models are available for this purpose in the literature (Hänseler et al., 2014). Another purpose of the state estimation is to perform spatial or temporal aggregation. The different spatial and temporal aggregations can be challenging to handle. When considering density for example, at least two methods exploiting differently the spatial dimension can be mentioned. The first one counts the number of pedestrians inside an area and then divides the number of people by the zone's area. The second case uses Voronoi tessellations as in Nikolić and Bierlaire (2018). Again, when discussing temporal aggregation then different possibilities exist: on one hand a snapshot can be used to compute the density or on the other hand a time interval can be used which leads to temporal average density. The state estimation step accomplishes this consolidation of the quantities of interest. Pedestrian simulation models are not needed for cases where only spatial or temporal aggregation must be performed.

There are two strongly interlinked underlying phenomena taking place here which create a fixed-point problem. The first is the loading, or assignment, of pedestrians to the supply (infrastructure):

$$\Delta(\tau^-) = \mathcal{L}^e\left(D(\tau^-), C(\tau^-), Y(\tau^-), \Delta(t^-), \Delta^*(L', \tau^-), \Delta^H(L', \tau^-)\right) \tag{3.2}$$

Pedestrians walk along their preferred path which creates congestion. The congestion levels depend on the layout of the walkable space, but more importantly, also on the configuration

of any control devices. In turn, the pedestrian's decisions depend on the congestion levels and quantities of interest Δ:

$$D(\tau^-) = \mathcal{B}^e\left(\Delta(\tau^-), C(\tau^-), Y(\tau^-), \Delta(t^-), \Delta^*(L', \tau^-), \Delta^H(L', \tau^-)\right) \tag{3.3}$$

As an example for the loading function $\mathcal{L}$, let's consider traffic lights at a pedestrian crossing. While the light is green people are allowed to cross the junction, but as soon as the light turns red people should stop crossing. The configuration of the lights, at time t, influences the way the supply is loaded by the demand.
The behavioural model $\mathcal{B}$ is used to simulate the choices of pedestrians: avoiding an obstacle, stopping to buy something, slowing down to look at an advertisement board, etc. These choices are influenced by the pedestrian's desired walking speed, origin and destination for example, but not only. Information provided to the users regarding the current state of the system will also influence their choices, just as the device configurations $C(T')$. Construction work on an elevator or the expected travel time to walk to a place are examples of information which can be provided to pedestrians. Stochastic pedestrian choices and public transport schedules are only two elements which induce stochasticity into the system. These stochastic elements mean the estimation procedure must deal with uncertainty.

State prediction Following the estimation problem comes the prediction problem. The state prediction over the interval $\tau^+ = [t^*, t^+]$, where t^+ is the prediction horizon, computes the quantities $\Delta(\tau^+)$ and the behavioural decisions $D(\tau^+)$:

$$\Delta(\tau^+), D(\tau^+) = \mathcal{S}^p\left(Y(\tau^+), C(\tau^+), \Delta(t^*), \Delta^H(L', \tau^+)\right). \tag{3.4}$$

The major difference with the state estimation is the absence of real time data Δ^*. Note that the results of the state estimation are included in the historical data. The same fixed-point problem with the supply loading and the behavioural decisions takes place, except for the prediction interval:

$$\Delta(\tau^+) = \mathcal{L}^p\left(D(\tau^+), C(\tau^+), Y(\tau^+), \Delta(t^*), \Delta^H(L', \tau^+)\right) \tag{3.5}$$

$$D(\tau^+) = \mathcal{B}^p\left(\Delta(\tau^+), C(\tau^+), Y(\tau^+), \Delta(t^*), \Delta^H(L', \tau^+)\right) \tag{3.6}$$

The prediction of the future state of the system allows the control strategies to use more complete information. The combination of the state estimation with the state prediction provides us with the quantities of interest $\Delta(T')$ and behavioural choices $D(T')$ over the interval $[t^-, t^+]$. The length of the intervals τ^- and τ^+ are not necessarily equal.
The prediction procedure must also deal with the stochasticity of the system. As the models which are used for the prediction are stochastic by nature then an estimation of the variance of the output must be considered. The reliability of the solution is usually estimated by repeating the predictive simulation multiple times to build distributions of the quantities of interest.

Control and information configuration generation The reaction of the users to the control and information strategies must be anticipated in order to compute the configuration. This creates a fixed-point problem. On one hand we have the configuration $C(\tau^+)$ and on the other hand we have the congestion $\Delta(\tau^+)$ and behavioural decisions $D(\tau^+)$. The fixed-point problem is defined as:

$$\mathcal{F} = \begin{cases} C(\tau^+) & = \mathcal{A}\big(\Delta(\tau^+), D(\tau^+), Y(\tau^+), \Delta(t^*), \Delta(\tau^+)\big) \\ \Delta(\tau^+), D(\tau^+) & = \mathcal{S}^p\left(Y(\tau^+), C(\tau^+), \Delta(t^*), \Delta^H(L', \tau^+)\right). \end{cases} \tag{3.7}$$

the generated configuration is said to be consistent if the state of the system on which the configuration is generated is likely to happen. An illustration of this problem can be made by considering a gate which regulates the pedestrian flow. The rate at which pedestrians are allowed through the gate is the control configuration. The choice of this rate will influence how many pedestrians choose to use the gate to reach their destination. The quantities Δ available are the density inside the main corridor and the future pedestrian flows. The control algorithm must take into account the expected flows as to prevent a large queue appearing in front of the gate. If the gate creates a large queue, then pedestrians will likely use an alternative route which they consider faster. Therefore, consistency is the equilibrium between the number of pedestrians who actually use the gate and the predicted number of pedestrians who use the gate. The strategy configuration is applied in a rolling horizon scheme, for further reading on this topic we refer to Peeta and Mahmassani (1995), Newell (1998), and Aboudolas et al. (2010).
The generation of the configuration can also involve the optimization of a given objective. This problem is defined as:

$$C^{opt}(\tau^+) = \operatorname{argmin} \mathcal{F}\left(C(\tau^+), \Delta(\tau^+), D(\tau^+), Y(\tau^+), \Delta(t^*), \Delta^H(L', \tau^+)\right). \tag{3.8}$$

Here, C^{opt} is the optimal control configuration where the function $\mathcal{F}$ is the objective function which computes the quantity used for the optimization. In many cases the control and information strategies will be beneficial for some users and penalize others. Therefore, an example of a strategy which involves online optimization is one where the configuration is optimized such that each group of users is penalized equally. The optimized quantity can be travel time or pedestrian density for example.

In this section we presented the different components of a dynamic pedestrian management system, including some examples of pedestrian specific situations. The general framework is inspired by DTMS for vehicular traffic and, therefore, DPMS and DTMS share several aspects. Nevertheless, we emphasized the main differences between pedestrian and road traffic management systems. Three elements stand out and the DPMS components which are influenced by them are highlighted in Figure 3.1. Firstly, and possibly the most challenging question to tackle, is the lack of compliance to control strategies. On one hand, when information is provided to pedestrians (location of congestion or fastest route for example) then the consistency challenge arises as for road traffic. On the other hand, compliance becomes even more challenging for

pedestrian flow management when strategies are considered which assume high levels of compliance to be successful but don't enforce compliance by design. The difference originates in the possibility for pedestrians to ignore the rules without any consequence. This aspect influences the design of the control strategies. The second difference concerns the wider range of choices that pedestrians can make and impacts the behavioural assumptions inside the models or the control algorithms. This larger choice set means that their movements are more complex. People on foot can stop and start freely or travel in groups for example. Finally, the higher complexity of assignment models for pedestrians means that modelling and predicting their behaviour is challenging. This specific aspect influences the complexity of the network loading process.
When implementing control strategies in practice, the control approach selection and, if needed, the model selection, should be done considering the case study. The computational cost of the control approach and model(s) should be considered to ensure that the control strategy can be applied in practice. Next, to illustrate the DPMS, we present a simple control strategy inspired from road traffic.

3.4 Gating

The first control strategy developed within this thesis exploits gates to regulate pedestrian flow. This "gating" strategy is directly inspired from one of the most widely spread traffic control techniques in vehicular traffic: ramp metering (Papageorgiou et al., 1991). The objective of dynamic gating is to regulate the pedestrian flow into an intersection. The goal is to prevent excessive congestion inside the intersection so that pedestrians can move freely. This approach exploits, in fact prevents, the capacity drop taking place when pedestrian density becomes so high that walking speed significantly drops. The excess time induced when waiting for the gate to open should ideally be compensated by the faster travel time through the intersection. This strategy was tested in a simulation environment by monitoring the pedestrian density inside the intersection and then regulating the flow into the same intersection.
We used a microscopic pedestrian simulator built around the NOMAD model (Campanella, 2016). The infrastructure setup is shown in Figure 3.3. The pedestrian flow through the gates is regulated while the flow along the horizontal access is unrestricted. The pedestrian demand coming through the gates is unidirectional and follows a non-homogeneous Poisson process with oscillating rate. The demand along the corridor follows a homogeneous Poisson process. The control algorithm links pedestrian density measured inside the intersection to the flow through the gates. The details of the control algorithm and DPMS specification are available in Appendix A.

Since the simulation is stochastic, 500 replications of the simulation scenario were performed to build a distribution of the pedestrians' travel time. The pedestrians are separated into two groups: those using the gates and those walking along the main corridor. In Figure 3.4, the distribution of the mean travel time for these two groups is compared to a reference scenario where no gates are present. On one hand, gating slightly increases the travel time for the group which uses the

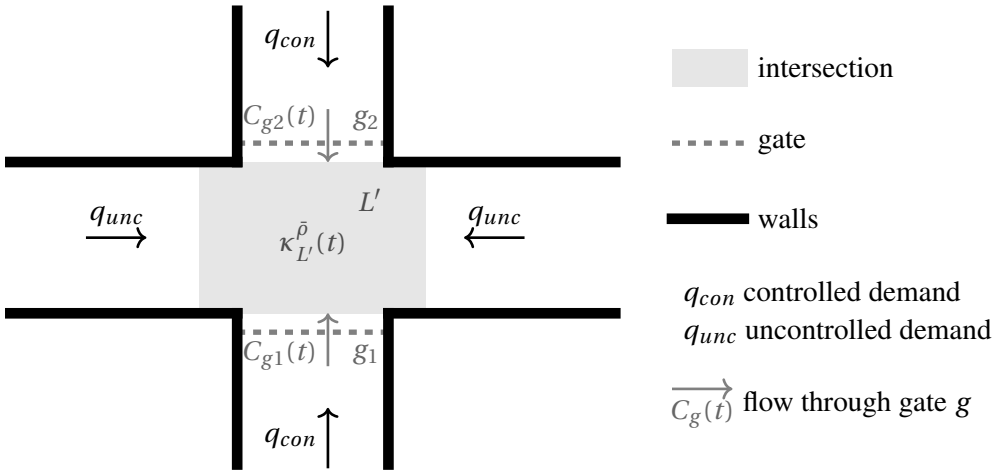


Figure 3.3: Infrastructure representation for the gating control strategy.

gates: the median of median travel time goes from 23.00 to 23.63 s. On the other hand, gating improves the walking times of pedestrians who don't go through the gates. Multiple reasons can explain this result. When pedestrians travel through the gates their travel time is composed of the walking time and the waiting time. When the waiting time exceeds the reduction in walking time induced by the gates, their trip time will increase compared to the reference scenario. Ideally this waiting time is more than compensated when they are allowed to walk through the gates into the intersection: their journey through the intersection should be faster given the lower density. Since the travel time indicator is higher, the excess travel time induced by the gates is not compensated by the faster journey through the intersection. Concerning the pedestrians who don't use the gates, their gain in travel time is explained by the faster walking speed through the intersection which is not hindered by the gates. Since the flow of pedestrians coming through the gates is "flattened" by the gates, it is easier for the pedestrians to move through the intersection.

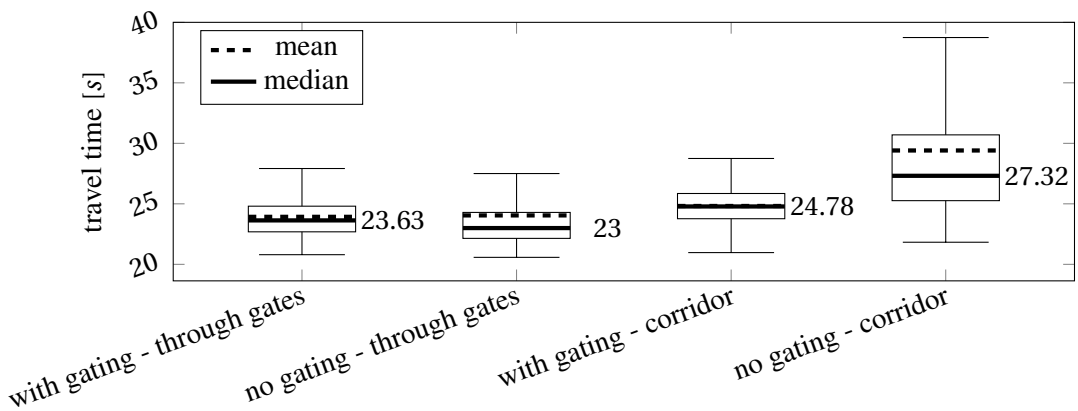


Figure 3.4: Travel time comparison for different OD groups

As supported by the fundamental diagram concept, high pedestrian densities decrease their walking speeds. To confirm these effects, we now consider the distribution of pedestrian density inside the intersection. Figure 3.5 presents the distribution of mean density computed using Voronoi diagrams. When gating is implemented, the mean density is significantly reduced. The control strategy also reduces the variance in density meaning more consistent situations are experienced by the users. The significant reduction in density confirms that the gain in travel time for the pedestrians who don't use the gates comes from the reduction in density in the intersection.

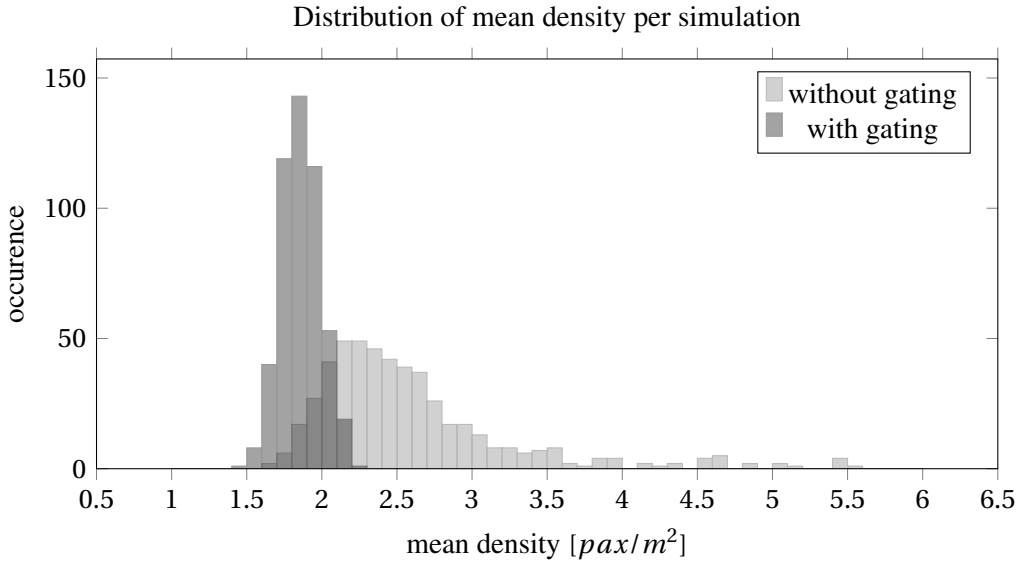


Figure 3.5: Travel time comparison for different OD groups

Through this example, we show that transposing ideas directly from road traffic like ramp metering to pedestrian traffic does not lead to significant improvement in pedestrian dynamics. Unlike car traffic, pedestrian traffic does not benefit substantially from this strategy (at least in this simple but representative case study). A decrease in pedestrian density inside the intersection is observed, but the travel time is not significantly improved. One explanation for the limited success of this strategy resides in the congestion level inside the intersection. For this strategy to be successful, the congestion must be sufficiently high for the pedestrian walking speed to decrease inside the intersection. The scenario considered here might not meet this criteria and although minor congestion takes place, pedestrians are still able to move around and leave the intersection. The heterogeneity of the congestion inside the intersection allows pedestrians to move around, although some pedestrians temporarily experience high congestion. This example emphasizes some characteristics of pedestrian dynamics. Even though congestion takes places, individuals are still capable of recourse. Designing an effective control strategy must therefore exploit the specifics of pedestrian dynamics in order to have significant positive effects.
Extending the usage of gates to monitor pedestrian congestion inside an infrastructure could be

evaluated using a control approach similar to perimeter control in road traffic control (Kouvelas et al., 2017; Keyvan-Ekbatani et al., 2019). Nevertheless, the challenge associated with the heterogeneity of congestion inside the infrastructure must be addressed. Partitioning the space into regions with homogeneous dynamics could be a promising approach (Haddad and Mirkin, 2017).

3.5 Conclusion

In this chapter we proposed a Dynamic Pedestrian Management Systems (DPMS) which can be used to implement control strategies to manage pedestrian flows. The structure of the framework is inspired by the logic of DTMS for vehicular traffic and the specific features related to pedestrian traffic are emphasized. In particular, three aspects are identified: compliance, wider pedestrian choices and the complexity of pedestrian assignment models. Then, by applying the DPMS framework with a simple control strategy inspired from road traffic, we show the limitations of taking ideas from road traffic. The gating strategy was not conclusive since the specificities of pedestrian traffic are not considered.

This example of an unsuccessful control strategy clearly emphasizes the need for a pedestrian dedicated approach. Tailoring the control strategies to address the different challenges of pedestrian dynamics like bidirectional flow or compliance should prove more successful. Furthermore, information provision about congestion could also lead to significant improvements in the user's satisfaction.

Apart from the development of pedestrian dedicated control strategies, the application of the DPMS framework aims to facilitate real world applications and provide the necessary data to each element required by the system. In this thesis, we exploit a simulation environment to evaluate the effectiveness of several control strategies, therefore the state estimation process is not necessary since the simulation environment generates the complete state data. The usage of accurate, reliable, consistent and computationally fast pedestrian assignment and loading models is critical when practical implementations are done. Such models are necessary for the state estimation and prediction processes. The inclusion of short-term predictions has proven successful for road traffic, hence this path should be explored for pedestrian flow management as well. Other practical aspects like cost effective measurement devices are also required to facilitate the transition from theory to practice.

4 Flow separators to prevent bidirectional flow

This chapter is based upon several sections from the following publication:

N. Molyneaux, R. Scarinci, and M. Bierlaire (Aug. 2021). "Design and analysis of control strategies for pedestrian flows". In: *Transportation* 48.4, pp. 1767–1807. ISSN: 1572-9435. DOI: 10.1007/s11116-020-10111-1. URL: https://doi.org/10.1007/s11116-020-10111-1.

4.1 Introduction

In the previous chapter, we defined the dynamic pedestrian management system and one control strategy inspired by road traffic. As briefly discussed, that strategy proved unsuccessful at significantly improving pedestrian dynamics inside corridor intersections. One possible explanation for this is the lack of consideration for pedestrian-specific flow characteristics. Therefore, the present chapter proposes a control strategy which exploits one of the challenging aspects of pedestrian flows: bidirectional flow.

It is common for pedestrians to experience bidirectional flow in crowded corridors. Lane formation is one natural solution that occurs within pedestrian flows to limit the negative effects of high density and bidirectional flow (Feliciani and Nishinari, 2016; Hoogendoorn and Daamen, 2005a). The capability of pedestrian motion models to reproduce this phenomenon is one of the validation criteria (Helbing and Molnár, 1998; Guo, 2014). Many models for reproducing bidirectional flow (also denoted counter flow) are available in the literature (Blue and Adler, 2001; Dai et al., 2013; Abdelghany et al., 2005). Nevertheless, little research has been done on the design of dynamic measures to manage or prevent bidirectional flow from taking place during daily operations.

The hypothesis explored in this chapter concerns the potential benefit of installing devices, that we call "flow separators", which prevent bidirectional flow from occurring. We achieve this by analysing the change induced by these devices on quantities like pedestrian travel time or speed.

The strategy we develop is inspired by a specific situation: bidirectional flow along a corridor. Strategies which exploit specificities of pedestrian flows is identified by contribution (d). Flow separators aim at preventing pedestrian bidirectional flow by dynamically allocating walking space to pedestrians based on their walking direction. Preventing bidirectional flow is beneficial to the system since the capacity drop induced by the head-on collisions is prevented (J. Zhang et al., 2012). This is true both for balanced and unbalanced flows in corridors (Feliciani and Nishinari, 2016). Corridors are considered since they are common in many walking environments. This strategy is implemented and evaluated in a simulation environment. The full capabilities of the DPMS are not exploited with this control strategy as no state estimation nor prediction are performed. Our motivation is to show the potential of dynamic traffic management tailored to pedestrian flows (contribution (c)). The inclusion of state estimation and prediction is left for further research. Two cases studies are used to analyse the effects of flow separators on the pedestrian dynamics. The first is a proof-of-concept setup with one single device in a straight corridor. The second case study is a subset from a real infrastructure already considered in this thesis: the train station of Lausanne. For both case studies, we follow the framework presented in section 3.3. We discuss how each component has been designed in the specific context of flow separators and pedestrian flows. Through these examples, we show the high potential and the hard challenges associated with the development of pedestrian management strategies. This chapter is concluded by discussing the limitations of this control strategy and the potential improvements which could be considered.

4.2 A simple corridor

This setup, where one flow separator device is installed in a straight corridor, is used to validate the concept of using flow separators as a control strategy to improve pedestrian dynamics. Straight corridors similar to this case study are found in nearly every pedestrian environment, hence investigating this setup contributes to understanding the benefits this strategy can provide in practical cases. The evaluation of this control strategy is done inside a simulation environment. We used the operational model from the NOMAD package (Campanella, 2016) with the default simulation parameters and combined it with a graph for the tactical navigation. The pedestrians follow the shortest path (in distance) to their destination.

Spatial and temporal representation We consider a corridor $35m$ long and $9m$ wide. This corridor is the spatial domain L that is modelled using two levels of representation. The first level is an open continuous space where pedestrians can move around. The second level is a graph which pedestrians use to navigate the infrastructure. The vertices from the graph are used as intermediate destinations by the motion model (Figure 4.1). This combination allows pedestrians to move around the infrastructure while avoiding obstacles and other pedestrians. Time is modelled as a continuous quantity. Nevertheless, the simulation environment enforces

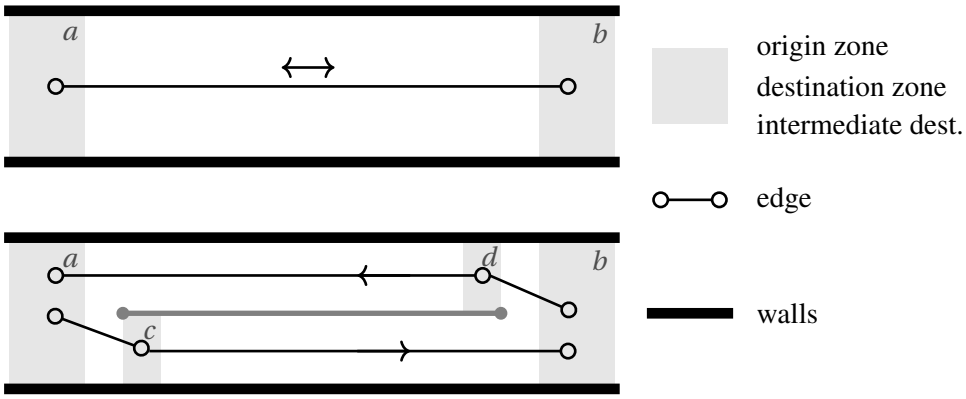


Figure 4.1: Infrastructure with the walls and navigational graph. Reference scenario (top) and flow separator installation (bottom).

some discretization for numerical reasons. We consider a time window of 6 minutes.

Supply All components which compose the infrastructure L are static except the flow separator which is dynamic by construction. No dynamic elements such as shops or a public transport schedule are used.

Demand The demand is composed of N pedestrians with specific origins and destinations. Each individual $n \in N$ has a free-flow walking speed v_n sampled from a normal distribution with a mean of $1.34 m/s$ (Weidmann, 1993). This walking speed distribution is comparable to the distribution of walking speeds computed from the empirical data. Their origin and destination are sampled inside zones representing the entrance and exit points from the infrastructure. There are two zones in this case study, one at either end of the corridor presented in Figure 4.1 denoted a and b. The infrastructure used for the case study does not contain multiple paths to the pedestrian's destination, therefore there is no route choice. For this scenario, pedestrians walk towards their final destination from their entrance point.
The pedestrian demand $D(T')$ is composed of two groups. The arrival times are sampled using a non-homogeneous Poisson process. The first group of pedestrians is the major one, moving from a ot b. The arrival rate is described by $q_{ab}(t) = (6 \cdot ((\sin(0.01 \cdot t) + 1) \cdot 0.49 + 0.015)$. The second group is the minor one, moving from b to a. The arrival rate of this group is described by $q_{ba}(t) = 6 \cdot ((\sin(0.01 \cdot t + 180) + 1) \cdot 0.49 + 0.015)$. Figure 4.2 presents these two arrival rates. The demand is generated during the first 300 seconds of the simulation. The concave curve is a rough approximation of the demand pattern induced by trains when passengers are alighting. The convex curve is the complementary demand such that a high demand takes place during the whole simulation.

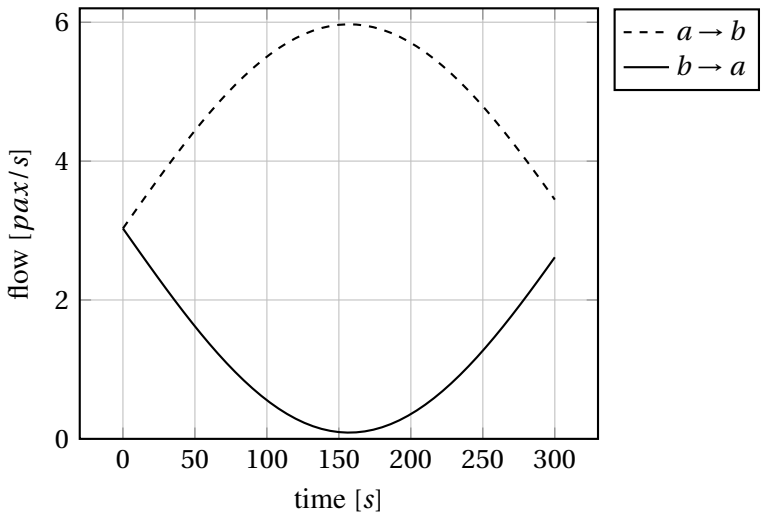


Figure 4.2: Demand pattern for the proof-of-concept scenario. The concave curve is an approximation of the empirical alighting rate observed in train stations.

