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Assessment of passenger management strategies within major railway terminals

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ABSTRACT

This paper addresses the problem of passenger flow management in major public transport terminals by proposing a new modeling approach for passenger flows management. Currently, passenger management is done based on the experience of station managers, while existing models generally view the passenger flows as continuous. In contrast, this research proposes modeling the flows of passengers as discrete, according to the behavior of passengers in major transport terminals with non-fixed platform allocation. The problem is modeled as mixed-integer linear programming (MILP) inspired by the alternative graph (AG) model. The case study results show that the model can be used to assess and compare passenger management strategies, for instance, the morning peak case study results show that 578 s of conflict which occur in one strategy can be traded off with 78 s of total tardiness by applying a different strategy. This model can be used to support station managers in assessing complex situations before making management decisions.

1. Introduction

Public transport systems in large cities are becoming more and more overcrowded (UITP, 2015, 2018) as the number of passengers has been constantly increasing (Eurostat, 2019; ORR, 2020). Whilst modern communication and control systems allow operators to run high-frequency services, it is difficult to increase the passenger capacity of transport termini in city centers due to several reasons (Oberlander, 2014). As a consequence, such stations may become severely overcrowded especially during peak hours or in the case of disruptions. In the case of railways in London, the number of passengers was reported to exceed the station capacity by 5 percent on average and by almost 10 percent at King's Cross (DfT, 2018). Additionally, more retail facilities have been installed in public transport stations, since retail sales and rent are major sources of revenue (ORR, 2018), and this contributes to the reduction of capacity, therefore worsening the overcrowded situation. Although the passenger demand decreased after the COVID-19 pandemic, the number is steadily recovering. While a certain portion of people may work at home, but as long as cities and their economy grow (and companies want employees back to their offices), crowding problems would come back at some points. To mitigate the overcrowding issues and maximize space utilization of these transport termini, it is necessary that passenger flows in stations are managed efficiently.

To effectively manage the passenger flows in public transport stations, it is important that passengers are able to safely navigate the station in a shortest time possible. This involves minimizing passenger density by separating passenger flows to prevent overcrowding situations. Existing guidelines on crowd management stress the importance of mitigating high-density conditions and

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preventing bi-directional and intersecting flows, emphasizing the necessity to segregated passenger flows (RSSB, 2020, 2009, 2007; NetworkRail, 2016). In practice, passenger management decisions are generally made by experienced station managers. However, in complex situations, a decision-support tool is sought after to allow the station managers to make more informed and effective decisions. Indeed the station overcrowding incident at the London Bridge station in 2015 highlighted the necessity for such a tool (ORR, 2015). Therefore, this study aims to develop a decision-support tool for the station managers. The passenger management problem is conceptualized as a resource allocation problem, specifically allocating time slots for each passenger group to occupy each area such that the flows are separated.

Based on our comprehensive literature review (Sections 2.2 and 2.4), there exist numerous passenger modeling tools, broadly categorized as microscopic and macroscopic models. While microscopic models can be used to assess passenger dynamics in many scenarios, they are unsuitable for addressing resource allocation problems due to their high computational demands. Executing a single scenario using microscopic models requires a considerable amount of time; therefore, an alternative approach is necessary for conducting comparisons across multiple scenarios. Conversely, macroscopic models require considerably less time to generate results, enabling the comparison of various scenarios within a limited time frame. Additionally, macroscopic models serve as the foundation for many studies on passenger flow/demand management.

However, these macroscopic passenger flow/demand management tools generally perceive passenger flows as continuous, i.e. evenly distributed over time (yue Xu et al., 2016; Xu et al., 2019; Wang et al., 2015b; Li et al., 2017; Niu and Zhou, 2013; Jiang et al., 2017; Solak et al., 2009; Wu and Mengersen, 2013). This assumption may only be appropriate for stations where platforms/boarding points are always the same (e.g. metro and urban railway stations). In such cases, passengers are familiar with the platform allocation and will proceed immediately upon arrival at stations, resulting in a continuous flow of passengers.

In contrast, there are stations where platform or boarding point allocations are not fixed, such as mainline railway termini. In these stations, passengers typically wait at designated locations, such as concourses, until directed (via platform numbers or boarding bay announcements). Once such directions are given, passengers heading for the same service move almost simultaneously toward the platform or boarding point, resulting in a pocket of high density, where passengers move collectively as a group rather than being uniformly distributed over time. Similarly for arrival passengers, as upon disembarking, they promptly proceed to the station exit. In this study, we characterize this type of passenger flow as discrete, involving passenger movement as a group. It is envisaged that this flexible platform allocation would be adapted by more stations, as the number of services (and destinations) would increase to accommodate passenger demand, while the stations cannot easily be expanded. As the existing passenger flow/demand management tools may not be suitable for these type of flow, this study aim to address this gap by proposing a new modeling method for supporting passenger management decisions, where passenger flows are seen as discrete. To our knowledge, this will be the first passenger flow management tool where the flows of passengers are viewed as discrete. Although the case study focuses on a railway station, the proposed tool is designed to be applicable to any transportation facility exhibiting similar passenger behavior, particularly those where departures and arrivals occur at irregular intervals and the boarding point allocations are not fixed.

Besides separating the flow of passengers, there are also others *regulation measures* which should be followed to ensure an adequate safety level in the stations and to maintain a good quality of service (De Oña and De Oña, 2015; Nathanail, 2008). Ideally, all the regulation measures should be followed; hence, we formulate the passenger management problem as a constraint satisfaction problem (CSP). However, in many situations, it may not be possible to satisfy all regulation measures (because of, for example, lack of physical space inside the station), and therefore some regulation measures need to be relaxed. In such case, the problem is turned into a job shop scheduling problem (JSP).

We chose to formulate both CSP and JSP as a mixed-integer linear programming (MILP) problem, inspired by the Alternative Graph (AG) model. This method allows us to model the necessary constraints and regulation measures, while it also gives us flexibility. It was used in Corman et al. (2017), Corman (2020), where the authors study the integration of the real-time train scheduling problem with the passenger delay management problem. Additionally, the AG has been successfully adopted for several production scheduling and transport scheduling problems, e.g. railway scheduling problems (D'Ariano et al., 2007, 2014; Corman et al., 2010; Samà et al., 2017b) and air traffic management (Samà et al., 2013, 2017c,a). Additionally, while the AG is used by limited number of researchers, the MILP is widely used for transport planning problems (Wang et al., 2013; Luathep et al., 2011; Sartor et al., 2023). By solving the MILP, the timings for each group proceeding through each area of the station are obtained, according to the specified strategies (which regulation measures are followed and which are relaxed). It also allows us to assess the results of the specified strategies in terms of key performance indicators (KPIs).

This paper is composed of six sections. Section 2 provides a review of literature related to this study, while the research gaps and the contribution of this study are also presented. Section 3 describes the passenger management problem and introduces definitions of *constraints* and *regulation measures*. We also introduce the concept of regulation measure relaxation and passenger management strategies. KPIs to be used in the evaluation of the results are also defined. Section 4 presents how the passenger management problem is formulated as CSP and JSP using the MILP and AG models. Section 5 presents the results of our London Euston station case studies, where we assess the result of applying each strategy to instances of real-world problems using the proposed tool. Finally, in the last section, the conclusion and the future work to be done are presented.

2. Literature review

There are four distinct areas of research that are related to the field of passenger management in transport stations. The first is research on *pedestrian dynamics and behavior*, which focuses on pedestrian and crowd dynamics and the influential factors on their behavior. Secondly, *pedestrian modeling*, where mathematical models are developed to simulate and describe pedestrian dynamics and behavior. The third area studies *crowd management measures* which is the area used in practice to manage passenger crowds in transport stations. The last is research on *passenger flow/demand management* where tools are developed to tackle the varying demands of passengers in transport stations (mainly railway stations).

2.1. Pedestrian dynamics and behavior

In this research area, the pedestrian speed–flow–density relationship, also known as *fundamental relationship*, has been widely studied (Fruin, 1971; Virkler and Elayadath, 1992; Wong et al., 2010; Daamen and Hoogendoorn, 2003). According to the fundamental relationship, the density of pedestrians has a great influence on their walking speed. In higher-density situations, there is less available space for each pedestrian which reduces their ability to walk freely and makes overtaking very difficult.

Additionally, in situations where there is a merge of pedestrian flow, the walking speed could be affected significantly (Shi et al., 2016). Simulation (Tajima and Nagatani, 2002; Craesmeyer and Schadschneider, 2014) and empirical studies (Shiwakoti et al., 2015; Zhang et al., 2011) results suggested that merging of pedestrian flows could lead to congestion and clogging. This is especially in the case where the merging flows are bi-directional (Lam et al., 2003; Liu et al., 2014; Flötteröd and Lämmel, 2015). The RSSB (2019, 2005) suggested that a bi-directional conflict situation could become severe enough to be a passenger safety risk, especially near stairs and escalators (Atkins, 2009). According to LU (2019) and NetworkRail (2011), the passenger flow in two-way passageways is approximately 20 percent lower than in one-way passageways. Additionally, the ability to evacuate during emergency situations would be reduced (Zhou et al., 2014; Vermuyten et al., 2016). Conflicting flows could also create confusion, especially for those who are not familiar with the station, e.g. passengers may follow the wrong group and go to the wrong platform. In situations where there is a risk of contagion of infectious diseases such as COVID-19, conflicting flows could also accelerate the spreading of the diseases.

2.2. Pedestrian modeling

Various mathematical models have been developed to describe pedestrian behavior. Two main categories exist: microscopic models, where each pedestrian is seen as a single entity, and macroscopic models, where pedestrians are treated as a whole.

Within microscopic models, three types are widely used: cellular automata (CA) (Blue and Adler, 2001; Klüpfel et al., 2001; Schadschneider, 2001), agent-based (Crooks et al., 2008; Bonabeau, 2002; Chooramun et al., 2012) and social force models (Helbing and Molnár, 1995, 1997). Microscopic models are used in several research papers to study passengers' behavior in transport facilities, for instance, to study the interaction among passengers inside transport facilities (Zhang et al., 2008; Davidich et al., 2013), assess the influence of station design on passengers (Tang and Hu, 2017; Rindsfüser and Klügl, 2007; Mekić et al., 2021; King et al., 2014; Seriani and Fernández, 2015) and simulate evacuation scenarios (Wan et al., 2014; Lei et al., 2012; Zhang et al., 2016). Although microscopic models allow a very detailed analysis on each individual pedestrian and the interactions among them, they often require considerable computation time and effort. Therefore, they are not suitable for assessing many scenarios (Hamacher and Tjandra, 2002).

In macroscopic models, the crowd are view as a whole rather than as individuals, where their properties are based on the fundamental relationship. The most widely used macroscopic model is the continuum model (Hughes, 2002; Huang et al., 2009; Twarogowska et al., 2014). As the macroscopic models do not capture each individual pedestrian's behavior, they do not require as much computational effort as the microscopic models. They can produce results in a shorter period of time. The macroscopic models are often used as descriptive models, e.g. to determine the throughput of pedestrians, identify the bottleneck(s) of the facility and determine the density distribution of pedestrians. The macroscopic models are the basis of many studies on passenger flow control inside transport facilities, especially in railway stations (Xu et al., 2019; Li et al., 2017; Wang et al., 2015b; Solak et al., 2009).

