Design and analysis of control strategies for pedestrian flows

Nicholas Molyneaux * Riccardo Scarinci *
Michel Bierlaire *

October 31, 2019

Report TRANSP-OR 191031
Transport and Mobility Laboratory
School of Architecture, Civil and Environmental Engineering
Ecole Polytechnique Fédérale de Lausanne
transp-or.epfl.ch

*École Polytechnique Fédérale de Lausanne (EPFL), School of Architecture, Civil and Environmental Engineering (ENAC), Transport and Mobility Laboratory, Switzerland, {nicholas.molyneaux, riccardo.scarinci, michel.bierlaire}@epfl.ch

Abstract

Exploiting the full potential of pedestrian infrastructure is becoming critical in many environments which cannot be easily expanded to cope with the increasing pedestrian demand. This is particularly true for train stations as in many dense cities space is limited and expansion is difficult and very costly. In this paper, we investigate how to improve the level-of-service experienced by pedestrians by regulating and controlling their movements with a dynamic traffic management system. Although dynamic traffic management systems have been widely investigated in the last two decades to mitigate vehicular traffic congestion, little attention has been given in the literature to dynamic traffic management systems for pedestrian flows.
The objective of this paper is to develop the concept of a dynamic traffic management system for pedestrian flows by building on the experience acquired from vehicular traffic traffic management systems. We first propose a general framework for dynamic traffic management systems which takes into account the specificities of pedestrian traffic. The specificities of pedestrian traffic are discussed and emphasized. Then we illustrate the framework by using a control strategy designed for pedestrian flows that mitigates the issues induced by bi-directional flows. We show the effectiveness of this strategy by simulating a subpart of the train station in Lausanne (Switzerland). The results show a substantial improvement despite the relative simplicity of the method. These results emphasize the under-explored potential of pedestrian control and guidance when integrated into a dynamic pedestrian management system.

Keywords Pedestrian flow modeling, dynamic pedestrian management, bidirectional pedestrian flow

1 Introduction

Just as road traffic, pedestrian traffic suffers from congestion which can induce extra travel time, cost and hazardous situations. Preventing such congestion should be a concern for the operator of any pedestrian infrastructure. This is true for conference centers, transportation hubs such as train stations and airports or even shopping malls for example. Although these infrastructure have different goals, the people using them have the same desire: being able to move without being hindered by other pedestrians. To achieve this, operators can rely on static design measures during the construction phase of an infrastructure. Dynamic devices to regulate the movement of pedestrians are still under-explored though. The latter requires the use of a framework common in road traffic: dynamic traffic management systems (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 traveler 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 (de Palma and Marchal, 2002).
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 move freely in the environment. Dedicated pedestrian control strategies are therefore required. As elaborated in the following literature review, relatively little attention has been given to dynamic traffic management systems for pedestrians. One possible reason for this resides in the lower social or political pressure to reduce pedestrian congestion compared to road traffic.
In this paper we start by investigating a general framework for dynamic traffic management for pedestrians. This Dynamic Pedestrian Management system (DPMS) is tailored to pedestrian traffic and is based on the specificities of their dynamics to regulate the flows of pedestrians. Next, we explore practical control strategies for pedestrian flows. The strategy we develop is inspired by some specificities of pedestrian motion. Flow separators aim at preventing pedestrian couterflow by dynamically allocating walking space to pedestrians based on their walking direction. This strategy is implemented and evaluated in a simulation environment. To evaluate the effectiveness of this strategies, we consider the main walking corridor from the train station in Lausanne (Switzerland) and investigate the potential benefits on passengers. Through these examples, we show the high potential and the hard challenges associated with the development of pedestrian

DTMS.
To reach this objective, the article is structured as follows. After this introduction, the second section presents the literature specific to road traffic and pedestrian traffic with a focus on traffic control and DTMS. The third section outlines the major specificities of a dynamic traffic management system for pedestrians. The fourth section presents in detail how flow separators can improve pedestrian dynamics. The appendix presents anther control strategy inspired by ramp metering. Finally, we conclude this article by discussing the potential of pedestrian control strategies and the need for more advanced strategies.

2 Literature review

There are two fundamental components in a DTMS: traffic models and control/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 these are central to traffic management, they are not sufficient and should be explained in detail. Traffic models can be decomposed into two parts which work together: traffic assignment models and demand models. Assignment models are responsible for the operational aspect of travel which assigns the demand to the network. Demand models take care of the strategical and tactical choices. Both of these groups of models can be split into different categories based on the level of detail which is used: macroscopic, mesoscopic or microscopic (Duives et al., 2013). Each category of models addresses the trade-off between computational time and the level of detail in different ways.
The following paragraphs cover the different elements which take part in a DTMS for both car traffic and pedestrian traffic. First we present the important elements regarding car traffic and then we provide an overview of control and information strategies. Following the paragraphs about car traffic, we present the relevant work on pedestrian traffic models and the state-of-the-art traffic control strategies.

2.1 Car traffic

Modelling the motion of vehicles has been an active area of research over the last decades. Microscopic, mesoscopic and macroscopic models are wide spread 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, 1995b, Zhang et al., 2015) have proved 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 DYNA-MIT (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 (1995a). One last category of models which has been investigated more recently rely 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 modes and 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). By combining dynamic route choice and the motion of vehicles the dynamic traffic assignment (DTA) problems arises. An extensive discussion about 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 are usually deterministic while simulation-based models are usually stochastic. This categorization can also be associated with the type of motion model.

As technology has evolved, so have the technologies available to measure vehicular traffic. Today the range of sensing technologies is wide and address 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 allow fast improvements in real-time detection and have opened up the way for autonomous vehicles (Janai et al., 2017).

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. Some examples are travel time, waiting time or delay (Ben-Akiva et al., 2001). In the context of highway traffic, Wang and Papageorgiou (2005) use extended Kalmann 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 & guidance 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, 1997, Chi et al., 2013). 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 throughout of the junction (Lämmer and Helbing, 2008, Varaiya, 2013). 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 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 and influence how they choose their route or speed for example. Often called advanced traveler 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 drivers' 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 require either real-time data or surveys to collect data in order to estimate discrete choice models which are then used to simulate the drivers' responses.

The combination of specific traffic control strategies with DTA leads to dynamic traffic management (DTMS, sometimes called advanced traffic management). In practice, the objectives of such systems are the monitoring, prediction and regulation of the traffic in order to improve the dynamics. By using measurements from the network, the current state of the system is estimated and short-term predictions are performed to anticipate future states. By using the information about the current and future states, appropriate control and guidance actions are taken to achieve the prespecified goal. This process has been used in simulation environments to develop, calibrate and evaluate potential control strategies. Many different combinations of traffic models and control strategies have been tested. DTMS became popular in the 90' during which multiple 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 de Palma and Marchal (2002) where the authors propose METROPOLIS as a framework for evaluating route guidance.

2.2 Pedestrian traffic

Dynamic traffic management systems tailored for pedestrians is still an underexplored area within the literature (Dubroca-Voisin et al., 2019). Steps have been taken in this direction as in Abdelghany et al. (2012). The elements which are required to build a DTMS for pedestrians are listed in Kabalan et al. (2017). Nevertheless, the fixed point problem between pedestrian traffic assignment and pedestrian beahviour is not discussed.

The models used for simulating pedestrian motion are usually organized in the same 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 (Antonini et al., 2006) lies in a

given zone. 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).
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 rely on a discretization of space. They are called "cell transmission models" (CTM) (Asano et al., 2007, Hänseler et al., 2014a).
Some studies have combined two of these modelling scales 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 modeling route choice. Graph-based and potential-based are two common approaches which can take into account congestion (Stubenschrott et al., 2014, Guo et al., 2013, Hoogendoorn and Bovy, 2004a).
The concept of DTA is the same for car and pedestrian traffic. Agents continuously reconsider the shortest 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 (2004b) 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 any graph representations.
Finally, the choice between this wide range of models depends on the scenario under investigation. If the scenario involves a compact infrastructure and the control strategies require disaggregate information, then a microscopic simulator is more appropriate. On the other hand, large scale infrastructures with strategies 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 bi-directional pedestrian flows challenging. 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 (Zhang et al., 2012, Zhang and Seyfried, 2014, Bosina, 2018).
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 Wifi 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). On one hand, pedestrian tracking and counting can take place at links or at specific positions, but on the other hand there also exists the possibility to track pedestrians over the full infrastructure. 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).

Similarly to road traffic, KPIs are computed from the measurement data. The possibilities are the same: speed, flow, density or more complex ones 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 producing a pedestrian specific density value for each pedestrian (Nikolić and Bierlaire, 2014).

Control & guidance Unlike vehicles, pedestrians (generally) are not constrained by lanes nor regulations. 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, 2004a).
Most the attention has been guided towards reactive and offline strategies. Demand management is performed in Abdelghany et al. (2012). The demand pattern of pilgrims heading to the Mecca 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. The optimal configuration of traffic lights for signalized crosswalks has been studied for example in 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. Recently, a framework for controlling level-of-service (LOS) in a pedestrian infrastructure has been presented in 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 generation of management strategies, no complete framework is proposed, indeed, each component is used independently. 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. 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.
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 where 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.
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).

Although interest is growing for strategies to control and regulate pedestrian flows, no comprehensive framework which discusses and integrates all blocks of a pedestrian dedicated dynamic traffic management system for dynamic control strategies is currently available. The simulation and prediction of pedestrian flows has been extensively covered with many different modelling schemes, but control and guidance strategies are still underexplored. In the next section, we describe the components of a DTMS with the pedestrian specific characteristics in mind.

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. In the following paragraphs, we present each component which plays a role in a dynamic pedestrian management system. Figure 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. But first, we discuss the spatial and temporal representation of the walkable environment.

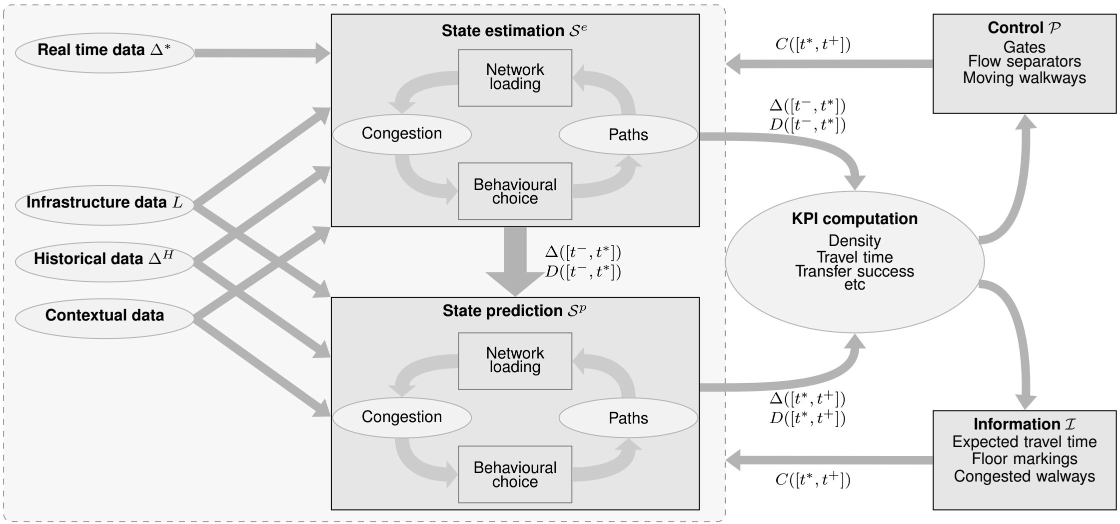


Figure 1: Dynamic Pedestrian Management System (DPMS).

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 must 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 pedestrian must walk around. Therefore, to be accurate, 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 usually take decisions in a discrete fashion based on stimuli. When a pedestrian sees a coffee shop for example, she might suddenly decide 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 (2004b), 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.
The static elements are generally the physical obstacles like walls, trash bins, benches, etc. On the other hand, the 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 pedestrian are more likely to seek sheltered paths when it is raining.

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'.
The decisions pedestrians take are characterized by many different components. Pedestrians start their trip at an origin which is usually dictated by activity chain

choices. Each pedestrian will walk towards their destination based on some purpose like commuting, tourism or shopping. The pedestrian's walking speed also depends on the trip purpose. The same individual is likely to have a different walking behaviour when she's going to work or when on holiday. Another explanation for the different walking beahviours are the socioeconomic characteristics like age or physical condition (Chattaraj et al., 2009). Alongside the desired walking speed, each individual has a desired arrival time. The concept of departure time also exists at an activity level, but when considering pedestrians inside a given infrastructure the departure time is usually given by the external elements, like the train arrival time for example. Finally, the element which links all these elements together is the path, which is the sequence of coordinates, cells or links a pedestrian uses.
A given individual walks along her preferred path starting from her origin and then ending at her destination. As the pedestrian walks along her path, she will continuously adapt the 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 his train, suddenly he might be confronted with a highly congested corridor forcing him to adapt his 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 pedestrian 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 ´, each indexed by γ. The main quantities of interest are pedestrian density, speed, flow and paths. From these quantities, we define two different categories of data: real time data ´$^{*}(\mathsf{L}', \mathsf{T}')$ and historical data ´$^{\mathsf{H}}(\mathsf{L}', \mathsf{T}')$, associated with the spatial context L' and temporal context T'.
The real time data of a given type γ is collected thanks to collection devices (or measurement 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 places 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 authors 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 $\acute{}^{H}(L', T')$. 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 $\acute{}^{*}_{\gamma}(L', T')$ could be flows discretized into one-minute intervals. The historical version of this quantity $\acute{}^{H}_{\gamma}(L', T')$ 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 *policy* $\mathcal{P}$ exploits a set of KPIs to "decide" how the *device* should act. This sequence of decisions makes the *configuration* $C_{\nu}(T')$ of a particular device ν. The policy 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 problem of compliance. The information *devices* can be smartphones, information boards or signs for example. The control/information policy uses the quantities of interest to compute the key performance indicators (KPIs). These KPIs reflect the goal of the strategy. The KPIs can be the same as the measured quantity like speed, density or flow. 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 *policy* is 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 situation more advanced tools are required.

One possibility for this is the usage of optimization frameworks. The specification of the control policy is the decision variable 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. On the other hand, 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.

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. One particularity of pedestrian traffic is bi-directional (or counter) flow. This is one source of increased travel time. Since pedestrians must slalom between the people coming in the opposite direction their travel times increase. By separating these antagonistic flows using accelerated moving walkways (Scarinci et al., 2017) for example, the dynamics could potentially be improved. 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 which does not oblige pedestrians to follow the "rules". 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's reactions to that information. This problem of consistency is central to any rolling horizon strategy. This 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 ´(T) and the demand D(T) for a given interval $T = [t^-, t^*]$. Recall that the current time is t^*.

$$\begin{aligned} &´([t^-, t^*]), D([t^-, t^*]) \\ &= \mathcal{S}^e \left[Y([t^-, t^*]), C([t^-, t^*]), ´(t^-), ´^*(L', [t^-, t^*]), ´^H(L', [t^-, t^*]) \right], \end{aligned} \tag{1}$$

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 $´^*$ or where it exists for the historical data $´^H$. Figure 2 presents this procedure schematically.
Measurement devices which produce the real-time data $´^*([t^-, t^*])$ 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. 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. Therefore to complete the puzzle state estimation is performed. Different models are available for this purpose in the literature (Hänseler et al., 2014b).
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):

$$\begin{aligned} &´([t^-, t^*]) \\ &= \mathcal{L}^e \left(D([t^-, t^*]), C([t^-, t^*]), Y([t^-, t^*]), ´(t^-), ´^*(L', [t^-, t^*]), ´^H(L', [t^-, t^*]) \right) \end{aligned} \tag{2}$$

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 $´$:

$$\begin{aligned} &D([t^-, t^*]) \\ &= \mathcal{B}^e \left(´([t^-, t^*]), C([t^-, t^*]), Y([t^-, t^*]), ´(t^-), ´^*(L', [t^-, t^*]), ´^H(L', [t^-, t^*]) \right) \end{aligned} \tag{3}$$

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 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 computes the quantities $´([t^*, t^+])$ and the behavioural decisions $D([t^*, t^+])$ where t^+ is the prediction horizon:

$$´([t^*, t^+]), D([t^*, t^+]) = \mathcal{S}^p \left[Y([t^*, t^+]), C([t^*, t^+]), ´(t^*), ´^H(L', [t^*, t^+])\right]. \quad (4)$$

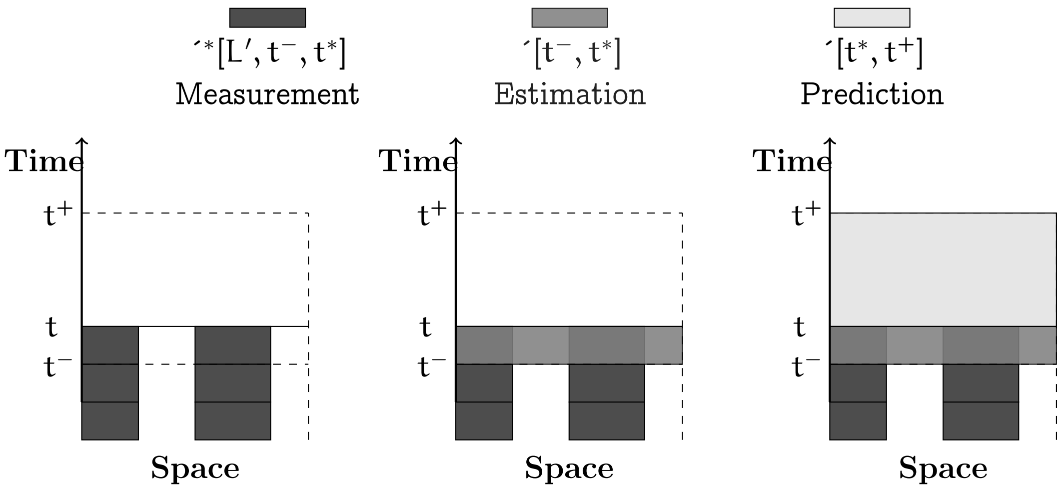
The major difference with the state estimation is the absence of real time data $´^*$. Note that the results of the state estimation are included in the historical data. The same fixed point problem with the supply loading and the behavioural decisions takes place, except for the prediction interval:

$$´([t^*, t^+]) = \mathcal{L}^p \left(D([t^*, t^+]), C([t^*, t^+]), Y([t^*, t^+]), ´(t^*), ´^H(L', [t^*, t^+])\right) \quad (5)$$
$$D([t^*, t^+]) = \mathcal{B}^p \left(´([t^*, t^+]), C([t^*, t^+]), Y([t^*, t^+]), ´(t^*), ´^H(L', [t^*, t^+])\right) \quad (6)$$

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 $´(T')$ and behavioural choices $D(T')$ over the interval $T = [t^-, t^+]$. The length of the intervals $t^* - t^-$ and $t^+ - t^*$ 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 $C[t^*, t^+]$ and on the other hand we have the congestion $´([t^*, t^+])$ and behavioural decisions $D([t^*, t^+])$. The fixed point problem is defined as:

$$\mathcal{F} = \begin{cases} C([t^*, t^+]) & = \mathcal{P}\left(´([t^*, t^+]), D([t^*, t^+]), Y([t^*, t^+]), ´(t^*), ´([t^*, t^+])\right) \\ ´([t^*, t^+]), D([t^*, t^+]) & = \mathcal{S}^p \left[Y([t^*, t^+]), C([t^*, t^+]), ´(t^*), ´^H(L', [t^*, t^+])\right]. \end{cases} \quad (7)$$



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

Figure 2: State estimation and prediction procedure.

the generated configuration is said to be consistent if the state 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 there destination. The quantities ´ available are the density inside the main corridor and the future pedestrian flows. The policy 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), Aboudolas et al. (2010).
The generation of the configuration can also involve the optimization of a given objective. This problem is defined as:

$$\begin{aligned} &C^{\mathrm{opt}}([t^*, t^+]) \\ &\quad = \arg\min \mathcal{F}\left(C([t^*, t^+]), \text{´}([t^*, t^+]), D([t^*, t^+]), Y([t^*, t^+]), \text{´}(t^*), \text{´}^{H}(L'[t^*, t^+])\right). \end{aligned} \tag{8}$$

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 quantity used for the optimization 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. We also emphasized the main differences between pedestrian and road traffic management systems. Three elements stand out. Firstly, and possibly the most challenging question to tackle, is the lack of compliance to control strategies. Secondly, the wider range of choices that pedestrians can make means that their movements are more complex. Finally, the higher complexity of assignment models for pedestrians mean that modeling and predicting their behaviour is challenging. To illustrate the DPMS, the next section presents two case studies using a simple control strategy designed for pedestrian flows. The full capabilities of the DPMS are not exploited as no state estimation nor prediction is performed. Our motivation is to show the potential of dynamic traffic management tailored to pedestrian flows. The inclusion of state estimation and prediction is left for future research.

4 Case studies

One of the most widely spread traffic control techniques in vehicular traffic is probably ramp metering. Therefore, it is natural to first evaluate a version of this method for pedestrian flows. Regulating the pedestrian flow into an intersection with a gating scheme is an adaptation of ramp metering (Papageorgiou et al., 1991). The goal is to prevent excessive congestion inside the intersection so that pedestrians can move freely. This strategy was tested by computing the pedestrian density inside the intersection and then regulating the flow into the section. The detailed description of the control strategy and the results are presented in Appendix A

Transposing ideas from road traffic like ramp metering to pedestrians traffic does not lead to significant improvement in pedestrian dynamics. Although some positive aspects can be mentioned like a decrease in pedestrian density, the benefits are not as substantial as in car traffic. The design of control strategies for pedestrian traffic should therefore exploit the specifics of pedestrian dynamics in order to have positive effects. The next control strategy is designed specifically to address one of the challenges with pedestrian flows: bidirectional flow.

As experienced by many individuals and shown in studies Burstedde et al. (2001), counter flow (or bidirectional flow) in pedestrian traffic is responsible for a significant increase in travel time. This happens as people have to "slalom" between the pedestrians coming in the opposite direction. In order to prevent this, we propose a control strategy for preventing counter flow in corridors: flow separators. We present two situations. The first is a simple setup with a single straight corridor and the second a more complex setup which corresponds to part of the train station in Lausanne (Switzerland). We use a simulation environment to explore the potential of this control strategy. The pedestrian motion model from the NOMAD

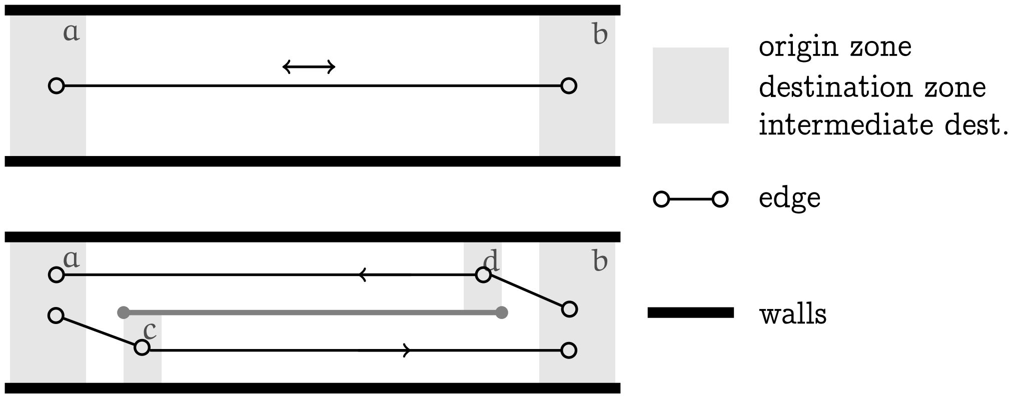


Figure 3: Infrastructure with the walls and navigational graph. Reference scenario (top) and flow separator installation (bottom).

package (Campanella, 2016) is considered the ground truth for the case studies

4.1 A simple corridor

We present the case study by following the framework presented in Section 3. We discuss how each component has been designed in the specific context of flow separators.

