Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Skip-Stop Strategy Patterns optimization to enhance mass transit operation under physical distancing policy due to COVID-19 pandemic outbreak

Charinee Limsawasd a, Nathee Athigakunagorn a,*, Phattadon Khathawatcharakun a, Atiwat Boonmee b

a Department of Civil Engineering, Faculty of Engineering at Kamphaeng Saen, Kasetsart University, Nakhon Pathom, 73140, Thailand
b Department of Industrial Engineering, Faculty of Engineering at Kamphaeng Saen, Kasetsart University, Nakhon Pathom, 73140, Thailand

A B S T R A C T

After the widespread impact of the COVID-19 pandemic, all public transport, including urban rail transit, inevitably adopted a vigorous physical-distancing policy to prevent the disease from spreading among passengers. Adoption of this measure resulted in a substantial reduction in train service capability and required control of the risk contact exposure duration. Thus, this paper proposes the Skip-Stop Strategy Patterns (3S–P) decision-support model to incorporate social distancing constraints in train operations. The 3S–P model is a two-stage, multi-objective optimization model for scheduling train skip-stop patterns to satisfy the study’s two main objectives of minimizing the average passenger travel time and unserved passengers. In the proposed model, the first optimization identifies the optimal train skip-stop patterns, while the second assigns these patterns to establish an hourly train schedule. The paper’s case study uses data from the Bangkok Mass Transit System (BTS) SkyTrain Silom Line in Bangkok, Thailand and considers the 0.5, 1, 1.5, and 2 m social distancing schemes. The results reveal that the optimal train skip-stop patterns are superior to the all-stop alternative with, on average, a 13.4% faster travel time at the same level of unserved passengers. Furthermore, the non-dominated schedules from the second optimization decrease the numbers of unserved passengers given equal average passenger travel times.

1. Introduction

The emergence of the COVID-19 outbreak was first reported in December 2019 in Wuhan, China before being announced as a pandemic by World Health Organization (WHO) in March 2020 (Sohrabi et al., 2020; World Health Organization, 2020a). This highly contagious, respiratory, infectious disease rapidly spread worldwide causing large numbers of infected people and deaths. According to WHO, as of January 2022, more than 300 million cases have been confirmed globally with approximately 5.65 million deaths (Worldometer, 2022). The severity of the outbreak resulted in many governments implementing “new normal” practices regarding prevention, such as physical distancing, working from home, and targeted lockdowns, to reduce the risk of exposure to contagion (Tirachini & Cats, 2020; Xu and Li, 2020).

Public transport has been forced to strictly comply with the physical distancing rules, due to the great risk of contagion, especially in closed environments (Nishiura et al., 2020; Qian et al., 2021). Although the physical distancing and work-from-home measures somewhat discouraged the use of public transport, many commutes were inevitable, especially during rush hours. To reduce the risk of contagion spread, WHO has recommended physical distancing by at least 1 m (m) between individuals (Chu et al., 2020; World Health Organization, 2020b). Several countries maintained 1–2 m physical distancing (Gkiotsalitis and Cats, 2021), complemented by other precautionary measures, such as face mask protection and frequent hygienic cleaning. For public transportation services, this physical distancing strategy imposes a substantial capacity decrease of up to 60–90% in some areas (Gkiotsalitis and Cats, 2020), which is contrary to the basic concept of public transport (Musselwhite et al., 2020). This situation tends to be more intense especially on rail mass transit due to the crowded environment in confined spaces.

The restricted regulation during the pandemic challenged transport service providers to arrange their service schedules to reasonably satisfy the levels of passenger occupancy while complying with the physical distancing policies.
distancing rules in several ways. First, the distancing measure causes a substantial reduction in train capacity (Gkiotsalitis and Cats, 2021). Sometimes, it is possible that the service cannot deliver all passengers, especially during peak periods, due to the imbalance in the high levels of travel demand and the limited train capacity (Lu et al., 2021). Train scheduling has been recognized a basic, traditional approach to handle congested and unbalanced travel situations (Niu and Zhou, 2013; Barrena et al., 2014; Mesa et al., 2014; Shi et al., 2018). Thus, competent schedule planning is needed to improve transport serviceability and to reduce unaccommodated passenger numbers in the system. Second, to assist in reducing virus transmission between infected and non-infected passengers in the closed environment, the exposure duration of passengers must be controlled (Tirachini & Cats, 2020). Consequently, the train schedule must be organized in such a way with reduced passenger travel times to minimize the possibility of contagion risks. As the travel time and passenger demand have been the primary concerns in establishing potential train schedules in many studies (Rajabighamchi et al., 2019; Boroum et al., 2020; Huang et al., 2021; Khawanpruk et al., 2021; Wang et al., 2021; Zhang et al., 2021; Khathawatcharakun and Limsawasd, 2022), the sensitive circumstances of a pandemic require greater attention to maintaining the level of system functionality and minimizing the exposure to the risk of contact. This complex issue needs the development of a decision-support tool to suggest an effective train schedule that can concurrently reduce the unserved passengers and minimize passenger travel times during the sensitive pandemic case and its aftermath. 