2.3. Crowd management measures

There are a number of existing passenger management measures typically used by railway practitioners. Hoogendoorn (2010) classified these measures into four categories: blockage prevention, traffic distribution, inflow limitation and increase of flow. Blockage prevention involves measures such as segregating activities to prevent obstructions in walking routes and separating cross flows between passengers. Flow enhancement strategies focus on identifying infrastructure bottlenecks and implementing appropriate mitigation measures. Passenger distribution can be done over space, by distributing passengers to less crowded areas, and over time, by staggering passenger flow across different time periods. Finally, it is crucial to limit the inflow of passengers to ensure that the density remains below critical levels. On the other hand, Oberlander (2014) classified the passenger management measures into two categories: permanent measures, e.g. route setting, escalator configuration and signage position, and temporary measures, e.g. closing a passage, holding passengers and limiting inflow.

The aims of these measures are to ensure adequate safety levels and to efficiently manage the flow of passengers through the station. However, some of these measures, e.g. limiting inflow and passenger holding, may affect the station quality of service (Wang et al., 2015c); therefore, they must be implemented carefully. While there is sufficient assessment time for permanent measures application, temporary measures are often implemented at an operational level which requires rapid decision. To support these decisions, passenger flow/demand control models are developed, which will be discussed in the next section.

2.4. Passenger flow/demand management

There are mainly two streams of research in the field of passenger flow/demand management: *train scheduling/rescheduling*, which focuses on developing responsive strategies for train service scheduling/rescheduling based on varying passenger demand, while *passenger flow control* focuses on determining passenger flow control strategies in railway stations.

In the field of train scheduling/rescheduling in mainline railway systems, Corman et al. (2017), Corman (2020) are among the first to integrate the problem of passenger delay management with real-time train scheduling problems. For metro and urban railway systems, many studies has been conducted on developing a responsive timetable, where the train schedules are adjusted according to the varying passenger demand (Wang et al., 2015a, 2018; Barrena et al., 2014; Niu and Zhou, 2013; Niu et al., 2015; Sun et al., 2014; Gao et al., 2016; Yin et al., 2021; Pan et al., 2023; Li et al., 2023).

While train scheduling/rescheduling can be effective, in a network where trains are already operating at the maximum frequency, passenger flow control in the stations is still necessary. Responsive passenger flow control strategies are studied in yue Xu et al. (2016), Li and Zhou (2013), yue Xu et al. (2014), Zhang et al. (2021), where the inflow of passengers is controlled according to the train service frequency and the number of passengers in each area of the station. Several research studies have also been done on coordinating passenger flow control in multiple stations, i.e. at line level and at network level (Xu et al., 2019; Wang et al., 2015b; Gao et al., 2020; Yuan et al., 2022; Liu et al., 2020). Additionally, Li et al. (2017), Jiang et al. (2017), Lu et al. (2022) present integrated strategies that combine both a train scheduling/rescheduling approach and a passenger flow control approach.

2.5. Summary

The pedestrian dynamics and behavior studies (Section 2.1) provide us with the basis of how to maximize pedestrian flows and which situations should be avoided. To manage the passenger flow accordingly, pedestrian models can be used to assess passenger behavior. Our literature review (Section 2.2) shows that, while microscopic pedestrian models can well describe passenger behavior in a large and complex station, due to their computationally resource-expensive nature, they are not able to assess many scenarios in a short time. Therefore, for the existing responsive passenger flow management tools, macroscopic approaches are adopted. However, these existing tools generally view the flow of passengers as a continuous flow, which can be an appropriate assumption only for stations with fixed platforms. A different approach is required for a more complex station, with multiple service patterns and large facilities, where passenger flows are better viewed discretely.

In practice, there have been many approaches to passenger crowd management (Section 2.3), but the implementation of these approaches is often based on the experience of station managers and on anecdotal evidence. Therefore, a tool that allows systematic evaluation in a computationally and resource-wise efficient way is required to support decisions. With such a tool, the operation of crowd management at the station level can be more efficient, i.e. station managers are able to compare several strategies within a short amount of time.

Although various tools have been developed for passenger flow management in public transport stations (Section 2.4), they typically model passenger flow as continuous, a perspective that is applicable only to certain types of stations. This research aims to address this gap by proposing a new pedestrian modeling approach, which can be used as a decision support tool for passenger flow management in complex public transport stations/hubs. The contributions of this paper are as follows:

- A decision support tool for passenger flow management in complex transport stations is presented in this paper. The purpose is to support station managers in making more informed and efficient management decisions.
- We present a new pedestrian modeling approach that discretizes the flows of pedestrians. The MILP model, which is inspired by AG, is used to model pedestrian flows.

3. Problem description

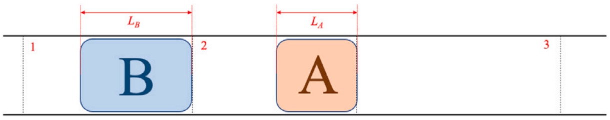
3.1. Passenger management problem

In stations where platform assignments are not predetermined, as discussed in Section 1, passenger flow distribution tends to be uneven. Although there may be variations in walking speeds among individual passengers within each group, the majority of each group would walk at a relatively consistent speed. The majority of passengers in each group can be regarded as concentrated areas of high density. It is these high-density pockets which will be mainly focused on, due to their critical role in generating congestion. The objective of this study is to avoid merging among these high-density pockets.

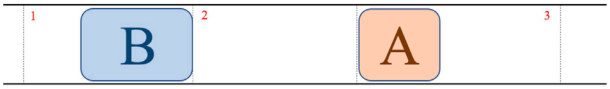
It is assumed that passengers will only travel between the concourse and the platforms, while transferring passengers are ignored for simplification purposes. Our objective is to guide passengers along the shortest and most direct route by minimizing resistance along this pathway.

This study divides the station into a number of areas, requiring each group to traverse a predefined sequence of areas. To enforce this condition, *constraints* are integrated into the formulation, ensuring adherence to the specified sequence of areas by passengers.

There are also constraints associated with the travel time of each group of passengers. The travel time can be divided into two major components: *passing time* and *clearing time*. The passing time is the time required for the first passenger of each group to traverse a specific area, while the clearing time is the time needed for the rest of the group to exit from that area. For instance, Fig. 1 illustrates two groups of passengers A and B traveling in the same direction through areas 1, 2 and 3. In Fig. 1(a) passenger group



(a) Passenger group A starting to enter area 3.



(b) All of passenger group A has exited from area 2.

(c) Passenger group A reaches the end of area 3.

Fig. 1. Two groups of passengers traveling in the same direction.

A has reached the end of area 2, while in Fig. 1(b) all passengers in group A have exited from area 2. The elapsed time between these two events is the clearing time of passenger group A from area 2. Fig. 1(c) shows passenger group A reaching the end of area 3. The elapsed time from Fig. 1(a) to Fig. 1(c) is the passing time required for passenger group A to traverse through area 3.

In this study, we also assume that passengers are walking at a constant speed v. The passing time p can be calculated as $p = l/v$, where l is the length of the corresponding area. To calculate the clearing time c, we first need to calculate the length of passenger group L (the distance from the first to the last passengers in a group denoted as L_A and L_B in Fig. 1(a)). The passenger group length L can be calculated as $L = n/(d \times w)$, where n is the number of passengers in the group, w is the corridor width and d is the passenger density. The clearing time can then be calculated as $c = L/v$.

It is necessary that these constraints are always followed, to keep the model accurate and realistic. Besides these constraints, there are also *regulation measures*, which are set out to ensure passenger safety and good quality of service (according to passenger management guidelines as reviewed in the Literature Review Section), as follows:

(A) *No-delay*: For each departing passenger group, we consider a *due date* which represents the scheduled departure time of the relevant train service. To maintain punctuality and service reliability, passengers should arrive at the platform and finish boarding before their due date.

(B) *No-conflict*: When more than one group of passengers are in the same area at the same time, they are considered as conflicting flows. To avoid such situations, we established that each area should host at most one group of passengers at a time, except the concourse.

(C) *No-holding*: Unlike train control systems, holding passengers in specific locations along their path presents a considerable challenge; thus, they will promptly move to the subsequent area upon reaching the end of one. While various methods, such as employing temporary barriers, may exist to detain passengers momentarily, such practices are not practical and are excluded from this study. Furthermore, while retaining passengers on-board after their arrival at the station is feasible, doing so could result in frustration and significantly affect passenger satisfaction. Therefore, passengers should be able to alight as soon as they arrive, without being held.

(D) *No-early*: On the platforms, there is a risk of a passenger falling onto the tracks, especially if the platform is crowded. Many other operation activities may take place before departure, such as cleaning, catering and other service setups. These activities sometime require the use of trolleys or small vehicles. Therefore, for safety purposes, passengers should not be allowed on the platform much earlier than the departure time. As it is assumed that passengers will start proceeding to the platform as soon as the platform number is announced, the announcement should not be made earlier than a predetermined time, although it should provide sufficient time for passengers to travel from the concourse to their platform.

Ideally, passenger flows should be managed in a way that all constraints and regulation measures are followed. While permanent measures could be applied, temporary measures are also necessary. According to an interview with the Gare Saint-Lazare (Paris) station manager, platform number announcement times can be used as an effective tool to control the passenger flows. In the context of mainline railway terminal stations, the announcement time would be the time at which each group should start proceeding from the concourse to their platforms. Therefore, we define the passenger management problem as a problem of assigning the appropriate platform number announcement time, in a way that satisfies all constraints and regulation measures.

3.2. Passenger management strategies and key performance indicators

Ideally, passengers should be managed according to all regulation measures. Unfortunately, there are many situations in which it is not possible to satisfy all of them. For instance, let us consider the example in Fig. 2. We have a railway station with four

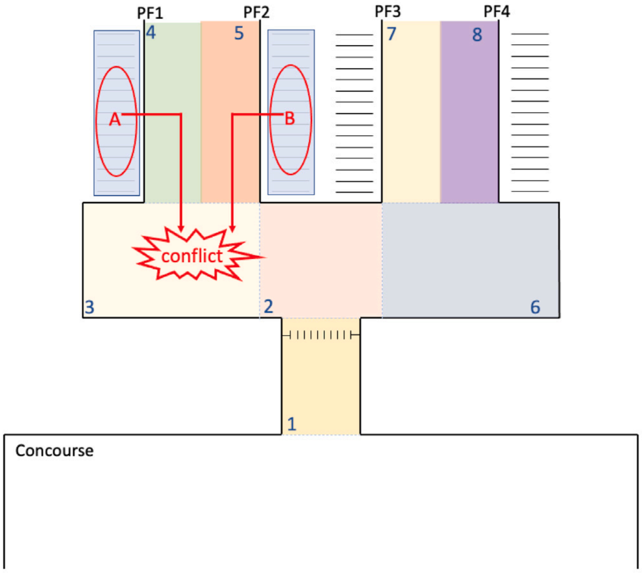


Fig. 2. Impasse situation.

platforms. The station is divided into 8 areas. We consider the case in which two trains are arriving at the same time on nearby platforms, i.e. platforms 1 and 2. If both groups alight immediately, they will both reach area 3 at the same time, thus causing a conflict. One possible way to avoid such a conflict is to hold one of the groups; however, it would violate the no-holding regulation measure. These situations are defined as *impasse situations*, in which it is not possible to follow all regulation measures.

When there is an impasse situation, regulation measures may be relaxed to provide an alternative solution. We define *passenger management strategies* to describe how passengers could be managed, i.e. which regulation measures are followed and which are relaxed. The following is the description of each passenger management strategy (including *conventional practice* and *ideal practice*):

(i) *Conventional Practice*: This strategy is used to represent how stations are conventionally managed, i.e. without a supporting tool. Specifically, platform numbers usually are announced when the train is ready for passengers to board. To represent this, it is assumed that all platform numbers are announced before their scheduled departure time for a certain amount of time. This time maybe vary for each service depending on several factors.

