



Optimising Electric Bus Departure Interval Considering Stochastic Traffic Conditions

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ABSTRACT

Electric buses (EBs) have attracted more and more attention in recent years because of their energy-saving and pollution-free characteristics. However, very few studies have considered the impact of stochastic traffic conditions on their operations. This paper focuses on the departure interval optimisation of EBs which is a critical problem in the operations. We consider the stochastic traffic conditions in the operations and establish a departure interval optimisation model. The objective function aims at minimising passenger travel costs and enterprise operation costs, including waiting time costs, congestion costs, energy consumption costs and operational fixed costs. To solve this problem, a genetic algorithm (GA) based on fitness adjustment crossover and mutation rate is proposed. Based on the Harbin bus dataset, we find that improved GA performance is 4.481% higher, and it can solve the models more accurately and efficiently. Compared with the current situation, the optimisation model reduces passenger travel costs by 20.2% and helps improve passenger travel quality. Under stochastic traffic conditions, total cost change is small, but passenger travel costs increase significantly. This indicates the high impact degree of random traffic conditions on passenger travel. In addition, a sensitivity analysis is conducted to provide suggestions for improving the EBs operation and management.

KEYWORDS

electric buses; public transit; departure interval; stochastic traffic conditions; genetic algorithm.

1. INTRODUCTION

In recent years, with the aggravation of the fuel resource shortage problem and the increasing environmental pressure, the public's attention to energy conservation and environmental protection has been greatly increased. In the sector of transportation, more and more fuel vehicles are being replaced by electric vehicles (EVs). Conventional fuel buses emit high levels of CO₂ in the air, leading to various environmental problems and degradation [1]. Compared with fuel vehicles, EVs have the benefits of reducing on-road pollution and high-quality on-board experiences, which is of great significance to reducing carbon emission, optimising the energy structure, ensuring energy security and other aspects [2]. There is evidence showing that the role of EBs in public transport is very important if we are to slow down climate change and reduce the impacts of fossil fuels on the environment [3].

Recently, EBs have received significant attention from the world and have also been used on a large scale in several countries [4]. The large-scale use of EBs may be motivated by government incentives, such as the TIGER programme in the US and the Green Bus Fund Programme in the UK. The German government also initiated a programme, Electric Mobility, to motivate research and development of transportation electrification [5]. According to Bloomberg New Energy Finance [6], the global market sales of EBs can account for

close to 80% by 2040, and EBs will account for more than 67% of the overall global bus fleet. The large-scale use of EBs may have started during the Beijing Olympics and the Shanghai World Expo. For example, more than 80 EBs were used in the Shanghai World Expo [4]. Among the world's new energy buses, China contributes 95%, which has the world's largest new energy bus fleet and has made remarkable achievements in the number of promotions.

Although EBs can achieve “zero emissions” in the operation process and are very environmentally friendly, they also have many shortcomings because of their construction. Compared with fuel buses, EBs have a limited battery capacity, leading to a shorter driving range per charge, which results in range anxiety [2]. Under a cold environment, the performance of the EBs power battery will be affected, which leads to great discharge instability [7]. By introducing EBs into the public transportation system, new challenges will appear in the ordinary public transportation operation and scheduling process [8]. Due to the limitations of the EBs technologies, the operation and scheduling mode of fuel buses is no longer applicable, and further adjustments have to be made to the current EBs transport planning and scheduling problems [9].

The bus operation and scheduling problem can be divided into three subproblems: timetabling, vehicle scheduling and crew scheduling [10]. These three subproblems are progressive relationships, in which the most basic one is the optimisation of the timetable. In the real operation process, bus operators/enterprises often make bus operation timetables to maximise their interests, which is unreasonable. Making bus operation timetables needs to comprehensively consider the interests of both operators and passengers so that the two can achieve a dynamic balance. The vehicle scheduling problem (VSP) aims to minimise the total number of vehicles used by rationally scheduling timetables and thus reducing total costs. When EBs are widely used in a public transport service, the scheduling problem is known as the electric vehicle scheduling problem (EVSP), which can be viewed as an extension of the VSP [11]. Unlike VSP, the EVSP is concerned with finding a vehicle scheduling timetable that covers the trips and satisfies the driving range and recharging requirements of EBs while minimising operational costs [9]. According to the number of depots involved, it can be divided into single depot scheduling problems and multiple depot scheduling problems (MDVSP). In China, bus operation and scheduling are generally handled by multiple enterprises, and buses are not allowed to operate across the lines. Therefore, it can be regarded as a simple single depot scheduling problem, which can be further simplified to the optimisation of the scheduling timetable.

In terms of bus operation and scheduling problems, many scholars have studied the optimisation of the scheduling timetable. Shui et al. [12] proposed a vehicle scheduling approach based on a clonal selection algorithm. An initial vehicle scheduling solution was produced and two heuristics were used to adjust the departure times of vehicles. Häll et al. [8] changed the timetabling and vehicle scheduling components with efficient and optimal methods considering the possibility of altering the existing network of routes. Jiang et al. [2] addressed a multiple depot EBs scheduling problem considering limited charging facility capacity and vehicle-depot constraint. Alwesabi et al. [13] have introduced joint and disjoint scheduling planning strategies for the current conventional bus fleet and the potential EBs fleet. Janoveca and Koháni [14] proposed a model for the EBs scheduling problem and tested the performance of the model on the dataset from the public transport system.

The above studies are all under certain traffic conditions. However, a lot of stochastic traffic conditions will add up to the scheduling process of public transport services when EBs are applied, such as stochastic passenger travel demand, stochastic bus speed, stochastic urban traffic conditions, battery discharge fluctuations etc., which will prevent EBs from following the established scheduling timetable. Some scholars have studied the stochastic traffic conditions of EBs scheduling problems. Tang et al. [15] proposed both static and dynamic scheduling models for trip time stochasticity and stochastic traffic conditions, respectively. Hadas and Shnaiderman [16] proposed a new approach to service frequency setting, which integrated costs, stochastic demand and travel time. Bie et al. [17] developed a scheduling method for the EBs route considering stochastic volatilities in trip travel time and energy consumption. Shen et al. [18] proposed a novel probabilistic model of VSP with the objectives of minimising the total cost and maximising the on-time performance. Although some scholars have studied the impact of stochastic traffic conditions on EBs scheduling, they mainly focus on the phenomenon, which is inconsistent with the actual operating conditions.

