Public Transport Disruption Management by Collaboration with Demand Responsive Services

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ABSTRACT

For large cities, public transport represents the backbone for commuters and thus plays a crucial role for society and for the economy. High-capacity public transport services such as metro and commuter trains are efficient during normal operations but are vulnerable to disruptions. Metro and commuter train disruptions can be handled in several ways. Very common are bridging buses that are called in to replace the rail-based service along the disrupted lines. These often take significant time to arrive and are costly to keep stand-by. Demand-responsive transport such as taxi can respond to demand almost immediately but is costly and must usually be arranged by the individual travelers. This study examines the integration and potential role of demand-responsive transport in disruption management. The analysis considers the impacts of limiting the serving area, varying the number of available vehicles, pursuing ridesharing, as well as a system-of-systems approach with collaboration between taxis and bridging buses. Results of computational experiments on the case study of Stockholm, Sweden reveal that integration of demand-responsive transport in the disruption management can bring large positive benefits in terms of average and maximum waiting times for travelers. This is especially the case for strategies including ridesharing. It is also shown that appropriate trade-offs between desired waiting times and costs can be achieved by collaboration of both bridging buses and demand-responsive transport. Additionally, it is expected that more robust public transport with increased reliability during disruptions can increase sustainability as more people may choose public transport instead of private cars.
INTRODUCTION

For many cities around the world, public transport represents the backbone for commuters, and the service is thus crucial for society, the economy and wellbeing in general. Especially for large cities, these systems transfer millions of people every day, and any disruption during peak hours on high capacity lines such as rail or metro can affect a significant number of travelers.

Depending on the type of disruption, there are several techniques to restore service in order to minimize the negative impacts for travelers. [1] conduct a survey among 71 international public transport agencies (PTA) regarding their strategies for managing unplanned service disruptions. The responses show that the approaches vary depending on if the disruption is a train failure or a line blockage. In the case of line blockages, bus bridging is the dominating strategy (85% of respondents). It is common, however, to use different approaches depending on location, time, duration, type of event, etc. Other approaches include single tracking/bypassing (51%), rerouting trains (23%), diverting to other lines (35%) or parallel public transport (47%), and improving frequency of parallel public transport (17%). The approach of hiring taxis is used by only a small fraction of respondents (5%).

A weakness of the bus bridging approach is that the buses and drivers must be either kept on stand-by or moved from their original lines. It often takes a substantial amount of time for the buses to arrive, and the normal schedules need to be rescheduled. As a result, passengers often have a negative attitude towards bus bridging [2].

Various forms of collaboration between public transport and taxi services are emerging around the world. Some cities such as Singapore have included demand-responsive service in the public transport for a special fee [3]. There are some recent studies of taxi, ride-sharing and public transport integration [4] and collaboration during disruptions [2]. Sharing of taxi trips is also getting more attention in the literature [5, 6, 7, 8] and patent applications [9, 10]. According to the report [11], about half of the taxi industry’s revenue in Sweden comes from contract work and about 60% in the Netherlands. This contract works involve the services for passengers that have difficulty using regular public transport.

Collaboration on disruption management between the PTA and demand-responsive transport (DRT) services could potentially reduce the negative impacts for travelers as well as decrease the costs for all stakeholders. The literature about collaboration between PTA and DRT for disruption management is limited. In Munich and Berlin, the tram operators handle short-term disruptions through collaboration with a local taxi operator to provide faster rail replacement service. The tram operators expect a reduced recovery time by using taxis rather than buses as rail replacement service [2]. Since taxis are operating over the entire city, they can be assembled considerably faster. In addition, using taxis allows the tram system control centers to concentrate on recovering the system. Analysis of the contract between a PTA and a taxi operator for disruption recovery service continues in [12]. A game theoretic model is developed to determine the reservation capacity, the consequences if the reserved capacity cannot meet the demand, and how the two parties should interact to achieve agreed-upon terms for capacity and compensation. In [13] discusses the replacement service options for providing quick response. The framework is used to determine whether to provide a replacement service, and whether taxis or buses should be selected as the service vehicles. Model and technical solution method for public transport disruption management utilizing multimodal resources (subway, buses, taxis, etc.) based on the availability of real-time AFC data about travel demand is presented in [14]. The availability of taxis is just theoretical as they are not used in experiments and evaluation. The data-driven evaluation results show that the solution improves the ratio of served passengers substantially compared with existing solutions.