(ii) *Ideal Practice*: Ideally, passengers should be managed in a way that all constraints and regulation measures are followed.

(iii) *Allowing Delay*: In this study, the platform number announcement time is utilized as a means to regulate passenger movement. By relaxing the *no-delay* regulation measure, it permits passengers to be held in the concourse area for an extended period. However, this could result in passengers not being able to board the train on time, i.e. delay.

(iv) *Allowing On-board Holding*: Using the platform number announcement time only allows us to control the departing passenger groups. One possible location which we could control the arrival groups is on-board before they start to alight. This can be done by keeping the doors closed, or having the driver approach the station slower. However, this would create frustration and reduce passenger satisfaction; therefore, the holding time should be limited to a certain amount, e.g. 60 s.

(v) *Allowing Early Announcement*: Limiting the earliest announcement time restricts how passengers could be managed. To allow more flexibility, the *no-early* regulation measure can be relaxed. However, if it is relaxed entirely, it would result in higher safety risk from passengers being on platforms too early. Therefore, the limitation is only relaxed to a certain level, i.e. allowing the announcement to be made earlier.

(vi) *Allowing Pre-Loading*: In the case where a platform area is large enough, it could be allowed to accommodate two groups of passengers at the same time. If this is allowed, i.e. the *no-conflict* regulation measure is relaxed for a platform area, boarding passengers may be able to wait in the designated area on the platform. As soon as the alighting group finishes alighting, boarding passengers can then board promptly. However, to allow boarding passengers to be on the platform earlier, the *no-early* regulation measure has to be relaxed as well.

Table 1 shows for each strategy which regulation measures are followed (✓) and which are relaxed (×). The proposed passenger management decision support tool would suggest the time and sequence in which each group of passengers should proceed through the station (controlled by the platform number announcement time) according to each strategy.

Even though regulation measures may be relaxed, breaches of regulation measures should still be kept at a minimum. To measure how much each regulation measure is breached, we define four KPIs that correspond to each regulation measure. The higher the KPIs value, the greater the breach in that aspect. The four KPIs are:

Table 1
Passenger management strategies.

Strategies	Regulation measures				
	(A)	(B) No-conflict		(C)	(D)
	No-delay	Uni-directional	Bi-directional	No-early	No-holding
(i) Conventional practice	✓	×	×	✓	✓
(ii) Ideal practice	✓	✓	✓	✓	✓
(iii) Allowing delay	×	✓	✓	✓	✓
(iv) Allowing on-board holding	×	✓	✓	✓	×
(v) Allowing early announcement	×	✓	✓	×	✓
(vi) Allowing Pre-loading	×	✓	×[a]	×	✓

✓: that regulation measure is followed, × : that regulation measure is relaxed.
[a] Bi-directional conflicts are only allowed on the platform.

- *Total tardiness* (TT): The total amount of time that each service departs after the scheduled departure time.
- *Conflict time*: The total amount of time that more than one group of passengers are in the same area at the same time. Uni-directional conflict and bi-directional *conflict time* can be measured separately.
- *On-board holding time*: The total amount of time that passengers are held on-board after they have reached their platforms.
- *Earliness*: How much earlier the platform number announcements are made, compared to the limitation of the case in which the *no-early* regulation measure is not relaxed.

Regarding *conflict time*, bi-directional conflicts are significantly more severe than uni-directional conflicts, as discussed in the literature review. Therefore, we measured them separately. Additionally, it should be noted that, while conflicts at different locations within the station may have varying impacts, this aspect falls outside the scope of the present study.

4. Problem formulation

To manage the passengers according to the *(ii) ideal practice*, the passenger management problem can be seen as a scheduling problem, where all constraints and regulation measures must be satisfied. Hence, it can be considered as a CSP.

Specifically, we consider each group of passengers as a *job* J_i, and the spaces that passengers can occupy, i.e. station areas, trains and track sections, as *resources*. An *operation* o_i, represents a utilization of a resource by a job, e.g. a group of passengers traverse through an area and passengers boarding/alighting a train. As each group needs to travel through a specific sequence of areas, each job would contain a set of operations which has to be processed in a specific sequence.

The variables related to this CSP are the *start time* t_i of each operation o_i and decision variables, which relay the order between pairs of operations on a common resource. The time variables are continuous variables, while the decision variables are binary. The solution to the CSP is the set of values to these variables which is in compliance with all constraints and regulation measures.

We model the CSP using the MILP formulation of an AG model, which composed of three sets: *node* N, *fixed directed arcs* F and *alternative pairs* A. The set of nodes N contains variables which are related to the start time of operations. The set of fixed arcs F contains constraints related to the order in which the operations must be done and the time required. The set F also contains other types of constraints, e.g. *releases*, *deadlines*, *due dates* and *no-holding* regulation measures. The set of alternative pairs A contains sequencing decision variables.

Each node $i \in N$ is associated with the start time t_i of operation o_i. In our case, the start time t_i can refer to the time that a group of passengers starts entering an area, starts boarding a train and arrives at/departs the station on a train. There is also a *start node* 0 which is used to represent the start of a schedule: $t_0 = 0$.

A fixed directed arc $(i, \sigma(i)) \in F$ represents an order in which the operations are done and the time required. Let node i and $\sigma(i)$ be the entrance operations of a certain group in two subsequent areas. The arc length f_i of arc $(i, \sigma(i)) \in F$ represents the minimum separation between t_i and $t_{\sigma(i)}$. Arc $(i, \sigma(i)) \in F$ is illustrated as shown in Fig. 3. As passing time p_i is required for passengers from when they enter the first area until they reach the subsequent area, as depicted in Fig. 4, the length of arc $(i, \sigma(i)) \in F$ is p_i, i.e. $t_{\sigma(i)} \geq t_i + p_i$.

According to the *no-holding* regulation measure, passengers would start entering the subsequent area immediately as soon as they reach the end of the first area. It can be implied that the passing time is also a maximum separation between t_i and $t_{\sigma(i)}$. This can be formulated as arc $(\sigma(i), i)$ of length $-p_i$, i.e. $t_{\sigma(i)} \leq t_i + p_i$. The *no-holding* regulation measure is obtained by using the two arcs $(i, \sigma(i)) \in F$ and $(\sigma(i), i) \in F$, as illustrated in Fig. 5.

For a departing group, if node i represents when passengers start boarding the train, the subsequent node $\sigma(i)$ would correspond to the train departure. The length of arc $(i, \sigma(i)) \in F$ would be the time required for passengers to board the train.

As the start node 0 represents the start of a schedule, a fixed arc from node 0, i.e. $(0, i) \in F$, with length r_i represents the earliest time that o_i can start compare to the start time of the schedule, i.e. $t_i \geq r_i$. We define the arc $(0, i) \in F$ as a *release arc*. The release arc is used to model the *no-early* regulation measure. Let operation o_h be the first operation of a departure job, i.e. passengers start proceeding from the concourse to their platforms, r_h indicates that passengers are not allowed to proceed before r_h, as shown in Fig. 6.

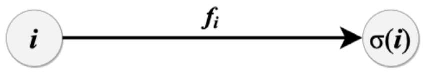


Fig. 3. Fixed directed arc.

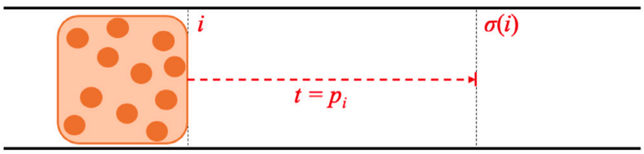


Fig. 4. Passing group of passengers.

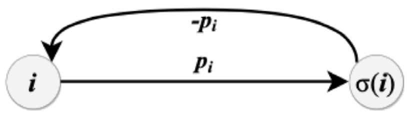


Fig. 5. AG formulation of *No-Holding* regulation measure.

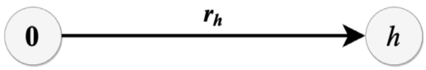


Fig. 6. Release arc.

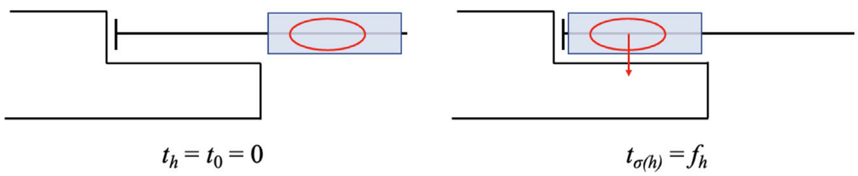


Fig. 7. Train arrival and passengers alighting.

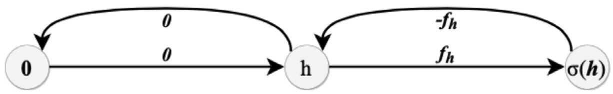


Fig. 8. AG formulation of train arrival and passengers alighting.

For an arrival job, the first operation o_h would correspond to the occupation of a train by passengers, which would generally have begun before the focused time frame. Hence, we assumed that it begins at t_0, i.e. $t_h = t_0$. This is modeled using an arc $(0, h) \in F$ and $(h, 0) \in F$ with null length. The subsequent node $\sigma(h)$ would correspond to the time when the train arrive at the platform and passengers start to alight. The length of arc $(h, \sigma(h)) \in F$ would be the scheduled arrival time, denoted by f_h. In addition, an arc $(\sigma(h), h) \in F$ with length $-f_h$ represents that passengers must alight immediately after the train arrives, according to the *no-holding* regulation measure. The train arrival events are shown in Fig. 7 and its AG formulation is shown in Fig. 8.

An arc $(i, 0) \in F$ with length $-D_i$ represents the latest time that o_i can start, i.e. $t_i \leq D_i$. We define this as a *deadline arc*, which is used to model the *no-delay* regulation measure. Let operation o_k be the last operation of a job. For a departure job, an arc $(k, 0) \in F$ with length $-D_k$ represents that train must not depart later than its scheduled departure time D_k, as shown in Fig. 9.

To avoid having more than one group of passengers in the same area at the same time, i.e. *no-conflict* regulation measure, there must be a separation between the two groups of passengers that use the same area. A sequencing decision is also needs to be made, i.e. which group should proceed first. The separation and sequencing decision is modeled using an alternative pair. Let i and $\sigma(i)$

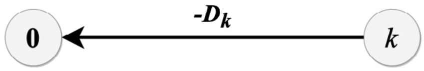


Fig. 9. Deadline arc.

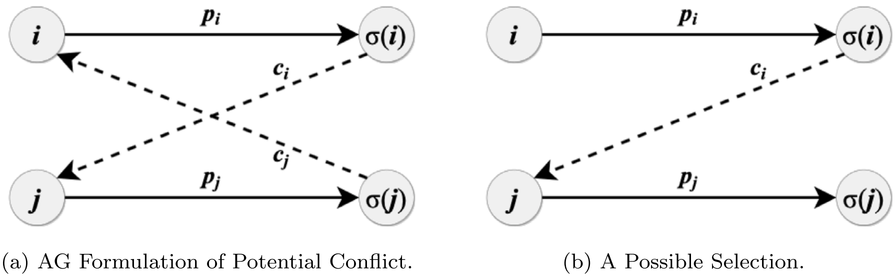


Fig. 10. Alternative arcs.

represent a group of passengers entering two consecutive areas, and j and $\sigma(j)$ represent another group of passengers. Given that the areas corresponding to i and j are the same, an alternative pair of arcs $((\sigma(i), j), (\sigma(j), i)) \in A$ is used to model the sequencing decision and the required minimum separation between these two groups. A pair $((\sigma(i), j), (\sigma(j), i)) \in A$ is composed of two arcs: $(\sigma(i), j)$ and $(\sigma(j), i)$ of length a_i and a_j, respectively. The arc length a_i (a_j) represents the minimum separation between $t_{\sigma(i)}$ and t_j ($t_{\sigma(j)}$ and t_i). In our case, a_i (a_j) would equal the clearing time c_i (c_j), as described in Section 3, i.e. $t_j \geq t_{\sigma(i)} + c_i$ ($t_i \geq t_{\sigma(j)} + c_j$). We illustrated the alternative pair $((\sigma(i), j), (\sigma(j), i)) \in A$ with dotted arcs, as shown in Fig. 10(a). If the group that corresponds to node i and $\sigma(i)$ is scheduled to proceed through this common area first, the arc $(\sigma(i), j)$ is selected, as shown in Fig. 10(b), and vice versa.