VSP is an important class of problems studied by many researchers in operations research and most of them are NP-hard, which means exact methods often cannot solve large instances encountered in practice [19]. At present, Lagrangian algorithm, column generation algorithm and heuristic algorithm are commonly used

to solve these problems. Teng et al. [20] developed a multi-objective particle swarm optimisation to get the Pareto-optimal solution set. Perumal et al. [21] proposed an adaptive large neighbourhood search that utilises branch-and-price heuristics to tackle the E-VCSP. Potthoff et al. [22] presented an algorithm based on column generation techniques combined with Lagrangian heuristics to reschedule the crews when a disruption of the railway network occurred. Huisman et al. [23] presented two different algorithms based on a combination of column generation and Lagrangian relaxation for integrated vehicle and crew scheduling in the multi-depot case.

To address VSP considering stochastic conditions, GA has good global search ability and better algorithmic adaptability compared with other algorithms. Xiong et al. [11] investigated a mixed optimal scheduling problem of an EBs fleet and charging infrastructure based on the plug-in charging mode and a GA procedure was proposed to solve the scheduling problem. Jiang et al. [24] proposed a long short-term memory model to predict bus travel time, developing a GA to improve the model's performance in terms of accuracy and efficiency. Gkiotsalitis et al. [25] developed a framework for allocating buses to lines in order to reduce costs and developed a GA meta-heuristic to solve the constrained optimisation problem. Li et al. [26] developed a hybrid intelligent algorithm to solve the model. Stochastic simulation and GA were both used to deal with the stochastic conditions.

As mentioned above, the current studies on the optimisation of EBs scheduling timetable are mostly based on determined conditions, seldom considering stochastic conditions in the scheduling process; in the studies discussing the stochastic conditions, most of them also ignore the stochasticity of EBs speed and the fluctuation of battery discharge. To fill these gaps, this paper investigates stochastic passenger travel demand, stochastic EBs speed and the power battery discharge fluctuations in the process of operation and builds the departure interval optimisation model based on multiple costs consisting of the waiting time cost, congestion cost, energy consumption cost and operational fixed cost. Then, an improved GA programme is designed to solve this problem. The solution approach is tested in a real-life case study and the results show the effectiveness of the proposed solution. At last, we perform sensitivity analyses to validate model features and make some reasonable suggestions. The main contributions of this paper are as follows.

It integrates passenger travel cost and enterprise operation cost and establishes a multi-cost departure interval optimisation model. The model can maximise the social welfare of EBs by calculating the passenger and enterprise costs.

It breaks traditional EBs scheduling research limitations, considers the influence of stochastic traffic conditions on EBs scheduling, and can more accurately achieve EBs scheduling optimisation.

It complements the traditional GA by optimising the crossover and mutation rates. The method can retain the advantages of the parents while ensuring the diversity of the population, making it possible to solve the problem more efficiently and accurately.

The remainder of this paper is organised as follows. Section 2 proposes the departure interval optimisation model and revises objective functions and constraints considering several stochastic traffic conditions. A GA that adjusted the process of crossover and mutation is developed to solve the departure interval optimisation problem. Then, section 3 provides a real-world case study by testing the solution approach and sensitivity analysis and discusses some suggestions to improve EBs operation. Finally, section 4 concludes the research findings and discusses further research directions.

2. METHODOLOGY

2.1 Problem description

The departure interval of EBs not only affects the passenger travel experience but also is closely related to the enterprise operation interest. Although shortening the departure interval can save passenger waiting time and reduce travel congestion, the fixed cost and the energy consumption cost will increase at the same time, which may cause unnecessary resource waste. On the other hand, the convenience of passengers will be greatly reduced with the departure interval increasing, which does not meet the attributes of public transportation. Therefore, determining the appropriate departure interval and setting a timetable is an important part of the operation and management of EBs.

At the same time, passenger travel demand is constantly changing at different times one day, so to maximise social benefits, departure intervals need to be constantly adjusted to meet travel demand. In this paper, we construct a multi-cost departure interval optimisation model by analysing the waiting cost, congestion cost, energy consumption cost and operational fixed cost. However, there are many stochastic traffic conditions in real operation, such as randomness in passenger travel demand, fluctuations in battery discharge and traffic status, and so on. General departure interval optimisation models are unable to respond effectively to this. We should analyse the impact of various stochastic traffic conditions on the operation, and optimise the departure interval optimisation model to calculate the optimal scheme of EBs departure interval in real operation scenarios.

2.2 Model assumptions

To ensure the model’s simplicity and the data correctness, we make the following assumptions:

- 1) Passenger travel demand is evenly distributed at all stations.
- 2) We assume that the EBs are fully charged at the beginning of the day.
- 3) The traffic conditions up and down of EBs lines are the same.

The list of sets, parameters and variables for the model are given in *Table 1*.

