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Optimal bus reassignment considering in-vehicle overcrowding

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ABSTRACT

Public transport services are often designed to meet travel demand under regular situations. However, severe weather conditions (e.g., heavy rainfall, snow, thunderstorms, etc.) can adversely impact the service operation, leading to problems such as in-vehicle overcrowding, delays, and trip cancellations. In this study, we propose a novel approach to address in-vehicle overcrowding issues during weather disruptions. In this approach, we dynamically reassign buses from low-demand trips to lines where the expected demand exceeds the capacity threshold of the in-service buses. This way, the existing capacity is utilized more efficiently without requiring additional vehicles or drivers. Considering the shortage of bus drivers in Europe, as well as in the Netherlands, this is a more efficient solution than other alternatives such as deploying additional buses from the depot. Experiments were conducted on a bus network in Enschede in the Netherlands. The results showed that in several disrupted situations, we can reassign bus trips to overcome overcrowding issues without significant negative impacts on the operation or passengers. However, the approach entails a trade-off between passengers of a canceled trip and an overcrowded trip. Some passengers must wait for the next bus or use other means of transport as a consequence of bus reassignment.

1 Introduction

In-vehicle overcrowding refers to the high density of passengers inside buses/trains (Tirachini et al., 2013). The occupancy rate or load factor is the most common quantitative method to assess the in-vehicle crowdedness. It is defined as the ratio between the number of passengers and the number of seats in a vehicle (Whelan and Crockett, 2009). In some studies, the load factor is used to determine the nominal capacity of a vehicle considering both seated and standing passengers. Following the latter definition, a bus is labeled as *overcrowded* when the number of in-vehicle passengers exceeds 80% of its capacity (Jara-Diaz and Gschwender, 2003; Wardman and Whelan, 2011).

Many factors could contribute to bus overcrowding issues, including large events in the area, weather conditions, vehicles' capacity, and capacity limits (e.g., COVID-19 imposed capacity limit). Weather is one of the most common sources of public transport (PT) disruptions in the Netherlands, which can induce considerable fluctuations in PT ridership, affecting people's travel decisions in choosing their destinations, departure times, and transport modes (Cools et al., 2010; Heinen et al., 2010; Gkiotsalitis et al., 2022). Severe weather conditions adversely affect the regular operation of buses, resulting in excessive delays and overcrowding issues (Tao et al., 2016), especially when a service operates close to its maximum capacity (Correia et al., 2021). Theoretically, a PT operator can design its service based on the maximum expected demand to have a robust service. However, no operator can have unlimited resources (vehicles and drivers) and therefore needs to make trade-offs between operation costs and fulfilling travel needs (Gkiotsalitis and Maslekar, 2018).

Several approaches have been proposed in the literature to deal with in-vehicle overcrowding in PT services, such as rescheduling (Suman and Bolia, 2019; Gkiotsalitis and Van Berkum, 2020b), stop skipping (Sun and Hickman, 2005; Delgado et al., 2009; Gkiotsalitis, 2021b), bus holding (Delgado et al., 2009; Gkiotsalitis and Van Berkum 2020a), capacity enhancement (Zhao et al., 2006), and peak spreading campaigns (Daniels and Mulley, 2013). Despite the undeniable effectiveness of the above solutions, there are some noticeable drawbacks in using these approaches to address in-vehicle overcrowding caused by weather disruptions or any other unexpected but predictable disruptions. First, many of these solutions are practically difficult to implement in day-to-day operations. PT operators usually have very little autonomy, at least in the Netherlands, to make ad-hoc changes to the bus services, for instance, adjusting timetables within a short period. Often, transport

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authorities need to agree with any ad-hoc changes in the service after the annual approval, making it nearly impossible to implement major changes without going through a lengthy administrative process. Second, the above methods primarily focus on mitigating overcrowding during regular operations, where spatiotemporal patterns can be identified for overcrowded trips. However, overcrowding caused by weather disruptions is irregular and uncertain. The most commonly used approach in such situations is keeping a reserved capacity all the time, which is not ideal for PT operators. It requires additional vehicles and drivers without directly generating any revenue. Furthermore, many PT operators in Europe are struggling with finding bus drivers for their regular operations (IRU, 2023), let alone hiring drivers for the reserved capacity.

In this study, we propose an alternative solution that is both practically feasible to implement and has low costs for operators: dynamic reassignment of buses from low-demand trips to overcrowded lines. We will develop an optimization model to efficiently reassign buses from trips with very low (or no) demand to trips where the demand exceeds the vehicle capacity during disrupted conditions. This approach offers a more flexible and cost-effective solution for mitigating the overcrowding issue caused by weather disruptions.

The remainder of this study is structured as follows. The next section (2) provides an overview of previous studies, followed by Section 3 on problem description. Section 4 illustrates the mathematical formulation. Section 5 presents the experiments and the results concerning the case study. A discussion is provided in section 6 and, finally, the conclusion in Section 7.

2 Literature review

Previous studies have shown that in-vehicle crowding has a significant influence on public transport ridership and punctuality (Tirachini et al., 2013; Kim and Kankanhalli, 2009). In addition to other factors like travel time, cost, and service frequency, in-vehicle crowding also affects travel choice behavior. High levels of crowds inside buses may not only cause physical discomfort (Li and Hensher, 2013) but also a range of psychological and social challenges, for instance, personal safety (Cox et al., 2006; Katz and Rahman, 2010), feeling of privacy invasion (Wardman and Whelan, 2011), anxiety and stress (Mohd Mahudin et al., 2012; Cheng, 2010), and potential loss of productivity in working inside trains and buses (Fickling et al., 2008). As the occupancy rate increases, reaching a threshold that new passengers cannot easily find seats or even a place to stand, the movement of passengers inside a vehicle slows down. As a result, the boarding and alighting times increase, leading to longer dwell times (Tirachini et al., 2013; Fletcher and El-Geneidy, 2013; Katz and Rahman, 2010). According to Fletcher and El-Geneidy (2013), dwell time starts increasing once the occupancy reaches 60% of its maximum capacity, which negatively affects its punctuality (e.g., departing or arriving late) and passengers' in-vehicle time (e.g., longer travel time). When there are standing passengers inside the vehicle, the average boarding and alighting times increase by 0.34 and 0.56 s, respectively (Tirachini et al., 2013). Milkovits (2008) found that the dwell time of buses increases by as much as the square of the number of standees at a stop, multiplied by the total number of passengers boarding and alighting at that stop.

Another negative consequence of in-vehicle overcrowding is the possibility of bus bunching (Abkowitz and Tozzi, 1987). When a bus is full and cannot pick up more passengers, the left-behind passengers will presumably wait for the next bus. This will create an unexpected demand for the next bus and require more time to board the additional passengers. As a result, the bus will likely face some delays that will consequently degrade the service performance and reliability (Tirachini et al., 2013). The problem becomes even more challenging when all buses operate close to their maximum capacity. Multiple consecutive buses could be full and the left-behind passengers have to wait until there is a bus that can pick up them or they need to look for alternative transport modes after waiting for a very long time.

When the in-vehicle crowd reaches the maximum capacity threshold, the chance of buses passing some stops without picking up passengers waiting to board is high, causing an increase in waiting time at stops and dissatisfaction with the service (Tirachini et al., 2013). Generally, overcrowding issues can be addressed at different stages of service planning, including tactical, operational, and real-time control. At the tactical planning level, PT operators can optimize the service frequency and timetable to enhance service robustness against unexpected disruptions. On the operational level, operators can optimize their capacity and resource allocation to meet travel demand and provide reliable services. Various real-time control approaches have also been proposed to mitigate overcrowding in PT, such as rescheduling (Suman and Bolia, 2019), stop skipping (Sun and Hickman, 2005; Delgado et al., 2009), bus holding (Delgado et al., 2009; Gkiotsalitis and Van Berkum, 2020a), real-time information (Drabicki et al., 2022) and peak spreading campaigns (Daniels and Mulley, 2013). For instance, Suman and Bolia (2019) found that optimally reassigning buses during peak hours while considering demand can reduce overcrowding issues by 1.6 times in New Delhi, India. Providing real-time information on the occupancy level of the next arriving bus is a demand management strategy to better distribute passengers over multiple consecutive buses and reduce the possibility of overcrowding (Kim et al., 2009; Drabicki et al., 2022). The result of a stated preference survey in the city of Warsaw (Poland) showed that 30–70% of passengers were willing to wait longer at stops to avoid a crowded bus if real-time occupancy information was provided (Drabicki et al., 2022). Off-peak traveling campaigns are another passive way to reduce the probability of overcrowded vehicles during peak hours. A study in Sydney, Australia, revealed that such campaigns could be very successful among students, who are the most dedicated PT users (Daniels and Mulley, 2013). Furthermore, the authors also found that encouraging private car users not to switch to PT during peak hours could also help reduce overcrowding issues.

The topic of in-vehicle crowd management attracted significant attention during the COVID-19 pandemic due to the regulation of keeping a 1.5 meter physical distance inside vehicles. As a result, passengers could not (did not want to) board once the buses reached the pandemic-imposed capacity threshold (Gkiotsalitis, 2021a). To spread the demand, Gkiotsalitis and Liu (2022) developed a periodic adjustment optimization model for two bus lines in Enschede, the Netherlands. The results showed that adjusting dispatching times while considering the passenger demand, travel time variations, and imposed capacity limit will evenly distribute passengers over several trips while fulfilling the physical distance regulation. In another study, Gkiotsalitis (2022) proposed a skip-stop solution to reduce the in-vehicle crowd during the pandemic. Even though both of the studies have focused on the pandemic situation, the nature of the in-vehicle overcrowding remains the same. In this study, we try to solve the in-vehicle overcrowding issue caused by weather disruptions.

3 Problem description

The *bus reassignment* problem can be defined as follows: given a bus network with multiple lines where the expected demand exceeds the maximum vehicle capacity for some trips while there are few to no passengers for other trips. Thus, we want to dynamically cancel low-demand trips and reassign these buses before or after overcrowded trips in order to minimize passengers' waiting time at the bus stops. The goal is to reallocate the existing capacity to lines where the current service is insufficient to meet the expected demand. As a result, we can enable PT operators to address the overcrowding issue during disrupted conditions without requiring spare buses and drivers.

Fig. 1 represents a hypothetical scenario of *bus reassignment* with two lines, 1 and 2. Suppose that several buses are operating on both lines based on a predetermined timetable. The y-axis represents the first and last stops and the x-axis shows departure times of bus trips on both lines.

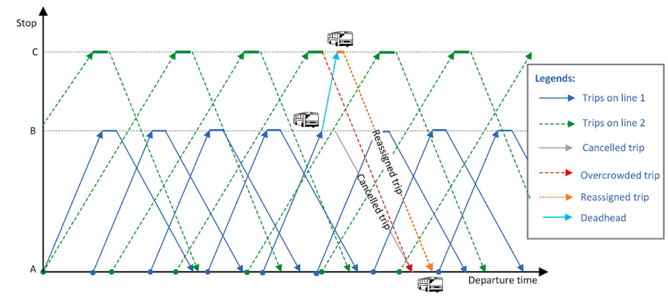


Fig. 1. Bus reassignment example.

Throughout the service period, a trip on line 2 dispatching from stop C (shown in red color) will be *overcrowded* at several segments and require another bus to pick up those passengers who are left behind. Instead of deploying an additional bus from the depot which might not be available, we want to cancel a trip from line 1 (shown in grey color) where there is a low passenger demand at the time, and reassign its bus after the overcrowded trip on line 2 (shown in orange color) where many people are still waiting for the next bus. After completing the reassigned trip, the bus will return to continue operating its next timetabled trip as usual.

Although the reassignment process shown in Fig. 1 seems straightforward, it is essential to acknowledge that canceling a trip from a line and reassigning its bus to another line entails inherent trade-offs between two groups of disrupted passengers. On the one hand, canceling a bus trip implies that the affected passengers have to wait for the next bus or seek alternative means of transportation. In a study by Currie and Muir (2017), the authors found that unplanned disruptions in PT services could increase passengers' level of dissatisfaction up to four times, depending on the recovery condition. From the passengers' point of view, canceling bus trips can be considered another type of unplanned disruption irritating the affected passengers. In such situations, PT users have certain waiting time tolerance thresholds before looking for alternative solutions (Rahimi et al., 2019). Additionally, the adverse impact of trip cancellation can cascade through the network, depending on the number of trips that are being canceled simultaneously. On the other hand, as the in-vehicle occupancy approaches the maximum capacity, passengers may experience delays and discomfort due to overcrowding. The issue becomes critical when some passengers are unable to board since the buses have reached their full capacity and cannot accommodate passengers anymore. In such a case, the left-behind passengers must wait for the next bus or find alternative modes. Such a complex trade-off demands meticulous consideration when implementing the bus reassignment strategy to address overcrowding issues during disrupted conditions.

Before proceeding with the problem formulation, the following assumptions are made:

- The buses operating in the network do not return to the depot at the end of each trip. This implies that the driving time from and to the depot is excluded from problem formulation.
- The first and the last trips of a day cannot be canceled. The reason is that people will have limited or no alternative if these trips are canceled.
- The original timetable (also drivers' schedules) remains intact except for those trips directly or indirectly affected by the reassignment process.
- Frequency setting and timetable design are already determined in the tactical planning stage.
- All buses operating in the network have the same capacity, which is 80 passengers (40 seats and 40 standing).
- A bus trip is identified as *overcrowded* when the in-vehicle crowd at one or multiple segments of a bus line during the trip exceeds the capacity threshold. In this study, we set the capacity threshold to 60 in-vehicle passengers. This implies that a bus is considered overcrowded if the ratio between standing and seating passengers is more than one-third or 75 % of the maximum capacity.

4 Mathematical formulation

In this section, the mathematical formulation of the problem is presented. Let $T = \{1, 2, \cdots, T\}$ denote the set of daily timetabled trips within the network and $S_t = \{1, 2, \cdots, m_t\}$ the set of stops served by trip $t \in T$. In order to differentiate between overcrowded trips and feasible trips for reassignment, we divide the set T into two subsets: T^a and T^r. $T^a \subset T$ is the subset of trips where the in-vehicle crowd exceeds that capacity threshold at one or multiple segments, and $T^r \subset T$ is the subset of trips that could potentially be canceled so that their buses could be reassigned to overcrowded lines. Let $L = \{(i,j) | i \in T^r, j \in T^a\}$ be the list of paired trips, where i is the feasible trip for cancellation and j is an overcrowded trip. Since there could be several *overcrowded* trips during the optimization time window, the decision should be made on which bus trip $i \in T^r$ should be reassigned before which overcrowded trip $j \in T^a$. The following preconditions should hold when generating these subsets:

- For any trip included in T^a, the in-vehicle crowd is exceeding the capacity threshold at least at one segment during the trip.
- For any trip included in the list of reassignable trips T^r, the expected demand for the very next trip on the same line should not exceed the capacity threshold. With this precondition, we ensure that if we want to cancel a trip from a bus line, the next trip on the same line should not be overcrowded. In other words, if we cancel a trip from a bus line to use its bus for serving another bus line, we should ensure that we do not unintentionally cause crowding problem to this line. Otherwise, passengers of the canceled trip have to wait for the next bus, which is already full with its regular passengers, let alone adding passengers from the canceled trip.
- For any trip included in the list of reassignable trips T^r, the in-vehicle crowd of the very next trip operated by the same bus should not expect overcrowding. The reason is the reassigned bus might experience some delays, which can adversely affect the timetable of its following trips.

4.1 Objective function

Ideally, the planned bus services can serve the expected demand, so there is no need to reassign any buses, so:

$$\vartheta_s^t \leq C, \forall t \in T, \forall s \in S_t \tag{1}$$

where ϑ_s^t is the in-vehicle crowd between stop s and $s+1$ during trip t and C is the capacity threshold. However, disruptive events could cause an increase in the in-vehicle crowd, which may lead to overcrowding issues. To encounter such issues, we either cancel planned trips so their buses can be reassigned to other lines or assign additional buses from the depot. In this study, we focus the first option. Nevertheless, this is a two-fold problem. On the one hand, trip cancellations mean additional waiting time for passengers whose bus trips are canceled. On the other hand, more passengers would be served if these buses operated the reassigned trips rather than executing the timetabled trips. Thus, the optimization objective is to minimize the waiting time of passengers who either cannot board buses due to overcrowding or due to trip cancellations (hereafter, disrupted passengers). We introduce two binary decision variables $x_{i,j}$ and $y_{k_i,j}$. The reassignment variable $x_{i,j}$ indicates whether trip $i \in T^r$ is cancelled and reassigned before or after trip $j \in T^a$. $x_{i,j} = 1$ if i is reassigned to j and 0 otherwise. $y_{k_i,j}$ is the imposed cancellation variable, which refers to canceling trip k_i as a consequence of reassigning i to j. For instance, the bus that is supposed to execute a timetabled trip i cannot return on time to operate its next timetabled trip k_i. $y_{k_i,j} = 1$ if a trip k_i is canceled and 0 otherwise. Let $F_i = \{1, 2, \cdots, k_i\}$ be the set of following trips for trip i operated by the same bus. The objective function can be stated as follows:

$$minf(x,y) = \sum_{(i,j)\in L}\sum_{s\in S_j}\zeta_s^j \cdot w_s^j \cdot x_{i,j} + \sum_{(i,j)\in L}\sum_{s\in S_j} 3\zeta_s^j \cdot w_s^j \cdot (1 - x_{i,j}) + \sum_{(i,j)\in L}\sum_{s\in S_i} 2\vartheta_s^i \cdot w_s^i \cdot x_{i,j} + \sum_{(i,j)\in L}\sum_{k_i\in F_i}\sum_{s\in S_{k_i}} 2\vartheta_s^{k_i} \cdot w_s^{k_i} \cdot y_{k_i,j} \tag{2}$$

where w_s^i, w_s^j and $w_s^{k_i}$ represent the average waiting time of passengers during trip i, j, and k_i at stop $s \in S_i$, $s \in S_j$, and $s \in S_{k_i}$, respectively. ζ_j^s is the total number of in-vehicle passengers exceeding the capacity threshold during trip j at stop $s \in S_j$. ϑ_s^i and $\vartheta_s^{k_i}$ are the total number of expected in-vehicle passengers during trip i and k_i at stop $s \in S_i$ and $s \in S_{k_i}$, respectively. The first part of Eq. (2) refers to the total waiting time of disrupted passengers during an overcrowded trip. In the case of assigning an additional bus before/after trip j, all passengers will be picked up by these two buses (regular and no passengers will be left behind. Thus, the waiting time of disrupted passengers will be the same as their original waiting time, assuming that one additional bus trip is enough to address the overcrowding issue of a single trip. This assumption is made based on a preliminary data analysis of overcrowded records in the past. On very rare occasions, more than one bus was needed to pick up all the left-behind passengers, for instance, during matches at the local football stadium.