Due to the high degree of complexity of the train scheduling problem, an efficient computational algorithm is required for this multi-objective optimization. With its huge operational search space and the nature of nonlinearity and discontinuity, the evolutionary algorithm has been proposed for such problem solving (Goldberg 1989). A genetic algorithm (GA), one of the evolutionary methods, has been recognized as a powerful unbiased optimization technique (Tabassum and Mathew 2014) with its superiority to other evolutionary algorithms (Deb et al., 2000). However, applying the optimization technique to the train scheduling problem to satisfy the planning objectives could produce nonrecurring schedules causing passenger confusion. Therefore, an innovative, two-stage GA optimization procedure was developed in this study to avoid the multiformality of proposed train skip-stop patterns. 

Extensive literature citations have examined the planning of train operational patterns for specific purposes. The time-oriented objective has been commonly emphasized in a substantial number of studies. Train schedule optimization approaches have been developed to minimize either the passenger waiting time or total travel time (Zhou and Zhong, 2007; Sels et al., 2016; Sun et al., 2018; Hassannayebi et al., 2019; Zhou et al., 2020), while some studies have aimed to reduce total train delays (Higgins et al., 1996; Narayanaswami and Rangaraj, 2013; Zhan et al., 2016). Furthermore, the train service efficiency has been concurrently considered to assure the demand and reduce unsatisfied passenger numbers. For example, Khawanpruk et al. (2021) constructed a timetable optimizer to determine the optimal number of trains and the time interval to effectively suit passenger demand. Wang et al. (2020) proposed an optimization model to minimize the passenger waiting time and the number of unserved passengers. Niu et al. (2015) introduced a timetable optimization scheme to minimize total passenger waiting time under time-dependent demand conditions. Yang et al. (2016) developed an optimization model for train scheduling and skip-stop planning to simultaneously minimize the total delay and dwelling times, subject to passenger demand constraints. Pan et al. (2020) proposed an optimal train skip-stop strategy capable of reducing total passenger waiting and delay times and avoiding overwhelming passenger densities during peak periods. 

In fact, these works studied train scheduling during non-pandemic situations. Nevertheless, for the COVID-19 pandemic, most of the existing studies focused on the state-of-the-art reviews and overview concepts (Budd and Ison, 2020; De Vos, 2020; Gkiotsalitis and Cats, 2020; Gutiérrez et al., 2020; Zhang, 2020), but lacked a technical aspect for practical implementation on transit scheduling patterns, especially under the restricted health protection regulations. There is evidence of only very few attempts to establish optimal transit schedules during the outbreak and its aftermath under physical distancing constraints, with most papers focusing on optimal service frequencies and headways. Gkiotsalitis and Cats (2021) developed an optimization model for determining the optimal frequencies for the metro line to concurrently balance the operational costs and passenger waiting times during the pandemic. Mutlu et al. (2021) developed an optimization model to minimize the total infection risk at transit bus stops by adjusting the time frequency interval, while Devasurendra et al. (2022) developed an optimization model to determine the optimal headway of a bus line by considering the costs of pandemic health risks. These frequency-setting strategies sometimes required additional resources and extended the total travel time. In contrast, Gkiotsalitis (2020) applied the concept of skip-stop patterns to construct an optimization model by focusing on the unserved passenger demand and excessive waiting time. Nevertheless, this work performed on bus lines and mainly focused on the dimension of service efficiency. The health-risk protection aspect should be further incorporated by controlling total passenger travel times to reduce the exposure duration between passengers.

To address all these research gaps, a multi-objective optimization model, namely, the Skip-Stop Strategy Patterns (3S-P) decision-support model, was developed in this paper to demonstrate its performance and capabilities in facilitating train scheduling to reduce the risk-prone situations associated with COVID-19 virus exposure, while accommodating passenger demand service levels during the pandemic crisis and its aftermath. Apart from facilitating transport service provider decision-making on crisis-oriented train schedules, the novelty of this study also covers the development of a two-stage optimization procedure incorporating GA that improves the calculation effort and the practicality of train scheduling for passengers. The 3S-P decision-support model assists train operators in planning train schedules to satisfy passenger demand while introducing controls regarding disease transmission. The model can suggest promising train schedules to alleviate the pressure of operating the train schedule and serving passengers to the utmost of the operator’s capability during the COVID-19 crisis.

2. Methodology

The 3S-P decision-support model consists of five modules, as presented in Fig. 1: (1) transportation data collection; (2) train capacity calculation; (3) travel demand development; (4) objective functions; and (5) two-stage optimization using a genetic algorithm. The following subsection provides information on each step of the 3S-P decision-support model in more detail, whereas Table 1 summarizes the model’s parameters.

2.1. Data collection

The decision makers (DMs) must gather the necessary data to evaluate the performance of the service to determine the optimal 3S-P conditions for operating a transit train service during specific circumstances, such as the COVID-19 pandemic. Three types of data were required in this study: (1) train characteristics; (2) train line data; and (3) passenger demand volume. The train characteristics needed were the number of cars and the car dimensions to define train capacity according to the different social distancing policies. The train line data consisted of the number of trains, the number of train stations, the headway between trains, and the train travel time between stations. These two data types were used for construction of the origin-destination (O-D) matrix (see Section 2.3), while the third type was used in passenger travel time calculations. The passenger demand volume was defined as the number of passengers using the train service for each station in the train line. These data were also an input in the O-D matrix.
2.2. Train capacity determination under COVID-19 situation

This step determined the train capacity using the social distancing management scheme. According to the different distances recommended by several public health and government agencies, this study varied the passenger spacing from 0.5 to 2 m in 0.5 m increments. The DMs must consider this spacing together with the type of disease transmission. If the disease is airborne spread (such as with tuberculosis or chickenpox), wider spacing must be applied to reduce the possibility of infection. In this paper, every second seat was allowed to be occupied by the passengers to maintain the social distancing policy and the available standing spots were allotted such that the distance between any adjacent standing passengers would not be less than the specified social distancing measure. Notably, for the BTS train, transparent partitions were installed at both ends of the seat row. However, a partition between each seat could be installed to increase the train capacity and reduce the transmission rate among adjacent seated passengers.

2.3. Travel demand development

To achieve the optimal skip-stop pattern, a train operating planner needs to identify the origin and destination stations of each passenger and the number of passengers for each origin-destination component before selecting the patterns. Due to its high commercial value or non-disclosure agreements, sometimes this information may not be available. This paper modified the gravity model from trip distribution (Sinha and Labi, 2011) and applied the following procedure to estimate the travel demand and develop the O-D matrix from the number of passengers at each station.
1. Calculate the average hourly number of passengers at each station ($P_{ave,j}$) by dividing the average daily number of passengers at each station by the total hours of operation per day.

2. Sum the average hourly number of passengers of all stations ($P_{ave}$).

Then, calculate the ratio of $P_{ave}$ to $P_{tot}$ ($R$).

3. Estimate the number of passengers boarding at station number $i$ and leaving at station number $j$ ($P_{ij}$) based on Eq. (1).

$$P_{ij} = P_{ave,j} \times R/(1-R); \ i < j$$ (1)

where $P_{ave,j}$ = average hourly number of passengers at station number $j$; $i$ = origin station number; $j$ = destination station number; and $R$ = ratio of average hourly number of passengers at station $i$ to average hourly number of passengers of all stations.

### 2.4. Objective functions module

The study aimed to minimize the passenger travel time ($TT$) and minimize the number of unserved passengers ($UP$) due to the skip-stop operating pattern resulting from the social distancing strategy in a rail transportation system during a pandemic. The subsection below provides the details for the $TT$ and $UP$ calculations and the required input constraints for the optimization module.

#### 2.4.1. Passenger travel time calculation

The passenger travel time comprises three components: 1) passenger waiting time, 2) passenger in-train time, and 3) vehicle-stop duration. The passenger waiting time ($WT_{p,i}$) measures the period from when a passenger enters the station ($ET_{p,i}$) until the passenger leaves the origin station (the time at which the train departs that station, $TD_i$). Notably, the study varied $ET$ for each passenger between 1 s (minimum) and the train frequency duration (maximum) before the first train of the hour arrives at the station. Eq. (2) represents this calculation step:

$$WT_{p,i} = TD_i - ET_{p,i}$$ (2)

where $WT_{p,i}$ = passenger $p$’s waiting time at station $i$ boarding train $k$; $TD_i$ = the departure time of train $k$ at station $i$; and $ET_{p,i}$ = passenger $p$’s entering time at station $i$.

The passenger in-train time ($IT$), determined by Eq. (3), is the period from when the passenger (and train) departs the origin station until that passenger arrives at the destination station. Notably, this component considers only when a train is in motion; therefore, it does not include the train-stop duration.

$$IT_{ij} = \sum_{n=0}^{i-1} IT_{n,i+1}$$ (3)

where $IT_{ij}$ = the in-train time of a passenger departing from station $i$ and leaving the train at station $j$.

The last component of the passenger travel time is the vehicle-stop duration at each station ($TST_i$). The paper assumed the passenger’s trip finished when the train arrived at the destination station. Therefore, there is no vehicle-stop duration at the destination station. Eq. (4) was used to calculate the travel duration:

$$TST_{i,k} = \sum_{n=1}^{i-1} (ST_{n,k})$$ (4)

where $TST_{i,k}$ = total train-stop time for a passenger boarding train $k$ at station $i$ and traveling to station $j$; and $ST_{n,k}$ = train-stop time of train $k$ at station $n$.

Lastly, all three components are summed for all trains and passengers and the average passenger travel time ($TT_{ave}$) was obtained based on Eq. (5):

$$TT_{ave} = \frac{\sum_{p=1}^{PS}\sum_{j=1}^{N} (TT_{p,j,k})}{PS_{tot}} = \frac{\sum_{p=1}^{PS}(WT_{p,k} + IT_{ij} + TST_{i,k})}{PS_{tot}}$$ (5)

where $TT_{p,j,k}$ = travel time of passenger $p$ boarding train $k$ at station $i$ and traveling to station $j$; and $PS_{tot}$ = total number of served passengers in the train system.

#### 2.4.2. Unserved passenger estimation

An unserved passenger ($UP$) is a passenger that is not accommodated by the train system due to the reduced train capacity from the skip-stop and social distancing strategy and was determined based Eq. (6):

$$UP = \sum_{n=1}^{N} (TP_n - SP_n)$$ (6)

where $UP$ = total number of unserved passengers in the train system; $TP_n$ = total passengers traveling at station $n$; and $SP_n$ = total served passengers at station $n$.

Additionally, in the optimizing procedure, the study combined two constraints to assure realistic solutions:

**Constraint 1:** Train frequency ($F_t$). Under normal circumstances, the train operator may vary the train frequency to accommodate the passenger travel demand, such as during peak and off-peak hours. Nevertheless, to compensate for the severely reduced capacity during the social distancing policy associated with the COVID-19 pandemic, the frequency could be set to a shorter time than normal situation.

**Constraint 2:** Station headways ($SH$). The station headway is the time difference between the former train leaving from and the following train arriving at a particular station. This constraint will prevent a train from overtaking the preceding train, as shown in Eq. (7):

$$SH_{i,k+1} = TA_{i,k+1} - TD_i \geq SH_{min}$$ (7)

where $SH_{i,k+1}$ = station headway between train $k$ and $k+1$ at station $i$; $SH_{min}$ = minimum station headway; and $TA_{i,k+1}$ = arrival time of train $k+1$ at station $i$.

### 2.5. Two-stage optimization module with genetic algorithm

The last module of this study modeled the procedure to identify the optimal skip-stop pattern to achieve the objectives of minimizing the average passenger travel time and the number of unserved passengers. The only decision variable for the optimization was whether to stop at or
to skip each station for all trains in any hour of operation. This study applied the non-dominated sorting genetic algorithm II (NSGA-II) from Deb et al. (2000) to determine the optimal or near-optimal solution. Other studies of infrastructure planning and scheduling with multi-objective optimization have implemented a genetic algorithm (GA) as a search engine and obtained promising solutions (Jeong and Abraham, 2009; Kandil and El-Rayes, 2006; Orabi et al., 2009; Orabi and El-Rayes, 2012).

The GA is a search heuristic technique that mimics the evaluation process using natural operators which imitate the biological mechanism (namely, selection, crossover, and mutation). The GA has shown promise in terms of search speed, reliability, and accuracy when solving challengeable tasks. The GA principle begins with chromosomes, which illustrate a potential solution. The chromosomes are made up of genes, each of which has a decision variable associated with it. These will be used to establish a new population (possible solutions) based on the fitness function (planning objective functions) (Mirjalili, 2019). Next, a pair of chromosomes (parents) with high fitness are “selected” to pass their genes to the next generation of solutions (offspring or children). The children solutions can “crossover” their genes to find a solution with higher fitness. Furthermore, some of the children solutions can have their genes mutated at an arbitrary possibility. The “mutation” process can preserve population variety and avoid early convergence.

This procedure continues iteratively until it reaches predefined criteria, and the optimal or near-optimal solutions are identified. Fig. 2 represents the GA procedure for optimizing the train stopping patterns in this study. However, the solution may contain numerous or non-recurring skip-stop patterns, which are not practical for a train schedule and will confuse some passengers. Hence, the current study introduced the two-stage optimization with NSGA-II to tackle the problem (see modules 5A and 5B in Fig. 1). For the NSGA-II settings, the study assigned the number of generations and populations as 500 and 1,000, respectively.

In the first optimization, the objective was to search for suitable skip-stop patterns. As mentioned above, to reduce the search space and maintain the uniformity of the train schedule, the output from this optimization was limited to four skip-stop patterns (Patterns A, B, C, and D). In addition, the case study in Section 3 considered 16 trains serving in one operating hour. Hence, there would be four trains for each pattern equally in an hour. The initial train order was fixed at this step to reduce a possible solution and focus only on the skip-stop patterns providing the lowest number of unserved passengers and the shortest average passenger travel time.

The first optimization step allows train operators/schedulers to scrutinize these preliminary results from this optimization and to select the best fit for their situation. For example, they can choose a skip-stop pattern that makes more stops or a stop at the major station. They also have the opportunity to consider the trade-off between the results of the two objectives to achieve a desirable level of service. Fig. 3a shows the train schedule of this optimization step.

The second optimization, after the four skip-stop patterns have been established, assigns the patterns (train schedules) to meet the objectives. In this step, the same NSGA-II and its parameters were applied as in the first optimization. All four skip-stop patterns, identified from the prior step, are available for the algorithm to assign to each of 16 trains. Therefore, the total possible schedules in the second optimization are $4^{16}$ solutions (see Fig. 3b). Finally, the procedures in modules 5A and 5B were repeated to determine the optimal solutions for the different social distancing schemes.

3. Case study

This paper considered a case study based on the Bangkok Mass Transit System (BTS) SkyTrain Silom Line, operating in Bangkok, Thailand, to demonstrate the use and capabilities of the developed 3S-P decision-support model in establishing “new normal” (living with COVID-19) train schedules. The BTS Silom line consists of 13 train stations with a total operating length of approximately 14 km (BTS, 2018a). Out of the 13 stations, 3 are major stations, namely stations CEN, S2, and S6, where the numbers of passengers are typically much higher than at the other stations and passengers can transfer to other transportation systems at these stations. Note that Station S4 was under construction at the time of the study and so was not considered in this study). The analyses were performed under a one-way trip operation within a 1-h timespan starting from the “National Stadium” station (W1) and ending at the “Bangwa” station (S12), as shown in Fig. 4, with the...
presentation of the values of travel durations between stations adopted from Sumpavakup et al. (2017).

Due to the restrictions on accessing some confidential data and the lack of detailed trip information, the published daily passenger demand from BTS (2018b) was used to estimate an hourly passenger demand between train stations. Table 2 provides the passenger volume at each station based on the original published data. The train operating hours are 18.5 h per day, according to BTS (2018c); thus, there were approximately 23,500 passengers during 1 h of operation. Table 2 also includes the estimated hourly number of passengers and $R_i$ values for each station for approximating passenger numbers between each set of origin and destination stations from the procedure presented in Section 2.3. The calculation process was repeated for all pairwise stations. The adjusted passenger demand was expressed in the form of the origin-destination (O-D) matrix, as shown in Table 3.

Under normal pre-pandemic conditions, the case study assumed 10 four-carriage trains with a full capacity of at least 1490 passengers per train according to BTS (2018a). However, the physical distancing measures considered in this paper resulted in a reduction in train capacity regarding passengers. As such, the new capacity was decreased to the numbers in Table 4.

As described above, the BTS reduced the train frequency during the COVID-19 pandemic from 6 to 3.45 min per train, to compensate for the

| Station     | Daily passenger demand (people) | Hourly passenger demand (people) | $R_i$ |
|-------------|---------------------------------|----------------------------------|------|
| W1          | 25,190                          | 1362                             | 0.06 |
| CEN         | 98,424                          | 5320                             | 0.23 |
| S1          | 9054                            | 489                              | 0.02 |
| S2          | 65,693                          | 3551                             | 0.15 |
| S3          | 44,666                          | 2414                             | 0.10 |
| S4          | 20,899                          | 1130                             | 0.05 |
| S5          | 82,800                          | 4476                             | 0.19 |
| Total       | 435,760                         | 24,331                           | 1    |

Table 2
Published daily passenger demand from BTS (2018b), estimated hourly passenger demand, and $R_i$ values of each station.
The time between two consecutive trains has a 3.45-min interval at the first station (BTS, 2018c). Thus, 16 trains per hour were utilized in this study. The physical distancing constraints required four-car train capacity for each passenger spacing.

Table 3

| From Station | To Station | National Stadium | Siam | Ratchadamri | Sala Daeng | Chong Nonni | Surasak | Saphan | Krung Thon Buri | Wongwian Yai | Pho Nimit | Talat Phlu | Wutthakat | Bang Wa |
|--------------|-----------|------------------|------|-------------|------------|-------------|--------|-------|----------------|-------------|-----------|-----------|-----------|--------|
| National Stadium | - | 333 | 29 | 217 | 145 | 72 | 275 | 58 | 87 | 14 | 29 | 29 | 72 | 1360 |
| Siam | - | - | 138 | 1036 | 691 | 345 | 1313 | 276 | 415 | 69 | 138 | 138 | 345 | 4904 |
| Ratchadamri | - | - | - | 75 | 50 | 25 | 95 | 20 | 30 | 5 | 10 | 10 | 25 | 348 |
| Sala Daeng | - | - | - | 418 | 209 | 794 | 167 | 251 | 42 | 84 | 84 | 209 | 2258 |
| Chong Nonni | - | - | - | - | 134 | 510 | 107 | 161 | 27 | 54 | 54 | 134 | 1181 |
| Surasak | - | - | - | - | - | 226 | 48 | 71 | 12 | 24 | 24 | 59 | 664 |
| Saphan | - | - | - | - | - | - | 221 | 332 | 55 | 111 | 111 | 276 | 1106 |
| Krung Thon Buri | - | - | - | - | - | - | - | 59 | 10 | 20 | 20 | 49 | 158 |
| Wongwian Yai | - | - | - | - | - | - | - | 14 | 28 | 28 | 69 | 139 |
| Pho Nimit | - | - | - | - | - | - | - | - | 4 | 4 | 11 | 19 |
| Talat Phlu | - | - | - | - | - | - | - | - | - | 12 | 30 | 42 |
| Wutthakat | - | - | - | - | - | - | - | - | - | - | 23 | 23 |
| Bang Wa | - | - | - | - | - | - | - | - | - | - | - | 0 |
| Total | - | - | - | - | - | - | - | - | - | - | - | - | - | 11,999 |

The reduction in train capacity due to the physical distancing constraints enforced (BTS, 2018c). Thus, 16 trains per hour were utilized in this paper. Therefore, the two constraints sets were: 1) the arrival time between two consecutive trains has a 3.45-min interval at the first station (so, for constraint 1, \( F_1 = 3.45 \text{ min} \)); and 2) at least 1 min station headway is enforced for any station. Consequently, it was not possible for any train to overtake another in this study.

4. Results and discussion
The analysis considered the performance of the developed 3S-P decision-support model in establishing potential train skip-stop patterns under the restrictions implemented due to a physical distancing policy. The results from the model demonstrated the explicit trade-off between passenger travel time and the number of unserved passengers (UP). The range of \( T_{TT_{ave}} \) varied from 3.5 to 26 min, whereas UP varied from 0 to approximately 11,000 passengers. However, the skip-stop pattern with 3.5 min \( T_{TT_{ave}} \) also produced the highest UP of 11,000 because the trains in this pattern skipped all the stations on the first half of the train line and stopped at some stations located on the second half of the train line. Therefore, the study was limited to considering only skip-stop patterns with 5000 UP or less. This section provides examples of the optimal skip-stop patterns from the model followed by discussion on the impact of the optimal skip-stop pattern on the planning objectives.

### 4.1. Optimal skip-stop patterns

After the first optimization was implemented, the non-dominated skip-stop patterns were identified. Fig. 6a to Fig. 6d show examples of optimal skip-stop patterns based on various physical distancing constraints. Two patterns per physical distancing, namely the shortest \( T_{TT_{ave}} \) with UP less than 5000 passengers and the longest \( T_{TT_{ave}} \) (the lowest UP), are presented here to investigate the skip-stop pattern from opposite perspectives. Generally, the pattern with more stops will serve more passengers but inevitably produce a longer average travel time under all social distancing schemes. Furthermore, the first two patterns (A and B) had more stops than the last two patterns (C and D), except for the 0.5 m physical distancing option, which provided relatively equal numbers of stops for all patterns because more stops at the beginning could reduce both \( T_{TT_{ave}} \) and UP, while later trains with fewer stops attempted to improve the overall \( T_{TT_{ave}} \). Notably, there was no all-stop alternative in the optimal pattern. Train operators may apply these observations to adjust the skip-stop pattern to meet their specific requirements before implementing the second optimization to create a train schedule.

### 4.2. Impact of optimal skip-stop pattern on planning objectives
When the two main planning objectives were considered simultaneously, the results demonstrated the trade-off between average passenger travel time and the number of unserved passengers from the skip-stop patterns derived in Section 4.1. Fig. 7 depicts a variety of possible and non-dominated solutions at different physical distances where one point represents sixteen-train-skip-stop patterns from the first optimization. The analysis showed there were no unserved passengers when 0.5 m distancing was implemented with an average 17.5 min of travel time per passenger (see the rightmost circle maker). Furthermore, the physical distance of 0.5 m seemed to be more effective in managing the train schedule and serving passengers than the other distances (1, 1.5, and 2 m). A substantial increase in the number of unserved passengers (on the Y axis) appeared between the 0.5 m and 1 m lines, while there were lower differences among the others. The minimum numbers of unserved passengers from the 1 m, 1.5 m, and 2 m distancing schemes were approximately 2,200, 3,500, and 4,300 passengers, respectively. However, all these patterns required an average passenger travel time of at least 24 min. In addition, no skip-stop pattern for these three distancing schemes was faster than 19 min for the average travel time when the number of unserved passengers was less than 5000 due to the large reduction in train capacity when the 1 m scheme was implemented instead of the 0.5 m scheme (see Table 4). Notwithstanding, a more cautious consideration must be taken for closer personal distances as the possibility of infection between onboard passengers could significantly increase. Other strict protective regulations, such as wearing a face mask at all times and installing hygienic protective partitions, might need to

### Table 4

| Passenger spacing (m) | Four-car train capacity (passengers) | Capacity reduction (%) |
|-----------------------|-------------------------------------|------------------------|
| 0.5                   | 796                                 | 46.6                   |
| 1.0                   | 304                                 | 79.6                   |
| 1.5                   | 216                                 | 85.5                   |
| 2.0                   | 172                                 | 88.5                   |
apply concurrently to reduce the chance of personal contact and virus spreading.

Next, the skip-stop patterns from the lowest unserved passenger (the rightmost blue circle marker of Fig. 7) were deemed the most desirable solution and were then selected to run the second optimization. Fig. 8 presents the train schedule with 0.5 m physical distancing from the second optimization and the improved solutions compared to the first optimization. A similar trade-off of non-dominated solutions was also generated with some improvement by serving a higher number of passengers within the same range of travel times. Fig. 8 also shows the results of the all-stop pattern with the same operating conditions (0.5 m physical distancing and a train frequency of 3.45 min). It was clear that the skip-stop patterns performed better by shortening the average travel time from 20 to 17.5 min (a reduction of about 12.5%) for the same number of unserved passengers. This could be important during the pandemic situation when indoor gatherings must be limited to prevent the possibility of infection.

The same procedure was adopted for the other three distances. Fig. 9a–c illustrate the results for physical distancing at 1.0 m, 1.5 m, and 2.0 m, respectively. Their trends were similar to the 0.5 m distancing previously shown, and all these cases delivered a considerable improvement from the all-stop alternative. Nevertheless, superior
Fig. 6. Skip-stop patterns at different social distancing measures, where filled circles indicate stopping stations.

(a) 0.5 m physical distancing

(b) 1 m physical distancing

(c) 1.5 m physical distancing

(d) 2 m physical distancing
results from the unserved passenger perspective were identified using the second optimization, especially when the train capacity decreased. For example, in the 2 m physical distancing case with the average travel time of 23.5 min, the output from the second optimization resulted in nearly 10% fewer unserved passengers than the former solution (see Fig. 9c). Notably, the second optimization still arranged the train schedule such that patterns with more stops were frequently scheduled before patterns with fewer stops, according to the explanations discussed in the preceding section. In fact, further physical distancing tended to produce more patterns with more stops than the closer distancing.

Table 5 summarizes the potential train skip-stop patterns that produced the lowest numbers of unserved passengers at different physical distances (the rightmost square markers in Figs. 8 and 9). The results showed little change in the average passenger travel time when the 1 m, 1.5 m, and 2 m policies were implemented. However, they had substantially different numbers of unserved passengers (see columns 2 and 3 in Table 5). Therefore, to strictly apply at least 1 m distancing among the passengers, transportation operators would select physical distancing at 1 m because of its capability to serving more passengers. Nevertheless, its number of unserved passengers was still high and required an integration with a stringent planning strategy to enable better passenger service. On the other hand, 0.5 m distancing could be adopted during the relaxed period after the pandemic outbreak, along with other hygienic measures (such as frequent cleaning, face masks, and protective partition walls), if the health regulations allowed.

In addition, the paper adopted a trade-off ratio to scrutinize the trade-off performance between the two objectives. A higher trade-off
Fig. 9. Improved solutions at 1.0 m, 1.5 m, and 2.0 m physical distancing.
ratio indicates a social distancing scheme with a better time-saving rate at the same travel passenger service percentage. Even though closer physical distancing results in a higher ratio, in some circumstances, the ratio may be helpful to detect and compare the performance drop when greater distancing is required. The ratio revealed there was no performance loss at 0.5 m distancing compared to the no social distancing scenario. On the other hand, the transport service provider can, for example, choose to operate the 2 m instead of the 1.5 m measure due to the slight difference in the ratios, specifically when social distancing is a concern, such as during the COVID-19 pandemic crisis. The sensitivity analysis was further applied to investigate and assess model output quality. The study replicated the situation when demand decreased according to a partial lockdown or a work-from-home policy. The demand was varied from 0 to 50% of the current demand to determine the average passenger travel time of the same stopping patterns obtained as the model’s outputs. Fig. 10 shows that the skip-stop alternatives still outperformed the all-stop alternatives for all social distancing schemes by yielding shorter $TT_{ave}$ values, which was consistent with the results of the initial demand. Notably, both alternatives produced comparable numbers of unserved passengers at all reduced demand levels.

Importantly, the current study was limited to a single-line train. The framework should be enhanced with certain practical constraints to handle the complete train network scheduling. In particular, the arrival time intervals between train lines can be used to create a skip-stop pattern that enables efficient passenger transfer to another train line or transportation mode at an interchange station. Future work should also examine the change in demand at each station due to skip-stop patterns. Alternatively, this extended framework may use real-time demand to determine precise patterns and schedules. The train operators should integrate additional policies to enhance infection protection. For example, queueing and advanced booking systems will lessen passenger overcrowding at the station and on the platform (Hörcher et al., 2021). Furthermore, a sign indicating the number of vacant positions available in each car would facilitate passengers boarding a train smoothly. The mentioned criteria can potentially reduce passenger travel time and, more importantly, the risk of infection under the social distancing policy during a pandemic.

5. Conclusion

Due to the recent outbreak of the COVID-19 pandemic, it is challenging for public transportation agencies to effectively arrange their operational schedules to satisfy passenger demand while also reducing the risk of contagious exposure among the passengers. This study proposed a three-pronged approach to tackle this issue. First, a multi-objective optimization model was developed, called the Skip-Stop Strategy Patterns (3S–P) Decision-Support Model, to assist public transportation agencies in planning train schedules when the train capacity is substantially and temporarily reduced, such as under the social distancing policy during the pandemic crisis. The model was designed to arrange the train skip-stop patterns and concurrently optimize the study’s two main objectives of minimizing the average passenger travel

| Physical distance (m) | Average passenger travel time (mins) | Unserved passengers | % Shorter travel time compared to all-stop | % Minimum unserved passengers to total demand | Trade-off ratio |
|-----------------------|---------------------------------------|---------------------|------------------------------------------|---------------------------------------------|----------------|
| 0.5                   | 17.5                                  | 0                   | 12.5                                     | 0.0                                         | N/A            |
| 1.0                   | 23.5                                  | 2175                | 14.6                                     | 18.1                                        | 0.80           |
| 1.5                   | 24                                    | 3583                | 12.7                                     | 29.9                                        | 0.43           |
| 2.0                   | 25                                    | 4328                | 13.8                                     | 36.0                                        | 0.38           |

Table 5
Comparisons of potential train skip-stop patterns for different distancing measures.
time and the number of uneussels passengers, according to various social distancing schemes.