A *selection* S is a set of alternative arcs, at most one selected from each pair. Set S is considered a *complete selection* S^c, if exactly one arc from each pair in set A is selected. A *feasible* solution would be a graph $(N, F \cup S^c)$ which has no positive length cycles. A positive length cycle represents an *infeasibility* where an operation precedes itself. For a feasible schedule S^c, the start time t_i for operation o_i is the length of the longest path from 0 to i, denoted by $l^{S^c}(0, i)$.

To conclude, the passenger management problem can be described as an MILP as follows:

$$
\begin{aligned}
& t_0 = 0 \\
& t_{\sigma(i)} \geq t_i + f_i && \forall (i, \sigma(i)) \in F \\
& \left.\begin{aligned} & t_j \geq t_{\sigma(i)} + a_i - M(1 - x_{\sigma(i)j}) \\ & t_i \geq t_{\sigma(j)} + a_j - M(x_{\sigma(i)j}) \end{aligned}\right\} && \forall ((\sigma(i), j), (\sigma(j), i)) \in A
\end{aligned}
$$

The variables of this MILP are: $|N|$ integer variables t_i, associated with the start time of each operation $i \in N$, and $|A|$ binary variable $x_{\sigma(i)j}$, associated with each alternative pair $((\sigma(i), j), (\sigma(j), i)) \in A$. If $(\sigma(i), j) \in S$, then $x_{\sigma(i)j} = 1$, otherwise $x_{\sigma(i)j} = 0$. M is a sufficiently large constant, e.g. the sum of all arc lengths.

Although the AG and its related MILP are very similar, the AG is slightly less flexible in terms of objective function, where it can only be set to minimize the maximum tardiness. The MILP is more flexible in this aspect, which will play a major role in the case where regulation measures are relaxed. Another advantage of the MILP is that it can be solved using commercial solvers. The solver employed in this study is AGLibrary, developed by Roma Tre University.

4.1. Regulation measure relaxation

In many cases, a solution to the CSP does not exist. Therefore, at least one regulation measure is needed to be relaxed. The regulation measure relaxations are done according to the passenger management strategies which are described in Section 3.2.

In all strategies beside *(i) conventional practice* and *(ii) ideal practice*, the *no-delay* regulation measure is relaxed. This is done by removing the deadline arc and an additional node n is added to the graph. A scheduled start time d_i of operation o_i is represented by arc (i, n) with length $-d_i$. If operation o_i starts later than d_i, it is considered delayed which is measured as the tardiness $td_i = max\{0, t_i - d_i\}$. For a departure job, let k be the node corresponding to the train departure, and the scheduled departure time is modeled by arc (k, n) of length $-d_k$, as illustrated in Fig. 11.

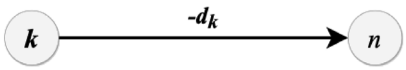


Fig. 11. AG formulation of scheduled departure time.

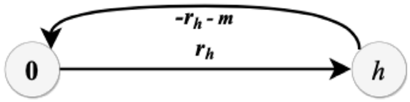


Fig. 12. Relaxing no-holding regulation measure.

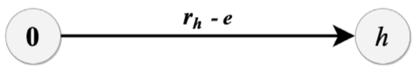


Fig. 13. Relaxing no-early regulation measure.

To minimize the total tardiness TT, the CSP is converted into a classical JSP where the objective function is $TT = \sum_{i \in N} td_i$. The MILP formulation of this JSP can be described as follows:

$$\begin{aligned} \text{obj.} \quad & \text{minimize } TT = \sum_{i \in N} td_i \\ \text{s.t.} \quad & t_0 = 0 \\ & t_{\sigma(i)} \geq t_i + f_i && \forall (i, \sigma(i)) \in F \text{ with } \sigma(i) \neq n \\ & \left. \begin{aligned} & t_j \geq t_{\sigma(i)} + a_i - M(1 - x_{\sigma(i)j}) \\ & t_i \geq t_{\sigma(j)} + a_j - M(x_{\sigma(i)j}) \end{aligned} \right\} && \forall ((\sigma(i), j), (\sigma(j), i)) \in A \end{aligned}$$

The *no-holding* regulation measure can be relaxed by modifying the related fixed arc. Let h be the node corresponding to passengers alighting. If passengers are allowed to be held on-board for a maximum of m units of time, the length of arc $(h, 0)$ becomes $-f_h - m$, as shown in Fig. 12.

The *no-early* regulation measure is relaxed by modifying the length of the release arc. If the announcement can be made up to e units of time earlier than the release time r_h, the length of arc $(0, h)$, with h the first node of a departing job, becomes $r_h - e$, as shown in Fig. 13.

For the *(vi) allowing pre-loading* strategy, the *no-conflict* regulation measure is relaxed for the platform area. The alternative pairs related to platform areas are removed, to allow more than one group of passengers on the platform area.

4.2. Illustrative example

Let us consider a fictitious railway station with four platforms as illustrated in Fig. 14. The station area is divided into the concourse and another eight areas. Three groups of passengers, denoted by A, B and C are considered. Group A is boarding train $T1$ at platform 1 (area 4), while group B is boarding train $T2$ at platform 2 (area 5). Group C is arriving on train $T2$ which is scheduled to stop at platform 2 (area 5). The areas that each group has to travel through are:

- A: concourse → 1 → 2 → 3 → 4 → $T1$ → depart;
- B: concourse → 1 → 2 → 3 → 5 → $T2$ → depart;
- C : $T2$ → 5 → 3 → 2 → 1 → concourse.

The trains for group A and B are scheduled to depart at time d_{Aout} and d_{Bout}, while the train for group C is scheduled to arrive at time f_{CT2}. In this case, according to the *no-early* regulation measure, we established that platform number announcements cannot be made earlier than 5 min before the scheduled departure times. Therefore, the release time for group A is $d_{Aout} - 300$ s, and for group B is $d_{Bout} - 300$ s. Additionally, the time it takes for passenger groups A and B to board their trains are f_{AT1} and f_{BT2}, respectively.

The AG in this instance where no regulation measures are relaxed (*(i) ideal practice*) is shown in Fig. 15. Each node (except 0) is denoted by a (<*passenger group*>, <*area*>) notation, which defines the group of passengers and the area it corresponds to, while *out* denotes the train departing or passengers arriving at the concourse. The positive arcs connecting these nodes represent the passing time or the time required for boarding, while the negative length arcs are used to model the *no-holding* regulation measures.

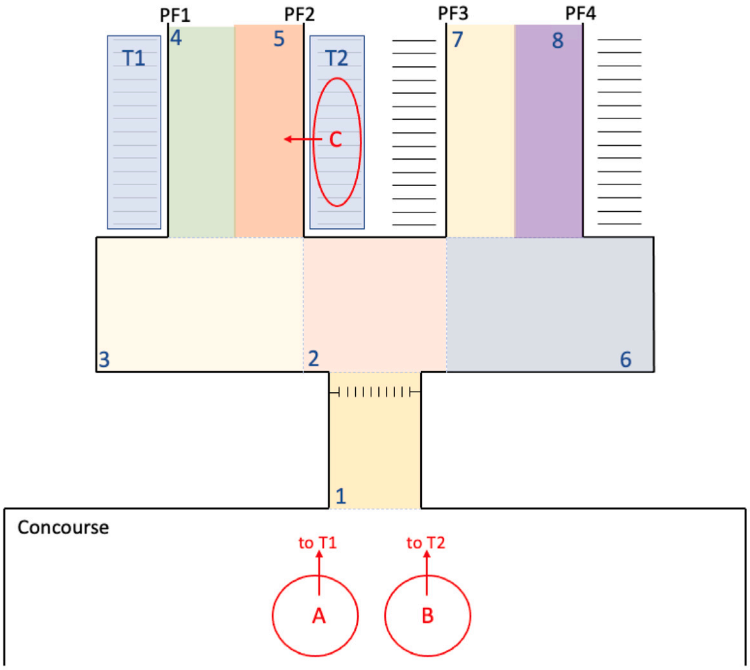


Fig. 14. Illustrative example.

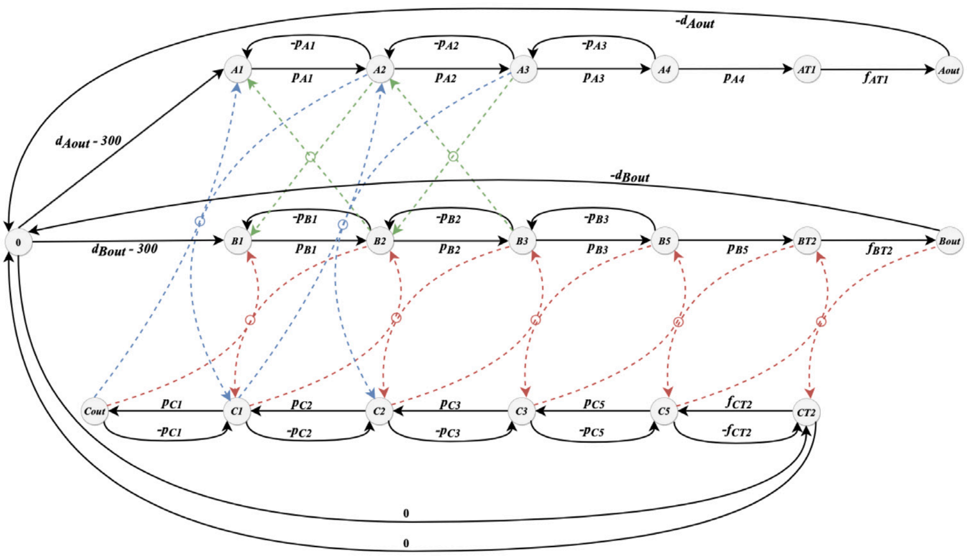


Fig. 15. AG formulation of illustrative example.

For departing passenger groups, the fixed directed arcs $(0, A1)$ and $(0, B1)$ are used to model the release time of passenger groups A and B, while their scheduled departure times are modeled with arcs $(Aout, 0)$ and $(Bout, 0)$. For the arrival group, the fixed directed arcs $(0, CT2)$ and $(CT2, 0)$ represent the fact that the train $T2$ is occupied by passengers from the beginning of the schedule. The scheduled arrival time of group C is modeled using arc $(CT2, C5)$, while arc $(C5, CT2)$ represents the *no-holding* (on-board) regulation measure.