The second part of Eq. (2) refers to the waiting time of disrupted passengers if no reassignment occurs. In this case, passengers who are left behind must wait for the next bus. Assuming that they have no prior knowledge of the overcrowded situation, they are already at the bus stops. So, their waiting time will increase by as much as their current waiting time plus the headway between two consecutive buses on that line or three times their original waiting time. The third part of the objective function accounts for the immediate impact of trip cancellation on the waiting time of disrupted passengers. The increase in their waiting time depends on whether the passengers are informed about their trip cancellation. In this study, we assume that the respective PT operator will inform the affected passengers a few hours in advance, so they do not leave home and wait at the bus stops too long. Therefore, they do not need to wait at the bus stops as much as the left-behind passengers do. However, since the headway on the line where trip cancellation happens is doubled, passengers' waiting time will also increase by as much as twice the original waiting time. Finally, the fourth part of Eq. (2) denotes the imposed cancellation. If a reassigned bus cannot return on time to execute its next timetabled trips ($y_{k_i,j} = 1$), the waiting time of these passengers will also be doubled. Depending on how many bus trips are canceled because of a single reassignment, the value of this part varies accordingly.

If we assume that (1) passengers arrive at stops uniformly and (2) arrivals of two consecutive buses are independent, the general formula for calculating the average passenger waiting time at stops could be as follows (Osuna and Newell, 1972):

$$w = \frac{E(H^2)}{2E(H)} = \frac{E(H)}{2}\left(1 + \frac{Var(H)}{(E(H))^2}\right) \tag{3}$$

where $E(H)$ and $Var(H)$ represent the headway mean and variance, respectively. Since the bus frequencies differ depending on the period of a year (e.g., fewer buses during school holidays compared to normal weekdays), the headway variance changes accordingly. Thus, we will calculate the average waiting time when solving the optimization problem.

4.2 Constraints

Bus arrival constraint: The bus operating trip i should be able to arrive on time to execute its reassigned trip before or after trip j. It means that the bus should drive from the first stop of its timetabled trip to the first stop of its reassigned trip. Furthermore, the bus should arrive no earlier than the departure time of the preceding bus and no later than the departure time of the following trip on the same line as trip j. These constraints guarantee that a reassigned bus is available on time to start its new trip. Let d_i denote departure time from the first stop of trip i and $\delta_{i,j}$ the deadhead time between the first stop of i and the first stop of j, d_{f_j} the departure time of the following trip of j from its first stop, and d_{p_j} to the departure time of the preceding trip of j on the same bus line. This constraint can be written as:

$$d_{p_j} \leq d_i + \delta_{i,j} \leq d_{f_j}, \forall (i,j) \in L \tag{4}$$

In addition to the above constraints, we introduce another constraint on arrival time window (τ) that further controls the arrival of a bus for its reassigned trip. This constraint introduces a threshold on when a bus should arrive for its reassigned trip to be effective in reducing the overcrowding of trip j:

$$d_j - \tau \leq d_i + \delta_{i,j} \leq d_j + \tau, \forall (i,j) \in L \tag{5}$$

Reassignment constraint: A bus trip can only be canceled once during the time window of optimization. Likewise, only one bus trip can be reassigned before or after an overcrowded trip. These constraints can be stated as follows:

$$\sum_{i\in L} x_{i,j} \leq 1, \forall i \in T^r \tag{6}$$

$$\sum_{j\in L} x_{i,j} \leq 1, \forall i \in T^a \tag{7}$$

The above constraints ensure that a single bus trip is not reassigned before multiple overcrowded trips or that several trips are not reassigned before a single overcrowded trip.

Imposed cancellation: This constraint ensures that if a reassigned bus cannot return on time to execute its next timetabled trip(s), the next trip (s) should also be considered when solving the problem.

$$d_i + (\delta_{i,j} + \lambda_j + \delta_{j,k_i}) x_{i,j} - M y_{k_i,j} \leq d_{k_i}, \forall (i,j) \in L, \forall k_i \in F_i \tag{8}$$

where F_i is a set of following trips for i, λ_j is the average travel time from the first stop to the last stop of j and d_{k_i} is the departure time of trip k from its first stop. Finally, δ_{j,k_i} is the deadhead time from the last stop of j to the first stop of k_i. To prevent the model from canceling k_i while its preceding trip i is not canceled, we introduced another constraint as follows:

$$x_{i,j} \leq y_{k_i,j}, \forall (i,j) \in L, \forall k_i \in F_i \tag{9}$$

Maximum imposed cancellations: To prevent the model from canceling too many following trips, we introduce a maximum threshold for imposed cancellations. This constraint limits the propagation of imposed cancellations on the rest of the network and prevents early cancellation of trips. The threshold value is set to two so that up to three consecutive trips operated by a single bus could be canceled in total.

$$\sum_{k_i\in F_i} y_{k_i,j} \leq 2, \forall (i,j) \in L, \forall k_i \in F_i \tag{10}$$

Deadhead time constraint: The deadhead constraint prevents the model from canceling a bus trip too early and limits the empty-driving time below a threshold. This constraint should be satisfied for both immediate and imposed cancelations.

$$\delta_{i,j} \leq \alpha, \forall (i,j) \in L \tag{11}$$

$$\delta_{k_i,j} \leq \alpha, \forall (i,j) \in L \tag{12}$$

Here, $\delta_{i,j}$ *and* $\delta_{k_i,j}$ denote the deadhead travel times and α is the threshold.

Considering the objective function and constraints, the *bus reassignment problem* can be formulated as follows:

$$\begin{aligned} min\ f(x,y) = & \sum_{(i,j)\in L}\sum_{s\in S_j}\zeta_s^j\cdot w_s^j\cdot x_{i,j} + \sum_{(i,j)\in L}\sum_{s\in S_j}3\zeta_s^j\cdot w_s^j\cdot(1-x_{i,j}) \\ & + \sum_{(i,j)\in L}\sum_{s\in S_i}2\vartheta_s^i\cdot w_s^i\cdot x_{i,j} \\ & + \sum_{(i,j)\in L}\sum_{k_i\in F_i}\sum_{s\in S_{k_i}}2\vartheta_s^{k_i}\cdot w_s^{k_i}\cdot y_{k_i,j} \end{aligned} \tag{13}$$

Subject to:

$$d_i + \delta_{i,j} \le d_{f_j}, \forall (i,j)\in L \tag{14}$$

$$-(d_i + \delta_{i,j}) \le -d_{p_j}, \forall (i,j)\in L \tag{15}$$

$$d_i + \delta_{i,j} \le d_j + \tau, \forall (i,j)\in L \tag{16}$$

$$-(d_i + \delta_{i,j}) \le -(d_j - \tau), \forall (i,j)\in L \tag{17}$$

$$\sum_{i\in L} x_{i,j} \le 1, \forall i \in T^r \tag{18}$$

$$\sum_{j\in L} x_{i,j} \le 1, \forall j \in T^a \tag{19}$$

$$d_i + (\delta_{i,j} + \lambda_j + \delta_{j,k_i})x_{i,j} - My_{k_i,j} \le d_{k_i}, \forall (i,j)\in L, \forall k_i \in F_i \tag{20}$$

$$\sum_{k_i\in F_i} y_{k_i,j} \le 2, \forall (i,j)\in L \tag{21}$$

$$x_{i,j} \le y_{k_i,j}, \forall (i,j)\in L, \forall k_i \in F_i \tag{22}$$

$$\delta_{i,j} \le \alpha, \forall (i,j)\in L \tag{23}$$

$$\delta_{j,k_i} \le \alpha, \forall k_i \in F_i \tag{24}$$

$$x_{i,j} \in \{0,1\}, \forall (i,j)\in L \tag{25}$$

$$y_{k_i,j} \in \{0,1\}, \forall k_i \in F_i \tag{26}$$

Based on the preliminary experiments, a guided set of steps can solve the problem quickly and efficiently. These steps are executed as follows:

1. Categorize trips by overcrowded and reassignable trips.
2. Create pairs of reassignable and overcrowded trips considering the preconditions.
3. Create pairs of potentially imposed cancellations and overcrowded trips.
4. Solve the optimization model.
5. Extract details of the reassigned trips and check whether additional buses from the depot are required.