The main contribution of this study is integration of DRT into PTA disruption management supported by simulation experiments. In these experiments, several different disruption management
strategies (DMS) are studied. The range of factors are considered in the experiments: travelers or PTA organizing the DRT trips; size of the serving area; the number of deployed vehicles; pursuing ridesharing for DRT vehicles; the use of bridging buses; and collaboration of bridging buses with DRT. To the best of our knowledge, in terms of the number of studied factors and strategies with integrating DTR in DMS, this is the most comprehensive analysis regarding the performance of such a system-of-systems to this date.

The transport network of Stockholm, Sweden, is used as case study. The travel demand affected by the disruption, including information about destinations, is inferred from public transport automatic fare collection (AFC) data. In Stockholm, metro and commuter train disruptions are handled in several ways. Bridging buses are called in to replace the rail-based service along the disrupted lines. Further, travelers who can show that they would have been at least 20 minutes late when taking the best public transport alternative can get reimbursement for their travel expenses in alternative modes such as taxi or private car. The individual travelers must arrange such alternative modes of transport themselves. The reimbursements are costly for the public transport operators, who are fined by the public transport authority (PTA) for any substantial delays. In turn, the PTA reimburses delayed travelers; in 2014, the administration paid out a total of SEK 9.7 million in reimbursements. In 2018, the sum had more than tripled to SEK 29.1 million [15] which is also motivation for this study that considers DRT and bridging buses.

The results of the computational experiments reveal the potential for substantial decreases of waiting times, delays, costs and vehicle hours which is closely related to the energy consumption and amount of CO₂ emissions. In addition, there is the potential that public transport that remains robust during disruptions will increase sustainability as more people may choose public transport instead of private cars.

The paper is organized as follows. First, disruption management strategies and the simulation framework are presented in the methodology section. The following section introduces the data and case study that are used for computational experiments. The section about computational experiments define the settings for the experiments, and results are presented in the subsequent section. Finally, we highlight the most important findings and possible directions for continued research.

METHODOLOGY

This paper investigates and examines several different DMS and how they affect travelers’ waiting times and PTA costs during disruption. The travelers’ waiting times represent the time travelers spend from their arrival until they board a vehicle. The cost for the PTA is estimated based on the occupied and unoccupied vehicles’ travel times. From here the geographical area or part of the public transport network affected by disruption is referred to as the disruption zone.

As discussed above in the literature review, there are several techniques and strategies for how the disruptions are handled. Figure 1(a) illustrates the general case with a functioning train connection with several stops, while Figure 1(b) shows the case with a disruption on first half of the train transit line and transport alternatives. Some travelers can use alternative public transport such as buses and trains. Some of them may prefer to wait for bridging buses, call DRT, walk or use their private cars.
Figure 1 Illustration of disruption management strategies. (a) Fully functioning train line without disruption. (b) Alternatives in case of disruption on the train line. (c) Affected travelers’ origins and destinations served by DRT without regulation from PTA. (d) Case when the PTA limits the serving area to the disrupted zone.

The considered disruption strategies include bridging buses, DRT, ridesharing and the simultaneous deployment of both buses and DRT. The strategies are organized into three main groups based on who is taking the active role: the travelers, the PTA, and mixed DMS. This study aims to analyze the performance of DRT and bridging buses in disruption management, whereas other alternatives such private cars and public transport are not considered.

This section is organized as follows: First, all strategies are described in more detail. Next, the simulation approach used for computational experiments is introduced and other attributes that can affect waiting times and costs.
Traveler-Centered Disruption Management Strategies (T-DMS)

These strategies represent the situation where travelers do not get any targeted information or help to deal with disruptions in order to reach their destinations. Each traveler has to be active and look for alternatives in public transport or calling DRT such as taxi.

Strategy 1: T-DMS with DRT only (T-DRT)

In this strategy we examine the extreme case when all travelers order DRT. To highlight the main difference to other PTA disruption management strategies, the traveler decides the origin and destination of each trip without any limitations (see the illustration in Figure 1(c)). Thus, the serving area is dispersed from the disruption zone, and travel times are long. It is expected that the extra travel times result in higher costs and waiting times. We also consider a version including ridesharing, denoted T-DRT-R.

PTA-Centered Disruption Management Strategies (PTA-DMS)

In these strategies, the PTA plays an active role in disruption management. It is expected that the PTA limits the DMS service area to the disruption zone in order to shorten waiting and travel times and potentially lower costs (see the illustration in Figure 1(d)). In all strategies below, the DRT trips and bridging buses operations are thus limited to the disruption zone. All demand inside the zone as well as the closest multimodal public transport hubs from which the public transport is fully functioning are assumed to be served. Depending on the PTA actions, we define different strategies below.