According to the *no-conflict* regulation measure, alternative pairs are used to model the sequencing decisions and minimum separation between different groups of passengers using the same area. The green pairs represent the separation between groups A and B, while the blue pairs are for groups A and C and the red pairs are for B and C. Small circle notations are added to show

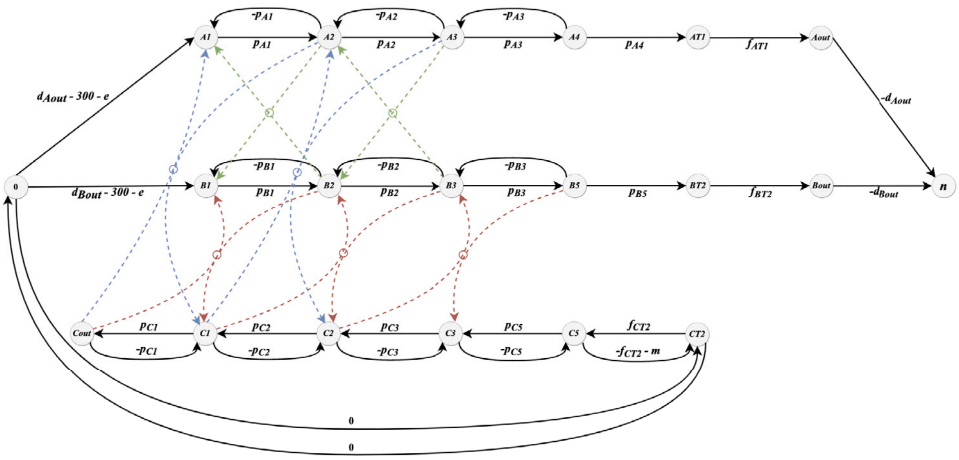


Fig. 16. AG formulation of regulation measures relaxation.

the intersection point of arcs from the same alternative pair. The length of these arcs are the clearing time, however, this is not included in this figure for simplification.

Fig. 16 shows the AG formulation of an instance of this problem, where all regulation measures are relaxed. To relax the *no-delay* regulation measure, arcs $(Aout, 0)$ and $(Bout, 0)$ are removed from the graph. Instead, arcs $(Aout, n)$ and $(Bout, n)$ of length $-d_{Aout}$ and $-d_{Bout}$, are added. For the ***(vi) pre-loading*** strategy, the alternative pairs associated with platform areas, i.e. $((BT2, C5), (C3, B5))$, is removed. In the case of ***(iv) allowing on-board holding*** strategy, given that passengers are allowed to be held on-board for maximum of m units of time, the length of arc $(C5, CT2)$ becomes $-f_{CT2} - m$. For the ***(v) early announcement*** strategy, given that platform numbers can be announced up to e time units earlier than usual, thus the length of arc $(0, A1)$ and $(0, B1)$ is changed to $d_{Aout} - 300 - e$ and $d_{Bout} - 300 - e$.

5. Case study

In our experimental campaign, we considered London Euston as the test case, being one of the busiest termini in London. This station (London Euston) was chosen as it provides an example of crowded railway termini where passenger circulation is controlled by station managers. These termini have many platforms and receive mixed traffic including distant services from multiple lines, and a decision support tool is required to support the control of complex passenger circulation. In the case of London Euston, passenger circulation issues are infamously labeled as the 'Euston Stampede' (Mirror, 2017).

We considered the May 2019 timetable from which we extracted four one-hour periods. Specifically, we considered periods both from morning (8:00–9:00) and evening peak hours (17:00–18:00 and 18:00–19:00) and also during normal operation time (14:00–15:00).

The simplified layout of London Euston station is illustrated in Fig. 17, where the station is divided into 33 areas. The areas are divided at the locations where there is a change of travel direction or at the locations where the flows from two or more areas may merge. The dimension (length l and width w) and the passing time p of each area are shown in Table 2. It should be noted that the passing time for the platform areas already include the time for passengers to reach the end of the platforms. Passengers are assumed to walk at a constant speed of 1.22 m/s, aligning with Fruin (1971)'s Level of Service C, rounded to the nearest integer, based on on-site observations. The clearing time is calculated according to the assumption that there are 200 passengers traveling to/from each train service (approximately half of the British Rail Class 390 train capacity). We assume that it takes 90 s for each passenger group to board/alight the train. In total, it takes approximately 4 min for each group to travel from the concourse to their platform and board the train. To prevent passengers being on platforms too early (*no-early* regulation measure), we established that the platform number should not be announced earlier than 5 min before the scheduled departure time, and 10 min in case of relaxation. Additionally, for the *(iv) allowing on-board holding* strategy, we considered two cases in which passengers could be held on-board up to 60 and 90 s, for each service. Please note that while operational details are set to be as much as possible in line with actual station operation, there might still be some differences. However, this should not hinder the scope of this case study.

In all four periods, we found that it is not possible to follow the *(ii) ideal practice*, i.e. the solution to the CSP does not exist. This is due to several reasons, e.g. several trains are scheduled to arrive/depart from nearby platforms around the same time. Therefore, to provide alternative solutions, we applied passenger management strategies (as proposed in Section 3.2). By solving the MILP associated with the specified strategy, we obtained the timing that each group of passengers should proceed to each area. Additionally, we were able to derive the *occupation time*, i.e. the time from when the first person enters the area until the last person leaves, and also the KPIs, as reported in Table 3.

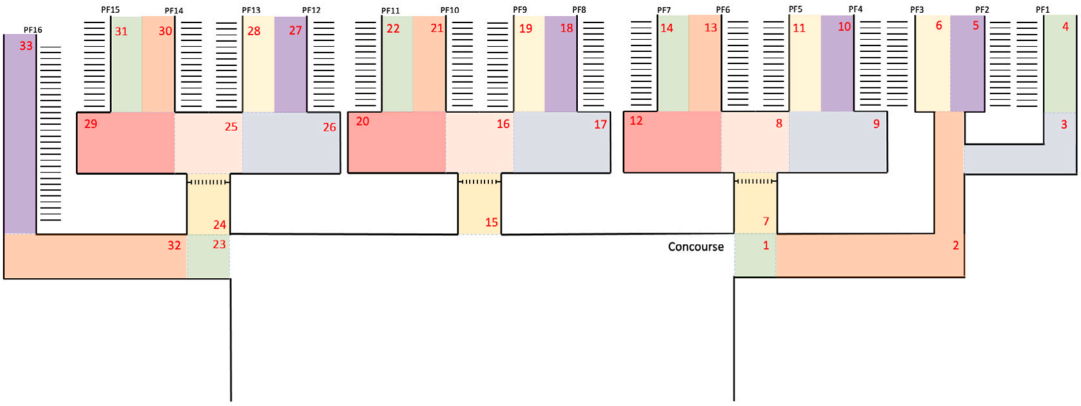


Fig. 17. London Euston station layout.

Table 2
Dimension and passing time of each area.

Area	l (m)	w (m)	p (s)	Area	l (m)	w (m)	p (s)
1	15	7	12	18	60	5.5	49
2	70	7	57	19	60	5.5	49
3	35	7	28	20	20	8	16
4	60	8.5	49	21	60	5.5	49
5	60	11	49	22	60	5.5	49
6	60	11	49	23	15	7	12
7	50	12	40	24	50	12	40
8	20	12	16	25	20	12	16
9	20	8	16	26	20	8	16
10	60	5.5	49	27	60	5.5	49
11	60	5.5	49	28	60	5.5	49
12	20	8	16	29	20	8	16
13	60	5.5	49	30	60	5.5	49
14	60	5.5	49	31	60	5.5	49
15	50	12	40	32	80	7	65
16	20	12	16	33	60	12	49
17	20	8	16				

For the *(i) conventional practice*, we assumed that passengers are managed according to a simple heuristic, i.e. all platform numbers are announced exactly 300 s before the scheduled departure time. While it gives sufficient time for passengers to reach their platform, i.e. $TT = 0$, it would result in a significant amount of conflict (uni- and bi-directional) as the announcement is made without considering the flow of passengers. The amount of conflict is reported in Table 3.

To avoid these conflicts, the *(iii) allowing delay* strategy could be applied. In all cases, besides the 14:00–15:00 case, the result shows no conflict if the *(iii) allowing delay* strategy is applied. However, it would result in passengers boarding their train late, as reported as TT in Table 3. In the 14:00–15:00 case, due to an impasse situation caused by two alighting passenger groups, similar to the situation in Fig. 2, there is no feasible solution.

To tackle the impasse situation, we need to intervene with regulation measures that are related to alighting passenger groups. The *(v) allowing on-board holding* strategy allows us control over the alighting groups. In the 14:00–15:00 case, the impasse situation is avoided by applying this strategy; however, it would result in TT and *on-board holding time*. It should be noted that the *on-board holding time* reported in Table 3 is the total holding time from all services, while the holding time limited is for each service. In other cases, with the ability to hold alighting groups on-board, the length of time that boarding groups are held in the concourse can be reduced. This would result in less TT, compared to previously discussed cases. Additionally, in the 14:00–15:00 and 17:00–18:00 cases, TT can be further reduced by allowing a longer on-board holding time. In the 18:00–19:00 case, since TT has already been eliminated by allowing a 60 s on-board holding period, it is unnecessary to relax it further.

In the *(v) allowing early announcement* strategy, both *no-delay* and *no-early* regulation measures are relaxed. As these two regulation measures are not directly related to the alighting groups of passengers, it does not help mitigate the impasse situation. For other cases with no impasse situation, as it allows departing passengers to proceed earlier, conflicts could be avoided while resulting in less TT than in the *(iii) allowing delay* cases. In the 17:00–18:00 and 18:00–19:00 cases (compared to the *(iii) allowing delay* cases), the TT can be reduced by more than half and totally eliminated in the 8:00–9:00 case. However, passengers would arrive on platforms earlier resulting in safety risks, which are measured as *earliness*.

In addition to allowing early announcement, the *(vi) pre-loading* strategy also allows conflicts on platform areas. Again, as the *(vi) pre-loading* strategy does not directly affect the alighting groups, the impasse situation in the 14:00–15:00 case is not mitigated.

Table 3
KPIs.

Time	Strategies	On-board holding (s)	Earliness (s)	Conflict time (s)		TT (s)
				Uni	Bi	
8:00–9:00	(i) Conventional practice	0	0	186	392	0
	(ii) Ideal practice			impasse		
	(iii) Allow delay	0	0	0	0	78
	(iv) Allow on-board holding					
	max 60 s	95	0	0	0	28
	max 90 s	95	0	0	0	28
	(v) Allow early announcement	0	1631	0	0	0
	(vi) Pre-loading			–		
14:00–15:00	(i) Conventional Practice	0	0	95	339	0
	(ii) Ideal practice			impasse		
	(iii) Allow Delay			impasse		
	(iv) Allow on-board holding					
	max 60 s	176	0	0	0	166
	max 90 s	309	0	0	0	28
	(v) Allow early announcement			impasse		
	(vi) Pre-loading			impasse		
17:00–18:00	(i) Conventional Practice	0	0	140	358	0
	(ii) Ideal practice			impasse		
	(iii) Allow Delay	0	0	0	0	692
	(iv) Allow on-board holding					
	max 60 s	168	0	0	0	97
	max 90 s	260	0	0	0	69
	(v) Allow early announcement	0	1609	0	0	198
	(vi) Pre-loading	0	2543	0	0	0
18:00–19:00	(i) Conventional Practice	0	0	0	209	0
	(ii) Ideal practice			impasse		
	(iii) Allow Delay	0	0	0	0	198
	(iv) Allow on-board holding					
	max 60 s	233	0	0	0	0
	max 90 s			–		
	(v) Allow early announcement	0	1315	0	0	50
	(vi) Pre-loading	0	2188	0	0	0

Compared to the *(v) allowing early announcement* strategy, some of the groups can proceed earlier in the case of the *(vi) pre-loading* strategy. As a result, the TT can be entirely eliminated in the 17:00–18:00 and 18:00–19:00 cases; however, it would result in more *earliness*. In the 8:00–9:00 case, as TT has already been eliminated by applying the *(v) early announcement* strategy, it would be unnecessary to further relax other regulation measures.

