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A Minimum-Cost Model for Bus Timetabling Problem

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Abstract In urban traffic, a bus' running speed is greatly influenced by the time-dependent road conditions. Based on historical GPS data, this paper formulates a bus' running speed between each pair of adjacent stops as a step function. A minimum-cost timetabling model is proposed, in which the total operation cost consists of the cost for a fixed setup and that for variable fuel consumption. Furthermore, a genetic algorithm with self-crossover operation is used to optimize the proposed integer nonlinear programming model. Fi-

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nally, a real-world case study of Yuntong 128 bus line in Beijing is presented. Comparisons among popular timetabling models are given, involving time-dependent running speed, minimum running speed, maximum running speed, and average running speed. The results demonstrate that the consideration of time-dependent running speed is helpful to improve the prediction accuracy of the fuel consumption cost by around 12.7%.

Keywords Bus timetabling · Time-dependent speed · Fuel consumption · Genetic algorithm

1 Introduction

With the rapid development of rail transit, customized buses and sharing bikes, the passenger volume of bus lines in Beijing has been greatly decreased (by 25% over the past three years). Most of bus carriers have been struggling to survive as a result of a sharp decrease in grants from the government. Therefore, how to reduce the operation cost has been arisen as a crucial matter to the survival and development of the bus carriers. The operation cost of the bus carriers is affected by many factors, such as fuel consumption, administrative and maintenance costs and the wages of the crew. Among them, the proportion of fuel consumption cost is about 30% to 40%. Yet, the fuel consumption cost of a bus trip is closely related to the time-dependent road conditions. Indeed, different departure times of a certain bus trip will encounter different road conditions, and then engender different fuel consumption costs. Thus, bus timetabling, in which the departure time of each bus trip is determined, has a great impact on reducing the fuel consumption cost.

Research into bus timetabling started in 1960's when Lampkin and Saalmans (1967) formulated bus network design and setting service frequencies for routes using mathematical programming techniques. Since then, the problem of bus timetabling has always been a hot research topic, and lots of previous studies have focused on considering minimizing the operation cost. For instance, Mekkaoui et al. (2000) considered a fixed cost per bus in the problem of optimizing bus frequency and associated timetable on a single bus route. Yan and Chen (2002) and Yan et al. (2006) established a cost minimization model for the problem of inter-city bus fleet routing and timetable setting, where the cost on a certain arc within a given fleet-flow network is incorporated as a fixed value in the objective function. With consideration of multiple depots, vehicle types and depot capacities, Kliewer et al. (2006) characterized an optimal schedule by minimizing fleet size and operational costs including those for unloaded trips and waiting time. Van den Heuvel et al. (2008) considered fuel and driver costs, which are calculated per unit of time (in terms of each minute), and also the fixed cost of a bus. The results indicated that a significant reduction of the operational costs can be achieved by optimization of the type and number of vehicles performing a service trip and by splitting service trips. Sun et al. (2008) showed that considering a higher traffic volume or a lower speed, the bus travel cost can be reduced through reasonable scheduling combination. Sun et al. (2015) proposed a timetable optimization model for a single bus line based on hybrid vehicle sizes. There is a different operational cost for a bus of a different vehicle size. The operational cost is a fixed value, consisting of time cost, personnel cost and space cost, as well as vehicle operational cost, such as fuel consumption cost and maintenance cost. The results reflected the advantage of incurring low costs via running a fleet of buses with hybrid vehicle sizes.

As outlined above, the majority of previous studies have focused on the problem of bus timetabling with consideration of fixed operation cost per bus trip, which may include fuel consumption cost, maintenance cost, personnel cost, etc. However, in real world, the fuel consumption cost of a bus trip is severely influenced by the time-dependent road conditions, especially in a congested city like Beijing. The road conditions fluctuate at different time periods (e.g., peak hours and off-peak hours), and any bus's running speed is limited to the road conditions. Whilst specific existing studies (Janson (1991), Mohaymany and Amiripour (2009), Xiao et al. (2017)) did consider the impact of road conditions within a certain urban traffic network, they usually assume that the road conditions are in an ideal situation, and that the bus' running speed is simply a constant or subject to a prespecified random distribution. Obviously, it is desirable to relax such harsh assumptions while handling bus timetabling problems.

