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# Formulation and solution framework for real-time railway traffic management with demand prediction

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## Abstract

Recent transport policies increasingly promote shifts towards rail travel aiming at a more sustainable transportation system. This shift is hampered by widespread unexpected perturbations in operations, resulting in perceived poor punctuality and reliability. When prevention of such perturbations is not feasible, traffic management must mitigate their effects, resolving arising conflicts to restore regular train operations and minimize delay. Current practice generally includes the assessment of railway performance in terms of train delays, but the quality of service to passengers is rarely explicitly accounted for. A railway traffic management framework is proposed that accounts for both passenger and train delays. To do so, a predictive optimization framework is proposed, integrating a demand prediction module, a passenger demand assignment module and a traffic management module. The first dynamically predicts future origin-destination passenger flows using linear regression on real-time observed smart card data. Then, the demand assignment module links predicted passengers to specific train paths, given a railway schedule. Finally, the traffic management module optimizes train scheduling and routing in real time, under the combined objective of minimizing train and passenger delays. The methodology is validated and benchmarked against equivalent passenger agnostic traffic management on a case study of the Copenhagen suburban railway network. The results show that it is possible to take into account passenger perspective in railway traffic management, without reducing the railway system efficiency compared to classic approaches.

## 1 | INTRODUCTION

In recent years, European and international transport policies have focused on the transition to sustainable and smart mobility, aiming to foster a major modal shift to railway. Railway systems offer substantial benefits. They efficiently transport a large number of passengers, help mitigate traffic congestion, and generate economic advantages by fostering agglomeration effects [1]. For medium-distance passenger transportation, high-speed trains are the only established alternative to aviation. Transport modes other than railways contribute significantly to energy consumption and emissions in the transport sector. Yet, railway alternatives are underutilized despite their potential. Currently, the railway sector carries about 8% of all passen-

ger traffic and 7% of all freight transport globally. Electric and diesel trains together give rise to around 3% of all well-to-wheel greenhouse gas emissions from the transport sector [2]. However, in many regions of the world, railway faces various challenges when compared to cars or other modes of transport, in part due to a lack of reliability and punctuality. In Europe, only 59% of passengers declare to be satisfied with the punctuality and reliability of railway travels [3]. Indeed, a study performed by UIC [4] on travellers' preferences shows that punctuality is among the top three criteria when choosing a mode of transport. Hence, a key factor encouraging the shift to railway is the improvement of train operations and the perceived punctuality of passengers in the event of traffic perturbations.

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In the outlook of the so-called Green Deal proposed by the European Commission, the International Energy Agency (IEA) has outlined future transport scenarios. These scenarios envisage a shift to railway from less efficient transport modes including cars, two/three-wheel vehicles, aviation and trucks [2]. In the best-case scenario, global passenger railway activity is projected to more than double (+116%) by 2030 in comparison to 2017 levels. Additionally, freight transportation is envisioned to match road transport activity by 2030, and to exceed road freight volumes by 2050. Optimizing railway traffic management is important not only to be able to accommodate increased demand, but also to improve service quality and railway attractiveness for users.

In nominal conditions, trains operate a timetable designed months in advance of its deployment to accommodate expected demand. Timetables plan for conflict-free train paths, that is, time-distance movement definitions in which no train has to slow down or stop due to traffic. However, operations are often affected by unexpected perturbations and disruptions due to, for example, technical failures, track obstructions, weather conditions, overcrowded stations, and passenger incidents. Whenever disturbances occur, it is the job of the infrastructure manager to identify and resolve arising conflicts. The problem faced by infrastructure managers to deal with everyday perturbations is known in the literature as the real-time railway traffic management problem (rtRTMP) [5]. The goal of the rtRTMP is to reduce delay propagation, with as little inconvenience to operators and passengers as possible.

As documented by the European Commission [6], many existing policies assess the quality of railway services by measuring the delay a train suffers compared to its scheduled arrival times. These policies consist of rules or guidelines that are established by infrastructure managers to govern the performance regime. In practice, they translate in addressing the rtRTMP by implementing traffic control decisions focused on improving train punctuality. Typically, these decisions are manually tackled within control centers where continuous traffic monitoring takes place, while passenger-related information is often lacking.

The policies regulating rtRTMP solution implicitly take passengers into account by considering the inherent influence of train delays on their travel. However, this implicit impact does not provide an accurate representation of how delays affect passengers. Undoubtedly, passengers experience delays on a personal level. People have different schedules and commitments during the day, which can influence the choice of their paths. Moreover, many passengers rely on timely transfers between the same or different modes of transportation, such as connecting trains or buses. A delay in one leg of their journey can result in missed transfers, extended layovers, or even the need to re-book entirely. Indeed, explicitly integrating passenger perspectives and their experience of delays in the solution of the rtRTMP would give a more accurate representation of service quality.

Digitization supports the integration of passengers into the rtRTMP by making data more accessible and easier to process. Modern ticket systems, such as automatic fare collection (AFC), record details of individual passenger trips, including origins and

destinations. These records, stored in large databases, offer valuable insights into travel patterns and demand. AFC systems can also provide real-time data, enabling the prediction of origin-destination (OD) matrices not just daily but in short intervals under an hour. By combining these predictions with assumptions about passenger behavior, it becomes possible to predict individual travel trips in real time.

In this paper, we introduce a real-time railway traffic management framework that explicitly takes into account actual demand data, demand prediction, and their dependence from traffic conditions. The framework aims to minimize both passenger and train delays, ensuring that traffic decisions respond to evolving demand and network perturbations. The exploitation of demand prediction makes rtRTMP decisions proactive, not just reactive. While instantaneous data alone provide reactive responses that can meet current demand, they fail to mitigate the cumulative effects of delays on passenger flow in the short-term future. Demand prediction anticipates how passenger flows will evolve over time and their distribution among trains. This helps the rtRTMP handle upcoming passenger flows before they materialize by improving train scheduling and platform assignment for the benefit of most passengers. For example, predicting real-time passenger load data can identify which trains will carry higher numbers of passengers in the near future. Prioritizing these trains for decisions related to train retiming, reordering, and rerouting would increase the satisfaction of a larger number of travelers. Additionally, incorporating information about passengers' transfers can allow optimizing schedules to accommodate adequate transfer times between train services.

The framework we propose combines three main modules into an automated decision support system. Specifically, we develop a *demand prediction module* which processes information about passenger flows and predicts upcoming ones, and a *demand assignment module* which identifies the expected paths used in response to traffic variations. This information is then used in the *traffic management module* to optimize railway traffic based on a microscopic representation of train movements, enabling rerouting and reordering. In particular, we integrate passenger prediction in a state-of-the-art mixed-integer linear programming (MILP)-based algorithm for the rtRTMP called RECIFE-MILP [7]. Based on this framework, we propose three solution approaches that differ in the interaction between demand assignment and traffic management modules. By integrating predicted passenger paths and real-time traffic conditions, our framework aims to adapt to real-time conditions, mitigate the consequences of delays for passengers, and be applicable to different railway networks.

The proposed framework addresses the rtRTMP, focusing on scenarios where unexpected perturbations cause conflicts between trains requesting to use the same track section simultaneously. These scenarios may include: minor malfunctions in signaling systems, switches, or train equipment that require brief reparations; small-scale incidents, such as objects on tracks or brief maintenance activities; moderate adverse weather, such as heavy rain or fog, causing slower train speeds or brief operational delays; prolonged boarding or alighting due to

overcrowding, passengers holding doors open, or emergency assistance. Our study aims at addressing conflicts arising in such scenarios, considering networks and timetable structures where traffic management measures as rerouting and rescheduling are pertinent. Such networks include features like multiple platforms at (some) stations and portions of track shared by multiple trains.

We validate our approaches on a case study of the Copenhagen suburban railway network. We benchmark it against the classic passenger-agnostic RECIFE-MILP. Our results show that the three solution approaches we propose achieve good results in reducing passenger delays without noticeably increasing train ones. The consideration of passenger reactions to traffic management decisions appears beneficial although its impact is not very strong in our case study.

With our research, we show that it is possible to take into account passenger perspective in railway traffic management, without reducing the system efficiency compared to classic approaches. This can lead to improved quality of service, enhanced customer satisfaction, and a more comprehensive evaluation of railway service performance beyond traditional metrics.

The rest of this article is structured as follows: Section 2 reviews the relevant literature on the rtRTMP integrating the operational and passenger perspectives; Section 3 formalizes the problem we consider in this paper; Section 4 discusses the proposed modelling framework; Sections 5, 6, and 7 provide a description of the demand prediction, assignment, and traffic management modules, respectively; Section 8 presents and discusses the computational results, and Section 9 summarizes the conclusions and suggests future research directions.

## 2 | LITERATURE REVIEW

In recent years, the evaluation of public transport performance has shifted from a managerial focus on cost efficiency to a greater emphasis on service quality from the passenger's perspective [8]. De Oña et al. [9] provide an extensive review of the factors influencing service quality and the methodological approaches used for its assessment. Notably, Soza-Parra et al. [10] and Kathuria et al. [11] have highlighted that variability in waiting and travel times is among the most influential factors that affect user satisfaction, ultimately influencing route choices [12]. Recent work has also highlighted that impacts on demand are not only limited to larger disruptions, but also arise from smaller and often more frequent traffic perturbations [13, 14].

The rtRTMP solution can reflect this dual perspective, considering both the managerial and passenger viewpoints. It is typically addressed from one of two optimization perspectives [15]: train-oriented or passenger-oriented. The first perspective consists in minimizing the impact of delays on train operations (e.g. total train delay or maximum delay at destination). The second perspective consists in minimizing the negative impact of delay propagation on passengers (e.g. total travel time, waiting time or train connections in stations).

Approaches developed for conventional railways are primarily train-oriented. However, established literature has extended the rtRTMP solution to include passengers. Pertaining to this branch of the literature, Schöbel [16] introduced for the first time the problem of delay management. It concerns passenger transfers, and decides whether trains receiving passengers should wait for a late feeder train or leave on time. The problem was formulated as a MILP model minimizing the sum of all passenger delays. The proposed model and solution approaches have been extended by follow-up studies [17, 18]. Heilporn et al. [19] proposed two MILP models for variable reduction in delay management, based on the one of Schöbel [16]. One model used a branch and cut procedure, while the other employed a constraint generation approach to solve the problem more efficiently. Dollevoet et al. [20, 21] extended the delay management problem by considering passenger rerouting on an event-activity network model. Kanai et al. [22] presented a model for delay management that minimizes a passenger disutility function, considering factors like in-vehicle time, waiting time, transfers, and train congestion rate. The authors combined simulation and a tabu search optimization approach [23], and performed computational tests on a Japanese railway network. Zu and Goverde [24] proposed a model that integrates timetable rescheduling and passenger reassignment, aiming to minimize generalized travel time by assigning passengers to paths based on path weights. The model incorporates rescheduling measures and utilizes an adapted fix-and-optimize algorithm to solve the passenger-oriented timetable iteratively, by considering few passenger groups in each iteration.

All the mentioned approaches use macroscopic representations of railway infrastructure and train movements. The choice of using these representations is driven by two main reasons. On the one hand, they allow the formulation of instances at a higher level of abstraction compared to the microscopic ones, which take into account fine-scale details and individual passengers. This abstraction has a big impact on algorithm efficiency: the rtRTMP is an NP-hard problem when it comes to train rescheduling and rerouting [25]. Including passenger-related variables and constraints adds even more computational difficulty to the problem. On the other hand, macroscopic representations provide a high-level perspective on passenger flows and delays in case of disturbances. This is particularly pertinent when large networks need to be optimized at once. However, macroscopic representations may fail to capture dynamics and interactions within the railway system accurately. These representations rely on assumptions and simplifications, which can introduce deviations from the actual behavior of trains and passengers. In fact, these models can produce solutions that are not feasible or practical to implement in real-world railway operations.

Because of computational complexity, approaches based on microscopic infrastructure representations are less developed in passenger studies for conventional railways. The following are some leading approaches in this regard. Corman et al. [26] developed a bi-objective delay management strategy that minimizes weighted passenger delays and missed connections using alternative graphs. In a follow-up work, Corman et al. [27] presented

algorithms for calculating upper and lower bounds, decomposing the problem into train rescheduling and passenger routing problems. Still based on the alternative graph, Espinosa-Aranda et al. [28] proposed the Avoid Most Delayed Alternative Arc approach for minimizing total passenger delay, comparing exact and heuristic methods for solving the problem. Sato et al. [29] introduced a model that minimizes passenger inconvenience while considering train arrival delays, incorporating three phases to manage passenger and operation-oriented objectives. Luan et al. [30] proposed an MILP model, identifying the train orders and timings and finding the best path for passengers while minimizing passenger delay.