Table 1 – Definitions of parameters and variables for the model

Variables		Notation	Units
Decision variables	The departure interval of time i	t_i	min
	The cost of type j	Z_j	RMB
	The cost weight of type j	α_i	-
Model parameters	The congestion response of time i	J_i	-
	The passenger travel demand of time i	T_i	Person
	The speed of time i	v_i	m/s
	Unit waiting time cost	φ	RMB·min ⁻¹
	The price of electricity	β	RMB·kWh ⁻¹
	Unit passenger congestion cost	γ	RMB·Person ⁻¹
	Unit task cost	c_0	RMB·count ⁻¹
	EBs’ weight	M_0	kg
Fixed variables	Average weight of a passenger	m_0	kg
	Fixed handover time	t_r	min
	Maximum battery capacity	Q_{max}	kWh
	EB’s number	N	veh
	EBs’ capacity	C	Person
	EBs charging power	P	kW
	Bus line mileage	L	m

2.3 Departure interval optimisation model based on multi-cost

Since the purpose of public transportation is to provide convenient travel for the public, we establish the objective function from the perspective of passenger travel and enterprise operation, including waiting time cost Z_1 , congestion cost Z_2 , energy consumption cost Z_3 and operational fixed cost Z_4 . The objective function is

$$\min \{ \alpha_1 (Z_1 + Z_2) + \alpha_2 (Z_3 + Z_4) \} \tag{1}$$

Waiting time cost. EBs run at a certain speed during the period i , so the arrival interval is fixed, and the average waiting time is half of the departure interval $t_i^w = 0.5t_i$. Waiting time cost is the sum of all passengers’ waiting time multiplied by the unit waiting time cost:

$$Z_1 = \sum_{i=1}^n 0.5\varphi t_i T_i \tag{2}$$

Congestion cost. The congestion not only affects the comfort of passengers but also leads passengers to give up taking EBs. The congestion cost is the mixed product of unit passenger congestion cost, the congestion response as well as the number of passengers:

$$Z_2 = \sum_{i=1}^n \gamma J_i T_i \tag{3}$$

Tang et al. [27] used a 100% congestion rate as the cut-off point for congestion cost response. However, in real life passengers will choose to stand although there are a lot of seats left, which means the personal space between each other is very narrow, resulting in congestion costs. So, we adjust the congestion response as:

$$J_i = \begin{cases} \frac{T_i t_i}{60C}, & \frac{T_i t_i}{60} \geq 0.6C \\ 0, & \frac{T_i t_i}{60} < 0.6C \end{cases} \tag{4}$$

Energy consumption cost. We use the following formula to calculate the energy consumption per unit distance at a certain speed [15]:

$$f(v) = \frac{1}{\eta} \left(\frac{1}{2} \rho C_w A_f v^2 + \mu M g \cos \alpha + M g \sin \alpha \right) \tag{5}$$

where $f(v)$ represents the energy consumption per unit distance with respect to the prevailing driving speed v ; the parameter ρ is the air density (kg/m^3); C_w represents the coefficient of drag; A_f denotes the frontal area of a bus (m^2); μ is the friction coefficient; M is the weight of a car (kg), included EB and passengers; g is the gravitational constant (m/s^2); η is an efficiency parameter to account for all complexities of battery and various losses; α represents the angle of road (radians), which represents the road slope.

$$Z_3 = \sum_{i=1}^n 60\beta f(v_i) L t_i^{-1} \tag{6}$$

Operational fixed cost. The fixed operating cost consists of battery loss, vehicle wear, driver labour cost, etc. incurred by each travel task:

$$Z_4 = \sum_{i=1}^n 60c_0 t_i^{-1} \tag{7}$$

We specify six constraints for the actual operation of EBs, as follows

$$t_{min} \leq t_i, i \in [1, n] \tag{8}$$

$$t_i \leq t_{max}, i \in [1, n] \tag{9}$$

$$\frac{2(60^{-1} L v_i^{-1} + t_r)}{N} \leq t_i, i \in [1, n] \tag{10}$$

$$\frac{T_i t_i}{60C} > \eta_{min}, i \in [1, n] \tag{11}$$

$$\tag{12}$$

$$N Q_{max} + \sum_{j=1}^i 60 t_j^{-1} t_r P - \sum_{j=1}^i 60 f(v_j) L t_j^{-1} \geq 0.3 N Q_{max}, i \in [1, n] \tag{13}$$

Equations 8 and 9 are constraints of departure interval to prevent waste of energy consumption and decline of passengers' convenience. Equation 10 guarantees drivers get enough rest and provide enough handover time between two tasks. Equations 11 and 12 are constraints of congestion rate to guarantee a certain level of service.

Equation 11 avoids deadhead travel. Equation 12 allows only a certain overload for EBs. Equation 13 ensures that the state of charge (SOC) is maintained at a normal level. This paper uses 30% as SOC.

2.4 Departure interval optimisation model considering stochastic traffic conditions

In this section, we consider the impact of three stochastic traffic conditions on EBs operations. This paper then revises the objective function and constraints of the model based on their characteristics.

Stochastic passenger travel demand

Not only does travel demand change over different times but also the number of passengers is not constant at the same time. Passenger travel demand is a random variable, $P(T_i = k)$ represents the probability that passenger travel demand is k in time i .

Only when $J_i > 0.6$, congestion cost is calculated. When passenger travel demand is a random variable, the calculation of congestion cost needs to introduce the concept of probability. If passenger travel demand is k , congestion cost is:

$$Z_2(k) = \begin{cases} \sum_{i=1}^{12} \gamma J_i k, & \frac{kt_i}{60} \geq 0.6C \\ 0, & \frac{kt_i}{60} < 0.6C \end{cases} \tag{14}$$

So congestion costs are integrated with respect to various probabilities, as:

$$Z_2 = \sum_{i=1}^{12} \left(\int_{60^{-1}kt_i \geq 0.6C} 60^{-1} C^{-1} \gamma t_i k^2 P(T_i = k) dk \right) \tag{15}$$

Since passengers travel demand is a random number, Equations 11 and 12 should be revised to:

$$P\left(\frac{T_i t_i}{60C} < \eta_{min}\right) < 0.5\alpha, \quad i \in [1, n] \tag{16}$$

$$P\left(\frac{T_i t_i}{60C} > \eta_{max}\right) < 0.5\alpha, \quad i \in [1, n] \tag{17}$$

Equations 20 and 21 represent confidence level $1-\alpha$, which ensures that the congestion rate of electric buses is within the range $[\eta_{min}, \eta_{max}]$.