Fundamental quantities & data The quantity of interest in this scenario is pedestrian flow, denoted q. The flow is measured at either extremity of the corridor using a one second discretization. The measured flows are denoted q^*_{AB} and q^*_{BA} in Figure 4.3. Real time data Δ^* are the only quantities of interest, no historical data is required. In practice the pedestrian flow can be measured using flow counters or cameras. In this case study we obtain it directly from the ground truth simulator (assessment model).

Control & information Separating pedestrian flows by direction is done by allocating part of the corridor to each direction. This control device f separates the corridor into two parts. This way, bidirectional flow can be prevented when pedestrians walk along the side of the corridor dedicated to their walking direction. We assume information is available (over head screens or floor markings for example) indicating which side of the flow separator the users must walk along. Compliance to such information is discussed later on. Figure 4.3 presents the infrastructure L where a flow separator is installed in the middle of the corridor.

The flow separator control can be categorized as open loop as the pedestrian flows are measured upstream from the devices with a simple infrastructure such as Figure 4.3. The separators will influence the pedestrian's routes by providing them with a section of corridor dedicated to their walking direction. Pedestrians should use their dedicated sides since they are considered as utility maximizers (Hoogendoorn and Bovy, 2004a) where each individual tries to minimize her travel time. However, full compliance may not be obtained.
The proposed strategy measures the flows near the beginning of the section where the device is installed. The flow separator therefore reacts to the flows in real time. The pedestrian flows which are measured are denoted q^*_{AB} and q^*_{BA}, respectively measuring the flow from A to B and

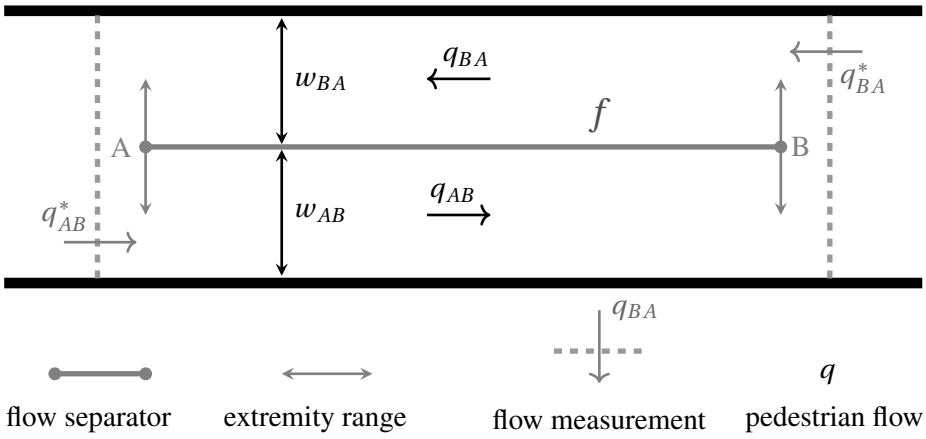


Figure 4.3: Schematic presentation of the flow separator. The width dedicated to each direction is adjusted based on the flows entering the corridor.

B to A. The width available for the pedestrians moving in each direction is therefore a function of the flows going from A to B and the flows going from B to A:

$$w_{AB}(t), w_{BA}(t) = \mathcal{A}_f(q^*_{AB}(t), q^*_{BA}(t)), \tag{4.1}$$

where w_{AB} (resp. w_{BA}) is the width dedicated to the people walking from A to B (resp. B to A) and $\mathcal{A}_f$ the control algorithm linking the measured flows to the available widths.
Making the strategy operational requires specifying the control algorithm $\mathcal{A}_f$. The functional form linking these two flows can take any shape. In general, increasing the complexity of the functional form increases calibration complexity. Therefore, to keep the calibration to a strict minimum, we propose a function which relies only the measured flows in a proportional way:

$$\mathcal{A}_f = \begin{cases} w_{AB} = & w \cdot \dfrac{q^*_{AB}}{q^*_{AB} + q^*_{BA}} \\ w_{BA} = & w \cdot \dfrac{q^*_{BA}}{q^*_{AB} + q^*_{BA}} \end{cases} \tag{4.2}$$

where w is the total corridor width. Naturally, as soon as the width of one side of the corridor is fixed, the width of the other part is also fixed given the limited and constant total corridor width w. Another advantage of this specification is the absence of parameters to calibrate.
We impose that neither sides of the corridor should be closed. This guarantees that there is always space for pedestrians to move freely even if there is a large opposing flow. This requires lower bounds on the width for each direction: w^{min}_{AB} and w^{min}_{BA}. These widths have been fixed based on the minimum width required by an individual to walk comfortably along a corridor (Weidmann, 1993). Taking into account these bounds, the full specification of the width for the side dedicated

to pedestrians moving from A to B is therefore:

$$w_{AB}(t) = \begin{cases} w_{AB}^{min}, & \text{if } w \cdot \dfrac{q_{AB}^*}{q_{AB}^* + q_{BA}^*} \leq w_{AB}^{min} \\ w - w_{BA}^{min}, & \text{if } w \cdot \dfrac{q_{BA}^*}{q_{AB}^* + q_{BA}^*} \leq w_{BA}^{min} \\ w \cdot \dfrac{q_{AB}^*}{q_{AB}^* + q_{BA}^*}, & \text{otherwise.} \end{cases} \tag{4.3}$$

The width of the corridor from B to A is naturally $w - w_{AB}$. This algorithm is applied in real time but in a discrete manner. The configuration is updated at one second intervals. Furthermore, an upper bound ($0.25 m/s$) has been fixed on the displacement rate of the flow separator to prevent excessively rapid changes in the configuration. Finally, the flow separators will only move if the change in opposing flow ratio is greater than 10%.
To get the control algorithm presented in the previous paragraphs closer to a practical application, the algorithm needs to be extended with safeguards in case congestion builds alongside the devices. First, the devices cannot be moved once congestion appears otherwise the pedestrians would be knocked over. Secondly, if congestion builds alongside the devices, then the flow values can decrease although many pedestrians wish to walk along the corridor. This must be addressed in future work by considering both flow and density measurements for example.

State estimation & prediction This control strategy does not rely on state prediction. State estimation is not required either since we are in a simulation environment and the flows can be measured directly at the extremities of the flow separator.

Control and information configuration generation The generation of the control configuration is done using (4.3). The absence of route choice and independence of the demand with respect to the control strategy means that consistency is implicit. Therefore, no fixed-point problem should be solved. Similarly, no optimization is involved hence equation (3.8) is not needed.

After having specified the different elements required to design a DPMS, we evaluate the effects of the control strategy on the pedestrian dynamics. First, the impact of the dynamic flow separator is compared to the "no strategy" situation and a static version of the flow separators. The static version is a fixed separator in the middle of the corridor. Secondly, the effectiveness of this control strategy is shown for different demand levels. Finally, a sensitivity analysis to the compliance is accomplished. The demand pattern shown in Figure 4.2 is used to evaluate the effectiveness of the dynamic flow separators. This pattern is used in all numerical experiments, except in some cases the amplitude is changed. Next, we present the results from the numerical simulations.

Influence of dynamic flow separators

The flow separators are tested on the section of corridor presented in Figure 4.3. The objective is to decrease the travel time and also the variation in travel time of the pedestrians. The improvement is significant when comparing the "no separator" scenario to the "with separator" scenarios (Figure 4.4). The median of median travel time goes from $37.93s$ to $31.53s$ when a static flow separator is installed. There is a further reduction when the flow separator is dynamic and adapts to the flows ($31.53s$ to $29.62s$). More importantly, a reduction in median travel time variance is observed. The duration of the journey becomes more consistent with dynamic separators.

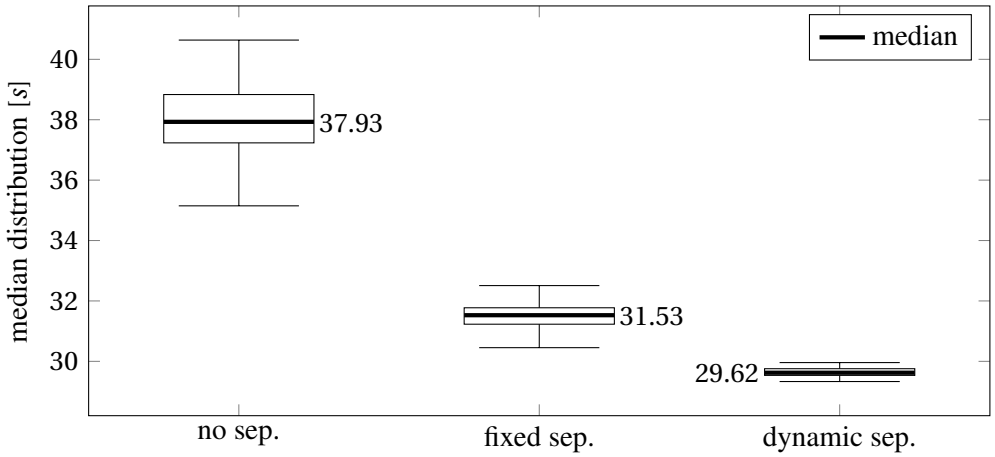


Figure 4.4: Median travel time distributions using 100 replications for the three scenarios: no flow separator, a static separation of the flows and a dynamic flow separator.

The number of simulation replications to perform has been determined by using Figure 4.5, where the mean square error (MSE) is computed using bootstrapping. This technique is used since no analytical solution exists for estimating the MSE of the medians. By increasing the number of simulations, the MSE decreases before stabilizing after 80 replications. The number of replications required to guarantee an acceptable MSE is fixed at 60. The MSE is already acceptable for our purpose and it decreases slowly after this point. For all subsequent simulations, we perform at least 60 replications since the MSE is kept at an acceptably low level.

Naturally, flow separators are not efficient for all scenarios and demand patterns. The results from the sensitivity analysis to demand are presented in Figure 4.6. For low demand levels, the flow separators induce a small increase in travel time since the pedestrians must add a small walking distance to cross the corridor. This excess is quickly compensated as from a demand of $1.0 pax/s$ the flow separators are beneficial when considering the medians of travel times (Figure 4.6a). If we consider only the medians, then dynamic flow separators have little benefit on the travel times compared to the static flow separators. Nevertheless, when considering the travel time variance per simulation, the dynamic flow separators are beneficial for the pedestrians. At high

demand levels, the variance is significantly lower when dynamic flow separators are used instead of static ones (Figure 4.6b). During simulations without any flow separator, the pedestrians create dynamic lanes but these only survive for a short time. By using flow separators the lanes are enforced by design.

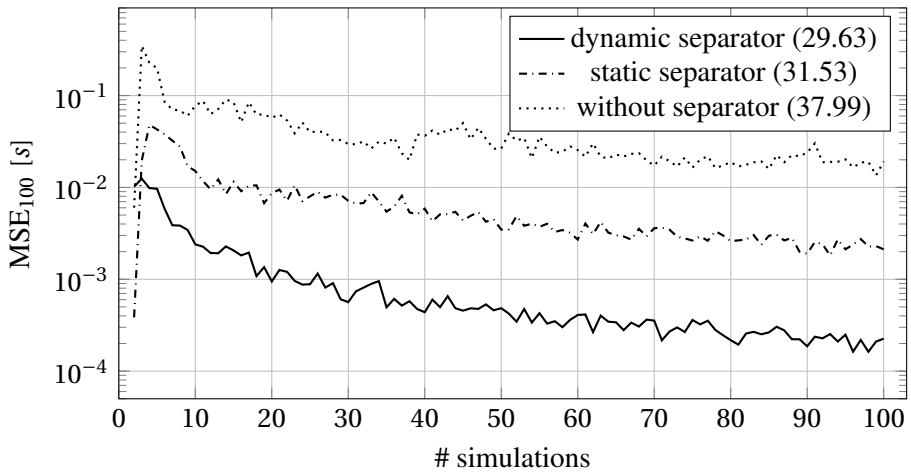
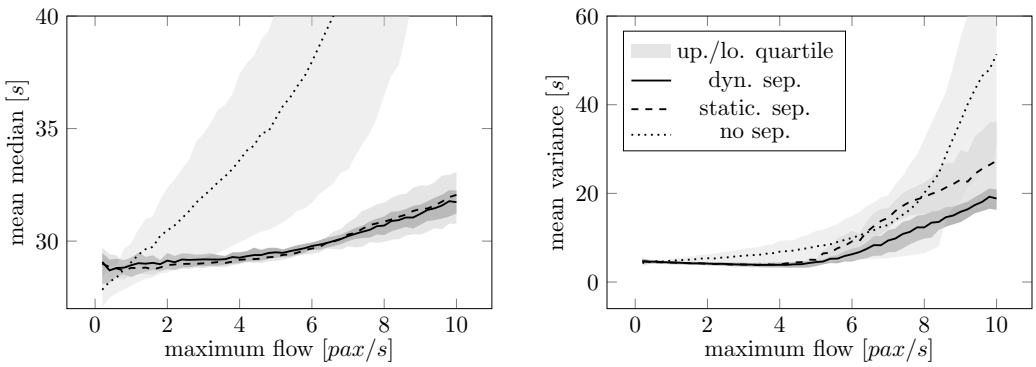


Figure 4.5: The mean square error computed using bootstrapping for the three scenarios. The number of replications of each simulation is varied to evaluate the decrease in MSE as the number of simulations is increased. The usage of flow separators means the required number of simulations to reach a given error is significantly lower.



(a) Mean of median travel times.

(b) Mean of travel time variance.

Figure 4.6: Travel time median and variance analysis for the different scenarios considered. The bands indicate the upper and lower quartiles of the distributions.

Sensitivity to compliance The impact of compliance to the rules is explored in this section. The objective is to explore the cost induced by a small percentage (5% or 10%) of the pedestrians taking the sub-corridor dedicated to the opposite walking direction.
Figure 4.8 shows the median travel time per direction for the three compliance scenarios. When considering Figure 4.7, it is clear that the case with 100% compliance shows the lowest variance in travel time, which is expected. As already seen from Figure 4.6b, the dynamic flow separators have a clear advantage as they keep the variance lower compared to a static separation of flows. This behaviour is also true for cases where a small percentage of pedestrians do not follow the rules. The dynamic flow separator keeps the travel time variance significantly lower than the static case, this is indicated by the grey lines being above the corresponding black lines from Figure 4.7.
By analysing the travel time medians per direction, we can see two opposite situations. The pedestrian flow going from A to B is the major flow, while the opposite flow from B to A is the minor one (i.e. a small group of people moving against a larger group). First of all, the general behaviour of the dynamic flow separator is to give more space to the larger flow. This means that the major flow will generally benefit from this strategy, while the minor flow will see it's reserved space decrease. Hence it is generally penalized by this approach. The impact on the travel times therefore reflects this idea, as seen in Figure 4.8. When comparing the dynamic to the static flow separator for the major flow (Figure 4.8a), the dynamic flow separator is beneficial for this group. On the other hand, for the minor flow (Figure 4.8b) the opposite is true: the dynamic version increases the travel times of the pedestrians. This happens because this group has less space to move around in, hence creating higher congestion.
This first application of the flow separator shows how efficient preventing counter flow is. By dedicating each part of the corridor proportionally to the incoming flows we can significantly decrease the pedestrian's travel time. Pedestrians who do not comply to the control strategy penalize the system. The dynamic flow separators mitigate the effect of these uncompliant pedestrians. Now, we test this control strategy in a larger environment with a more realistic and complex demand pattern.

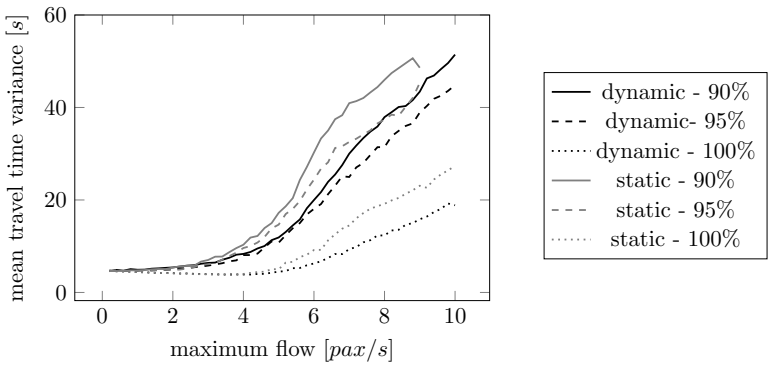
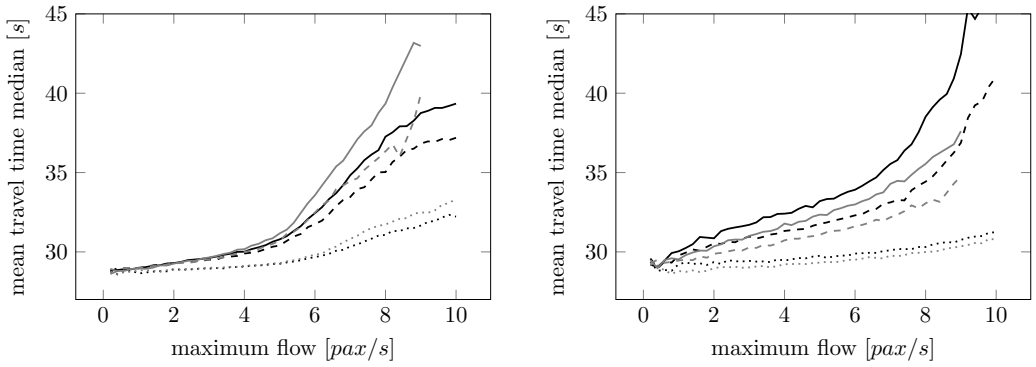


Figure 4.7: Travel time variance for different levels of uncompliant pedestrians.



(a) Pedestrians moving from $A \rightarrow B$.

(b) Pedestrians moving from $B \rightarrow A$.

Figure 4.8: Travel time sensitivity to different levels of uncompliant pedestrians. The dynamic flow separators are useful for reducing the impact of the uncompliant pedestrians. No control travel time: $37.93s$. Same legend as in Figure 4.7.

4.3 Train station corridor

After exploring the impact the separation of pedestrian flows has on a single straight corridor, the impact of flow separators on a busy corridor from a train station is explored. The train station in Lausanne (Switzerland) is reaching saturation as a pedestrian infrastructure. Increasing the pedestrian flow capacity is therefore required. Two underpasses link the city to the train platforms. We consider one of these underpasses as the infrastructure for the second case study. We chose this corridor since it's the busiest of the two underpasses and pedestrian tracking data was collected in 2013. The tracking system relies on a network of cameras (Alahi et al., 2010).

Spatial and temporal representation The infrastructure used for this case study is the western underpass of the train station in Lausanne (Switzerland). This infrastructure is presented in Figure 4.9. The overall length of the corridor is approximately $100m$ and the approximate width is $8m$. The short corridors leading off from the main corridor are the access ramps or stairs to the platforms and main building of the station. The areas where the access ramps join the main corridor are considered as intersections. The time horizon used for the simulation is 90 minutes, which corresponds to the morning peak hour for this station. The motion and route modelling choices are the same as described in 4.2. Figure 4.9 presents the graph used by pedestrians to navigate the infrastructure.

Supply We consider only static elements except from the flow separators. The shops "Aldi" and "Tekoe" are only shown in Figure 4.11 as landmarks and have no influence on the case study.

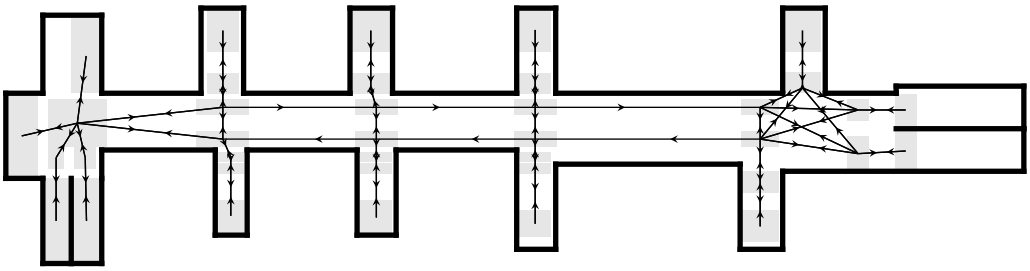


Figure 4.9: Navigational graph used for the western underpass of the station in Lausanne (Switzerland).

Demand Individual tracking data has been collected for ten days in 2013 for both pedestrian underpasses of the main station in Lausanne, Switzerland. This data is used as demand scenarios for testing the effectiveness of pedestrian flow separators. The demand pattern is presented in Figure 4.10. Each curve represents one day (ten days in total). The influence of the cyclic timetable is visible at 7h15, 7h45 and 8h15 since a peak in demand appears at those times. We considered these ten days as independent scenarios. For each of these ten scenarios, one hundred replications were performed to build the distribution of indicators used to evaluate the effectiveness of the control strategy. In this case, we used travel time and mean walking speed.

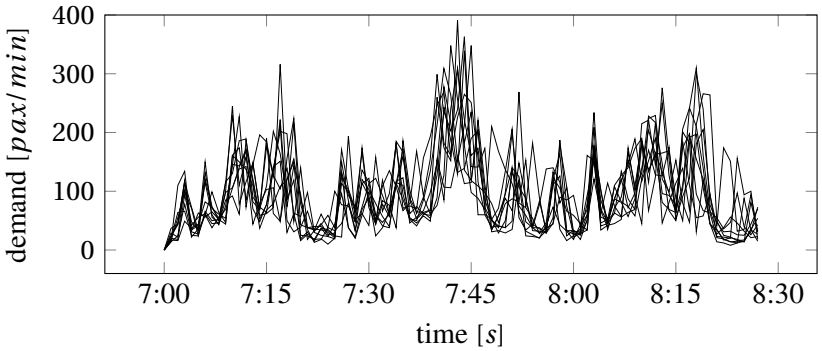


Figure 4.10: Aggregate empirical demand pattern used as input in the simulations for evaluating the flow separators.

The pedestrians have been classified into groups in order to investigate in depth the impact of flow separators. Two criteria are used: trip length and number of times pedestrians must cross the "junctions" (or equivalently the number of left turns they must do). The groups are summarized in Table 4.1. This leads to nine groups in total since there are three different trip lengths and three different groups of left turns: zero left turns (*G0*), one left turn (*G1*) and two left turns (*G2*). The three length groups correspond to the trip length accomplished inside the corridor. If pedestrians use the first stairway/ramp then they get categorized as a short trip (*L0*). If they skip the first stairway/ramp they see, then it is considered a medium trip (*L1*) and if they skip two or more stairways/ramps then they get categorized as long (*L2*).

We simulated three different scenarios of control (summarized in Table 4.1). Firstly, as a reference case, we performed simulations without any flow separator installed (*S0*). Secondly, we used the exact same origin and destination pattern as the empirical data (*S1*). Thirdly, we allowed the pedestrians to adapt their destinations based on their target platform (*S2*). After a pedestrian has walked along a flow separator, she is allowed to use the closest ramp or stairway to reach her platform. For example, a pedestrian following the "G2" path in Figure 4.11 will turn right after walking alongside the flow separator, instead of left. This was done to avoid unrealistic and excessive crossing of the junction areas observed in *S1*. With this scenario, the category with two left turns (*G2*) disappears as the closest access ramp/stairway to the platform is always the one to their right after walking along a flow separator.

Scenario/Group/Length	ID	Description
No control	S0	No traffic control is applied.
Control with fixed destinations	S1	Flow separators are used but pedestrian use their original origin and destination nodes.
Control with adapted destinations	S2	Flow separators are used where pedestrians can adapt their destination to the closest ramp/stairway.
Same side without intersections	G0	The origin and destination of the pedestrians are on the same side and they don't need to cross any intersection.
Cross side	G1	The origin and destination are on opposite sides of the corridor.
Same side with intersections	G2	The origin and destination are on the same side but pedestrians must cross two intersections to perform their trip.
Short	L0	Pedestrians use the first stairway/ramp they meet.
Medium	L1	Pedestrians skip one stairway/ramp.
Long	L2	Pedestrians skip two or more stairways/ramps.

Table 4.1: Summary of the different scenarios under investigation and the different pedestrian groups.

Fundamental quantities & data As for the single flow separator presented in Section 4.2, pedestrian flow is computed at the extremities of each flow separator presented in Figure 4.11.

Control and information Instead of using one flow separator, we simulate the installation of three separators along the main corridor as presented in Figure 4.11. The general idea is the same as previously presented: prevent counter flow between pedestrians by dedicating parts of the corridor to each flow direction. Each flow separator is independent and uses independent flow measurements.

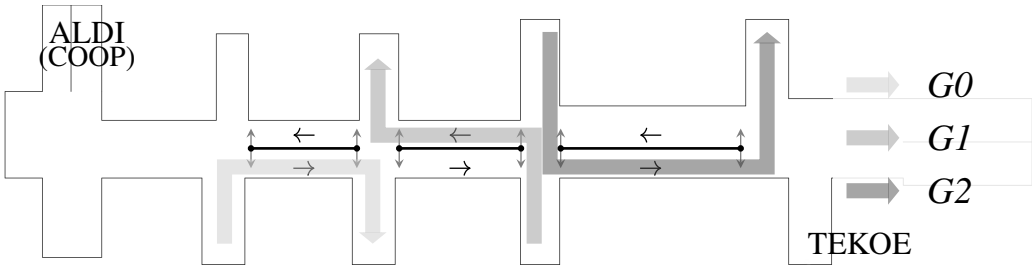


Figure 4.11: Western pedestrian underpass from the station in Lausanne, Switzerland. Three flow separators are installed in the central part of the corridor.

State estimation and prediction No state estimation nor prediction is needed for this strategy.

Control and information configuration generation We keep the same logic as for the simple corridor example. Therefore, equation (4.3) is used to move the flow separator based on the computed flows. We recall that each flow separator is independent from the others.