Strategy 2: PTA-DMS with DRT only (PTA-DRT)

The strategy is equivalent to T-DRT with one exception. The PTA will organize DRT trips by limiting them to the disruption zone only, the re-distribution of vehicles or ridesharing is exactly the same as in T-DRT strategy. Thus, the effects of the size of the serving area can be examined by comparing T-DRT and PTA-DRT. The case when the PTA is responsible for the operations can be especially valuable if ridesharing is pursued in the DRT operational strategy; this strategy version is denoted PTA-DRT-R.

Strategy 3: PTA-DMS with DRT as fixed line (PTA-DRT-line-R)

In this strategy, the PTA fully controls the management of DRT trips in the form of fixed lines. These lines serve stations or stops in the disrupted zone. DRT vehicles operate in cycles just like fixed line public transport services including ride sharing. In other words, DRT vehicles represent “buses” with very small capacity. The impact and efficiency of fixed line service and demand-responsive service can be evaluated by comparing this strategy with the PTA-DRT-R strategy.

Strategy 4: PTA-DMS with bridging buses (PTA-BB)

This common strategy uses bridging buses without DRT. The buses operate on the same fixed lines as used in PTA-DRT-line. The main differences from PTA-DRT-line are the number and the capacity of the vehicles, and the time until first bus is dispatched, which can be significantly higher for bridging buses compared to DRT vehicles.
Mixed Disruption Management Strategies (Mix-DMS)

Mixed strategies represent combinations of the above strategies when bridging buses and DRT operate at the same time and share the travelers. It is assumed that DRT services can respond very fast compared to bridging buses and keep the queues and waiting time lower until the high capacity bridging buses can be assembled.

Strategy 5: PTA-DMS with DRT and bridging buses (PTA-DRT-R+BB)

In this strategy the DRT operates as in strategy PTA-DRT-R along with bridging buses. The case when DRT operates according to strategy T-DRT represents common practice in Stockholm. However, it is expected that performance of the PTA-DRT-R strategy is higher, and thus it is used here.

Ridesharing

We consider a simple ridesharing scheme for DRT vehicles. An empty vehicle at a certain location $i$ boards the longest waiting traveler according to a FIFO (first-in first-out) queue, and sets the vehicle destination to that of the passenger. The remaining longest waiting travelers on the location $i$ with the same destination, will board the vehicle until its capacity is reached, or until there are no further travelers in the queue with the same destination. No additional travelers along the shortest path to the destination are considered.

Simulation Framework

In order to examine and estimate the effects of the DMS introduced above, a discrete event simulation is used to model both DRT and fixed line services. The simulation consists of a timeline with events executed one by one in time order. There are only two types of events: traveler arrivals to locations, and vehicle arrivals to locations. It is expected that arrival times of travelers are known or generated before simulation and thus added to the timeline at the start. The locations of vehicles are also known and all of them are considered as available at the start of simulation.

Furthermore, a “fleet manager” is responsible for handling the assignment and re-distribution of the vehicles. There are two slightly different fleet managers: one for DRT and one for every fixed line service. These managers can operate simultaneously and serve the same travelers or locations. In strategy PTA-DRT-R+BB each traveler requests service from DRT but takes the first available vehicle. The fleet managers are described in more details below.

Demand-Responsive Service Fleet Manager

The manager keeps a list of available empty vehicles assigned to particular locations or coordinates. The traveler registers to the DRT fleet manager at the time of arrival to the origin location. The fleet manager keeps registered travelers in a FIFO structure at the system level as well as the location level. If there are available vehicles at the time of registration, the closest is sent to pick up the traveler immediately, otherwise the traveler is placed in the FIFO queue. Each vehicle arrival event follows an exact sequence of rules in the following order:
• If the vehicle arrives at location $i$ with travelers on board, all of them alight.
• If there are waiting travelers at location $i$.
  o If the vehicle is sent to pick up a particular traveler $k$ and the traveler was not
taken by another vehicle, the traveler boards.
  o Otherwise, if the traveler $k$ is not present at location $i$ and the vehicle is empty,
the longest waiting traveler boards.
  o If the vehicle still has available capacity, travelers with same destination $j$ as the
first boarding traveler board to fill its capacity.
  o The new vehicle arrival event for destination $j$ is added to the timeline. Let $t_{ij}$
denote the travel time between locations $i$ and $j$, and let $t^*$ denote the current
simulation time. Then the execution time for the new event is set to $t^* + t_{ij}$.
• Otherwise, if there are no waiting travelers, the vehicle registers as available to the fleet
manager, which will redistribute vehicle to the longest waiting or first registered traveler
$k$ if the vehicle is the closest to the traveler’s location $j$. In that case, the new vehicle
arrival event to location $j$ to pick up traveler $k$ with arrival time $t^* + t_{ij}$ is added to the
timeline of simulation.