Stochastic speed

The speed of EBs on urban roads is not constant, and the fluctuations range also varies with time. Normal distribution is often used to describe the distribution of speed [28]. In time i the speed of EBs is $v_i \sim N(\bar{v}_i, \sigma_i^2)$, where \bar{v}_i and σ_i^2 are the mean and variance of EBs speed at time i , respectively.

When EBs speed changes, the delay of arrival caused by stochastic speed will affect passengers' waiting time t_i^w .

Take any line as the research object, and divide it into m segments in equal parts. When considering the stochastic speed, each segment of travel time is related to each segment of speed. The total travel time t_b of a task is the sum of each segment, so $t_b = \sum_{j=1}^m \frac{l_j}{u_j} = \frac{L}{m} \sum_{j=1}^m \frac{1}{u_j}$, where l_j and u_j are the distance and speed of part j , and u_j follows $N(v, \sigma^2)$.

Regardless of speed fluctuations, the travel time of a task is $t_n = \frac{L}{v}$.

Because $u = \frac{L}{t_b} = \left(\frac{1}{n} \sum_{j=1}^m \frac{1}{u_j} \right)^{-1}$ is like the space mean speed of the bus line, and v is the time mean speed, we

know that $u = v - \frac{\sigma^2}{v}$, so $t_b = \frac{L}{v - \sigma^2 v^{-1}}$.

Thus, considering the speed fluctuations, passengers average waiting time at time i is:

$$t_i^w = \frac{t_i}{2} + \frac{1}{2} \left(\frac{L}{v_i - \sigma_i^2 v_i^{-1}} - \frac{L}{v_i} \right) \tag{18}$$

Then the passengers' waiting cost is revised to:

$$Z_1 = \sum_{i=1}^n \phi t_i^w T_i \tag{19}$$

Battery discharge fluctuations

As the EBs battery discharge is easily affected by other factors such as urban traffic characteristics and EBs travel conditions etc., the energy consumption fluctuation is revised to:

$$f(v_i) = \frac{\kappa_i}{\eta} \left(\frac{1}{2} \rho C_w A_f v_i^2 + \mu M g \right) \tag{20}$$

where κ_i is the battery discharge correction factor, and it is a random variable.

In summary, under considering stochastic traffic conditions the objective function is the expectation of total cost:

$$\min \{ E(\alpha_1 (Z_1 + Z_2) + \alpha_2 (Z_3 + Z_4)) \} \tag{21}$$

2.5 Genetic algorithm

The GA has good global search ability and can quickly search out a satisfactory solution in the solution space. The selection, crossover and mutation of GA have a great influence on itself, which means that the problem of premature convergence often appears due to the wrong crossover rate and mutation rate. Therefore, we optimise the crossover and mutation based on chromosome fitness to improve the efficiency and accuracy of GA.

The framework for this process is shown in *Figure 1*.

Initial population generation

This paper uses binary coding and the chromosome includes departure interval information in which each gene length is 5, so the chromosome length is 5n. Each gene is converted to decimal to calculate its phenotype, and the phenotype of the gene i can be calculated as:

$$t_i = \frac{t_{max} x_i}{x_{max}} \tag{22}$$

where x_i is a phenotype of one gene; x_{max} is the biggest phenotype, in this model $x_{max} = 2^5 - 1$.

In *Figure 2* the departure interval of time 1 and time n are 5.9 min and 1.4 min, respectively.

Population initialisation uses the method of random generation, in which the optimal individual is selected to join the initial population and this process is repeated until the target population size is reached.

Crossover

During crossover, the parents' chromosome fragments are exchanged to form the offspring. If the crossover rate is too large, it will cause the parent genotype with higher fitness not to survive to the next generation, so this paper modifies the crossover rate based on the fitness, and the crossover rate of chromosome i is

$$pc_i = pc_0 \frac{f_{ave}}{f_i} \tag{23}$$

where pc_0 is the average crossover rate; f_{ave} is the average fitness of the population; f_i is the fitness of chromosome i . When the population gap is not large, the difference in chromosomes' crossover rate is also not large.