Spatial and temporal representation We consider a corridor 35m long and 9m wide. This corridor is the spatial domain L that is modeled 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 3). This combination allows pedestrians to move around the infrastructure while avoiding obstacles and other pedestrians. Time is modeled as a continuous quantity. Nevertheless, the simulation environment enforces some discretization for numerical reasons. We consider a time window of 6 minutes.

Supply The infrastructure L used for this case study is a single straight corridor as presented in Figure 5. All components are considered 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 1.34m/s (Weidmann, 1993). 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

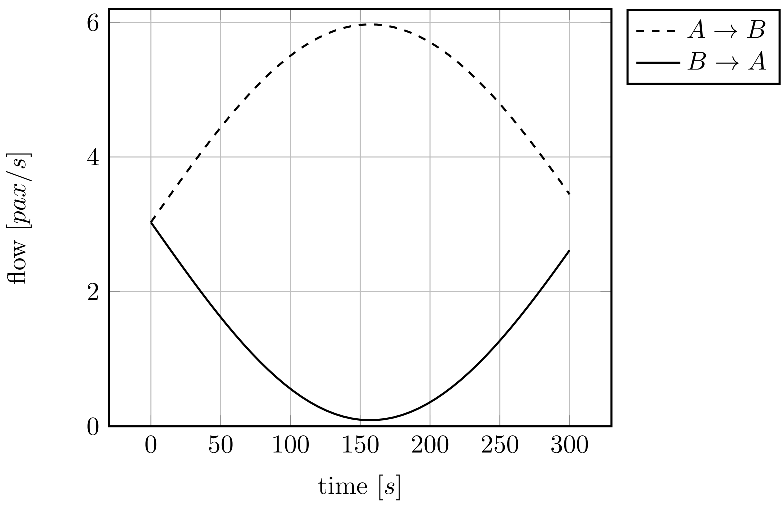


Figure 4: Demand pattern for the proof-of-concept scenario.

of the corridor presented in Figure 3 denoted a and b. The infrastructure used for the case study does not contain multiple paths to the pedestrian's destinations, therefore there is no route choice. For this scenarios, 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 dominant 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 dominated 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 presents these two arrival rates. The demand is generated during the first 300 seconds of the simulation. The shape of the demand pattern is a rough approximation of the demand pattern induced by trains when passengers are alighting.

Fundamental quantities & data The quantity of interest is pedestrian flow q in this scenario. The flow is measured at either extremities of the corridor using a one second discretization. The measured flows are denoted q^*_{AB} and q^*_{BA} in Figure 5. Real time data $\acute{}^*$ 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.

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 counter flow can be prevented when pedestrians walk along the side of the corridor dedicated to their walking direction. Figure 5 presents the infrastructure L where a flow separator is installed in the middle of

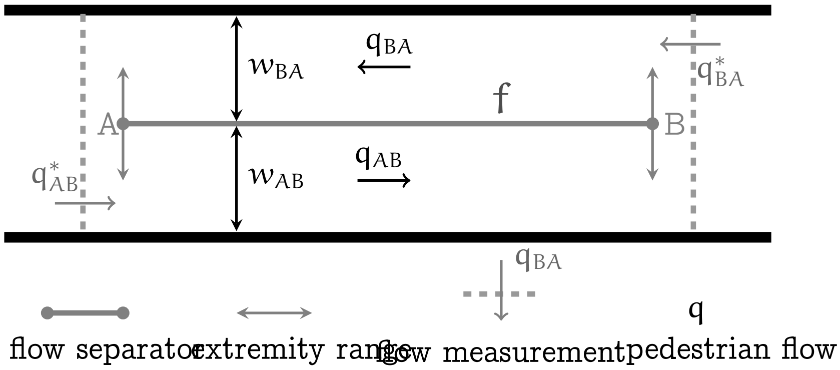


Figure 5: Schematic presentation of the flow separator. The width dedicated to each direction is adjusted based on the flows entering the corridor.

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 5. 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, 2004b) where each individual tries to minimize his travel time. Indeed, pedestrians try to choose the route which minimizes their travel time. However, full compliance may not be obtained. This topic is discussed below.

The proposed strategy measures the flows near the beginning of the section where the device is installed. This means that the flow separators 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 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:

$$w_{AB}(t), w_{BA}(t) = \mathcal{P}_f(q^*_{AB}(t), q^*_{BA}(t)), \tag{9}$$

where w_{AB} (resp. w_{BA}) is the width dedicated to the people walking from A to B (resp. B to A) and $\mathcal{P}_f$ the control policy linking the measured flows to the available widths.

Making the strategy operational requires specifying the control policy $\mathcal{P}_f$. 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 calibrations to a strict minimum, we propose a function which relies only the measured flows in a proportional way:

$$\mathcal{P}_f = \begin{cases} w_{AB} = & w \cdot \dfrac{q^*_{AB}}{q^*_{AB} + q^*_{BA}} \\ w_{BA} = & w \cdot \dfrac{q^*_{BA}}{q^*_{AB} + q^*_{BA}} \end{cases} \tag{10}$$

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. Using this specification makes the width of each side of the corridor proportional to the measured flows. 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_{AB}^{min} and w_{BA}^{min}. 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:

$$w_{AB}(t) = \begin{cases} w_{AB}^{min}, & \text{if } w \cdot \dfrac{q_{AB}^*}{q_{AB}^* + q_{BA}^*} \leq w_{AB}^{min} \\ w - w_{BA}^{min}, & \text{if } w \cdot \dfrac{q_{BA}^*}{q_{AB}^* + q_{BA}^*} \leq w_{BA}^{min} \\ w \cdot \dfrac{q_{AB}^*}{q_{AB}^* + q_{BA}^*}, & \text{otherwise.} \end{cases} \tag{11}$$

The width of the corridor from B to A is naturally $w - w_{AB}$. This policy is applied in real time but in a discrete manner. The configuration is updated at one second intervals. Furthermore, an upper bound ($0.25m/s$) 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%.

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 flow can be directly measured at the extremities of the flow separator.

Control and information configuration generation The generation of the control configuration is done using (11). 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 (8) is not needed.

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 is used

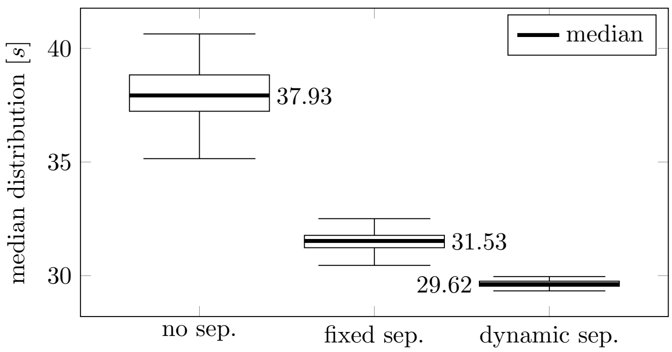


Figure 6: Median travel time distributions using 100 replications for the three scenarios: no flow separator, a static separation of the flows and a dynamic flow separator.

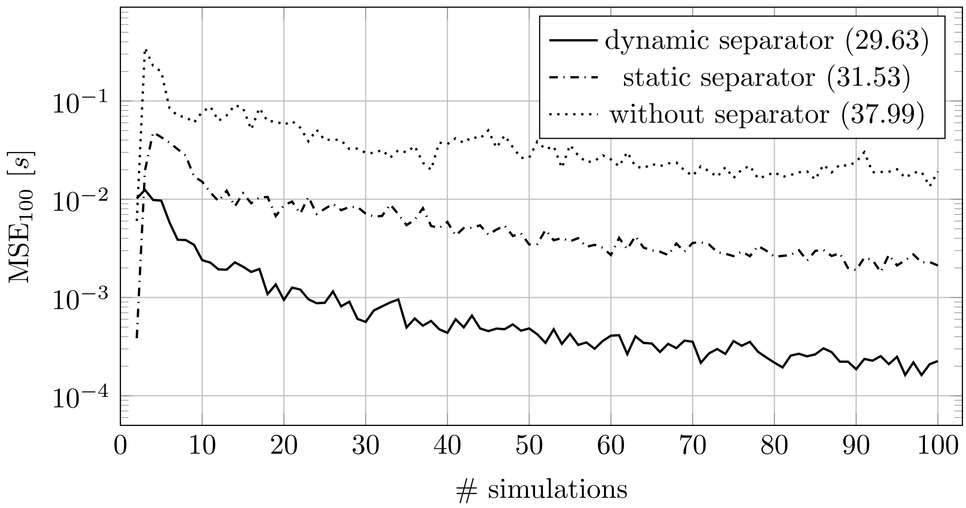
to evaluate the effectiveness of the dynamic flow separators. This pattern is used in all numerical experiments, except in some cases the amplitude is changed.

Influence of dynamic flow separators The flow separators are tested on the section of corridor presented in Figure 5. 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 6). 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.

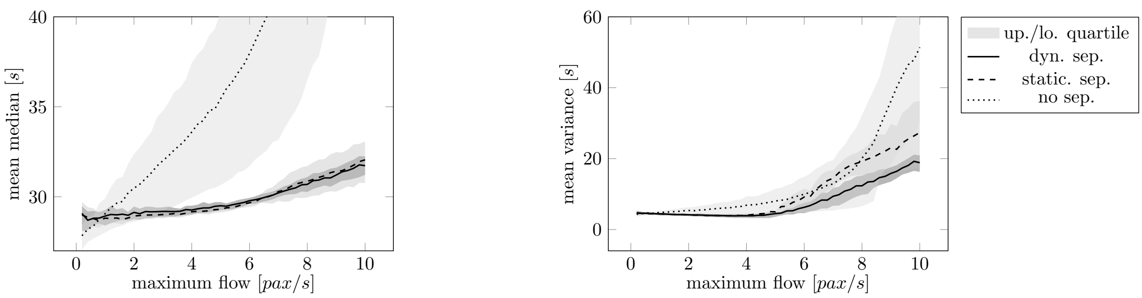
The number of simulation replications to perform has been determined by using Figure 7, where the mean square error (MSE) is computed using bootstrapping. This technique is used since no analytical solution exists for estimating the MSE of the medians. The number of replications required to guarantee 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.

Naturally, flow separators are not be efficient for all scenarios and demand patterns. The results from the sensitivity analysis to demand are presented in Figure 8. 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 to the same side. 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 8a). 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

Figure 7: The mean square error computed using bootstrapping for the three scenarios. The usage of flow separators means the required number of simulations to reach a given error is significantly lower.



is significantly lower when dynamic flow separators are used instead of static ones (Figure 8b).



(a) Mean of median travel times.

(b) Mean of travel time variance.