Second, two-stage optimization in the 3S–P model was introduced to enable the scheduler to specify a more functional and practical train schedule while still maintaining the main objectives. The first optimization in the two-stage optimization module focused on identifying the skip-stop patterns by limiting the train order. This also narrowed the search space to accelerate the calculation time. The train operators could use these outputs as primary results from which to select appropriate patterns to meet passenger demand or the outbreak situation. The second optimization scheduled the trains from the patterns defined in the former step, which ultimately improved the results according to the study objectives. Third, the trade-off ratio developed in this study examined the degree to which train operation performance degraded from the patterns applied to effectively combat the pandemic.

Measures (such as advanced booking and intelligent signs) must be used to reduce the numbers of unserved passengers for high-speed railways. A new technology is needed for demand management under the Covid-19 crisis. Transportation 1–30. https://doi.org/10.1111/sotn.12192.

Huang, Z., Niu, H., Gao, R., Fan, H., Liu, C., 2021. Optimizing train timetable based on passenger flow control strategy and train scheduling and stop planning on double-track railway systems. INFOR Inf. Syst. 679. https://doi.org/10.1080/03155986.2020.1746100.

Lu, Y., Yang, L., Yang, K., Gao, Z., Zhou, H., Meng, F., Qi, J., 2021. A Distributively Robust Optimization Method for Passenger Flow Control Strategy and Train Scheduling on an Urban Rail Transit Line. Engineering. https://doi.org/10.1016/j.eng.2021.09.016.

Xin, H., Wang, H., Song, Z., 2021. Optimization-based train timetables generation with demand forecasting for high-speed railways. Transp. Res. Part B Methodol. 69. https://doi.org/10.1016/j.trb.2021.101393.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley, New York.

Chen, S., 2020. Improving train timetables using a hybrid simulation and meta-model approach. Comput. Ind. Eng. 138, 106110 https://doi.org/10.1016/j.cie.2019.106110.

Higgins, A., Kozan, E., Ferreira, L., 1996. Optimal scheduling of trains on a single line track. Transp. Res. Part B Methodol. 30 (2), 147–161. https://doi.org/10.1016/0191-2615(95)00022-6.

Hörcher, D., Singh, R., Graham, D.J., 2021. Social distancing in public transport: mobilising new technologies for demand management under the Covid-19 crisis. Transportation 1–30. https://doi.org/10.1111/sotn.12192.

Huang, Z., Niu, H., Gao, R., Fan, H., Liu, C., 2021. Optimizing train timetable based on passenger flow control strategy and train scheduling and stop planning on double-track railway systems. INFOR Inf. Syst. 679. https://doi.org/10.1080/03155986.2020.1746100.

Lu, Y., Yang, L., Yang, K., Gao, Z., Zhou, H., Meng, F., Qi, J., 2021. A Distributively Robust Optimization Method for Passenger Flow Control Strategy and Train Scheduling on an Urban Rail Transit Line. Engineering. https://doi.org/10.1016/j.eng.2021.09.016.

Mesa, I.A., Ortega, F.A., Pozo, M.A., 2014. Locating optimal timetables and vehicle schedules in a transit line. Ann. Oper. Res. 222 (1), 439–455. https://doi.org/10.1007/s10479-013-1393-5.

Mirjalili, S., 2019. Evolutionary algorithms and neural networks. In: Studies in Computational Intelligence, vol. 870. https://doi.org/10.1007/978-3-319-93025-1.

Musselveiwhite, C., Avineri, E., Susilo, Y., 2020. Editorial JTH 16–The coronavirus disease COVID-19 and implications for transport and health. J. Transport Health 16, 100053. https://doi.org/10.1016/j.jth.2020.100053.

Mori, M.M., Akouy, I.C., Alver, V., 2021. COVID-19 transmission risk minimization at public transportation stops using Differential Evolution algorithm. Eur. J. Transport Infrastruct. Res. 21 (3), 53–69. https://doi.org/10.18757/EJTIR.2021.21.15129.

Narayanaswami, S., Kangaraj, N., 2013. Modelling disruption and resolving conflicts optimally in a railway network. Comput. Ind. Eng. 64 (1), 469–481. https://doi.org/10.1016/j.cie.2012.08.004.

Nishurina, H., Oshitani, H., Kobayashi, T., Saito, T., Sunagawa, T., Matsu, T., Wakita, T., Ministry of Health Labour Welfare COVID-19 Response Team, Suzuki, M., 2020. Closed environments facilitate secondary transmission of coronavirus disease 2019 (COVID-19). medRxiv. https://doi.org/10.1101/2020.02.28.2002927.

Niu, H., Zhou, X., 2013. Optimizing urban rail timetable under time-dependent demand and oversaturated conditions. Transport Rev. 33 (2), 122–230. https://doi.org/10.1080/03081060.2013.810616.