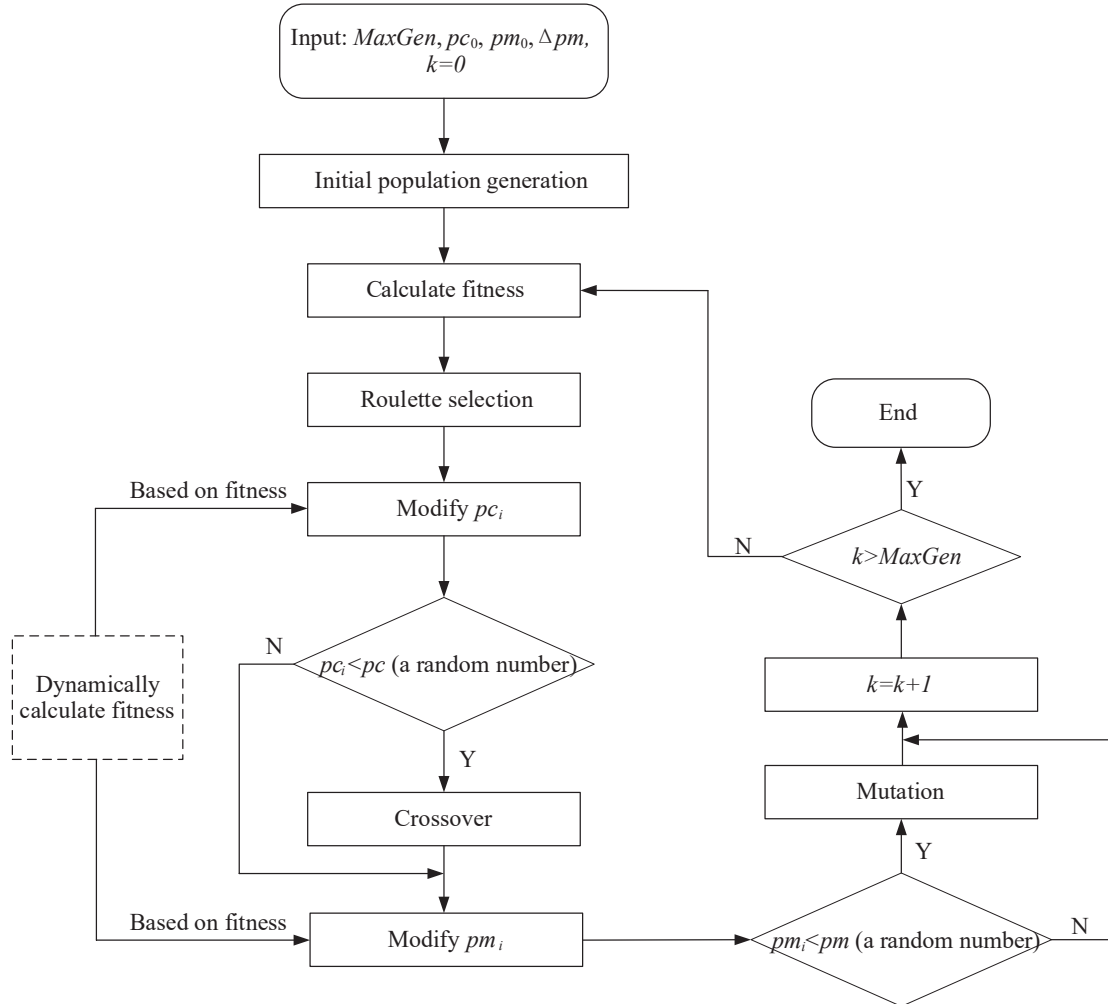


Figure 1 – Framework of the GA



Figure 2 – Schematic diagram of chromosomes

Since the departure interval of each time is independent of each other, this paper decides on the crossover range based on gene location in order to facilitate the child to fully obtain the advantages of parents. The start position of the crossover is randomly selected, and the end position of the crossover is the end of the gene where the starting point is located. As shown in Figure 3 below, the crossover position is selected at the second part of the second gene where the length of crossover is 4, and the result of the offspring is as follows.

Mutation

The mutation may be counterproductive when the fitness of the parent is already large, but a certain mutation rate is conducive to maintaining population diversity. This paper adjusts the mutation rate based on the fitness and the mutation rate is small when the fitness of the parent is large, and vice versa. The mutation rate of chromosome i is calculated as:

$$pm_i = pm_0 + \frac{f_{max} - f_i}{f_{max} - f_{min}} \Delta pm \tag{24}$$

where pm_0 is the basic mutation rate, in order to ensure population diversity; f_{min} and f_{max} are the smallest and biggest fitness; Δpm is the change’s degree of mutation rate.

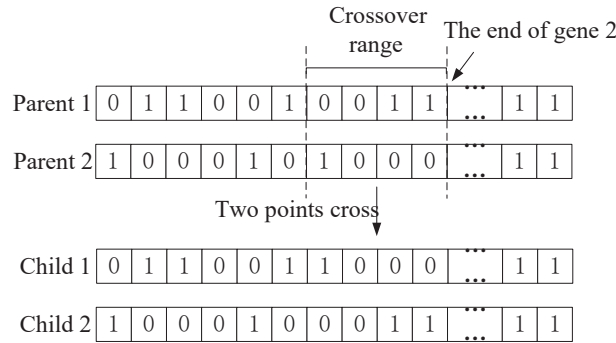


Figure 3 – Illustration of crossover

3. RESULTS AND DISCUSSION

3.1 Case study and parameters description

In this section, we test the model based on real-world data from line 206 in Harbin, China. The one-way travel distances are 26 km and the type of EBs used in line 206 is YUTONG E10 whose relevant technical indicators are shown in Table 2. Harbin’s speed data come from the AutoNavi Big Data Platform and Baidu Map Traffic Big Data Platform.

Table 2 – Values of relevant technical indicators

Technical indicators	Value
M_0	16,500 kg
Q_{max}	181 kWh
N	36 veh
A_f	2.27 m ²
η	0.9
C_w	0.29
μ	0.012
α	0
C	32
β	0.82 RMB·kWh ⁻¹
c_0	50 RMB·count ⁻¹

In order to ensure a certain service level for EBs, we stipulate that t_{min} is 3 min and t_{max} is 15 min. The maximum congestion rate acceptable to passengers is 200%, and the minimum is 10%. Based on another study [29], the unit passenger congestion cost γ is 0.69 RMB·People⁻¹. According to Harbin’s minimum hourly wage regulations, the unit waiting time cost is 0.3 RMB·min⁻¹.

3.2 General optimisation model solving

The parameters of the GA are set as follows: population size is 1,000, $pc_0=0.6$, $pm_0=0.005$, $\Delta pm=0.005$, MaxGen=1,000. All experiments were run on a PC with Windows 10, AMD Ryzen 9 5900HX, 3.30 GHz and 32 GB RAM.

Experiments are performed to test the difference between the solution results of the improved GA and the general GA. Table 3 shows the results of each algorithm including the average, minimum and standard deviation of the objective function of the last-generation population.

Table 3 – Results of each algorithm

Algorithm	Average value	Minimum	Sd
Improved GA	5287.128	5056.680	186.667
General GA	5535.174	5107.690	276.877

As indicated in Table 3, improved GA has better performance than general GA. The value of its objective function is relatively small and the average can be decreased by 4.481%. Moreover, the standard deviation of the improved GA is small, indicating that it has better stability. So improved GA can solve the models more accurately and efficiently.

In China, some companies are in charge of the operation and management of EBs and they tend to value their profits, leading to the weight of enterprise operation costs on the high side. To facilitate government management of EBs, we calculate the model objective function under the different enterprise operating cost weights, as shown in Figure 4.

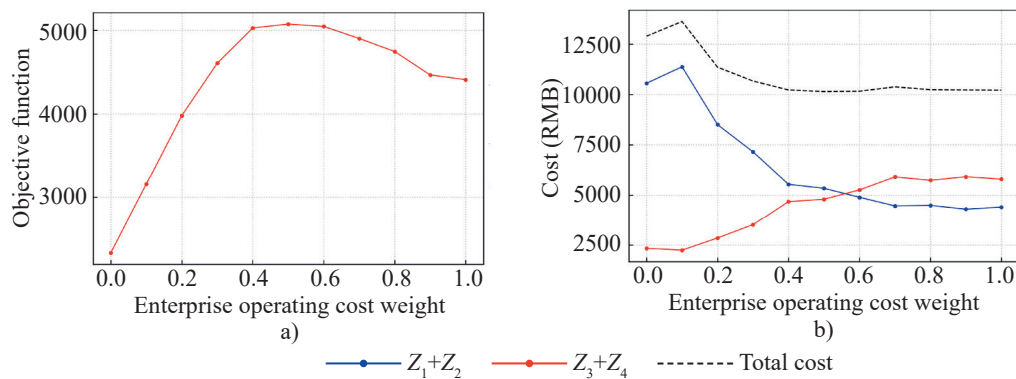


Figure 4 – Objective function and cost vary with enterprise operating cost weight

From Figure 4a, the value of the objective function first increases with the increase of the enterprise cost weight. When the weight is 0.5, the objective function is 5072.680 at most and then decreases as the weight increases. According to Figure 4b, the total cost of passenger travel and enterprise operation decreases with the increase of enterprise cost weight, and the decrease is very insignificant after being greater than 0.4. Moreover, when the cost weight of the enterprise is greater than 0.7, the passenger travel cost and the operating cost of the enterprise do not change much, which can indicate that if the enterprise attaches too much importance to its interests, the effect obtained is not obvious. By analysing each cost, we suggest that when dispatching electric buses, the cost weight of enterprises should be between 0.4-0.6 for the best effect. Therefore, we use 0.5 for the rest of the article.

From Table 4, we can find that when the weight of passenger travel cost and the weight of enterprise operation cost are both 0.5, the total cost of the optimisation solution decreases by 162.63 RMB. The passenger travel cost decreases by about 20.2%, but the enterprise operation cost increases by about 21.6%. It can be found that the price of the lower passenger travel cost is the reduced departure interval and the increased enterprise operation cost.

Table 4 – Travel demand and departure interval during each period

Cost	Current situation	After optimisation
Passenger travel cost (RMB)	5713.430	4556.250
Enterprise operation cost (RMB)	4597.967	5592.517

Table 5 shows the optimised departure interval scheme and total cost of every period compared to the current situation. The departure frequency of Line 206 is relatively fixed, the departure interval fluctuates within

10–15min. It is not adjusted in combination with passenger travel demand and urban traffic conditions, for example, passenger travel demand is larger at 9:00–10:00 and 11:00–12:00, but the departure frequency is lower, affecting the convenience and comfort of passengers. The departure interval is reduced in the optimisation, especially in peak passenger travel demand, so that the social welfare of EBs improves significantly. In addition, we find that the change in total cost for each time between the current situation and after optimisation is not significant. But combined with the results of passenger travel cost and enterprise operation cost, we can find that the model is conducive to improving the level of passenger travel service.

Table 5 – Travel demand and departure interval during each period

Time	Travel demand	Current departure interval [min]	Optimised departure interval [min]	Current total cost (RMB)	Optimised total cost (RMB)
7:00–8:00	173	10	7.3	1151.349	1151.308
8:00–9:00	205	10	7.7	920.939	936.490
9:00–10:00	211	15	13.1	1035.414	970.874
10:00–11:00	205	10	11.6	919.927	922.452
11:00–12:00	222	15	6.8	1087.579	1007.730
12:00–13:00	213	10	7.3	945.212	968.975
13:00–14:00	128	15	10.2	683.020	696.152
14:00–15:00	123	12	14.5	665.323	657.182
15:00–16:00	142	10	11.1	739.661	722.142
16:00–17:00	199	10	8.2	902.233	910.018
17:00–18:00	160	15	13.1	809.527	779.758
18:00–19:00	68	15	14.0	451.210	461.488

Figure 5 shows the change in congestion rates for Ebs before and after optimisation. In the current situation, most congestion rates are larger than 100%, which affects the comfort of passengers. After optimisation, congestion rates decrease a lot and the average congestion rate after optimisation is 91.6%, indicating that it fully meets the travel needs of passengers and the Ebs’ resources are not wasted.

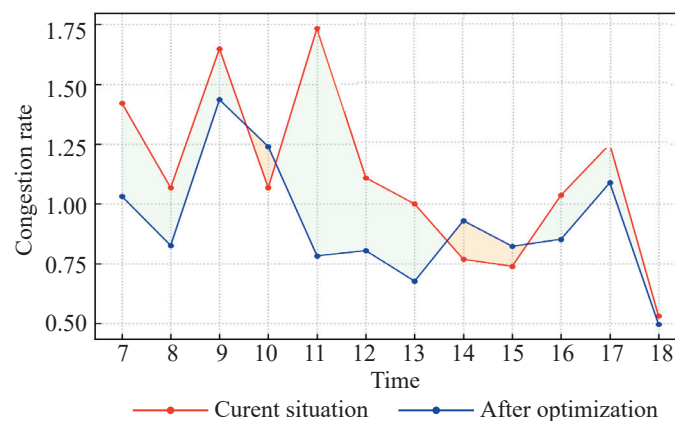


Figure 5 – Graph congestion rate variation

3.3 Model solving considers stochastic traffic conditions

We draw the speed box chart of Harbin at different times, as shown in Figure 6. We can find that the speed changes significantly in the morning. Moreover, when the average speed is low, the speed distribution is more concentrated; when the average speed is high, the speed distribution is more dispersed.

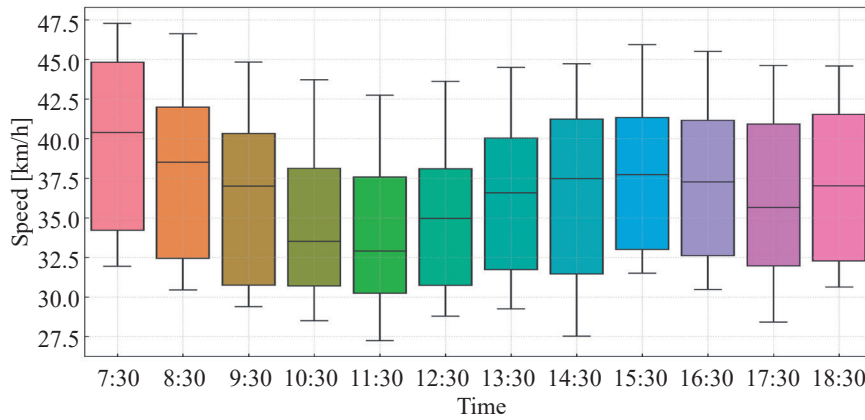


Figure 6 – Box diagram of speed during each period

Figure 7 shows the passenger travel demand and the departure interval optimisation scheme at different times. It can be found that with considering stochastic traffic conditions, the departure interval is larger when the travel demand is low and the departure interval is smaller when travel demand peaks, which is caused by stochastic travel demand. It can indicate that based on stochastic traffic conditions we could cope with phenomena such as peak passenger demand well.

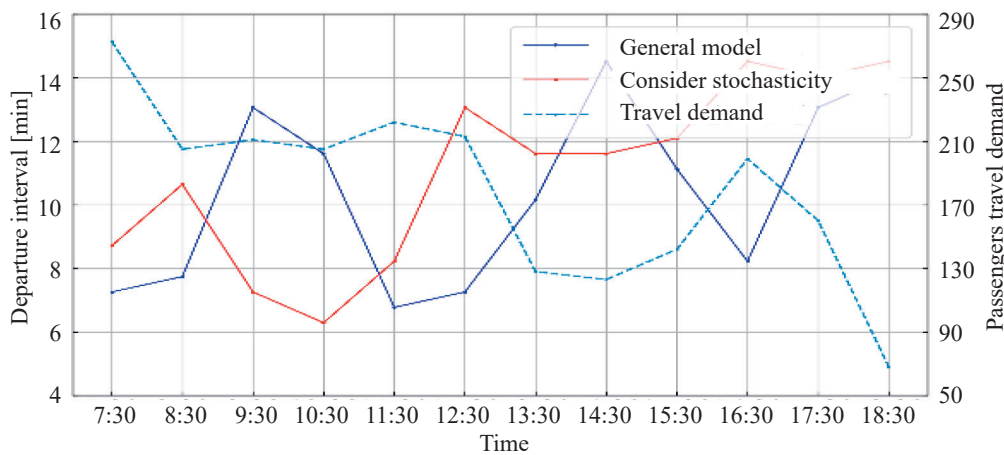


Figure 7 – Comparison of departure intervals during each period

Further calculation yields Table 6. From Table 6, we can find that when considering stochasticity, the passenger travel cost becomes larger but the enterprise operation cost becomes smaller, which suggests that various random factors in the operation of EBs have a great impact on passengers’ travel. In real bus operations, because of various stochasticity, enterprises often reduce costs at the expense of passengers’ convenience, which is not justified. Therefore, the government should strengthen the management of EBs to ensure the convenience of passengers’ travel.

Table 6 – Comparison of different costs

Cost (RMB)	General model	Consider stochasticity	Variation (%)
Waiting time cost	3165.53	3411.51	7.770
Congestion cost	1390.72	1518.74	9.205
Energy consumption cost	1123.01	1061.51	- 5.477
Operational fixed cost	4469.50	4203.18	-9.986
Total cost	10148.76	10194.94	0.455

3.4 Sensitivity analysis

To explore the effects of the maximum mileage of the EBs’ capacity (C) and the bus line mileage (L) on the optimised results, different experiments are performed by varying their value settings.

Figure 8 shows the changes in passenger travel cost and enterprise operation cost at different EB’s capacities. We can find that the total cost decreases with the increase of EB’s capacity, but the decline is getting smaller, indicating that appropriately increasing the EB’s capacity is conducive to saving resources and improving service levels. Among them, the enterprise operating cost is not greatly affected by the capacity of EBs and shows a fluctuating trend. The passenger travel cost shows a clear downward trend with the increase of the EB’s capacity, which should be due to the decrease in congestion of EBs after the increase of capacity.

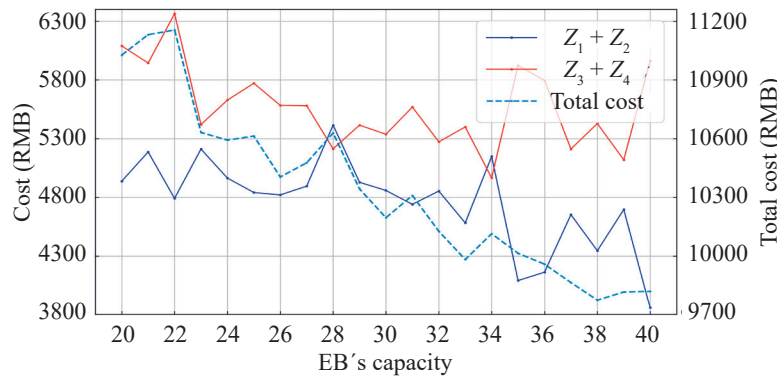


Figure 8 – Different costs vary with EB’s capacity

We solve the model without considering stochasticity, Figure 9 shows the changes in passenger travel cost and enterprise operation cost at different bus line mileage. In contrast to EB’s capacity, the total cost increases as the bus line mileage increases. With the increase in bus line mileage, the energy consumption cost of one task increases, and the enterprise operation cost increases significantly, while the relationship between passenger travel cost and bus line mileage is not significant. However, the effect of capacity is reversed.