These passenger-integrated rtRTMP models for conventional railways rely on static OD matrix to represent passenger demands. Moreover, they aggregate passengers in rather large groups to reduce the computational complexity of the problem. Static passenger data refer to demand flow predictions that are independent from the traffic management choices. In real-time management, this static data does not capture the evolution of passenger decision-making and preferences. The studies of Yalçınkaya and Bayhan [31] and Xu et al. [32] highlighted that passenger demands are dynamic and uncertain, and this has an impact on the quality of decisions. In particular, the arrival patterns of passengers at a station and the path choices can vary dynamically over time in response to timetable perturbations and rescheduling. Dynamic passenger data provide a more accurate and up-to-date understanding of passenger flows, allowing for responsive adjustments in the rtRTMP solution.

Approaches that integrate dynamic passenger information are being developed for traffic management in urban railway systems. Below we report the more relevant literature related to our work. For a broader literature review on the subject, we refer the reader to Sharma et al. [15]. Among the first works in this research area, Zhen and Jing [33] designed a rescheduling method in which the departure times of delayed trains is updated to allow dynamic passenger path choice. Experiments conducted by the authors on the Beijing subway show that their method reduces the combination of total travel time and the number of passenger travel cancellations compared to the delayed timetable with no change. Yin et al. [34] proposed a stochastic model that captures dynamic passenger flow using a non-homogeneous probability distribution for passenger arrivals, adapting to time-varying passenger demand. The authors solved the rescheduling problem with an approximate dynamic programming-based algorithm for a case study of the Beijing subway. Their approach is shown to reduce passenger delay in comparison with a heuristic that simply postpones the arrival times and departure times for all the delayed trains. Similarly, Hao et al. [35] explored passenger-oriented rescheduling through a Markov decision process, considering the interaction between train operations and passenger behavior. They minimized passenger and operational costs, while regulating the train running time and the number of boarding passengers. Rather than using a time-dependent OD matrix, Li et al. [36] developed a coupled dynamic model that regulates passenger flow and train rescheduling based on dynamic passenger demand related to train headway. This model integrates passenger demand

evolution, train control actions, and headway regularity into a weighted cost function, which is optimized through model predictive control. Their results showed that in a metro system, the delay was effectively managed through train regulation and passenger control to return to the normal operating schedule as soon as possible. More recently, Hassannayebi et al. [37] formulated a rescheduling framework incorporating short-turn and skip-stop strategies, aimed at minimizing passenger waiting times. Here, the passenger arrival rate at stations is characterized by a non-stationary Poisson distribution. The method was tested on the Tehran metro network, and the results showed a significant improvement over the manual control procedure managed by railway experts.

Overall, the mentioned approaches show that including dynamic passenger information leads to effective urban railway traffic management in comparison with methods that either disregard passengers or consider static passenger data. However, because these approaches are developed for urban railway systems, they exclude train rerouting and reordering since urban systems are mainly characterized by railway lines with independent tracks [36]. As a result, such approaches are not suitable for more complex urban networks and can hardly be generalized to conventional ones.

Kroon et al. [38] and Veelenturf et al. [39] offer key insights into iterative frameworks for managing dynamic passenger flows, though they primarily focus on seat capacity constraints as the central aspect for dealing with demand variability. Kroon et al. [38] address large-scale disruptions by reallocating rolling stock based on a predetermined timetable, while Veelenturf et al. [39] expand upon this by incorporating real-time updates to both rolling stock allocation and timetable modifications in response to evolving passenger demand. However, the adjustments in Veelenturf et al. [39] specifically refer to the addition of extra stops. Both studies approach the problem from the perspective of train operating companies, aiming to assign rolling stock to an adjusted timetable to accommodate passengers, taking into account seat availability and boarding decisions. In contrast, our study takes the infrastructure manager's perspective, focusing on optimizing the timetable in real time through a traffic management module that integrates passenger flows as a critical component of the rescheduling process. Furthermore, while both previous studies adopt a macroscopic view of the network, abstracting detailed infrastructure elements, our study includes a wider range of traffic management decisions within a detailed microscopic model of the railway infrastructure. Additionally, unlike the static origin-destination (OD) matrices assumed in these studies, our model dynamically predicts OD matrices based on real-time conditions, allowing for continuous updates to passenger assignments. For an extensive review of relevant literature dealing with passengers in problems beyond the scope of this paper, we refer the reader to Sharma et al. [15].

Our study introduces a novel framework for solving the rtRTMP that bridges existing gaps. Our framework accounts for dynamic passenger data and optimizes the railway traffic accordingly, regardless of the type of network at hand. We consider a microscopic representation of the railway infrastructure, and we implement train retiming, reordering, and rerouting

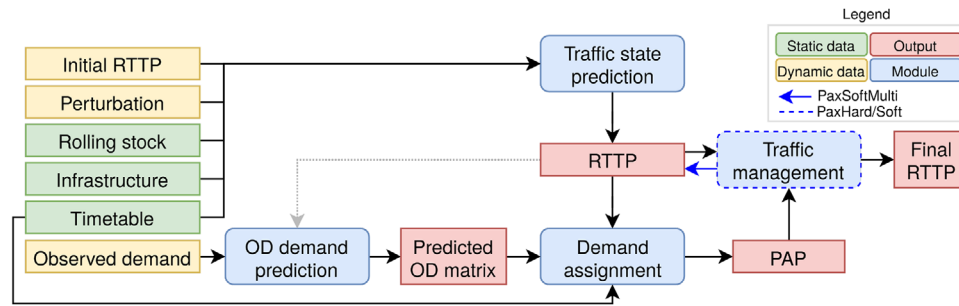


FIGURE 1 Illustration of the proposed framework.

decisions. This provides practical and high quality rtRTMP solutions adaptable to both conventional and urban systems. We decline the proposed framework in three solution approaches. They differ in the way passenger transfers are considered in the rtRTMP, and in how passengers react to traffic changes.

### 3 | PROBLEM DESCRIPTION

As mentioned in the introduction, train operations are coordinated by a timetable planned beforehand. The timetable defines the passing, arrival and departure times of trains in stations, their route across the network, and the train passing orders over common track sections.

The rtRTMP is the formalization of the problem faced by dispatchers in control centers. Here, train operations are monitored and managed in real time to ensure efficient operations in *control areas*, which consist of the railway infrastructure and the interlocking system within a limited geographical area. For each control area, dispatchers monitor the position and the speed of trains to detect potential deviations from the timetable. Unexpected events such as mechanical failures, track obstructions, adverse weather conditions, or large crowds can disturb the planned train operations. Disturbances that can be dealt with by dispatchers alone are referred to as *perturbations*, while *disruptions* require major changes to the timetable and imply negotiations between various stakeholders. In this article, we only consider perturbations. In case of perturbations, dispatchers identify potential *conflicts*, that occur if two trains running according to the scheduled speed would simultaneously occupy the same section of track, so at least one train needs to slow down or stop. In this case, dispatchers may take traffic control actions, such as retiming, reordering or rerouting the trains, to minimize the propagation of delays. Retiming decisions involve adjusting arrival, departure and stop times. Reordering decisions establish train passing orders on shared track sections, while rerouting decisions select routes across the network. Alternative routes share stopping stations with the timetable, but pass through different track sections. We call *train line* a sequence of stopping stations served by at least one train.

With the policy we propose, the objective of the rtRTMP consists in the minimization of both passenger and train delay. Minimizing passenger delay requires predicting passenger demand, in the form of origin, destination, and desired arrival

time. This translates into solving a demand prediction problem. Moreover, when the network allows for multiple route options for different origin-destination pairs, passenger path choices must be accounted for, resulting in an assignment problem to be solved. Along a chosen path, passengers may have to perform transfers. Being passenger data dynamic, demand assignment must consider that, when passengers miss a planned transfer, they may decide to take the next train along the same path or completely change path.

The solution of the rtRTMP requires a flexible and context-aware deployment. Because railway traffic varies rapidly in real time, the rtRTMP must respond quickly to disturbances to propose appropriate solutions. To this purpose, the problem can be solved either periodically or triggered by the detection of a disturbance. In the context of periodic solution, the rtRTMP is addressed at regular intervals, proactively managing potential deviations from the timetable to maintain consistent operational efficiency. Instead, the trigger-driven solution is activated in response to observed disturbances. In both cases, when decisions and adjustments are made to the timetable being executed, a Real-Time Traffic Plan (RTTP) is produced [40] and shared for further validation or immediate implementation. The RTTP includes microscopic details on train movements across the network for a predefined time horizon. In this paper, we consider the periodic rtRTMP solution at regular intervals.

### 4 | PROPOSED FRAMEWORK AND SOLUTION APPROACHES

In this section, we present the framework we propose to formalize the new policy for the rtRTMP, minimizing both passenger and train delay. Moreover, we detail the solutions approaches we introduce for its application. In particular, the framework deals with the problem described in Section 3 and specifies the inputs, outputs and modules involved in the production of an RTTP.

The novel framework involves the interaction of a demand prediction, a demand assignment, and a traffic management modules, as depicted in Figure 1. The left-hand side of the figure shows the input data considered. This data is split in static and dynamic data. The former is fixed, the latter varies depending on traffic situation and passenger flow. Specifically, static data includes the microscopic representation of the infrastructure, the planned timetable, and the description of the rolling

stock in use. Dynamic data, instead, concerns the initial RTTP, that is, the traffic plan currently being implemented, the information on the expected and observed perturbations in terms of train delays, and the currently observed demand. The inclusion of this last dynamic input in railway traffic management is a first novelty with respect to the current practice. The rest of the figure depicts the process and intermediate outputs involved in the production of the final RTTP.

First, a short-term Traffic State Prediction (TSP) is computed based on the initial RTTP, the perturbations, and the static data. Assuming that the traffic management decisions in the initial RTTP are executed, the TSP predicts the evolution of train movements in the short term, considering the current perturbations. Based on the TSP, an updated RTTP is defined: train routing and ordering are the same as in the initial RTTP, while timing changes due to observed and expected delays.

In parallel, the OD demand prediction module produces a predicted OD matrix capturing the passenger flow within a time horizon, based on the observed demand.

Taking as input the RTTP and the predicted OD matrix, the demand assignment module outputs a Passenger Assignment Plan (PAP). The PAP reports the expected number of passengers traveling between each pair of origin and destination stations per *train-based path*. A train-based path is a sequence of trains that can be used for an OD pair. The sequence has more than one element if the path includes transfers. Various alternative train-based paths can be available for an OD pair. Each train-based path is associated with expected times of departure and other attributes including travel and waiting times, along with any associated transfers.

The traffic management module uses the TSP and the PAP to solve the rtRTMP, where the general objective function based on train delay minimization [7] is extended with passenger delays at destination. Moreover, passenger connections are accounted for, to allow the execution of train-based paths as defined in the PAP. The output is the final RTTP to be implemented until the next application of the framework. The consideration of PAP and passenger delay is the second novelty we bring to rtRTMP standard practice.

The third and most original novelty of our framework is represented by the feedback loop between traffic management and demand assignment modules. Indeed, we consider demand as dynamic data, that is, we reckon that passenger behavior is at least partially driven by traffic conditions. Iterations between the traffic management and the demand assignment modules concretize this feedback loop: passenger delay is assessed based on a passenger assignment that reflects traffic conditions, which are in turn defined by traffic management decisions. An option that may constitute an extension to this framework involves considering a similar feedback loop for the OD demand prediction module. Indeed, also passenger flows may be influenced by transport supply, as people may decide to change mode or even daily activities to respond to very regular or very unreliable traffic, for example.

We propose three solution approaches to apply this framework. They differ in the traffic management module definition

and in the presence of a feedback loop between this module and the demand assignment one. The three approaches are:

- *PaxHard*: The traffic management module includes demand prediction in its formulation. In the module definition, passenger transfers are set as hard constraints, to ensure the feasibility of the train-based paths in the PAP even in case of delay of the feeder train. Here, demand is considered as partially static data: passenger assignment to trains depends on the initial RTTP but not the final one. To some extent, this approach mimics a policy in which passengers are taken into account in the optimization, but they are not supposed to be promptly reactive to traffic management decisions.
- *PaxSoft*: The traffic management module includes demand prediction in its formulation. In this module definition, soft constraints are set to favor the preservation of the predicted passenger transfers. These constraints are introduced with violation penalties in the objective function. Penalties are proportional to the planned headway on the train line of the receiving train: the logic behind this choice is that, if the receiving train does not wait for the feeder one, passengers missing the former will have to wait for an additional time that can be approximated as the planned headway.
- *PaxSoftMulti*: The traffic management module is defined as in the *PaxSoft* approach, as for passenger transfers. However, it represents a situation in which passengers are expected to quickly react to traffic management changes. Here, a feedback loop between traffic management and demand assignment modules is put in place. With the *PaxSoftMulti* definition of the former module, it creates multiple RTTPs based on an input TSP and PAP. These RTTPs are all supplied as input to the demand assignment module, which produces a PAP for each of them. Finally, the traffic management module evaluates passenger and train delays for each RTTP using the corresponding PAP, and chooses the best one to implement. The use of this approach implies the deployment of a traffic management policy that also involves an efficient passenger information system, to allow immediate reactions.