5 Experiments

The *bus reassignment* experiments are performed considering the Enschede bus network, which is part of the Twente concession in the Netherlands. Enschede is a city in the eastern Netherlands in the province of Overijssel with around 160,000 population. In total, 15 bus lines are operating in the city, including 1, 2, 3, 4, 5, 6, 7, 8, 9, 60, 61, 62, 802, 505, and 506. Bus line 802 operates only on Saturdays and Sundays, connecting P + R parking (park and ride) in the south to the central station. Thus, the trips of this bus line are excluded from the test case. Additionally, lines 8, 60, 61, and 62 are excluded from the experiment.

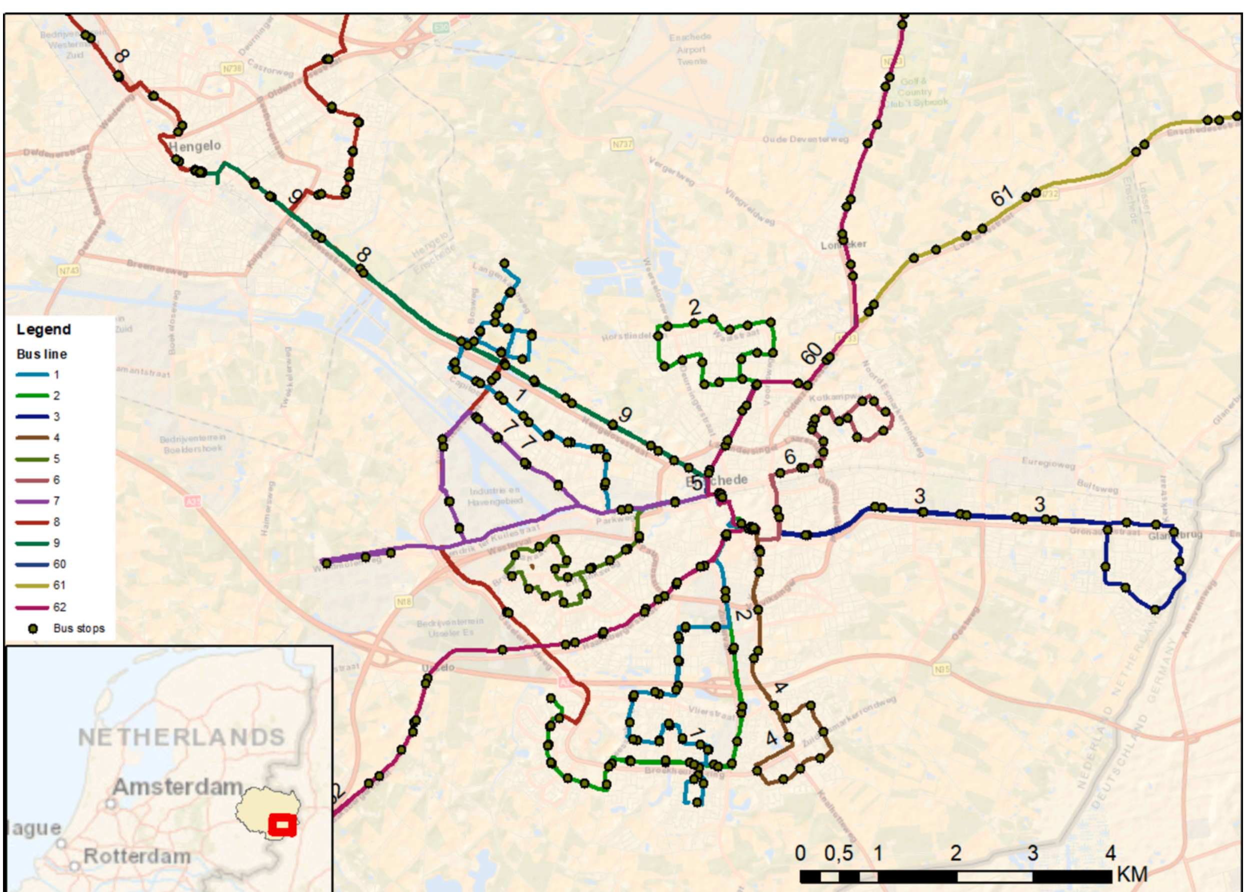


Fig. 2. Case study bus lines.

These lines connect Enschede to neighboring cities/villages, where travel time is significantly longer than the inner-city lines. However, bus trips on these lines could be canceled because of reassignments (imposed cancellations); therefore, they are kept when solving the problem. Lines 505 and 506 are neighborhood buses (buurtbus), so they are also excluded from the experiment. Fig. 2 represents the bus lines used in our case study.

5.1 Input data

The input data includes the following information:

1. In-vehicle occupancy: the experiments were performed using actual data and predictions. The actual data refers to the in-vehicle crowd obtained from boarding and alighting records via smart-card and tickets collected from January 1*st* and December 30th, 2019. Fig. 3 shows in-vehicle occupancy during different weather conditions. For instance, trip 42411 (Fig. 3a) experienced overcrowding during a period when the temperature was below zero (−1.3 to 0.7 °C). While there were only less than 20 passengers on a similar trip when the temperature was above zero (Fig. 3b). Considering this fact, we tested the bus reassignment model within a real-life pilot in Enschede in the Netherlands between September 12th and 30th, 2022.
2. Bus network: The bus network is considered as a directed graph $G = (N, A)$ with a set of nodes N and a set of arcs A. A node represents stops, and arcs represent the segment between two consecutive stops. Reassignment happens only from (to) nodes related to the first and last stops of each trip.
3. Timetable: The timetable dataset includes trip number, line number, direction, stops, departure and arrival times, and vehicle numbers.
4. Deadhead time: The deadhead time is calculated based on Google Maps API (distance matrix). After comparing the travel times of buses without passengers (deadhead driving) and cars on the city roads, it was found that the travel time difference is very marginal. Therefore, car travel time is used as the deadhead driving time of buses between two stops.

5.2 Experiment results

The bus reassignment optimization model was experimented on several overcrowded scenarios in 2019 that occurred during severe weather conditions (e.g., heavy rainfall (+6mm/hour), strong wind (+11 m/second), temperature below zero, and thunders). We solved the problem using Python 3 with Gurobi Optimizer (version 10.0.0). We ran the model only for those days when weather disruptions occurred and therefore overcrowded trips were expected. Optimal solutions were often found within seconds with the standard settings using Apple M1