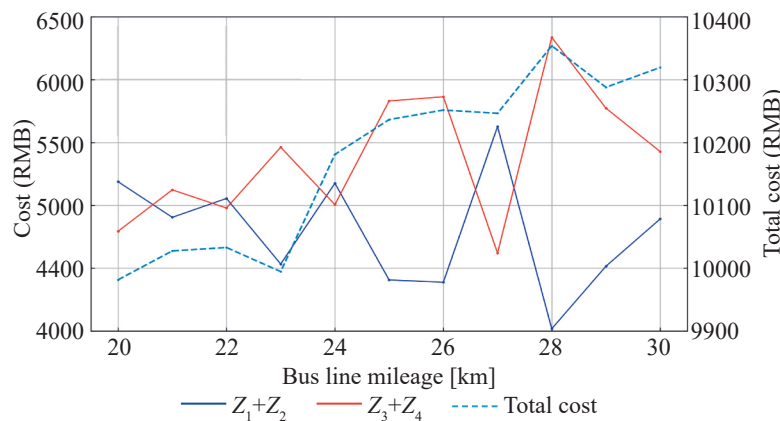


Figure 9 – Different costs vary with bus line mileage

From the above study, we can find an interesting phenomenon: the increase or decrease in passenger travel cost and enterprise operation cost is always the opposite, which is a contradiction and suggests it is important to choose the right departure interval of EBs. On the one hand, the government should strengthen the management of bus enterprises. On the other hand, establishing a reasonable bus network and choosing the right EBs can reduce costs and improve the attractiveness and competitiveness of EBs.

3.5 Policy suggestions

According to the research and analysis above, this paper puts forward some reasonable improvements and suggestions for the development of EBs in Harbin:

Public transportation management perspective. Reduce the impact of stochastic traffic conditions and improve the efficiency of passenger travel. On the one hand, public transportation management should improve

the operation as well as management of EBs and strengthen the management of EBs operating enterprises. Make the operating enterprises pay more attention to the passengers' interests and social benefits. On the other hand, the public transport management can subsidise the enterprises according to the number of EBs dispatched to compensate for the increase in operating costs caused by lower passenger travel costs. At the same time, bus management should pay attention to the status of buses in urban transportation. The impact of stochastic traffic conditions can be reduced by improving the operating efficiency and improving the technical index of EBs to improve passenger travel quality.

Operating enterprises perspective. Improve the technical index of EBs and optimise the setting of bus routes. Enterprises can choose vehicles with high electrical energy conversion efficiency and stable operation speed. At the same time, enterprises can modify EBs to increase vehicle transportation capacity and improve passenger travel comfort. In addition, enterprises can optimise the layout of bus lines to improve travel efficiency and reduce operating costs.

4. CONCLUSION

This paper presents a model for EBs departure interval optimisation, which considers the stochastic traffic conditions in EBs operation. The multi-objective function aims at minimising total cost including waiting time cost, congestion cost, energy consumption cost, as well as operational fixed cost. To solve this model, a GA was developed, in which the crossover rate and mutation rate of chromosomes are modified based on fitness. To verify the effectiveness of the solution, a case study is conducted based on EBs in Harbin and some suggestions for the development of EBs are proposed based on the experimental results.

Some important conclusions regarding the proposed solution are listed as follows:

- 1) The performance of the improved GA is significantly better than the conventional GA, the objective function value is reduced by 4.481%, and the overall level of the population is better. The optimisation results show that the passenger travel cost decreases by 20.2% without increasing the total cost. Moreover, the model can effectively cope with the peak phenomenon of travel demand, which is conducive to the improvement of EBs service level.
- 2) Under the consideration of stochastic traffic conditions, the total cost of the scheme solved by the model does not change much, but the passenger travel cost increases, and the waiting time cost and congestion cost increase by 7.770% and 9.205% respectively, which is inevitable.
- 3) In the sensitivity analysis, the larger the capacity of EBs is, the lower the total cost is, among which the passenger travel cost decreases significantly, but the enterprise operation costs are not significantly affected. The larger the bus line mileage is, the higher the total cost is, and the passenger travel cost and the enterprise operation cost are both rising.

This paper is based on the single line of EBs operation, which lacks a specific analysis of the charging situation of each vehicle. In the follow-up research, multiple bus lines can be combined and optimised, and the problems caused by the scheduling of the vehicle and the specific charging time can be further studied. At the same time, it is interesting to consider the impact of charging on the grid and changes in the EBs number.

ACKNOWLEDGEMENTS

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考虑随机交通现象的电动公交发车间隔优化

摘要

近年来, 电动公交车因其节能和无污染的特点吸引了越来越多的关注。然而, 很少有研究考虑到随机交通现象对其运营的影响。本文重点讨论了电动公交的发车间隔优化, 这是运营中的一个关键问题。我们考虑了电动公交运营中的随机交通现象, 并建立了一个出发时间间隔优化模型。目标函数旨在最小化乘客出行成本和企业运营成本, 包括等待时间成本、拥堵成本、能耗成本和运营固定成本。为了解决这个问题, 我们提出了一种基于适应度调整交叉率和变异率的遗传算法。基于哈尔滨公交车数据集, 我们发现改进后的遗传算法性能提高了4.481%, 它可以更准确、更有效地解决模型。与公交运营现状相比, 该优化模型降低了20.2%的乘客出行成本, 并有助于提高乘客出行质量。在随机交通条件下, 总成本变化不大, 但乘客出行成本明显增加。这表明随机交通状况对乘客出行的影响程度很高。此外, 本文还进行了敏感性分析, 为改进电动公交运营和管理提供建议。

关键字

电动公交; 公共交通; 发车间隔; 随机交通现象; 遗传算法.