From the results, it can be noticed that each strategy would have its own specific effects. Each strategy may have the ability to eliminate/reduce certain KPIs; however, it may result in other KPIs. To better illustrate their specific effects, we show the occupation time of each group of passengers in each area. The 17:00–18:00 instance is used as an example. In this instance, there are a total of 53 train services, named by letter from A to BA. For simplification, only the occupation time of areas 15 to 22 will be shown as they are related to the busiest platforms during this period. This will be shown for the cases of *(i) conventional practice*, *(iii) allowing delay*, *(v) allowing early announcement* and *(iv) allowing on-board holding* in Figs. 18, 19, 20, and 21, respectively.

When passengers are managed according to the *(i) conventional practice* strategy, there could be significant conflict among passengers, as shown in Figs. 18 where there are overlaps among the occupation time of each group of passengers. For instance, passenger group G (Q) arrives at t = 480 s (t = 1080 s) and alight immediately on to area 19 (21). While passenger group M (V) starts proceeding through area 15 at t = 480 s (t = 1080 s), which is 300 s before their scheduled departure time, according to our assumption. As a result, there are bi-directional conflicts between groups G and M in area 16 for 9 s and in area 17 for 37 s, as shown by the red box marked with (a) in Figs. 18, and between groups Q and V in areas 16 and 20 for the same amount of time, as shown by the red box marked (b). Additionally, Fig. 18 also shows that overlapping occurs mostly in areas 15 and 16, indicating that they are the bottleneck of the station as they are most commonly used by the passengers traveling to/from the four busiest platforms.

By applying the *(iii) allowing delay* strategy, conflict among passengers can be avoided, as can be seen in Fig. 19. The *(iii) allowing delay* strategy avoids these conflicts by delaying the time departing passengers start to proceed to their platforms. Take the groups Q and V for example; by having group V start proceeding 139 s later than in the *(i) conventional practice* case, conflict between groups Q and V can be avoided. This is shown in Fig. 19, where the occupation time of group V is shifted to the right (as highlighted by the red box) and it no longer overlaps with Q. However, this would cause group V to board their train 50 s later than the scheduled time and result in TT.

Instead of delaying the proceeding time of departing passengers which may result in TT, conflicts can be avoided by having departing passengers proceed earlier in the case of the *(v) allowing early announcement* strategy. Let us again consider groups Q and

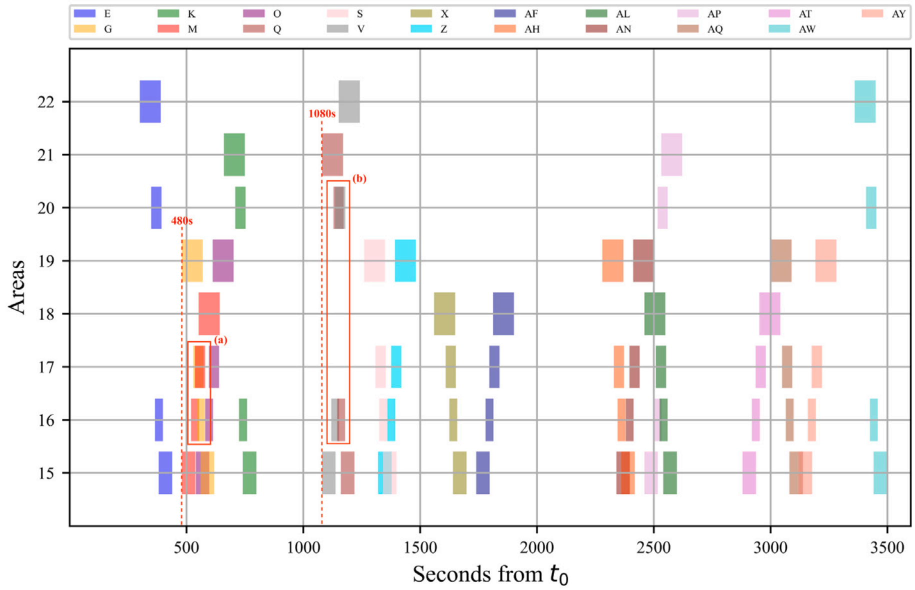


Fig. 18. Area 15 to 22 occupation time for 17:00–18:00 (i) conventional practice case.

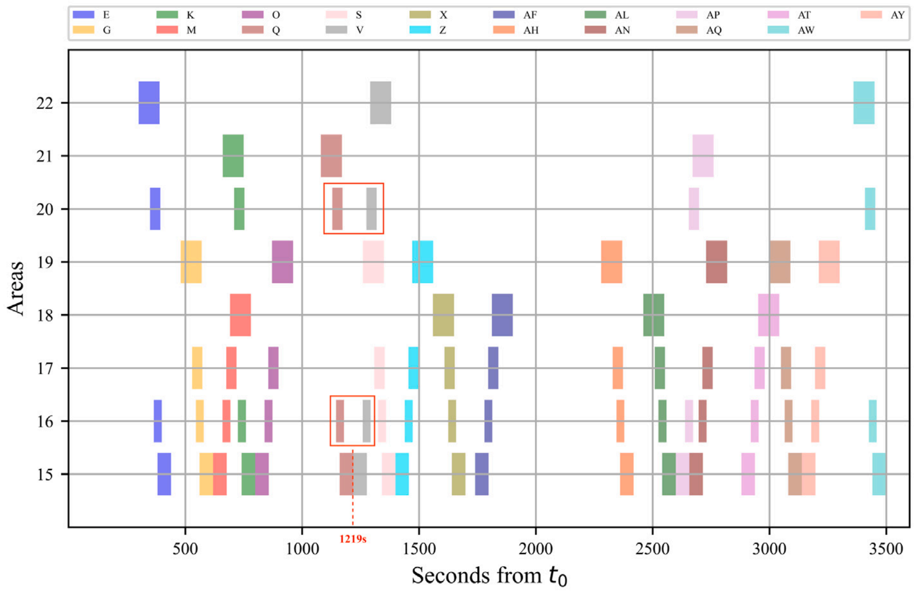


Fig. 19. Area 15 to 22 occupation time for 17:00–18:00 (iii) Allowing delay case.

V. In this case, the conflict between the two groups is avoided by having group V proceed 51 s earlier than in the *(i) conventional practice* case, as shown in Fig. 20.

Beside controlling only the departing passenger groups, the *(iv) allowing on-board holding* strategy allows further control over the alighting groups. Let us consider passenger groups G and M. By allowing group G to start alighting 51 s later (than in the *(i) conventional practice* case), conflict can be avoided. Fig. 21 shows that the occupation time of group G is shifted 51 s to the right and their occupation time no longer overlaps with group M, as highlighted by the red box.

While each strategy has its own specific effects, there are also some significant differences in applying each strategy in different instances. The results show no specific dependence between KPIs, i.e. reducing (or increasing) one does not necessarily means improving (or worsening) another. For example, comparing the 8:00–9:00 and 17:00–18:00 cases, it can be noticed that the conflict time in the *(i) conventional practice* cases and the TT in the *(iii) allowing delay* cases are not proportional. While the conflict time

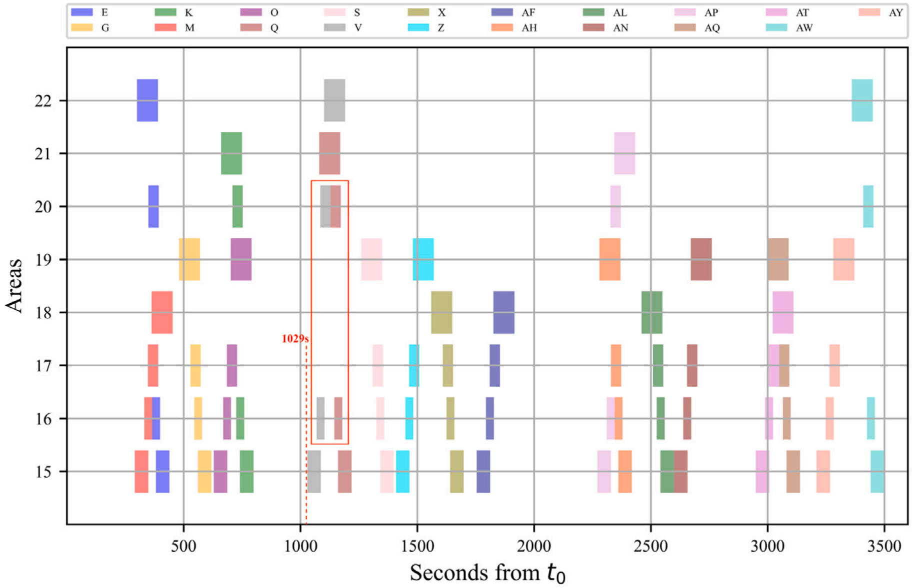


Fig. 20. Area 15 to 22 occupation time for 17:00–18:00 (vi) Allowing early announcement case.

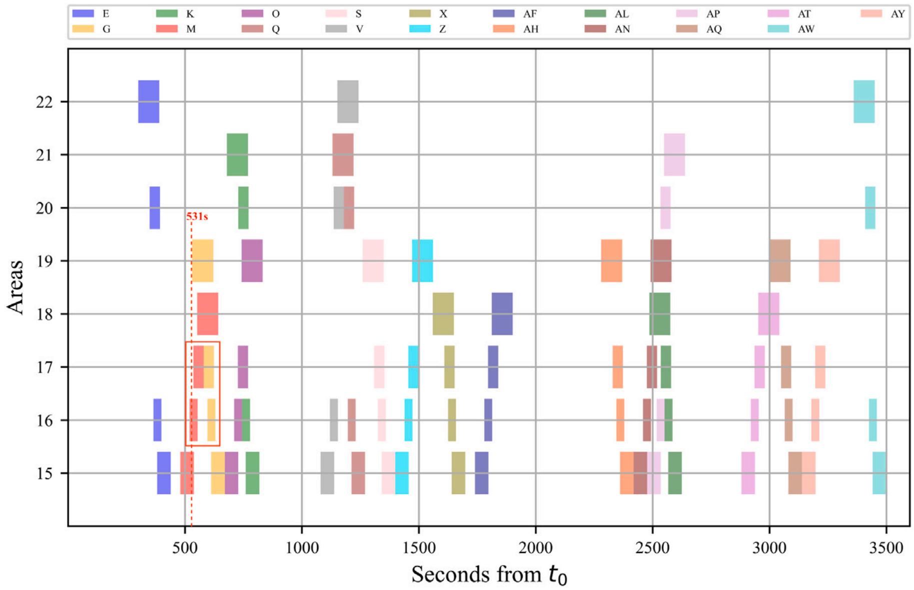


Fig. 21. Area 15 to 22 occupation time for 17:00–18:00 (v) Allowing on-board holding case.

in the 8:00–9:00 case is higher, if the *(i) conventional practice* strategy is applied, the TT in the 17:00–18:00 case is significantly greater if the *(iii) allowing delay* strategy is applied. Therefore, it depends on the circumstances which strategy should be applied.