In the following sections, we describe the OD demand prediction, the demand assignment and the traffic management modules.

## 5 | OD DEMAND PREDICTION

The purpose of the OD demand prediction module is to predict the incoming flow of passengers for each OD pair within a given time horizon  $\tau$ .

The input of the proposed model includes real-time OD demand from an AFC system. The principle of the prediction model is that demand can be described as a set of time series with spatial and temporal correlations on different scales. These correlations comprise daily and weekly recurrent patterns, within-day temporal correlations, and spatial correlations between related OD pairs. Other information may correlate with demand and could be explored for extensions to the

model in the future. In many European countries, urban public transport competes with cycling. Those cycling may choose to use public transport on days with precipitation, thus increasing demand, making weather variation a possible predictor of demand deviations. Reliability of travel time is also a natural factor for passengers when choosing public transport over other modes. Punctuality and cancellations of trains affect travel times, thus possibly making such variables useful in demand prediction, too. Predictors may also include events generating extraordinary demand, for example, sports events, concerts, or festivals. For the purposes of this paper, we estimate a linear regression model based on historical AFC records, namely trip origin *tap-in* and trip destination *tap-out* records. Specifically, the location and time of these tap-ins and tap-outs are used to track each passenger. This information is aggregated into OD matrices for discrete time intervals. We assume that tap-ins and tap-outs can be observed immediately. As long as passengers are tapped in, but not tapped out, only the tap-in time and location can be observed. Some AFC systems also record transfers, which define the exact routes chosen, but due to lack of reliable data sources on this, transfer records are ignored in this paper. The current model implicitly accounts for the impact of disturbances and disruptions on passenger demand through historical data, which includes periods with varying levels of service reliability. However, the model does not differentiate between normal operational conditions and periods of disruption.

We consider time interval  $\tau$ . We then define the OD matrix of  $\tau$  as  $\delta_\tau = (\delta_{\tau ij})$  where  $\delta_{\tau ij}$  represents the number of trips that start at station  $i$  in  $\tau$  and end at station  $j$ . We define, for  $l \in \mathbb{N}$ ,  $\hat{\delta}_{\tau-l, \tau} = (\hat{\delta}_{\tau-l, i, j, \tau})$  as the provisional OD matrix for time interval  $\tau - l$  as observed at  $\tau$ , that is, consisting of OD trips that are started in  $\tau - l$  and completed before the start of  $\tau$ . We use the OD demand of the  $m$  most recent intervals, that is,  $\hat{\delta}_{\tau-1, \tau}$  through  $\hat{\delta}_{\tau-m, \tau}$  as independent variables to predict OD demand of the current interval,  $\delta_\tau$ , based on the principle that recent volumes of OD demand correlate with current and future OD demand [41, 42].

The prediction model in this paper consists of a linear regression for each OD pair  $(i, j)$ . We denote the estimated regression parameters for each OD pair as  $\beta_{ij} = (\beta_{ij,0}, \beta_{ij,1}, \beta_{ij,2}, \dots, \beta_{ij,m})$ , where  $\beta_{ij,l}$  is the coefficient for the feature  $\hat{\delta}_{\tau-l, i, j, \tau}$  for any  $\tau$  and  $l$  a strictly positive integer. We formalize the prediction of OD demand as follows using linear regression as outlined above:

$$\begin{aligned} \delta_{\tau ij} &= f(\hat{\delta}_{\tau-1, i, j, \tau}, \hat{\delta}_{\tau-2, i, j, \tau}, \dots, \hat{\delta}_{\tau-m, i, j, \tau}) \\ &= \beta_{ij,0} + \beta_{ij,1} \hat{\delta}_{\tau-1, i, j, \tau} + \beta_{ij,2} \hat{\delta}_{\tau-2, i, j, \tau} + \dots \\ &\quad + \beta_{ij,m} \hat{\delta}_{\tau-m, i, j, \tau} \end{aligned} \quad (1)$$

The predicted demand covers a single time interval into the future from the time of prediction and we estimate the linear regression for each OD pair separately. For estimation, we remove the *weekly recurrent trend* within the period from both the input features and the target. The weekly recurrent trend specifies for each weekday and time interval a value that equals the

mean of the data points associated with the same weekday and interval across the weeks of the period. This way, the model predicts only the correlations between deviations from the trend since the recurrent trend is easy to estimate on its own and can be added to the prediction of the deviation to get an absolute prediction [43].

In our framework, we opt for a linear regression model for demand prediction due to its simplicity and efficiency. Recent studies have explored various methods for railway and urban transit networks, emphasizing the balance between accuracy and computational efficiency [44]. Linear regression offers a straightforward implementation, including a regularization term to mitigate overfitting, which makes it highly suitable for situations where real-time computation is critical. In addition, its ability to handle dynamic updates efficiently ensures that it can adapt quickly to changing traffic conditions. Our approach was benchmarked against state-of-the-art methods such as XGBoost (XGB), Graph Convolutional Networks (GCN), and Neural Relational Inference GNN (NRI-GNN) in a recent study by Nguyen et al. [45]. The comparison revealed that while sophisticated models offer greater accuracy in capturing spatiotemporal relationships, linear regression performs comparably in terms of accuracy and significantly better in terms of computational efficiency. This balance is crucial for real-time traffic management in railway networks affected by perturbations, where frequent updates and rapid reassignments of passengers are required. Other advanced techniques, such as spatiotemporal convolutional networks [46] and multi-graph convolutional networks [47], have shown significant improvements in handling large-scale networks and deep learning methods, as highlighted by Zou et al. [48], have demonstrated enhanced performance during operational disruptions. Although these models hold promising potential for future applications, our current focus is on models such as linear regression that balance computational efficiency with real-time adaptability.

## 6 | DEMAND ASSIGNMENT

The demand assignment module probabilistically assigns individual passengers from the flows supplied by the OD demand prediction module to trains in the input RTTP, given origin-specific arrival time distributions and a pre-defined path choice model.

We start from prediction  $\delta_{\tau ij}$ , indicating the number of passengers starting their trip at station  $i$  in time interval  $\tau$  and ending it at station  $j$ . To transform this prediction into an assignment, we construct a pipeline that successively computes distributions of: (1) passenger *incidence times* and expected desired arrival time at destination, and (2) *train-based path choices*. By incidence time, we mean the arrival time of each passenger at their origin station, corresponding to the smart card tap-in time. A set of passengers with the same OD, incidence time and train-based path choice constitutes a *passenger group*  $p$ . In formal terms, a passenger group  $p$  is indexed  $p_{ij\hat{\tau}, \pi}$ , where  $i$  is the origin station,  $j$  the destination station,  $\hat{\tau}$  the incidence time interval



corresponding to a subset of the interval  $\tau$ , and  $\pi$  is a path in  $\Pi_{ij\hat{t}}$ , the set of train-based paths available for OD pair  $(i, j)$  at incidence time  $\hat{t}$ . Let the probability of incidence at station  $i$  in interval  $\hat{t}$  be  $\rho_{i\hat{t}}$ , with  $\sum_{\hat{t} \in \tau} \rho_{i\hat{t}} = 1$  for any given  $i$ , and let the probability of a passenger choosing path  $\pi \in \Pi_{ij\hat{t}}$  be  $\sigma_{ij\hat{t}\pi}$ , with  $\sum_{\pi \in \Pi_{ij\hat{t}}} \sigma_{ij\hat{t}\pi} = 1$  for any given OD pair  $(i, j)$  and incidence interval  $\hat{t}$ . The demand  $\Gamma_{ij\hat{t}\pi}$  associated with passenger group  $p_{ij\hat{t}\pi}$ , for  $\hat{t} \in \tau$ , is then calculated by:

$$\Gamma_{ij\hat{t}\pi} = \delta_{\tau ij} \rho_{i\hat{t}} \sigma_{ij\hat{t}\pi}. \quad (2)$$

To compute incidence times and path choices, we use assumptions on passenger behavior in transit networks, then calibrated for our case-study [49]. In particular, we assume that:

1. *waiting time* distributions are known for each station. This is the time between the incidence time and the departure of the train boarded by a passenger. Considering the scheduled departure time of trains, we use the waiting time distributions to compute incidence time distributions at each station, within time interval  $\tau$  (Section 5). For each OD pair, given the number of passengers in the OD demand prediction in  $\tau$ , we compute the expected number of passengers with incident time equal to each instant in  $\tau$ . We discretize the incidence distribution into small time intervals of 1 min in order to assign demand on a quasi-continuous range and maintain fast computation. In addition, we compute the expected *desired arrival time* at destination of each passenger group. The desired arrival time is the time at which each group of passengers arrives at their destination according to the nominal timetable: we apply the just described procedure considering originally planned schedules rather than the ones of the RTTP;
2. we associate passengers with specific trains in the RTTP based on a route-choice model. We do so in three steps. First, we pre-compute a set of train-based paths that passengers may use. Second, we compute the probability with which each path in the set will be chosen. Third, we use this probability distribution to assign passengers to trains. This results in a continuous-valued discrete distribution of the overall demand volume.

For the identification of train-based paths, we perform a pre-processing that finds a set of available *line-based paths* for each OD pair, based on train lines. Each of them comprises a sequence of train lines that can be used to get from the origin to the destination. For any time, a line-based path set can be traduced into a train-based path set, by enumerating combinations of trains traveling along the specific lines from that time, as scheduled in the input RTTP. We consider minimum transfer times between arriving and departing trains as a lower threshold for a train-based path to be valid, if transfers are planned. As the access to a train-based path depends on the incidence time of a passenger, we generate train-based path sets for each OD pair and discrete incidence time at the origin station.

To compute the probability of selecting a particular train-based path, we utilize a random utility route choice model [50]. In this model, passengers make decisions based on the utility of each available path, where the utility is formulated as a linear combination of observable path attributes and a random disturbance term that accounts for unobserved factors. The utility of a passenger group  $p$  choosing a path  $\pi$  from station  $i$  to  $j$  during time period  $\hat{t}$  is expressed as:

$$U_{ij\pi\hat{t}} = \beta_X X_{ij\pi\hat{t}} + \epsilon_{ij\pi\hat{t}}. \quad (3)$$

Here,  $X_{ij\pi\hat{t}}$  represents the vector of path attributes for the alternative  $\pi$  at time  $\hat{t}$ ,  $\beta_X$  is the corresponding vector of parameters to be estimated from data, and  $\epsilon_{ij\pi\hat{t}}$  is a random error term, assumed to follow an independently and identically distributed (i.i.d.) extreme value type I distribution across alternatives and passengers. The key path attributes considered include in-vehicle travel time, walking time during transfers, waiting time at boarding points, number of transfers along the path, and pathsize (which captures the degree of overlap between the paths in the choice set) [51]. Access and exit travel times are excluded because the route choice model only considers stop-to-stop decisions. The case-specific parameters for attributes are computed from the RTTP.

For each OD pair and incidence time, we rank the utility of choosing each train-based path, and we discard the ones with utility below a threshold. Then, we apply a standard multinomial logit model to the non-discarded train-based paths to obtain the probability distribution of choices [49]. The probability of traveler  $p$  choosing path  $\pi$  from station  $i$  to  $j$  during time period  $\hat{t}$  can be then written as follows:

$$\sigma_{ij\pi\hat{t}} = \frac{e^{\beta_X X_{ij\pi\hat{t}}}}{\sum_{\pi'=1}^{J_{ij\hat{t}}} e^{\beta_X X_{ij\pi'\hat{t}}}}. \quad (4)$$

In summary, the output PAP contains, for each passenger group: the origin and destination stations, the incidence time, the desired destination arrival time, the chosen train-based path, and the number of passengers in the group ( $\Gamma_{ij\hat{t},\pi}$ ) spread according to the probability of choosing the current train-based path.

## 7 | TRAFFIC MANAGEMENT

In the traffic management module, we integrate passenger modeling in the state-of-the-art rrRTMP solver called RECIFE-MILP [7].

RECIFE-MILP microscopically models the railway infrastructure on a *track-circuit* level and it considers a *route-lock sectional-release* interlocking system. A track-circuit is a track section where the presence of a train is automatically detected, and a sequence of track-circuits between two consecutive signals defines a block section. In the route-lock sectional-release interlocking system, when a train has to use a block section, it reserves all the track-circuits belonging to that block section.