**Fixed Line Service Fleet Manager**

The fixed line service fleet manager does not register travelers and it control the movement of vehicles
from stop to stop along the fixed line. Let $N$ to denote the number of stops on line $k$ then vector
$s_k = (s_{k,1}s_{k,2}, ..., s_{k,N})$ contain the ordered list of locations on line $k$. Vehicles registered to the fixed line
fleet manager always ask the manager about the next stop from the current location $i$. We assume that all
time lines are defined as the cycle departing and terminating at the same location, the last location $s_{k,N}$ is the
opposite direction to the location $s_{k,1}$. Thus, for the location $s_{k,N}$ the following location is $s_{k,1}$.

The passengers are waiting in FIFO queues at their locations. For fixed line service passengers
are able to make transfers if there is no direct service route. The transfers are pre-computed before the
simulation based on fixed line network routing. Each vehicle arrival event follows an exact sequence of
rules in the following order:

• If the vehicle arrives at location $i$ with travelers on board, all travelers with destination
or transfer at location $i$ alight. The travelers continuing their trips to the next transfer or
destination are added to the FIFO queue.
• If the vehicle has available capacity, the travelers with destination in the sub-vector
$s_k = (s_{k,i+1}s_{k,i+2}, ..., s_{k,N})$ of line $k$ board the vehicle.
• The new vehicle arrival event for location $s_{k,i+1}$ is added to the timeline with arrival
time $t^* + t_{s_k,i}s_{k,i+1}$

**DATA AND CASE STUDY**

The introduced disruption management strategies are evaluated in a case study for Stockholm, Sweden.
The simulation experiments consider a hypothetical disruption of the metro system on 1 February 2017.
The disruption study is limited to the evening peak 14:30 – 19:00 and affects 23 metro stations south east
of the city center (see Figure 2(b)). The evening peak is selected as it is expected that the most people
desire to get home for the night, and it is less likely that someone consider alternatives to traveling such as
home office or sick day.
The travel demand used in the simulation experiments represents actual public transport travelers who used the metro system on 1 February 2017 based on automatic fare collection (AFC) data. In this section we first introduce the inference of metro trips from the AFC data followed by a detailed description of scenarios that are used for computational experiments. Finally, the spatial distribution of taxis operating in the Stockholm area at the start of the simulation experiments is presented.

**Metro Trips Inference**

AFC data are used to infer the complete public transport trips. The public transport ticket system in Stockholm, Sweden is a tap-in only system. Thus, tap-outs have to be inferred to get the complete trip information. When inferring tap-out locations, all multimodal tap-in data are used. We use a radius around the next tap-in location to infer the stop along the same line as the previous tap-in. The closest such station is considered as the tap-out location. This approach that uses radiuses and walking distances is very common in literature [16]. The AFC data provide demand for all modes of public transport including ferries, trains, trams, metro and buses. For this study only trips within the metro system are considered.

Figure 2 shows the 118,033 complete metro trips inferred for 1 February 2017 that originate or terminate in the disrupted zone during the afternoon peak. Figure 2(b, c) illustrate the geographical dimensions of the case study with origins and destination of trips. Figure 2(a) shows flows of travelers across stations. In order to provide readable migration plot, the stations outside the disrupted zone are aggregated to zones A, B and C. Figure 2(a) shows that most trips go from or to the central zone A, followed by station 5: Liljeholmen. The demand for zones B and C is small considering the number of stations there.

**Demand Scenarios**

In order to investigate the DMS introduced above we define two main scenarios. Since the true origins and destinations of the travelers are unknown, we consider metro stations as origins and destination for all trips. The arrival time of each traveler is inferred based on the tap-in time.

**Demand Scenario for T-DMS**

This demand scenario represents demand patterns for the disruption management strategy T-DRT and T-DRT-R in which travelers can call DRT from any metro station and request transit to any of the metro stations in case that at least one of them is in the disrupted zone. Thus, it considers all 118,033 trips with their desired origins and destinations according to Figure 2.