In this paper, we address the bus timetabling problem with consideration of time-dependent road conditions. Based on historical GPS data, the running speed between each pair of adjacent stops is expressed as a step function. A novel bus timetabling model is proposed to minimize the total fuel consumption cost of bus trips within the timeframe of one day, in which the fuel consumption cost is considered as a function of the bus's running speed. The contributions made in this study include: (i) The proposed model is data-driven, and the time-space running speed is derived from real GPS data (as opposite to the common assumption made in the previous studies where a bus' running speed is typically presumed to be subject to a given random distribution); (ii) A genetic algorithm with self-crossover operation is redesigned according to this specific problem to perform the optimization of the proposed model; (iii) The prediction accuracies of the fuel consumption cost of different prediction models are compared, which can reveal the value and importance of the GPS data.

The rest of this paper is organized as follows. Section 2 describes the problem and proposes a minimum-cost model for the bus timetabling problem. In Section 3, a genetic algorithm with self-crossover operation is used to optimize the proposed model. Section 4 provides a comparative case study to illustrate the efficacy of the model introduced herein. Finally, Section 5 presents the conclusion and future research directions.

2 Problem Description and Formulation

Without losing generality, consider a case where a bus line has a total of I stops. On this bus line, K bus trips are required in one direction during one day's operation time. For each bus trip, there will be a corresponding operation cost. The goal of the bus carrier is to minimize the total operation cost in one day. Here, only one direction of the bus line is concerned.

The operation cost consists of many aspects, such as fuel consumption, administrative and maintenance costs and the wages of the crew that operate the vehicle (Hurdle (1973), Oldfield and Bly (1988)). The administrative and maintenance costs and the wages of the crew are relatively fixed for a bus trip, which can be seen as the fixed setup cost of a given bus trip. The fuel consumption cost is determined primarily by the bus' running speed, which can be seen as the flotation cost of a bus trip. Therefore, the problem is to determine the departure time of each bus trip from the starting station so as to minimize the total operation cost in one day. In order to formulate this problem briefly, the notations used are listed in Table 1.

Table 1: List of notations

Notations	
Sets	
I	Set of bus stops, $i \in I$
K	Set of bus trips, $k \in K$
L	Set of time intervals, $l \in L$
Parameters	
$D_{i,i+1}$	Distance between stop i and stop $i+1$
$v^l_{i,i+1}$	Running speed between stop i and stop $i+1$ in the l-th time interval
H_{min}	Minimum allowable headway time between two adjacent bus trips
H_{max}	Maximum allowable headway time between two adjacent bus trips
p	Unit fuel price
Decision variables	
t_{k1}	Departure time from the starting stop for the k-th bus trip

2.1 Objective

A bus' running speed is significantly dependent upon the road conditions. Suppose that the one day's operation time is divided into L time intervals with an equal length. In each time interval, the bus' running speed between two adjacent stops is different, which can be learned from historical GPS data. Given these (practically reasonable) presumptions, for the k-th bus trip, the running speed between each pair of adjacent stops, stop i and stop $i+1$, can be formulated as a step function about the departure time from the stop i,

t_{ki}, such that

$$v_i(t_{ki}) = \begin{cases} v^1_{i,i+1}, & t_{ki} \in [T_s, T_s + \delta) \\ v^2_{i,i+1}, & t_{ki} \in [T_s + \delta, T_s + 2\delta) \\ \vdots & \\ v^L_{i,i+1}. & t_{ki} \in [T_s + (L-1)\delta, T_s + L\delta] \end{cases} \tag{1}$$

A bus' fuel consumption is mainly related to its running speed. Based on the speed-fuel consumption equation in the report "Road vehicle emission factors 2009" (Department for Transport, UK, 2009) the fuel consumption per unit distance of the k-th bus trip from stop i to stop $i+1$ can be calculated by

$$F_{ki} = \frac{h(a+bv_i(t_{ki})+cv_i(t_{ki})^2+dv_i(t_{ki})^3+ev_i(t_{ki})^4+fv_i(t_{ki})^5+g_v v_i(t_{ki})^6)}{v_i(t_{ki})}, \tag{2}$$

in which a, b, c, d, e, f, g, h are all fixed constants associated with the inherent characteristics of the buses run.

Denote the distance between stop i and stop $i+1$ by $D_{i,i+1}$, and the unit fuel price by p. Then, the fuel consumption cost of the k-th bus trip from stop i to stop $i+1$ can be computed by

$$p * F_{ki} D_{i,i+1}. \tag{3}$$

Thus, the total fuel consumption cost of bus trips in one day is

$$p \sum_{k=1}^{K} \sum_{i=1}^{I-1} F_{ki} D_{i,i+1}. \tag{4}$$

which should be minimized, forming the objective of this work.