This prevents other trains from using block sections sharing at least one track-circuit with the reserved one. When the train ends using a track-circuit, that track-circuit is released.

The state-of-the-art formulation of RECIFE-MILP [7] simultaneously considers train retiming, reordering and rerouting variables associated with the possible control decisions. Retiming variables consist of non-negative continuous variables for modelling the start and end times of each track-circuit reservation and other timing events. For train reordering and rerouting decisions, the formulation employs binary variables. The train reordering variables establish the precedence relationship between trains on each shared track-circuit. The rerouting variables indicate whether a train uses a specific route among its alternative ones. Train rescheduling variables (retiming and reordering variables) are managed by means of *disjunctive constraints*, including a big-M coefficient. These constraints model the route-lock sectional-release interlocking system. The complete formulation is reported in Appendix A.

RECIFE-MILP solves the problem in two optimization steps. In the first (at most) 30 s of computation, a MILP solver tackles the train scheduling problem, assuming that each train is using its timetable route. The best train scheduling solution is used to reduce the value of the big-M coefficient and as a warm start in the second step, which jointly addresses the train scheduling and routing problems. For more details, we refer the reader to the original paper [7].

Next, we will illustrate the contribution of this paper, which integrates passenger decisions into the RECIFE-MILP formulation. Based on the demand assignment module in Section 6, in RECIFE-MILP, we assume that passengers are aggregated in groups, each having the same OD pair, incidence time, train-based path choice and desired arrival time. Moreover, the formulation assumes that rolling stock capacity is not a constraint, as it focuses on typical operational conditions where demand remains within the available capacity.

To describe the novel contribution, we use the following notation:

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$T, R, \mathcal{TC}$ ,	set of trains, routes, track-circuits, passenger groups and
$P, C$	passenger transfers, respectively;
$p$	passenger group in $P$ ;
$c(t, t', s)$	indicator function: 1 if passengers in $p \in P$ get off train $t$ and transfers to $t'$ at station $s$ , 0 otherwise;
$ms_{t',s}$	minimum transfer time to allow passengers from $t$ to transfer to $t'$ at $s$ ;
$R_t, S_t$	set of routes available to $t$ , with $R = \cup_{t \in T} R_t$ , and set of stations $s$ where $t$ has a scheduled stop;
$\mathcal{TC}^r$	set of track-circuits belonging to route $r \in R$ ;
$s_{r,tc}$	track-circuit following $tc \in \mathcal{TC}^r$ along $r \in R$ ;
$\tau_{r,ty,tc}$	running time of $tc \in \mathcal{TC}^r$ along $r \in R$ for a train of type $ty$ ;
$o_{t,r,tc}$	continuous non-negative variable: time in which $t \in T$ starts the occupation of $tc \in \mathcal{TC}^r$ along $r \in R_t$ ;
$x_{t,r}$	binary variable equal to 1 if train $t \in T$ uses route $r \in R_t$ , 0 otherwise;
$D_t$	continuous non-negative variable: delay suffered by $t$ when exiting the control area or reaching its terminal station therein.

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In this article, we introduce the non-negative continuous variable  $D_p$  for each passenger group  $p \in P$ . This variable corresponds to the passenger delay at destination: it is the difference between the *actual arrival time* and the desired arrival time at destination. For each  $p \in P$ , the actual arrival time is the time at which the last train in the train-based path arrives at  $p$ 's destination.

The objective function is the minimization of the weighted sum of train and passenger delays at destination, with  $w_t$  and  $w_p$  representing the weights assigned to train and passenger delays, respectively. These weights allow the infrastructure manager to adjust the priority between train and passenger delays based on strategic goals or operational needs. In addition, the passenger delay is weighted according to the number of passengers  $n_p$  of each group using the corresponding train-based path specified in the PAP.

$$\min \sum_{t \in T} w_t D_t + \sum_{p \in P} w_p n_p D_p. \quad (5)$$

As mentioned in Section 4, we consider two alternative methods for modeling passenger connections:

1. Hard constraints ensure that the predicted passenger transfers are respected. Specifically, Constraints (6) state that the minimum transfer time must be ensured between the arrival of  $t$  and the departure of  $t'$  at station  $s$ .

$$\begin{aligned} \sum_{\substack{t' \in R_{t'} \\ t' \in \mathcal{TC}^{r'} \cap \mathcal{TC}^s}} o_{t',r',s,t'} &\geq \sum_{\substack{r \in R_t \\ tc \in \mathcal{TC}^r \cap \mathcal{TC}^s}} o_{t,r,tc} \\ &+ (mc_{t',s} + \tau_{r,ty,t'})x_{t,r} \\ \forall t, t' \in T, s \in S_t \cap S_{t'} : c(t, t', s) &= 1. \end{aligned} \quad (6)$$

2. Soft constraints link trains involved in connections. For each transfer  $c \in C$ , we define the binary variable  $z_c = 1$  if  $c(t, t', s)$  is broken and  $z_c = 0$  otherwise. When  $z_c = 0$ , Constraints (7) ensure a minimum separation time between the arrival of  $t$  and the departure of  $t'$ , to allow passenger transfers. When a connection is broken, and  $z_c = 1$ , the constraints are trivially satisfied and a cost  $T_c$  is added to the objective function in Equation (8). This cost is a proxy of passenger delay due to the missed transfer: as discussed in Section 4, it is proportional to the planned headway on the train line of the receiving train for the transfer.

$$\begin{aligned} Mz_c + \sum_{\substack{r \in R_{t'} \\ tc \in \mathcal{TC}^r \cap \mathcal{TC}^s}} o_{t',r,s,tc} &\geq \sum_{\substack{r \in R_t \\ tc \in \mathcal{TC}^r \cap \mathcal{TC}^s}} o_{t,r,tc} \\ &+ (mc_{t',s} + \tau_{r,ty,t'})x_{t,r} \\ \forall t, t' \in T, s \in S_t \cap S_{t'} : c(t, t', s), \end{aligned} \quad (7)$$

$$\min \sum_{t \in T} D_t + \sum_{p \in P} n_p \left( D_p + \sum_{c \in C_p} z_c T_c \right). \quad (8)$$



**FIGURE 2** Schematic representation of the part of Copenhagen urban network used as a case study.

## 8 | COMPUTATIONAL ANALYSIS

We perform a computational analysis on a small case study to validate our proposed framework in a controlled setting. It serves as a proof of concept in a real-world scenario, and to assess the effectiveness of the three approaches proposed in Section 4, though on a small scale.

In this section, we start with the presentation of the case study and the validation of the OD demand prediction module in Sections 8.1 and 8.2, respectively. Then, we proceed to the assessment detailed in Section 8.3. In Section 8.4, we compare the three solution approaches with two benchmarks: one representing the non-optimized rtRTMP solution and the other the state-of-the-art passenger-agnostic RECIFE-MILP. The former consists in applying the train orders and routes planned in the timetable, with no further optimization. Here, we evaluate the impact of the policy we propose in this paper for railway traffic management, when assessed on actual demand realizations. Finally, Section 8.5 analyzes the traffic management decisions made for one representative situation.

### 8.1 | Case study

For the experimental analysis, we consider the case study related to the part of the Copenhagen suburban railway network in Figure 2, with a focus on Hellerup station, the busiest node in the area. This network acts mainly as a commuter service during the weekdays, where most of the stations on the branches serve the homes of commuters traveling to commercial areas of the city center of Copenhagen in the morning, and back in the afternoon. The network includes 12 stations and 36 platforms. The railway lines between stations are one-way double-tracks. Train reordering and rerouting are possible in stations with more than two platforms (Hellerup and Lyngby). Additional reordering

decisions can be made when trains access the common track between Svanemøllen and Nordhavn.

For the computational experiments, we use 64 instances representing 1 h of perturbed railway traffic in the area. Specifically, given a workday timetable, we apply train delays between 5 and 15 min to the entry time of 20% of trains [52]. Which trains to delay and the value of the delay applied are chosen randomly from uniform distributions. We perform the random delay assignment four times, thus obtaining four different one-day perturbed timetables. For each perturbed timetable, we consider 16 time horizons of 1 h, starting every 20 min between 6:00 and 12:00. During peak hours, there are approximately 90 trains in the network.

For the OD demand prediction module, we consider 20-min time horizons. This time horizon length is on the same order of magnitude as those in previous work [41], and it corresponds to the daytime frequency across all train lines in the case study. Moreover, this duration is consistent with passenger travel times in the network considered. This ensures that each prediction period aligns with a complete cycle of passenger flow through the system. This mitigates the sensitivity of the model towards the frequency and specific time of prediction as the minute-to-minute variation in demand is assumed to be closely related to departure times of trains. Selecting a prediction interval equal to the overall rhythm of the network makes the model more likely to capture changes in demand due to reliability, which is desired. By considering a longer horizon for train scheduling than for demand prediction, we ensure that all passengers starting their trip within the latter will manage to end it within the former.

We estimate the prediction model using actual data covering 20-min consecutive time intervals in the period 6:00 and 12:00 on weekdays (Monday through Friday) in the period from 30 January to 8 September 2017. This period covers 32 weeks, five days per week, and 18 intervals per day for a total of 2880 intervals. A maximum of 250 trips per hour are observed with start and end within the considered network, with 20% of the passengers requiring a transfer.

In the demand assignment module, we use case-study specific assumptions. In the incidence time estimation, we follow the study of Ingvarðson et al. [53, 54]. We consider the waiting time distributions estimated for different train headways for the Copenhagen suburban railway network. We adopt a mixture between a Beta and a uniform distribution as the preferred waiting time distribution. The waiting time (normalized according to headway) is  $X \sim \zeta \text{Beta}(\alpha, \beta) + (1 - \zeta) \text{Unif}(0, 1)$ . Considering each railway line independently, we use the headway between trains on the same line to select the distribution parameters. The parameters are displayed in Table B.1 in Appendix B. For the train-based path choice, we select the following parameters, inspired by Anderson et al. [55]: in-vehicle travel time, waiting time (incl. transfers), transfer walking time, and number of transfers. Being directly applicable to our case study, the values of the parameters are adopted from the same study. Table B.2 in Appendix B shows the parameter values for the selected attributes.

**TABLE 1** Validation results for horizon times-of-day within case study. Prediction error and average total demand per day for linear regression (LR) vs. weekly historical average (WHA) for data in the validation set, including true average total demand per day. Two error metrics used: root mean squared error (RMSE) and mean absolute error (MAE). Smaller error values are preferable. The best performing method in terms of error and average total demand per time-of-day is marked in bold.

Time horizon	LR		WHA		Average total demand		
	RMSE	MAE	RMSE	MAE	LR	WHA	True
06:00–06:20	0.398	0.191	<b>0.395</b>	<b>0.189</b>	20.11	<b>20.17</b>	20.73
06:20–06:40	0.595	0.310	<b>0.591</b>	<b>0.307</b>	34.48	<b>34.71</b>	39.35
06:40–07:00	<b>0.716</b>	0.390	0.718	<b>0.389</b>	<b>45.15</b>	44.90	55.98
07:00–07:20	<b>0.946</b>	<b>0.550</b>	0.955	0.553	<b>79.05</b>	77.98	96.00
07:20–07:40	<b>1.437</b>	<b>0.854</b>	1.456	0.861	<b>134.82</b>	134.29	180.15
07:40–08:00	<b>1.594</b>	<b>0.939</b>	1.659	0.967	<b>162.47</b>	159.48	218.70
08:00–08:20	<b>1.428</b>	<b>0.852</b>	1.504	0.879	<b>172.51</b>	167.87	201.08
08:20–08:40	<b>1.822</b>	<b>0.863</b>	1.890	0.885	<b>166.06</b>	163.56	196.30
08:40–09:00	<b>1.348</b>	0.718	1.353	<b>0.709</b>	<b>114.29</b>	111.94	132.13
09:00–09:20	<b>1.120</b>	0.590	1.131	<b>0.585</b>	<b>91.34</b>	89.79	99.40
09:20–09:40	1.072	0.607	<b>1.055</b>	<b>0.596</b>	<b>87.77</b>	87.44	95.80
09:40–10:00	1.028	0.525	<b>1.011</b>	<b>0.510</b>	<b>68.12</b>	67.88	73.33
10:00–10:20	1.005	0.495	<b>0.995</b>	<b>0.483</b>	<b>61.90</b>	61.67	65.98
10:20–10:40	0.973	0.489	<b>0.956</b>	<b>0.479</b>	<b>62.73</b>	61.84	63.65
10:40–11:00	0.895	0.450	<b>0.887</b>	<b>0.444</b>	<b>54.48</b>	54.28	56.70
11:00–11:20	0.869	0.482	<b>0.854</b>	<b>0.476</b>	<b>61.23</b>	60.91	63.13
11:20–11:40	0.979	0.506	<b>0.974</b>	<b>0.504</b>	<b>66.20</b>	66.13	71.58
11:40–12:00	0.905	0.512	<b>0.895</b>	<b>0.510</b>	<b>69.13</b>	68.54	73.60

## 8.2 | OD demand prediction validation

In this section, we validate the proposed OD demand prediction described in Section 5. The linear regression (LR) model is estimated based on a training set as described in the previous Section 8.1. To validate the model, we select data in the same format as those used for training but from a different period, between 11 September and 3 November 2017, covering 8 weeks, that is, 720 intervals. The baseline used for assessing the prediction performance of LR is the weekly historical average (WHA) model, which corresponds to the weekly trend of the training data.