Figure 8: 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 9 presents the travel time variance for full compliance, 95% and 90% of compliant pedestrians. Figure 10 shows the median travel time per direction for the three compliance scenarios. When considering Figure 9, it is clear that the case with 100% compliance shows the lowest variance in travel time, which is expected. As already seen from Figure 8b, 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 gray lines being above the corresponding black lines from Figure 9.

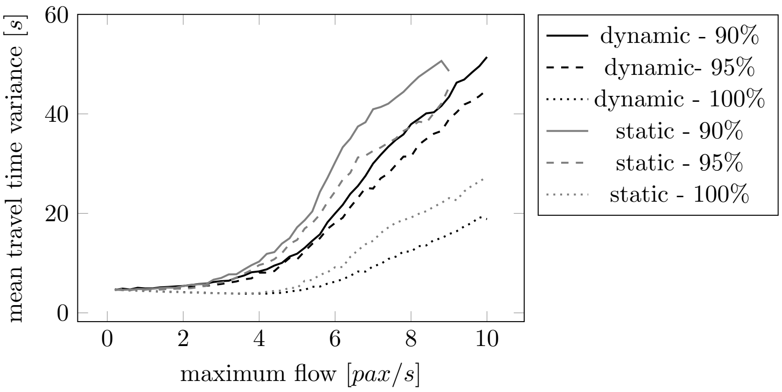
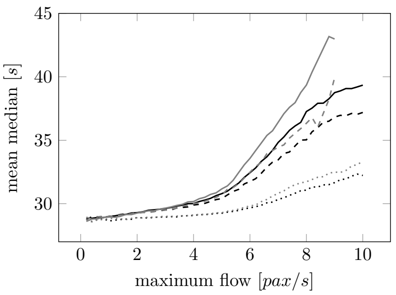
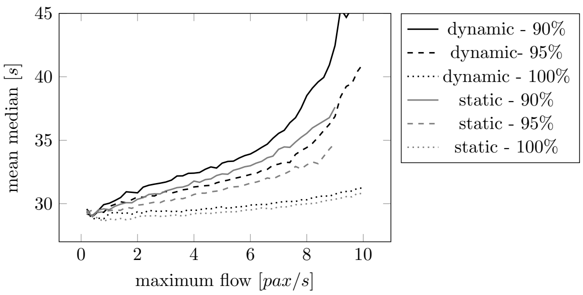


Figure 9: Comparison of the travel time variance between the static flow separators and the dynamic ones for different compliance levels. The dynamic flow separators effectively reduce the variance in travel time for higher demand levels.

By analyzing the travel time medians per direction, we can see two opposite situations. The pedestrian flow going from A to B is the dominant flow, while the opposite flow from B to A is the dominated 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 dominant flow will generally benefit from this strategy, while the dominated 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 10. When comparing the dynamic to the static flow separator for the dominant flow (Figure 10a), the dynamic flow separator is beneficial for this group. On the other hand, for the dominated flow (Figure 10b) 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.



(a) Pedestrians moving from A → B.



(b) Pedestrians moving from B → A.

Figure 10: Travel time comparison for the opposing directions with different compliance levels. The dynamic flow separators are useful for reducing the impact of the uncompliant pedestrians.

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 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.

4.2 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.

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 13. The total length is approximately 100m long and 8m wide. 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 modeling choices are the same as described in 4.1. Figure 11 presents the graph used by pedestrians to navigate the infrastructure.

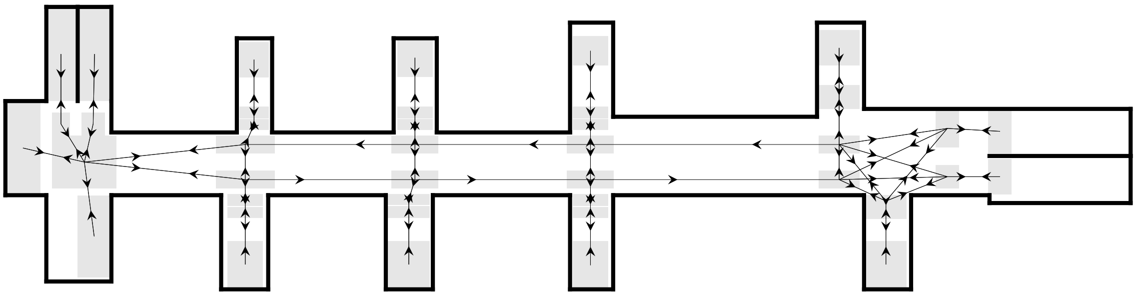


Figure 11: Navigational graph used for the western underpass of the station in Lausanne (Switzerland).

Supply We consider only static elements except from the flow separators. The shops ”Aldi“ and ”Tekoe“ are only shown in Figure 13 as a landmark and have no influence on the case study.

Demand Individual tracking data has been collected for ten days in 2013 for both pedestrian underpasses (PIs) 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 12. 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 time. We considered these ten days as independent scenarios. For each of these ten scenarios, one hundred replications where 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.
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 1. This leads to nine groups in total since there are three different trips 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 corresponds to the trip length accomplished inside the corridor. If pedestrians use the first stairway/ramp then they get categorized as a short (*L0*) trip. If they skip the first stairway/ramp they see then it is considered a medium (*L1*) trip and if they skip two or more stairways/ramps then they get categorized as long (*L2*).
We simulate three different control scenarios (*S1*, *S2* and *S3*). *S1* is the reference without flow separators, *S2* and *S3* use flow separators. The original demand pattern is used for *S1* and *S2*. For the third scenario, *S3*, the original demand pattern used by the pedestrians has been slightly altered. The pedestrian's destination has been altered such that they use the closest one after passing the flow separators. This is done as pedestrians would otherwise be using a destination

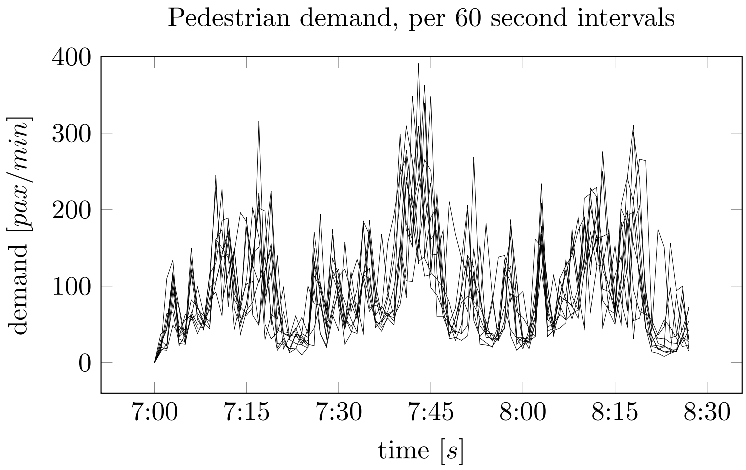


Figure 12: Aggregate empirical demand pattern used as input in the simulations for evaluating the flow separators.

which is significantly further than their closest destination. This shows how control strategies can influence pedestrian demand. This aspect is further discussed in the results.

Fundamental quantities & data As for the single flow separator presented in Section 4.1, pedestrian flow is computed at the extremities of each flow separator. The directional flow into each flow separator is measured at each end of the control devices presented in Figure 13.

Control and information Instead of using one flow separator, we simulate the installation of three separators along the main corridor as presented in Figure 13. 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.

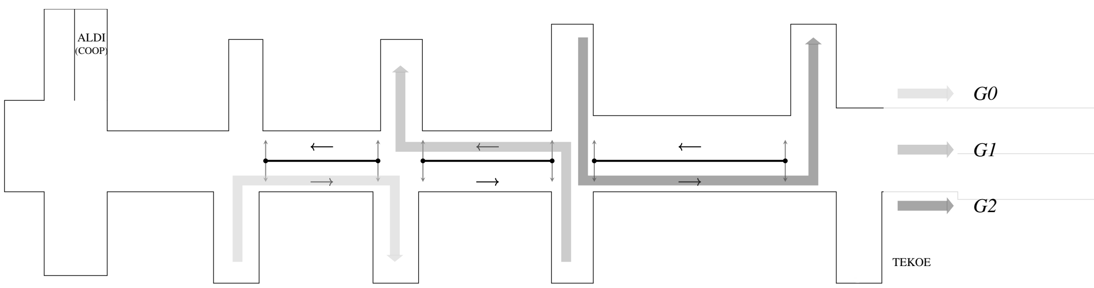


Figure 13: Western pedestrian underpass from the station in Lausanne, Switzerland. Three flow separators are installed in the central part of the corridor.

State estimation and prediction No state estimation no prediction is needed for this strategy.

Control and information configuration generation We keep the same logic as for the simple corridor example. Therefore, equation (11) is used to move the flow separator based on the computed flows. We recall that each flow separator is independent from the others.

Three different scenarios of control have been simulated (summarized in Table 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*). When pedestrians use the flow separators, if the side of the corridor dedicated to their desired walking direction is on the opposite side from where they enter the corridor and their destination is on the same side as their origin, then pedestrians would have to walk twice through the intersection to reach their original destination. We assume that pedestrians would choose to use the closest ramp/stairway to their desired platform, therefore in the simulations we allowed the pedestrians to choose the closest access way to the platform which they wish to reach. With this scenario, the category with two left turns (*G2*) disappears.
Firstly, the travel time of all pedestrians is considered. The box plots of the median travel time per replication are represented in Figure 14 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 can come either from the shorter distance traveled by the pedestrians when they change destinations or from the reduced number of intersections which must be crossed by the users. Of course, a combination of these reasons is likely.
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 category 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 15 and 16. In these

Table 1: Summary of the different scenarios under investigation and the different pedestrian groups.

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 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.

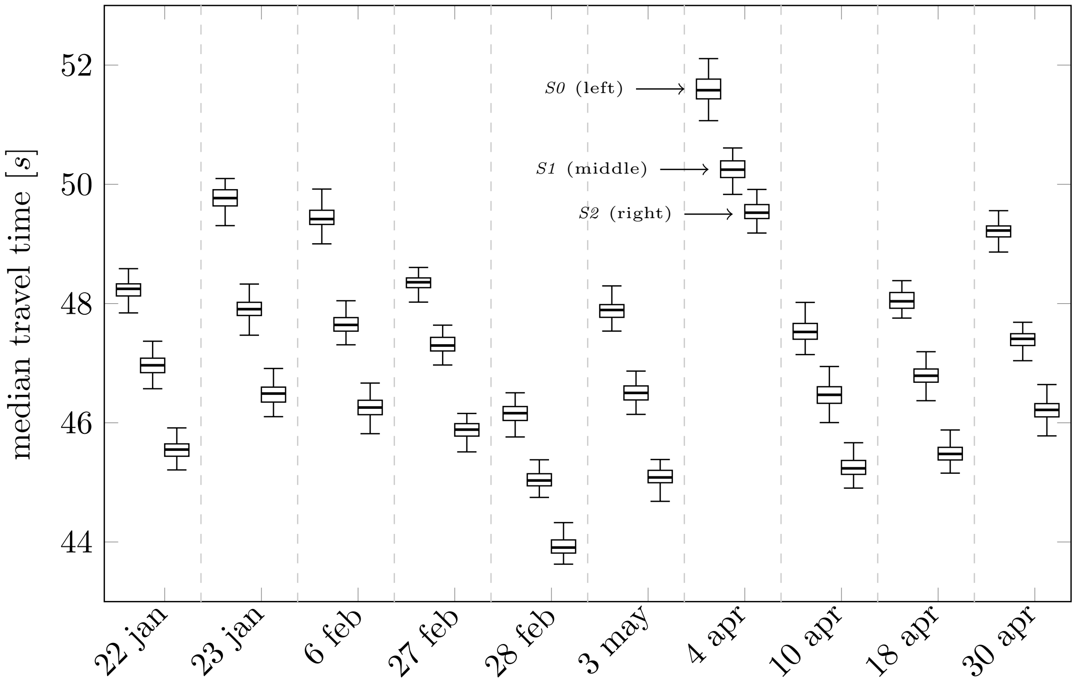


Figure 14: Comparison of the distribution of the median travel times of the ten different scenarios for the three setups of the flow separators. Each triplet of box plots represents one demand scenario and within each demand scenario the left box plot is control scenario *S0*, the middle box plots are *S1* and the right box plots are *S2*.