Influence of dynamic flow separators

Firstly, the travel time of all pedestrians is considered. The box plots of the median travel time per replication are represented in Figure 4.12 for the ten different demand scenarios and each different setup of flow separator. For all demand scenarios the same effect is observed. When flow separators are used but the pedestrians must use their original destinations, a decrease of 1 to 2 seconds is measured in the travel time medians. This improvement can be explained by the travel time reduction induced by the prevention of counter-flow. Nevertheless, pedestrians must still cross the junctions which can also induce delay. For the third control setup, where pedestrians can adjust their destination, another decrease of approximately 1 second is observed in all demand scenarios compared to the case with flow separators. The decrease is approximately 5% compared to the reference case. The cause for this gain is two-fold. The gain comes from the shorter distance travelled by the pedestrians when they change destinations and from the reduced number of intersections which must be crossed by the users.
Since the travel time of all pedestrians are not impacted the same way, we now investigate the walking times of pedestrians categorized into groups based on the trip characteristics to understand further which categories of users benefit from this strategy. This is investigated as we expect different benefits and loses based on the different categories. The comparison of the median of median travel time and average walking speed for each group are presented in Figures 4.13 and 4.14. In these figures, each point represents the difference of the median of median travel time (or mean speed) between the control setup and the reference case. These values are computed based on one hundred replications of each scenario.

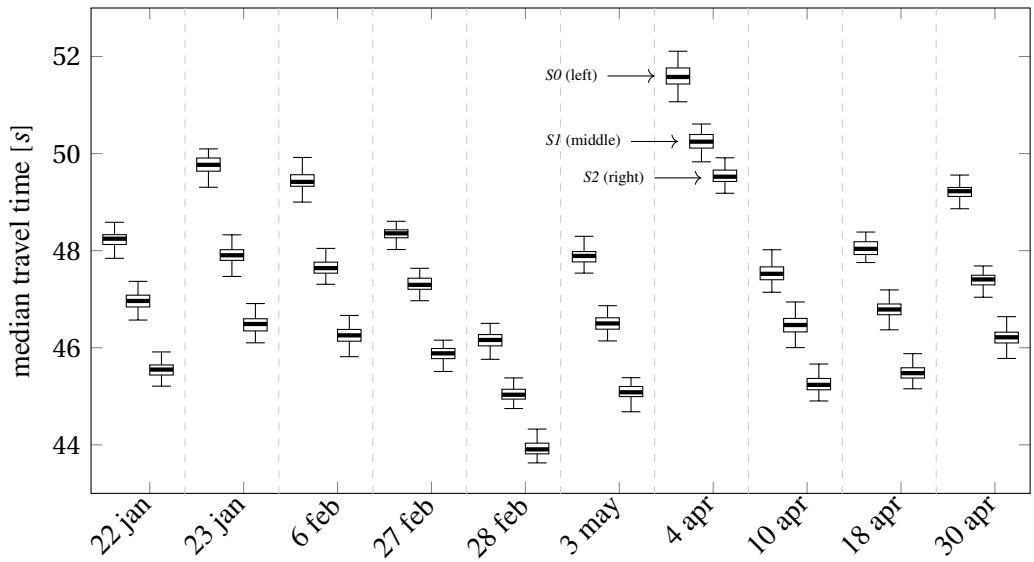


Figure 4.12: Comparison of the distribution of the median travel times of the ten different scenarios for the three setups of the flow separators. Each triplet of box plots represents one demand scenario and within each demand scenario the left box plot is control scenario *S0*, the middle box plots are *S1* and the right box plots are *S2*.

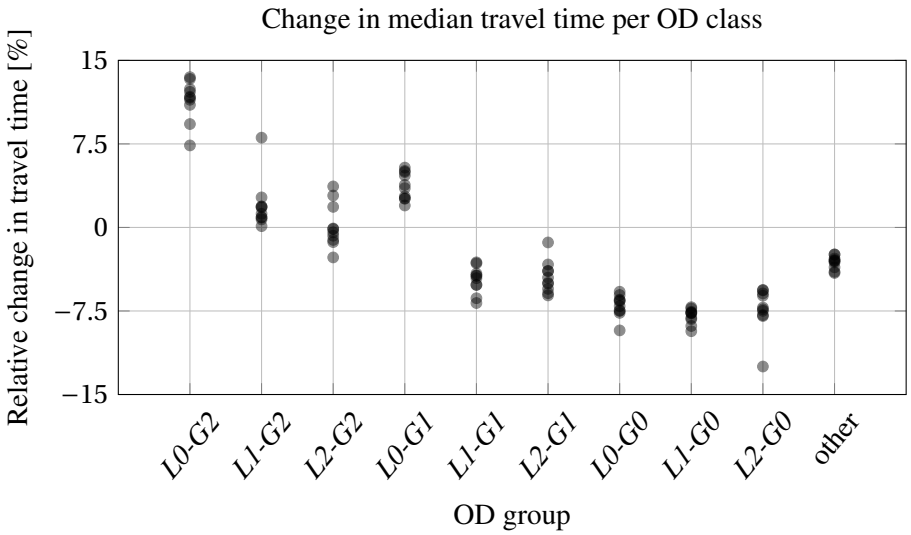
We start by discussing the case where pedestrians must use their original destinations, i.e. *S1*. As expected, the impact on travel time of the flow separators depends on the group under examination (Figure 4.13a). If pedestrians do not need to make any left turns (i.e. cross the junction areas), their travel time decreases regardless of the length of their trip (group *G0*). This sub-population benefits from this control strategy. The group of pedestrians doing one left turn (group *G1*) is positively influenced if the pedestrians are doing a lengthy trip (*L1* or *L2*). The short trips where the pedestrians change corridor side (one left turn, *G1*) suffer from an increased travel time. Finally, trips involving two left turns (group *G2*) are at best not affected by the flow separators. This is the case since the walking time gained by the separated flow is compensated by the time needed to cross the junctions twice.

Although some groups experience an increased travel time, by considering the change in average walking speed (Figure 4.14a) it is clear that all groups of pedestrians benefit from the flow separators as their walking speeds increase. The flow separators therefore effectively prevent the weaving effects and head-on collisions between pedestrians.

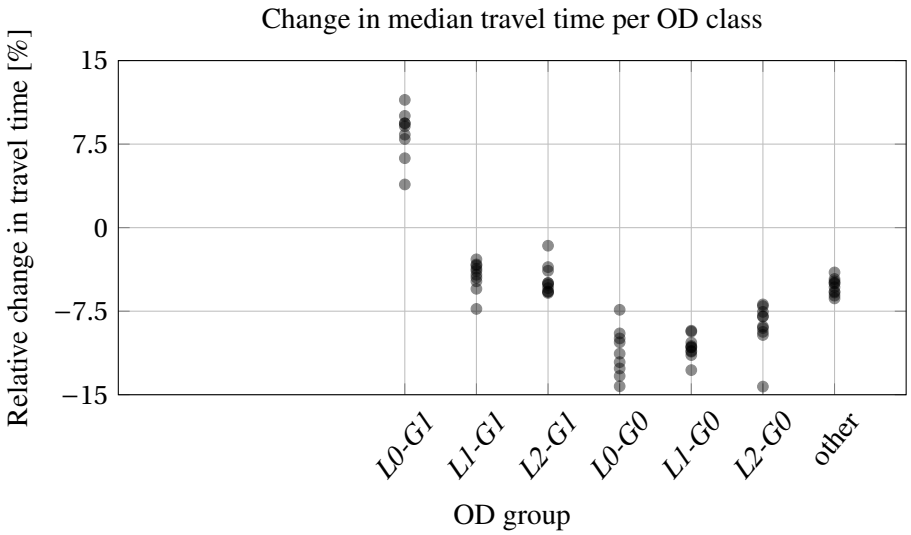
The setup where pedestrians can adapt their destination (*S2*) amplifies the positive impact for some groups whereas for one group the travel time increases. Pedestrians changing side and doing short trips (*L0-G1*) actually suffer from the change in destination when considering travel time. On the other hand, in terms of average walking speed, this group benefits from the change in destination. This can be explained as some pedestrians changing from the *L0-G2* group to the *L0-G1* have a slightly longer trip to perform than others. Indeed, one sub-section of the corridor is longer than the other two. Regarding the other groups, pedestrians who don't cross the corridor

benefit in terms of travel time and walking speed. The pedestrians who perform other trips (*other* group in Figures 4.13 and 4.14) also benefit from the change in destination.
The flow separators are therefore beneficial for most groups of pedestrians for this infrastructure. The travel time of the system as a whole improves as Figure 4.12 shows and the detailed analysis also showed the groups of pedestrians who are slightly penalized by the control strategy.

This control strategy, although relatively simple, proves effective at reducing pedestrian travel times. For the given speed distribution, the travel times are reduced by 5 to 10 percent for most users while the walking speed of all pedestrians increases. The detailed analysis shows that most users benefit from the strategy. Nevertheless, a small group of users is penalized. The implementation linked to the available technology and the user acceptance are maybe the two most important challenges with the flow separator control strategy. Practically, engineering solutions like floor lighting or projections could be used to install dynamic flow separators. These solutions circumvent physical barriers, but then compliance becomes critical. Through these two case studies using flow separators, we show that addressing the behaviours which induce extra travel time significantly improves the pedestrian dynamics. The numerical results naturally depend on the choice of speed distribution and geometrical dimensions. Exploiting other weaknesses of pedestrian traffic like stationary pedestrians or the large range of walking speeds could lead to further improvements.

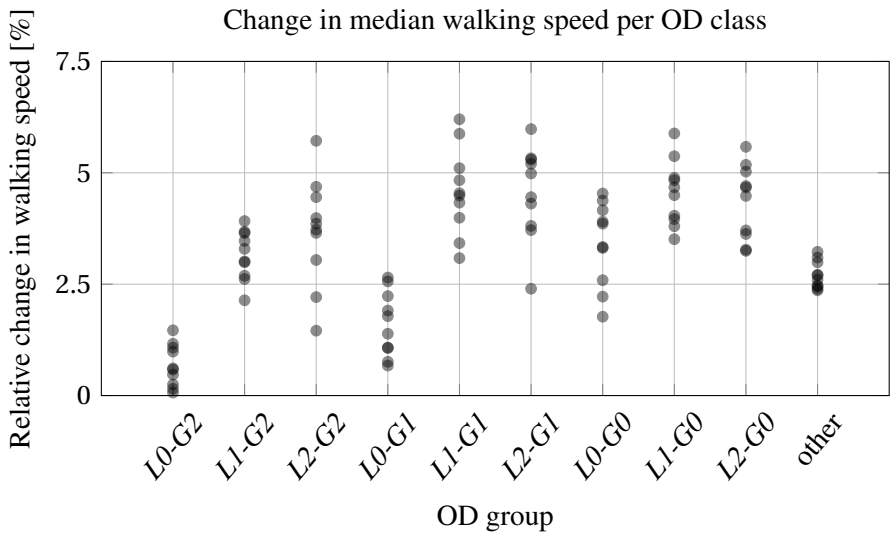


(a) Travel time change per OD group when flow separators are installed in the main corridor. The travel times decrease for groups which don't cross the corridor. For longer trips, the travel time decreases even if pedestrians must cross the corridor.

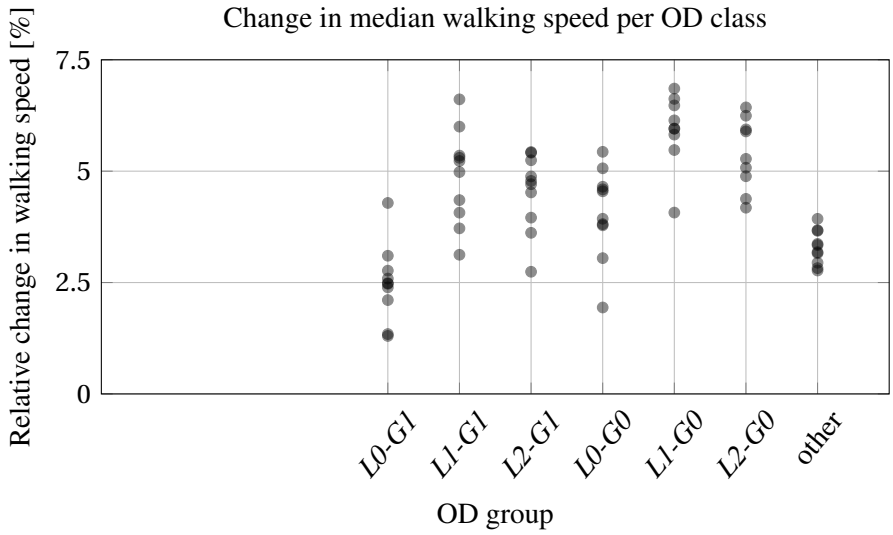


(b) Change in travel time when pedestrians can change their destination to an equivalent platform access ramp. The travel time for pedestrians doing short trips and who must cross the corridor increases compared to the case when the original destination is used.

Figure 4.13: Impact of the flow separators on the travel time of the pedestrians using the western underpass. The top figure (a) presents the change between S0 and S1 while the bottom figure (b) shows the change between S0 and S2.



(a) Mean speed evolution with flow separators installed. The mean speed per OD group significantly increases for all groups except two: pedestrians who cross the corridor with short trips.



(b) Change in mean speed medians when pedestrians can slightly alter their destination. The change in speed is more important compared to the situation where pedestrians must use their original destination.

Figure 4.14: Impact of the flow separators on the average walking speed of the pedestrians using the western underpass. The top figure (a) presents the change between S0 and S1 while the bottom figure (b) shows the change between S0 and S2.

4.4 Conclusion

This chapter presented a control strategy which addresses a specific aspect of pedestrian dynamics: bidirectional flow. The numerical results show a significant reduction in pedestrian travel time when flow separators are used. The user compliance to the direction was also considered and the simulations show that at low demand uncompliant users don't significantly penalise the system. The effectiveness of the devices also depends on the trip characteristics like length and number of left turns.

The efficiency of flow separators under heavy congestion is yet to be determined. On one hand this control strategy has the potential to delay the formation of congestion by preventing head collisions in opposing flows. On the other hand, the walking space available to the users is reduced when highly unbalanced bidirectional flows occur since part of the corridor is always dedicated to the minor flow. Furthermore, the control algorithm must be able to detect congestion alongside the devices to prevent them from moving and creating hazardous situations.

Two interlinked challenges come with this control strategy: compliance and practical implementation. The first challenge is getting pedestrians to respect the designated walking direction. Information can be provided to the users but enforcing compliance is challenging since pedestrians benefit from nearly unhindered freedom of movement. The second challenge concerns practical measures to split a corridor in two parts. If a moving barrier would be used, several dangerous situations could occur. If congestion builds up alongside the flow separator then the device cannot be moved otherwise severe health hazards will occur. Installing gates at either extremity would work to address the compliance issue but this approach raises safety issues in case of congestion. Furthermore, gates can reduce the walking speed of pedestrians. Therefore, a device which is safe for the users and also clearly understandable for first time users should be considered. Instead of dynamically allocating the whole width of the corridor, a system of lanes could be used. Doing so, the direction of each lane can be decided without having any moving mechanical parts. Static separation of corridors is done in practice and emphasize the compliance challenge since users often ignore the flow direction indications. One of the negative aspects of static separations is the waste of capacity during peaks in demand. Therefore, a lane system can take advantage of both elements: dynamic and safe.

The flow separator strategy has highlighted some of the challenges with the development of pedestrian dedicated control strategies. Addressing a specific aspect is beneficial, but challenges remain. Therefore, the development of future control and management strategies should focus on specific aspects of pedestrian dynamics. The present algorithm only exploits real time measurements of pedestrian flows. The added value of integrating short term predictions inside control strategies for pedestrian flows will be evaluated in the next chapter with different control devices.

5 Controlling pedestrian flows with moving walkways

This chapter is based upon the following technical report:

> N. Molyneaux and M. Bierlaire (2021b). *Controlling pedestrian flows with moving walkways*. Technical Report TRANSP-OR 210218. Lausanne, Switzerland.

5.1 Introduction

Although the previous control strategy successfully improves the pedestrian dynamics by preventing bidirectional flow, the strategy uses devices which open several practical challenges. Therefore, to reduce these implementation issues, in this chapter, we propose the use of dynamically controlled moving walkways to reduce congestion and decrease pedestrian travel time. The speed and direction of the devices can be controlled to optimize a given objective. One advantage of such hardware is that pedestrians already use them in many different contexts. Although moving walkways are common inside airports, few studies consider these devices outside of their usual context as a transportation mode. Moving walkways can be considered in the context of "Smart cities" to decarbonate individual transport. Furthermore, a trend towards improving walkability of cities means pedestrian demand might increase in the coming decades (Fonseca et al., 2020).

The many successful control strategies for road traffic motivates the exploration of different flavours of the control algorithm. For example, many different variations of the original ramp metering control strategy are available in the literature: reactive versions which exploit traffic flow measurements (Ben-Akiva et al., 2003; Abuamer et al., 2016) or predictive versions which use short-term predictions (Bellemans et al., 2006; Roncoli et al., 2016). When considering signalized intersections, fixed-time solutions are also widespread (Papageorgiou et al., 2003). Therefore, we explore the same three variations of control algorithms (fixed, reactive and predictive) which exploit moving walkways to improve the pedestrian dynamics. The fixed strategy is designed

offline based upon historical data. The reactive strategy adapts the control measures based upon real-time traffic conditions. The predictive strategy exploits a model to gain insight into the traffic conditions which are going to occur in the near future.
These three control algorithms are analysed and their effect upon pedestrian travel time and density is discussed. We discuss three aspects. Firstly, we investigate whether moving walkways can be used to improve pedestrian flows, as highlighted by contribution (d). Secondly, we analyse the benefits of including short-term predictions into the control strategy, as opposed to schemes using only historical or real-time data. The third and final hypothesis concerns the predictive scheme: we discuss whether multi-objective optimization can be used inside pedestrian specific flow control schemes. Both of these hypotheses address contribution (e). The predictive algorithm relies upon an optimization framework to minimize a defined objective function by searching for the best speed profile of the moving walkways in the short-term future. To achieve this, an objective function relying on a combination of pedestrian centric metrics must be defined. The choice of metrics included in the objective function is discussed, alongside their impact on the pedestrian dynamics. This optimization procedure is computationally expensive, hence it's added value must be evaluated.
Mechanical and geometric considerations for speed, acceleration, capacity, etc. of moving walkways are provided in Scarinci et al. (2017). The authors discuss the benefits of installing moving walkways to move pedestrians around at a city level. They propose accelerated moving walkways as a transportation mode. An optimization framework which analyses the trade-off between installation cost and benefit is used. Furthermore, many practical considerations are discussed concerning the installation constraints.
The following sections discuss the three control algorithms and the required input data. Next, we present the results from two case studies where we simulated the installation of moving walkways. The three control algorithms are tested and their effects on the pedestrian dynamics are discussed before concluding this chapter.

5.2 Moving walkways as a control strategy

Moving walkways as control devices have the potential of influencing the pedestrian flows since the speed and direction of these devices can change over time. To the best of our knowledge, moving walkways (MW) have not yet been used by a dynamic control strategy. We present and discuss the major elements which are needed to design a control algorithm using these devices. We propose three different flavours of the control algorithm: a fixed (or static), a reactive and a predictive version. Although many implementation details must be considered to use the control devices in practice, such considerations are beyond the scope of this thesis in which we analyse the benefits of using such devices on the pedestrian dynamics. Nevertheless, some assumptions must be made to design control algorithms which are feasible in practice. Moving walkways as a control strategy and the different control algorithms are evaluated inside a simulation environment (assessment model). This must be accomplished to evaluate the feasibility of the considered

control approach. We start by presenting and discussing these assumptions.
The walkable environment in which the moving walkways can be used as control devices must be one where pedestrians wish to reduce their travel time and avoid congestion. Train stations during the peak hours are a typical example. Pedestrians already use moving walkways in airports to travel long distances or inside shopping malls to change floors for example (Young, 1999). Therefore, an advantage of moving walkways compared to other novel technologies is the user acceptance. Users will not be exposed to a new technology, hence no learning phase is required. This leads to the first assumption concerning compliance. We assume that the pedestrians respect the direction of the moving walkway. Secondly, we assume that pedestrians walk while on the moving walkway.
The following assumptions concern the devices themselves. We assume that the speed of a moving walkway must be selected from a discrete and predetermined set of speeds. Note that the speed may be signed, so that the walkway can be operated in two directions. The speeds are considered discrete for safety and comfort reasons. Safety issues will arise if the speed of the MW changes continually. Furthermore, a pedestrian who is standing on the MW will feel uncomfortable if every few seconds the speed increases or decreases. If individuals don't feel safe on the devices, then user acceptance will be low and they will prefer to walk instead.
When a MW changes direction, a buffer time must be given to the pedestrians to clear the device before it changes direction. This buffer time should be long enough such that an individual who has just entered the MW can leave it before the MW changes direction. Furthermore, during this buffer time, no pedestrians should be allowed to enter the MW. Although the MW can change direction at any time to move in the same direction as the larger pedestrian flow, the direction should not change too often. The assumptions about the speed discretization and buffer time will be formally defined in the following paragraphs.
At a tactical level, the installation of moving walkways adds another alternative path pedestrians can choose from. Each individual must now choose from walking or using the moving walkway to reach his next intermediate destination. Therefore, two parallel flows of pedestrians between two locations can exist: one walking and one using the MW.
The two assumptions regarding compliance raise challenging practical and safety questions. User compliance towards the direction is generally respected in practice. On the other hand, the assumption where no pedestrians enter the moving walkway during the clearing buffer time before a direction change is more delicate. To prevent pedestrians from entering the MW, a clear means of information or physical obstruction needs to be used. The use of a physical obstacle (such as a gate) may raise safety issues, while the absence of such an obstacle may generate a lack of compliance. These practical issues are not discussed further in this chapter. Before advancing to the input requirements of the control algorithm, we recall the terminology defined in section 3.3 concerning a control strategy:

Control devices: Hardware used to apply the control strategy, in this case moving walkways.

Control algorithm: Equation or function which defines the state of the control devices based upon measured and predicted data.

Control configuration: Set of variables generated from the control algorithm and applied using the control devices. In the present case, the speeds of the moving walkways.

We define the following notation concerning the temporal and spatial representations. A specific moment in time (a snapshot) is denoted t, while a time interval $[t_{start}, t_{end}]$ is denoted by τ. The walkable environment in which the pedestrians can move around is denoted L, while a specific sub-element (region or line) is $L' \subset L$. The collection of moving walkways installed in the walkable environment is $\mathcal{W}$. Each moving walkway $\omega \in \mathcal{W}$ has a static origin o and destination d. The area near the origin of the MW is denoted ϕ_o and the area at the end is ϕ_d. The speed of a given walkway ω during the time interval $\tau = [t, t + \Delta t_s]$, where Δt_s is the time interval length, is $s_\omega(\tau)$. The speed of the MW cannot change during the interval τ. It is positive if the direction of movement is going from ϕ_o to ϕ_d, and negative if moving from ϕ_d to ϕ_o. The set of possible speeds is $\mathcal{S}$, hence $s_\omega(\tau) \in \mathcal{S}$. The maximum speed of moving walkways is $s^{max} = 3m/s$ in practice (Scarinci et al., 2017). An example of a moving walkway installed in a corridor is shown in Figure 5.1.

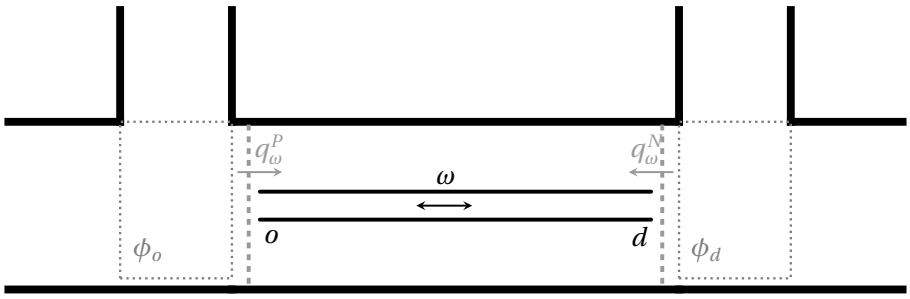


Figure 5.1: Schematic presentation of a moving walkway.

5.2.1 Control algorithm input

The control strategy, more specifically the different control algorithms, require input data to generate the control configurations. The control strategy we propose uses three different quantities: pedestrian flow, density and travel time.

The pedestrian flow $q(L', \tau)$ is the number of pedestrians who enter the area or cross the line L' during time interval τ. For a given moving walkway ω, we define two parallel flows (one per direction) as the pedestrian flows which are using ω or that could use ω. Therefore, for each MW, we define q_ω^P and q_ω^N as the flows moving in the positive, respectively negative, direction of ω. Figure 5.1 presents both parallel flows. All pedestrians crossing the grey dashed lines are those counted in the "parallel flows". The pedestrian density inside area L' at a given time t is denoted by $\rho(L', t)$. The spatial context L' can be a corridor or junction linking corridors for example. The density threshold above which we consider congestion takes place is ρ^c. The travel time of individual n is denoted tt_n. The travel time is defined as the duration the pedestrian spent inside

the spatial context L between when he enters until when he leaves.
The different flavours of the control algorithms need different temporal contexts of the quantities. The collection of quantities of interest (flow or density for example) is denoted Δ. For any fundamental quantity of interest, we define the historical, real-time, and predicted counterparts. Historical versions are denoted $\cdot^H$, real-time versions are denoted $\cdot^*$, while predicted values are denoted $\cdot^+$. The historical data is collected over the previous days, months or years. Real-time data is collected using measurement devices in the very short-term past like the previous few minutes or seconds. Predicted data covers the short-term future. Since the predicted data is uncertain by nature, the predicted data is provided as distributions of the quantities. This allows the control algorithm to exploit the uncertainty of the forecast and potentially give more weight to predicted quantities with less variance.
In this chapter, the distributions are generated from R replications of the short-term predictions accomplished using a simulator. We assume that the quantities generated by the simulator are unbiased. Furthermore, we assume that the variance in the quantities does not vary over the prediction horizon.
The different quantities of interest, for both the real-time and predicted time contexts, are provided by the DPMS framework presented in chapter 3. We assume that such a system is available to provide the data. The details of the DPMS implementation are described in the case studies.