Table 1 summarizes the validation results in terms of the pattern in prediction performance of the LR model over time-of-day compared with the WHA model. The prediction performance is compared on two standard metrics, namely the root mean squared error (RMSE) and the mean absolute error (MAE). The prediction error denotes the difference between the predicted and true demand volume of specific OD pairs and time horizons. The RMSE is the square-root of the mean of squared prediction errors, and the MAE is the mean of the absolute prediction errors. Furthermore, the table also contains the mean of predicted total demand volume of the two

models across days, compared with the mean of the true total demand volume.

The overall results in Table 1 show that the current performance in terms of RMSE is in line with that of other documented state-of-the-art models, such as that of Noursalehi et al. [41], Zhang et al. [56] and Zhong et al. [57].

By comparing the performance of LR with WHA, we observe that LR performs better than WHA in rush hours. The formal rush hour period in the case study is 07:30–09:30, which is reflected in the true numbers of total passengers which peak within this period. Specifically, looking at the error, we see that the RMSE and MAE metrics show better performance of the linear regression model between 07:00 and 08:40 and the RMSE metric between 6:40 and 9:20. The linear regression performs better in the rush hours due to larger average demand volumes having larger fluctuations on specific days. These deviations are more likely to be expressed in the features selected for the LR model than are the smaller deviations for smaller demand volume OD pairs and time intervals.

Outside the rush hours, the WHA has a smaller error, possibly due to the weaker deviation signal which is captured just as well by the WHA as by the LR model. Within the rush hours, the performance gap is up to 5% in favor of LR for the RMSE and MAE metrics. Instead, the gap outside the rush hours is at most 1.7% and 2.9% in favor of WHA. Thus, the performance gap outside peak hours is both minor and less influential: the traffic management decisions made within periods of many passengers have the most impact on the system performance, thus it is more important to have accurate predictions in the rush hour periods.

In summary, we argue that the gains in prediction power of LR within the rush hours outweigh the weaker performance outside the rush hours. The total number of predicted passengers with LR is consistently closer to the true number than the WHA is.

Moreover, by providing a balance between sufficient accuracy during peak periods and the computational speed required for rapid updates [45], the LR model contributes positively to accurate traffic optimization from the passenger perspective.

## 8.3 | Setup for the assessment of solution approaches

As above mentioned, we compare five solution approaches for the rtRTMP. In addition to the three approaches proposed in Section 4 (*PaxHard*, *PaxSoft* and *PaxSoftMulti*), we consider two benchmarks: *TTorder* and *NoPax*. The former represents non-optimized traffic management, according to which the realization of train operations adheres to the routing ordering in the nominal timetable. The latter represents the state-of-the-art RECIFE-MILP [7], that is, the minimization of total train delay without considering passenger information.

In our experiments, we set in the objective function  $w_t = w_p = 1$ , to maintain a neutral balance between the train and

**TABLE 2** Results over all instances in the case of predicted demand. All values are in seconds and represent the total train and passenger delay.

Approach	09_09		14_09		22_09		25_09	
	Train	Passenger	Train	Passenger	Train	Passenger	Train	Passenger
TTorder	35720	28843	35588	32810	37362	29344	35588	22363
NoPax	<b>13844</b>	19900	<b>13804</b>	22441	<b>13806</b>	21247	<b>13858</b>	15317
PaxHard	13903	19659	13850	22008	13873	20902	13891	15103
PaxSoft	13895	19600	13870	21994	13859	20917	13891	14986
PaxSoftMulti	13913	<b>19556</b>	13893	<b>21945</b>	13871	<b>20866</b>	13907	<b>14943</b>

passenger delay components, as we do not have specific information regarding the relative importance of delays. We emphasize, however, that these weights are flexible and can be adjusted by the infrastructure manager to reflect strategic priorities or specific policy goals.

We solve the rtRTMP using a rolling horizon experimental setup. As mentioned in Section 8.1, for each one-day perturbed timetable, we consider 16 time horizons, with a frequency of 20 min between 6:00 and 12:00. Specifically, we consider all trains that are present in the control area within 1 h from the beginning of each time horizon. For the first time horizon, the initial RTTP used to produce the TSP (Section 4) is the one implementing routes and orders from the timetable. For later horizons  $b + 1$ , it is the one returned for the previous horizon  $b$ . This iterative process mimics the periodic deployment discussed in Section 3.

In our experiments, we assess the performance of the different approaches for each time horizon  $b$ , considering historical demand realizations for four *assessment days*. We consider days in which no unusual demand patterns are observable, namely September 9, 14, 22, and 25, 2017. Remark that they do not belong to the OD demand prediction training period. For the assessment, given a final RTTP, we produce a PAP for the observed historical demand for  $b$ . This PAP is intended to represent the trips that would have been performed by passengers who actually traveled in a day, given the timetable resulting from the application of one of the five considered approaches. Based on the final RTTP and PAP, we evaluate performance indicators related to train and passenger travel times and delays. To preserve the comparability of the approaches on single 1 h instances, we use the same initial RTTP at each time horizon. Specifically, we use the one produced by NoPax. By doing so, we assess the quality of the traffic management decisions of each approach independently of the moment in which these decisions are made. In particular, we avoid good or bad decisions made in the first horizons to propagate their impact on later ones in different ways for different approaches.

All experiments are performed on a workstation Intel Xeon 16 core 3.5 GHz processor with 128 GB RAM, under Linux Ubuntu distribution. CPLEX 12.6 is used by RECIFE-MILP. In accordance with the existing literature [40], in our experiments, we impose a 3 min computational limit for RECIFE-MILP.

In Section 8.4, we assess the three approaches we propose to implement the policy that explicitly accounts for passengers in railway traffic management.

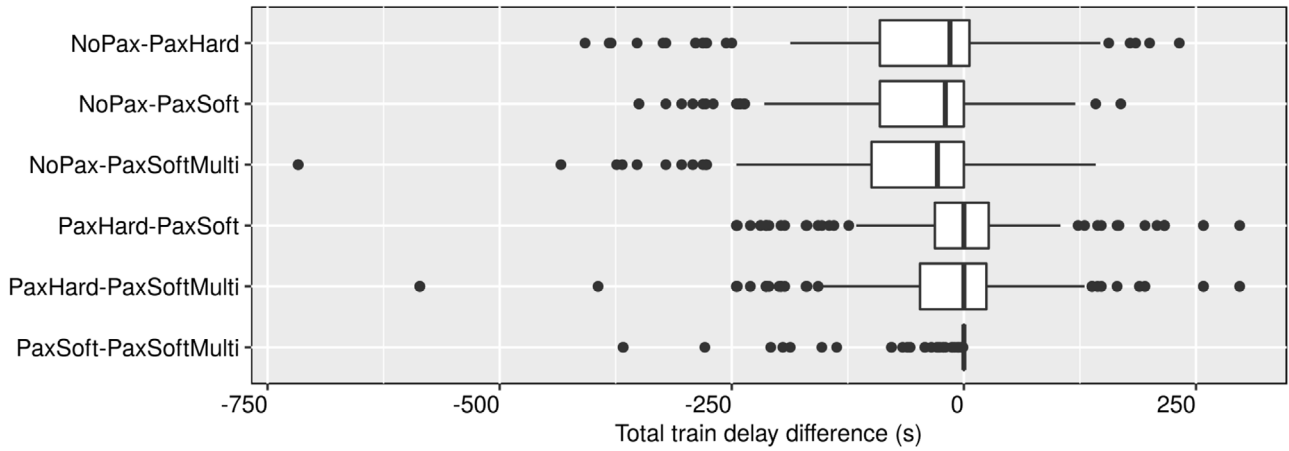
## 8.4 | Comparison between rtRTMP solution approaches

Table 2 presents the results obtained by the five considered rtRTMP approaches for each assessment day. The average number of passengers in a 20-min horizon for each day is, respectively, 96, 108, 102, and 73. We report the results for each day separately in order to assess whether there are similar patterns among the results. For each day, we report the total delay of trains and passengers averaged over the 16 time horizons of the day. The lowest train and passenger delays are highlighted in bold. Recall that the objective of the optimization is the minimization of the sum of these delays, that is, the total delay.

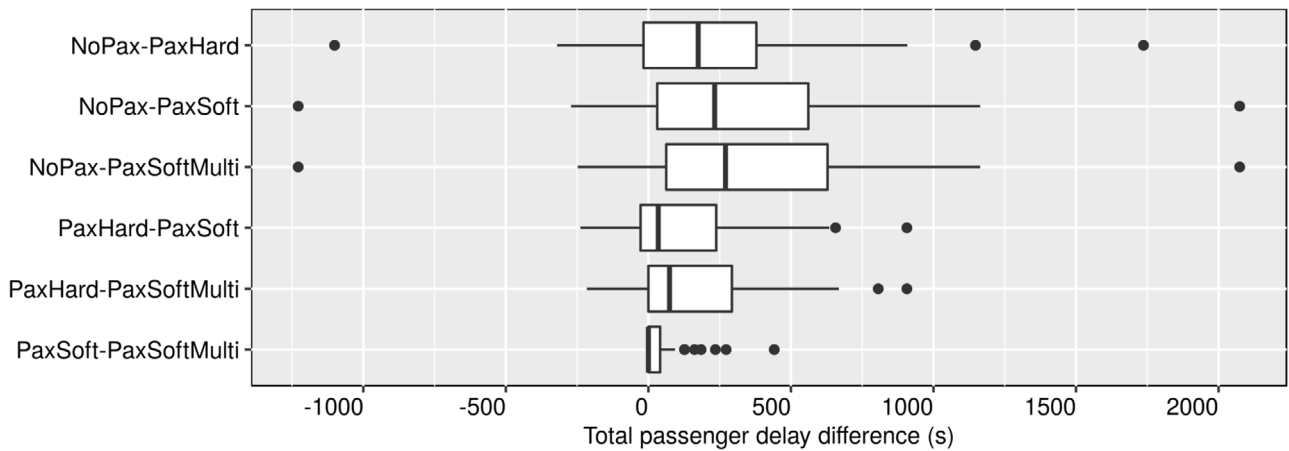
We further assess the difference between the three solution approaches implementing the policy we propose and NoPax in the boxplots in Figure 3. The boxplots compare (a) the total train delay, (b) the total passenger delay, and (c) the total delay obtained by the different approaches. The difference is calculated for each time horizon and day used in the experiments. The boxplots show the first (left) quartile, the median and the third (right) quartile. The whiskers indicate the minimum and the maximum values, while outliers that differ significantly from the rest of the dataset are plotted as individual points beyond the whiskers on the boxplots. As the smaller the delay the better, boxplots falling on the positive side of the graph indicate better results achieved by the second element of the subtraction.

First of all, the results in Table 2 show that optimizing traffic management brings a definite improvement with respect to TTorder, disregarding the specific approach considered. The improvement is around 50% and 30% for trains and passengers, respectively.