**Demand Scenario for PTA-DMS**

This demand scenario represents demand patterns for all strategies coordinated by the PTA. It contains the same number of 118,033 trips as the first scenario but all demand to and from zone A, B and C in Figure 2 is aggregated to public transport hub Slussen (see Figure 3 for reference). In this scenario Slussen is the nearest station with fully functioning metro and serves as the main gate between the city and the disrupted zone.
Figure 2 Illustration of the demand scenario for T-DMS and its demand, origins, destinations and OD flows of the affected travelers on 1 February 2017 during the afternoon peak (14:30–19:00). (a) Visualization of OD flows. (b) Locations of travelers’ origins. (c) Locations of travelers’ destinations.
Figure 3 Illustration of the demand scenario for PTA-DMS and its demand, origins, destinations and OD flows of the effected travelers on 1 February 2017 during the afternoon peak (14:30–19:00). (a) Visualization of OD flows. (b) Locations of travelers’ origins. (c) Locations of travelers’ destinations.
In order to compute realistic waiting times for the first travelers affected by the disruption, the starting locations of DRT vehicles must be provided. Floating car data (FCD) collected from ca. 1,500 taxis operating in the Stockholm region in February 2016 are used. Each vehicle reports its ID, GPS coordinates, timestamp, and information whether it is occupied or not with an average frequency of once every two minutes. There is no information about the true origin and destination of the trip, which can only be inferred based on changes of the taxi’s status.

We extract the first unoccupied location report of each taxi in the afternoon peak period across 10 days. The vehicles are ordered in the way their locations were collected in February 2016. This generates a dataset of the first available location for approximately 15,000 vehicles which enables us to get the starting location for a varying number of vehicles. We define 36 zones with centroids representing the start locations of taxis for the simulation. All vehicles’ locations are aggregated to these points based on the zones shown in Figure 4. The spatial distribution across the zones is relatively similar regardless of the number of vehicles selected from the dataset.

**Figure 4** Spatial visualization of DRT vehicles and their inferred locations used at the start of simulations. (a) Spatial distribution of 200 vehicles. (b) Spatial distribution of 6,000 vehicles.

**COMPUTATIONAL EXPERIMENTS**

The performance of the five defined DMS (seven with ridesharing) are investigated using the corresponding demand scenarios introduced above. We investigate the effects of several attributes: the number of deployed vehicles; the size of the serving area; ridesharing for DRT; bridging buses; and collaboration of DRT and bridging buses.

To study the impact of the number of available vehicles, we vary their number as: 200; 500; 1,000; 2,000; 4,000; and 6,000 vehicles. The number of 6,000 taxis represents the approximate number of
taxis operating in the Stockholm area. The main reason behind studying this attribute is that it is unknown how many DRT vehicles can be available to handle disruption travelers.

Comparison of the T-DRT and PTA-DRT strategies reveals the impact of the serving area size on the waiting times and costs. Here we aim to answer the research question about the possible benefits when the PTA limits or organizes DRT trips to the disruption zone only. This is expected to improve the overall performance of the DMS and lower the costs.

Pursuing ridesharing for DRT vehicles can be a key attribute to improve performance and lower the operating costs. We assume that the maximum capacity of each DRT vehicle with ridesharing is four travelers. We allow ridesharing for travelers with the same origin and destination as the longest waiting traveler to board the vehicle. We quantify the benefits of ridesharing by comparing the T-DRT and T-DRT-R strategies, and the PTA-DRT and PTA-DRT-R strategies.

The fixed lines are the same for strategies PTA-DRT-line and PTA-BB. There are several possibilities for how to establish the fixed lines. We have achieved the best performance with a simple setup of two lines operating from each end of the red metro line to station Slussen (see stations 24–1–24 and 10–1–10 in Figure 3). In this case there is only a small fraction of travelers that need to transfer at station 5 to get to the other end of the metro line. The vehicles are allocated between the two lines considering the total demand as well as the number of stations. Within each line vehicles are allocated with respect to the demand on the pre-defined start stations.

In the PTA-DRT-line-R strategy we study the organization of DRT in fixed lines. It is expected that this way of organizing trips will result in longer travel times because of detours caused by vehicles following the fixed line routes, instead of the shortest travel time routes. Comparison between the PTA-DRT-R and PTR-DRT-line-R strategies can reveal the differences in performance and costs when operating the same fleet of vehicles according to demand-responsive or fixed line operations. For the DRT the dispatching time for first vehicle is 0 minutes and the travel time from the initial location of each taxi to the pre-defined start location on the line is included in the evaluation.