5.2.2 Control variables

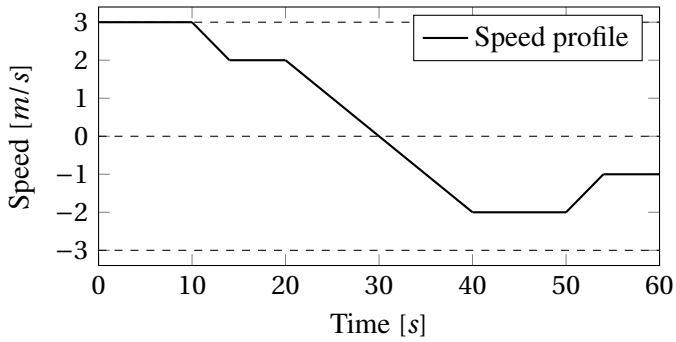
For a collection of moving walkways installed inside an infrastructure, the control variables are the speeds of each moving walkway. For a time period T decomposed into intervals of equal duration Δt_s, the control configuration is:

$$\mathcal{C}_\omega(T) = \{s_\omega(\tau)\} \quad \forall \tau \in T, \tag{5.1}$$

where $s_\omega(\tau)$ is the speed of walkway ω over interval τ. The speed at the end of interval $\tau_i = [t_i, t_i + \Delta t_s]$ can change to any value within $\mathcal{S}$ for the next interval $\tau_{i+1} = [t_i + \Delta t_s, t_{i+1} + 2\Delta t_s]$. The speed transition phase (or acceleration/deceleration phase) takes place at the beginning of τ_{i+1}. Therefore, the new speed is only applied after the transition time. The acceleration of the moving walkways is $0.25 m/s^2$ (Scarinci et al., 2017). An example speed profile with the acceleration phases is shown in Figure 5.2. The transition between the first interval $[0, 10]$ and the second interval $[10, 20]$ lasts four seconds since the speed difference is $1 m/s$ and the acceleration is $0.25 m/s^2$. The speed profile includes the acceleration/deceleration phases such that the configuration is enforced at the end of each interval.

Time $[s]$	Speed $[m/s]$
0-10	3.0
10-20	2.0
20-30	0.0
30-40	-2.0
40-50	-2.0
50-60	-1.0

(a) Control configuration



(b) Moving walkway speed profile example

Figure 5.2: Control configuration example of a MW with the corresponding speed profile.

5.3 Control algorithms

Maybe the most challenging aspect of designing a new control strategy is the development and calibration of the control algorithms. The algorithm links the fundamental data to the control configuration of the devices. With this chapter, we aim to investigate whether moving walkways are beneficial for pedestrians. Furthermore, we discuss whether predictive control shows a significant improvement over reactive control. To achieve this, we propose three variations of the control algorithms. The first is a fixed (or static) approach, the second a reactive algorithm and the third a predictive algorithm. These three control algorithm flavours generate the control configuration based upon input data:

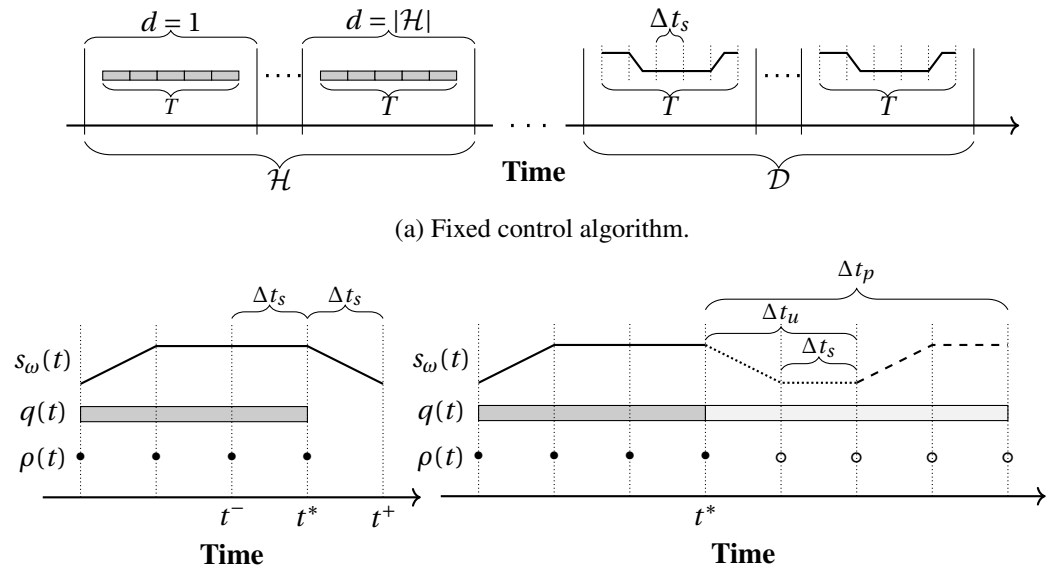
$$\mathcal{C}_f = \mathcal{A}_f\left(\Delta^H\right) \tag{5.2}$$

$$\mathcal{C}_r = \mathcal{A}_r\left(\Delta^*\right) \tag{5.3}$$

$$\mathcal{C}_p = \mathcal{A}_p\left(\Delta^*, \Delta^+\right) \tag{5.4}$$

where $\mathcal{C}_f$, $\mathcal{C}_r$ and $\mathcal{C}_p$ are the fixed, reactive and predictive control configurations. $\mathcal{A}_f$, $\mathcal{A}_r$ and $\mathcal{A}_p$ are the fixed, reactive and predictive control algorithms. The fixed algorithm exploits historical data. The reactive algorithm exploits real-time data and the predictive algorithm exploits predicted data. The predictive algorithm needs the real-time data to generate the predictive data. Figure 5.3 presents the temporal notations for all three control algorithms. The algorithms which are presented in the following sections exploit pedestrian flow and pedestrian density to generate the control configurations.

All three algorithms share a common goal: they aim at moving pedestrians as fast as possible to their destination. The total travel time of all pedestrians (system optimum) is minimized, not the pedestrian specific travel times (user optimum). This objective must be balanced with congestion since transporting many pedestrians into the same area of the infrastructure can lead to hazardous congestion. Therefore, a trade-off between minimizing travel time and minimizing congestion must be addressed.



(a) Fixed control algorithm.

(b) Reactive control algorithm.

(c) Predictive control algorithm.

Figure 5.3: Temporal contexts and notations for the three control algorithms.

5.3.1 Fixed control algorithm

A fixed control configuration is generated based upon the average observed flows computed for short time intervals. The idea is to have the moving walkways carrying pedestrians in the same direction as the maximum observed average pedestrian flow in each time interval. The speed of the moving walkway is set to the fastest value from $\mathcal{S}$. For example, let's consider the morning peak hour between 7:00 and 8:00 and one single moving walkway. We discretise this time period into 5-minute intervals and compute, for each interval, the average over the historical data of the pedestrian flow in each direction of the MW. Then, for each time interval, the direction of the moving walkway is set to match the maximum average flow. This example is formalized in the following paragraphs.

The input data consists of a historical data set $\mathcal{H}$ composed of data covering the same time period T (the morning peak hour for example), indexed by d. The control configuration, generated by the fixed control algorithm, will be used for the set of days $\mathcal{D}$. The time period under consideration T is divided into intervals of length Δt_s. The temporal context for the fixed control algorithm is presented in Figure 5.3a. The average observed parallel flows for each moving walkway is computed for each interval $\tau \in T$:

$$\overline{q^P_\omega}(\tau) = \frac{1}{|\mathcal{H}|} \sum_{d \in \mathcal{H}} q^{H,P}_{\omega,d}(\tau), \quad \overline{q^N_\omega}(\tau) = \frac{1}{|\mathcal{H}|} \sum_{d \in \mathcal{H}} q^{H,N}_{\omega,d}(\tau) \quad \forall \tau \in T, \omega \in \mathcal{W} \tag{5.5}$$

where $\bar{\cdot}$ represents the mean, $q^{H,P}_{\omega,d}(\tau)$ is the observed pedestrian flow moving in the positive direction of ω during interval τ of historical data d. The average parallel flows for each time

interval are $\overline{q_\omega^P}(\tau)$ and $\overline{q_\omega^N}(\tau)$ in the positive and negative directions. These values are used by the fixed control algorithm which is presented in Algorithm 1. The "speed transitions" insert acceleration and deceleration phases, when needed, to have a feasible speed profile (as described in section 5.2.2).

Algorithm 1: Fixed control algorithm $\mathcal{A}_f$.

Input:

time period of interest T

historical data: $q_\omega^{H,P}(T)$ and $q_\omega^{H,N}(T)$

Control:

compute $\overline{q_\omega^P}(T)$ and $\overline{q_\omega^N}(T)$ using (5.5)

for $\tau \in T, \omega \in \mathcal{W}$ **do**

  if $\overline{q_\omega^P}(\tau) > \overline{q_\omega^N}(\tau)$ **then**

    $s_\omega(\tau) = +s^{\max}$

  else

    $s_\omega(\tau) = -s^{\max}$

  end

  insert speed transitions

end

Output: fixed control configuration $\mathcal{C}_f$

5.3.2 Reactive control algorithm

The second control scenario we propose is a reactive approach. We exploit pedestrian flow and density data collected inside the walkable space to update the direction and speed of the moving walkways dynamically by defining $\mathcal{A}_r$. This control algorithm uses the data provided by the DPMS covering the recent past to first decide on the direction of the MW based upon pedestrian flow data, then to set the speed according to density data. The direction is decided by considering pedestrian inflow near the extremities of the moving walkway. The direction is set such that pedestrians are carried away from the extremity into which the majority of pedestrians are entering. Then, the speed is set using a proportional-integral (PI) controller regulating density. The direction and speed of each MW are updated at regular intervals Δt_s. Considering the rapid changes in pedestrian dynamics which can occur, the update interval should be short. This is especially true for the speed, while the direction could be updated less often. The time at which an update is computed (the present time) is denoted t^*. The next update will occur at $t^+ = t^* + \Delta t_s$. The previous update took place at $t^- = t^* - \Delta t_s$. Figure 5.3b summarizes the temporal context. We recall that the MW speeds are considered constant over time intervals, therefore we define the

following notation: τ^- is the interval $[t^-, t^*]$ and τ^+ is the interval $[t^*, t^+]$, hence the MW speed during the previous interval is $s_\omega(\tau^-)$ while the speed during the next interval is $s_\omega(\tau^+)$.
We propose the utilization of a rule based upon pedestrian flow. The direction of the MW for the next interval is set using the following:

$$\text{if } \operatorname{sign}(s_\omega(\tau^-)) = +1 \rightarrow \operatorname{sign}\left(s_\omega(\tau^+)\right) = \begin{cases} +1 & \text{if } m \cdot q_{\phi_o}(\tau^-) > q_{\phi_d}(\tau^-) \\ -1 & \text{otherwise} \end{cases} \tag{5.6}$$

$$\text{if } \operatorname{sign}(s_\omega(\tau^-)) = -1 \rightarrow \operatorname{sign}\left(s_\omega(\tau^+)\right) = \begin{cases} -1 & \text{if } q_{\phi_o}(\tau^-) < m \cdot q_{\phi_d}(\tau^-) \\ +1 & \text{otherwise} \end{cases} \tag{5.7}$$

where $\operatorname{sign}(s_\omega)$ indicates the direction of movement of ω, the parameter m reflects how much the flows must change before the direction changes, $q_{\phi_o}(\tau^-)$ and $q_{\phi_d}(\tau^-)$ are the inflows of pedestrians into areas ϕ_o and ϕ_d during τ^-. This direction update rule is applied only if a direction change is allowed to take place. To prevent excessive direction changes, after a direction change has occurred, we prevent the moving walkway from changing direction again for a given time. The duration while the direction change is prohibited is denoted δ_{dir}. Assume a direction change has taken place at t^*, then the next direction change cannot take place before $t_{dir} = t^* + \delta_{dir}$.
The parameter m allows the operator to influence the balance between changing direction to match the major flow and preventing excessive direction changes. Changing direction as soon as the flow coming in the opposite direction to the MW exceeds by 1% the flow in the same direction of the MW is likely to be counterproductive. The parameter m represents by what fraction the flow coming in the opposite direction must exceed the flow moving in the same direction before changing direction.
Next, we define how the speed is updated at each interval. Similarly, to many traffic control methods (Baskar et al., 2011), we propose a speed update rule using a PI controller. The calibration process is discussed alongside the DPMS specification in the next section. We regulate density by controlling the speed of the moving walkway. The PI controller generates speeds which are continuous, hence the speed is rounded to the nearest value found in the set of possible speeds $\mathcal{S}$ before being enforced. We recall that the MW speeds are rounded to prevent excessive adaptations which would render the trip uncomfortable for the users. Since we aim at preventing excessive congestion at either end of the moving walkway, we provide the PI regulator with a set point: ρ^s. This is the density the regulator targets. The error between the set point and measurement at time t, monitored in zone ϕ, is denoted $e^\rho_\phi(t) = \rho^s - \rho(\phi, t)$. Similarly to Tympakianaki et al. (2014), the PI regulator equation linking the speed of the moving walkway ω to the density at the downstream exit is:

$$s_\omega(\tau^+) = \left\lfloor s_\omega(\tau^-) - e^\rho_\phi(t^*)\left[K_p + K_I\right] + e^\rho_\phi(t^-)K_P \right\rceil^{\mathcal{S}} \tag{5.8}$$

where $\lfloor\cdot\rceil^{\mathcal{S}}$ represents the operation of rounding to the nearest value in $\mathcal{S}$, K_P and K_I are respectively the proportional and integral gains, $e^{\rho}_{\phi}(t^*) = \rho^s - \rho_{\phi}(t^*)$ and $e^{\rho}_{\phi}(t^-) = \rho^s - \rho_{\phi}(t^-)$ are the density errors measured at t^* and t^-. The regulator tries to drive the errors to 0. The density measurements are taken from the downstream exit. If the MW is moving in the positive direction, then measurements in $\phi = \phi_d$ are used, otherwise, if the MW is moving in the negative direction, then measurements are taken in $\phi = \phi_o$. The complete algorithm is presented in Algorithm 2.

Algorithm 2: Reactive control algorithm $\mathcal{A}_r$.

```
Input:
parameters: m, δ_dir, K_P, K_I
flow and density data: Δ*
Control:
for τ⁺ = [t*, t* + Δt_s] do
    for ω ∈ W do
        if t* > t_dir then
            update direction using (5.6) and (5.7)
            update t_dir = t* + δ_dir
        end
        update s_ω(τ⁺) using (5.8)
    end
    insert speed transitions
end
Output: updated speed and direction for all MW
```

5.3.3 Predictive control algorithm

The final control algorithm we propose exploits short-term predictions of the pedestrian dynamics. One of the advantages of a predictive algorithm is the ability to anticipate the demand and hence decrease the negative effects of changing the direction of motion of the moving walkways. We recall that a moving walkway must close for some time when it changes direction. Therefore, by considering the short-term future, the algorithm can set the direction of motion before the pedestrians reach the devices, and not only after the pedestrian flow has been detected by the real time measurement devices.

We define the predictive control algorithm $\mathcal{A}_p$ which exploits Δ^* and Δ^+ to generate the control configuration. The rolling horizon paradigm allows the specification of a control configuration for the short-term future by exploiting predictions of the demand and quantities of interest. The predictions are accomplished using a pedestrian simulator. We recall that we are evaluating

the strategy inside a simulation environment, hence state estimation is not needed since the assessment model produces the quantities of interest Δ^*. In practice, the current state data Δ^* is collected thanks to measurement devices and completed using state estimation. Then, state prediction generates the data for the near future Δ^+. The duration of the prediction horizon is denoted by Δt_p. The prediction horizon $T^+ = [t^*, t^* + \Delta t_p]$ is discretised into intervals of length Δt_s. The temporal context can be found in Figure 5.3c. The speed of each MW for each interval in the prediction horizon is the control configuration. The specification of the control configuration is accomplished by minimizing an objective function computed from predictions of the quantities of interest Δ^+ by using an optimization algorithm. The key assumption under which the optimization problem is relevant is that the quantities of interest (travel time, density, flow) depend on the speed and direction of the moving walkways. The optimal control configuration is applied until it gets updated. The predicted control configurations are updated at regular intervals Δt_u. This procedure is summarized in Algorithm 3.
The decision variables of the optimization problem are the control configurations of each moving walkway. We recall that the speeds are discretised in time and magnitude. The decision variables are therefore the collection of all speeds of all moving walkways:

$$\mathbf{s} = \{s_\omega(\tau)\} \quad \forall \tau \in T^+, \omega \in \mathcal{W}, \tag{5.9}$$

with $s_\omega(\tau) \in \mathcal{S}$ since the speeds are discrete. The optimal control configuration is denoted $\mathbf{s}_{opt}$. Two versions of the predictive algorithm are proposed which differ by using different optimization algorithms. The first is a single objective variation and the second is a multi-objective variation.

Algorithm 3: Predictive control algorithm $\mathcal{A}_p$.

Input:

flow, density and travel time data: Δ^* and Δ^+

optimization algorithm: $\mathcal{O}$

Control:

for $T^+ = [t^*, t^* + \Delta t_p]$ **do**
  find optimal configuration $\mathbf{s}_{opt}$ using $\mathcal{O}$

end

apply $\mathbf{s}_{opt}$ until update at $t_u = t^* + \Delta t_u$

Output: optimal control configuration over T^+

Single objective predictive algorithm

The objective function is computed from the predicted state data Δ^+. We consider travel time as the objective to minimize. The mean travel time of all pedestrians inside the predicted horizon is used to take travel time into consideration:

$$\chi^{T^+}(\mathbf{s}) = \frac{1}{|N|} \sum_{n \in N} tt_n(\mathbf{s}) \tag{5.10}$$

where $tt_n(\mathbf{s})$ is the travel time of pedestrian n which depends on the control configuration $\mathbf{s}$ and N the collection of pedestrians inside the simulation. Since the short-term predictions rely on a pedestrian simulation which is stochastic, we perform R replications of the short-term prediction at each evaluation of the objective function to build distributions of the indicator. We then compute the mean value from these distributions to evaluate the objective function:

$$\overline{\chi^{T^+}}(\mathbf{s}) = \frac{1}{|R|} \sum_{r \in R} \chi_r^{T^+}(\mathbf{s}). \tag{5.11}$$

The optimization problem which the predictive control algorithm must solve at each iteration of the rolling horizon scheme can therefore be written as:

$$\begin{aligned} \mathbf{s}_{opt} = \arg\min_{\mathbf{s}} \quad & \overline{\chi^{T^+}}(\mathbf{s}) \\ \text{s.t.} \quad & \mathbf{s} \in \mathcal{S} \end{aligned} \tag{5.12}$$

The predictive control algorithm solves the optimization problem (5.12) each time the configuration is updated. Considering the discrete nature of the decision variables and the simulation-based objective function, we propose the utilization of the adaptive large neighbourhood search algorithm for solving (5.12). This algorithm is flexible since it can handle single and multi-objective problems (Ropke and Pisinger, 2006).

Adaptive large neighbourhood search Adaptive large neighbourhood search (ALNS) is a meta-heuristic optimization algorithm which uses a collection of heuristics (operators) to generate new solutions from an existing one. The original algorithm is adapted to include the acceptance criteria from simulated annealing (Gendreau and Potvin, 2010). This reduces the risk that the algorithm gets trapped in local minima. Algorithm 4 shows the complete algorithm.

Algorithm 4: Single objective ALNS using the simulated annealing selection criteria.

```
Input:
feasible solution: x, operator set: Θ
Initialization:
operator weights: g
iteration counter: i = 0, maximum number iterations: n
random number generator: r, temperature: T
best solution: x^b = x, current solution: x^i = x
Iterations:
while i < n do
    select operator o ∈ Θ using g
    x^{i+1} = o(x^i)
    if c(x^{i+1}) < c(x^b) then
        x^b = x^{i+1}
    else if exp(c(x^{i+1}) − c(x^b)) / T > r then
        x^b = x^{i+1}
    else
        reject x^{i+1}
    end
    update g
    decrease T
    i = i + 1
end
Output: best solution x^b
```

Operators A collection of operators Θ is used to generate new solutions from the current solution. They have been developed specifically for the purpose of optimizing the control configuration of moving walkways. One operator $o \in \Theta$ is selected at each iteration. This operator is selected using the adaptive weights method proposed in Ropke and Pisinger (2006). At iteration i, the current solution x^i is transformed using operator o to generate the next solution: $x^{i+1} = o(x^i)$. The collection of operators is presented below. The operators are described assuming only one MW is available for the sake of clarity. Each operator has a parameter, denoted α, which controls the distance between x^i and x^{i+1}.

Increase speed A randomly sampled fraction $\alpha \in [0.2, 0.8]$ of the decision variables are increased. The fraction of decision variables to change is equal to α. Then, the speed is increased to the next discrete value. For example, for $x^i = [2, 2, 1, 0, -1, -2]$ and a fraction to change $\alpha = 0.5$, then $x^{i+1} = [3, 3, 1, 0, 0, -2]$.

Decrease speed Analogous to the previous operator, except that the speeds are decreased to the next discrete value. For example, for $x^i = [2, 2, 1, 0, -1, -2]$ and a fraction to change $\alpha = 0.5$, then $x^{i+1} = [1, 1, 1, 0, -1, -3]$.

Accelerate A fraction $\alpha \in [0.2, 0.8]$ of the speeds is selected and their amplitude is increased.

The moving walkways are moving pedestrians faster after this operator. For example, for $x^i = [2,2,1,0,-1,-2]$ and the fraction to change $\alpha = 0.5$, the next solution becomes $x^{i+1} = [3,3,1,0,-2,-2]$.

Slow down Analogous to the previous operator, this operator slows down a fraction of the control configuration. For example, for $x^i = [2,2,1,0,-1,-2]$ and the fraction to change $\alpha = 0.5$, the next solution becomes $x^{i+1} = [1,1,1,0,0,-2]$.

Direction matches flow Each MW is selected with probability $\alpha = 0.5$. For each moving walkway which has been selected, the direction is set to be the same as the largest predicted parallel flow of that MW. The magnitude of the moving walkway speed is set to the largest value. This operator is combined with the "Decrease speed" and "Increase speed" operators to induce variability in the solution.

Change direction A randomly selected fraction $\alpha = [0.2, 0.8]$ of the control configuration changes direction, but keeps the speed amplitude. For example, for $x^i = [2,2,1,0,-1,-2]$ and a fraction to change $\alpha = 0.5$, then $x^{i+1} = [-2,-2,1,0,1,-2]$.

Density comparison The direction of the moving walkway is set such that it moves pedestrians from high density to low density. This way it tends to reduce congestion in the more congested areas of the infrastructure. Each moving walkway is selected with a probability $\alpha = 0.5$.

Random speed Each MW is selected with a probability $\alpha = 0.5$. For each selected MW, set a randomly selected constant speed for all time intervals. After that, the "Decrease speed" and "Increase speed" operators are applied to induce variability in the solution.

Resample best solution This operator will add replications to the existing best solution to increase confidence in the computed indicators.

Both the "accelerate" and "increase speed" operators help the ALNS algorithm in the solution space exploration. The "accelerate" operator makes a MW move faster, hence positive speeds are more positive, while negative speeds are more negative. On the other hand, the "Increase speed" operator moves speeds closer to the positive upper bound. The "Accelerate" operator is useful for exploring the high speed solutions, while the "Increase speed" helps explore the intermediate speed solutions. When moving walkways must be selected, the selection probability is fixed to 50% ($\alpha = 0.5$). This choice is made to guarantee that the operator has a reasonable probability of changing the control configuration without entirely changing the configuration. With a low MW selection probability, the operator would often return the same control configuration, and for a high MW selection probability, the operator would return a completely different control configuration.

Multi-objective predictive algorithm

The single objective predictive control algorithm considers only travel time as an objective. Monitoring only travel time can lead to unbalanced dynamics inside the infrastructure. For example, one corridor intersection could present very high congestion, hence acting as a barrier preventing some pedestrians from moving, while giving the other users ample space to reach their destinations. To prevent such unfair, and possibly dangerous situations, we propose a second variant of the predictive control algorithm which uses a multi-objective optimization approach (Algorithm 5). We define two new objectives and keep travel time as well (eq. 5.10). The first is average pedestrian congestion inside a collection of regions Φ within the walkable environment. Congestion is incorporated by integrating over the prediction horizon T^+, for a given area $\phi \in \Phi$ and draw r, density which exceeds the congestion threshold:

$$\rho_{\phi,r}^{T^+} = \int^{T^+} \max(0, \rho(\phi, t)_r - \rho^c) dt. \tag{5.13}$$

The total congestion in all zones is the sum of the individual congestion in each zone:

$$\rho_{\Phi,r}^{T^+} = \sum_{\phi \in \Phi} \rho_{\phi,r}^{T^+}. \tag{5.14}$$

Finally, the average congestion in each zone for draw r is:

$$\overline{\rho_{\Phi,r}^{T^+}} = \frac{1}{|\Phi|} \rho_{\Phi,r}^{T^+} \tag{5.15}$$

We compute the mean across all draws to reduce the distribution to a scalar:

$$\overline{\rho_{\Phi}^{T^+}}(\mathbf{s}) = \frac{1}{|R|} \sum_{r \in R} \overline{\rho_{\Phi,r}^{T^+}} \tag{5.16}$$

Equation (5.16) is the second metric monitored. The third metric we include in the multi-objective optimization algorithm is a measure of congestion variability across zones. We wish to measure the gap between the average congestion and the largest congestion observed in the areas Φ. We achieve this by computing the difference between the average congestion and the largest congestion:

$$\overline{\rho_{\Delta}^{T^+}}(\mathbf{s}) = \frac{1}{|R|} \sum_{r} \max_{\phi \in \Phi} \rho_{\phi,r}^{T^+} - \overline{\rho_{\Phi,r}^{T^+}}. \tag{5.17}$$

As for the average congestion in each zone, we compute the mean value across the different simulation draws. For the sake of notational simplicity, the explicit dependence on the control configuration $\mathbf{s}$ has been omitted in places. Nevertheless, the three indicators naturally depend on the control configuration $\mathbf{s}$.

Including three different objectives in the optimization problem requires adaptations to the minimization algorithm. Instead of using a linear combination of these three indicators which require the definition of weights, we propose an adaption of the ALNS algorithm which exploits

the concept of a Pareto frontier. This approach not only circumvents the need for weights which are challenging to define, but also broadens the search since a collection of solutions are maintained. Instead of having one single solution available for generating the next candidate, the algorithm now has a collection of solutions to use for generating candidates. From this collection of solutions, one must be selected and implemented during the next interval Δt_u. We suggest the selection of the control configuration which produced to lowest travel time measure. This choice emphasises travel time over congestion. The problem which is solved for the multi-objective predictive control algorithm is the following:

$$\begin{aligned} \mathbf{s}_{opt} = \underset{\mathbf{s}}{\arg\min} \quad & \overline{\chi^{\tau^+}}(\mathbf{s}), \overline{\rho_{\Phi}^{T^+}}(\mathbf{s}), \overline{\rho_{\Delta}^{T^+}}(\mathbf{s}) \\ \text{s.t.} \quad & \mathbf{s} \in \mathcal{S} \end{aligned} \tag{5.18}$$

The operators used for this multi-objective ALNS are the same as those used for the single objective algorithm. Nevertheless, one new element is introduced: the neighbourhood size $\alpha \in [0, 1]$ is controlled by the algorithm, and not drawn randomly. The values of α are selected from a predefined list $\mathcal{P}$, sorted in increasing value. The neighbourhood size α is linked to the fate of the current solution. Each time a solution is added to the Pareto frontier, the value of α is set to the first value in $\mathcal{P}$. Then, for each iteration, α is set to the next value from $\mathcal{P}$, hence α will increase at each iteration until a new solution is inserted into the Pareto frontier. This procedure gradually increases the distance between the reference solution x^c and the generated solution x^{i+1}.