6. Conclusion and future research

There are several possible methods to manage passenger flows in transport stations. While each method may have its own benefits, it may also result in different drawbacks as well. As can be seen in Table 3, each KPI can be traded off with other KPIs, by applying different strategies. There is no definite answer to which strategy is best, as it rather depends on the circumstances. It also depends on the preference of the station managers, who may have a different perspective on which KPIs should be maintained and which could be sacrificed. The proposed passenger management tool provides suggestions on how to manage the passenger flows in the station according to the specified strategies and allows an assessment of the expected result. This would allow station managers to make more informed and effective decisions in complex situations.

It should be noted that the strategies and the uses of the proposed tool are not limited to what we have presented in this paper. Existing research suggests that it could potentially be extended to deal with more complex cases and that some assumptions made in this study can be relaxed. Furthermore, even though a railway station is used as a case study in this research, the proposed tool can also be used in other transport facilities with similar characteristics and also multi modality facilities.

In this study, the walking speed of passengers is assumed to be constant. However, in reality, it can vary due to several reasons. Future research on implementing a variable walking speed model could significantly increase the model's accuracy. Additionally, it is important to note that conflicts at different locations within the station may have varying impacts. However, this aspect is beyond the scope of the present study and should be explored in future research. Another limitation to this study is that the tool only intakes information at the beginning of the instance. In actual situations, there can be many changes in situations, e.g. train delays, platform reallocations and service cancellations. It is suggested that further research on real-time implementation should be conducted.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Atkins, 2009. Farringdon station redevelopment integrated ticket hall building - passenger areas human factors assessment.

Barrena, E., Canca, D., Coelho, L.C., Laporte, G., 2014. Exact formulations and algorithm for the train timetabling problem with dynamic demand. Comput. Oper. Res. 44, 66–74. http://dx.doi.org/10.1016/j.cor.2013.11.003.

Blue, V.J., Adler, J.L., 2001. Cellular automata microsimulation for modeling bi-directional pedestrian walkways. Transp. Res. Part B: Methodol. 35, 293–312. http://dx.doi.org/10.1016/S0191-2615(99)00052-1.

Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. Proc. Natl. Acad. Sci. USA 99, 7280–7287. http://dx.doi.org/10.1073/pnas.082080899.

Chooramun, N., Lawrence, P.J., Galea, E.R., 2012. An agent based evacuation model utilising hybrid space discretisation. Saf. Sci. 50, 1685–1694. http://dx.doi.org/10.1016/j.ssci.2011.12.022.

Corman, F., 2020. Interactions and equilibrium between rescheduling train traffic and routing passengers in microscopic delay management: A game theoretical study. Transp. Sci. 54, 785–822. http://dx.doi.org/10.1287/trsc.2020.0979.

Corman, F., D'Ariano, A., Marra, A.D., Pacciarelli, D., Samà, M., 2017. Integrating train scheduling and delay management in real-time railway traffic control. Transp. Res. Part E: Logist. Transp. Rev. 105, 213–239. http://dx.doi.org/10.1016/j.tre.2016.04.007.

Corman, F., D'Ariano, A., Pacciarelli, D., Pranzo, M., 2010. A tabu search algorithm for rerouting trains during rail operations. Transp. Res. Part B: Methodol. 44, 175–192. http://dx.doi.org/10.1016/j.trb.2009.05.004.

Craesmeyer, M., Schadschneider, A., 2014. Simulation of merging pedestrian streams at t-junctions. Transp. Res. Procedia 2, 406–411. http://dx.doi.org/10.1016/j.trpro.2014.09.045.

Crooks, A., Castle, C., Batty, M., 2008. Key challenges in agent-based modelling for geo-spatial simulation. Comput. Environ. Urban Syst. 32, 417–430. http://dx.doi.org/10.1016/j.compenvurbsys.2008.09.004.

Daamen, W., Hoogendoorn, S.P., 2003. Experimental research of pedestrian walking behavior. Transp. Res. Rec. 1828, 20–30. http://dx.doi.org/10.3141/1828-03.

D'Ariano, A., Pacciarelli, D., Pranzo, M., 2007. A branch and bound algorithm for scheduling trains in a railway network. European J. Oper. Res. 183, 643–657. http://dx.doi.org/10.1016/j.ejor.2006.10.034.

D'Ariano, A., Samà, M., D'Ariano, P., Pacciarelli, D., 2014. Evaluating the applicability of advanced techniques for practical real-time train scheduling. Transp. Res. Procedia 3, 279–288. http://dx.doi.org/10.1016/j.trpro.2014.10.007.

Davidich, M., Geiss, F., Mayer, H.G., Pfaffinger, A., Royer, C., 2013. Waiting zones for realistic modelling of pedestrian dynamics: A case study using two major german railway stations as examples. Transp. Res. Part C: Emerg. Technol. 37, 210–222. http://dx.doi.org/10.1016/j.trc.2013.02.016.

De Oña, J., De Oña, R., 2015. Quality of service in public transport based on customer satisfaction surveys: A review and assessment of methodological approaches. Transp. Sci. 49, 605–622. http://dx.doi.org/10.1287/trsc.2014.0544.

DfT, 2018. Rail passenger numbers and crowding on weekdays (RAI02).

Eurostat, 2019. Railway passenger transport statistics-quarterly and annual data, 7. p. 7, URL https://ec.europa.eu/eurostat/statisticsexplained/.

Flötteröd, G., Lämmel, G., 2015. Bidirectional pedestrian fundamental diagram. Transp. Res. Part B: Methodol. 71, 194–212. http://dx.doi.org/10.1016/j.trb.2014.11.001.

Fruin, J.J., 1971. Designing for pedestrians: a level-of-service concept. Highw. Res. Rec. 377, 1–15.

Gao, J., Gong, J., He, J., Zhang, D., Qiu, G., Zhang, J., 2020. Experimental study on pedestrians' uni- and bi-directional movement on staircases under emergency conditions. J. Stat. Mech. Theory Exp. 2020, http://dx.doi.org/10.1088/1742-5468/abb459.

Gao, Y., Kroon, L., Schmidt, M., Yang, L., 2016. Rescheduling a metro line in an over-crowded situation after disruptions. Transp. Res. Part B: Methodol. 93, 425–449. http://dx.doi.org/10.1016/j.trb.2016.08.011.

Hamacher, H.W., Tjandra, S.A., 2002. Mathematical modelling of evacuation problems: a state of the art. Pedestr. Evacuation Dyn. 24, 227–266.

Helbing, D., Molnár, P., 1995. Social force model for pedestrian dynamics. Phys. Rev. E 51, 4282–4286. http://dx.doi.org/10.1103/PhysRevE.51.4282.

Helbing, D., Molnár, P., 1997. Self-organization of complex structures. From individual to collective dynamics.

Hoogendoorn, S.P., 2010. Sturen op verkeersstromen: Waarom we niet zonder verkeersmanagement kunnun. Tech. Rep.

Huang, L., Wong, S.C., Zhang, M., Shu, C.W., Lam, W.H., 2009. Revisiting hughes' dynamic continuum model for pedestrian flow and the development of an efficient solution algorithm. Transp. Res. Part B: Methodol. 43, 127–141. http://dx.doi.org/10.1016/j.trb.2008.06.003.

Hughes, R.L., 2002. A continuum theory for the flow of pedestrians. Transp. Res. Part B: Methodol. 36, 507–535. http://dx.doi.org/10.1016/S0191-2615(01)00015-7.

Jiang, M., ying Li, H., yue Xu, X., peng Xu, S., rui Miao, J., 2017. Metro passenger flow control with station-to-station cooperation based on stop-skipping and boarding limiting. J. Central South Univ. 24, 236–244. http://dx.doi.org/10.1007/s11771-017-3424-x.

King, D., Srikukenthiran, S., Shalaby, A., 2014. Using simulation to analyze crowd congestion and mitigation at canadian subway interchanges: Case of bloor-yonge station, Toronto, Ontario. Transp. Res. Rec. 2417, 27–36. http://dx.doi.org/10.3141/2417-04.

Klüpfel, H., Meyer-König, T., Wahle, J., Schreckenberg, M., 2001. Microscopic simulation of evacuation processes on passenger ships. Theory Pr. Issues Cell. Autom. 63–71. http://dx.doi.org/10.1007/978-1-4471-0709-5_8.

Lam, W.H., Lee, J.Y., Chan, K.S., Goh, P.K., 2003. A generalised function for modeling bi-directional flow effects on indoor walkways in Hong Kong. Transp. Res. Part A: Policy Pr. 37, 789–810. http://dx.doi.org/10.1016/S0965-8564(03)00058-2.

Lei, W., Li, A., Gao, R., Hao, X., Deng, B., 2012. Simulation of pedestrian crowds' evacuation in a huge transit terminal subway station. Phys. A 391, 5355–5365. http://dx.doi.org/10.1016/j.physa.2012.06.033.

Li, S., Dessouky, M.M., Yang, L., Gao, Z., 2017. Joint optimal train regulation and passenger flow control strategy for high-frequency metro lines. Transp. Res. Part B: Methodol. 99, 113–137. http://dx.doi.org/10.1016/j.trb.2017.01.010.

Li, Z., Yin, J., Chai, S., Tang, T., Yang, L., 2023. Optimization of system resilience in urban rail systems: Train rescheduling considering congestions of stations. Comput. Ind. Eng. 185, http://dx.doi.org/10.1016/j.cie.2023.109657.

Li, W., Zhou, J., 2013. The optimize management of passenger organization in transfer station based on dynamic passenger flow analysis. Procedia - Soc. Behav. Sci. 96, 1322–1328. http://dx.doi.org/10.1016/j.sbspro.2013.08.150.

Liu, R., Li, S., Yang, L., 2020. Collaborative optimization for metro train scheduling and train connections combined with passenger flow control strategy. Omega (United Kingdom) 90, http://dx.doi.org/10.1016/j.omega.2018.10.020.

Liu, X.D., Song, W.G., Huo, F.Z., Jiang, Z.G., 2014. Experimental study of pedestrian flow in a fire-protection evacuation walk. Procedia Eng. 71, 343–349. http://dx.doi.org/10.1016/j.proeng.2014.04.049.

LU, 2019. Station Planning. Tech. Rep., pp. 75–92. http://dx.doi.org/10.4324/9780080524160-5.

Lu, G., Ning, J., Liu, X., Nie, Y.M., 2022. Train platforming and rescheduling with flexible interlocking mechanisms: An aggregate approach. Transp. Res. Part E: Logist. Transp. Rev. 159, 102622. http://dx.doi.org/10.1016/j.tre.2022.102622, URL https://doi.org/10.1016/j.tre.2022.102622.

Luathep, P., Sumalee, A., Lam, W.H., Li, Z.C., Lo, H.K., 2011. Global optimization method for mixed transportation network design problem: A mixed-integer linear programming approach. Transp. Res. Part B: Methodol. 45, 808–827. http://dx.doi.org/10.1016/j.trb.2011.02.002.

Mekić, A., Ziabari, S.S.M., Sharpanskykh, A., 2021. Systemic agent-based modeling and analysis of passenger discretionary activities in airport terminals. Aerospace 8, http://dx.doi.org/10.3390/aerospace8060162.

Mirror, 2017. Panic and "stampede" at London euston station as terrified passengers are evacuated. URL https://www.mirror.co.uk/news/uk-news/panic-stampede-london-euston-station-11304686.

Nathanail, E., 2008. Measuring the quality of service for passengers on the hellenic railways. Transp. Res. Part A: Policy Pr. 42, 48–66. http://dx.doi.org/10.1016/j.tra.2007.06.006.

NetworkRail, 2011. Station capacity assessment guidance. p. 84.

NetworkRail, 2016. Station capacity planning guidance. p. 5.