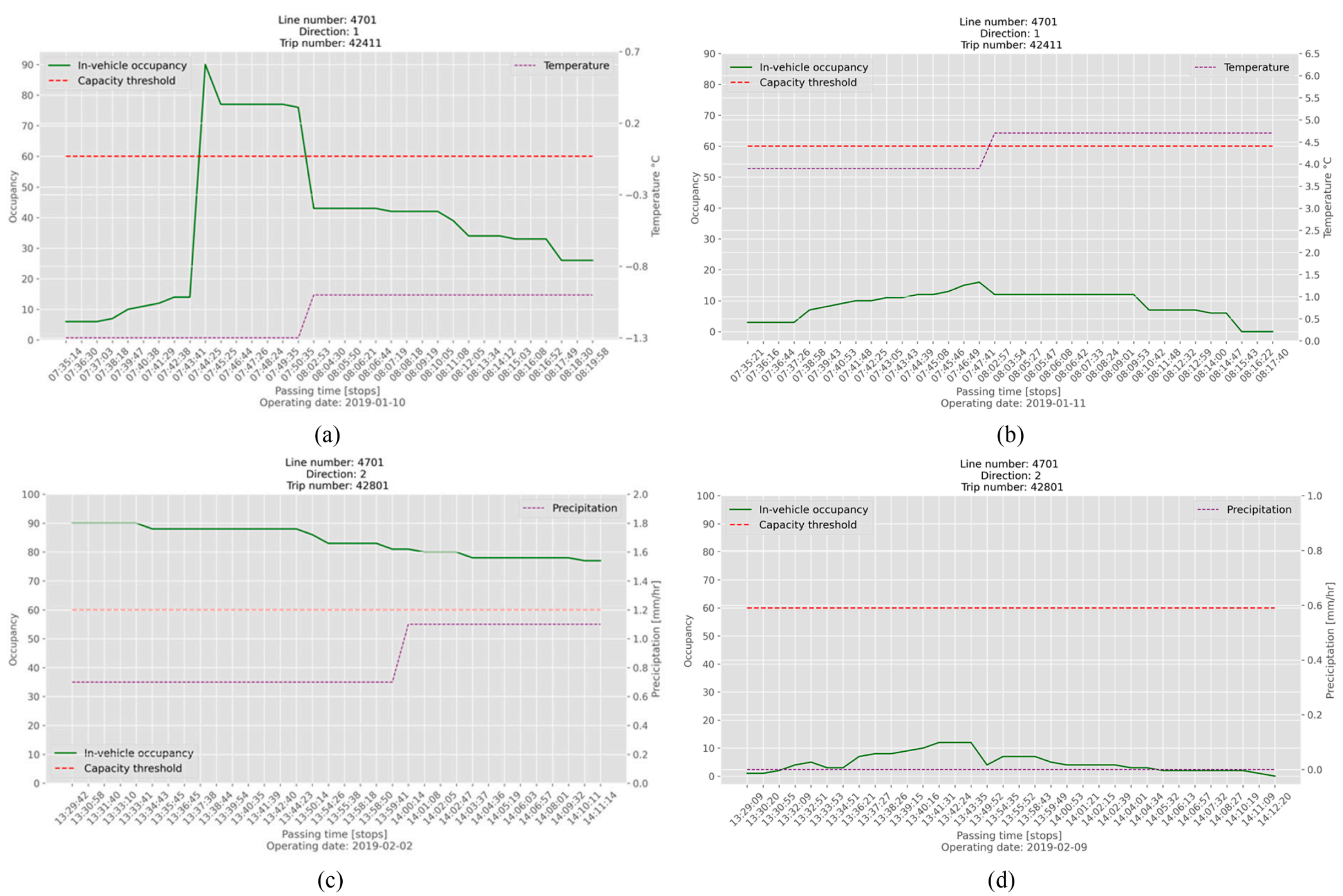


Fig. 3. In-vehicle occupancy versus weather conditions: (a) occupancy and temperature (below zero), (b) occupancy and temperature (above zero), (c) occupancy and rainfall (rainy day), (d) occupancy and rainfall (dry day).

Table 1
Gurobi optimization output.

Operation date	2019-02-02
Gurobi Optimizer	Version 10.0.0
CPU model	Apple M1 Pro
Thread count	10 physical cores, 10 logical processors, using up to 10 threads
Optimize a model with	57,309 rows, 23,576 columns and 117,575 nonzeros
Model fingerprint	0xc84974ee
Variable types	0 continuous, 23,576 integers (23576 binary)
Coefficient statistics	Matrix range [1e + 00, 2e + 12]
	Objective range [1e-03, 2e + 06]
	Bounds range [1e + 00, 1e + 00]
	RHS range [1e + 00, 8e + 04]
Found heuristic solution	objective: 5.062846e + 09
Pre-solve removed	57,309 rows and 23,576 columns
Pre-solve time	0.02 s
Pre-solve	All rows and columns removed
Solution time	0.06 s (0.04 work units)
Solution count 2	5.05451e + 09 5.06285e + 09
Tolerance	1.00e-04
Best objective	5.054511950928e + 09, best bound 5.054511950928e + 09, gap 0.0000 %

The above table means that:

- Our model has 57,309 constraints.
- Our model has 23,576 variables, all of which are binary.
- Using a simple heuristic, a feasible solution with an objective function score of 5.062846e + 09 was found. This initial solution is the upper bound of our model.
- Using the Branch & Bound, the lower bound is established to be equal to the upper bound: the 2nd solution is equal to the 1st solution found by the heuristic and the gap is 0.0%.
- The Branch & Bound method terminates with finding a globally optimal solution that has an objective function score of 5.062846e + 09.
- The problem was solved in 0.06 s.

Pro 16 GB Memory.[1] An overview of the Gurobi output is presented in Table 1.

Table 2 presents the bus reassignment outputs based on the actual occupancy data. As can be seen in the table, the optimization model could find reassignable buses to be assigned before/after overcrowded trips on several overcrowded cases. The left side of the table presents details of timetabled trips that were identified as *overcrowded*. The trip number is a unique number used to trace details of a bus trip, including vehicle number, line, direction, departure time, and occupancy data. The right side of the table provides information on the optimal solutions after executing the model. For instance, on a day in February, 2019, the bus departing at 08:11 (trip 42420) on line 1, direction 1 experienced overcrowding. Based on our optimization model, trip 43840 departing at 8:02 on line 3 direction 2 could be cancelled so that its bus is reassigned to line 1. However, the bus should drive to the dispatching stop of its reassigned trip, which in this example was 13 minutes going from line 2 to line 1.[2] Since the travel time on line 1 is longer than line 3, the bus cannot return on time to execute its very next timetabled trip. Therefore, the next trip of this bus (trip 45524) is canceled too, which we call imposed cancellation. The imposed cancellation can be 'None' if the vehicle completes its reassigned trip and returns to the first stop of its next timetabled trip on time. The empty rows in the table imply that trip cancellation was not the optimal solution at the time.

Overall, it was found that bus reassignment is more plausible when several segments of a trip experience overcrowding issues. Interestingly, all overcrowding happened on line 9 (Hengelo Central Station – Enschede Central Station) and line 1 (University of Twente – Enschede Central Station – De Posten (south of the city)). Table 3 provides details of reassigned buses, including the vehicle numbers, new departure times, and return times to their planned schedule. Nevertheless, in some cases, bus reassignment was not the optimal solution, mainly because the overcrowded issue was not severe enough to cancel another trip. In such situations, it is better to drive mini-buses to carry a small portion of passengers or leave the issue unsolved if the service punctuality is not significantly hampered.

To better understand how the bus reassignment will benefit more passengers, Fig. 4 shows the in-vehicle occupancy of both overcrowded and reassigned trips. As shown in Fig. 4a-top, the in-vehicle passengers exceed the capacity threshold along multiple segments of line 1 during the morning peak hour in January, 2019, departing at 7:35 AM from De Posten. The reason could be that many people travel to the central train station in the morning. Since the temperature was below zero (-1.3 $C°$), modal shifts from cycling to public transport often happen in the country. Similarly, there was a severe weather condition in February with moderate rainfall, snow, and temperature around zero. Many bus trips experienced overcrowding issues on this day, mostly on line 1. Fig. 4b-top presents the in-vehicle occupancy of a trip on line 1, where more than 80 passengers were in the bus for the entire trip. At the same time, there were a maximum of four passengers in the bus on line 3 that operated at almost the same time (Fig. 4b-bottom). Even though the following planned trip conducted by the reassigned bus must also be canceled (imposed cancellation), there was almost no demand for that trip. Therefore, reassigning this bus to line 1 could solve the overcrowding issue without adversely affecting too many passengers.

Similar to bus line 1, there were several overcrowding issues on the bus line between Hengelo and Enschede. Fig. 5-top presents two cases on line 9. In the first case (Fig. 5a), a bus from line 1, and in the second case (Fig. 5b), a bus from line 7 could be reassigned after the overcrowded trips. In both cases, the buses could return before departure times of their very next timetabled trips.

However, it is not always possible to cancel in-operation trips to

[1] The Python script can be found in this GitHub repository: https://github.com/zakirfarahmand/BusReassignmentOpt.git

[2] Note: to differentiate between line numbers in different cities, the respective PT operator uses an internal numbering format, i.e., line number 4701 which represents bus line 1.

Table 2
Experiment output based on data from 2019.

Date	Overcrowded trip				Reassigned trip				DT (min)	Imp.*
	N	L	D	Dep.	N	L	D	Dep.		
2019-01-10	42411	4701	1	07:35:14	42,984	4702	1	07:35:36	7	None
2019-01-24	45337	4709	1	10:10:00	–	–	–	–	–	–
2019-02-02	42420	4701	1	08:11:40	43840	4703	2	08:02:21	13	45524
2019-02-02	42441	4701	1	09:46:02	43022	4702	1	09:45:58	7	43389
2019-02-02	42473	4701	1	11:16:22	43053	4702	1	11:05:12	7	43415
2019-02-02	42503	4701	1	12:46:23	43896	4703	2	12:31:19	13	45588
2019-02-02	42533	4701	1	14:17:05	–	–	–	–	–	–
2019-02-02	42566	4701	1	15:46:04	43942	4703	2	15:34:28	13	45633
2019-02-02	42599	4701	1	17:16:35	45023	4705	2	17:09:55	12	44757
2019-02-02	42625	4701	1	18:46:49	–	–	–	–	–	–
2019-02-02	42714	4701	2	08:59:13	–	–	–	–	–	–
2019-02-02	42740	4701	2	10:29:05	43392	4702	2	10:26:38	7	43058
2019-02-02	42771	4701	2	11:59:19	43419	4702	2	11:46:37	7	43086
2019-02-02	42,801	4701	2	13:29:42	43106	4702	1	13:25:51	13	43461
2019-02-02	42833	4701	2	14:59:44	–	–	–	–	–	–
2019-02-02	42866	4701	2	16:30:37	43173	4702	1	16:15:19	13	43531
2019-02-02	42897	4701	2	18:01:04	–	–	–	–	–	–
2019-02-02	42916	4701	2	19:32:07	–	–	–	–	–	–
2019-02-04	45340	4709	1	10:19:37	–	–	–	–—	–	–
2019-02-09	42821	4701	2	14:30:02	–	–	–	–	–	–
2019-02-25	45341	4709	1	10:30:16	45262	4707	1	10:24:30	15	None
2019-03-07	45314	4709	1	08:22:24	–	–	–	–	–	–
2019-04-11	42755	4701	2	11:12:45	–	–	–	–	–	–
2019-04-11	45333	4709	1	09:50:37	45262	4707	1	10:18:55	15	None
2019-05-09	43484	4702	2	15:00:18	–	–	–	–	–	–
2019-05-13	45307	4709	1	08:00:06	42702	4701	2	08:07:51	10	None
2019-05-13	45340	4709	1	10:20:01	–	–	–	–	–	–
2019-12-05	45314	4709	1	08:21:56	45258	4707	1	08:22:33	15	None
2019-12-05	45340	4709	1	10:20:12	45262	4707	1	10:26:31	15	None

N: Trip number, L: Line number, D: Direction, Dep.: Departure time DT: Deadhead Time in minutes.
*imposed cancellation due to reassignment.
– no reassignable bus trip was found.

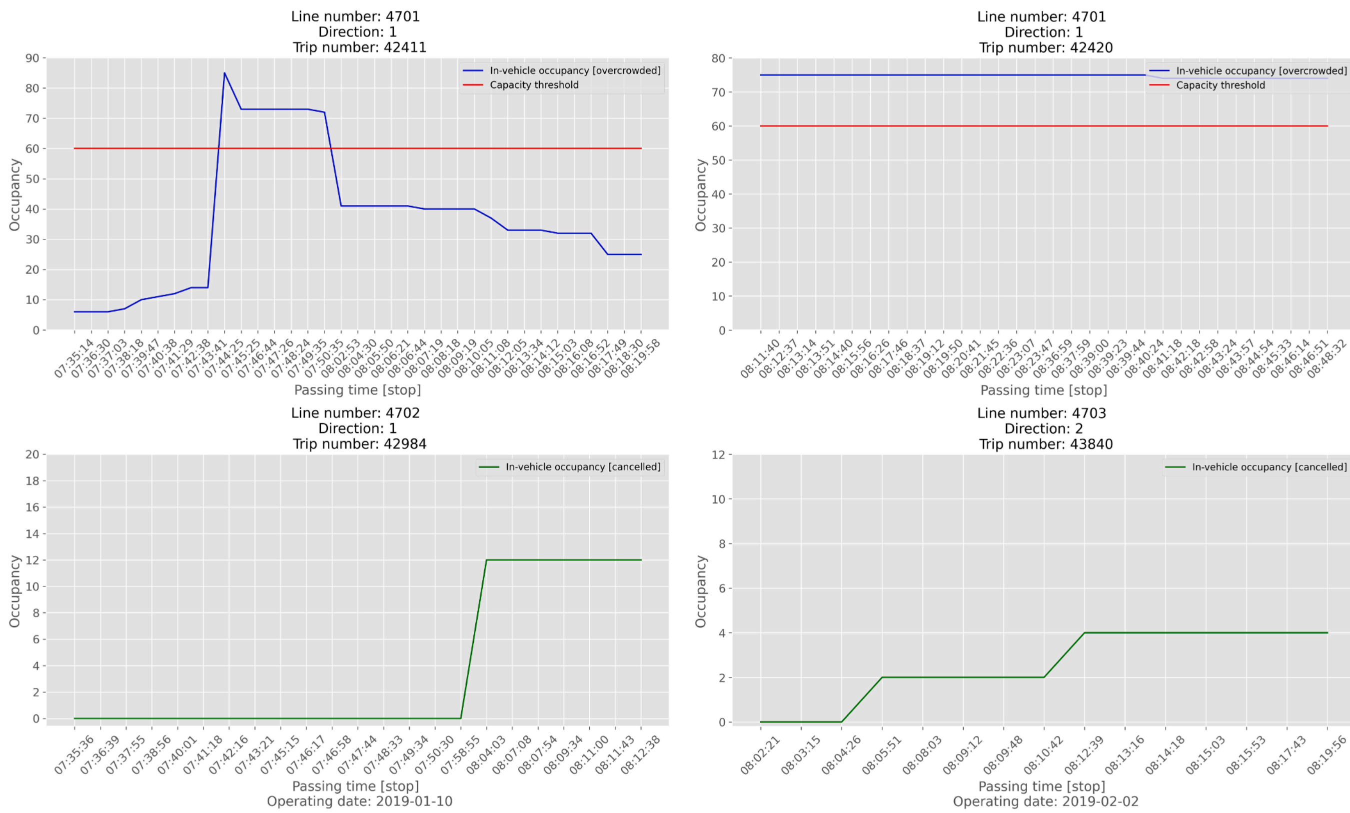
Table 3
Details of reassigned bus trips.

date	number	line	direction	vehicle number	departure	Imposed cancellation	return
2019-01-10	42984	4701	1	443	07:42:36	None	08:17:45
2019-02-02	43840	4701	1	507	08:15:21	45524	08:45:51
2019-02-02	43022	4701	1	455	09:52:58	43389	11:06:36
2019-02-02	43053	4701	1	455	11:12:12	43415	12:25:55
2019-02-02	43896	4701	1	479	12:44:19	45588	13:27:27
2019-02-02	43942	4701	1	464	15:47:28	45633	16:18:47
2019-02-02	45023	4701	1	419	17:21:55	44757	17:40:02
2019-02-02	43392	4701	2	478	10:33:38	43058	11:51:10
2019-02-02	43419	4701	2	478	11:53:37	43086	13:10:55
2019-02-02	43106	4701	2	496	13:38:51	43461	14:55:37
2019-02-02	43173	4701	2	501	16:28:19	43531	17:45:08
2019-02-25	45262	4709	1	561	10:39:30	None	11:04:05
2019-04-11	45262	4709	1	561	10:33:55	None	10:58:30
2019-05-13	42702	4709	1	502	08:17:51	None	09:00:52
2019-12-05	45258	4709	1	416	08:37:33	None	09:03:44
2019-12-05	45262	4709	1	416	10:41:31	None	11:06:06

reassign their buses to other lines. As can be seen in Table 2, there were several overcrowded cases where the optimal solution was to not reassign buses from other lines. This is either because overcrowding was not a significant issue (e.g., Fig. 6b) or bus reassignment is not the best solution (e.g., Fig. 6a). Thus, the service operator can either take no action or assign an additional bus from their reserved capacity.

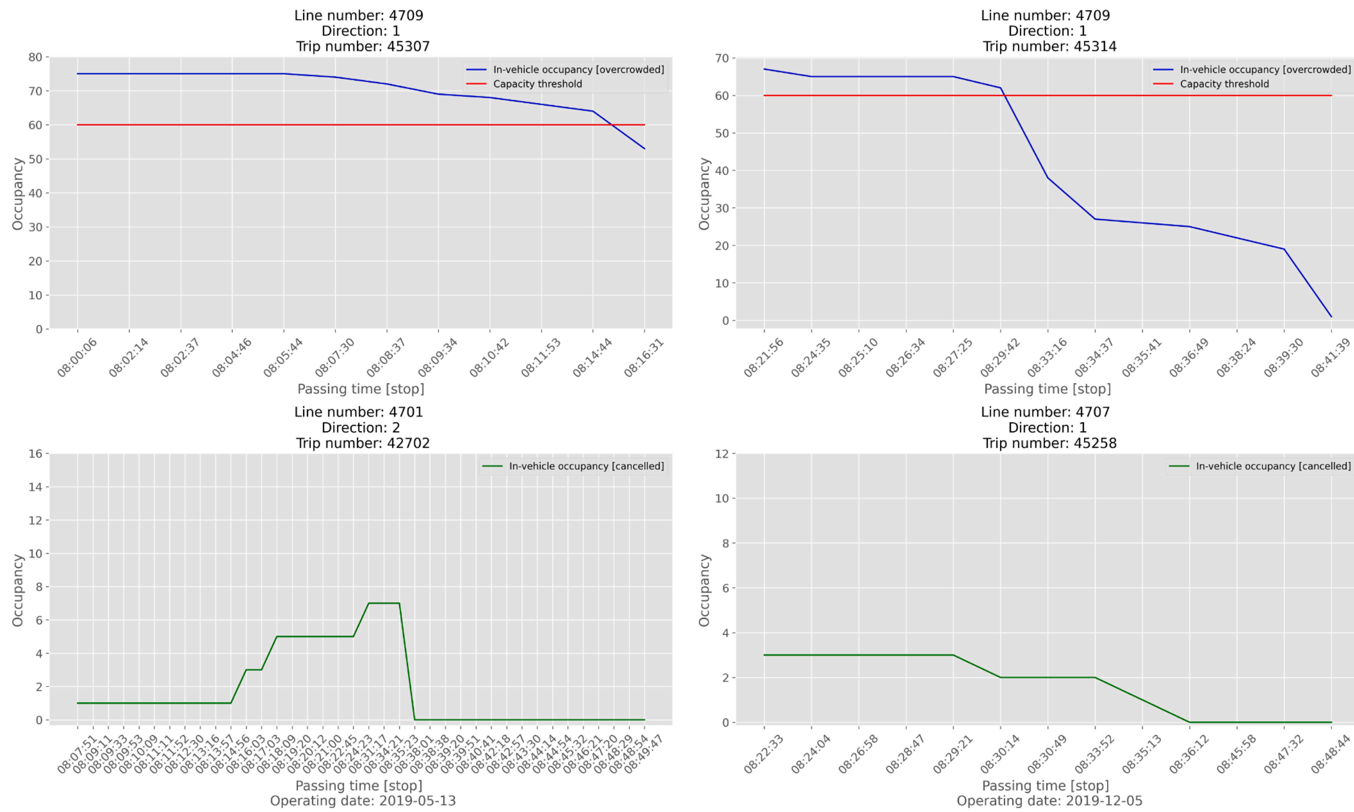
The bus reassignment optimization model performed well considering the historical data; however, in practice, we need to predict which bus trips are likely to experience overcrowding during weather disruptions. PT operators have to update their timetables and inform the affected passengers about potential adjustments in the bus services in (quasi-) real-time. To address this matter, we further tested the bus reassignment model considering predicted demand. We used a deep learning algorithm developed in our previous study (see Farahmand et al., 2023 for more details) to predict the crowdedness of the buses considering external parameters such as weather conditions. The general prediction framework remained the same as the original one, except that the number of boarding passengers was replaced with the in-vehicle crowd between two consecutive stops. Instead of training a single model for the entire network, separate models were trained for each bus stop. The models were also adjusted regarding the covariate parameters such as weather and football matches. We used historical meteorological data retrieved from the KNMI[3] to train the models and used the weather

[3] Koninklijk Nederlands Meteorologisch Instituut – the Dutch national weather service.



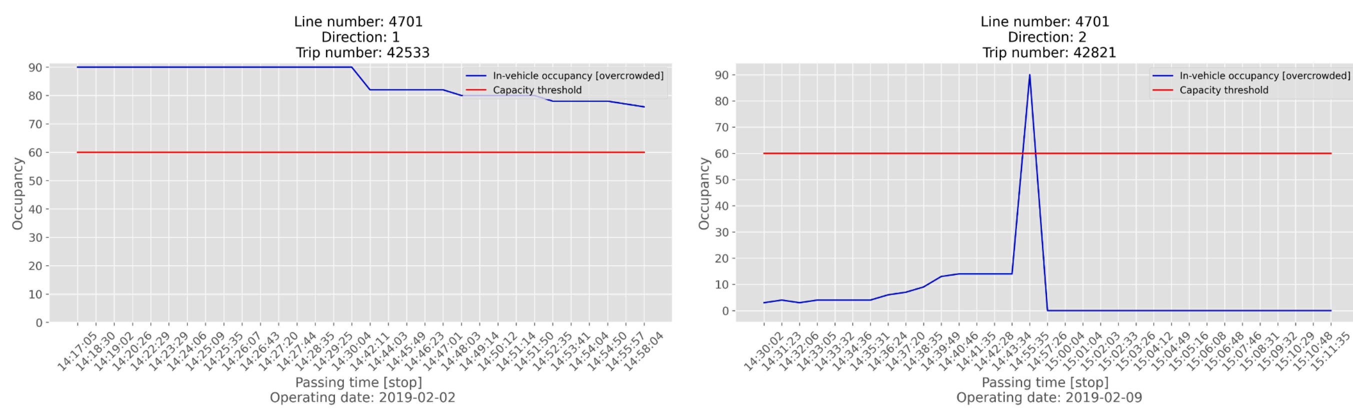
(a) (b)

Fig. 4. In-vehicle occupancy of overcrowded trips on line 1 and cancelled trips from line 2 and line 3, top: overcrowded, bottom: reassigned.



(a) (b)

Fig. 5. In-vehicle occupancy of overcrowded trips on line 9 and cancelled trips from line 1 and line 7.



(a) (b)

Fig. 6. Overcrowded trips without reassignment, (a) line 1 direction 1, (b) line 1 direction 2.

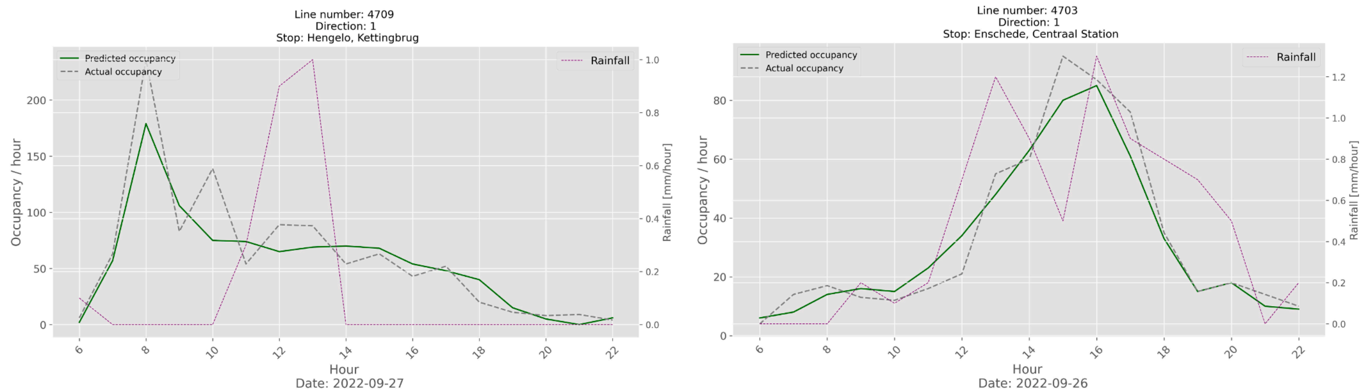
forecast obtained from OpenWeather[4] and Buienalarm[5] to predict passenger demand. Fig. 7 shows predicted occupancy versus actual occupancy on two randomly selected stops and days.

Table 4 provides the reassignment results for the last week of September 2022 based on the prediction data. The problem formulation remains the same as it was with the actual data. The only difference is that the planned timetables were considered while solving the problem. Similar to the actual data, the most overcrowded cases occurred during the morning rush hours. However, the model could only find one reassignable bus trip (41299) that could be dispatched after the overcrowded trip on line 3 (40999). The reassigned bus can be dispatched from the first stop of line 3 (Glanerbrug, Ekersdijk) at 9:36, just four minutes after the overcrowded trip. Though no passenger was expected for the canceled trip, the reassigned bus will miss its next trip. Trip 41300 on line 7 was canceled as a result of reassigning this bus to line 3. Considering the travel time on line 3 direction 2, the reassigned bus could return to its planned trip at 9:49.

Fig. 8 presents the predicted crowdedness of trip 40999 on line 3 and

[4] Openweather is a meteorology company providing historical, current, and forecast weather data via light-speed APIs.

[5] Buienalarm is weather website that informs its users about severe weather conditions, mainly precipitations.

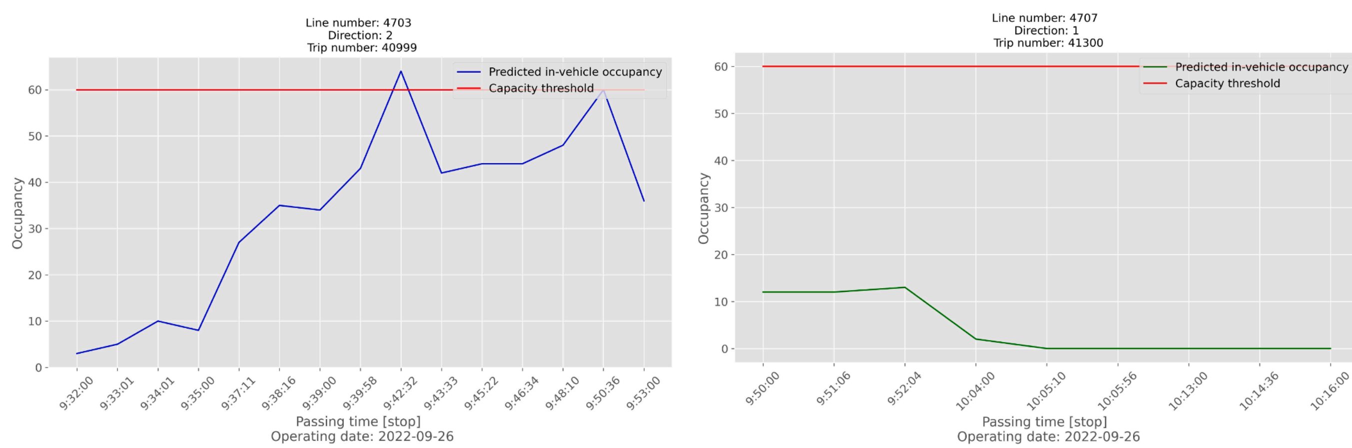


(a) (b)

Fig. 7. In-vehicle occupancy predictions on line 9 and line 1 during moderate-heavy rainfalls.

Table 4
Experiment output based on prediction data from 2022.

Date	Overcrowded trip				Reassigned trip					
	N	L	D	Dep.	N	L	D	Dep.	DT	Imp.
2022-09-26	40741	1	2	8:40	–	–	–	–	–	
2022-09-26	40999	3	2	9:32	41,299	7	1	9:20	16	41,300
2022-09-27	40741	1	2	8:40	–	–	–	–	–	
2022-09-28	40741	1	2	8:40	–	–	–	–	–	
2022-09-29	40742	1	2	8:56	–	–	–	–	–	



(a) (b)

Fig. 8. In-vehicle occupancy of an overcrowded trip on line 1 and cancelled trip from line 7.

the canceled trip on line 7. As shown in the figure, the bus started with no passengers onboard at the first stop and got crowded halfway towards the last stop. Since the buses in our network have 40 seats each, it means that fewer passengers were onboard than the number of seats. While, in the second half, some passengers had to stand. At two segments of the trip, the bus was slightly overcrowded, in other words, more passengers were expected than the capacity threshold. On the other hand, the canceled trip (Fig. 8b) on line 7 was expected to have at most 13 passengers in the bus throughout the first three segments and almost empty during the remaining parts of its trip.

In other cases, overcrowding happened only in one or two segments during a bus trip. For instance, 40741 and 40742 were expected to experience overcrowding issues only during a few segments in the middle of bus line 1 between the Enschede central station and the Twente Hospital (MST), as shown in Fig. 9. For the remaining segments of the line, there were very few passengers inside the buses. As discussed in the problem formulation, the optimization model trades off between the number of passengers whose bus trips were canceled and those who would be served by a reassigned bus; therefore, it is better to drive additional buses from the depot if available address such overcrowded

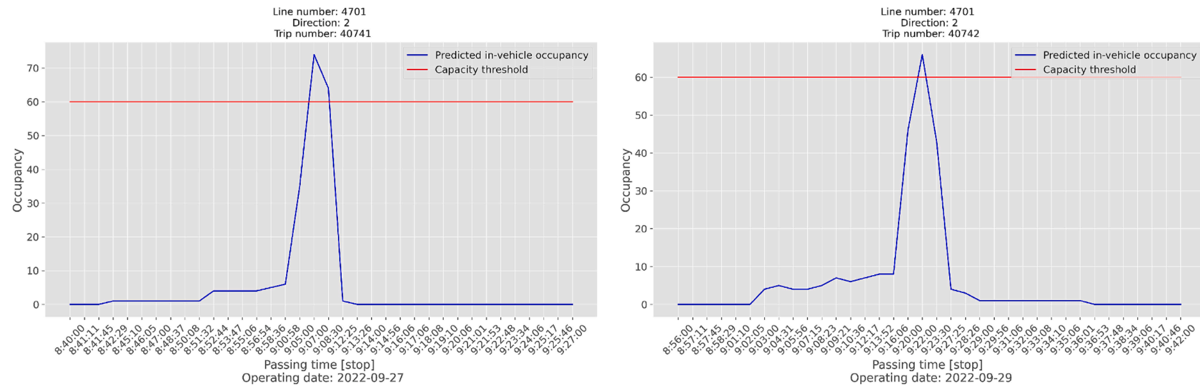


Fig. 9. In-vehicle occupancy based on prediction data for two trips on line 1.

cases.

6. Discussion

The results showed that severe weather conditions disrupt the regular operation of bus services and, in some cases lead to in-vehicle overcrowding. Currently, the public transport operator in the area drives additional buses from the depot whenever the expected demand is high. However, this solution has obvious shortcomings. First, the service operator must have a reserved capacity that is used a few times per year. Maintaining such an extra capacity (vehicles and drivers) only for disrupted situations can be costly for the service operator. Second, the shortage of bus drivers is a concerning challenge for PT operators in Europe (IRU, 2023). According to the IRU (2023) report, around 20 % of bus and coach driver positions remained unfilled in 2023 in the Netherlands. It is predicted that the driver shortage will double in the next five years. Thus, deploying additional buses to encounter overcrowding issues under disrupted conditions is not an appealing solution, and sometimes is infeasible. Thus, we proposed for an alternative solution to use the existing capacity more efficiently.

Based on the historical data from 2019, severe weather conditions, such as heavy rainfall, strong wind, and freezing temperatures had caused in-vehicle overcrowding issues in the network. In several cases, the number of in-vehicle passengers exceeded the maximum capacity limit. The fact that overcrowding occurred implies that either the service operator was not prepared for the weather disruptions or did not have enough reserved buses/drivers to deal with the overcrowding issues. Furthermore, it is likely that some travelers could not get into the buses if the buses were already full. This means that overcrowding could have been worse than what the data shows. On the other hand, severe weather conditions rarely resulted in major overcrowding issues in 2022. The reason is that bus demand has significantly decreased as a consequence of COVID-19. Even though almost all Covid-19 restrictions in the Netherlands were removed during the pilot test, bus ridership was still not at the same level as before Covid-19. However, the service operator was operating with almost the same level of service as pre-Covid. There were minor changes in the bus schedules compared to the substantial reduction in demand. In other words, the bus service was oversupplied for the expected demand in the network. Thus, weather disruptions, or any disruptions for that matter, were less problematic for the current level of service, at least not causing major overcrowding issues. Further research is required to assess the alignment between the supply and demand of bus services after Covid-19.

It should be mentioned that even though bus reassignment can contribute to the efficient use of the existing capacity, it is not without drawbacks. A portion of passengers whose bus trips were canceled will be dissatisfied with the service. For a high-frequency line, the level of dissatisfaction would be much lower since passengers can easily take the next bus. Nevertheless, travelers might switch to other modes, probably less environmentally friendly like private cars if the waiting time becomes excessive. In this research, all disrupted passengers were treated equally for simplicity. Future research could further explore adding weights to disrupted passengers due to overcrowding issues and trip cancellations. For instance, canceling trips could be very frustrating for passengers and, therefore, more weight could be given to these passengers than disrupted passengers due to overcrowding. On the other hand, weather disruptions could be a serious problem in a bus network, so priority should be given to these passengers.

Regarding the mathematical problem formulation, the *bus reassignment* problem is similar to a multi-depot vehicle assignment problem, in which depots refer to the first and last stops of each line. However, the formulation does not consider drivers' schedules. Since each driver is entitled to have a 10-minute coffee break after executing several trips, reassigning him/her to another line might shorten the coffee break time. Their willingness to cooperate plays a key role in the successful implementation of this approach. Moreover, a fixed dwell time is implicitly embedded in the inter-station travel time. Nevertheless, dwell times depend on the number of boarding/alighting passengers, fare collection systems, and characteristics of buses (Soroush Rashidi and Ranjitkar, 2023). Further research is required to take drivers' schedules and variable (passenger-dependent) dwell times into consideration.

Furthermore, we estimated the waiting time as a function of headway mean and variance. In the case of trip cancellations, it was required to inform passengers a few hours in advance about potential changes in the bus schedule to ensure that passengers do not leave their homes and wait at the bus stops too long. This would have been done by updating the bus schedules on the travel app (9292), not directly informing the affected passengers. Therefore, we did not know and could not measure if updating the travel app a few hours in advance would have any effect on adjusting departure times from homes. Since measuring the actual waiting time based on smart-card data is nearly impossible, we estimated the waiting time as a function of the headway mean and variance (Equation (3)), without considering passengers' information about the bus schedules.

7. Conclusion

Our study found that reassigning buses from low-demand trips to overcrowded trips could be a more efficient alternative solution to reserved capacity to deal with overcrowding issues under disrupted conditions. First of all, the operating costs could be reduced since reassigning buses does not require reserved vehicles or drivers. For many PT oper facing shortage of drivers, this approach enables them to utilize their existing capacity more efficiently. Second, the service operator can allocate their reserved capacity to other parts of the network to encounter different types of disruptions, for example, incidents, technical failures, and drivers' sickness. Furthermore, considering the shortage of drivers, bus reassignment will help the PT operator to keep its reserved drivers at a minimum level.

The results showed that reassigning bus trips was more plausible when multiple segments throughout a bus line were overcrowded, especially at the beginning of trips. When a bus is already full from the start, it cannot pick up more passengers who are waiting at downstream stops. Since the in-vehicle occupancy data from 2019 included only passengers who checked in the buses, the demand could have been even more than what was reflected in the data. However, it was not always possible to find reassignable buses for overcrowded lines. Furthermore, it was not justifiable to cause excessive waiting time for a large number of passengers whose bus trips would be canceled. In our post-COVID-19 pilot, in many disrupted situations, the in-vehicle occupancy exceeded the capacity threshold throughout a few consecutive segments.

In future research, the proposed model can be tested in more severe weather conditions (our pilot took place in September 2022). In addition, implementing our model in new pilots with post-Covid conditions with higher passenger demand may yield more bus reassignments.

CRediT authorship contribution statement

Zakir H. Farahmand: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation. **Konstantinos Gkiotsalitis:** Writing – review & editing, Supervision. **Karst T. Geurs:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Data availability

The data that has been used is confidential.

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