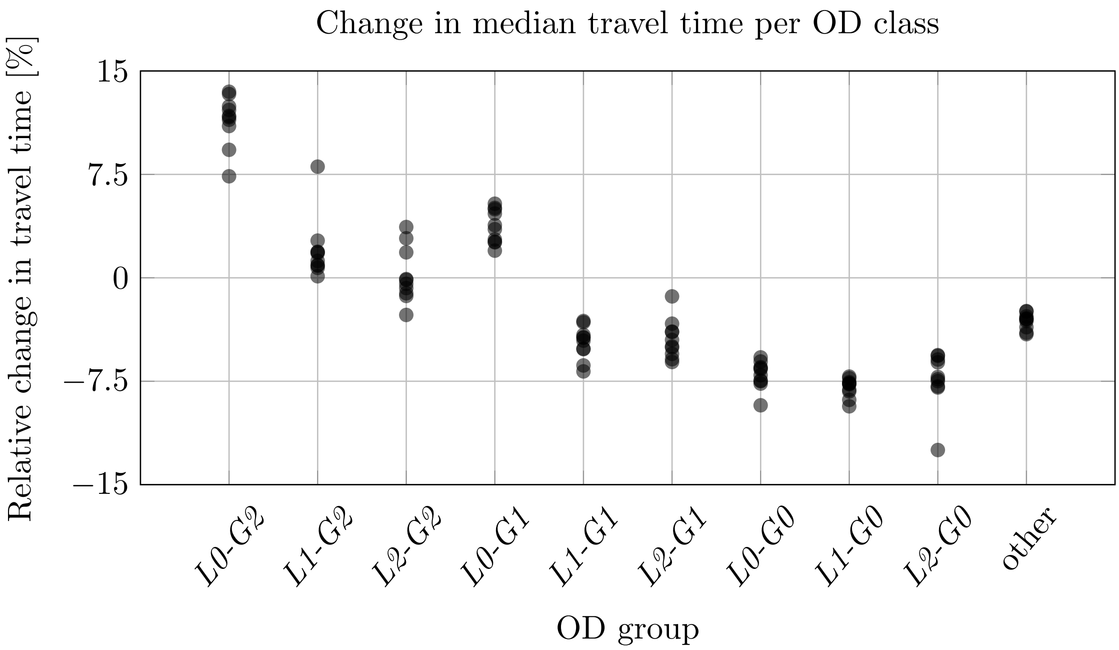
figures, each point represents the difference of the median of median travel time (or mean speed) between the control setup and the reference case. These values are computed based on one hundred replications of each scenario.

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 flows separators depends on the group under examination (Figure 15a). If pedestrians do not require 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*) are positively influenced if they are doing a lengthy trip (*L1* or *L2*). The short trips where the pedestrian change side of the corridor (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 twice the junctions.

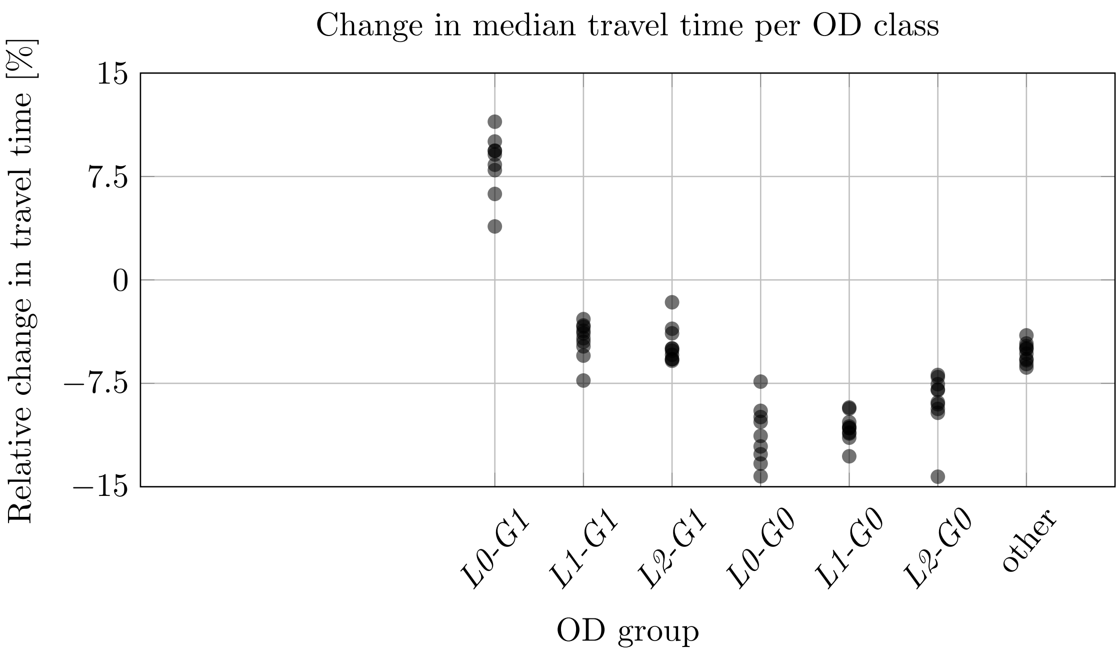
The cause for the increased travel time could be caused solely by the extra walking distance induced by the usage of flow separators. Nevertheless, by considering the change in average walking speed (Figure 16a), it is clear that all groups of pedestri-

ans benefit from the flow separators as their walking speeds increase. This happens since the flow separators effectively prevent the weaving effects and head-on collisions between pedestrians. Some groups do indeed walk a longer distance, but their travel time is not impacted since they can walk it faster.
The setup where pedestrians can adapt their destination, i.e *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. One explanation for this result lies from the shift in group ownership. The pedestrians who previously where in the *G2* group are now in the *G1* group. For the *L0* category, there is one section which is slightly longer than the others (the right one in Figure 13), therefore a shift from the *L0-G2* group to the *L0-G1* group can induce an increase in travel time although their walking speed increases. This effect could be dependent on the demand pattern, since the original OD data show that this specific OD pair is one of the most used ones in the western underpass. 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 15 and 16) 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 14 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. 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. Floor lighting or projections could be used to 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. Exploiting other weaknesses of pedestrian traffic like stationary pedestrians or the large range of walking speeds could lead to further improvements.

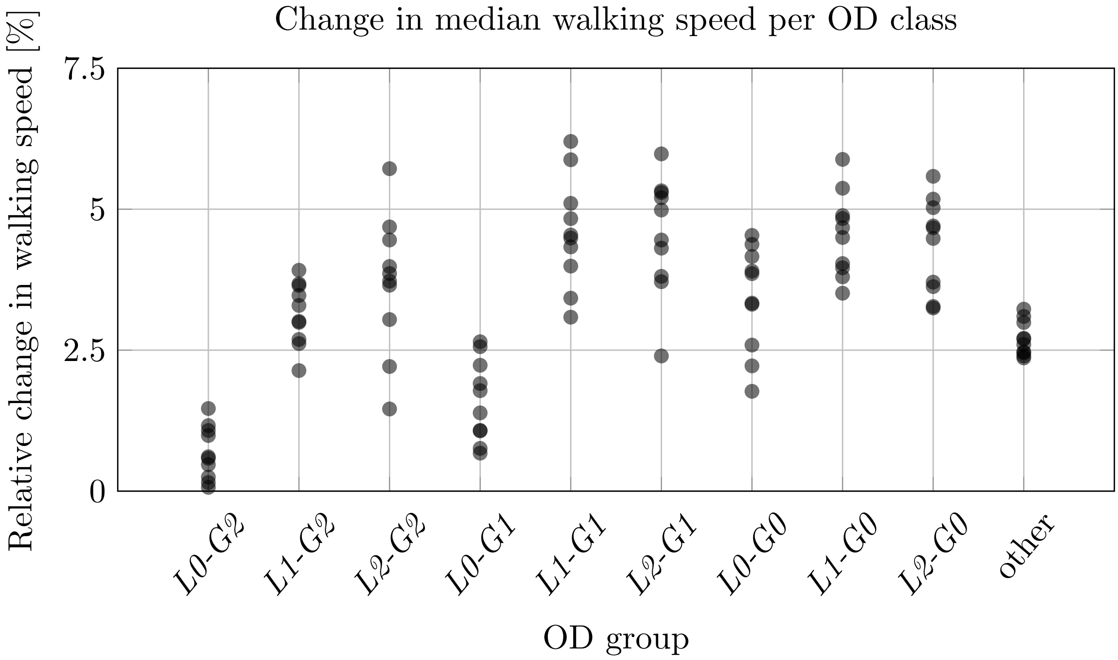


(a) Travel time change per OD class when flow separators are installed in the main corridor. The travel times decreases for class which don't involve crossing the corridor in any way. For longer trips, the travel time decreases even if pedestrians must cross the corridor.

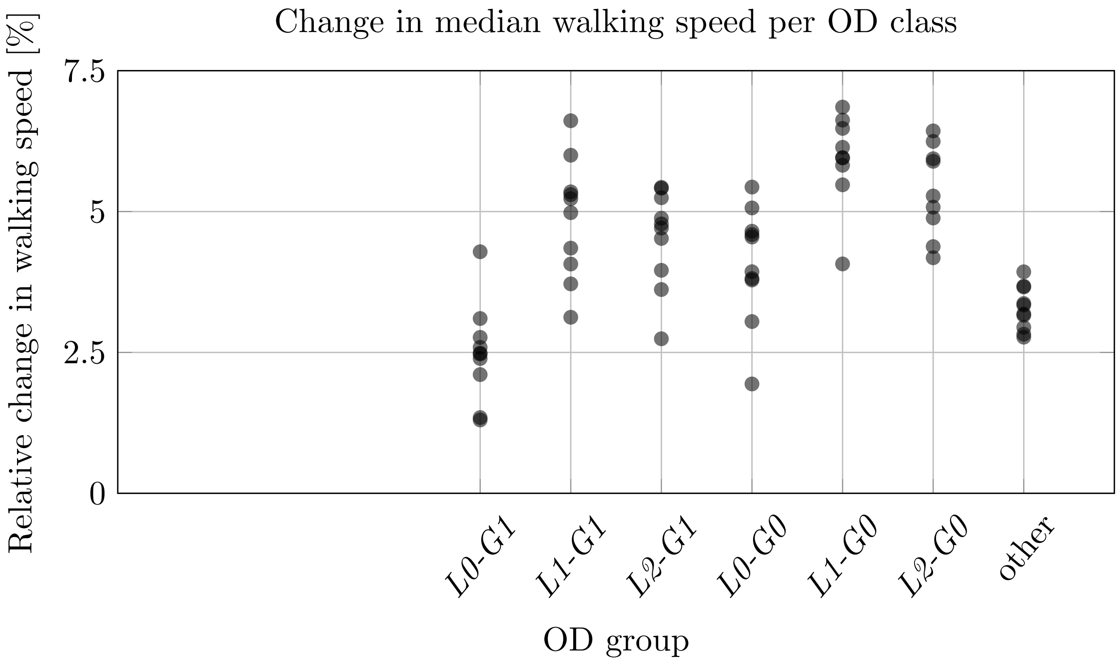


(b) Change in travel time when pedestrian can change their destination to an equivalent platform access ramp. The travel time for pedestrian doing short trips and who must cross the corridor increases compared to the case when the original destination is used.