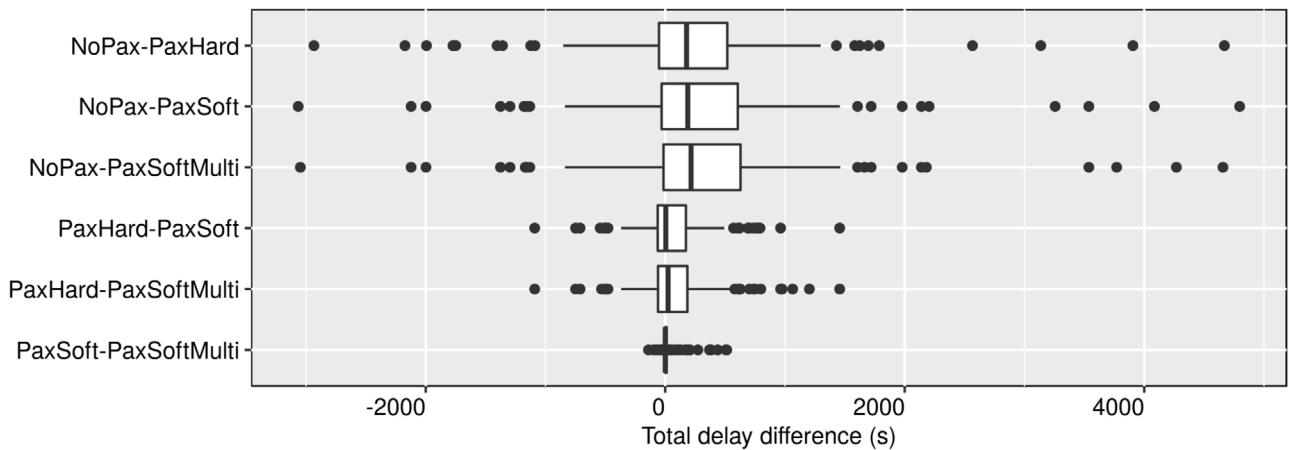
Comparing the four optimization approaches, the overall results show that PaxHard, PaxSoft and PaxSoftMulti allow a reduction in passenger delays at the cost of an increase in train delays compared to NoPax. This additional delay of trains is due to the enforcement of passenger connections and the allocation of priority to trains with a significant number of passengers. Nevertheless, the traffic management decisions considering the passenger perspective result in a greater reduction in passenger delays than the corresponding increase in train delays. Looking at Table 2, PaxSoftMulti, which has on average the largest increase in train delay of 89 s compared to NoPax (on September 14), concurrently reduces passenger delay by 496 s. The same result can be observed in the boxplots in Figure 3a.



(a) Boxplot of the train delay difference between the different approaches.



(b) Boxplot of the passenger delay difference between the different approaches.



(c) Boxplot of the total delay difference between the different approaches.

**FIGURE 3** Statistical results for the comparison between the different approaches.

Here, the top three boxplots which are mainly in the negative part of the graph indicate that in about 75% of the instances, the total train delay of NoPax is less than the one of PaxHard, PaxSoft and PaxSoftMulti. Still, the 25% percentile of the distribution of the differences is around 100 s, which is

quite small as in average there are 90 trains in one instance. Instead, in Figure 3b we observe a mirrored situation compared to Figure 3a. Specifically, PaxHard, PaxSoft and PaxSoftMulti outperform NoPax for 75% of the instances, as indicated by their boxplots predominantly located above zero. The positive

difference indicates that NoPax leads to greater passenger delay than the passenger-integrated approaches, highlighting the pertinence of these ones. In particular, PaxSoftMulti leads to the greatest reduction in passenger delay: in 50% of the instances, the total passenger delay is at least 250 s less than when using NoPax; in 25% of the instances is at least 700 s less; and the maximum reduction is around 1200 s.

Focusing on the three solution approaches implementing the policy we propose in this article, we observe that the passenger delay brought by PaxHard is consistently higher compared to PaxSoft and PaxSoftMulti. The average values of PaxHard are higher in three out of four days in Table 2. Moreover, the last three boxplots in Figure 3b are contained in the positive range of values, indicating that PaxSoft and PaxSoftMulti have less delay than PaxHard for 75% of the instances. The performance of PaxHard is particularly affected by transfers involving few passengers: having a train staying longer at a station to ensure these transfers leads to a benefit for a reduced number of passengers, but to a train delay propagation that penalizes many others. Thus, hard constraints for passenger transfers are not necessarily a good choice in general. Soft constraints are typically preferable, as they allow for an evaluation of the delays derived from whether or not a transfer is ensured. The solutions achieved with PaxSoft show that not being forced to comply with all passenger transfers allows a reduction in train delays with respect to PaxHard, without necessarily increasing passenger delays. Yet, the achieved passenger performance is not the best due to the lack of insight into the dynamic redistribution of passengers in response to the traffic management decisions made. Relying only on a single RTTP hinders the determination of the best train-based paths for passengers. By considering passenger reactions in the decision making, PaxSoftMulti manages to reduce passenger delays, although at the cost of a little increase of train delay.

The observations in Figure 3b recur in Figure 3c. This confirms that the increase in train delay has less impact than the reduction in total passenger delay for PaxHard, PaxSoft and PaxSoftMulti. To ensure that the improvements brought by the approaches we proposed are statistically significant, we perform the Wilcoxon signed rank test with a confidence interval (CI) of 95%. In the test, we evaluate the differences in passenger and train delay, as computed in Figure 3. For the sake of clarity, the detailed computational results of the Wilcoxon signed rank test are provided in Table C.1, Appendix C.

In conclusion, the results of the Wilcoxon test show that the policy consisting of accounting for passenger delay in railway traffic management brings a significant reduction of passenger delay without much worsening train one. In addition, PaxSoftMulti proves to always lead to reduced passenger delays compared to PaxSoft, although the differences are sometimes extremely small.

## 8.5 | Analysis of a representative situation

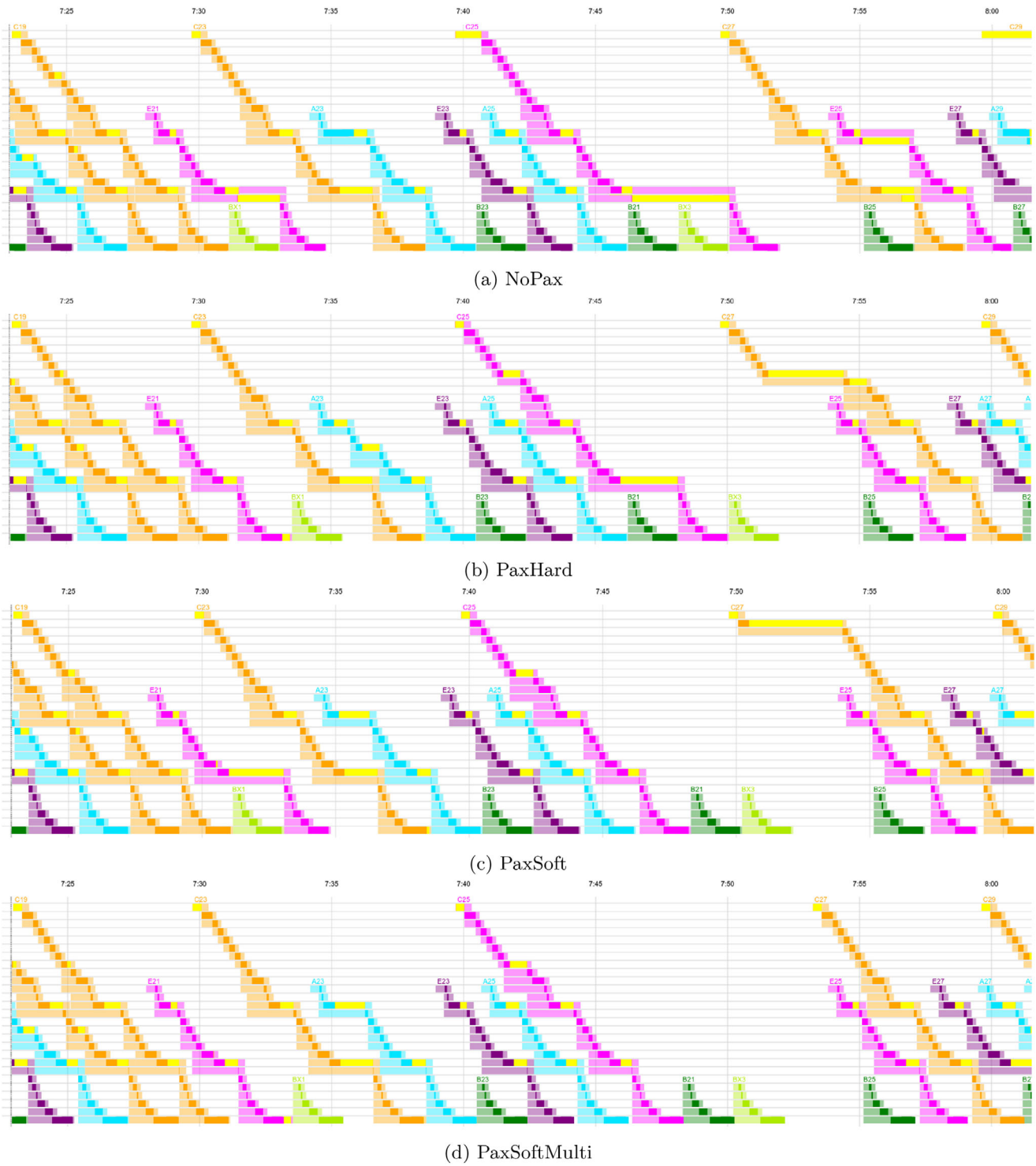
In this section, we explain the impact of the implementation of the proposed policy in an instance corresponding to a representative traffic situation.

In Figure 4, we compare the train movements of RTTPs obtained with (a) No Pax, (b) PaxHard, (c) PaxSoft, and (d) PaxSoftMulti, respectively. The train paths are represented in a utilization diagram corresponding to a space-time diagram in which the  $y$ -axis represents space and the  $x$ -axis represents time. Each horizontal line represents a track-circuit and a colored rectangle indicates how long a track-circuit is utilized by a train: in dark, the period the train physically occupies the track-circuit; in light, the reservation period. A yellow part indicates a running time longer than the minimum one, hence a stop at station or a delay. The illustrated trains run along the A, E, C, B, Bx lines to Nordhavn station (Figure 2). In addition, the barplots in Figure 5 show (a) the number of passengers on each train and (b) the total passenger delay per train. The latter is the train each passenger uses to arrive at their destination. For the sake of clarity, in these barplots we only show the trains running in one direction, that is, the one of the trains interesting for the purposes of the discussion.

Let us focus on trains E21, C25 and E25, which are highlighted in magenta in Figure 4. The last bottom yellow rectangle on the route of these trains represents Hellerup station. After this station, in the direction of Nordhavn, there is a junction joining two railway lines into a single one. This convergence involves trains of lines B and Bx on one side, and trains of lines A, C, and E on the other side. In case of traffic perturbations, the order of trains from these two sets of lines is a critical decision.

In Figure 5a we observe that the number of passengers for the three trains is very similar for the different solution approaches, with minimal variations in the order of decimals. Recall that the number of passengers in our model is a continuous number obtained from a probabilistic assignment of passengers to incidence times and train-based paths (Section 6). Trains C25 and E21 carry approximately 5 passengers each, and train E25 carries around 22 passengers. Despite this similarity, we observe in Figure 5b that the total passenger delay for these trains changes among solutions. The delay is the highest with NoPax. Indeed, it optimizes the delay of trains and ignores passengers on board. In Figure 4a we see that the three magenta trains pass the junction after trains BX1, BX3, and C27, which appear with little utilization time stairways in Figure 5b. This reduces the sum of train delays since the time magenta trains have to wait is in total 498 s shorter than the one the BX1, BX3, and C27 trains would have to wait if passing second: the passage of E21, C25, and E25 by seconds increases their total delay by 702 s; while the passage of BX1, BX3, and C27 by seconds increases their total delay by 1200 s. The total train delay with the NoPax solution is 14,687 s, while the passenger one is 39,588 s.

On the contrary, minimizing the total passenger delay, in addition to the train one, changes the priority of trains in the junction in favor of trains with more passengers. Indeed, differently from the NoPax solution, in the PaxHard one (Figure 4b), E21 passes before BX1, C25 before BX3, and E25 before C27. BX1, BX3 and C27 have nearly no passenger on board (Figure 5a), which makes their contribution to the total delay negligible compared to the one of E21, C25 and E25. In total, the delay becomes 14,940 s for trains and 38,741 s for passengers.



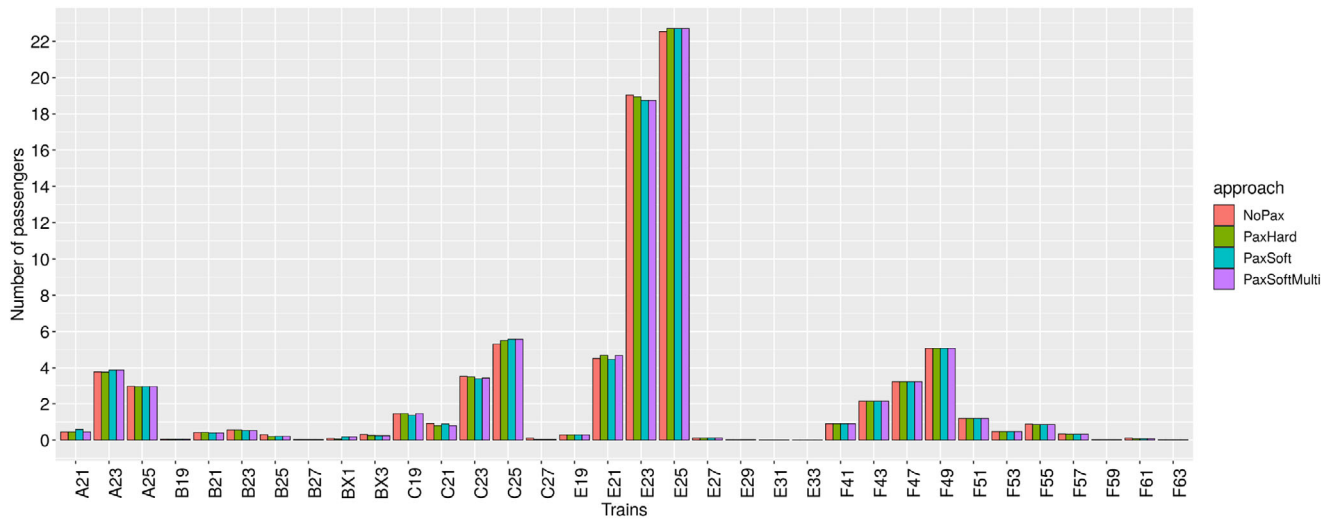
**FIGURE 4** Track-circuit utilization diagram solutions obtained with the different approaches.

The PaxSoft solution in Figure 4c changes with respect to the PaxHard one: C25 passes before not only BX3, but also B21. This different priority becomes convenient as a transfer is broken: passengers that in PaxHard are allowed to transfer to C25 from a train traveling on the A line to Lyngby (not shown in the figure because it uses a different track), here cannot take it and must use a later

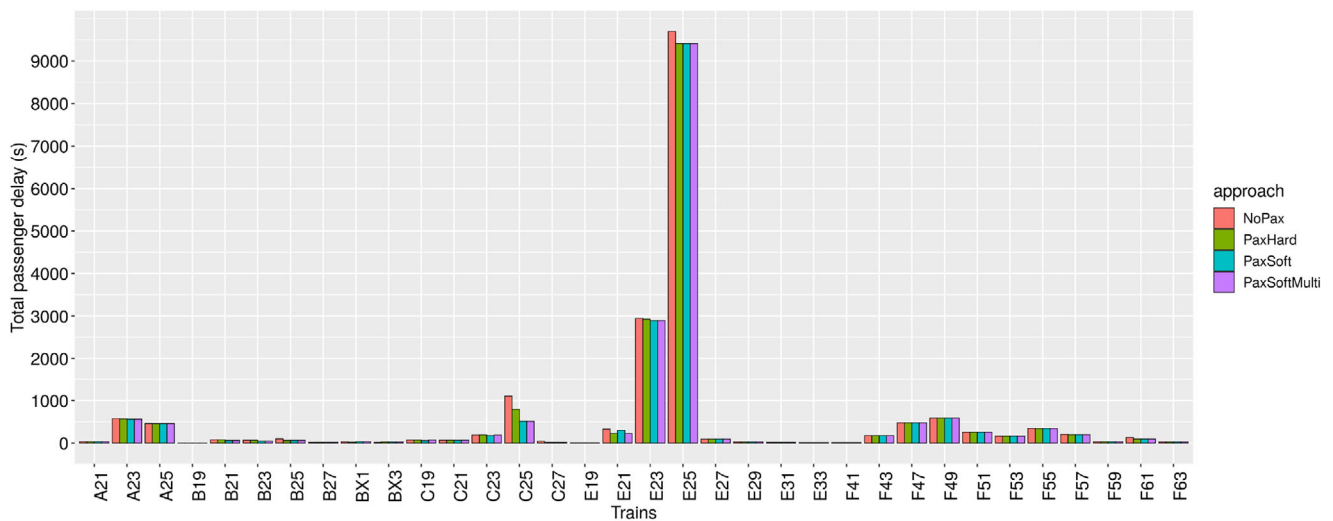
train instead. This change increases passenger delay by only 75 s, reducing train one by 212 s. Analogous changes for trains not represented in the figures lead to the final total train and passenger delay of 14,907 and 38,402 s, respectively.

Not meeting the initial passenger connections does not result in an increase of total passenger delays compared to PaxHard,





(a) Number of passengers on trains



(b) Total delay of passengers on each train

**FIGURE 5** Distributions of (a) the number of passengers and (b) the total passenger delay among the trains represented in Figure 4.

as all passengers can use different train-based paths to get to their destination.

Finally, the studied trains in the PaxSoftMulti solution are scheduled as in the PaxSoft one, but for the order of E21 and BX1 (Figure 4d). This order is chosen because, by assessing the PAPs for multiple RTTPs, PaxSoftMulti sees that passengers in E21 have a delay smaller than 65 s when this train passes earlier. This and other analogous changes allow reducing passenger delay of 70 s with respect to PaxSoft, while increasing train one by 67 s.

## 9 | CONCLUSIONS

Recent transport policies promote greener and smarter mobility, favoring the shift to rail. Improved train operations and passenger punctuality during traffic disturbances may play a major role

toward this shift. When disturbances occur, infrastructure managers must quickly resolve conflicts and limit delay propagation. This problem, known as the rtRTMP, is currently managed by policies minimizing train delays, while the passenger perspective is not explicitly considered.

In this article, we proposed a railway traffic management policy that minimizes both passenger and train delays by considering dynamic demand prediction based on current traffic conditions. This policy helps infrastructure managers allocate resources more efficiently by accounting for variations in passenger demand and mitigating the impacts of delays on passengers and train operations. We formalize this policy by a framework in which three modules interact. The demand prediction module predicts future passenger flows using a linear regression on real-time observed smart card data. Based on traffic variations, the demand assignment module identifies the expected paths passengers will choose. This information

is then used in the traffic management module to optimize train movements using an advanced MILP-based algorithm called RECIFE-MILP.

We presented the following solution approaches using the framework: the PaxHard approach enforces hard constraints for passenger transfers in traffic management; the PaxSoft approach sets soft constraints for passenger transfers with violation penalties for favoring the predicted transfers; the PaxSoftMulti combines soft constraints with a feedback loop simulating passenger reactions to traffic changes. We extensively assess our framework and each solution approach on the Copenhagen suburban railway network. We evaluated our proposed OD demand prediction model against a weekly historical average model and benchmarked our approaches against the application of timetable routes and orders and the passenger-agnostic RECIFE-MILP (NoPax). We consider instances representing traffic evolution within an hour, with passengers entering the system in the first 20 min.

The results show that explicitly accounting for passengers in decision making effectively guides traffic management toward the reduction of passenger delays without remarkably penalizing trains, compared to the classic railway traffic management policy. Indeed, PaxHard, PaxSoft and PaxSoftMulti reduce passenger delays with only a small increase in train delays compared to NoPax. The largest average increase in total train delay of 90 s, achieved by PaxSoftMulti, leads to a reduction in total passenger delay of 495 s. This outcome derives from prioritizing trains with more passengers and better managing transfer options.

Comparing the solution approaches, the results show that hard constraints for passenger transfers can hinder performance when few passengers are involved. Instead, soft constraints are better as they allow for an evaluation of the delays derived from whether or not a transfer is preserved. Moreover, PaxSoftMulti leads to the best solutions thanks to the consideration of the dynamic redistribution of passenger demand in response to different possible traffic configurations. Nonetheless, the improvement brought by this consideration is minor in our experiments, probably due to the reduced size of the network dealt with.

To better understand and evaluate the full impact of the proposed policy, in future research, we envision creating a closed-loop system that integrates traffic and passenger simulation. This holistic approach will provide a comprehensive view of the policy's performance under various conditions and help refine its implementation in real-world scenarios.

We also acknowledge the significance of testing our approach in larger and more interconnected rail networks. As a railway network grows in size and connectivity, it typically involves more stations, tracks, and transfers. This expansion leads to a greater number of possible routes and makes the demand dynamics more complex. The interaction of multiple train lines can result in higher variations of demand patterns, travel times, and passenger path preferences. Coping with this demand variability presents challenges in demand prediction. To enhance the accuracy under varying demand flows, we will develop advanced passenger prediction models, exploiting the machine learning state of the art. Moreover, we will enhance our predic-

tion approach by integrating real-time service reliability metrics and delay information to address the effects of operational disturbances on passenger demand more explicitly. Additionally, future work could consider rolling stock capacity constraints, especially in cases of larger disruptions or highly congested networks, where capacity limitations may become more critical for the effective implementation of the proposed framework. Finally, future research should investigate the impact of adjusting the weights assigned to train and passenger delays in the objective function, to better understand how prioritizing different strategic goals or policy objectives influences overall system performance. Furthermore, one should assess the need for a more flexible framework that would allow for variable prediction and optimization intervals, ultimately aiming at even more agile and responsive railway traffic management.

## AUTHOR CONTRIBUTIONS

**Bianca Pascariu:** Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing—original draft; writing—review and editing.

**Johan Victor Flensburg:** Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing—original draft; writing—review and editing.

**Paola Pellegrini:** Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; writing—original draft; writing—review and editing.

**Carlos M. Lima Azevedo:** Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; supervision; validation; writing—original draft; writing—review and editing.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data sharing is not applicable as the data that support the findings of this study are subject to third party restrictions.

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### APPENDIX A

In this section, we report the original RECIFE-MILP formulation modeling train operations.

#### Notation

RECIFE-MILP uses the following sets:

- $T$ : the set of trains;
- $\Theta$ : the set of train types (i.e. passenger train, freight train etc.);
- $R_t$ : the set of routes available to train  $t \in T$ , with  $R = \bigcup_{t \in T} R_t$  the total set of routes;
- $\mathcal{TC}^r$ : the set of track-circuits belonging to route  $r \in R$ ;

- $\mathcal{TC}_t$ : the set of track-circuits which can be used by train  $t \in T$ . Remark that  $\mathcal{TC}_t = \bigcup_{r \in R_t} \mathcal{TC}^r$ ;
- $OTC_{ty,r,tc}$ : the set of track-circuits such that, if a train  $t \in T$  of type  $ty \in \Theta$  traverses them along  $r \in R_t$  and has its head at their end, it holds that  $t$ 's tail has not yet left  $tc$ .  $OTC_{ty,r,tc} = \{tc\}$  if  $t$  is shorter than  $tc$  itself;
- $S_t, \mathcal{CS}_{t,s}$ : the set of stations where  $t \in T$  has a scheduled stop and set of track-circuits that can be used by  $t$  for stopping at  $s \in S_t$ ;
- $S$ : the set of stations;

and parameters:

- $tc_0$  and  $tc_\infty$ : dummy track-circuits representing the entry and the exit locations of the infrastructure considered, where the former precedes all track-circuits corresponding to route origins, the latter follows all track-circuits corresponding to route destinations and their running time is null;
- $sched_t$ : scheduled arrival time of train  $t \in T$  at destination;
- $ty_t$ : type corresponding to train  $t$  (train characteristics);
- $init_t, exit_t$ : earliest time at which train  $t \in T$  can be operated and earliest time at which it can reach its destination given  $init_t$ , the route assigned in the timetable and the intermediate stops;
- $i(t', t)$ : indicator function equal to 1 if  $t'$  and  $t$  use the same rolling stock and  $t$  results from the turnaround, join or split of  $t'$ , 0 otherwise;
- $ms_{t,t'}$ : minimum separation between the arrival and the departure of trains  $t$  and  $t'$  using the same rolling stock;
- $rt_{r,ty,tc}, ct_{r,ty,tc}$ : running and clearing time of  $tc \in \mathcal{TC}^r$  along  $r \in R$  for a train of type  $ty \in \Theta$ ;
- $ref_{r,tc}$ : reference track-circuit for the reservation of  $tc \in \mathcal{TC}^r$  along  $r \in R$ , depending on block section structure and interlocking system;
- $e(tc, r)$ : indicator function equal to 1 if track-circuit  $tc \in \mathcal{TC}^r$  belongs to either the first or the last block section of  $r \in R$ , 0 otherwise;
- $bs_{r,tc}$ : block section including track-circuit  $tc \in \mathcal{TC}^r$  along route  $r \in R$ ;
- $for_{bs}, rel_{bs}$ : formation and release time for block section  $bs$ ;
- $dw_{t,s}, a_{t,s}, d_{t,s}$ : minimum dwell time, scheduled arrival and scheduled departure times for train  $t \in T$  at station  $s \in S_t$ ;
- $p_{r,tc}, s_{r,tc}$ : track-circuits preceding and following  $tc \in \mathcal{TC}^r$  along  $r \in R$ ;
- $w_t$ : weight of train  $t$  delay;
- $M$ : a large constant.

Remark that all trains of the same type are considered to be planned to travel in the same way across a track-circuit along a route. If train-specific running and clearing times need to be considered,  $rt_{r,ty,tc}$  and  $ct_{r,ty,tc}$  can be indexed on the train itself rather than on its type.

The model makes use of the following variables, which include binary variables representing routing and scheduling decisions and continuous variables used to evaluate the travel time and potential delays of the trains on each track-circuit:

- $sU_{t,tc}$ ,  $eU_{t,tc}$ : continuous positive variables representing the time at which  $tc \in TC_t$  starts and ends being utilized by  $t \in T$ ;
- $x_{t,r}$ : binary variable equal to 1 if train  $t \in T$  uses route  $r \in R_t$ , 0 otherwise;
- $y_{t,t',tc}$ : binary variable equal to 1 if train  $t \in T$  utilizes track-circuit  $tc$  before train  $t'$ , such that index  $t$  is smaller than index  $t'$  ( $t < t'$ ), with  $tc \in TC_t \cap TC_{t'}$ , and 0 otherwise. Given the list of trains, index  $t$  corresponds to the position of train  $t$  within the list. If  $i(t, t') = 1$  or  $i(t', t) = 1$  then this variable is not created for the track-circuits of the block section in which the connection takes place to allow both trains to occupy the same track-circuit;
- $o_{t,r,tc}$ : time in which  $t \in T$  starts the occupation of  $tc \in TC^r$  along  $r \in R_t$ ;
- $l_{t,r,tc}$ : longer stay of the head of  $t \in T$  on  $tc \in TC^r$  along  $r \in R_t$ , due to dwell time and scheduling decisions (delay);
- $D_{t,s}$ : delay suffered by train  $t$  when stopping at station  $s \in S_t$ , defined for all stations different from the train origin;
- $D_t$ : delay suffered by train  $t$  when exiting the infrastructure, if the exit does not correspond to a station.

All these variables are imposed to be non-negative.

### Original model

RECIFE-MILP minimizes the weighted total delay suffered by trains when exiting the infrastructure or arriving at a planned stop:

$$\min \sum_{t \in T} w_t \left( D_t + \sum_{s \in S_t} D_{t,s} \right). \quad (\text{A.1})$$

The model has to respect the following sets of constraints:

$$o_{t,r,tc} \geq \text{init}_t x_{t,r} \quad \forall t \in T, r \in R_t, tc \in TC^r, \quad (\text{A.2})$$

$$o_{t,r,tc} \leq Mx_{t,r} \quad \forall t \in T, r \in R_t, tc \in TC^r, \quad (\text{A.3})$$

$$o_{t,r,tc} = o_{t,r,p_{r,tc}} + l_{t,r,p_{r,tc}} + \text{rt}_{r,y_{t,t',tc}} x_{t,r} \\ \forall t \in T, r \in R_t, tc \in TC^r, \quad (\text{A.4})$$

$$o_{t,r,s_{r,tc}} \geq d_{t,s} x_{t,r} \quad \forall t \in T, r \in R_t, s \in S_t, tc \in TCS_{t,s} \cap TC^r, \quad (\text{A.5})$$

$$l_{t,r,tc} \geq dw_{t,s} x_{t,r} \quad \forall t \in T, r \in R_t, s \in S_t, tc \in TCS_{t,s} \cap TC^r, \quad (\text{A.6})$$

$$D_{t,s} \geq \sum_{r \in R_t} \sum_{tc \in TC^r \cap TCS_{t,s}} (o_{t,r,tc} + \text{rt}_{r,y_{t,t',tc}} x_{t,r}) - a_{t,s} \\ \forall t \in T, s \in S_t \quad (\text{A.7})$$

$$D_t \geq \sum_{r \in R_t} o_{t,r,tc_\infty} - \text{sched}_t \quad \forall t \in T, \quad (\text{A.8})$$

$$\sum_{r \in R_t} x_{t,r} = 1 \quad \forall t \in T, \quad (\text{A.9})$$

$$\sum_{r \in R_t, tc \in TC^r : p_{r,tc} = tc_0} o_{t,r,tc} \geq \sum_{r \in R_{t'}, tc \in TC^{r'} : s_{r,tc} = tc_\infty} o_{t',r,tc} \\ + (ms_{t,t'} + \text{rt}_{r,y_{t,t',tc}}) x_{t',r} \quad \forall t, t' \in T : i(t', t) = 1, \quad (\text{A.10})$$

$$\sum_{r \in R_t : s_{r,tc_0} = tc} x_{t,r} = \sum_{r \in R_{t'} : p_{r,tc_\infty} = tc} x_{t',r} \\ \forall t, t' \in T : i(t', t) = 1, tc \in TC_t : p_{r,tc} = tc_0 \quad (\text{A.11})$$

$$\sum_{tc \in TC_t : \exists r \in R_t, p_{r,tc} = tc_0} sU_{t,tc} \leq \sum_{tc \in TC_{t'} : \exists r \in R_{t'}, s_{r,tc} = tc_\infty} eU_{t',tc} \\ \forall t, t' \in T : i(t', t) = 1, \quad (\text{A.12})$$

$$sU_{t,tc} = \sum_{r \in R_t : tc \in TC^r} \left( o_{t,r,ref_{r,tc}} - \text{for}_{bs_{r,tc}} x_{t,r} \right) \\ \forall t \in T, tc \in TC_t : (\nexists t' \in T : i(t', t) = 1) \\ \vee (\forall r \in R_t : tc \in TC^r, ref_{r,tc} \neq s_{r,tc_0}), \quad (\text{A.13})$$

$$eU_{t,tc} = \sum_{\substack{r \in R_t : \\ tc \in TC^r}} o_{t,r,tc} + \sum_{\substack{t' \in TC^r : \\ tc \in OTC_{y_{t',r},tc}}} l_{t',r,t'} \\ + (\text{rt}_{r,y_{t,t',tc}} + \text{ct}_{r,y_{t,t',tc}} + \text{rel}_{bs_{r,tc}}) x_{t',r} \\ \forall t \in T, tc \in TC_t, \quad (\text{A.14})$$

$$eU_{t,tc} - M(1 - y_{t,t',tc}) \leq sU_{t',tc} \\ \forall t, t' \in T, t < t', tc \in TC_t \cap TC_{t'} : \\ i(t, t') \sum_{r \in R_t} e(tc, r) = 0 \wedge i(t', t) \sum_{r \in R_{t'}} e(tc, r) = 0, \quad (\text{A.15})$$

$$eU_{t',tc} - My_{t,t',tc} \leq sU_{t,tc} \\ \forall t, t' \in T, t < t', tc \in TC_t \cap TC_{t'} : \\ i(t, t') \sum_{r \in R_t} e(tc, r) = 0 \wedge i(t', t) \sum_{r \in R_{t'}} e(tc, r) = 0. \quad (\text{A.16})$$

Constraints (A.2) and (A.3) force train  $t$  to be operated no earlier than  $\text{init}_t$  on its chosen route and set all track-circuit occupations to 0 on the alternative routes.

In Constraints (A.4), a train starts occupying a given track-circuit along a route after spending its running time in the

preceding one plus the longer stay cumulated there, if the route is used.

Constraints (A.5) and (A.6) ensure that train  $t$  which stops at station  $s$  along route  $r$  does not leave track-circuit  $tc \in \mathcal{TC}_{t,s} \cap \mathcal{TC}^r$  before the scheduled departure time from  $s$ , and in any case spends at least its minimum dwell time on  $tc$ .

Constraints (A.7) and (A.8) quantify non-negative delay at each station when train  $t$  has a scheduled stop and at its exit from the infrastructure. Remark that  $t$  is assumed to stop at the end of the track-circuit where the stop occurs. The non-negativity of the continuous variables allows neglecting the negative contribution of trains arriving in advance.

In Constraints (A.9), a single route is chosen for train  $t$ .

Constraints (A.10), (A.11) and (A.12) are used to guarantee consistency for trains using the same rolling stock, that is, the respect of the minimum separation time between their arrival and departure, the use of the same arrival and departure track-circuit, and the overlapping utilization times to maintain the track-circuit occupied during the turnaround, as discussed below.

In Constraints (A.13), a train's utilization of a track-circuit starts as soon as the train starts occupying track-circuit  $ref_{r,tc}$  along one of the routes including it, minus the formation time. Constraints (A.13) are imposed as inequalities ( $\leq$ ) when they concern a track-circuit of the first block sections of the route ( $ref_{r,tc} = s_{r,tc0}$ ) and the train  $t$  results from the turnaround, join or split of one or more other trains ( $\exists t' \in T : i(t', t) = 1$ ). This is a consequence of the need of keeping platform track-circuits utilized. Indeed, if  $t$  results from  $t'$ , Constraints (A.12) ensure that the track-circuit where the turnaround takes place starts being reserved by  $t$  as soon as  $t'$  arrives. However,  $t$  needs to wait at least for a time  $ms_{t',s}$  before departing. The occupation of the track-circuit by  $t$  is however starting from its actual departure, for guaranteeing the coherence of the occupation variables and the running time (Constraints (A.4)). Hence,  $t$ 's reservation starts much earlier than its occupation.

In Constraints (A.14), the utilization of a track-circuit lasts till the train exits it along any route, plus the release time. If the train is long enough to keep occupying the track-circuit when its head is at the end of the following ones (the ones included in set  $OIC_{t_j, r, tc}$ ), also the longer stay of the train on these further track-circuits has to be accounted for.

**TABLE B.1** Mixture beta-uniform distribution parameters used for incidence time distribution in demand assignment module.

Headway (min)	Beta-share	Uniform-share	Beta-component	
	$\zeta$	$1 - \zeta$	$\alpha$	$\beta$
5	0.43	0.57	1.14	1.57
10	0.52	0.48	1.21	2.16
20	0.64	0.36	1.24	3.35
30	0.90	0.10	1.55	4.98
60	0.93	0.07	1.57	9.65

**TABLE B.2** Path choice parameter values (utilities) for selected attributes.

In-vehicle travel time	Waiting time	Walking time	Number of transfers
-0.076	-0.083	-0.132	-2.020

Finally, Constraints (A.15) and (A.16) ensure that track-circuit utilizations by two trains do not overlap. This must hold unless they use the same rolling stock and the track-circuit is at the extreme part of their routes, where the reutilization must take place.

**APPENDIX B**

The following tables contain the values of the parameters used in the demand assignment module, namely incidence time distribution parameters and path choice utility parameters.

Table B.1 contains, for service headways of 5, 10, 20, 30, and 60 min, distribution parameters for a mixed Beta and uniform distribution  $\zeta\text{Beta}(\alpha, \beta) + (1 - \zeta)\text{Unif}(0, 1)$ , where  $\zeta \in [0, 1]$  is the mixture parameter, and  $\alpha \in \mathbb{R}_+$  and  $\beta \in \mathbb{R}_+$  are shape parameters of the Beta distribution.

Table B.2 contains utility parameters of four attributes of rail transport trips, namely in-vehicle travel time, waiting time, walking time, and number of transfers.

**APPENDIX C**

Table C.1 presents the results of the Wilcoxon signed rank test for the difference of passenger and train delay obtained by

**TABLE C.1** Statistical results of Wilcoxon signed rank test.

Approach	Passenger delay				Train delay			
	$p$ -value	$\mu$	LCI	UCI	$p$ -value	$\mu$	LCI	UCI
NoPax-PaxHard	4.53E-08	248.47	152.32	346.67	2.25E-05	-38.00	-65.50	-19.00
NoPax-PaxSoft	3.95E-09	269.91	172.45	382.26	1.94E-07	-46.50	-68.50	-29.00
NoPax-PaxSoftMulti	2.60E-10	312.52	207.69	424.35	1.87E-09	-59.00	-82.50	-40.00
PaxHard-PaxSoft	2.33E-02	34.47	4.75	72.27	6.67E-01	-3.50	-26.00	17.50
PaxHard-PaxSoftMulti	6.48E-05	67.66	31.62	113.71	6.07E-02	-19.50	-43.50	0.50
PaxSoft-PaxSoftMulti	1.40E-09	55.02	33.29	95.05	3.81E-07	-50.00	-104.00	-32.00

the different approaches proposed in this paper. We use the test to determine whether the pseudo-median of the sample  $\mu$  is equal to zero (null hypothesis) with a Confidence Interval (CI) of 95%. If the pseudo-median  $\mu$  resulting from this test is equal to zero (null hypothesis), no significant improvement is recorded. Positive values of  $\mu$  and of the lower (LCI) and upper (UCI) bounds of the CI means that the results achieved by the second approach of the subtraction are significantly

better, and vice versa, it does not with negative values. The first column of these tables indicates the solution approaches used in the comparison. The probability value ( $p$ -value), in the second column, is a statistical measure describing how likely the data would have occurred by random chance. The remaining columns represent the above mentioned pseudo-median  $\mu$ , and the lower (LCI) and upper (UCI) bounds of the CI.