In this section, we have proposed three variations of the control algorithm. The fixed algorithm exploits only historical data, the reactive algorithm uses real-time data, while the predictive algorithm uses short-term predictions. The data used by the control algorithms is provided by a DPMS. The implementation detail and modelling assumptions made to build the simulation environment in which these algorithms are tested are presented in the beginning of the following section which presents the first case study.

Algorithm 5: Multi-objective ALNS

```
Input:
feasible solution: x
operator set: Θ
Initialization:
operator weights: g
iteration counter: i = 0
maximum number iterations: n
reference solution: x^c = x
pareto set: S = {}
dominated set: D = {}
Iterations:
while i < n do
    select operator o and neighbourhood size α
    update reference solution x^c
    generate new solution x^{i+1} = o(x^c, α)
    evaluate c(x^{i+1})
    if x^{i+1} ∈ S then
        solutions dominated by x^{i+1} : d
        S = S ∪ {x^{i+1}}
        S = S \ d
        D = D ∪ d
    else
        D = D ∪ {x^{i+1}}
    end
    update g
    i = i + 1
end
Output: pareto optimal set of solutions
```

5.4 Single corridor infrastructure

The three control algorithms we described in the previous section are tested inside a simulation environment. By doing so, we can assess whether moving walkways are promising devices for controlling pedestrian flows and whether the predictive control algorithms are better than the reactive algorithm. The first case study is a subset of a train station with one single corridor. The second setup is a more complex infrastructure with two corridors. After describing the infrastructure configuration of the first case study, we present the modelling decisions and DPMS implementation details.

The first case study we present is a subset of the train station in Lausanne, Switzerland. This is the same physical walkable space used in the previous chapter where flow separators were considered. A pedestrian tracking system was used in 2013 in the station to collect empirical data. This data set is used as the demand scenario for the simulations. We simulated the installation of moving walkways along the busiest pedestrian underpass of the station (Figure 5.4). The positions of the moving walkways were chosen such that the access ramps and stairs to the platforms were not blocked and such that the remaining corridors were as wide as possible.

The three control algorithms described in section 5.3 are tested and their impacts are analysed with regard to pedestrian travel time and density. Four different sets of simulations have been performed. The first is the reference scenario without any moving walkway installed. This setup is used as the reference scenario for measuring the impact of the different moving walkway configurations. The second scenario is the use of moving walkways with a fixed control algorithm built upon historical data. The third scenario uses the reactive control algorithm. The fourth and final scenario uses the single-objective predictive control algorithm. These four scenarios are referred to as, in order, “no-mw”, “fixed”, “reactive” and “predictive”. For all scenarios, 100 replications of the simulations are performed to build a distribution of the performance indicators. The time horizon is set to five minutes. A short time period (five minutes) was chosen such that the predictive control strategy can optimize the control configuration over the whole interval in one horizon.

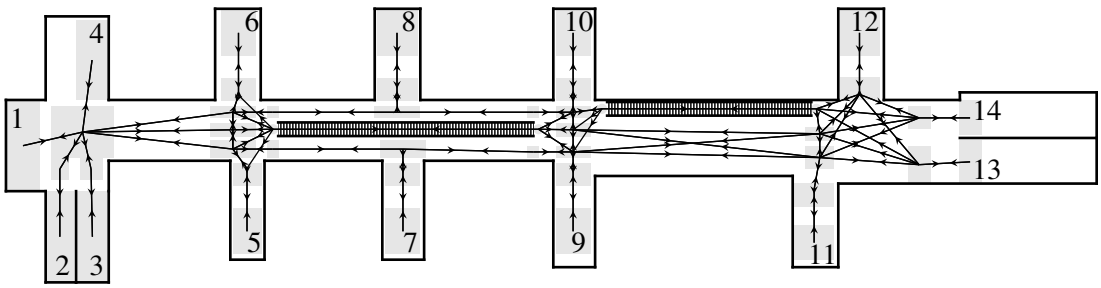


Figure 5.4: Single corridor infrastructure representation. MW-1 is on the left and MW-2 is on the right.

DPMS specification The components needed to implement a DPMS are detailed in Chapter 3, where definitions of spatial and temporal representations, supply, demand, fundamental quantities and data, control, state estimation and prediction and finally control configuration generation are provided. The first element we discuss is the spatial representation.

The ground truth representation (assessment model) uses a bi-level approach for modelling the spatial environment, similarly to the previous chapter. The walkable floor space is modelled as a continuous space in which pedestrians avoid obstacles and other pedestrians. This operational model is taken from the NOMAD package with the default parameters (Campanella, 2016). The tactical model relies on a graph which allows pedestrians to navigate the walkable space. We assume pedestrians have full knowledge of the congestion inside the infrastructure (Hoogendoorn and Bovy, 2004b). This is modelled by updating the travel time of each link every time a pedestrian leaves the link. The tactical route choice decisions are modelled using the shortest path. All elements composing the infrastructure L are static except for the collection of moving walkways $\mathcal{W}$.

We model pedestrians individually. The demand is modelled such that each pedestrian $n \in N$ has the following attributes: desired walking speed sampled from a normal distribution ($\mu = 1.34 m/s$, truncated at $3.0 m/s$), origin and destination zones and generation time. Pedestrians are generated at a disaggregate level according to empirical observations.

The computation of density used in this case study is based upon Voronoi tessellations. This method generates pedestrian-specific density values inside a defined area L'. Therefore, Voronoi tessellations generate a density distribution inside a given area. We compute the upper quartile (75% percentile) of this distribution to obtain a scalar value for density inside L' at time t:

$$\rho(L', t) = Q_3 \left[\rho_n(t) \quad \forall n \in N_{L'}(t) \right], \tag{5.19}$$

where Q_3 represents the upper quartile, ρ_n the density associated with individual n and $N_{L'}(t)$ the pedestrians inside L' at time t. The utilization of Voronoi tessellations decreases the dependency on the arbitrary area in which density is computed (Nikolić et al., 2016). Since the individual density values show high variability over time, we use the upper quartile, instead of the maximum, to reduce the density distribution to a scalar. This reduces sudden jumps in the density computation over time. The density threshold above which we consider congestion takes place is set to $\rho^c = 1.08 pax/m^2$. This threshold corresponds to the level-of-service E defined in Fruin (1971).

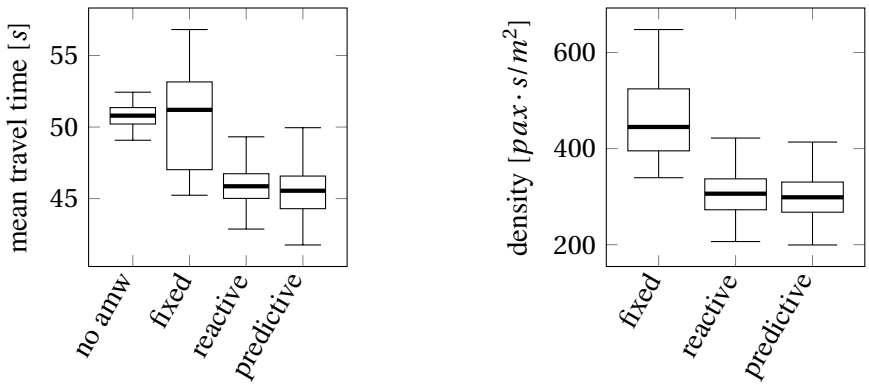
For the reactive control algorithm, the calibration of the controller gains is accomplished empirically according to the "trial-and-error" procedure described in Mulholland (2016). A sequence of steps to follow for estimating the regulator gains is provided. They rely on observing the process output after applying changes in the controller gains. The set point for the PI controller is set to $\rho^s = 1.08 pax/m^2$.

The predictive control algorithm uses the single-objective optimization algorithm. The short-term predictions are run with 150 iterations of the single-objective ALNS algorithm and 12 replications of each control configuration evaluation. The short-term predictions are performed using the

same simulator as the assessment model (ground truth simulator). This means the predictive algorithm has access to "perfect" information regarding the short-term future. The numerical results obtained with this setup are likely upper bounds on the improvements we can expect since the control algorithm has access to perfect information. Considering we design and test the moving walkways as a control strategy in a simulation environment, a model for state estimation is not needed. The simulator generates the required data.
Performing short-term predictions over the whole simulation period would not be feasible in practice. Nevertheless, this provides valuable insight regarding the capacity of the algorithm to improve the pedestrian dynamics. A rolling horizon scheme will likely not achieve the same performance, hence this solution can be considered an upper bound to the improvements we can expect from the predictive control algorithm. The utilization of the same simulator for the short-term predictions as for the assessment model is done for practical reasons. Firstly, it removes the need to implement a second pedestrian simulator. Secondly, there is no need for temporal synchronization and spatial aggregation/disaggregation between different models. Furthermore, we assume that the data collection process is perfect and complete. In practice, such assumptions cannot be made for multiple reasons. The assessment simulator replaces real-life dynamics, hence one single pedestrian simulator used for the short-term predictions is sufficient. Nevertheless, measurement devices are needed and generate data with errors and biases. Furthermore, collecting data covering the whole infrastructure can be costly, hence measurement devices cover only certain areas of the walkable space. With partial data coverage state estimation is needed, which induces uncertainty into the data. Therefore, even though the usage of perfect prediction information simplifies the problem at hand, investigating the different algorithms in such a simulation environment will produce valuable information regarding their effect on the pedestrian dynamics. The robustness of the control algorithms to measurement errors and the state estimation process is left for future research.
Next, we present the results from the different simulation scenarios and analyse the impact of the different control strategies on the pedestrian dynamics. We start by discussing aggregate indicators.

Aggregate indicators

We start by discussing the effect of the different control strategies on aggregate indicators. Figure 5.5 shows box plots for different aggregate indicators: mean travel time (eq. 5.11) and congestion, based on eq. (5.16). One small alteration has been made to eq (5.16). Instead of considering the mean congestion per zone, we consider the total congestion in all zones. The mean travel time box plots (Figure 5.5a) show the advantage of control algorithms which dynamically update the configuration based on the measured KPI. The mean travel time decreases by approximately 9% when such control strategies are used. Secondly, the "fixed" control strategy is poor at decreasing travel time compared to the "no-mw" scenario. The density box plots (Figure 5.5b) show that the congestion experienced by pedestrians in the corridor junctions is lower for dynamically



(a) Mean travel time.

(b) Integral of congestion.

Figure 5.5: Box plots of aggregate performance indicators for the different scenarios.

controlled moving walkways. We expected the "reactive" and "predictive" algorithms to improve travel time and density compared to the "fixed" algorithm since they adapt to the demand (unlike the "fixed" algorithm). Congestion is measured in each corridor intersection and at both extremities of each moving walkway since these control devices tend to attract pedestrians at their ends and create congestion. The difference between the "reactive" and "predictive" strategies is negligible in terms of both travel time and density. Since the moving walkways concentrate congestion in the intersections, comparing the congestion in the intersections between the "no-mw" algorithm and the control algorithms is not meaningful.

OD specific travel times

As shown previously, the dynamic control algorithms successfully improve travel time but no difference between the "reactive" and "predictive" flavours has been observed. Therefore, we discuss the impact of theses strategies at an origin/destination level. Figure 5.6 presents the change in relative travel time for all origin and destination pairs. The Welsch T-Test (unequal variance and unequal sample size) is used to test the null hypothesis that the mean travel times per origin/destination are equal. The test is performed between the reference scenario and a given control algorithm. The OD pairs are sorted based on the category of trip they represent (Figure 5.6d). The different categories are based on the usage of moving walkways and the length of the "walking legs". Group A represents passengers changing platform but don't have any MW along their path, for example walking from zone 5 to zone 7 (Figure 5.4). Group B includes trips where one MW can be used and no walking legs are required (zone 5 to 9 for example). Group C covers trips with one MW and a walking leg (zone 1 to 9). Category D covers all trips with two MW on their path. Finally, E covers the other OD trips (zone 11 to 14 for example).
Figure 5.6a shows, for each OD pair, the relative change in travel time between the reference scenario and the fixed control algorithm. Each dot is one OD pair. The type of dot depends on the confidence one can give to its value. Black circles mean that at least five pedestrians have

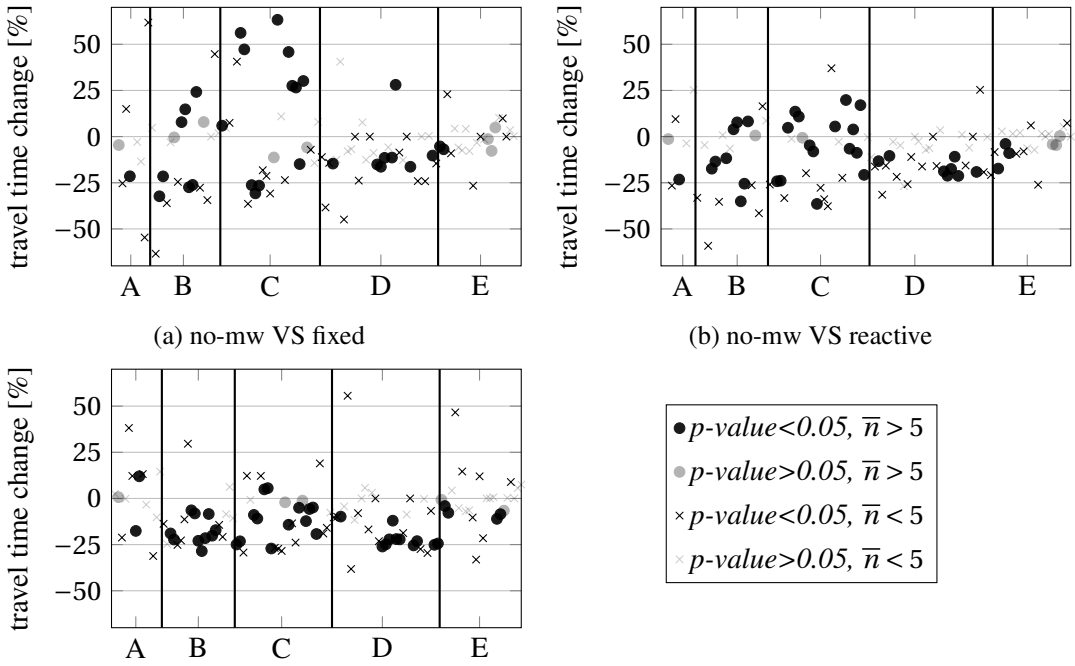
used it per replication and that the value is statistically significantly different from 0 (equal mean hypothesis). Grey circles indicate that at least five people have used the OD, but the T-Test does not reject the null hypothesis. Black crosses are OD pairs where less than five people have used this OD pair (on average), and the null hypothesis is rejected. Finally, grey crosses indicate that less than five people have used the OD pair and the null hypothesis cannot be rejected. Figures 5.6b and 5.6c show the results for the reactive and predictive control algorithms.

The "fixed" control algorithm decreases, but also increases travel times for many OD pairs. This is expected as the direction and speed of the walkways does not change based on the occurring pedestrian dynamics. Therefore, the walkways will not slow down if downstream congestion occurs, neither will they change direction if the majority of pedestrians are moving in the other direction. OD pairs which use one moving walkway sometimes benefit and are sometimes penalized by this control algorithm (groups B and C). Most of the OD pairs from groups B and C which are penalized by the walkways are those involving zones 7 and 8. The explanation is found by considering the position of the left moving walkway. Since it's installed in the middle of the corridor, two narrow corridors are created either side of it. This separation reduces the space available for the pedestrians walking to/from zones 7 and 8. This situation is therefore more prone to congestion under high demand. OD pairs which allow the usage of both moving walkways generally benefit from the installation of moving walkways on the other hand.

The analysis of Figure 5.6b reveals the advantage of dynamically controlled moving walkways: fewer OD pairs suffer from an increased travel time and the amplitude of these negatively affected ODs is small. The pedestrians who suffer from the moving walkways are found in the same group as those suffering from the "fixed" control algorithm. Furthermore, they are also those entering or exiting the simulation through zones 7 and 8. Finally, the overall changes in travel time are more compact compared to the "fixed" algorithm, hence the change in travel time is more consistent across OD pairs.

The predictive control algorithm further improves the overall travel times per OD. The number of OD pairs which suffer from this control algorithm are further reduced compared to the reactive algorithm (sub-figure 5.6c). The pedestrians which are negatively and (statistically) significantly impacted are those moving from zone 8 to zones 13 and 14. The explanation provided before regarding the width of the available corridor explains this increase. Pedestrians using two moving walkways (group D) clearly benefit from the strategy, like with the reactive algorithm. The second major difference between the predictive and reactive algorithms lies in the consistency across OD pairs. The reductions in travel times are slightly smaller than those with the reactive algorithm, but few OD pairs suffer from an increased travel time. Hence the predictive algorithm is a scenario which can be considered fairer between pedestrians.

Finally, we should mention that pedestrians who don't use any moving walkway (group E) are not significantly impacted by the algorithm choice. The majority of the change in travel times are not statistically significantly different from the reference scenario.



(a) no-mw VS fixed

(b) no-mw VS reactive

(c) no-mw VS predictive

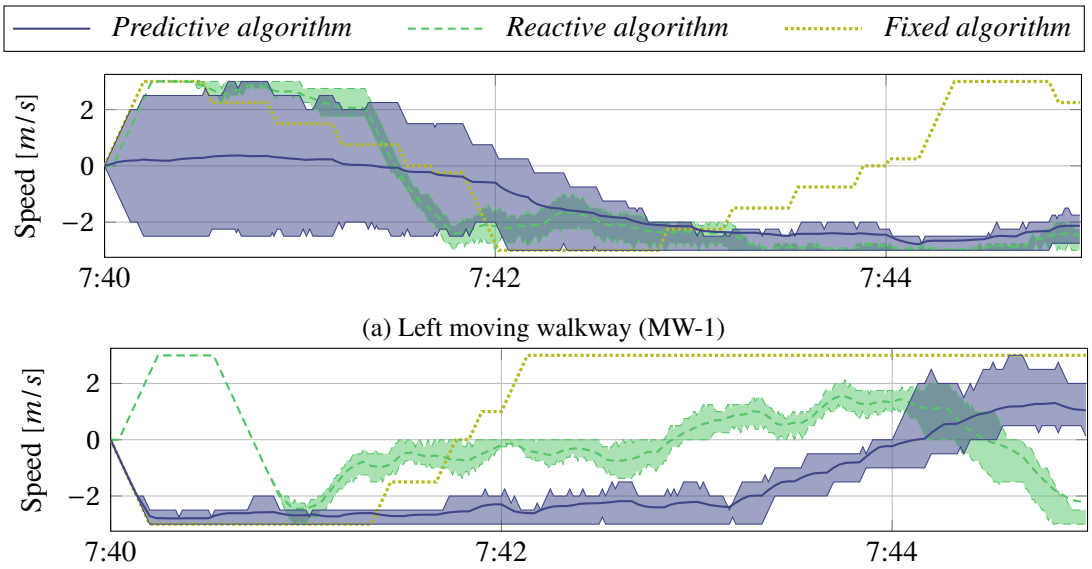
Label	Description	origin/destination IDs
A	Neighbouring platform without moving walkway	5-6 ↔ 7-8 & 7-8 ↔ 9-10
B	Single moving walkway without walking leg	5-6 ↔ 9-10 & 9-10 ↔ 11-14
C	Single moving walkway and walking leg	1-4 ↔ 9-10 & 7-8 ↔ 11-14
D	Two moving walkways	1-6 ↔ 11-14
E	Other	

(d) Origin-destination categorisation

Figure 5.6: Relative travel time comparison between the three moving walkway control algorithms and the reference scenario without moving walkways.

Average moving walkway speeds and pedestrian density

Understanding and explaining the different impacts of the reactive and predictive control algorithms requires in-depth analysis of the moving walkway speed profiles and density measurements. Figure 5.7 presents the average speed profile for the three control scenarios. The dotted line represents the speed profile for the "fixed" algorithm computed from historical data, hence it is the same for all replications. Two bands, one for the reactive algorithm and one for the predictive algorithm, represent the interquartile range of the MW speed based on the 100 replications of the simulation scenario. The band with solid lines concerns the predictive algorithm, while the band with the dashed line represents the MW speeds for the reactive scenario.



(a) Left moving walkway (MW-1)

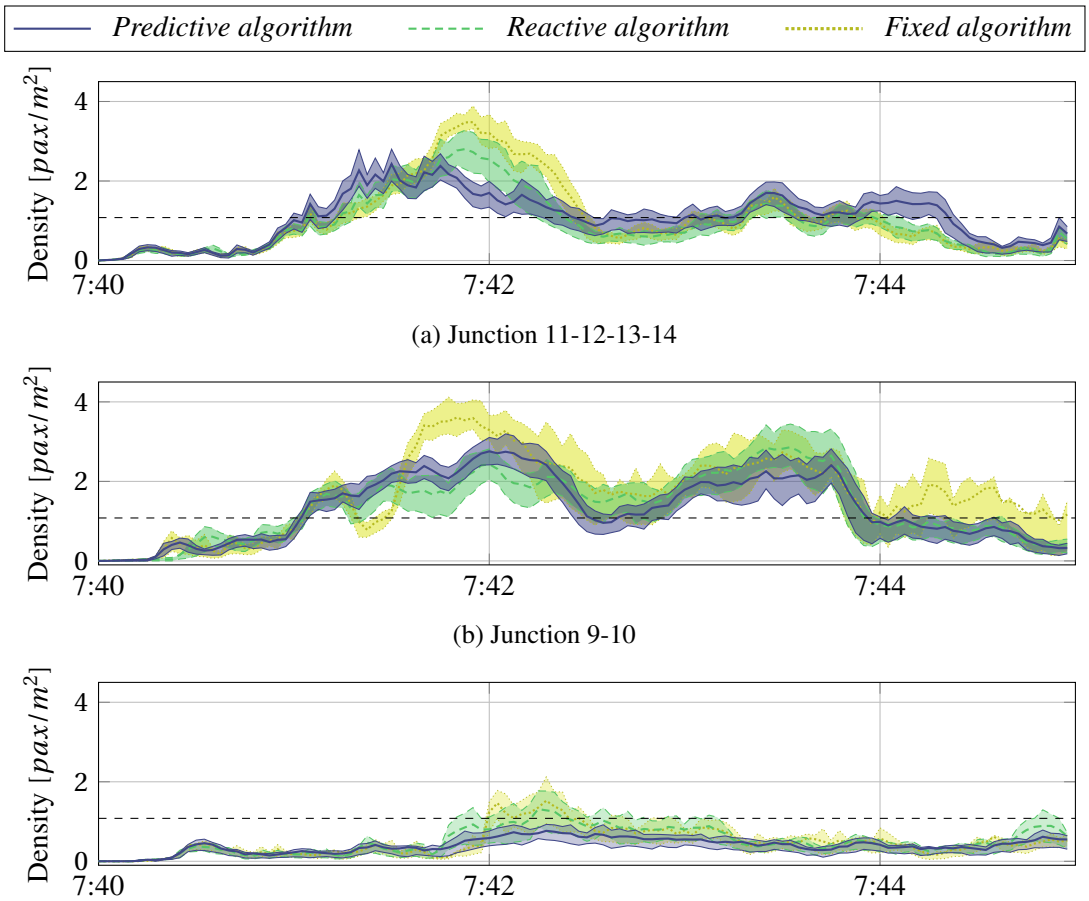
(b) Right moving walkway (MW-2)

Figure 5.7: Moving walkway average speed profile for the three different control algorithm scenarios.

The first observation we can make concerns the consistency of the "reactive" speed profile over the first 60 seconds of the simulation for MW-2 and over the first 100 seconds for MW-1. This is the case as the density measured inside the junctions is low for those time periods. When considering the density profiles from Figure 5.8, we see that little congestion occurs before 7:41 for all zones. Therefore, the "reactive" moving walkways are always at maximum speed until congestion builds up. This changes as soon as congestion appears in the junctions. The "reactive" MW-2 slows down from 7:41 since congestion builds up in "junction 9-10".

On the other hand, the large variance in moving walkway configuration for the "predictive" version of MW-1 should be explained. We see that for the first minute of the simulation period, no congestion occurs at either end of this moving walkway (5.8b and 5.8c). Secondly, we also see that the pedestrian flows parallel to MW-1 are both low (Figure 5.9). The combination of these two observations indicate that the predictive algorithm can choose either direction at high speeds as an optimal solution, which explains the large variance in speed profiles.

Later in the simulation, from 7:42, for both dynamic algorithms, MW-1 tends to operate close to the maximum speed moving pedestrians from junction 9-10 towards junction 5-6 (i.e. backwards, hence the negative speed). This direction is consistent with the pedestrian flows parallel to MW-1 shown in Figure 5.9. The flow moving in the negative direction of MW-1 is larger over all the time period of interest than the flow moving in the positive direction. Furthermore, the density in junction 9-10 is larger than that in junction 5-6 over all the time period, hence confirming that moving pedestrians away from junction 9-10 makes sense.



(a) Junction 11-12-13-14

(b) Junction 9-10

(c) Junction 5-6

Figure 5.8: Density evolution over time for all four junctions.

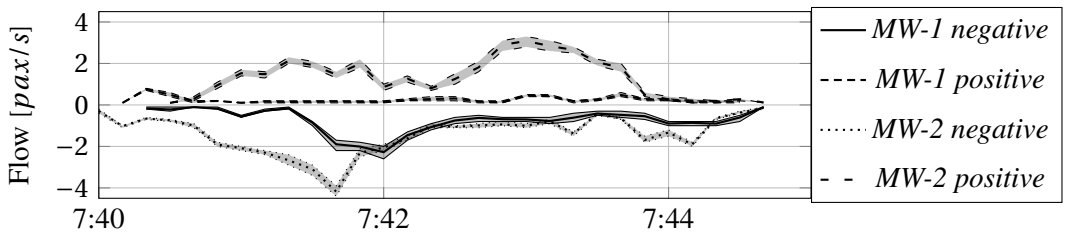


Figure 5.9: Pedestrian flow along the main corridors parallel to the moving walkways computed from the reference scenario “no-mw”. A negative flow corresponds to pedestrians walking in the same direction as a moving walkway with negative speed.

