

Article

Research on Bus Scheduling Optimization Considering Exhaust Emission Based on Genetic Algorithm: Taking a Route in Nanjing City as an Example

Meixia Wang¹, Baohua Guo^{1,2,*} , Zhezhe Zhang¹ and Yanshuang Zhang¹

¹ School of Energy Science and Engineering, Henan Polytechnic University, