Optimized Passenger Redirection During Incidents in Urban Public Transportation Systems

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ABSTRACT

Incidents disrupt the public transportation (PT) operation daily causing parts of the PT system to be temporarily out of services. The dispatchers in the operations control center (OCC) take multiple dispositive measures to resolve the incident and to mitigate its negative effects on the PT services. Usually, such measures are supply-centric readjustments of PT lines. Recent studies have shown that passenger-centric extensions can further mitigate the negative effects of incidents. This paper presents a passenger-centric incident management method, in which the passengers directly affected by an incident are given a redirection path advice to systematically reduce their total delay. This advice is consistent for all passengers associated with the same origin-destination-relation. It is assumed that dispatchers in OCCs often have quite a good intuition on the duration of incidents and have access to demand estimations. Based on these assumptions this study compares a heuristic and an optimization-based approach. First, the procedure simulates scenarios with and without an incident to set the lower and higher benchmark for the overall delay, respectively. In the latter case solely supply-centric measures (line-splitting, rerouting PT lines) are taken into account. Then SUMO simulations evaluate the benefits of the additional path advice from the heuristic and optimization-based passenger-centric procedures. The results show that both approaches can significantly lower overall passenger delay with optimization providing the best results.

Keywords: Public Transport, Incident Management, Disruption, Passenger-centric, Optimization

INTRODUCTION

In public transportation (PT) operations incidents occur every day. Incidents are understood here as events which disrupt the scheduled PT service. Depending on the kind of incident and its location in the network, it can have light or severe consequences for the travel time of PT users. Light consequences are, for example, caused by a passenger fall, door failures or a bus break down, whereas traffic accidents, deployment of emergency forces, track switch failures or train break downs can lead to more severe consequences in terms of cancellations and long delays. Depending on the incident, the dispatchers in operations control centers (OCCs) have certain dispositive measures at hand to resolve the incident and lead the service back to planned operations. Besides informing the emergency forces and organizing towing services, typical measures for mitigating the negative effects of incidents are holding, stop(s)-skipping, line-splitting, short-turning, rerouting, rescheduling, bus bridging and dispatching extra or standby PT vehicles (*1–4*). Since these measures only adjust the PT supply to limit negative effects caused by the incident, they are referred to as supply-centric. The method which is introduced here, however, focuses on the passengers' perception of incidents and investigates, how passengers can be involved actively in mitigation strategies by informing them about the present situation. Such approaches are therefore referred to as passenger-centric. The goal is to smartly redirect passengers during incidents to reduce the overall delay of affected passengers during incidents. This is achieved by introducing a novel heuristic and optimization-based approach and comparing their performances against each other in SUMO. The remainder of this paper is organized as follows: Section two gives a short but comprehensive literature review, in section three the actual problem is stated. Next, a novel solution to solve the problem is introduced in the methodology. Section four describes the conducted case studies. Results are discussed in the fifth section. Finally, section six concludes the findings and give a short outlook to future work.

LITERATURE REVIEW

The literature has a large variety of investigations concerning incident and disturbance management of PT. In most works the focus lies on the operator's perspective as dispositive measures are developed and evaluated. These measures describe procedures in which the PT supply is rearranged and adjusted towards the occurred incident (*1–5*).

However, as already pointed out by Gkiotsalitis and Cats (4), the development of information and data collection technology enables the collection of a vast amount of demand-side information and allows to dynamically inform PT users about the real-time PT service through a variety of information channels. There are several sources for demand data, such as automatic passenger counts, automatic fare collection, ticket sales or sample census (*6*). In recent years several investigations have also been conducted on passenger-centric methods, which will be presented in the following. Their common goal is to reduce the delay for passengers affected by an incident by providing them with adequate passenger information (PI). The term "adequate PI" is understood here as PI which enables the passengers to adjust their travel plans according to the PT services altered by an incident. This means that passengers, who are affected by an incident, are at least informed about the incident, its location and its estimated duration (i.e. the time needed to dissolve the incident), the changes of the PT service or that they are even provided with advice for a concrete alternative path.

Zhu and Goverde (7), for instance, develop a reassignment model for train travelers in case of a major disruption in parts of the Dutch railway network. The model assigns each affected passenger individually onto an alternative path with the assumption that passengers leave the PT system if their delay exceeds a certain threshold. The same authors extended this method by forming indivisible passenger groups according to their origin and destination instead of reassigning individuals. Furthermore, the passenger reassignment model is coupled with a rolling stock rescheduling model to build a passenger-oriented train rescheduling system. Hence, the available alternative paths of affected passengers are considered during the train rescheduling process (*8*). Müller-Hannemann et al. (9) use the RAPTOR (Round bAsed Public Transit Optimized Router) (*10*) to find alternative trains for indivisible passenger groups affected by canceled and severely delayed long distance trains in the German railway system. Leng and Corman (11) investigate the role of PI availability during disruptions in the PT network of Zurich, Switzerland. Three different schemes of PI have been tested, which differ in their timing, namely: no information, timely information at the start of the incident and advanced information for cases in which the incident is known beforehand, such as construction sites. Furthermore, in (*12*) and (*13*) these information schemes are combined with supply-centric measures such as rescheduling rolling stock, increasing vehicle capacity and line frequencies. The passengers are informed about the incident and the changes to the PT service it causes. The same PI, namely estimated arrival times of PT vehicles, is forwarded to the affected passengers in the case study by Cats and Jenelius (14) in the PT network of Stockholm, Sweden. In all but one of their test cases, the PI decreases the incident-induced delays; however, in this one case the PI causes an increase in the overall delay. Too many of the affected and adequately informed passengers transfer onto the same alternative PT services, exceeding the remaining capacity of such services. Thereby, a secondary incident is induced through overcrowding causing additional delays. Especially in situations, in which the disrupted PT line has a significantly higher capacity than the alternative options, this effect can easily occur. The authors conclude that by customizing the content of the PI according to the available capacity, such negative effects could be avoided.

Van der Hurk et al. (*15*) show such customized PI by giving the affected passengers specific path advice according to the available capacities in the network. The path advice model is coupled with a rolling stock model which determines an ideal solution from the passengers' perspective. The authors also account for passengers who do not follow the path advice by introducing a compliance rate. Besides testing scenarios with deterministic compliance rates, a compliance model based on a logarithmic function, which considers the difference in travel time between the fastest alternative path and the suggested alternative path of the path advice, is examined. The method is applied to parts of the Dutch railway system. In (*16*), particular alternative paths are suggested to affected passenger groups according to their origin and destination as well. The authors mathematically formulate their passenger-centric approach as a flow distribution problem and test it in the metro network of Chicago, USA. In addition to taking the capacity of the PT system into account, the model considers uncertain demand due to passengers leaving the PT system when incidents occur. For a more comprehensive overview of investigations in the field of passenger-centric incident management (PCIM) in PT systems, we refer to (*17*).

All these investigations suggest that providing adequate PI has mainly positive effects on the delay of affected passengers. However, the developed methods are tested in rail-bound PT services with mostly severe service disruptions. This study extends the macroscopic concept introduced in (*18*) to handle incidents in a PT bus system from a microscopic viewpoint, which is necessary for real-world implementation. A heuristic and an optimization procedure to solve the resulting problem are introduced and evaluated via simulation. Whereas the macroscopic approach by Bachmann et al. (18) works with passenger- and supply-flows and presents merely a numerical example, the approaches introduced here take each single vehicle and passenger into account and are implemented in a simulation study.

PROBLEM STATEMENT

The goal of the methodology introduced here is to minimize the overall delay of passengers induced by an incident in a PT bus network by providing them with path advice. It is therefore assumed that an incident occurs in a PT network which affects some of the PT users. As pointed out in (*1, 19*), all information about incidents, such as its location and the disrupted PT lines, are gathered at OCCs. Moreover, the authors found out that dispatchers have a good intuition about the estimated duration of an incident, thereby it is assumed that an estimation of the incident duration is given. From the list of dispositive measures to counteract the incident, two measures are tested: line-splitting (scenario LS), in which an affected PT line is split and it operates in loops on both ends of the incident, and line rerouting (scenario LR), in which affected PT lines are rerouted via alternative routes.

If U represent all of the passengers, then in the following we differentiate between three different kind of PT users or passengers:

- The affected PT users ($U_a \subset U$) are the passengers whose original trip plan is disrupted by the incident, as one of the PT lines they planned to take is one of the disrupted lines.
- indirectly affected PT users ($U_{ina} \subset U$), are the ones whose planned trip is not disrupted, however, they use PT lines which observe additional demand due to the affected passengers transferring onto some of these lines.
- The unaffected PT users are the ones who travel at a different time or at a completely different location in the PT network and thereby do neither use one of the disrupted lines nor a line on which affected passengers are transferring onto, hence, they are not affected by the incident in any way ($U_{una} \subset U$).

It is assumed that nobody leaves the PT system when an incident occurs, and therefore, the demand stays the same compared to a situation in which there is no incident. An estimation of the passenger demand is assumed to be available in the form of an origin-destination (OD) matrix. Furthermore, different compliance rates are considered in this work expressing how many of the affected PT users follow a certain path advice. Passengers not following it are assumed to stick with their original travel plan and wait for the incident to be dissolved.

As noted in (*1*), there are several PI channels available in a PT system, namely: speakers, dynamic displays at stops and in vehicles, the PT operators' online presence on websites and on social media, as well as trip-planning smartphone applications from operators or third parties (e.g. Citymapper, Oeffi, GoogleMaps). These channels can be used to convey the path advice to the affected passengers. Besides, as explained in (*9*), it is not apparent which passengers know each other and travel together as one group. Consequently, it is reasonable to group all affected passengers who share the same origin of redirection and destination to the same OD-pair (od). The origin of redirection is understood here as the stop from which affected passengers need an alternative path. For affected passengers who have not started their trip at the beginning of the incident, this stop remains the same as the origin of the original trip. For affected passengers who are already in the PT system at the beginning of the incident, this is the next stop in their current trip.

The OCC provides suitable path advice to the PT users which should satisfy several conditions. For one, all travelers of one *od* should receive the same path advice for their redirection to prevent confusion (*9, 15, 18, 20*). This consistency in information avoids that affected passengers receive different path advice from different PI channels as well as that the members of the same group of travelers receive different path advice. Moreover, the path recommendations should consider sufficient remaining capacity to avoid secondary incidents through overcrowding by the redirected passengers.

The following list summarizes the assumptions above:

- Dispatchers can estimate the duration of the incident
- Capacity and occupancy of PT services is given
- Estimation of passenger demand is known as OD-matrix
- Nobody leaves the PT system
- Passengers not taking the path advice are sticking with their original plan and wait for the incident to be dissolved

METHODOLOGY

To solve the stated problem, the conceptual framework introduced in (*18*) is significantly extended from a macroscopic, numerical approach to a microscopic simulation study. In this section the PCIM methodology, its detailed processes and the evaluation strategy of this paper are explained. First, the overall procedure shown in Fig. 1 is shortly explained. Second, the representation of the PT network graph is elaborated, before the actual procedure is described. Two different approaches to redirect passengers during incidents are introduced, a heuristic and an optimization-based approach. To implement and evaluate these strategies in a simulation study, the microscopic traffic simulation tool SUMO (Simulation of Urban MObility) (*21, 22*) is used. During the procedure illustrated in Fig. 1 several SUMO simulations are run (with and without incident in steps 1 and 3, respectively), and their outputs are then processed by the Python scripts. Afterwards, the developed algorithm (Python script) solves the redirection problem using the passengers' trips and timetable information collected from the SUMO simulations. Finally, SUMO simulations are run again with the incident and the above the redirection strategy to evaluate the developed method with SUMO. The individual steps in Fig. 1 are explored further by the corresponding boxes in Fig. 3. The passengers associated to certain OD-pairs (*od*s) are given a clear path advice through the PT network. In order to compare different scenarios, the same passengers are used in terms of their identification number and *od* to be able to analyze their change in travel time among the different scenarios. When a PT system is disrupted by an incident, crowding at stops can be one of the consequences. SUMO considers that by allowing passengers to queue at stops, if a stop's capacity is reached, passengers continue to queue on the sidewalk. As long as there are free spots in a PT vehicle and the passengers are able to reach it, they will board it (*22*).

Network Graph

One main input to the framework is the PT supply. In this study the PT supply is represented by a directed network graph $G = (N, L)$ with nodes N and links L. The set of nodes is divided into two subsets: 1) a set of stop-nodes $N_P \subset N$ representing the physical PT stops of the PT network and 2) a set of line-nodes $N_L \subset N$ which connect the stop-nodes with the individual PT lines. As shown in Fig. 2, for each PT line serving a particular physical PT stop, there is a line-node representing the corresponding PT line. Each line-node is connected to its corresponding stop-node via a link,

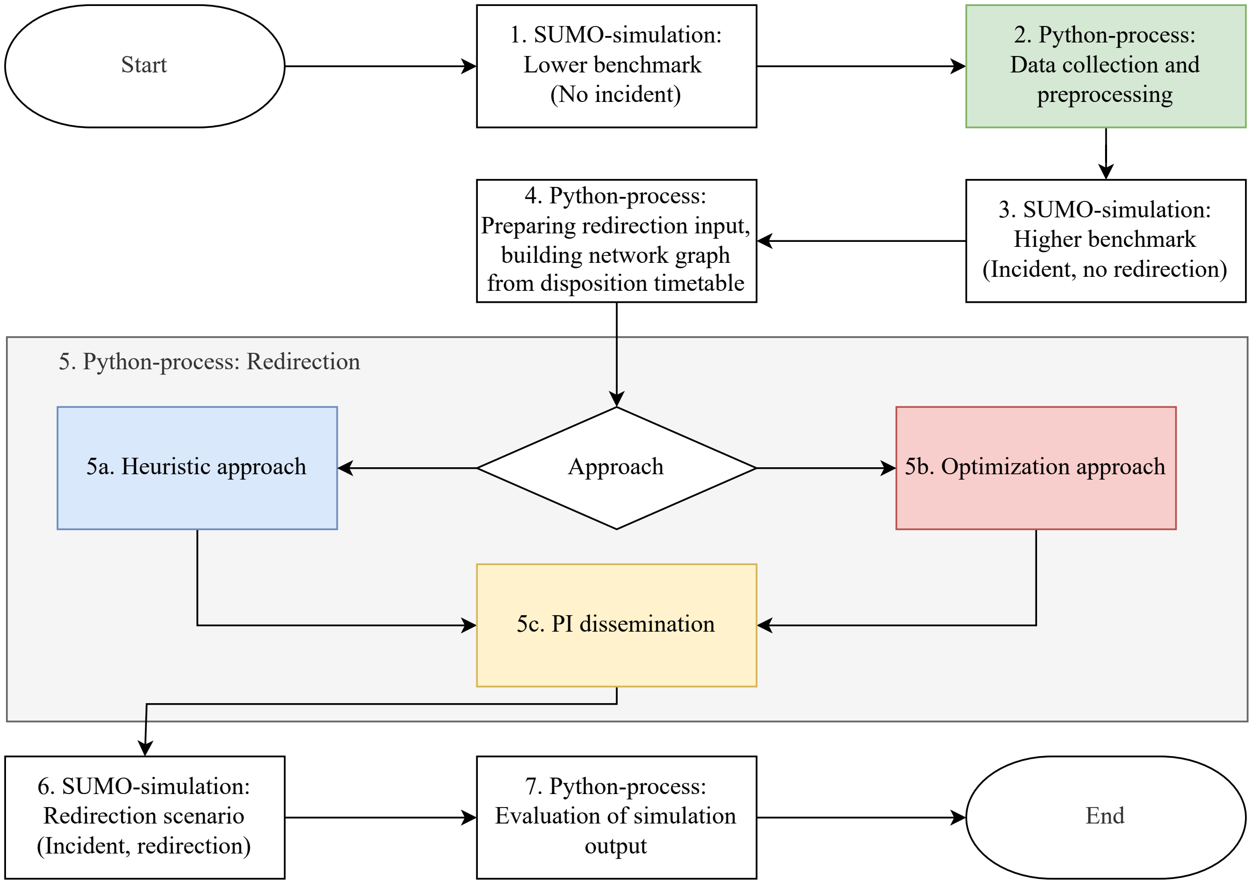


FIGURE 1: Framework of the overall procedure

which passengers use for getting on and off a PT line as well as for transferring to other lines. Therefore, each PT line (e.g. blue, orange or green line in Fig. 2) is connected to two line nodes at each stop area, one for each direction. PT links connect the respective line nodes at different stop areas (e.g. S2).

Since a single area of the PT network can have multiple stop-nodes (e.g. S2_1, S2_2, S2_3 and S2_4 in Fig. 2), the stop-nodes in the same area are connected by walking links. These walking links can represent crossing the street to take a PT service in another direction. A bigger transportation hub can have more than two stop-nodes, for example stop area S2 in Fig. 2. If a stop-node is served by more than one line, and thereby possesses more than one line-node, these are connected in accordance with their timetable, representing the transfer from one line to another at the same stop. The travel time on the transfer links also take the waiting time for the next PT service into account. For each line serving two subsequent stops there is a link between the corresponding line nodes of the two stops in the respective direction of travel.

As mentioned before, the capacity of PT services plays a vital role in PCIM methods. The line capacities can be derived from these links as well as the occupancy of the vehicles operated on the lines. The link capacity (c_l) is derived by summing up the free spots on all PT vehicles passing $l \in L$.

An incident is defined by its start t_s^i and end time t_e^i as well as the set of links it disrupts in the network ($L_i \subset L$). As an incident causes many changes to the PT system, two network

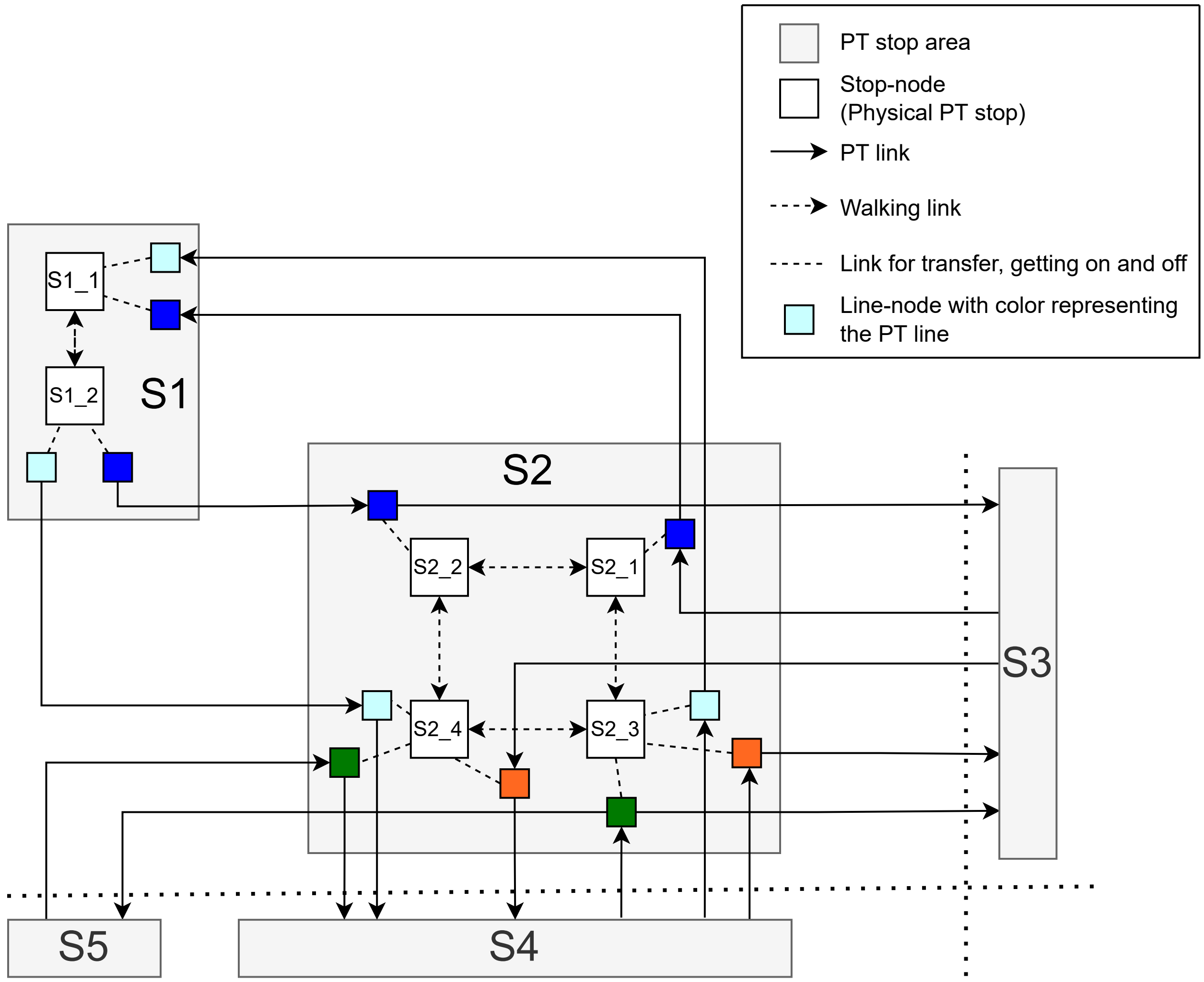


FIGURE 2: Example for the used network graph structure

graphs are built: one for the base scenario, representing the planned PT service, and another one based on the disposition timetable, representing the PT service during the incident with the applied supply-centric measures (step 3 and 4 in Fig. 1).

PCIM Method

After the base scenario without an incident is run in SUMO (step 1 in Fig. 1) the travel data (origin, destination, travel time, etc.) of the demand can be extracted. This travel data represents the assignment on the undisrupted PT system. Step 2 in Fig. 1 collects and preprocesses this travel data. The green area of the PCIM procedure in Fig. 3 shows this process in more detail. Once all required information are provided, the redirection strategy can be executed as fifth step in Fig. 1 (either blue or red area in Fig. 3) before informing the PT users (yellow area in Fig. 3). In the following, the steps refer to Fig. 3.

Data Collection and Preprocessing: First, the method needs to determine who is affected by the incident. As mentioned in the problem statement, it is assumed that some estimation of the demand is available and that it does not change during the incident. In practice, historical data and real-time data can be used (*6, 20, 23*). Here, the SUMO simulation of the base scenario is used to manufacture "historical" travel data and to identify the affected passengers (U_a). The output of this base scenario is also used to calculate the delay of all passengers in the other scenarios. The procedure identifies the affected buses by checking which ones are passing one of the affected links $l \in L_i$ during the incident in step 1. It then determines which passengers would ride these affected buses under normal circumstances. These are denoted as U_a (step 2). In the 3rd step, the procedure identifies the origins of redirection $o \in N$ of the affected passengers. From these origins of redirection the passengers require a suitable path to their respective destinations. A path p is defined as a set of subsequent and connecting nodes from $o \in N$ to $d \in N$. To avoid confusing path advice on an individual level, the affected passengers are then associated with OD-pairs ($od \in OD_a$) according to their origin of redirection and respective destination in the 4th step. OD_a being the set of all affected od.

The orange parallelogram "Set of all available paths" represents a preprocessing step in which all simple (i.e. non-circular) paths between each two stops of the network are determined. This can be preprocessed so that the paths only need retrieval once an incident occurs. In step 5, the procedure associates each of the affected ods with a corresponding set of reasonable paths P_{od}. Here, a path is defined as reasonable if each PT line and PT stop is visited at most once, it does not contain one of the affected links ($l \in L_i$) and it results in a shorter travel time than would sticking to the original path despite the incident. For the calculation of the travel time, its components (riding time, waiting time, transfer time, etc), are not considered individually. Additionally, there is no penalty considered for transfers. During special situations such as incidents, it is assumed that passengers are willing to transfer between lines as long as it reduces their overall delay. Once the expected end of the incident is approaching, it makes more sense to stick to the original path again. For this matter, a redirection duration is calculated for each alternative path ($p \in P_{od}$) of each od (step 6). The redirection duration T^p_{od} expresses how long (measured from the start time of the incident) it is reasonable to redirect passengers of a certain od onto a particular p. Eq. 1 states that the redirection should occur as long as p is faster than waiting for the incident dissolution and sticking to the original planned path:

$$T^p_{od} = (t^i_e - t^i_s) + (tt^{od}_0 - tt_p) - t_{con} \tag{1}$$

Thereby, t^i_e corresponds to the expected ending time of the incident, t^i_s to its start time, tt^{od}_0 to the travel time on the original path of od and tt_p to the travel time of p. Eq. 1 has been altered from the equation introduced in (*18*): A time constant t_{con} has been added to consider longer travel times because of a missed PT vehicles and interference with other passengers. The equation states that the longer the additional travel time on p is, the shorter is the remaining redirection duration. As a consequence, the shorter the remaining redirection duration is, the smaller is the number of passengers of an od which profit from the path advice.

The passengers of an od are divided into two groups in step 7: a redirection group rg^p_{od} and a waiting group wg^p_{od}. The redirection group contains all affected passengers of an od, who arrive at the origin of their redirection before their corresponding redirection duration elapsed (T^p_{od}). Contrarily, all affected passengers of an od arriving later are put into the waiting group. The waiting group represents all affected passengers of an od for whom it is time-wise more convenient to wait for the dissolution of the incident and stick with their original path (0_{od}). As T^p_{od} depends on p's travel time tt_p, this division into groups is done for each $p \in P_{od}$ of each od.

In reality, not every affected passenger receiving a path advice will follow it, as some travelers will stick to their original path. To account for these passengers, a compliance rate is also considered in the model. If a compliance η_{od} of less than 100% is assumed, an additional share of $(1 - \eta_{od})$ passengers are shifted from the redirection group to the waiting group for each path of an od. However, experienced PT users, such as commuters, who know the PT network well, might choose another alternative path than the one that the given path advice suggests, which is not considered in this methodology.

Following the above process, the required inputs to apply redirection strategies for od onto specific p are available. This paper studies two approaches, hence, the procedure splits into a heuristic and an optimization-based approach at step 8.

Heuristic Approach: The rule-based heuristic approach, highlighted in the blue area in Fig. 3, assigns the redirection groups of each $od \in OD_a$ (rg^p_{od}) to alternative paths sequentially. The main assumption of the heuristic is that it is more beneficial for the overall delay to assign larger groups to their corresponding fastest possible alternative paths first. Therefore, the affected ods are sorted by the size of rg^p_{od} in descending order (step H9 in the blue area). This sorting of od is done for the respective fastest $p \in P_{od}$ of each od as it results in the largest respective rg^p_{od}. As elaborated before, the smaller the travel time of an alternative path, the longer the redirection duration and the bigger the redirection group of an affected od. Accordingly, the set of alternative paths (P_{od}), is sorted by travel time with the fastest path on top.

In step H10, the first, hence the fastest, alternative path of the first od is checked for its remaining capacity. The remaining capacity takes into account the indirectly affected passenger (U_{ina}), which already occupy parts of the PT system's capacity. U_{ina} do not receive path advice and are assumed to remain on their original path. If an alternative path can provide sufficient remaining capacity for rg^p_{od} (step H11), the assignment is set (step H13a) and the paths' capacities are updated accordingly. If the remaining capacity of a path p is too small, it is checked whether there are paths left in P_{od} (step H12); if that is the case, the next p is checked for its remaining capacity. Since P_{od} is sorted by the paths' travel times, the further down a path is in the set, the longer is its travel time, the shorter is its corresponding redirection duration, the smaller is the redirection group and, therefore, the higher is the chance that rg^p_{od} can be assigned to a p. If none of the $p \in P_{od}$ offers sufficient remaining capacity, rg^p_{od} is assigned to its original path (0_{od}) (step H13b), which means all passengers associated with that od will have to wait for the dissolution of the incident. wg^p_{od} is always assigned to the respective 0_{od}. In this manner the heuristic approach iterates the whole set of affected ods, until, in step H14, all ods are checked and the redirection strategy is set (step 15). This is comparable to the greedy algorithm introduced in (*9*). However, the order of ods is random in their approach.

Compared to the heuristic procedure presented in (*18*), the heuristic in this study goes far more into detail and is therefore more precise. One example is the determination of the size of the redirection groups. In (*18*) the passenger flow is simply multiplied by the redirection duration, whereas in this study, expected numbers of passenger are represented by individual agents associated with a certain od who are checked whether they arrive in time at the origin of the redirection or not.

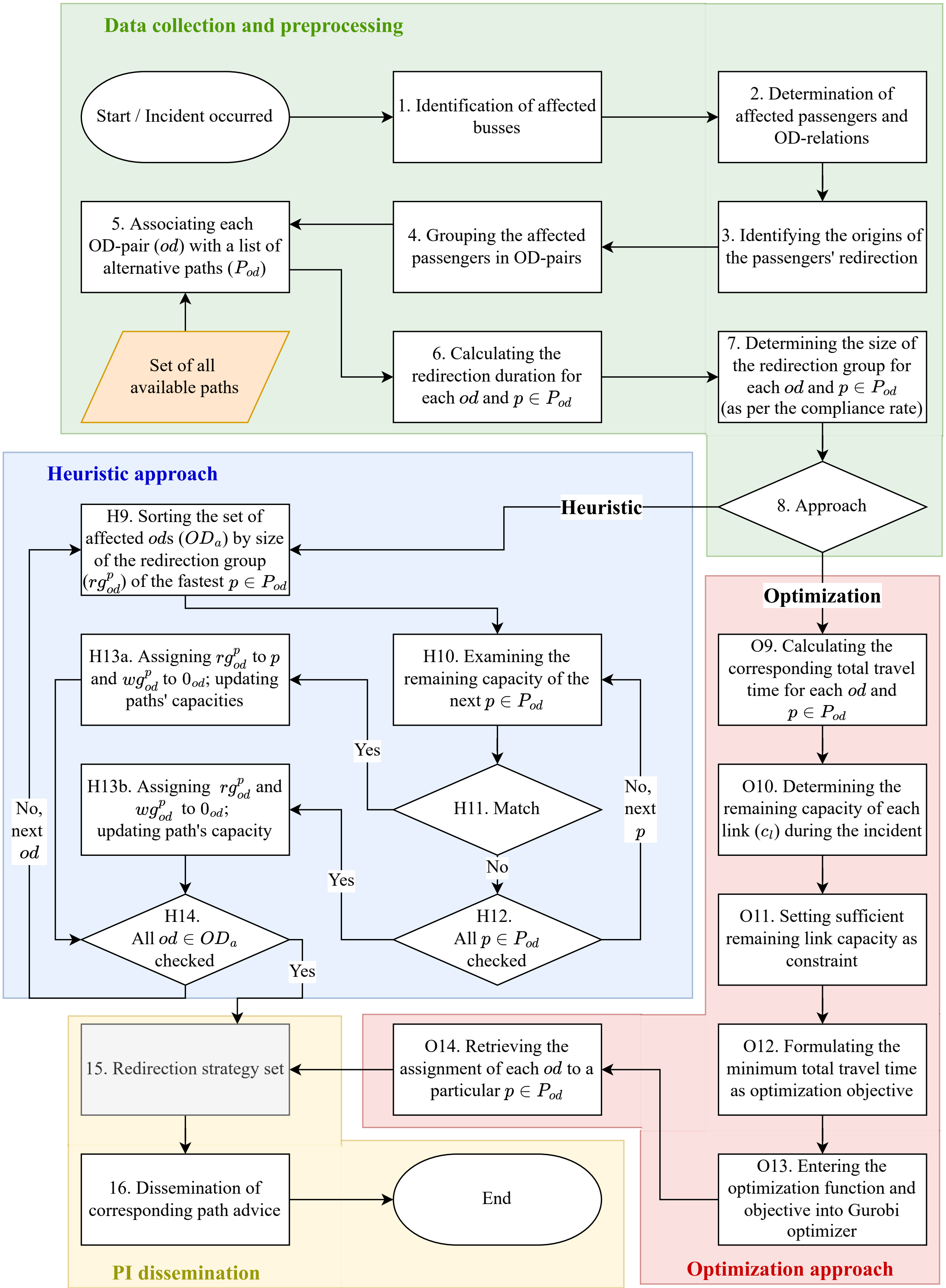


FIGURE 3: PCIM procedure

Optimization Approach: In this approach, the redirection of passengers during incidents is formulated as an optimization problem. The goal is to minimize the overall delay by matching the affected ods to the corresponding available paths (P_{od}) in the best possible way. For this, the optimization problem is formulated as follows: First, for each od and each available path ($p \in P_{od}$) the total travel time TT_{od}^{p} is calculated (step O9 in the red area in Fig. 3):

$$TT_{od}^{p} = |rg_{od}^{p}| \cdot tt_p + \left(|wg_{od}^{p}| \cdot tt_0^{od} + \sum_{j \in wg_{od}^{p}} t_j^i \right) \tag{2}$$

where rg_{od}^{p} is the redirection group, tt_p is the travel time of the corresponding p, wg_{od}^{p} is the waiting group, tt_0^{od} is the travel time of the respective original path 0_{od} and t_j^i is the remaining waiting time until the end of the incident for passenger $j \in wg_{od}^{p}$. The first term represents the total travel of the redirected passengers while the second term represent the total travel time of the passengers that are waiting for the incident to end.

Through this process the travel time of each od is known for each $p \in P_{od}$. In step O10 the remaining capacity (before giving any path advice) of each link is determined by checking the remaining capacity of all PT vehicles crossing a particular link during the incident. As in the heuristic approach, the remaining capacity considers the indirectly affected PT users (U_{ina}) which are already assigned to their corresponding paths and occupy parts of the PT system's capacity.

The output assigns each od of all affected OD-pairs ($OD_a \subset OD$) to a particular path using the decision variable $x_{od}^{p} \in \{0,1\}$. Each od is assigned to exactly one path (Eq. 4). Similarly, Eq. 5 ensures that the redirection group of an od does not exceed the remaining capacity of a path (step O11). Considering the case where no alternative path fits an od, the original path 0_{od} is also included in P_{od}. In such a case, all passengers of an od are assigned to their respective 0_{od} and wait for the dissolution of the incident.

$$\min_{x_{od}^{p}} \sum_{od \in OD_a} \sum_{p \in P_{od}} x_{od}^{p} \cdot TT_{od}^{p} \tag{3}$$

subject to

$$\sum_{p \in P_{od}} x_{od}^{p} = 1 \qquad \forall od \in OD_a \tag{4}$$

$$\sum_{od \in OD_a} \sum_{p \in P_{od}} x_{od}^{p} \cdot |rg_{od}^{p}| \cdot m_{pl} \leq c_l \qquad \forall l \in L \tag{5}$$

Here, $M \in \{0,1\}^{|P_{od}| \times |L|}$ is the path-link matrix, in which the element m_{pl} is 1 for every link $l \in L$ that is part of the specific path p.

The optimization problem formulated in Eq. 3 (step O12) is solved by the Gurobi optimizer (*24*) (step O13). In step O14 an assignment of each od to a particular path can then be retrieved. The yellow area in Fig. 3 shows the last steps of the introduced method. At this point in the procedure the heuristic (blue area) or optimization (red area) have come to a solution for the redirection of passengers onto available paths and the strategy is set (step 15). If the proposed PCIM method is implemented in practice, the corresponding PI will then be disseminated through the available and aforementioned channels (step 16).

CASE STUDY

This section describes the setup and the results of the conducted case studies.

Setup

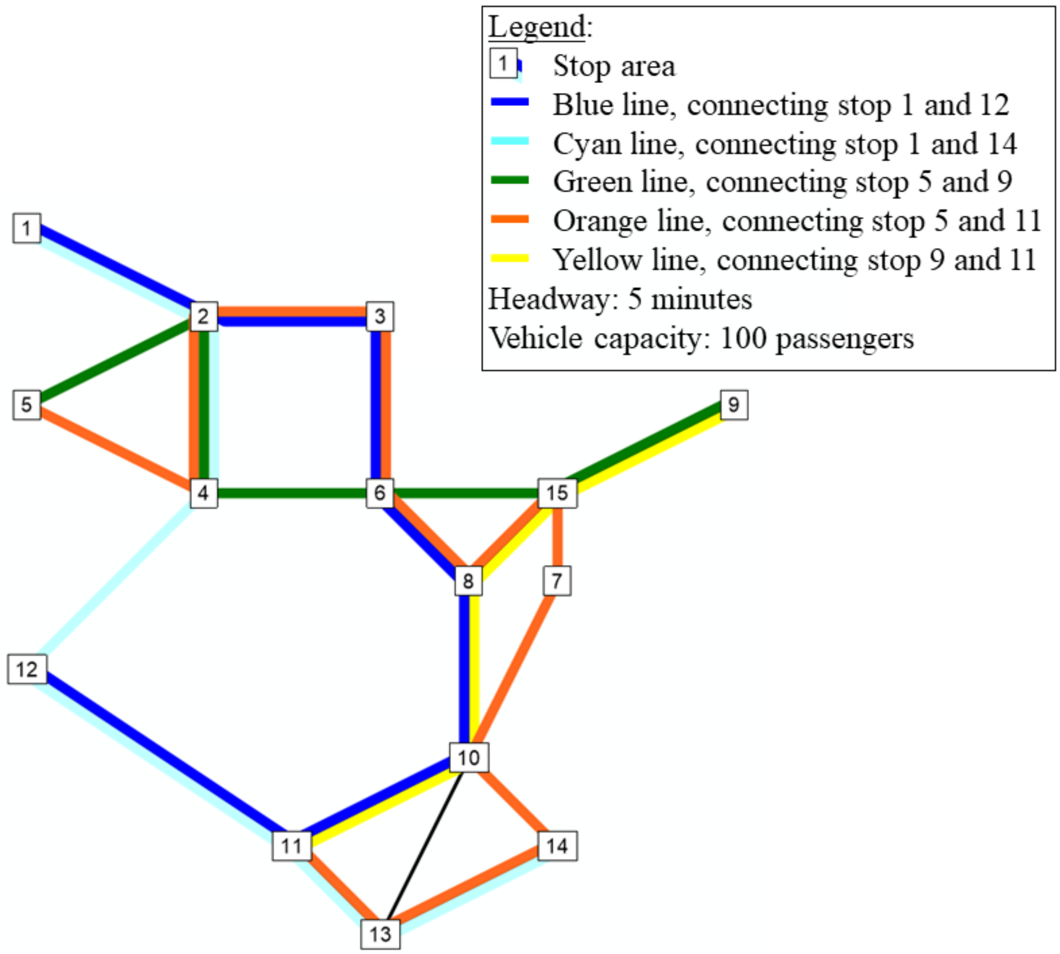


FIGURE 4: Mandl-PT network

For the conducted case study the Mandl-network (*25*) is used. It was published with link travel times and an OD-matrix. However, it originally was published as a road network. Several studies addressed the PT network design problem using the Mandl-network, therefore, several Mandl-PT networks are publicly available. This work builds on a solution designed by Ul Abedin (26). Fig. 4 shows the PT network and all operating lines. For the sake of simplicity, the PT network has been modified in a way that the headway of all lines are uniformly set to five minutes and all PT lines are bus lines. Each bus is assumed to have a capacity of 100 passengers. The OD-matrix published in (*25*) shows demand for 24 hours. For this study, the demand is scaled up; twice the demand from (*25*) is taken and spread over a period of four hours as demand input. In this way the PT system is under a lot of pressure and the consequences of an incident are very severe in terms of delays. Therefore, the effects of the redirection of passengers can be observed clearly in the results. The passengers are set to only use the PT system without leaving it, even if severe delays occur. The incident is assumed to occur between node 8 and node 10 and disrupts the yellow and the blue line. Two incident duration are tested, 30 and 60 minutes.

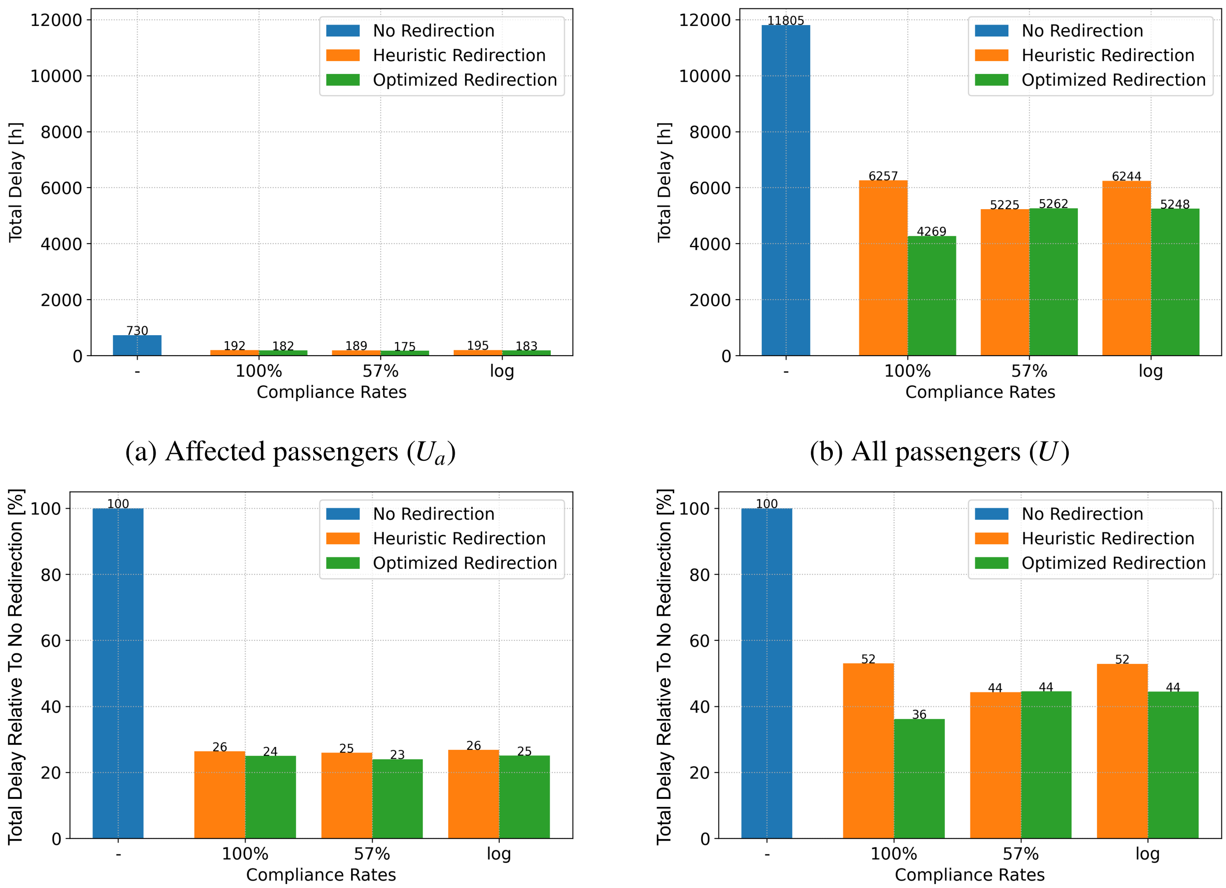
The previously described methodology to redirect passengers during incidents is tested in combination with two typical dispositive measures, line-splitting (scenario LS) and line-rerouting (scenario LR). For LS, the yellow line is operating in loops between nodes 10 and 11 as well as between 8 and 9, whereas the blue line's loops are between nodes 10 and 12 and between 1 and 8. For LR, the blue line is rerouted via nodes 15 and 7 with a stop at node 8 and continues the original route from there towards node 1. For the blue line, no stop is skipped due to rerouting. The yellow line is rerouted via node 7 to node 15. At node 15 it continues its original route to node 9. For the yellow line, node 8 is skipped during the rerouting. For the blue line the rerouting adds about three minutes to the travel time between node 8 and 10. The yellow line's travel time is reduced by about one minute between nodes 10 and 15.

For each of the two scenarios, four settings are tested, namely: "No Incident": This serves as lower benchmark (step 1 in Fig. 1), in which no incident occurs and no dispositive measures are taken and is used to calculate the delay of passengers occurring in the other settings; "No Redirection": This serves as higher benchmark case, in which an incident occurs and one of the aforementioned supply-centric measures (LS or LR) is taken (step 3 in Fig. 1) and two redirection cases: "Heuristic Redirection": in which in addition to the dispositive measure the passengers are redirected with the heuristic approach, and "Optimized Redirection": in which in addition to the dispositive measure the passengers are redirected with the optimization approach (step 5 in Fig. 1).

In total, 24 different cases have been tested by building all combinations of the following: two different dispositive measures, LS and LR, two different incident duration, namely half an hour and one hour, as well as three different compliance rates, namely 100%, 57% and a logarithmic-function based compliance rate. All these cases have been conducted with both approaches. The constant compliance rate is based on a passenger survey, which showed that 57% of the passengers are willing to follow a path advice in case of an incident (*27*). The logarithmic function is adopted from (*15*), which takes the difference of travel time between the suggested path and the fastest alternative path into account. Each of the aforementioned 24 cases have been conducted with three different passenger data sets (generated with varying seed values).

Results

Fig. 5a shows the total delay of the affected passengers in the scenario LS with incident duration of half an hour. The delay of the affected passengers (U_a) is the smallest with 57% compliance rate and the optimization-based redirection. The percentage reduction of delay is 77% compared to the higher benchmark (no redirection): the total delay is decreased from 730 hours to 175 hours. The heuristic approach produces also a significant reduction of 75% from 730 hours to 189 hours. Among all scenarios, the case of the heuristic with the logarithmic compliance rate shows the smallest, but still very good improvement with a delay reduction of 74%. As a comparison, the optimization approach with the logarithmic compliance rate achieves a delay reduction of 75%. Looking at the total delay of all passengers (U) in the same scenario (Fig. 5b), the heuristic in case of a 100% compliance results in the worst performance with a delay reduction of 48% and the best result by the optimization in the same case with a delay reduction of 64%. In case of a compliance rate of 57%, the two approaches result in similar delay reduction of about 56%. In



(a) Affected passengers (U_a)

(b) All passengers (U)

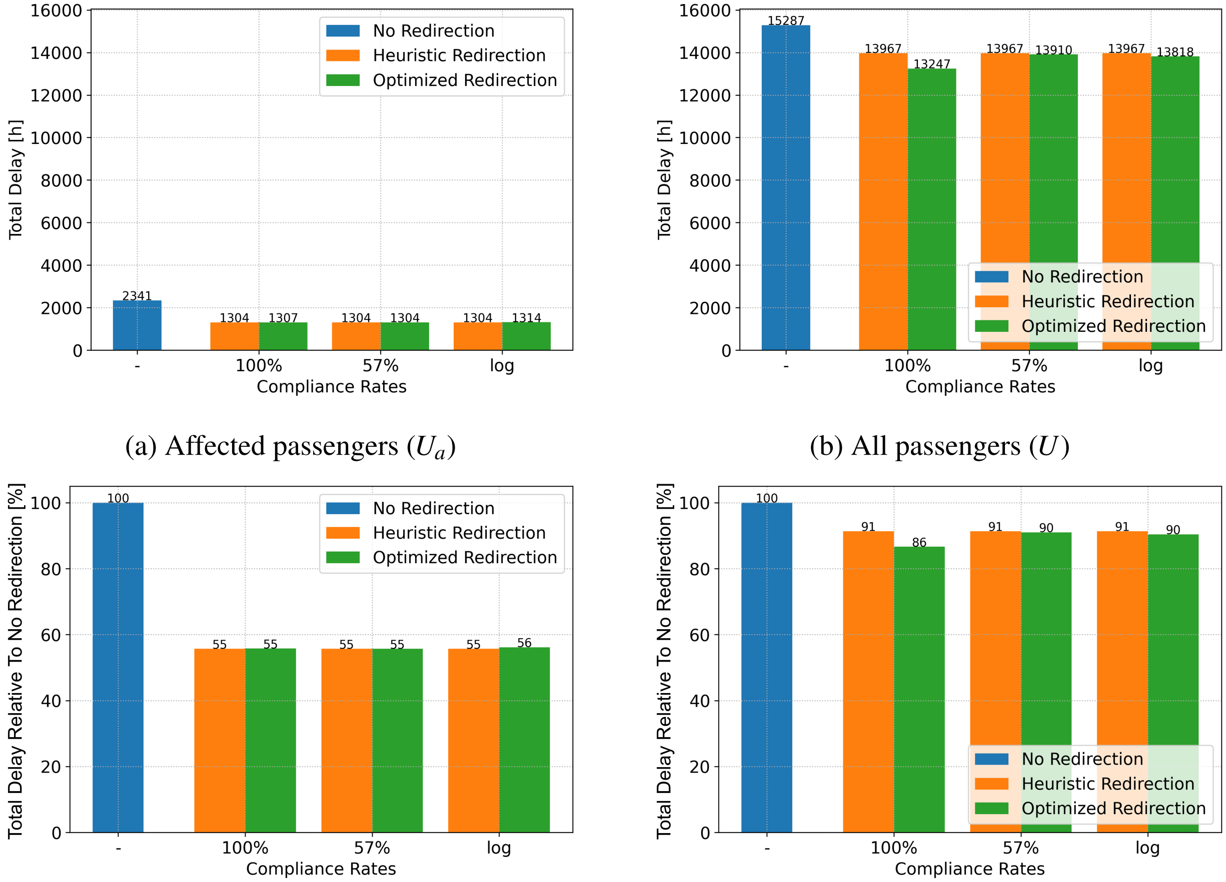
(c) Affected passengers (U_a)

(d) All passengers (U)

FIGURE 5: Overall delay with an incident duration of 30 minutes in scenario LS

the case of the logarithmic compliance, the optimization performs better with a delay reduction of 56% compared to the heuristic with a reduction of 48%. Looking at the same scenario with an incident duration of one hour (Fig. 6c), the differences between the different cases of compliance rates decrease. The reduction of the delay for the affected passengers is in almost all cases 45%, only the optimization in the case of the logarithmic compliance rate preforms one percent point worse. For all passengers, the situation is obviously worse than in the case with half an hour incident. The best result is achieved by the optimization in case of 100% compliance with 14% reduction of delay. The other results lie between 9 and 10%.

Besides the scenario LS in which the disrupted PT lines are split, a scenario LR in which they are rerouted is tested. Comparing Fig. 5 and Fig. 7 shows that delays can be reduced even without redirection. With redirection, the optimization (Fig. 7c) performs slightly better (83%) than the heuristic (82%) in the cases with 100% and 57% compliance from the perspective of the affected passengers. With a logarithmic determined compliance, the two approaches achieve both a reduction of 82%, however, the optimization achieves two hours less of delay for the affected passengers than the heuristic (Fig. 7a). Looking at all passengers in all cases a delay reduction of 96% can be achieved. For an incident duration of a full hour, the cases with 100% or 57% of



(a) Affected passengers (U_a)

(b) All passengers (U)

(c) Affected passengers (U_a)

(d) All passengers (U)

FIGURE 6: Overall delay with an incident duration of 60 minutes in scenario LS

compliance perform best with a reduction of 67% for the affected passengers, regardless which approach is taken (Fig. 8c). For the case with a compliance rate determined in a logarithmic manner, the heuristic (34%) slightly outperforms the optimization (33%). The results for all passengers showcase, in which both redirection approaches worsen the situation in matters of the overall delay of all passengers by 15%. In the cases of 100% and 57% compliance, the heuristic improves the situation by 43% whereas the optimization improves it by 46%.

Fig. 9 shows box plots of the delay distribution of the affected passengers in the scenarios LS and LR with both tested incident duration (30, 60 minutes). The results show that with a longer incident duration also the spread of the distribution of delays increases. The scenario LS shows a bigger range of delays than the scenario LR. In scenario LR some of the affected passengers achieve less delay compared to the lower benchmark scenario with no incident. For LS this is only achieved in the redirection scenarios. The compliance rate seems to have a minor influence on the distribution of delays.

The computation time for the redirection process, including steps 4 to 15 in Fig. 3, takes about 20 seconds. The whole computation was done on an Intel Xeon W-2133 CPU with 3.60 Gigahertz and 32.0 Gigabyte of RAM. The algorithm is implemented in Python. The fastest run takes

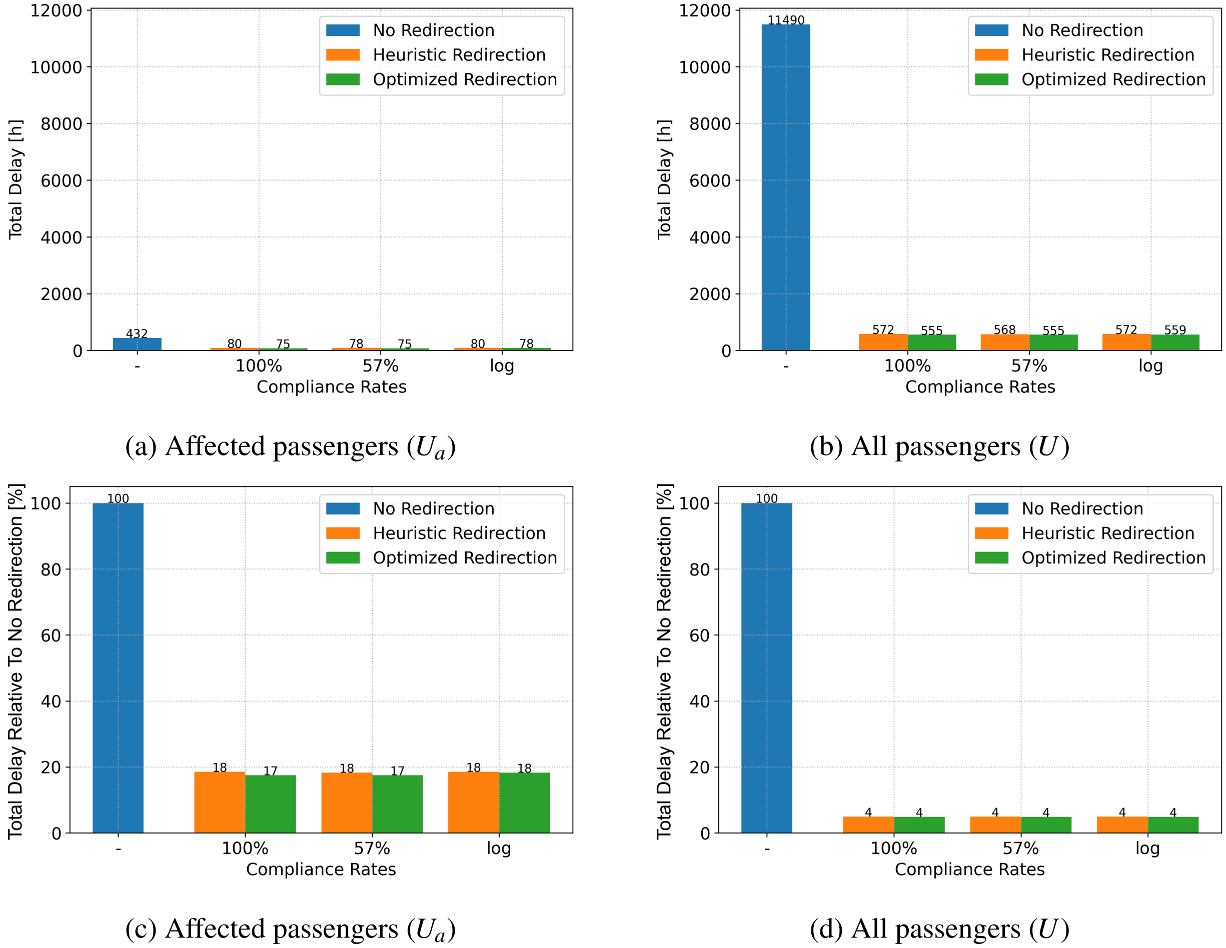
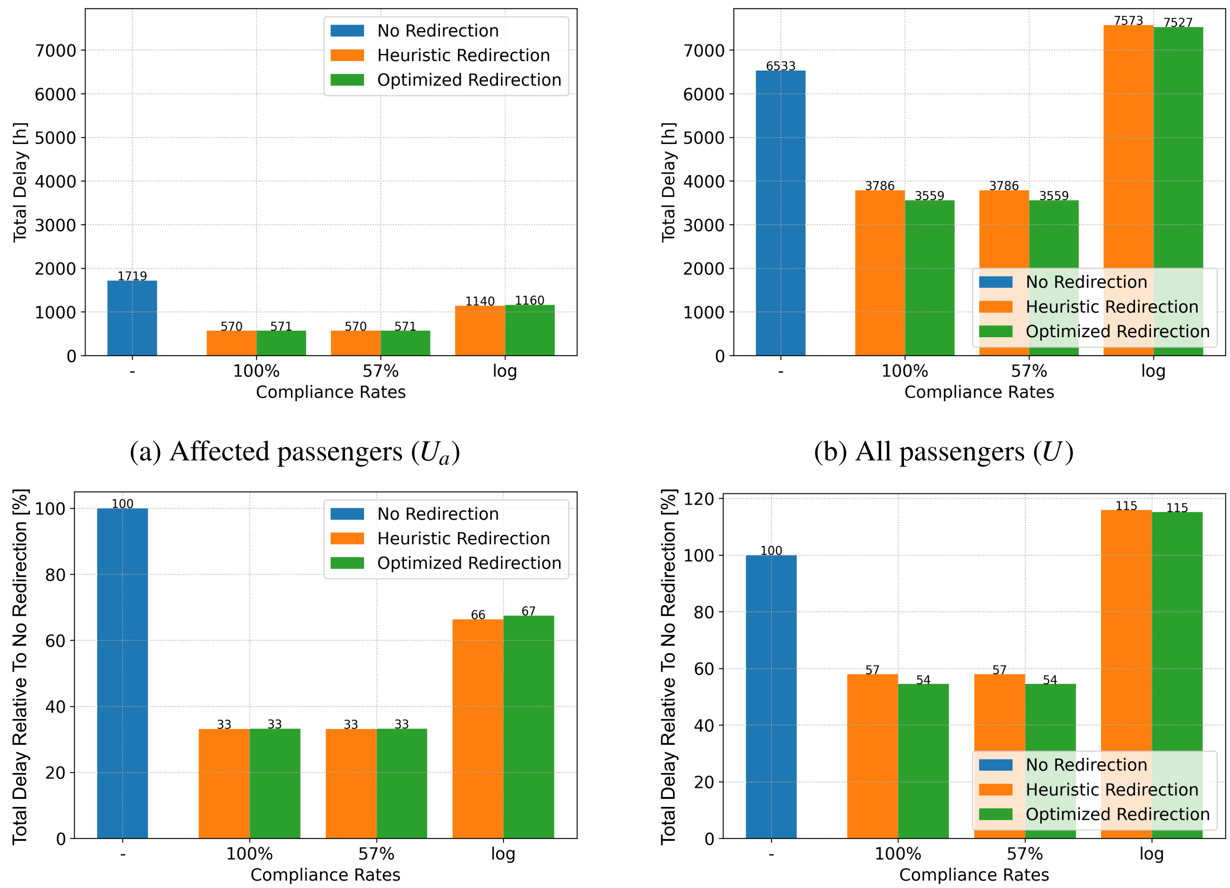


FIGURE 7: Overall delay with an incident duration of 30 minutes in scenario LR

18.97 seconds for the scenario LS with an incident duration of 30 minutes, a compliance rate of 100% and the heuristic approach. The slowest computation time was observed for the scenario LR with an incident duration of 60 minutes, a compliance rate of 57% and the optimization approach (22.06 seconds). In general, the whole process works faster with a shorter incident duration. Similarly, the heuristic runs a bit faster than the optimization. However, the real performance difference between heuristic and optimization can only be measured when applied to bigger networks.

DISCUSSION

When comparing the case of "No Redirection" with the redirection cases, both the heuristic and optimized redirection show a significant reduction in the overall delay of the affected passengers (U_a) as well as all passengers (U). The results also show that in the cases with an incident duration of one hour, the benefits are less than in the cases with half an hour incident duration. Moreover, in addition to U_a, the indirectly affected passengers (U_{ina}) and "unaffected" passengers (U_{una}), who represent the rest ($U \setminus U_a$), also experience severe delays in the "No Redirection" case. This can be explained by the fact that the demand is set very high which causes queuing at bus stops. In SUMO, when bus stops reach their capacity, passengers start queuing on the sidewalk (*22*). Even though the $U \setminus U_a$ are not the focus of the PCIM method, they also benefit from it. However, it is ar-



(a) Affected passengers (U_a)

(b) All passengers (U)

(c) Affected passengers (U_a)

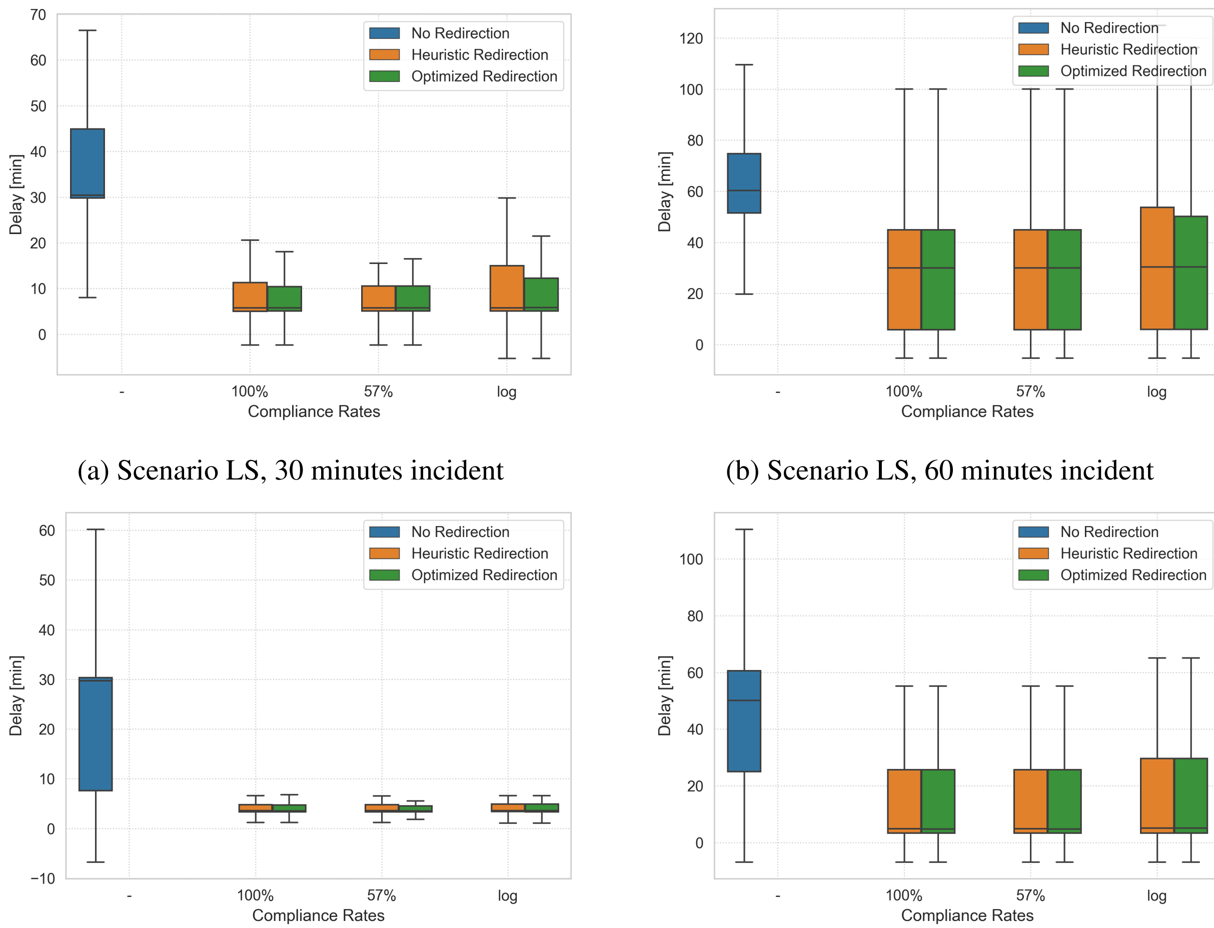
(d) All passengers (U)

FIGURE 8: Overall delay with an incident duration of 60 minutes in scenario LR

guable to which extent the queuing behavior as it is simulated in SUMO is representing real-world dynamics; if bus stops are overcrowded in reality, people would probably make sure that services are still board-able to a certain extent. This is worth further investigation. The same is true for the validation of the PCIM method with less demand; it can be expected that with less stress on the system the optimization objective (total delay of U_a) is more aligned with system optimum (total delay of U) as the passengers in U_{ina} and U_{una} are likely less affected than in the high-demand scenarios.

This also is true for the compliance rates. The logarithmic compliance rate taken from (*15*) is not adapted to the PCIM method introduced here. Even though this compliance rate considers the difference in travel time between the suggested and the fastest alternative path, passengers not following the path advice do not take the fastest alternative path, but stick with their original travel plan and wait for the dissolution of the incident. In addition to sticking to the original travel plan and taking the path advice, passengers should realistically also be able to redirect themselves or leave the PT system. The logarithmic function for the compliance rate should then also consider all four decision possibilities.

The results show that — compared to the heuristic approach — the optimization-based



(a) Scenario LS, 30 minutes incident

(b) Scenario LS, 60 minutes incident

(c) Scenario LR, 30 minute incident

(d) Scenario LR, 60 minute incident

FIGURE 9: Distribution of the delay of affected passengers

approach achieves positive results with respect to delay reductions for all passengers U in almost all cases. The results varied from a decrease of 96% (in the LR-scenario with incident duration of half an hour and a compliance rate with 100%) to an increase of 15% (LR-scenario with an incident duration of one hour and the logarithmic determined compliance) of the overall delay. Even though most results show a clear potential of the introduced method, it also shows that there is room for improvement. It is also possible that the heuristic approach sometimes produces a better solution than the optimization-based approach because of temporal dynamics: Handling one *od* at a time has the advantage that the remaining capacity of an alternative path can be examined in different time intervals whereas the optimization-based approach uses a single capacity value (Eq. 5) for the whole incident duration. It aggregates the temporal component and does not consider at which section in the network a rg^{p}_{od} would arrive for each possible assignment option.

While the computational times of the two approaches are comparable, the optimization-based approaches lead to better results. Overall the computational time is in the range of 20 seconds making it applicable for real world applications. Nevertheless, parts of the algorithms are NP-hard (finding all alternative paths and solving the optimization problem). In future, the performance of the procedure should be evaluated for real world network sizes. Nonetheless, if the presented methodology is implemented in practice, alternative paths can be preprocessed and retrieved from a database in accordance with the taken dispositive measure. In practice, the steps involving SUMO (Fig. 1) could be replaced by real data and better PT models. Since all the required information for the presented method is available to OCCS, it is reasonable to integrate this method into the infrastructure of an OCC and connect it to its intermodal transport control system (ITCS) as suggested in (*17*).

Looking at the two different dispositive measures which were simulated here in combination with the redirection of passengers, it seems that the rerouting of PT lines works better with the redirection of passengers than the line-splitting, at least in most cases. One exception is the case of the logarithmic compliance, in which the situation even worsens. However, also in the no redirection scenario rerouting of PT lines shows less passenger delays than the line-splitting. This is understandable as with line-splitting the disruption of the PT system is worse than with rerouting. When lines are split, passengers using this service along the incident site have to transfer to another line. Nevertheless, for some passengers, line-splitting can also have a positive effect: the frequency of the buses is increased for the first run after the incident begins as the buses turn around at the incident site. Furthermore, the demand on the disrupted lines is less, as it does not serve the other side of the incident anymore, which might improve the situation for some of the U_{ina} using that line on either side of the incident.

When PT lines are rerouted, the travel time is just prolonged but the corresponding PT lines are still running and serve at least most of their stops. Rerouted PT lines sometimes even cause for better connections for some passengers if they connect stops which are normally not directly connected. In the presented case, there is a faster connection due to a skipped stop. This phenomenon can also be seen in the distribution of delays in Fig. 9 where in some cases there are also negative delays. In real-world bus operations rerouting is more likely than line-splitting as the dense road network of cities usually provide sufficient alternative routes. In the cases studied it also causes significantly less delay. However, Bachmann et al. (1) also describe a case in which a bus route is disrupted through a malfunction of a gate at a rail crossing. Line-splitting normally is used for rail bound services as they are limited to the rougher mashed railway network with significantly less alternative routes. Even though the discussion mentions several points for enhancing the introduced method, the results show the positive effects of the combination of supply-centric and passenger-centric incident management and give incentives for further investigation.

CONCLUSION & OUTLOOK

The paper introduces a PCIM method in which PT users, who are directly affected by an incident on their planned path, receive path advice to reduce the overall delay of passengers in a PT system. Two approaches, a heuristic and optimization-based, are presented and tested in a simulation case study conducted in SUMO. The method has been combined with two typical supply-centric incident management methods, line-splitting and rerouting of PT lines. The results show that the developed PCIM methods significantly reduce the overall delay of passengers during incidents. However, some limitations of the method could be observed: First, the optimization approach can be further enhanced, for example by introducing a time-based variable for remaining capacity of paths in its formulation. Using queuing theory at its basis might also be an interesting direction for further development. Second, even though the heuristic approach calculates the remaining capacity of a path rather precisely path section by path section (divided by used services), it seems to over exploit it and causes additional delays to indirectly affected passengers. These secondary incidents already mentioned in (*14*) need to be avoided. The remaining capacity of a PT system plays a crucial role in redirection strategies just as the one presented here. The exact relation between a system's capacity reserve and the demand is worth further investigation. Therefore, also variation of the demand should be tested in the future. Furthermore, the consideration of crowding in the redirection process as well as during passenger boarding would be an improvement in this matter. Third, Eq. 1 can be further improved. The role of the introduced time constant for the consideration of missed buses and the interaction between passengers in the simulation or the real world is not fully understood and worth further investigation. If it is set differently or even further developed into a dynamic variable, it might reduce the negative effects of the redirection onto the indirectly affected passengers. As the redirection duration influences the size of redirection group and therefore the pressure on the alternative path, a further development the time constant and corresponding sensitivity analysis might further reduce the negative influence on indirectly affected passengers. Furthermore, even though Bachmann et al. (1) point out, that dispatchers in the OCCs have quite a good intuition about the duration of an incident, an incident can always develop differently than initially anticipated (*1, 19*). Therefore, the possibility to update the considered incident duration could be implemented. Fourth, as already mentioned in the methodology section, the presented algorithm does not consider affected passengers who redirect themselves and thereby ignore the advice for an alternative path. However, it is reasonable to assume, that especially travelers who know the PT network well, such as commuters for example find an alternative path on their own. Future work could thereby include a corresponding third group, next to the redirection and waiting group, of each OD-pair that will always travel the fastest alternative path independently of the suggestion. Fifth, the results show that the redirection of passengers seemed to work better with the dispositive measure of rerouting PT lines than splitting PT lines. It should also be tested with other supply-centric dispositive measures or even with a combination of such. In (*18*) also the reallocation of vacant capacities in the PT system is proposed and shows potential for further delay reduction. Moreover, this might be further enhanced with the deployment of on-demand mobility as alternative paths during incidents. Nevertheless, this study showed the high potential of PCIM methods to reduce delays caused by incidents. Sixth, the algorithm should be tested on real world problem sizes to evaluate if the computational time is still applicable. Overall, the results show that the here introduced novel PCIM method makes PT systems more reliable and by that more attractive.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Frederik R. Bachmann, Florian Dandl, Arslan Ali Syed, Roman Engelhardt, Klaus Bogenberger; data collection: Frederik R. Bachmann; analysis and interpretation of results: Frederik R. Bachmann, Florian Dandl, Arslan Ali Syed, Roman Engelhardt; draft manuscript preparation: Frederik R. Bachmann, Florian Dandl, Arslan Ali Syed, Roman Engelhardt. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Bachmann, F. R., L. Briem, F. Busch, and P. Vortisch, Dynamics and Processes in Operations Control Centers in Urban Public Transport: Potentials for Improvement. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 10, 2022, pp. 17819–17834.
2. Ceder, A., *Public Transit Planning and Operation: Modeling, Practice and Behavior*. Chapman and Hall/CRC, Boca Raton, 2nd ed., 2016.
3. Ge, L., S. Voß, and L. Xie, Robustness and disturbances in public transport. *Public Transport*, 2022.
4. Gkiotsalitis, K. and O. Cats, At-stop control measures in public transport: Literature review and research agenda. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 145, 2021, p. 102176.
5. Ibarra-Rojas, O. J., F. Delgado, R. Giesen, and J. C. Muñoz, Planning, operation, and control of bus transport systems: A literature review. *Transportation Research Part B: Methodological*, Vol. 77, 2015, pp. 38–75.
6. Barry, J. J., R. Newhouser, A. Rahbee, and S. Sayeda, Origin and Destination Estimation in New York City with Automated Fare System Data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1817, No. 1, 2002, pp. 183–187.
7. Zhu, Y. and R. M. Goverde, Dynamic Passenger Assignment for Major Railway Disruptions Considering Information Interventions. *Networks and Spatial Economics*, Vol. 19, No. 4, 2019, pp. 1249–1279.
8. Zhu, Y. and R. M. Goverde, Integrated timetable rescheduling and passenger reassignment during railway disruptions. *Transportation Research Part B: Methodological*, Vol. 140, 2020, pp. 282–314.
9. Müller-Hannemann, M., R. Rückert, and S. S. Schmidt, Vehicle Capacity-Aware Rerouting of Passengers in Delay Management: Schloss Dagstuhl - Leibniz-Zentrum fuer Informatik GmbH, Wadern/Saarbruecken, Germany. *OpenAccess Series in Informatics*, Vol. 75, 2019, pp. 7:1–7:14.
10. Delling, D., T. Pajor, and R. F. Werneck, Round-Based Public Transit Routing. *Transportation Science*, Vol. 49, No. 3, 2015, pp. 591–604.
11. Leng, N. and F. Corman, The role of information availability to passengers in public transport disruptions: An agent-based simulation approach. *Transportation Research Part A: Policy and Practice*, Vol. 133, 2020, pp. 214–236.
12. Leng, N., Z. Liao, and F. Corman, Role of Timetable, Rolling Stock Rescheduling, and Information Strategies to Passengers in Public Transport Disruptions. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2674, No. 9, 2020, pp. 135–147.
13. Rahimi, M., Z. Ghandeharioun, A. Kouvelas, and F. Corman, Multi-modal management actions for public transport disruptions: an agent-based simulation. In *2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, IEEE, 2021, pp. 1–6.
14. Cats, O. and E. Jenelius, Dynamic Vulnerability Analysis of Public Transport Networks: Mitigation Effects of Real-Time Information. *Networks and Spatial Economics*, Vol. 14, No. 3, 2014, pp. 435–463.

15. van der Hurk, E., L. Kroon, and G. Maróti, Passenger Advice and Rolling Stock Rescheduling Under Uncertainty for Disruption Management. *Transportation Science*, Vol. 52, No. 6, 2018, pp. 1391–1411.
16. Mo, B., H. N. Koutsopoulos, M. Z.-J. Shen, and J. Zhao, Robust Path Recommendations During Public Transit Disruptions Under Demand Uncertainty. In *101st Annual Meeting of the Transportation Research Board*, Washington D.C., 2022.
17. Bachmann, F. R., A. Tsakarestos, F. Busch, and K. Bogenberger, State of the Art in Passenger-centric Incident Management of Public Transport Systems. *Submitted for publication to Public Transport*, 2023.
18. Bachmann, F. R., A. Rau, and F. Busch, Redirecting Passengers and Reallocating Capacities during Incidents in Public Transport. In *100th Annual Meeting of the Transportation Research Board*, 2021.
19. Briem, L., H. S. Buck, M. Magdolen, L. Lange, and P. Vortisch, Incident Management in Public Transport - Surveying Dispatchers' Actions. In *European Transport Conference*, 2020.
20. Mo, B., H. N. Koutsopoulos, and J. Zhao, Inferring passenger responses to urban rail disruptions using smart card data: A probabilistic framework. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 159, 2022, p. 102628.
21. Lopez, P. A., M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, Microscopic Traffic Simulation using SUMO. In *21st International Conference on Intelligent Transportation Systems (ITSC)*, IEEE, 2018, pp. 2575–2582.
22. *SUMO User Documentation*. https://sumo.dlr.de/docs/, 2022.
23. Bagchi, M. and P. R. White, The potential of public transport smart card data. *Transport Policy*, Vol. 12, No. 5, 2005, pp. 464–474.
24. *Gurobi Optimizer Reference Manual*. https://www.gurobi.com/, 2022.
25. Mandl, C., *Applied Network Optimization*. Academic Press Inc., 1979.
26. Ul Abedin, Z., *A Methodology to Design Multimodal Public Transit Networks - Procedures and Applications*. Dissertation, Technical University of Munich, Munich, 2019.
27. German Federal Ministry of Transport and digital infrastructure (BMVI), *Kollektive dynamische Fahrgastlenkung - Phase 3: Endbericht (German) [Collective dynamic passenger guidance - Phase 3: final report]*. Bonn, 2019.