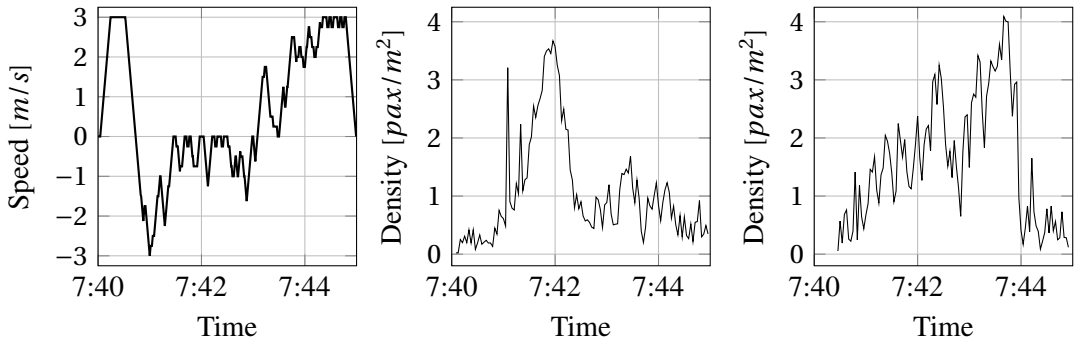
The direction of MW-2 over the first 150 seconds of the simulation can be explained using the flows from Figure 5.9 as well. The flow moving in the negative direction of MW-2 is larger than the flow moving in the positive direction. Nevertheless, the amplitude of the speed of the “reactive” MW-2 is significantly lower than that of the “predictive” MW-2. The density measured in junction 9-10 (sub-figure 5.8b) explains the decreased speed of the “reactive” MW-2. Since

the density is above the target value of $1.08 pax/m^2$, the reactive algorithm will reduce the speed of the moving walkway to prevent downstream congestion.
The pedestrian density during high demand (around 7:42) is different for both dynamic algorithms. The density in junction 9-10 is lower for the reactive algorithm compared to the predictive algorithm (5.8a). The opposite is observed in junction 11-12-13-14. There, the density is lower for the predictive algorithm (5.8b). The density levels are similar in both junctions for the predictive algorithm. This conclusion is similar to the previous conclusion about the travel times. The predictive control algorithm is fairer across users.
An unexpected peak in pedestrian density occurs, in junction 11-12-13-14, for the "predictive" algorithm around 7:44. The pedestrian density reaches a higher plateau with the predictive algorithm than it does for the other control algorithms. This small, congested period occurs at the same time that MW-2 changes direction (Figure 5.7b), at 7:44. During a change in direction, the moving walkway must close for a short period of time. Furthermore, we see a small peak in the demand curve corresponding to the negative direction of MW-2. The congestion is therefore induced by this peak in demand and the closed moving walkways. The fixed and reactive algorithms, on average, are open during this small peak hence congestion does not occur.

Detailed MW-2 analysis

Figure 5.10 shows the speed profile of the "reactive" MW-2 and the density measurements in both junctions at either end of the moving walkway for one draw of the simulations. This is a classical example showing the limitations of the reactive algorithm. From 7:41 to 7:43, the moving walkway is transporting pedestrians from junction 11-12-13-14 to junction 9-10 (negative speed). As soon as the density exceeds the congestion threshold ($1.08 pax/m^2$), the reactive controller reduces the speed of MW-2 to prevent excessive congestion. The oscillating effects of the MW-2 speed are visible in Figure 5.10a, and the corresponding oscillations can be observed in Figure 5.10c. Meanwhile, the density inside junction 11-12-13-14 is increasing which implies that MW-2 should accelerate to empty this junction. Therefore, a trade-off between the density levels in both junctions should be made. The predictive strategy is capable of addressing this trade-off since it monitors pedestrian travel time in the whole infrastructure and is capable of anticipating pedestrian demand. Improving the calibration process of the PI controller can also reduce the oscillating behaviour.

Through this first case study we have shown that the dynamic strategies are significantly better than a fixed precomputed control configuration. Nevertheless, the "predictive" algorithm presents only little benefit over the "reactive" algorithm. Therefore, the added value of the short-term predictions is not obvious at this point. The next section presents a second, more complex case study.



(a) Speed profile for MW-2 (b) Density in jun. 11-12-13-14. (c) Density in jun. 9-10.

Figure 5.10: Speed profile and density measurements for a single realisation of the reactive control algorithm.

5.5 Double corridor infrastructure

The previous case study highlighted the advantage of dynamic control strategies, but the short-term predictions did not provide a substantial benefit. To understand whether a predictive control algorithm for controlling moving walkways can positively impact pedestrian dynamics in a larger environment, we have analysed a more complex infrastructure. The walkable space is a simplification of the whole station of Lausanne, Switzerland. We have two corridors linking three platforms. A representation of the infrastructure is found in Figure 5.11. We simulate pedestrian movements along the platforms since individuals can walk along the platforms and choose which corridor to use. Four moving walkways are used in this infrastructure, two in each corridor. Route choice now becomes significant as pedestrians can change corridors to reach their destination. The time period of interest is 15 minutes long.

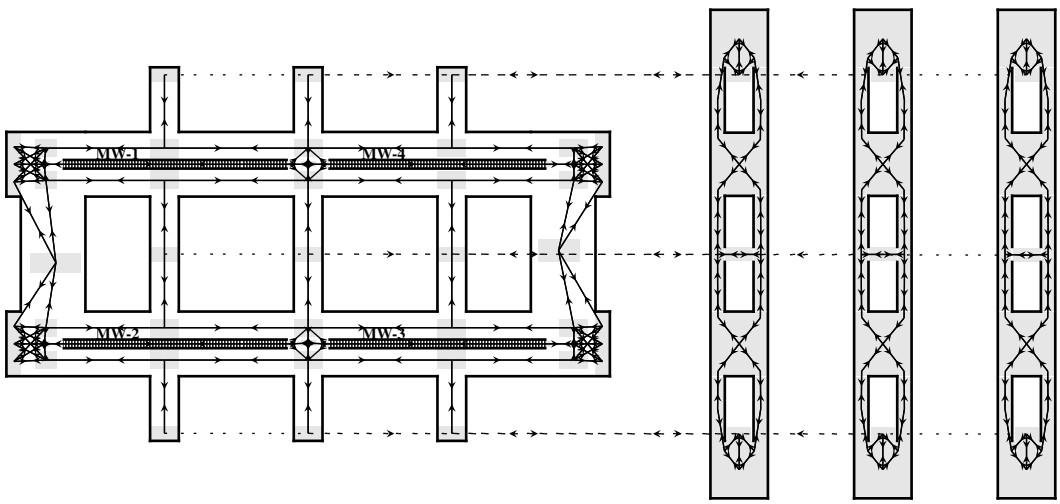
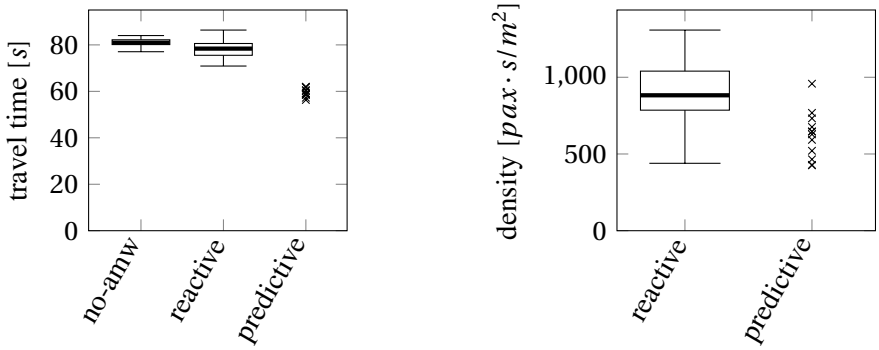


Figure 5.11: Three platforms infrastructure representation. The moving walkways are numbered counter clockwise: MW-1 top left, MW-2 bottom left, MW-3 bottom right, MW-4 top right.

We use the same simulation environment as described at the beginning of the previous section, except for the tactical route choice model. Route choice is modelled using the path-size logit model (Prato, 2009; Ben-Akiva and Bierlaire, 2003). The parameters are taken from Y. Liu et al., 2020. The route is updated each time a pedestrian reaches a vertex in the graph. Given the poor benefits of the "fixed" control algorithm for the previous case study, we do not use this algorithm in this case study. We keep both dynamic control algorithms. The "reactive" algorithm is the same as previously presented. The "predictive" algorithm is applied in a true rolling horizon approach this time since we work on a longer time period. Furthermore, we use the multi-objective predictive control algorithm. The reference scenario and reactive control algorithm assessment simulations were replicated at least 100 times. The predictive simulation assessment was replicated twelve times due to computational time. The short-term prediction horizon is 3 minutes long and is updated every 1.5 minutes. 150 iterations of the multi-objective ALNS were performed at each prediction update, with 32 replications of the objective function at each iteration. We recall that the multi-objective control algorithm returns the Pareto optimal set of solutions, hence one particular solution must be selected from this set. The control configuration which is applied for the horizon is the one with the lowest travel time.
By monitoring congestion alongside travel time, we gain further insight into the trade-off taking place between the different metrics. The previous case study showed that the reactive and predictive algorithms had similar effects on pedestrian dynamics. Therefore, by explicitly including congestion into the optimization algorithm, and not only analysing it a posteriori, we emphasize how the different algorithms impact pedestrian flows. Another reason for explicitly monitoring the spread in congestion in the different intersections (eq. 5.17) is to prevent a significant unbalance in congestion throughout the walkable environment.

Aggregate indicators

The aggregate travel time and congestion data plotted in Figure 5.12 tells a different story than the previous case study. Here, the predictive control algorithm is significantly better than the reactive algorithm. The mean travel time is reduced by approximately 25%. The congestion experienced by pedestrians at the extremities of the moving walkways is also lower for the predictive control algorithm. The reactive algorithm only improves the travel time by 5%. In the following paragraphs we will discuss the results in more detail to understand why the predictive and reactive algorithms induce different results for this case study.



(a) Mean travel time.

(b) Integral of congestion.

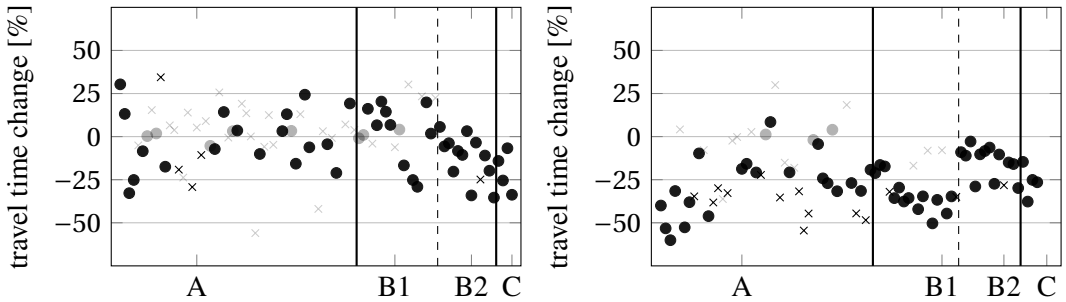
Figure 5.12: Box plots of aggregate performance indicators for the different scenarios.

OD specific travel times

The OD specific travel times are presented in Figure 5.13. Similarly, to Figure 5.6, we present the OD specific relative change in travel time. The categorisation is different though. Three main groups are used based upon the number of MW along the route between the origin and destination. The second group (one MW) is split into two subgroups: towards platforms (B1) and leaving platforms (B2).

The reactive algorithm decreases but also increases travel time for many OD pairs. The group of ODs which do not use any moving walkway show a large dispersion in relative travel time change. No clear pattern stands out concerning the direction of pedestrian flow for these OD pairs. The travel times of pedestrians who could use one moving walkway can be split into two groups: those moving from platforms towards the main corridors, and those moving from the corridors towards the platforms. On one hand, when pedestrians move to platforms (group B1), they are generally penalized by the reactive control algorithm. Three ODs pairs do not follow this rule (the three black circles below zero in group B1). On the other hand, when pedestrians move from the platforms into the corridors (group B2) they all benefit from the reactive algorithm. The groups of pedestrians which have two moving walkways along their path all benefit from the reactive algorithm.

The predictive algorithm boasts more consistent results in terms of travel times. Except for one OD pair, all statistically significant differences are improvements. Furthermore, all OD pairs with moving walkways along their paths benefit from the control algorithm. Another difference is visible when comparing the amplitude of the improvements between both graphs: the predictive algorithm shows larger improvements than the reactive algorithm. This observation is the opposite compared to the previous case study (Figure 5.6). Finally, the pedestrians which can use one moving walkway and are walking towards the platforms are those who benefit the most in terms of travel time. This is the opposite to the reactive algorithm. In general, the predictive algorithm is fairer across ODs than the reactive algorithm since nearly all ODs pair benefit from the control strategy.



(a) no-AMW VS reactive

(b) no-AMW VS predictive

Label	Description
A	no MWs along path
B1	one MW along path, to platforms
B2	one MW along path, from platforms
C	two MW along path

- ● *p-value<0.05*, $\overline{n} > 5$
- ● *p-value>0.05*, $\overline{n} > 5$
- × *p-value<0.05*, $\overline{n} < 5$
- × *p-value>0.05*, $\overline{n} < 5$

Figure 5.13: Relative travel time change for the reactive and predictive algorithms compared to the reference scenario without moving walkways.

Pedestrian walking speed and demand

The mean pedestrian walking speed computed over time is presented in Figure 5.14. The pedestrians have been grouped into intervals based on their entry time into the system. Both dynamic control algorithms improve the pedestrian walking speed compared to the reference scenario. Nevertheless, no clear advantage of one dynamic algorithm over the other is apparent. The pedestrian inflow into the system is presented in Figure 5.15. By comparing the mean speed with the pedestrian inflow, we see that speed decreases as demand increases. This is clearly visible between 7:41 and 7:42 where many pedestrians enter the system. During this high demand period the walking speed decreases due to congestion inside the infrastructure.

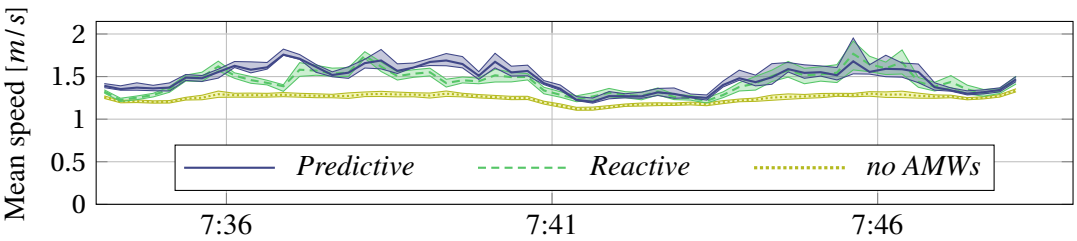


Figure 5.14: Pedestrian walking speed over time.

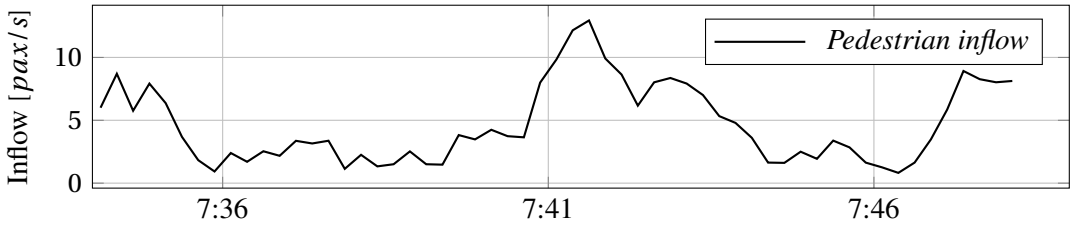
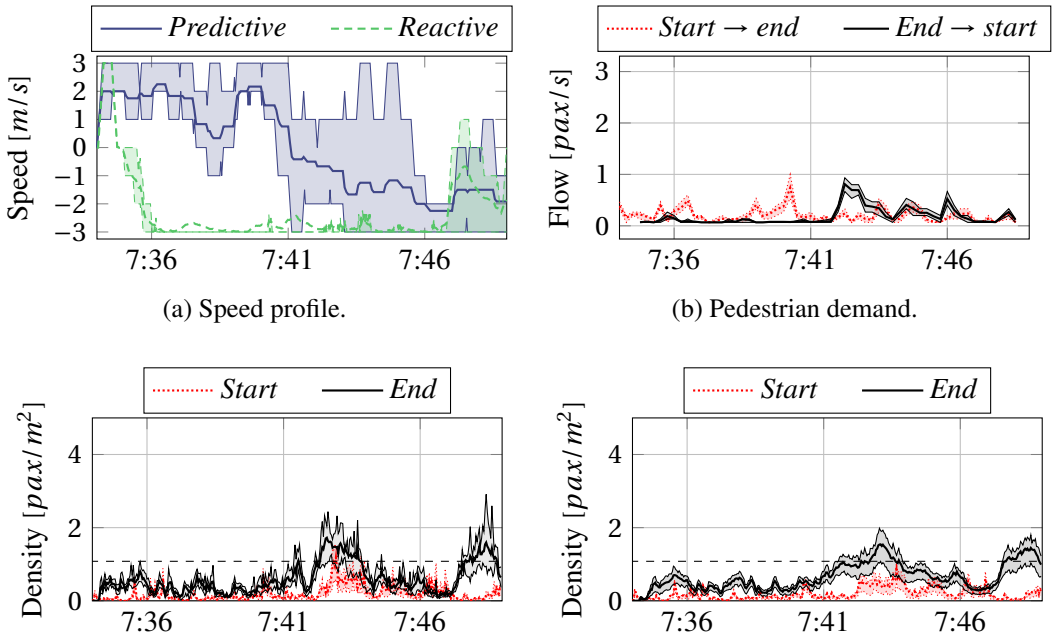


Figure 5.15: Pedestrian inflow into the infrastructure over time.

Moving walkway speed and pedestrian dynamics

The moving walkway speed profiles, pedestrian density at both extremities and parallel flows for all four moving walkways are presented in Figures 5.16, 5.17, 5.18 and 5.19. In the following paragraphs, we discuss how the reactive and predictive control algorithms influence the pedestrian densities.

MW-1 and MW-2 The reactive algorithm behaves similarly for MW-1 and MW-2. During most of the simulation period they operate at maximum speed, moving pedestrians from their "end" to their "start", hence the negative speed (Figures 5.16a and 5.17a). Few pedestrians are using this sub-route (Figures 5.16b and 5.17b) and the density is higher at their "end" areas. Therefore, the reactive algorithm is moving pedestrians from the high density area to the low density area.
With the predictive algorithm, the speed profiles are different for MW-1 and MW-2. MW-1 shows positive speeds for the first half of the time period (until 7:41), then a shift towards negative speeds happens. Nevertheless, a large variance in speeds is visible (Figure 5.16a). Similarly, to the reactive algorithm, congestion vary rarely takes place (Figure 5.16c). The consistent positive speeds are a consequence of the absence of congestion and the slightly larger pedestrian flow moving in the positive direction. Since the predictive strategy minimizes travel time, the larger pedestrian flow contributes more to the mean travel time decrease than the smaller flow. Concerning the predictive MW-2, a large variation is observed in the speed profile except around 7:41 and for the last 2 minutes of the simulation (Figure 5.17a). MW-2 moves people in the negative direction just after 7:41 to limit the congestion taking place at 7:43 (Figure 5.17c). Compared to the reactive algorithm, the predictive algorithm reduces more the amount of congestion taking place at 7:42. During the last few minutes of the simulation, MW-2 systematically moves pedestrians from the "end" to the "start" to decrease density. Although the reactive MW-2 is moving in the same direction, the density peak at 7:47 is larger for the reactive algorithm, hence the explanation for this density peak must be found elsewhere.



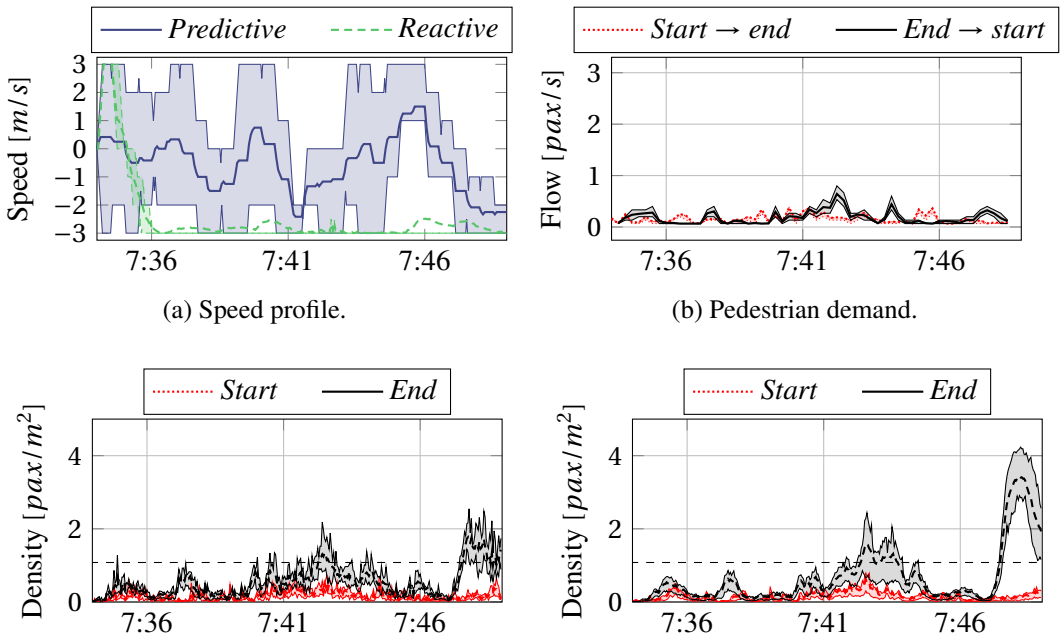
(a) Speed profile.

(b) Pedestrian demand.

(c) Predictive algorithm.

(d) Reactive algorithm.

Figure 5.16: Speed, density and flow data for MW-1.



(a) Speed profile.

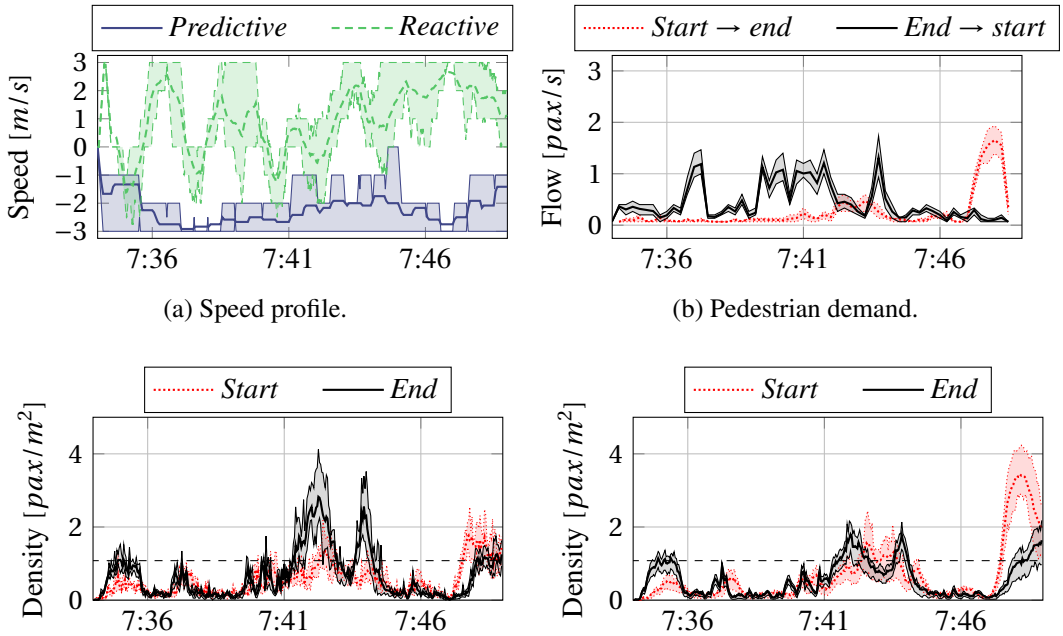
(b) Pedestrian demand.

(c) Predictive algorithm.

(d) Reactive algorithm.

Figure 5.17: Speed, density and flow data for MW-2.

MW-3 The speed profile for MW-3 differs significantly for the reactive and predictive algorithms. We first discuss the speed profiles in light of the density at the "end" zone of MW-2, which is also the "start" zone of MW-3. In this area, we previously saw that the pedestrian density is significantly higher for the reactive control algorithm near 7:47. In Figure 5.18a, near 7:47, we see that the reactive and predictive algorithms have different behaviours. The reactive algorithm produces positive speeds, while the predictive algorithm produces negative speeds. The reactive algorithm behaves "as expected" since it moves people away from the high density occurring in it's "start" zone. The predictive algorithm, on the other hand, is moving pedestrians towards the "start" area where higher density occurs, but at reduced speed. The predictive algorithm is making the pedestrians leave the "start" area on foot, hence preventing the large queue forming at the beginning of MW-2. By forcing the pedestrians moving in the positive direction to walk, the predictive algorithm spreads the demand in space, hence exploiting the full walkable space. This prevents congestion building up (the formation of a queue) at the "start" of the moving walkway, which is what happens for the reactive algorithm. With the predictive algorithm, the pedestrians moving in the opposite direction can use the moving walkway. This counter intuitive result shows the added value of an optimization-based predictive algorithm.



(a) Speed profile.

(b) Pedestrian demand.