Bridging buses are considered in strategy PTA-BB. The deployment of bridging buses is expected to take longer time also because of their unknown availability. Thus, we vary the dispatching time of the first vehicle in the simulation study as: 20, 40 and 60 minutes after the disruption occurred. Based on the dispatching time we denote PTA-BB_{20}, PTA-BB_{40} and PTA-BB_{60}. Further, it is assumed that the buses will be arriving at predefined locations during the following 20 minutes from the dispatching of the first vehicle. This assumption is used also for PTA-DRT-line-R. With this we aim to consider two things: that not all buses will be immediately and simultaneously available; and in order to set headways for the fixed line service. Preliminary experiments show that the frequency of the buses is important. Not surprisingly, dispatching all buses immediately provides lower overall performance than if they are assembled during the following 20 minutes. The number of bridging buses in the simulation is varied as follows: 20, 50 and 100 buses. Analysis of AFC and AVL data suggests that these numbers are realistic for Stockholm, although the precise number of bridging buses available depends on the nature of the disruption and is difficult to infer from the data.

The cost for the PTA of each strategy is considered to be proportional to the total vehicle hours traveled (VHT). We do not have enough information to calculate more accurate costs for bridging buses as this may involve some fixed vehicle costs, costs for vehicles and drivers in emergency mode, and indirect costs caused by relocating vehicles from their normal operations. Vehicle travel times for DRT services may be easily transformed to monetary costs, but to facilitate comparisons the costs for all strategies are represented by VHT. It is important to note that the costs of bridging buses are most likely underestimated in this study.
RESULTS

This section considers the effect of the different attributes in the following order: the number of deployed vehicles; the size of the serving area; ridesharing for DRT; bridging buses; and collaboration of DRT and bridging buses. For each attribute the effects on the waiting times and cost are discussed based on results visualized in Figure 5 and effect on in-vehicle times and total VHT in Figure 6.

Number of Deployed Vehicles

The number of deployed vehicles has an exponential effect on the average and maximum waiting times. When the number of deployed vehicles is small, increasing the number of vehicles can lead to a drastic decrease of waiting times (see Figure 5 Error! Reference source not found.a)). The rate of decrease in waiting times drops as the number of deployed vehicles increases, while the slope depends on the particular strategy. For example, the decrease of average waiting time for strategy T-DRT is 26 hours when increasing the number of vehicles from 200 to 500. When increasing the fleet size from 2,000 to 6,000 the decrease in average waiting time is about 2.3 hours; however, the decrease to only 80 seconds average waiting time is still significant. For the mixed strategy PTA-DRT-R+BB_40 with 100 buses with first dispatched 40 minutes after the disruption start, the average waiting time decreases about 6 minutes when the number of DRT vehicles increases from 200 to 500, and only 9 seconds from 2,000 to 6,000. There is a similar effect for the maximum waiting times (see Figure 5(b)).

The effect of the number of deployed vehicles on the costs (see Figure 5(c)), represented by vehicle hours traveled, strongly depends on the strategy. It is not surprising that the costs are the same regardless of the number of vehicles deployed for pure DRT strategies T-DRT and PTA-DRT without ridesharing (see Figure 5). The costs for these strategies are among the highest.

Figure 5 Results of computational experiments for all strategies as functions of fleet size. (a) Average waiting times. (b) Maximum waiting times. (c) Costs represented by vehicle hours traveled (VHT). For strategies T-DRT and PTA-DRT the total costs represented by vehicles seconds include occupied trips only. For PTA-DRT-line-R and PTA-BB operating on fixed lines the total vehicles hours are considered.
For the PTA-BB strategy the cost is not strongly dependent on the number of deployed vehicles since the vehicle capacity is high and allows for many passengers to board and alight along the line stations. For the remaining strategies the costs increase with the number of vehicles.

For the non-mixed strategies the number of vehicles has no effect on the average and maximum in-vehicle times (see Figure 6(a,b)). For mixed strategies, by using DRT vehicles both the average and maximum in-vehicle time decreases. Not surprisingly, Figure 6(c) shows that the total VHT increases across all strategies.

**Size of the Serving Area**

The impact of the size of the serving area can be revealed by comparing strategies T-DRT and PTA-DRT, or T-DRT-R and PTA-DRT-R. In the first demand scenario used for T-DRT and T-DRT-R, travelers can set the destination or origin of the DRT service outside the disruption zone. Thus, the serving area is significantly wider compared to the second demand scenario used for strategies PTA-DRT, PTA-DRT-R and all other strategies. The effect of the size of the serving area is large. For example, with a fleet size of 2,000 vehicles the average waiting time can drop from 2.37 hours to 1.45 hours.

As expected, the size of serving area has a large effect on the costs represented by the VHT (see T-DRT and PTA-DRT in Figure 5(c)).