Niu, H., Zhou, X., 2013. Optimizing urban rail timetable under time-dependent demand and oversaturated conditions. Transp. Res. Part C: Emerg. Technol. 36, 212–230. http://dx.doi.org/10.1016/j.trc.2013.08.016.

Niu, H., Zhou, X., Gao, R., 2015. Train scheduling for minimizing passenger waiting time with time-dependent demand and skip-stop patterns: Nonlinear integer programming models with linear constraints. Transp. Res. Part B: Methodol. 76, 117–135. http://dx.doi.org/10.1016/j.trb.2015.03.004.

Oberlander, H., 2014. An Investigation into the Management of Passenger Congestion on the London Underground. Tech. Rep.

ORR, 2015. Station management at Network Rail London Bridge station between January and March 2015. Tech. Rep.

ORR, 2018. Network Rail Strategic Business Plan - Property Income Forecast Review. Tech. Rep.

ORR, 2020. Estimates of Station Usage , Great Britain , 2018 - 19. Tech. Rep.

Pan, H., Yang, L., Liang, Z., 2023. Demand-oriented integration optimization of train timetabling and rolling stock circulation planning with flexible train compositions: A column-generation-based approach. European J. Oper. Res. 305, 184–206. http://dx.doi.org/10.1016/j.ejor.2022.05.039.

Rindsfüser, G., Klügl, F., 2007. Agent-based pedestrian simulation a case study of the bern railway station. Disp 170, 9–18. http://dx.doi.org/10.1080/02513625.2007.10556985.

RSSB, 2005. Managing large events and perturbations at stations - crowd relocation and risk evaluation framework. Tech. Rep, pp. 1–2.

RSSB, 2007. Management of football fans on the railways. Education 1–2.

RSSB, 2009. Crowd management on trains - a good practice guide. Tech. Rep.

RSSB, 2019. Developing up to date industry guidance on the management of crowds : Technical report , literature review. Tech. Rep.

RSSB, 2020. Crowd management good practice : Case study library.

Samà, M., D'Ariano, A., Corman, F., Pacciarelli, D., 2017a. Metaheuristics for efficient aircraft scheduling and re-routing at busy terminal control areas. Transp. Res. Part C: Emerg. Technol. 80, 485–511. http://dx.doi.org/10.1016/j.trc.2016.08.012.

Samà, M., DAriano, A., Corman, F., Pacciarelli, D., 2017b. A variable neighbourhood search for fast train scheduling and routing during disturbed railway traffic situations. Comput. Oper. Res. 78, 480–499. http://dx.doi.org/10.1016/j.cor.2016.02.008.

Samà, M., D'Ariano, A., D'Ariano, P., Pacciarelli, D., 2017c. Scheduling models for optimal aircraft traffic control at busy airports: Tardiness, priorities, equity and violations considerations. Omega (United Kingdom) 67, 81–98. http://dx.doi.org/10.1016/j.omega.2016.04.003.

Samà, M., D'Ariano, A., Pacciarelli, D., 2013. Rolling horizon approach for aircraft scheduling in the terminal control area of busy airports. Transp. Res. Part E: Logist. Transp. Rev. 60, 140–155. http://dx.doi.org/10.1016/j.tre.2013.05.006.

Sartor, G., Mannino, C., Nygreen, T., Bach, L., 2023. A MILP model for quasi-periodic strategic train timetabling. Omega (United Kingdom) 116, http://dx.doi.org/10.1016/j.omega.2022.102798.

Schadschneider, A., 2001. Cellular automaton approach to pedestrian dynamics - theory. URL http://arxiv.org/abs/cond-mat/0112117.

Seriani, S., Fernández, R., 2015. Planning guidelines for metro–bus interchanges by means of a pedestrian microsimulation model. Transp. Plan. Technol. 38, 569–583. http://dx.doi.org/10.1080/03081060.2015.1039235.

Shi, X., Ye, Z., Shiwakoti, N., Tang, D., Wang, C., Wang, W., 2016. Empirical investigation on safety constraints of merging pedestrian crowd through macroscopic and microscopic analysis. Accid. Anal. Prev. 95, 405–416. http://dx.doi.org/10.1016/j.aap.2015.10.009.

Shiwakoti, N., Gong, Y., Shi, X., Ye, Z., 2015. Examining influence of merging architectural features on pedestrian crowd movement. Saf. Sci. 75, 15–22. http://dx.doi.org/10.1016/j.ssci.2015.01.009.

Solak, S., Clarke, J.P.B., Johnson, E.L., 2009. Airport terminal capacity planning. Transp. Res. Part B: Methodol. 43, 659–676. http://dx.doi.org/10.1016/j.trb.2009.01.002.

Sun, L., Jin, J.G., Lee, D.H., Axhausen, K.W., Erath, A., 2014. Demand-driven timetable design for metro services. Transp. Res. Part C: Emerg. Technol. 46, 284–299. http://dx.doi.org/10.1016/j.trc.2014.06.003.

Tajima, Y., Nagatani, T., 2002. Clogging transition of pedestrian flow in T-shaped channel. Phys. A 303, 239–250. http://dx.doi.org/10.1016/S0378-4371(01)00424-1.

Tang, M., Hu, Y., 2017. Pedestrian simulation in transit stations using agent-based analysis. Urban Rail Transit 3, 54–60. http://dx.doi.org/10.1007/s40864-017-0053-5.

Twarogowska, M., Goatin, P., Duvigneau, R., 2014. Comparative study of macroscopic pedestrian models. Transp. Res. Procedia 2, 477–485. http://dx.doi.org/10.1016/j.trpro.2014.09.063.

UITP, 2015. Urban public transport in the 21st century. pp. 1–8, https://www.uitp.org/sites/default/files/cck-focus-papers-files/UITP_StatisticBrief_nationalPTstats.pdf.

UITP, 2018. European countries ridership data 2018. URL https://cms.uitp.org/wp/wp-content/uploads/2020/08/description-European-countries-ridership-data-2018-MiS.pdf.

Vermuyten, H., Beliën, J., De Boeck, L., Reniers, G., Wauters, T., 2016. A review of optimisation models for pedestrian evacuation and design problems. Saf. Sci. 87, 167–178. http://dx.doi.org/10.1016/j.ssci.2016.04.001.

Virkler, R., Elayadath, S., 1992. Pedestrian speed-flow-density relationships. Transp. Res. Rec. 1438.

Wan, J., Sui, J., Yu, H., 2014. Research on evacuation in the subway station in China based on the combined social force model. Phys. A 394, 33–46. http://dx.doi.org/10.1016/j.physa.2013.09.060.

Wang, Y., D'Ariano, A., Yin, J., Meng, L., Tang, T., Ning, B., 2018. Passenger demand oriented train scheduling and rolling stock circulation planning for an urban rail transit line. Transp. Res. Part B: Methodol. 118, 193–227. http://dx.doi.org/10.1016/j.trb.2018.10.006, URL https://doi.org/10.1016/j.trb.2018.10.006.

Wang, Y., De Schutter, B., van den Boom, T.J., Ning, B., 2013. Optimal trajectory planning for trains - a pseudospectral method and a mixed integer linear programming approach. Transp. Res. Part C: Emerg. Technol. 29, 97–114. http://dx.doi.org/10.1016/j.trc.2013.01.007.

Wang, Y., Tang, T., Ning, B., van den Boom, T.J., De Schutter, B., 2015a. Passenger-demands-oriented train scheduling for an urban rail transit network. Transp. Res. Part C: Emerg. Technol. 60, 1–23. http://dx.doi.org/10.1016/j.trc.2015.07.012.

Wang, L., Yan, X., Wang, Y., 2015b. Modeling and optimization of collaborative passenger control in urban rail stations under mass passenger flow. Math. Probl. Eng. 2015, http://dx.doi.org/10.1155/2015/786120.

Wang, L., Yan, X., Zhang, Y., 2015c. Coordinative passenger flow control during peak hours in urban rail stations. In: CICTP 2015 - Efficient, Safe, and Green Multimodal Transportation - Proceedings of the 15th COTA International Conference of Transportation Professional. pp. 1153–1164. http://dx.doi.org/10.1061/9780784479292.107.

Wong, S.C., Leung, W.L., Chan, S.H., Lam, W.H., Yung, N.H., Liu, C.Y., Zhang, P., 2010. Bidirectional pedestrian stream model with oblique intersecting angle. J. Transp. Eng. 136, 234–242. http://dx.doi.org/10.1061/(ASCE)TE.1943-5436.0000086.

Wu, P.P.Y., Mengersen, K., 2013. A review of models and model usage scenarios for an airport complex system. Transp. Res. Part A: Policy Pr. 47, 124–140. http://dx.doi.org/10.1016/j.tra.2012.10.015.

Xu, X., Li, H., Liu, J., Ran, B., Qin, L., 2019. Passenger flow control with multi-station coordination in subway networks: algorithm development and real-world case study. Transp. B 7, 446–472. http://dx.doi.org/10.1080/21680566.2018.1434020, URL https://doi.org/10.1080/21680566.2018.1434020.

yue Xu, X., Liu, J., ying Li, H., Hu, J.Q., 2014. Analysis of subway station capacity with the use of queueing theory. Transp. Res. Part C: Emerg. Technol. 38, 28–43. http://dx.doi.org/10.1016/j.trc.2013.10.010.

yue Xu, X., Liu, J., ying Li, H., Jiang, M., 2016. Capacity-oriented passenger flow control under uncertain demand: Algorithm development and real-world case study. Transp. Res. Part E: Logist. Transp. Rev. 87, 130–148. http://dx.doi.org/10.1016/j.tre.2016.01.004.

Yin, J., D'Ariano, A., Wang, Y., Yang, L., Tang, T., 2021. Timetable coordination in a rail transit network with time-dependent passenger demand. European J. Oper. Res. 295, 183–202. http://dx.doi.org/10.1016/j.ejor.2021.02.059.

Yuan, Y., Li, S., Yang, L., Gao, Z., 2022. Real-time optimization of train regulation and passenger flow control for urban rail transit network under frequent disturbances. Transp. Res. Part E: Logist. Transp. Rev. 168, 102942. http://dx.doi.org/10.1016/j.tre.2022.102942.

Zhang, Q., Han, B., Li, D., 2008. Modeling and simulation of passenger alighting and boarding movement in Beijing metro stations. Transp. Res. Part C: Emerg. Technol. 16, 635–649. http://dx.doi.org/10.1016/j.trc.2007.12.001.

Zhang, J., Klingsch, W., Schadschneider, A., Seyfried, A., 2011. Transitions in pedestrian fundamental diagrams of straight corridors and T-junctions. J. Stat. Mech. Theory Exp. 2011, http://dx.doi.org/10.1088/1742-5468/2011/06/P06004.

Zhang, L., Liu, M., Wu, X., AbouRizk, S.M., 2016. Simulation-based route planning for pedestrian evacuation in metro stations: A case study. Autom. Constr. 71, 430–442. http://dx.doi.org/10.1016/j.autcon.2016.08.031.

Zhang, P., Sun, H., Qu, Y., Yin, H., Jin, J.G., Wu, J., 2021. Model and algorithm of coordinated flow controlling with station-based constraints in a metro system. Transp. Res. Part E: Logist. Transp. Rev. 148, 102274. http://dx.doi.org/10.1016/j.tre.2021.102274, URL https://doi.org/10.1016/j.tre.2021.102274.

Zhou, X.M., Ji, X.F., Huang, H., Yang, X.G., 2014. Simulation of bidirectional pedestrian flow in transfer station corridor based on multi forces. J. Central South Univ. 21, 2520–2525. http://dx.doi.org/10.1007/s11771-014-2207-x.