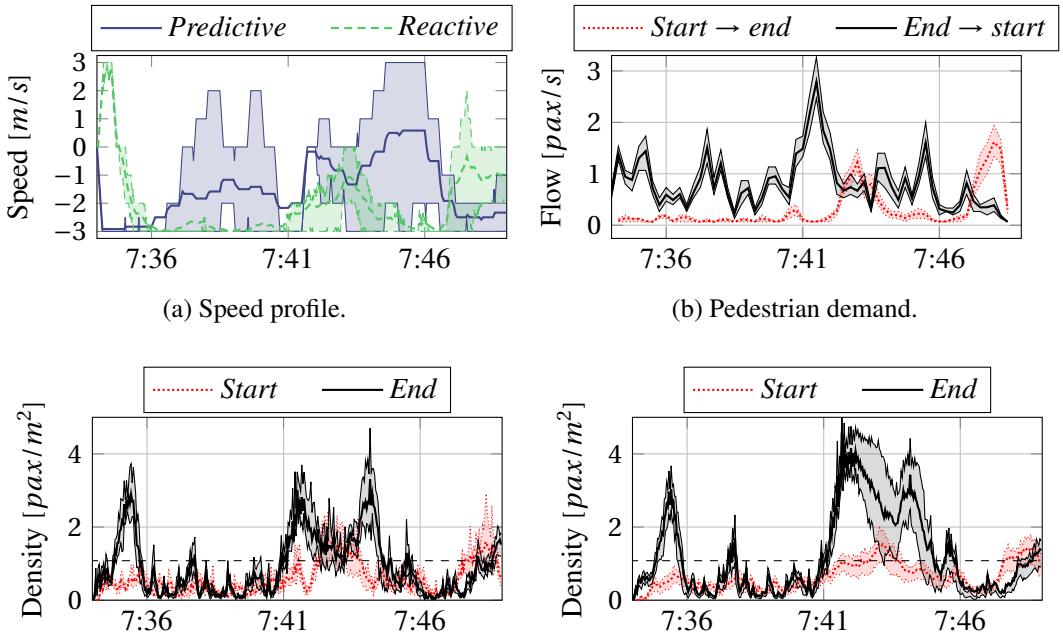
(c) Predictive algorithm.

(d) Reactive algorithm.

Figure 5.18: Speed, density and flow data for MW-3.

MW-4 The fourth and last moving walkway emphasizes the "slower is faster" effect. During the peak in demand around 7:42 (Figure 5.19b), the reactive algorithm consistently reduced the speed of MW-4 to prevent congestion building up in the "start" area (Figure 5.19a). Strong

congestion takes place at the "end" (Figure 5.19d) and the moving walkway is moving the pedestrians away from this area (negative speed). Nevertheless, congestion also starts to build up at the "start" area of MW-4, hence the speed reduces to prevent congestion. Therefore, although severe congestion occurs at the "end", the MW cannot operate at high speed since there is also congestion downstream. The predictive algorithm behaves in a similar way. MW-4 operates at high negative speeds to move the pedestrians away from the congestion during the first few minutes of the time period (Figure 5.19a). This is confirmed by the negative pedestrian flow in Figure 5.19b. Then, at 7:41, the predictive algorithm consistently closes the moving walkway. By doing so, pedestrians must walk along both sides of the moving walkway and don't aggregate near the entrance of the moving walkway. This reduces the congestion occurring at the "end" zone. By reducing the moving speed of pedestrians, the predictive algorithm is able to spread the congestion in time and space.



(a) Speed profile.

(b) Pedestrian demand.

(c) Predictive algorithm.

(d) Reactive algorithm.

Figure 5.19: Speed, density and flow data for MW-4.

Through the analysis of the behaviour of the reactive and predictive control algorithms in this second case study, we showed in which situations the predictive algorithm can reduce pedestrian congestion inside the infrastructure. We have seen that the predictive algorithm can generate solutions which are significantly different from the ones generated by the reactive algorithm. The predictive algorithm makes large pedestrian flows walk to prevent excessive congestion in the junctions. By doing so, the predictive algorithm balances travel time and congestion.

Pareto frontier analysis

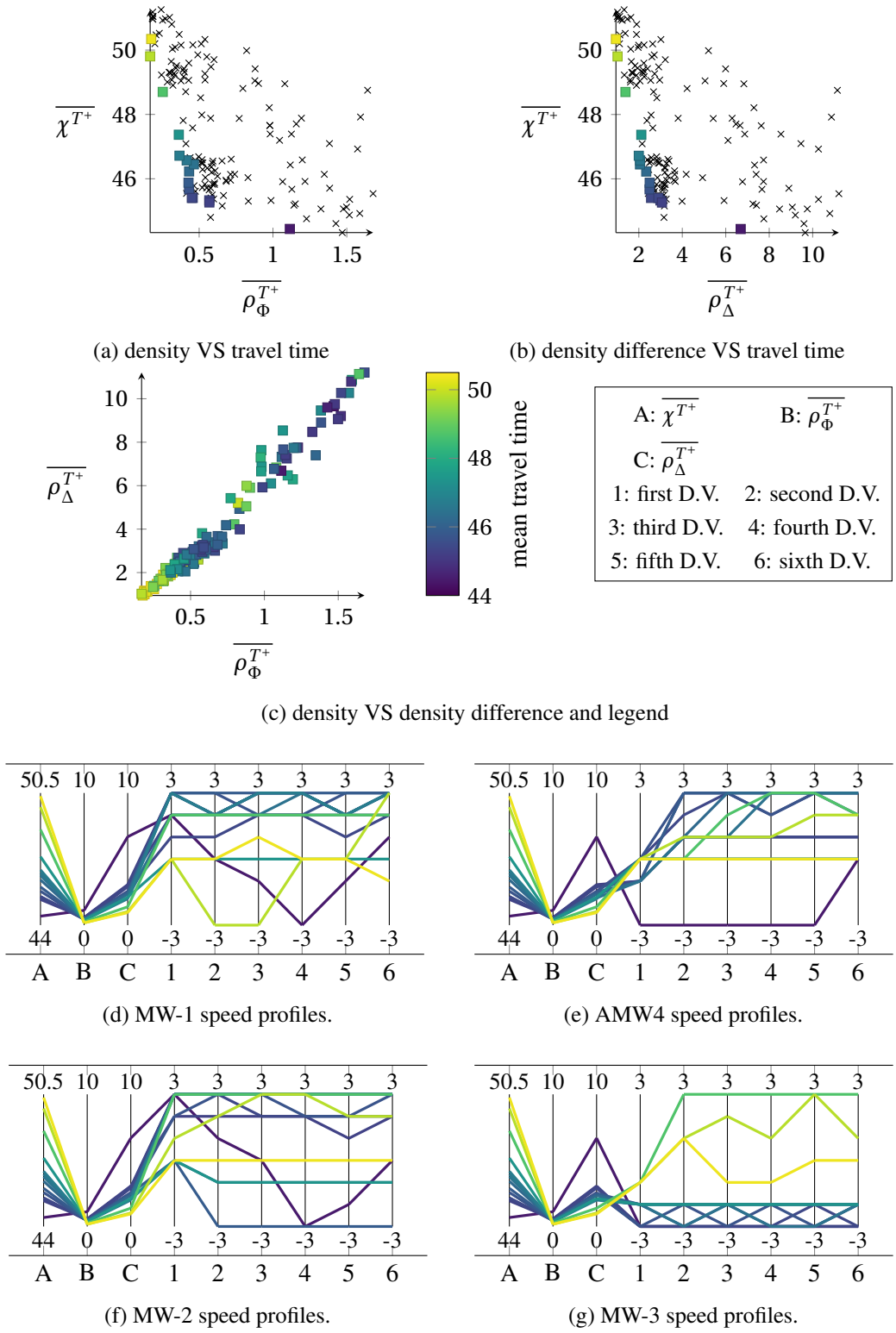
The predictive algorithm relies on solving the optimization problem where the moving walkway speeds are the decision variables, and the objective function is a collection of indicators which summarize the pedestrian dynamics. The following paragraphs discuss the results from the multi-objective ALNS algorithm presented in section 5.2 for two cases: low and high pedestrian demand. We recall the three objectives which are used: mean travel time $\overline{\chi^{T^+}}$ (eq. 5.11), mean congestion $\overline{\rho_{\Phi}^{T^+}}$ (eq 5.16) and congestion variability $\overline{\rho_{\Delta}^{T^+}}$ (eq. 5.17). Furthermore, we recall that during one optimization horizon, the moving walkway speeds are split into intervals of 30 seconds.

Low demand Figure 5.20 contains the Pareto front for the three variables and the visualization of the control configurations for each point on the Pareto front for a prediction horizon with low density (7:37 - 7:40). The decision variables are therefore the MW speeds for the following time intervals: [7:37:00, 7:37:30], [7:37:30, 7:38:00], [7:38:00, 7:38:30], [7:38:30, 7:39:00], [7:39:00, 7:39:30], [7:39:30, 7:40:00]. The control configurations are visualised using parallel coordinate graphs. Each vertical axis is one quantity. In the present case, the first three columns, labelled A, B, and C, are the three objectives used by the optimization algorithm. The other six columns, labelled one to six, are the decision variables (MW speeds) over the prediction horizon. Each line represents one solution from the Pareto set. By using this visualisation, we can link the MW speed profile (i.e. solution) with the corresponding objective functions. The line colours are function of the mean travel time objective function $\overline{\chi^{T^+}}$.

The first conclusion we can make concerns the strong correlation between two indicators: $\overline{\rho_{\Phi}^{T^+}}$ and $\overline{\rho_{\Delta}^{T^+}}$ (Figure 5.20c). This is also visible in the Pareto front comparing travel time to both measures of density (Figures 5.20a and 5.20b) where the Pareto fronts are nearly identical. Therefore, one of the density indicators is redundant for low density scenarios.

The control configurations for each point on the Pareto front provide us with insight into the trade-off between travel time and density which must be made. This is most visible in Figure 5.20g (MW-3) where the three solutions with the highest mean travel time stand out from the other solutions. On one hand, these solutions present the lowest congestion, but on the other, they present the highest travel time. The control configurations for these three solutions are different from the rest of the solutions. Most of the solutions have speeds between $-2m/s$ and $-3m/s$ during the whole optimization procedure, whereas for these three solutions which stand out their speeds are either positive or changing direction during the horizon.

The differences in objective function values can be explained when considering the pedestrian demand in the corridor where MW-3 is installed. The pedestrian flow in the negative direction along the corridor where MW-3 is installed is significantly larger the demand in the positive direction (Figure 5.18b). Therefore, two situations appear. In the first case, most of the solutions are moving the larger group of pedestrians with a higher speed thanks to the moving walkway, hence the lower travel time but creating some congestion in the process. For the second case, the three



(a) density VS travel time

(b) density difference VS travel time

(c) density VS density difference and legend

(d) MW-1 speed profiles.

(e) AMW4 speed profiles.

(f) MW-2 speed profiles.

(g) MW-3 speed profiles.

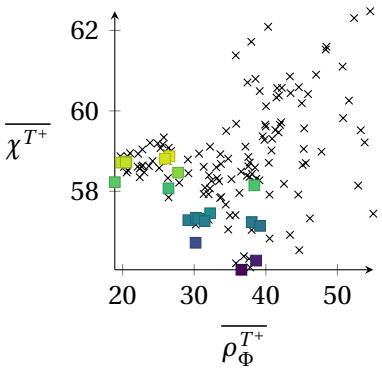
Figure 5.20: Pareto frontier and AMW speed profiles for a low demand period (7:37 - 7:40).

solutions with lower density but higher travel time are moving the smaller group of pedestrians, hence having less impact on travel time, but also preventing congestion from appearing.
One other solution stands out in these other graphs as well: the solution with the lowest travel time. This solution is particularly visible in 5.20e. A similar analysis can be made as with the three high travel time solutions. The pedestrian demand parallel to MW-4 is larger in the negative direction than the positive one. This particular solution is favouring travel time over density since this solution also boasts the highest density values.
These two examples of different categories of solutions, hence of control configurations, emphasize the added value of considering a multi-objective approach when searching optimal control configurations. Since the set of Pareto-optimal solutions contains the trade-off, the control strategy has the potential to give priority to different aspects of the pedestrian dynamics.

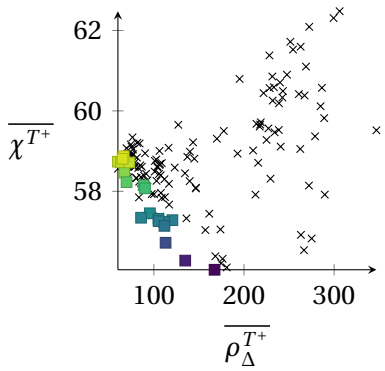
High demand The results for the high demand prediction are presented in Figure 5.21. The correlation we observed between both density indicators is not as clear in this context. On one hand, when one density indicator is low, so is the second one. On the other hand, when the mean density increases, the variance in $\overline{\rho_{\Delta}^{T^+}}$ (5.17) becomes large. Therefore, if the objective is to minimize density, then one density indicator is sufficient. But when a trade-off is explored between density and travel time, both density metrics are needed to distinguish the solutions. The lowest values of travel time are found with intermediate values of congestion (dark points in Figure 5.21c), again emphasizing the need to carefully study the trade-off between congestion and travel time.
For MW-3 (5.21g), we see that two solutions are identical (the two dark lines). The speed is $-3m/s$ for the whole interval for these solutions. This gives us insight into the variance of the system. They are very close in terms of travel time and average density, but the $\overline{\rho_{\Delta}^{T^+}}$ indicator differs for both solutions.
The solutions on the Pareto front can be grouped into three categories based upon the three indicators: high travel time and low density (light lines), low travel time and high density (dark lines), intermediate travel time and density (intermediate lines). These three groups can be found in the control configurations of MW-1 (5.21d) and MW-3 (5.21g). For MW-2 and MW-4 these groups are not visible (5.21f and 5.21e).
We can distinguish the three groups when considering the speeds in MW-3 (5.21g). The group with high travel time (light lines) contains speeds which peak to $+3m/s$ for the third decision variable while the other decision variables are close to $0m/s$ or $-1m/s$. The group with intermediate travel time and density values are solutions where the speed is generally between $0m/s$ and $-1m/s$. The two solutions with low travel time and high density have speeds fixed to $-3m/s$.
Similarly, when considering the speed profiles for MW-1 (5.21d), we can also distinguish the three groups of solutions. These three groups of control configurations show that different speed profiles will give priority to different objectives (travel time or density). When looking at the control configurations for MW-2 and MW-4, the speed profiles do not allow us to differentiate the three groups of solutions. They operate between $+1m/s$ and $-1m/s$ in general. We can therefore

conclude that the Pareto front is governed by MW-1 and MW-3 since for the other two walkways the indicators are not directly affected by the different control configurations.
Finally, we discuss the variance of the indicators with respect to the variance of the solutions. Since several MW are used, and for each of them 6 decision variables are defined, distinguishing between stochastic noise and the influence of the decision variables on the objectives is challenging. For example, in Figure 5.21e, the control configurations are generally consistent with each other (between $-1m/s$ and $+1m/s$) although the objective functions vary. Another example can be found in Figure 5.20g. For most of the solutions in the Pareto front, the speeds are between $-2m/s$ and $-3m/s$ and the travel time indicator varies between $44s$ and $47s$ for these solutions. These two examples highlight the fact that not all MW have a significant impact on the objective functions. Furthermore, in light of Figure 5.20g, using a coarser discretisation of the MW speeds will likely generate similar results while simplifying the optimization problem since the solution space would be smaller. Longer intervals would also simplify the optimization procedure and make the results more robust to the simulator's noise.

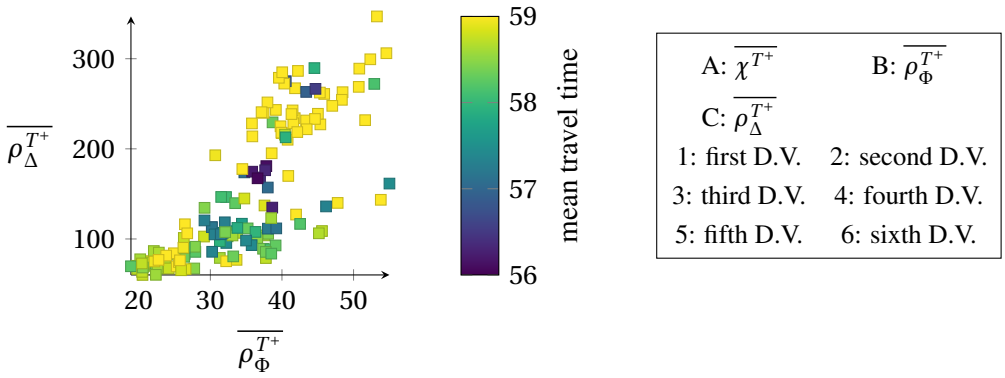
By analysing the solutions on the Pareto front for two different demand contexts, we have emphasized the added value of a multi-objective optimization framework for predictive control configuration generation. Even when demand is low, different control configurations have different impacts on the travel time of the pedestrians. This effect is amplified for high demand cases. Different control configurations will lead to different dynamics where travel time or congestion are low. Furthermore, not all control devices have the same impact on the system. Some moving walkways significantly impact the indicators while others only have minimal impact.



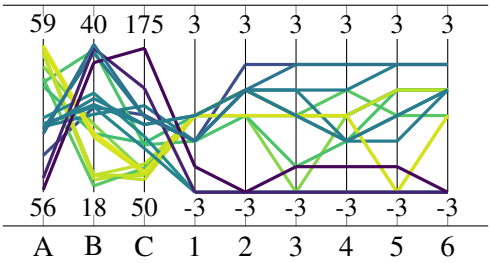
(a) density VS travel time



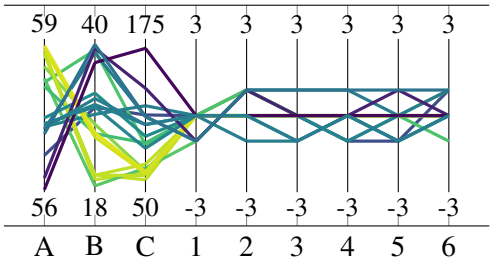
(b) density difference VS travel time



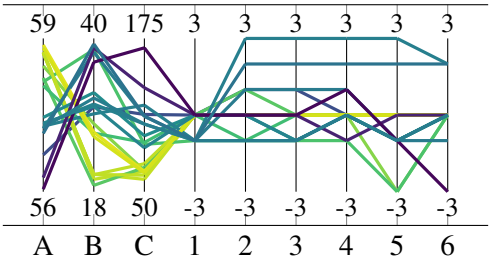
(c) density VS density difference and legend



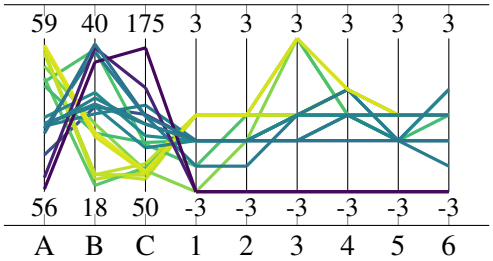
(d) MW-1 speed profiles.



(e) AMW4 speed profiles.



(f) MW-2 speed profiles.



(g) MW-3 speed profiles.

Figure 5.21: Pareto frontier and AMW speed profiles for a high demand period (7:41:30 - 7:44:30).

5.6 Conclusion

With this chapter, we addressed the question of dynamic control strategies for pedestrians. We proposed several variations of a control strategy which exploits existing pedestrian dedicated devices. The usage of moving walkways as a control strategy is interesting since pedestrians have the habit of using them, hence no technological barrier must be overcome. Furthermore, moving walkways address the problem of compliance since pedestrians cannot feasibly use them in the wrong direction.

The first hypothesis regarding the effectiveness of moving walkways to manage pedestrian flows has clearly been shown through both case studies. Although the fixed control algorithm produced poor results, the dynamic strategies effectively reduced pedestrian travel time and decreased congestion. Next, we have shown that a predictive algorithm can significantly improve pedestrian dynamics in more complex scenarios. Furthermore, the predictive algorithm is generally fairer across different categories of pedestrians than the reactive algorithm. Finally, the advantages of considering multiple objectives in the optimization algorithm used by the predictive algorithm are emphasized when analysing the Pareto set of solutions. The trade-off between travel time and congestion stands out and provides insight to the operator when decisions must be made.

The different responses to the dynamic control strategies of each case study emphasize the need for in depth analysis of the demand scenario and infrastructure configuration. Considering the challenge of integrating short-term predictions into control strategies, effort should be invested in reactive strategies to develop more advanced control algorithms which could possibly reach similar benefits as the predictive algorithms. Identification of the scenarios and contexts where reactive and predictive algorithms produce similar results should be done to better understand when short-term predictions are needed.

Before practical implementations can be considered, a sensitivity analysis to the prediction parameters must be accomplished. By doing so, the trade-off between the computational cost and the algorithm's efficiency can be explored. The usage of a disaggregate pedestrian simulator for the short-term predictions induces prohibitive computational times, therefore practical implementations should probably consider mesoscopic or macroscopic simulators for large case studies.

Consolidation of these results with applications to different environments would provide further insights into the conditions where predictive algorithms are better than reactive ones. Exploring different demand structures and different walkable environments can help achieve this objective.

Although moving walkways improve the dynamics for most of the users, infrastructure or demand specific issues like local bottlenecks might not be prevented. The development of control strategies which are robust to measurement errors and biases is critical for real world applications. This should first be addressed in a simulation environment by using a different simulator for the ground truth and prediction simulators. In such a context, measurement errors, detector defects or biases can be simulated to develop a robust control strategy. Practical considerations regarding compliance and safety should also be investigated prior to any full-scale installations inside existing pedestrian infrastructure.

6 Conclusion

Through the chapters of this thesis, we stepped through the different stages needed to pursue the creation and design of control strategies for managing pedestrian flows. The following paragraphs summarize the main findings and relate to the research questions announced in the opening chapter.

Intra-hub pedestrian dynamics In Chapter 2, we analysed pedestrian tracking data and evaluated the advantages of an integrated modelling approach. We combined models for intra-hub pedestrian dynamics and urban public transit dynamics together. The integrated modelling between the urban transit network and the intra-hub dynamics did not yield the expected results. Although both models benefited from more detailed input data, the added value in terms of modelling was limited. Very little reciprocal influence between the models was observed. We suspect the infrastructure configuration and low congestion levels are the reason for this. Repeating the numerical experiment for a transportation hub suffering from high congestion may lead to different conclusions. This unsuccessful approach emphasized the need to design intra-hub pedestrian control strategies to efficiently improve pedestrian satisfaction and comfort inside transportation hubs.

Dynamic pedestrian management systems By comparing the specificities of road traffic and pedestrian flows, we were able to propose the Dynamics Pedestrian Management System (DPMS) in Chapter 3, which addresses the first research question. The overall concepts are similar to DTMS, except for several areas which increase the complexity of DPMS: user compliance, wider pedestrian choices and the complexity of pedestrian assignment models. The complexity induced by the pedestrians' freedom of choice and movement also stands out when considering the success of the three control strategies presented in this thesis. The initial idea of transposing concepts from road traffic to pedestrian flows provided very limited benefit. Carrying over traffic lights and ramp metering to a pedestrian environment was not very successful. On the other hand, the

strategies which prevent, or reduce, bidirectional flow boast significantly better results. Therefore, development of pedestrian dedicated control or management strategies must focus on addressing specifics of pedestrian dynamics.

Pedestrian dedicated control strategies The second research question is addressed thanks to the two strategies which successfully improve pedestrian dynamics: flow separators and moving walkways. The numerical simulations show that reductions in travel time up to 15% can be obtained for specific trips inside the infrastructure while decreasing or limiting congestion. Naturally, the values strongly depend on the case study, but these examples show that the users can significantly benefit from adequate control measures. Nevertheless, not all users will take advantage of such measures. Depending on the context, some users will be penalized by the application of control devices. This was the case with both the flow separators and the moving walkways strategies. The negative effects of the devices were mitigated when using the predictive algorithm.
Furthermore, two major benefits of using a predictive control algorithm have been identified. The first, already hinted at in the previous paragraph, concerns the fairness across user categories. Indeed, the predictive algorithm reduced the inequalities induced by the application of the control strategy. The second advantage is the quantification of the trade-off between travel time and density made explicit by analysing the Pareto front. Unfortunately, these insights come at a high computational cost, hence carrying over the models used in this thesis to industrial applications will be unpractical.

To summarize, in this thesis we developed and discussed the DPMS which was used within a simulation environment to test several control strategies. The control strategies which addressed specific issues occurring within pedestrian dynamics are more efficient at reducing congestion or travel time. The advantage of including short term predictions was also evaluated thanks to the control strategy which exploits moving walkways. Although the strategies successfully improved pedestrian dynamics, further work is needed to make the strategies operational and to consolidate the results.

6.1 Towards practical applications

Several control strategies dedicated to pedestrian flows are proposed in this thesis alongside the DPMS framework. The ultimate objective is to design strategies which are applicable in practice. Before this can be achieved, a given strategy must be calibrated and evaluated inside a simulation environment to reduce the risk of negative effects or hazardous situations. This can be accomplished using a pedestrian simulation environment. By doing so, we can theoretically answer many questions before practical experiments take place. Some examples are 1) the evaluation of the impact of uncompliant users on the system, 2) the optimal positioning of devices

in the walkable environment, 3) the effect of the control strategies on future demand scenarios or 4) the impact of including short term predictions in the control algorithm. Nevertheless, several challenges remain before practical implementations become widespread inside pedestrian infrastructure.
Although control strategies can be autonomous, the infrastructure operator is still necessary to overlook the system and deal with unexpected events. Emergency situations requiring medical attention is one example when a human operator must take actions to facilitate the intervention of the medical staff. Major sensor defects which cannot be anticipated by the control algorithm is another scenario which can require human intervention. Furthermore, the demand patterns can evolve over the years rendering the calibration of the control algorithm, or event the control devices, obsolete. Detecting this can be challenging for an automated system, hence operator expertise is valuable to ensure long term safe and efficient pedestrian dynamics.

Safety Although decreasing pedestrian travel time is desirable, the question of pedestrian safety is central and must never be overlooked. Maybe the most classical metric to consider safety is pedestrian density. To ensure no hazardous situations occur, the operator must be able to guarantee that at any point in time and space the users are not put in danger. We discuss two situations: public transport platforms and corridors.
On-platform congestion can decrease the attractivity of the network, but the operator must ensure that passengers do not risk being pushed off the platform onto train tracks for example. Monitoring the pedestrian accumulation, or density, of the waiting passengers can be done to achieve this. If the measured density goes above a threshold, then measures must be taken to prohibit more pedestrians from reaching the platform. The framework discussed in this thesis can be used to accomplish this.
The other context where pedestrian density must not exceed a given threshold is inside closed spaces like corridors. Dramatic events have occurred with casualties when pedestrian density has become excessively high. To prevent this from happening, the operator must guarantee that under any scenario density does not reach hazardous levels. This should be done at the design phase using simulation, but measures can also be used in practice to deny entry to pedestrians.
In both cases presented above, pedestrian safety can be maximized by monitoring or simulating maximum pedestrian density. This should be one of the central objectives of any pedestrian-focused control strategy. Safety, through maximum pedestrian density considerations, is one of the main driving points from the operator's perspective to design and apply pedestrian control strategies.