Figure 6 shows that limiting the size of the serving area naturally lowers the maximum possible in-vehicle time, which results in a reduction in average in-vehicle time, total VHT and energy consumption. It enables to save about 25% of energy consumption which can be closely related to CO₂ emission.

![Graphs showing average, maximum in-vehicle time, and total vehicle hours traveled for different scenarios](image)

**Figure 6** Results of computational experiments for all strategies as functions of fleet size. (a) Average in-vehicle times. (b) Maximum in-vehicle times. (c) Total vehicle hours traveled (VHT) that can be used for estimating CO₂ emission.
Ridesharing for Demand-Responsive Transport

As expected, the ridesharing effects are enormous for DRT performance and costs. The allowing or pursuit the ridesharing can result in a huge drop of average and maximal waiting times (see T-DRT and T-DRT-R or PTA-DRT are PTA-DRT-R in Figure 5(a, b)). The drop of average waiting time for T-DRT strategy can be for only 500 vehicles from 15.5 hours to only 3 hours and for PTA-DRT-R it drops to only 1.5 hour with maximal waiting time 3.5 hours. For the 1,000 vehicles PTA-DRT-R the maximal waiting time is 40 minutes only and average waiting time is less than 7 minutes. This is significantly better performance as for PTA-DRT with 2,000 vehicles which average waiting time is 1.45 hours and better as 23 minutes for T-DRT with 4,000 vehicles.

The ridesharing allows rapid savings on the VHT. Strategy T-DRT-R with 500 vehicles can save more the 70% of vehicles seconds and 72% for strategy PTA-DRT-R. Costs for PTA-DRT-R with 500 vehicles is lower about 42% as PTA-DRT-R with 2,000 vehicles and about almost 60% as with 6,000 vehicles.

Strategy PTA-DRT-line-R with DRT ridesharing on fixed lines service brings improvement only for average waiting times especially for small number of vehicles. Interesting is that it seems to have almost not affect the maximum waiting times (see Figure 5(b)) and costs in the form of VHT are the highest from all the strategies (see Figure 5(c)). It is because large number of vehicles operating in circles produces a lot of empty trips not usually representing the shortest path for traveler and all these seconds are counted for fixed lines services as well. Thus, PTA-DRT-line-R seems to be the strategy with worst trade-off of costs, average and maximum waiting times performance.

Ridesharing used in this study has no effect on maximum and average in-vehicle times, but it can enable to save more than 60% total VHT or CO₂ emission.

Bridging Buses

The bridging buses are high capacity vehicles (100 travelers on board) the effects of the number of used vehicles is larger than in the case of small DRT vehicles. Even the 100 buses dispatched after 20 minutes PTA-BB₂₀ perform with average waiting time about 48 minutes, while the maximal waiting time is 5.7 hours are less effective as the 1,000 DRT vehicles. To compare the PTA-DRT-R strategy with 1,000 vehicles can achieve average waiting time about 7 minutes and maximum waiting time only 40 minutes. The total capacity of the buses is 10,000 travelers while 1,000 DRT vehicles can take maximum of 4,000 travelers on board at the same time. It seems the fixed line operation brings not a very efficient use of capacity in compare to DRT vehicles with lower capacity are able to serve more traveler as the buses within the same time period.

However, the costs for bridging buses are the lowest as the high capacity and low number of vehicles is playing huge role here. Operating the 100 buses create only 21% VHT of 1,000 vehicles operated based on strategy PTA-DRT-R generates. It is important to note that the expanses for keeping and operating bridging buses are not included.

In case there is no 100 vehicles available, the strategy PTA-DRT-R+BB₄₀ with 50 buses and 500 DRT vehicles under strategy PTA-DRT-R can provide performance of average waiting time less than 12 minutes with maximal waiting time less than 42 minutes. The cost of such service is about 2,200 VHT from which only 230 is made by bridging buses. In strategy PTA-BB₄₀ with 50 buses the 765 VHT is used but the average waiting time is 2.4 hours and maximal waiting time is 13.7 hours.
Collaboration of DRT and Bridging Buses

For clarity in Figure 5 we show only the results for mixed strategies with dispatching of first vehicles 40 minutes after disruption occurrence. Collaboration of bridging buses and DRT vehicles operated based on strategy PTA-DRT-R allows to decrease all attributes of interest, especially for lower numbers of DRT vehicles. There is clear tendency for all mixed strategies to strongly converge to PTA-DRT-R performance for all attributes when more than 1,000 vehicles is used (see black lines in Figure 5 and 6). This is happening because of oversaturation of vehicles and capacity for particular demand, and thus the offerings of more vehicles even with higher capacity brings only slight difference as the queues are small and buses are in average over-dimensional the necessary capacity which is different in compare to case with lower number of DRT vehicles.