Figure 15: Impact of the flow separators on the travel time of the pedestrians using the western underpass. The top figure (a) presents the change in travel time when pedestrian use their original destination while the bottom figure (b) shows the travel time change when pedestrians choose the closest ramp to their target platform.



(a) Mean speed evolution after flow separator are used. The mean speed per OD class significantly increases for all classes except two: pedestrians who cross the corridor with short trips (*crossShort* and *crossSideShort*).



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

Figure 16: Impact of the flow separators on the average walking speed of the pedestrians using the western underpass. Like Figure 15, the top figure use the original destination and for the bottom case pedestrian could adjust their destination to the closest ramp to their desired platform.

5 Conclusion

In this paper we investigate the potential of Dynamic Pedestrian Management Systems (DPMS). We have proposed a general framework for DPMS that we illustrate with two case studies where pedestrian flows are controlled. 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 integrating relatively simple control strategies into the framework, we show the effectiveness of control strategies tailored to pedestrians.

The flow separator control strategy significantly improved the pedestrian dynamics despite the relative simplicity of the approach. These results confirm the high potential of management strategies designed specifically for pedestrian traffic.

Future research directions include the development of strategies which take full advantage of the DPMS framework. The added value of state prediction in particular needs to be assessed. In particular, we expect that predictive control and information strategies to be even more efficient in environments like train stations and airports where demand is induced by timetables which are known in advance. Another direction for future work is the development of new strategies which exploit the specificities of pedestrian traffic and its environment. An interesting strategy would consist in using accelerated moving walkways to control the movements of pedestrians (Scarinci et al., 2017). Both the direction and the speed of each device can be controlled. At a larger scale, controlling pedestrian movements at a city level during special events also presents high potential. Finally, integrating DPMS with management systems of public transportation would be an interesting direction of future research. Spreading the load over the public transport network by providing guidance could prevent high congestion at specific locations.

A Control strategy: gating

The movement of pedestrians can be controlled in a way similar to ramp metering (Papageorgiou et al., 1991) and signalized intersections (Febbraro et al., 2004). With the high temporal variations in pedestrian demand, congestion can occur in some areas of the infrastructure while others are still empty. To mitigate the risk of dangerous situations, the flow of pedestrians can be regulated to prevent high levels of congestion. As in road traffic, intersections where multiple streams of pedestrian join are likely to reach higher congestion. Since pedestrian traffic is not constrained by lanes, each pedestrian can choose his sub-route through the junction. In order to guarantee a good level-of-service through the intersection the pedestrian density must not become excessive. To accomplish this, we propose a reactive gating scheme which can control the flow of pedestrians in real-time.

Spatial and temporal representation The spatial domain L is represented 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. 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.

Supply For this case study, the supply data is considered static. We dot not use elements such as shops or a public transport schedule. The infrastructure used for this case study is a four-way intersection, presented in Figure 17. This setup is common in train stations for example.

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 $1.34m/s$ (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 17). The infrastructure used for the case study does not contain multiple paths to the pedestrian's 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 17). 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 18 through their respective arrival rates. A Poisson process is used to generate the individual entrance times based on the arrival rate. On the 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.

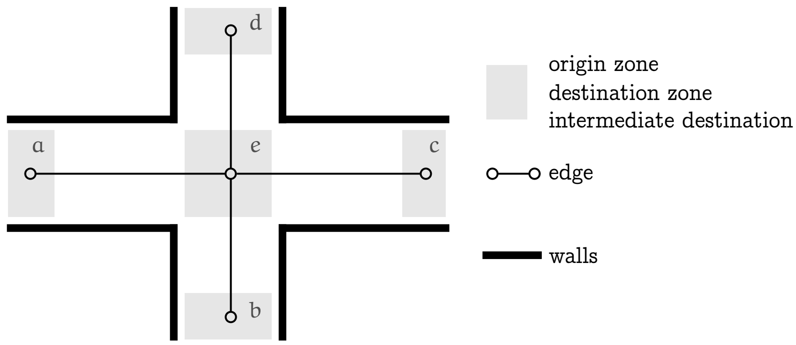


Figure 17: Route graph and zones used as origin, destination or intermediate destination.

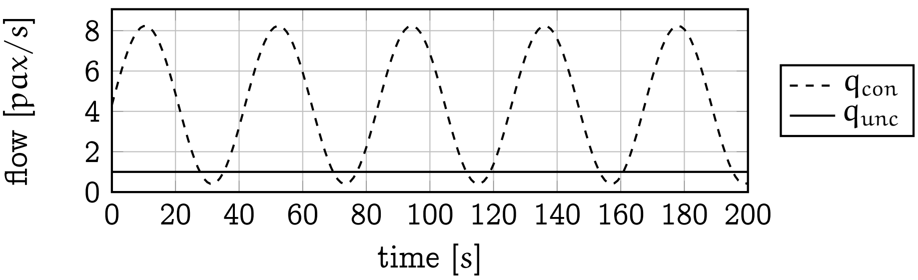


Figure 18: Demand pattern used to evaluate the effectiveness of the gating strategy.

Fundamental quantities & data The fundamental quantities of interest ´ 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 17 the gray zone in the center, 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 ´* 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 19, 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.
To avoid radical changes in the device's configurations, the policy 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 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:

$$\kappa_{L'}^{\bar{\rho}}(t) = \sum_{n \in N'} [\rho_n(t) > \bar{\rho}], \tag{12}$$

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 policy 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 policy as:

$$C_g([t^*, t^+]) = \mathcal{P}_g(\kappa_{L'}^{\bar{\rho}}(t^*)), \tag{13}$$

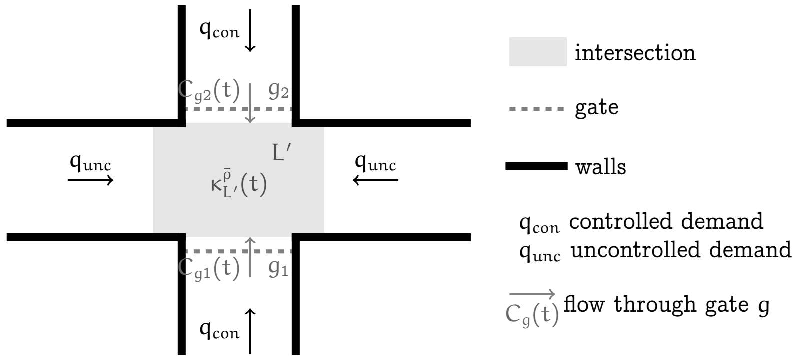


Figure 19: Infrastructure used to simulate the usage of gates to control pedestrian flows.

where $\mathcal{P}_g$ is the control policy 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 policy $\mathcal{P}_g$ in order to work. For the present case, an offline simulation-based optimization algorithm has been used to find the best control policy 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 policy has been constrained to a quadratic function $\mathcal{P}_g(\kappa) = a + b \cdot \kappa + c \cdot \kappa^2$ (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 $75^t h$ percentile of the travel time distributions divided by the $75^t h$ percentile of the travel times. The second element is median of the $75^t h$ percentile of the travel times distribution through the area L' divided by the $75^t h$ 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

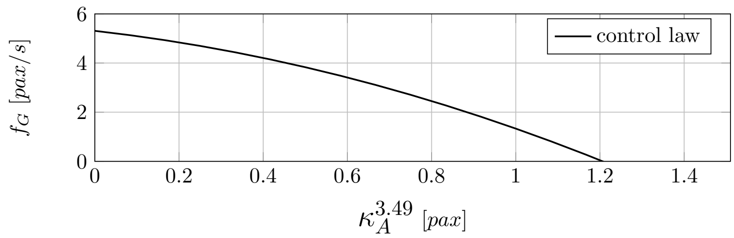
$$\frac{med(TT^{75})}{TT^{75}_{ref}} + \frac{med(TT^{75}_{L'})}{TT^{75}_{L',ref}}, \tag{14}$$

where TT^{75} is the $75^t h$ 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 20a alongside a visualization of

the control policy (Figure 20b). 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 20b it is apparent that the best control policy 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 20: Specification of the control policy for both gates used in the case study presented in Figure 17.

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 (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 (12). The length of the interval $[t^*, t^+]$ is one second.

A.1 Results

For each replication of the simulation, the median travel time of all pedestrians is computed. We then visualize the distribution of these medians by using a boxplot. The results for the reference scenario without gates and the case with gates are presented in Figure 21. It is apparent that the median travel times do not change significantly between both scenarios. Gating slightly decreases the mean of the median travel times. The median of median travel times increases when gating is used. Although the travel times are not significantly improved, a positive effect on travel time variance is observed. This is visible through the reduction in variance in the box plots. Without gating the interquartile range is 2.6 seconds, which is then reduced to 2.06 seconds when gating is used.

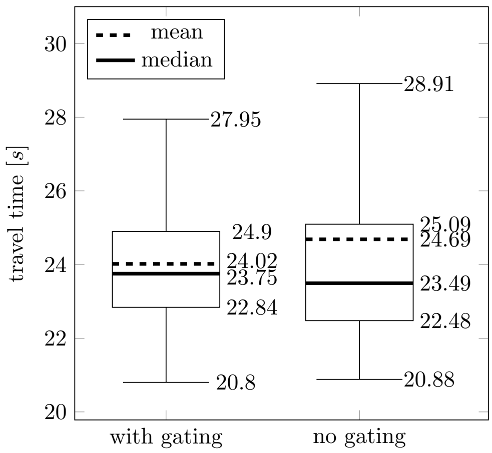


Figure 21: Distribution (500 replications) of the median travel time for both scenarios. No major difference in terms of travel time is visible between both scenarios.

To further understand the influence gating has, we can investigate the median travel time distribution per origin-destination group. The pedestrians are classified into two groups: the first group contains pedestrians who go through the gates while the second group is composed of pedestrians not using the gates. Figure 22 presents the median travel time distribution per group for both scenarios. On one hand, gating slightly increases the travel time for the group which use the gates, the median of median travel time goes from 23.00s to 23.63s. On the other hand, gating significantly improves the walking times of pedestrian 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 also 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 travel through the intersection. Concerning the pedestrians who don't use the gates, their significant 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.
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 23 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 pedestrian who don't use the gates comes from the reduction in density in the intersection.

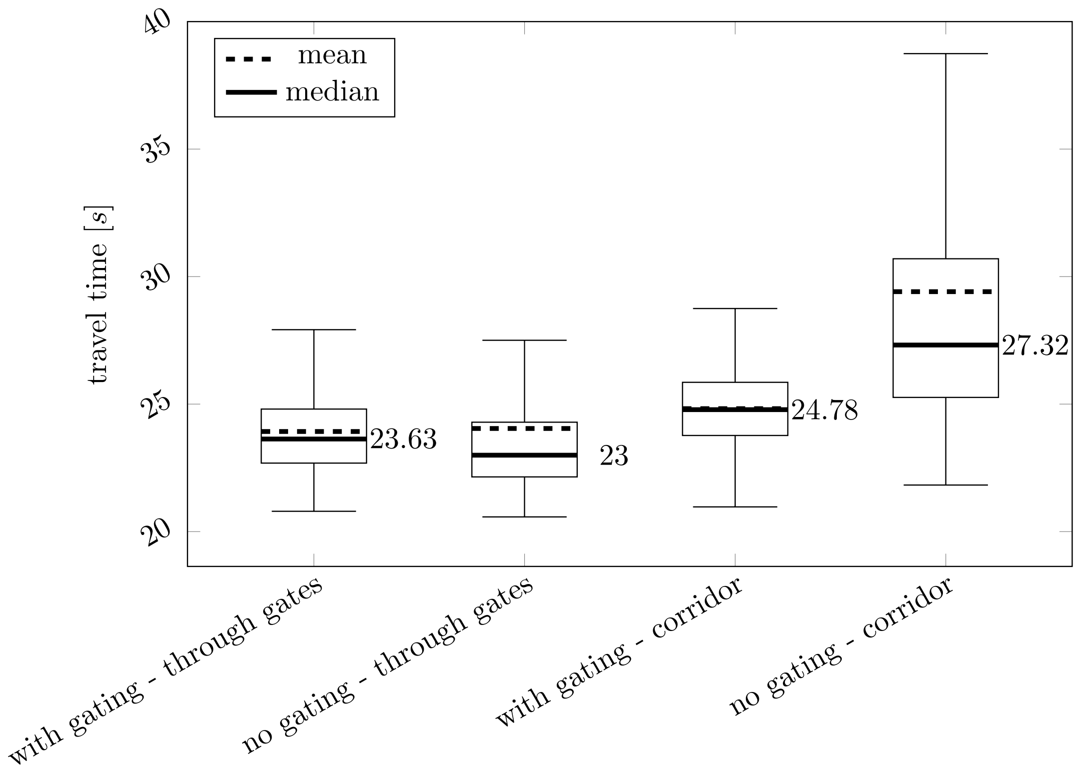


Figure 22: Distribution (500 replications) of the median travel time for both OD groups for both scenarios. Gating significantly improves the travel time for pedestrians walking along the main corridor.

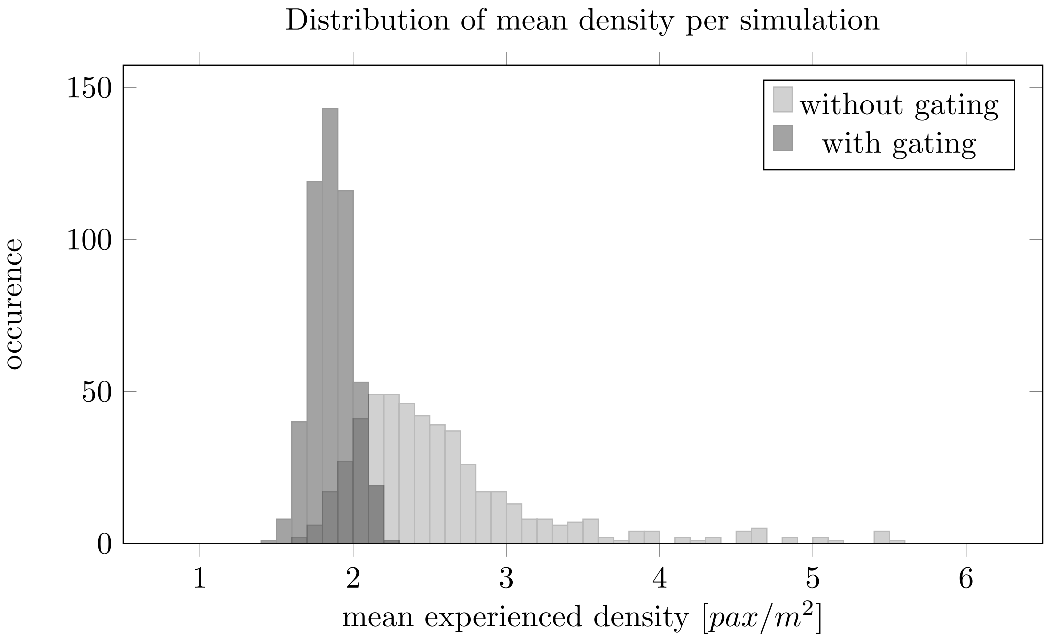


Figure 23: Distribution (500 replications) of mean individual density for both scenarios. Gating significantly reduces the density that pedestrians experience.

References

Abdelghany, A., Abdelghany, K., Mahmassani, H. S., and Al-Zahrani, A. (2012). Dynamic simulation assignment model for pedestrian movements in crowded networks. *Transportation Research Record*, 2316(1):95–105.

Aboudolas, K., Papageorgiou, M., Kouvelas, A., and Kosmatopoulos, E. (2010). A rolling-horizon quadratic-programming approach to the signal control problem in large-scale congested urban road networks. *Transportation Research Part C: Emerging Technologies*, 18(5):680–694.

Alahi, A., Vandergheynst, P., Bierlaire, M., and Kunt, M. (2010). Cascade of descriptors to detect and track objects across any network of cameras. *Computer Vision and Image Understanding*, 114(6):624 – 640. Special Issue on Multi-Camera and Multi-Modal Sensor Fusion.

Algadhi, S. A. and Mahmassani, H. S. (1990). Modelling crowd behavior and movement: application to makkah pilgrimage. *Transportation and traffic theory*, 1990:59–78.

Ali, M., Törn, A., and Viitanen, S. (2002). A direct search variant of the simulated annealing algorithm for optimization involving continuous variables. *Computers & Operations Research*, 29(1):87 – 102.

Antonini, G., Bierlaire, M., and Weber, M. (2006). Discrete choice models of pedestrian walking behavior. *Transportation Research Part B: Methodological*, 40(8):667 – 687.

Asano, M., Sumalee, A., Kuwahara, M., and Tanaka, S. (2007). Dynamic cell transmission–based pedestrian model with multidirectional flows and strategic route choices. *Transportation Research Record*, 2039(1):42–49.

Bauer, D., Seer, S., and Brändle, N. (2007). Macroscopic pedestrian flow simulation for designing crowd control measures in public transport after special events. In *Proceedings of the 2007 Summer Computer Simulation Conference*, SCSC '07, pages 1035–1042, San Diego, CA, USA. Society for Computer Simulation International.

Ben-Akiva, M., Bierlaire, M., Burton, D., Koutsopoulos, H. N., and Mishalani, R. (2001). Network state estimation and prediction for real-time traffic management. *Networks and Spatial Economics*, 1(3):293–318.

Ben-Akiva, M., Bierlaire, M., Koutsopoulos, H., and Mishalani, R. (1998). Dynamit: a simulation-based system for traffic prediction. In *DACCORD Short Term Forecasting Workshop*, pages 1–12.

Biedermann, D. H., Kielar, P. M., Handel, O., and Borrmann, A. (2014). Towards transitum: A generic framework for multiscale coupling of pedestrian simulation models based on transition zones. *Transportation Research Procedia*, 2:495 – 500. The Conference on Pedestrian and Evacuation Dynamics 2014 (PED 2014), 22-24 October 2014, Delft, The Netherlands.

Bierlaire, M. and Robin, T. (2009). Pedestrians choices. In *Pedestrian Behavior: Models, Data Collection and Applications*, pages 1–26. Emerald Group Publishing Limited.

Blue, V. J. and Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B: Methodological*, 35(3):293 – 312.

Bosina, E. (2018). *A New Generic Approach to the Pedestrian Fundamental Diagram*. PhD thesis, ETH Zurich, Zürich.

Burstedde, C., Klauck, K., Schadschneider, A., and Zittartz, J. (2001). Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A: Statistical Mechanics and its Applications*, 295(3):507 – 525.

Campanella, M., Halliday, R., Hoogendoorn, S., and Daamen, W. (2015). Managing large flows in metro stations: The new year celebration in copacabana. *IEEE Intelligent Transportation Systems Magazine*, 7(1):103–113.

Campanella, M., Hoogendoorn, S., and Daamen, W. (2009). Effects of heterogeneity on self-organized pedestrian flows. *Transportation Research Record: Journal of the Transportation Research Board*, (2124):148–156.

Campanella, M. C. (2016). Microscopic modelling of walking behaviour.

Chattaraj, U., Seyfried, A., and Chakroborty, P. (2009). Comparison of pedestrian fundamental diagram across cultures. *Advances in Complex Systems*, 12(03):393–405.

Chi, R., Hou, Z., Jin, S., Wang, D., and Hao, J. (2013). A data-driven iterative feedback tuning approach of alinea for freeway traffic ramp metering with paramics simulations. *IEEE Transactions on Industrial Informatics*, 9(4):2310–2317.

Daganzo, C. F. (1995a). The cell transmission model, part ii: Network traffic. *Transportation Research Part B: Methodological*, 29(2):79 – 93.

Daganzo, C. F. (1995b). A finite difference approximation of the kinematic wave model of traffic flow. *Transportation Research Part B: Methodological*, 29(4):261 – 276.

Daganzo, C. F. (2007). Urban gridlock: Macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological*, 41(1):49 – 62.

Danalet, A. (2015). Activity choice modeling for pedestrian facilities. page 188.

de Oliveira, L. B. and Camponogara, E. (2010). Multi-agent model predictive control of signaling split in urban traffic networks. *Transportation Research Part C: Emerging Technologies*, 18(1):120 – 139. Information/Communication Technologies and Travel Behaviour Agents in Traffic and Transportation.

de Palma, A. and Marchal, F. (2002). Real cases applications of the fully dynamic metropolis tool-box: An advocacy for large-scale mesoscopic transportation systems. *Networks and Spatial Economics*, 2(4):347–369.

Dia, H. (2002). An agent-based approach to modelling driver route choice behaviour under the influence of real-time information. *Transportation Research Part C: Emerging Technologies*, 10(5):331 – 349.

Dubroca-Voisin, M., Kabalan, B., and Leurent, F. (2019). On pedestrian traffic management in railway stations: simulation needs and model assessment. *Transportation Research Procedia*, 37:3 – 10. 21st EURO Working Group on Transportation Meeting, EWGT 2018, 17th-19th September 2018, Braunschweig, Germany.

Duives, D. C., Daamen, W., and Hoogendoorn, S. P. (2013). State-of-the-art crowd motion simulation models. *Transportation Research Part C: Emerging Technologies*, 37:193 – 209.

Farooq, B., Beaulieu, A., Ragab, M., and Dang Ba, V. (2015). Ubiquitous monitoring of pedestrian dynamics: Exploring wireless ad hoc network of multi-sensor technologies. In *2015 IEEE SENSORS*, pages 1–4.

Febbraro, A. D., Giglio, D., and Sacco, N. (2004). Urban traffic control structure based on hybrid petri nets. *IEEE Transactions on Intelligent Transportation Systems*, 5(4):224–237.

Fosgerau, M., Frejinger, E., and Karlstrom, A. (2013). A link based network route choice model with unrestricted choice set. *Transportation Research Part B: Methodological*, 56:70 – 80.

Frejo, J. R. D., Papamichail, I., Papageorgiou, M., and Schutter, B. D. (2019). Macroscopic modeling of variable speed limits on freeways. *Transportation Research Part C: Emerging Technologies*, 100:15 – 33.

Fruin, J. J. (1971). *Designing for pedestrians: A level-of-service concept*. Number HS-011 999.

Gartner, N. H., Pooran, F. J., and Andrews, C. M. (2001). Implementation of the opac adaptive control strategy in a traffic signal network. In *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No.01TH8585)*, pages 195–200.

Geroliminis, N. and Daganzo, C. F. (2008). Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological*, 42(9):759 – 770.

Guo, R.-Y., Huang, H.-J., and Wong, S. C. (2013). A potential field approach to the modeling of route choice in pedestrian evacuation. *Journal of Statistical Mechanics: Theory and Experiment*, 2013(02):P02010.

Hänseler, F. S. (2016). *Modeling and estimation of pedestrian flows in train stations*. PhD thesis, ENAC, Lausanne.

Hänseler, F. S., Bierlaire, M., Farooq, B., and Mühlematter, T. (2014a). A macroscopic loading model for time-varying pedestrian flows in public walking areas. *Transportation Research Part B: Methodological*, 69:60 – 80.