DPMS Without considering software implementations and communication technologies which are beyond the scope of this thesis, several aspects regarding the DPMS framework must be addressed: pedestrian choices and acceptance, or measurement errors and biases are two examples. Pedestrians generally benefit from freedom of movement inside infrastructure. The choices

and possibilities which pedestrians can exploit are usually incorporated into models by using behavioural assumptions. Such assumptions should be carefully considered and incorporated into the DPMS framework, and the control strategies, such that they remain valid in practice. Consider compliance to floor markings as an example. Although the operator may assume that pedestrians will follow floor markings since it improves their trip experience, in practice, nothing is forcing the users to do so. This problem must be addressed when designing the control and information strategies themselves, and also considered when using models for the assessment, state estimation or state prediction. Many pedestrian simulation models have been calibrated in either controlled experiments or real-world applications where control strategies to manage the flows either don't exist or are ignored. Therefore, the validity of such models must be evaluated when control and information strategies are simulated or applied.
Another challenge with pedestrians is the heterogeneity between them. Some users are carrying luggage hence walking slowly. Other people are commuting to work hence they know the infrastructure layout very well. Socio-economic characteristics like age and gender also influence the behaviour of the pedestrians. Therefore, all these different behaviours must be accounted for when designing DPMS. One method for addressing this is by paying particular attention to providing clear and adequate information such that all users understand how the control strategy works.
Data collection techniques also raise several challengers. The assumptions made in this thesis about perfect information for pedestrian flow and density measurements do not hold in practice since measurement devices collect data with errors and biases. Therefore, robustness to these limitations must be explored. Furthermore, the data coverage (spatial and temporal) is generally not complete for economic reasons. One solution to complete the spatial and temporal coverage is state estimation. By doing so, the operator can get a complete picture of the dynamics taking place and the control algorithm gains access to more information. Furthermore, state estimation can provide insight into the confidence in the data. Practical applications of pedestrian flow control must account for sensor errors, biases and incomplete coverage. One solution to mitigate sensor reliability is redundancy in the data coverage.

Flow separators Applying dynamic flow separation based upon walking direction raises several practical challenges. The first is safety when moving devices operate. Two solutions come to mind to circumvent moving barriers. Firstly, dynamic floor markings or lights can be used. This way, no physical obstacle is present. Nevertheless, pedestrians can easily ignore this solution which opens the question of compliance. A second solution using lanes delimited by static barriers can be conceived. The walking direction of each lane, statically delimited by barriers, can be decided dynamically based upon demand. The direction can be indicated using overhead screens for example. This approach has the advantage of removing all moving parts.
If lanes are used, the transitions between each direction must be handled correctly by allowing sufficient time for the users to clear each lane before changing the direction. Otherwise, individuals walking in opposite directions will meet in a confined space and this can lead to very poor

user experience and possibly hazardous situations. Again, user compliance to such information is vital to prevent this from happening and to ensure the strategy's success.

Moving walkways Moving walkways are common devices in airports and shopping malls, hence users are already accustomed to them. Therefore, the same hardware can be used, except with a dynamic control algorithm, to influence pedestrian flows. The challenge resides in managing the different characteristics of the users. Some individuals will stop walking once on the device, while others wish to continue walking. To prevent the capacity drop induced by pedestrians who are stopped, one solution is to design a moving walkway wide enough such that a stream of walking pedestrians can overtake stationary ones. Similarly to flow separators, the transitions between moving directions must be carefully managed and adequate information must be provided so users follow the expected behaviour.
Today, both moving walkways and devices to collect pedestrian focused data are used in practice. Therefore, combining these two elements together to build dynamic control strategies should not require significant work. A simple control algorithm must be designed and calibrated. This can be achieved by restricting the possible speeds to a single value and using a rule where the direction of the MW must match the dominant pedestrian flow. State estimation or prediction are not necessary as long as measures to address sensor defects are taken. By starting with simple control algorithms and existing devices, dynamic control strategies can be implemented in practice with a manageable effort.
As highlighted in the previous paragraphs, most of the components to apply management strategies are already used in practice. A bold step must be made by operators to develop the missing links between the elements and test various strategies. Naturally, the calibration process must be accomplished, and thorough understanding of the dynamics are required to ensure the application is a success. The devices' positioning, dimensions and number will strongly influence the overall effectiveness. An accurate simulation environment can be used to accomplish this. We can expect more advanced control strategies to provide more significant improvements to the users compared to simpler strategies. This remains to be explored within simulations environments and is discussed in the following section about future research.

6.2 Future research

The previous section discussed steps towards practical implementations. Although the devices like moving walkways already exist, the control algorithms to use them will most certainly benefit from further development. In this thesis, we proposed a reactive and a predictive algorithm. In both cases, refinement is needed before use in real environments. The reactive algorithm needs better calibration while the predictive algorithm suffers from slow computational time. Further development of the algorithms is therefore one aspect which must be addressed. Nevertheless, the tools needed to evaluate and calibrate the control strategies must also be explored.

Modelling assumptions and limitations The numerical results discussed in this thesis rely upon several models which have been presented in the previous chapters. One critical question concerns the validity of the behavioural assumptions embedded into these models when control strategies are applied. Since pedestrian dedicated dynamic control measures are rare in practice, many models are calibrated and designed without considering such measures. To address this, effort should be invested to analyse the assumptions built into the models to verify whether they are still valid when dynamic control strategies are used.
We developed several strategies assuming that pedestrians wish to minimize their travel time. Therefore, as long as the strategy's main effect is to decrease journey time, we can reasonably assume that the pedestrians would use them in practice. This could be verified with surveys or empirical data.
The usage of the same model for the short-term predictions as for the assessment model (simulation environment) was done to reduce the software implementation load. This choice means the assessment model has access to perfect information about the future which is not a valid assumption in practice. Using this setup leads to optimistic estimates of the benefits of the control strategy since no errors exist in the predictions. In practice, measurement devices induce errors and biases into the quantities of interest like density or flow.

Control algorithms The fixed control strategy for controlling moving walkways did not perform well against the other control algorithms. An intermediate solution between a fixed and reactive control approach using a rule-based or scenario-based control algorithm could be explored. The direction of motion of the moving walkway could be decided based upon aggregate demand or contextual data like train arrivals into the station. The poor performance of this strategy emphasized the need for dynamic solutions which adapt to the ongoing pedestrian dynamics.
The calibration of the proportional-integral controller inside the reactive algorithm accomplished in this thesis should be re-considered using several different scenarios to develop a more generally applicable controller. Furthermore, the calibration process of the reactive algorithm to control the moving walkways could be improved by using reinforcement learning. In this context, the optimal control algorithm is the model which must be learnt, while the pedestrian dynamics is the gains/penalties function. The optimization algorithm will therefore learn the optimal control algorithm based upon the feedback it obtained from the pedestrian dynamics. The advantage of this approach lies in the fewer input requirements concerning the control algorithm structure. Using such methodologies, a calibration for different environments and setups can be done to create a toolbox of different control algorithms which are easy to apply in practice.
The predictive algorithm also needs significant work to build an applicable algorithm. The models selected for the development and evaluation of the control strategies are not usable in the current state for the optimization of the control configuration over short-term predictions. Two clear reasons justify this. First of all, the implementation cannot be considered industry standard. Secondly, the choice of a disaggregate model means high computational cost and very detailed predictions. A trade-off using a mesoscopic model could be promising to develop fast optimization procedures.

Analysing the impact of the predictive control measures as a function of the prediction horizon, update frequency, and other parameters should be accomplished to reach the most cost-effective solution. On one hand, frequently updating the short-term predictions can be done with fast macroscopic simulation models. On the other hand, computationally expensive but highly detailed models can be used for the short-term prediction if the update frequency is low. Although disaggregate models have an advantage when localized congestion occurs since they can capture pedestrian specific dynamics, longer intervals between updates increase the dependency of the prediction's quality on the demand estimation. Therefore, the trade-off between computational cost, prediction detail and prediction accuracy should be addressed in simulation environments before practical applications.
Beyond the calibration and computational aspects, the design of the algorithms can certainly be improved and refined. Different metrics and algorithm structures should be considered to find the combination which provides the most benefit to the system. Exploring metrics like transfer success or specific origin-destination travel time, or walking speed, could provide substantial benefit to users in the case of transfers. Another example would be coordinated reactive control algorithms inside the infrastructure. By doing so, the performance of the whole pedestrian infrastructure can be taken into account without relying on short terms predictions. The robustness to measurement errors (sensor failure or bias for example) is also critical for the strategy to work autonomously. The inclusion of state estimation, and the confidence in the results from the estimation, should be top priority to accelerate the transition from academic simulation environments to industrial applications.

Strategy development Different methods for combining devices like distributed or centralized control approaches can be explored. Since centralised approaches consider all devices together, they can coordinate the configuration of each device to generate efficient solutions at the whole network level. Nevertheless, the computational cost is usually prohibitive for large networks. To circumvent this, distributed or decentralized solutions can be used. Since pedestrians are capable of rapid recourse and their dynamics are rapidly evolving, the advantages of centralised solutions over decentralised ones must be evaluated. This goes in line with the evaluation of the added value of rolling horizon schemes given their computational cost.
The two strategies which proved successful addressed specific aspects of pedestrian dynamics. Therefore, this path should be followed in the development of future strategies. Their success depends on their capability at addressing challenging situations of pedestrian dynamics, like bidirectional flow for example. Although using existing devices is appealing for practical purposes, the future design of strategies must explore innovative solutions. Providing information to the users about the current and future congestion levels would significantly impact the pedestrian's route planning process. Disruptive solutions to improve pedestrian dynamics should also be considered as to broaden the catalogue of available measures.
Exploring various control strategies and improving the algorithms is necessary to exploit the full potential of existing pedestrian infrastructure. Considering control and management strate-

gies in existing infrastructure is useful to extend the infrastructure's life, but such measures should also be considered when new infrastructure is designed. By doing so, the lifespan can be increased, user satisfaction increased and cost potentially reduced. Furthermore, operators of walkable environments should consider their infrastructure in the larger context. Transportation hubs should be analysed within the public transit network for example. The chapter devoted to analysing the transfer dynamics inside transportation hubs and the connections between intra-hub dynamics and urban transit dynamics emphasized the need to consider each link in transportation networks. Explicitly considering the dynamics inside the hub has the potential to lead to better transfer experiences for passengers, notably by reducing the missed connections for example. Nevertheless, the numerical results from the hub and urban integration also emphasized the need to be open minded and consider the cost-benefit advantages of measures. Thorough understanding of the dynamics taking place, be it inside pedestrian infrastructure or urban transit networks, is a preliminary step to the successful application of any management or control measure.

6.3 Final remarks

The major steps for developing control and management strategies tailored to pedestrian dynamics have been discussed in this thesis. Although simple applications could be implemented with limited effort, significant work must be accomplished before the state-of-the-art will reach the same level of efficiency as road traffic DTMS. Taking inspiration from successful road traffic strategies must be done with caution but can be an interesting source of inspiration. Naturally, the results from this thesis are case study dependent, but the potential for improving pedestrian dynamics is strong. Applying such measures in different environments is possible assuming adjustments to the local context are done. The methods are applicable to environments like airports, conference centres or even outdoor areas like city centres.

Future development of control and management strategies for pedestrian flows should be accomplished in tight collaboration between industrial partners (practitioners) and academic partners. This path is a promising way to develop the necessary theoretical and practical aspects. On one hand, practitioners have invaluable access to data, regarding both the infrastructure and the pedestrian flows. On the other hand, academic partners have experience in the modelling and analysis tasks which are needed to develop the methodological aspects.

A Gating: control algorithm details

This appendix is based upon the appendix from the following publication:

N. Molyneaux, R. Scarinci, and M. Bierlaire (Aug. 2021). "Design and analysis of control strategies for pedestrian flows". In: *Transportation* 48.4, pp. 1767–1807. ISSN: 1572-9435. DOI: 10.1007/s11116-020-10111-1. URL: https://doi.org/10.1007/s11116-020-10111-1.

Spatial and temporal representation The spatial domain L is modelled in a hybrid way. Firstly as an open continuous space in which pedestrians can move around, and secondly as a graph used for route choice. The operational model is taken from the NOMAD package with the default parameters (Campanella, 2016). The tactical decisions are modelled using the shortest path algorithm with travel distance as cost. Time is considered continuous, although the numerical implementation enforces some level of discretization. The graph is used by the pedestrians to navigate the infrastructure and find the path to their destinations. Each node in the graph is an intermediate destination. The motion model uses these intermediate destinations and makes individuals walk towards them.

Demand The demand is composed of pedestrian flows with specific origins and destinations. Each individual $n \in N$ has a free-flow walking speed v_n sampled from a normal distribution with a mean of $1.34 m/s$ (Weidmann, 1993). Their origin and destination are sampled inside zones representing the entrance and exit points from the infrastructure (zones a, b, c and d from Figure A.1). The infrastructure used for the case study does not contain multiple paths to the pedestrians' destinations, therefore route choice is reduced to route following. For a given origin and destination, only one single route exists.
For the sake of simplicity, we assume that the pedestrian demand originates in the extremities of

the short corridor sections. The pedestrian demand $D(T')$ comes from two different sources. The first group comes from pedestrians who are walking along the main corridor (moving between a and c in Figure A.1). The second group of pedestrians are those who disembark from trains (entering through zones b or d and walking towards a or c). The demand patterns are different for both of these groups and are represented in Figure A.2 through their respective arrival rates. A Poisson process is used to generate the individual entrance times based on the arrival rate. On one hand. we assume that the pedestrian demand along the main corridor is uniform ($q_{unc} = 1.0$) and on the other we assume that the demand coming from the trains is sine-shaped (the total arrival rate is $q_{con}(t) = 8.0(0.49(\sin(0.15t) + 1) + 0.05)$). We use a sine-shaped demand pattern since this is a rough approximation of the demand pattern induced by trains when passengers are alighting.

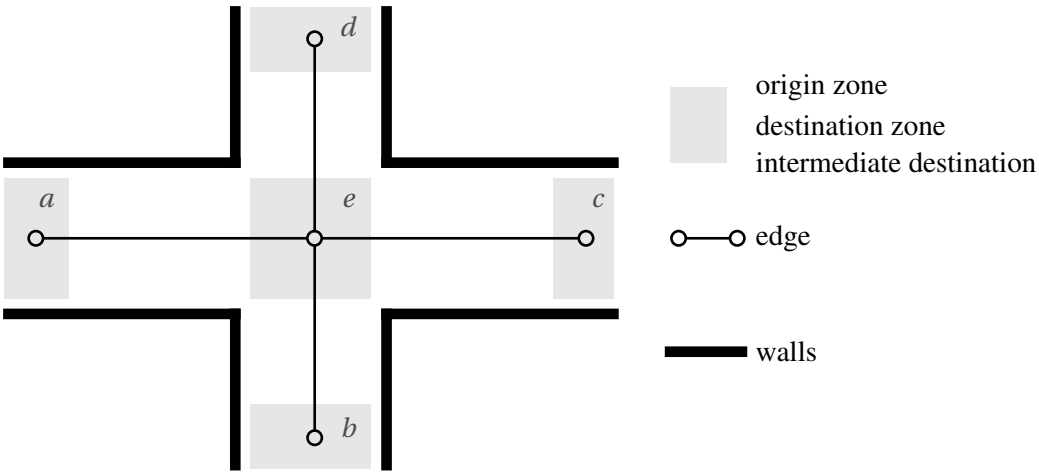


Figure A.1: Route graph and zones used as origin, destination or intermediate destination.

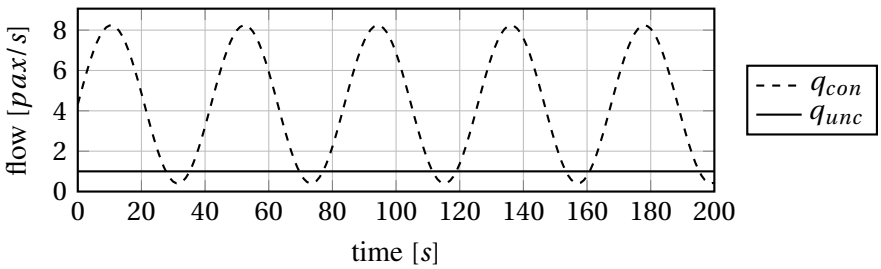


Figure A.2: Demand pattern used to evaluate the effectiveness of the gating strategy.

Fundamental quantities & data The fundamental quantities of interest Δ in this analysis are pedestrian density ρ and flow q. Density is computed using Voronoi diagrams (Nikolić and Bierlaire, 2014). By using Voronoi tessellations, an individual density value is obtained for each pedestrian at a given time snapshot. This definition of density reduces the influence

of the physical characteristics of the area in which the density is computed and captures the heterogeneity of the pedestrian dynamics. This method significantly reduces the influence of the size of the zone on the density computation, which is the major drawback of the classical average density. The Voronoi density of pedestrian n at time t is denoted by $\rho_n(t)$. We recall that the density is computed at regular intervals of one second. The density is not measured in the whole environment but in the spatial context L'. In Figure A.1 the grey zone in the centre, denoted L', is the area inside which density is measured. The pedestrian flow is not measured since it is the quantity controlled by the strategy. The real time data Δ^* is used by the controller but no historical data is used. In this simulation environment, the quantities are computed during the simulations, but in a true life scenario, these quantities are accessible thanks to cameras or flow counters.

Control & information Since the objective is to regulate the pedestrian flows entering the intersection we propose the usage of gates to achieve this objective. These *control devices* place an upper bound on the flow of pedestrians. In Figure A.3, two gates are represented with the symbols g_1 and g_2. The configuration $C_{g_1}(T')$ and $C_{g_2}(T')$ of these gates is the sequence of flows allowed through the devices over time. The pedestrian flow is modulated continuously over time.

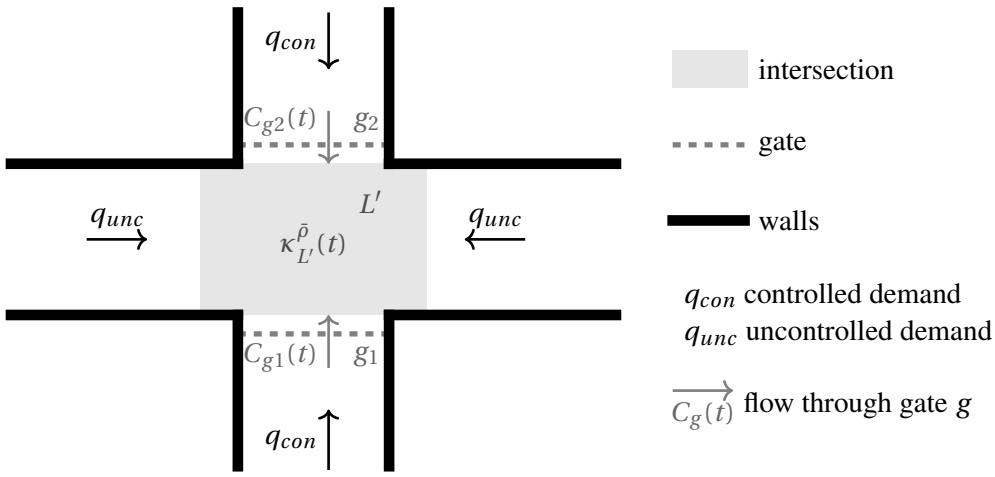


Figure A.3: Infrastructure used to simulate the usage of gates to control pedestrian flows.

To avoid radical changes in the device's configurations, the algorithm updates the configuration at regular intervals of one second. The simulation environment uses a discrete event simulator (DES) to manage the events linked to the control strategy. This DES is combined with the time-based motion model from NOMAD.

The key performance indicator needs to be defined in order to measure excessive congestion inside the intersection. As we have detailed information regarding the current level-of-service that each pedestrian is experiencing, we can define an indicator which takes into account the high

spatial variability. As pedestrians who experience low density can still move freely, we wish to define an indicator which focuses on those experiencing high densities. Firstly, we define the difference between "low density" and "high density". This is done by setting a threshold $\bar{\rho}$, below which pedestrians are considered to be in an uncongested environment. Using this threshold, we can define the indicator:

$$\kappa_{L'}^{\bar{\rho}}(t) = \sum_{n \in N'} [\rho_n(t) > \bar{\rho}], \tag{A.1}$$

where $\kappa_{L'}^{\bar{\rho}}(t)$ can be read as "the number of people inside intersection L' at time t who's density exceeds the threshold $\bar{\rho}$ ". N' is the set of pedestrians inside the intersection L'.

After defining a suitable KPI, we need to specify the control algorithm linking the KPI to the controlled variable. The objective is to regulate the inflow of pedestrians into the intersection based on the pedestrian density which is occurring in the intersection. Here, a reactive scheme is used, hence the density is computed at time t and we then fix the inflow of pedestrians based on $\kappa_{L'}^{\bar{\rho}}(t)$. The strategy configuration is linked to the control algorithm as:

$$C_g([t^*, t^+]) = \mathcal{A}_g(\kappa_{L'}^{\bar{\rho}}(t^*)), \tag{A.2}$$

where $\mathcal{A}_g$ is the control algorithm for gate g. This function must be specified in order to make the control strategy operational.

As stated previously, each gate in the system requires an explicit control algorithm $\mathcal{A}_g$ in order to work. For the present case, an offline simulation-based optimization algorithm has been used to find the best control algorithm specification given an objective function (Ali et al., 2002). Since the simulation is a stochastic process, multiple replications of each scenario are performed to compute the distributions of the indicators under investigation. For this case study, 500 replications are used. In order to reduce the computational burden of the optimization procedure, the control algorithm has been constrained to a quadratic function $\mathcal{A}_g(\kappa) = a + b \cdot \kappa + c \cdot \kappa^2$ (for the sake of readability the indices have been dropped on κ). Furthermore, the density threshold $\bar{\rho}$ above which the pedestrians are considered congested is also a decision variable in the optimization procedure. The goal of the optimization is to find the optimal quadruplet $\{a, b, c, \bar{\rho}\}^*$.

The objective function used for this optimization is a combination of two elements. The first element is the median of the 75th percentile of the travel time distributions divided by the 75th percentile of the travel times. The second element is the median of the 75th percentile of the travel times distribution through the area L' divided by the 75th percentile of the travel times through L'. The division by the reference values gives equal weight to each component. This objective function can be written mathematically as

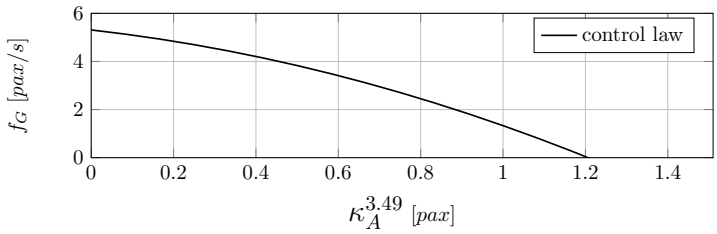
$$\frac{med(TT^{75})}{TT_{ref}^{75}} + \frac{med(TT_{L'}^{75})}{TT_{L',ref}^{75}}, \tag{A.3}$$

where TT^{75} is the 75th percentile of the travel times distribution from one simulation. The

subscript ref refers to the reference scenario before gates where installed and the subscript L' refers to the travel times through the intersection L'. This definition gives emphasis on improving the travel time through the intersection without neglecting the system as a whole.
The optimal set of parameters is shown in Figure A.4a alongside a visualization of the control algorithm (Figure A.4b). The optimal value of the density threshold is high in terms of pedestrian level-of-service. A value of $3.49 pax/m^2$ gets categorized as LOS F (Fruin, 1971). A level-of-service (LOS) of F corresponds to a pedestrian density above $1.66 pax/m^2$. Secondly, based on Figure A.4b it is apparent that the best control algorithm will nearly close the gates as soon as one pedestrian experiences congestion. When one pedestrian experiences a density equal or higher than $3.49 pax/m^2$, the inflow into the intersection is reduced to $1.33 pax/s$.

parameter	value
a	5.31
b	-1.94
c	-2.04
$\bar{\rho}$	3.49

(a) Set of optimal parameters.



(b) Control law visualization

Figure A.4: Specification of the control algorithm for both gates used in the case study presented in Figure A.1.

State estimation & prediction The control strategy does not rely on prediction. Furthermore, in this example, state estimation is not necessary as the data is readily accessible.

Control and information configuration generation The pedestrians' reactions to the control and information strategies should be taken into account by addressing the consistency problem materialized by the fixed point problem (3.7). Since the present case study does not give pedestrians any choice regarding routes or compliance to information, the consistency problem is neglected. The demand is not affected by the control strategy.
The gate's configuration is therefore computed as:

$$C_g([t^*, t^+]) = 5.31 - 1.94\kappa(t^*) - 2.04\kappa(t^*)^2$$

where $\kappa(t^*)$ is the KPI computed using (A.1). The length of the interval $[t^*, t^+]$ is one second.

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NICHOLAS MOLYNEAUX

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EXPERIENCE

Research & teaching assistant

École Polytechnique Fédérale de Lausanne (EPFL)

September 2016 – September 2021 | Lausanne, Switzerland

Pedestrian flow modelling

- simulator implementation
- design and evaluation of pedestrian flow control strategies
- data analysis and visualisation
- demand modelling

Project collaboration

- international industrial and academic project collaboration
- research project supervision

Teaching

- course lecturer (>100 students)
- exercise session supervision
- exam creation and correction

Internship

ASE (Analysis Simulation Engineering) AG

Oct 2013 – May 2014 | Zürich, Switzerland

- Emergency pedestrian evacuation modelling.
- Production line analysis and simulation.

EDUCATION

PhD. in Pedestrian flow management

École Polytechnique Fédérale de Lausanne (EPFL)

Sept 2016 – September 2021

- Mathematical modelling of behaviour and data analysis courses.
- International journal publications and conference proceedings.

Msc. in Computational Science and Engineering

École Polytechnique Fédérale de Lausanne (EPFL)

Sept 2014 – July 2016

- Projects on finite element analysis and computational fluid dynamics.
- Courses on numerical analysis, parallel computing, optimization and algorithms.
- Msc. thesis on bioinformatics

Bsc. in Civil Engineering

École Polytechnique Fédérale de Lausanne (EPFL)

Sept 2010 – July 2013

- Courses on structural engineering, fluid mechanics, transportation, hydraulics.
- Bsc. thesis on pedestrian flow modelling in train stations.

PROJECTS

Pedestrian data

- Online visualisation tool
- Hosted on AWS

CAD file processing

- Automated CAD file processing
- Data conversion to JSON

SKILLS

Scala | Latex | Data visualisation | Python | Java | C++

Autonomous | Curious | Problem solver

LANGUAGES

French	●●●●●
English	●●●●●
German	●●○○○

INTERESTS

Badminton

- 20+ years as player
- team captain since 2015
- club president since 2021

Skiing

- resort skiing since child
- ski touring since 2010

Cycling

- commuting
- day races
- multi-day trips