Let’s consider the results across all strategies introduced here and assume that for disruption planning expert it is desired to have average waiting time under 20 minutes and minimize the cost of disruption management in the form of VHT. The best performance with low number of DRT vehicles which are costly is mixed strategy with 100 buses. The average waiting time in case of only 200 DRT vehicles operated with ridesharing is about 7.8 minutes and most likely even lower number of DRT vehicles can be sufficient. The maximum waiting time is 1.13 hours with total 1,438 VHT from which 800 is made with DRT vehicles and 638 by buses.

Figure 6 shows that DRT vehicles enable to significantly decrease the average in-vehicle time. The maximum in-vehicle time is less sensitive. Since traveler choice for one of the modes is not considered, but only one FIFO queue is used for each location, there is a chance that someone with significantly longer travel time by bus will still board the bridging bus. It is likely that in real-world cases the traveler with long travel times with bridging buses and short travel time with DRT will prefer to wait longer to board the next arriving DRT vehicle.

When comparing Figure 5(a,b) and Figure 6(a,b), another interesting effect of the number of bridging buses can be observed, whereas the larger number of buses leads to shorter waiting times, it results in longer in-vehicle times as more travelers will board buses instead of DRT vehicles.

CONCLUSIONS

In this paper, different disruption management strategies using demand-responsive transport and bridging buses are evaluated. Simulation experiments are performed on a case study based on public transport smart card data and taxi probe data in region Stockholm, Sweden. The results of the computational experiments reveal the following main conclusions:

- Limiting the serving area to the disruption zone only, has significant potential to decrease the waiting times and costs.
- Pursuing ridesharing for demand-responsive vehicles has large potential impact, as it enables to rapidly decrease the waiting times, delays and costs for all involved actors.
- It is beneficial to operate demand-responsive services as this enables to allocate the capacity to the demand more efficiently. The main disadvantage of fixed line services is a large number of empty or partially occupied vehicles movements. Results shown that operating the same fleet of demand-responsive vehicles on a fixed line is costly, and resulting in only modest improvements regarding average waiting times, which are not significant compared to other demand-responsive strategies with ridesharing or bridging buses.
- Operating both bridging buses and demand-responsive transport can provide the best tradeoff between the costs and waiting times. Especially when combining ridesharing with demand-responsive transport, a very small number of vehicles can likely provide a sufficient level of service for disruption management at low costs compared to independent strategies.
- In addition, total vehicle hours, which are closely related to the energy consumption and amount of CO₂ emissions, can be reduced. Not surprisingly the bridging buses, ridesharing and limited serving area produce the least vehicle hours.
- Improving the public transport options also during the disruption as integrating demand-responsive services will increase sustainability as more people may choose public transport instead of private cars.

The aim of this work was to examine the potential of different disruption management strategies at a high level of abstraction. The results reveal several beneficial attributes for the disruption management strategies. It is relevant in future work to include more details and assumptions to the simulation.

The boarding and alighting times can be considered, as well as vehicle bunching, which is not considered at the moment. Including the other public transport alternatives and the possibility for travelers to walk some short distances, can provide a more realistic representation of the demand for disruption management. In this study both demand-responsive and bridging buses are operating simultaneously, it thus can be worth for future work to investigate different levels of collaboration such as allowing taxi operation for some part of the disruption only; or alternatively, use taxis for the entire area and thus provide time to PTA to plan a suitable disruption management strategy. Other possible future research directions are: to examine different business models across stakeholders; design the most appropriate disruption management strategies for particular disruptions; and to consider a realistic end of disruption at a particular time, evaluating the performance of particular strategies within the disruption period only.

The historical public transport smart card data allows to study historical disruptions and reveal the patterns for how travelers use the public transport alternatives during disruptions in particular areas and increase the frequencies and capacity on these public transport alternatives. Considering all these details may bring deeper understanding of the wider implications of handling disruptions.

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Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: M. Cebecauer, E. Jenelius, W. Burghout; data collection: M. Cebecauer; redistribution algorithms: T. Babicheva; simulation design, implementation and experiments M. Cebecauer, D. Leffler, T. Babicheva; analysis and interpretation of results: M. Cebecauer, E. Jenelius, D. Leffler; draft manuscript preparation: M. Cebecauer, E. Jenelius, W. Burghout, T. Babicheva and D. Leffler. All authors reviewed the results and approved the final version of the manuscript.
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