2.2 Constraints

Constraint (5) below indicates what is imposed over the time flow conservation, guaranteeing that the arrival time at a stop equals to the sum of the departure time at the last stop and the running time between the two stops:

$$t_{ki} + \frac{D_{i,i+1}}{v_i(t_{ki})} = t_{k,i+1}, \quad \forall k, i = 1, 2, \ldots, I-1. \tag{5}$$

Constraint (6) guarantees that two adjacent bus trips must satisfy the maximum and minimum headway time such that

$$H_{min} \leq t_{k+1,1} - t_{k,1} \leq H_{max}, \quad k = 1, 2, \ldots, K-1. \tag{6}$$

Constraint (7) specifies the departure times of the first and last bus trips in a day:

$$t_{11} = T_s, \quad t_{K1} = T_e. \tag{7}$$

Constraint (8) prescribes that the decision variables are integers, in order to facilitate the execution of the bus timetable:

$$t_{k1} \text{ is integer}, \quad \forall k. \tag{8}$$

From these, we can propose a minimum-cost model for the bus timetabling problem as follows:

$$\begin{aligned} \min \quad & p \sum_{k=1}^{K} \sum_{i=1}^{I-1} F_{ki} D_{i,i+1} \\ \text{s. t.} \quad & \text{Constraints (5)-(8)} \end{aligned} \tag{9}$$

Note that since the values for the number of bus trips, K, and the setup cost per bus trip are both fixed, the total setup cost of bus trips in one day is of a definite value. Therefore, the objective of the proposed model (9) is equivalent to minimizing the total fuel consumption cost in one day. It is obvious that the proposed model (9) is an integer nonlinear programming. For integer nonlinear programming, it is in general, impossible to be optimally solved using traditional brute-force methods. Therefore, we will rely on a heuristic optimization algorithm, namely genetic algorithm, to solve the proposed model (9) in the next section.

3 Genetic Algorithm with Self-crossover Operation

Genetic algorithm (GA), which was firstly proposed by Holland (1975), is a method to search for the optimal solution by simulating the natural evolution process. Because of the powerful computational intelligence mechanism, GA has been widely studied and applied to a variety of practically integer and nonlinear models. For example, Do et al. (2016) applied GAs to minimize generated emissions from trucks and cranes at container terminals. In Weckman (2015), a novel GA is applied to solve the mathematical model proposed for the location and routing in facilities and disposal sites. Proon and Jin (2015) presented an innovative GA by incorporating a local search strategy for resource-constrained project scheduling. The local search strategy employed can improve the efficiency of the search while maintaining the underlying randomness of the GA algorithm.

GAs work through a sequential procedure that processes a population of artificial chromosomes into subsequent new populations. There are five main processes used in the genetic algorithm, namely: initial population setup, fitness calculation, chromosome selection, chromosome crossover and mutation. In this section, we will developed a modified GA to solve the proposed model (9).

- **Representation Structure**

A feasible solution to the bus timetabling problem is a vector of the headway times of bus trips $v = (H_{12}, H_{23}, \cdots, H_{K-1,K})$, where $H_{k-1,k}$ is the headway time between the k–1-th bus trip and the k-th bus trip. Figure 1 shows the structure of a chromosome in such a GA-based solution, where t_{11} denotes the departure time of the first bus trip from the starting stop within a given day, i.e., $t_{11} = T_s$, and t_{K1} denotes the departure time of the last bus trip from the starting stop in that day, i.e., $t_{K1} = T_e$. Then the departure time of the k-th bus trip from the starting stop can be obtained by a recursive equation $t_k = t_{k-1} + H_{k-1,k}$.

Fig. 1: Structure of chromosome

- **Initialization**

Define an integer *pop_size* as the size of population. Use the MATLAB function *randfixedsum* to randomly generate $K-1$ numbers $H_{k-1,k}, k = \{2, 3, \cdots, K\}$ from $[H_{min}, H_{max}]$ satisfying $\sum_{i=2}^{K} H_{k-1,k} = T_e - T_s$ to obtain a feasible chromosome. Repeat the above procedures *pop_size* times to generate the initialized population $v_i, i = 1, 2, \cdots, pop\_size$.

- **Evaluation Function**

Evaluation function assigns each chromosome a probability of reproduction so that its likelihood of being selected is proportional to its fitness relative to the other chromosomes in the population. That is, the chromosomes with a higher fitness will have more chance to produce offspring.

For the current programming problem, a chromosome with a smaller objective value is better. Rearrange the *pop_size* chromosomes from high quality to low based on their objective values. Then, the fitness of the ith chromosome v_i can be calculated using the evaluation function as defined by

$$Eval(v_i) = \alpha(1-\alpha)^{i-1}, \quad i = 1, 2, \ldots, pop\_size,$$

where α is a real number in $(0, 1)$. This evaluation function can assign each chromosome a fitness value in $(0, \alpha] \subseteq (0, 1)$, which can effectively avoid that the GA falls into a local optimal solution. Furthermore, this evaluation function is very easy to calculate, which is benefit for the running speed of GA.

- **Selection Process**

The method of spinning the roulette wheel is used here to select chromosomes which breed a new generation. First, calculate the reproduction probability q_i for each chromosome $v_i, i = 1, 2, \cdots, pop\_size$, as follows

$$q_0 = 0, \quad q_i = \sum_{j=1}^{i} Eval(v_j), \quad i = 1, 2, \ldots, pop\_size.$$

Second, generate a random number r in $(0, q_{pop\_size}]$, and select the chromosome v_i such that $q_{i-1} < r \leq q_i$. Repeat the second step pop_size times and obtain pop_size chromosomes. It is obvious that the chromosomes with larger fitness are typically more likely to be selected.

- **Self-crossover Process**

Crossover is one of the commonly applied operations for generating a new population in GAs. Once the parent chromosomes are selected, the crossover operator will be applied onto the parent chromosomes to create children. Here, we propose a self-crossover operation as follows. Randomly select a chromosome v as a parent. Suppose that the probability of crossover is P_c. Generate a random number r from $[0, 1]$, and if $r \leq P_c$, conduct the following crossover operation: Firstly, randomly select two disjoint gene sections with equal length. Secondly, exchange the two corresponding gene sections to obtain a child chromosome, as shown in Figure 2. This self-crossover operation can ensure that the child chromosome satisfies $\sum_{i=2}^{K} H_{k-1,k} = T_e - T_s$. Repeat the above process pop_size times to generate a new population.

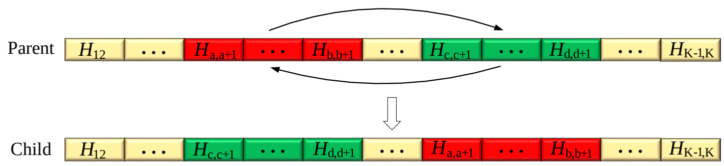

Fig. 2: Self-crossover operation

- **Mutation Process**

For each chromosome, set the probability of mutation to be P_m. Randomly generate a real number r from $[0, 1]$. If $r < P_m$, the chromosome is selected as a parent to conduct the mutation operation. Firstly, randomly select a gene section with length N. Denote SUM as the sum of the selected N genes. Secondly, use the MATLAB function *randfixedsum* to randomly generate N numbers from $[H_{min}, H_{max}]$ satisfying the sum of N numbers is SUM. Thirdly, obtain a new child chromosome using the newly generated N numbers to replace the selected gene section, as shown in Figure 3.

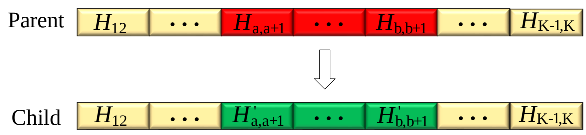

Fig. 3: Mutation operation

• **General Procedure**

Following selection, crossover and mutation operations, a new population is generated. The GA will terminate after a given number of iterations of the above steps. The general procedure for such a GA is summarized in Algorithm 1.

Algorithm 1	Genetic Algorithm
Step 1	Randomly initialize *pop_size* chromosomes.
Step 2	Calculate the objective values for all chromosomes.
Step 3	Evaluate the fitness of each chromosome via the objective value.
Step 4	Select the chromosomes by spinning the roulette wheel.
Step 5	Update the chromosomes using crossover and mutation.
Step 6	Repeat Step 2 to Step 5 for a given number of iterations G.
Step 7	Report the best found chromosome as the optimal solution.

Remark 1 Consider that the self-crossover operation being an internal crossover, we can properly increase the probability of mutation P_m in order to generate more new chromosomes for a given practical application.

4 Case study

In this section, we validate the proposed model based on a real-world bus line, Yuntong 128 bus line, in Beijing. In Section 4.1, we introduce the characteristics of Yuntong 128 bus line. The experimental results are presented in Section 4.2, and a comparative study is conducted in Section 4.3.

4.1 Overview of Yuntong 128 bus line

Yuntong 128 bus line runs from BEI JING SHI SHANG YE XUE XIAO stop to LAI GUANG YING BEI stop, as shown in Figure 4. It is 21.44 km long with 31 bus stops, that is $I = 31$. The operation duration in any one day is from 5:30 to 22:00, that is, $T_s = 5:30$ and $T_e = 22:00$. The bus line is

Fig. 4: Route of Yuntong 128 bus line

required to complete 74 trips in one direction every day, that is $K = 74$. The maximum headway time between two adjacent bus trips is $H_{max} = 20$ min, and the minimum headway time between two adjacent bus trips is $H_{min} = 8$ min.

4.2 Data preparation

The field data about Yuntong 128 bus line were obtained from Beijing Transportation Information Center, including the distance between stations and bus GPS data. We partition the whole day (5:30-24:00) into 74 time intervals with equal length of 15 minutes. After statistically processing the field data, a running speed matrix $V = [v^l_{i,i+1}]_{30\times 74}$ can be obtained, an element of which means the running speed of a bus from stop i to stop $i+1$ in the l-th time interval. Figure 5 shows the running speed from YAN CHENG YUAN LU

KOU NAN stop to QI XING LU NAN KOU stop. We can observe that the running speed can change very violently in a day.

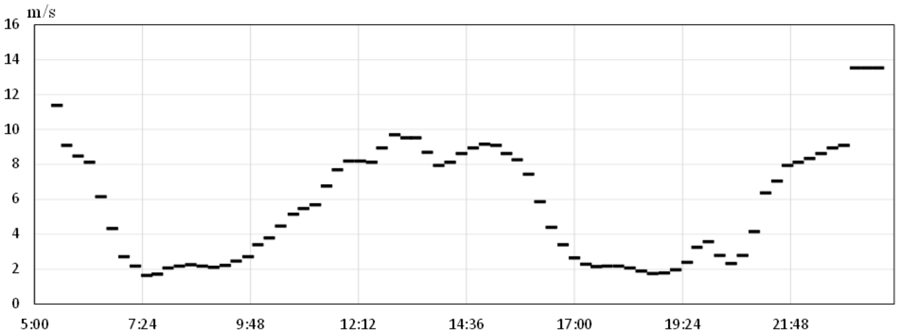

Fig. 5: Running speed from YAN CHENG YUAN LU KOU NAN stop to QI XING LU NAN KOU stop

4.3 Results

According to the inherent characteristics of the buses running on this line, the parameters in the speed-fuel consumption equation can be specified as $a = 15343.559, b = 334.436, c = -1.916, d = 0.039, e = 0, f = 0, g = 0, h = 0.037$. The unit fuel price is $p = 6.43$ Yuan/L. The GA parameters are obtained empirically: $G = 500, pop\_size = 200, \alpha = \frac{1}{2}, P_c = 0.8$ and $P_m = 0.7$.

We run the proposed GA on a personal computer with 4GB RAM and Inter(R) Core(TM) i7-6500U 2.50GHz CPU to obtain the optimized bus timetable. The minimum fuel consumption cost in one day is 3351 Yuan. The convergence of optimal objective value is shown in Figure 6, which indicates the proposed GA is effective to solve the proposed model.

4.4 Comparison

The timetabling model proposed in this study assumes that the running speed is time-dependent. Based on historical GPS data, a bus' running speed between each pair of adjacent stops in each 15 min interval is obtained. However, when timetabling in practice, bus carriers do not necessarily have a precise record of the GPS data. What they do as a rule of thumb is to use a sampling method, which usually can only estimate a bus' running speed between each pair of adjacent stops within one hour interval. In order to verifying the necessity of this consideration of time-dependent running time within the present study, we compare the proposed timetabling model with the following three other timetabling models:

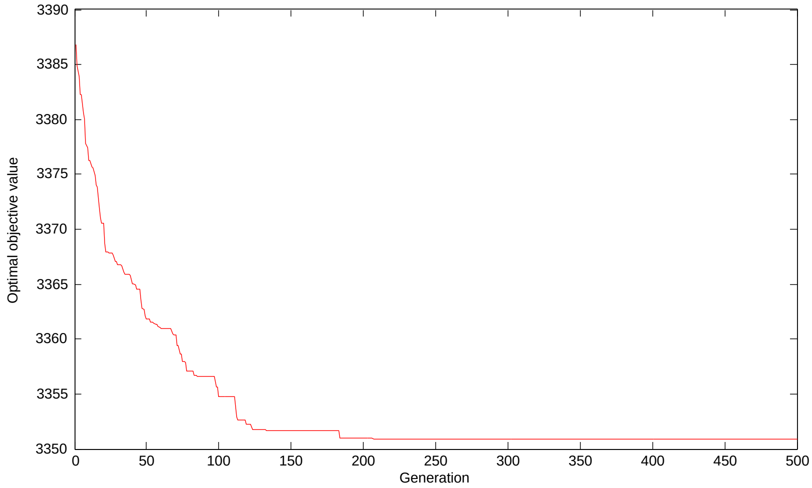

Fig. 6: Convergence of GA

1. Timetabling model with minimum running speed. The running speed between each pair of adjacent stops is set to a constant value within each hour, which is estimated as the minimum value in the four 15 min intervals.
2. Timetabling model with maximum running speed. The running speed between each pair of adjacent stops is set to a constant value within each hour, which is estimated as the maximum value in the four 15 min intervals.
3. Timetabling model with average running speed. The running speed between each two adjacent stops is set to a constant value within each hour, which is estimated as the average value in the four 15 min intervals.

The comparison results are listed in Table 2. For the timetabling model with minimum running speed, the fuel consumption cost is 2880 Yuan, whose deviation ratio from that of the timetabling model with time-dependent running speed is $|2880 - 3351|/3351 \approx 14.06\%$. For the timetabling model with maximum running speed, the fuel consumption cost is 3979 Yuan, whose deviation ratio from that of the timetabling model with time-dependent running speed is $|3979 - 3351|/3351 \approx 18.74\%$. For the timetabling model with average running speed, the fuel consumption cost is 3529 Yuan, whose deviation ratio from that of the timetabling model with time-dependent running speed is $|3529 - 3351|/3351 \approx 5.31\%$. As we can see, the averaged deviation ratio between the fuel consumption cost estimated by three alternative timetabling models and that estimated by the proposed timetabling model with time-dependent running speed is $(14.06\%+18.74\%+5.31\%)/3 \approx 12.7\%$. This clearly shows the advantage of the work developed herein.

Table 2: Comparison results

	Total fuel consumption cost (Yuan)	Deviation ratio
Time-dependent running speed	3351	0%
Minimum running speed	2880	14.06%
Maximum running speed	3979	18.74%
Average running speed	3529	5.31%

5 Conclusion and future work

In this study, a computational model has been proposed for the problem of bus timetabling while considering time-dependent road conditions. The objective of this work is to minimize the total fuel consumption cost of bus trips within a given timeframe (which is set to one day in the experimental investigation, though other durations may be used). Based on historical GPS data, a bus' speed between each pair of adjacent stops is formulated as a step function. A genetic algorithm with self-crossover operation is used to solve the proposed integer nonlinear programming model. The chromosomes are represented as the headway times between two adjacent bus trips.

A real-world case study, running over Yuntong 128 bus line in Beijing, has been presented to demonstrate the efficacy of the proposed model and GA-based solution. In order to verify the necessity of this study, the proposed timetabling model with time-dependent running speed is compared with three different timetabling models: minimum running speed, maximum running speed and mean running speed. The results show that the averaged deviation ratio between the fuel consumption cost estimated by three other timetabling models and that estimated by the timetabling model with time-dependent running speed is 12.7%. This study therefore, offers an effective means to provide optimization support for the preparation of operation plans of bus carriers. The methods presented in this study are designed for but not limited to bus timetabling. It can be extended to the timetabling and operations management for train, ferry and other types of passenger transport.

In this study, the number of bus trips in one day is given in advance. Research related to the optimal timetable design can be developed further by investigating various challenging problems, including the consideration of: different evaluation mechanisms, optimization of the number of buses, optimization of the number of bus trips, and the crew scheduling. These issues are all of great practical significance and will be addressed in future research.

Compliance with ethical standards

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Conflict of interest

All authors declare that they have no conflict of interest in this research.

Human and animal rights

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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