Hänseler, F. S., Bierlaire, M., Farooq, B., and Mühlematter, T. (2014b). A macroscopic loading model for time-varying pedestrian flows in public walking areas. *Transportation Research Part B: Methodological*, 69:60 – 80.

Hänseler, F. S., Lam, W. H., Bierlaire, M., Lederrey, G., and Nikolić, M. (2017a). A dynamic network loading model for anisotropic and congested pedestrian flows. *Transportation Research Part B: Methodological*, 95:149 – 168.

Hänseler, F. S., Molyneaux, N. A., and Bierlaire, M. (2017b). Estimation of pedestrian origin-destination demand in train stations. *Transportation Science*, 0(0):null.

Hassan, F. H., Swift, S., and Tucker, A. (2014). Using heuristic search with pedestrian simulation statistics to find feasible spatial layout design elements. *Journal of Algorithms*, 2(4):86–104.

Hegyi, A., Schutter, B. D., and Hellendoorn, H. (2005). Model predictive control for optimal coordination of ramp metering and variable speed limits. *Transportation Research Part C: Emerging Technologies*, 13(3):185 – 209.

Helbing, D. and Molnár, P. (1995). Social force model for pedestrian dynamics. *Phys. Rev. E*, 51:4282–4286.

Hoogendoorn, S. and Bovy, P. (2004a). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B: Methodological*, 38(2):169 – 190.

Hoogendoorn, S. P. and Bovy, P. H. (2004b). Dynamic user-optimal assignment in continuous time and space. *Transportation Research Part B: Methodological*, 38(7):571 – 592.

Hoogendoorn, S. P., van Wageningen-Kessels, F. L., Daamen, W., and Duives, D. C. (2014). Continuum modelling of pedestrian flows: From microscopic principles to self-organised macroscopic phenomena. *Physica A: Statistical Mechanics and its Applications*, 416:684 – 694.

Horni, A., Nagel, K., and Axhausen, K. W. (2016). *The multi-agent transport simulation MATSim*. Ubiquity Press London.

Janai, J., Güney, F., Behl, A., and Geiger, A. (2017). Computer vision for autonomous vehicles: Problems, datasets and state-of-the-art. *arXiv preprint arXiv:1704.05519*.

Janson, B. N. (1991). Dynamic traffic assignment for urban road networks. *Transportation Research Part B: Methodological*, 25(2):143 – 161.

Jenelius, E. and Koutsopoulos, H. N. (2013). Travel time estimation for urban road networks using low frequency probe vehicle data. *Transportation Research Part B: Methodological*, 53:64 – 81.

Jiang, Z., Fan, W., Liu, W., Zhu, B., and Gu, J. (2018). Reinforcement learning approach for coordinated passenger inflow control of urban rail transit in peak hours. *Transportation Research Part C: Emerging Technologies*, 88:1 – 16.

Kabalan, B., Leurent, F., Christoforou, Z., and Dubroca-Voisin, M. (2017). Framework for centralized and dynamic pedestrian management in railway stations. *Transportation Research Procedia*, 27:712 – 719. 20th EURO Working Group on Transportation Meeting, EWGT 2017, 4-6 September 2017, Budapest, Hungary.

Klein, L. A., Mills, M. K., Gibson, D. R., et al. (2006). Traffic detector handbook: Volume i. Technical report, Turner-Fairbank Highway Research Center.

Kotsialos, A., Papageorgiou, M., Mangeas, M., and Haj-Salem, H. (2002). Coordinated and integrated control of motorway networks via non-linear optimal control. *Transportation Research Part C: Emerging Technologies*, 10(1):65 – 84.

Lemer, G., Hochstaedter, A., and Kates, R. (2000). The interplay of multiple scales in traffic flow: coupling of microscopic, mesoscopic and macroscopic simulation. In *World Congress on Intelligent Trans-portation Systems, Torino*.

Levinson, D. (2003). The value of advanced traveler information systems for route choice. *Transportation Research Part C: Emerging Technologies*, 11(1):75 – 87.

Lighthill, M. J. and Whitham, G. B. (1955). On kinematic waves ii. a theory of traffic flow on long crowded roads. *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, 229(1178):317–345.

Loder, A., Ambühl, L., Menendez, M., and Axhausen, K. W. (2017). Empirics of multi-modal traffic networks – using the 3d macroscopic fundamental diagram. *Transportation Research Part C: Emerging Technologies*, 82:88 – 101.

Lu, Y., Seshadri, R., Pereira, F., OSullivan, A., Antoniou, C., and Ben-Akiva, M. (2015). Dynamit2.0: Architecture design and preliminary results on real-time data fusion for traffic prediction and crisis management. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pages 2250–2255.

Lämmer, S. and Helbing, D. (2008). Self-control of traffic lights and vehicle flows in urban road networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(04):P04019.

Mahmassani, H. and Herman, R. (1984). Dynamic user equilibrium departure time and route choice on idealized traffic arterials. *Transportation Science*, 18:362–384.

Mahmassani, H. S. (2001). Dynamic network traffic assignment and simulation methodology for advanced system management applications. *Networks and Spatial Economics*, 1(3):267–292.

Melotti, G., Premebida, C., d. S. Goncalves, N. M. M., Nunes, U. J. C., and Faria, D. R. (2018). Multimodal cnn pedestrian classification: A study on combining lidar and camera data. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 3138–3143.

Muñoz, J. C., Soza-Parra, J., Didier, A., and Silva, C. (2018). Alleviating a subway bottleneck through a platform gate. *Transportation Research Part A: Policy and Practice*, 116:446 – 455.

Newell, G. (2002). A simplified car-following theory: a lower order model. *Transportation Research Part B: Methodological*, 36(3):195 – 205.

Newell, G. F. (1998). The rolling horizon scheme of traffic signal control. *Transportation Research Part A: Policy and Practice*, 32(1):39–44.

Ng, K. M., Reaz, M. B. I., and Ali, M. A. M. (2013). A review on the applications of petri nets in modeling, analysis, and control of urban traffic. *IEEE Transactions on Intelligent Transportation Systems*, 14(2):858–870.

Ngai, K. M., Burkle, F. M., Hsu, A., and Hsu, E. B. (2009). Human stampedes: A systematic review of historical and peer-reviewed sources. *Disaster Medicine and Public Health Preparedness*, 3(4):191–195.

Nikolić, M. and Bierlaire, M. (2014). Pedestrian-oriented flow characterization. *Transportation Research Procedia*, 2:359 – 366.

Nikolić, M. and Bierlaire, M. (2018). Data-driven spatio-temporal discretization for pedestrian flow characterization. *Transportation Research Part C: Emerging Technologies*, 94:185 – 202. ISTTT22.

Papageorgiou, M., Diakaki, C., Dinopoulou, V., Kotsialos, A., and Yibing Wang (2003). Review of road traffic control strategies. *Proceedings of the IEEE*, 91(12):2043–2067.

Papageorgiou, M., Hadj-Salem, H., and Blosseville, J.-M. (1991). Alinea: A local feedback control law for on-ramp metering. *Transportation Research Record*, 1320(1):58–67.

Papageorgiou, M., Hadj-Salem, H., and Middelham, F. (1997). Alinea local ramp metering: Summary of field results. *Transportation Research Record*, 1603(1):90–98.

Papageorgiou, M., Papamichail, I., Messmer, A., and Wang, Y. (2010). *Traffic Simulation with METANET*, pages 399–430. Springer New York, New York, NY.

Peeta, S. and Mahmassani, H. S. (1995). Multiple user classes real-time traffic assignment for online operations: a rolling horizon solution framework. *Transportation Research Part C: Emerging Technologies*, 3(2):83–98.

Peeta, S. and Ziliaskopoulos, A. K. (2001). Foundations of dynamic traffic assignment: The past, the present and the future. *Networks and Spatial Economics*, 1(3):233–265.

Robin, T., Antonini, G., Bierlaire, M., and Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research Part B: Methodological*, 43(1):36 – 56.

Scarinci, R., Markov, I., and Bierlaire, M. (2017). Network design of a transport system based on accelerating moving walkways. *Transportation Research Part C: Emerging Technologies*, 80:310 – 328.

Seriani, S. and Fernandez, R. (2015). Pedestrian traffic management of boarding and alighting in metro stations. *Transportation Research Part C: Emerging Technologies*, 53:76 – 92.

Shende, A., Singh, M. P., and Kachroo, P. (2011). Optimization-based feedback control for pedestrian evacuation from an exit corridor. *IEEE Transactions on Intelligent Transportation Systems*, 12(4):1167–1176.

Stubenschrott, M., Kogler, C., Matyus, T., and Seer, S. (2014). A dynamic pedestrian route choice model validated in a high density subway station. *Transportation Research Procedia*, 2:376 – 384. The Conference on Pedestrian and Evacuation Dynamics 2014 (PED 2014), 22-24 October 2014, Delft, The Netherlands.

Teknomo, K. (2006). Application of microscopic pedestrian simulation model. *Transportation Research Part F: Traffic Psychology and Behaviour*, 9(1):15 – 27.

Tolujew, J. and Alcalá, F. (2004). A mesoscopic approach to modeling and simulation of pedestrian traffic flows. In *Proceedings of the 18th European Simulation Multiconference*, pages 123–128.

Varaiya, P. (2013). Max pressure control of a network of signalized intersections. *Transportation Research Part C: Emerging Technologies*, 36:177 – 195.

Wang, Y. and Papageorgiou, M. (2005). Real-time freeway traffic state estimation based on extended kalman filter: a general approach. *Transportation Research Part B: Methodological*, 39(2):141 – 167.

Weidmann, U. (1993). Transporttechnik der fußgänger: transporttechnische eigenschaften des fußgängerverkehrs, literaturauswertung. *IVT Schriftenreihe*, 90.

Xiong, M., Cai, W., Zhou, S., Low, M. Y. H., Tian, F., Chen, D., Ong, D. W. S., and Hamilton, B. D. (2009). A case study of multi-resolution modeling for crowd simulation. In *Proceedings of the 2009 Spring Simulation Multiconference*, page 17. Society for Computer Simulation International.

Xiong, M., Lees, M., Cai, W., Zhou, S., and Low, M. Y. H. (2010). Hybrid modelling of crowd simulation. *Procedia Computer Science*, 1(1):57 – 65. ICCS 2010.

Zhang, J., Klingsch, W., Schadschneider, A., and Seyfried, A. (2012). Ordering in bidirectional pedestrian flows and its influence on the fundamental diagram. *Journal of Statistical Mechanics: Theory and Experiment*, 2012(02):P02002.

Zhang, J. and Seyfried, A. (2014). Comparison of intersecting pedestrian flows based on experiments. *Physica A: Statistical Mechanics and its Applications*, 405:316 – 325.

Zhang, Y., Atasoy, B., Akkinepally, A., and Ben-Akiva, M. (2019). Dynamic toll pricing using dta system with online calibration. *Transportation Research Record Journal of the Transportation Research Board*.

Zhang, Y., Su, R., and Zhang, Y. (2017). A macroscopic propagation model for bidirectional pedestrian flows on signalized crosswalks. pages 6289–6294.

Zhang, Z., Jia, L., and Qin, Y. (2016). Level-of-service based hierarchical feedback control method of network-wide pedestrian flow. *Mathematical Problems in Engineering*, 2016.

Zhang, Z., Wolshon, B., and Dixit, V. V. (2015). Integration of a cell transmission model and macroscopic fundamental diagram: Network aggregation for dynamic traffic models. *Transportation Research Part C: Emerging Technologies*, 55:298 – 309. Engineering and Applied Sciences Optimization (OPT-i) - Professor Matthew G. Karlaftis Memorial Issue.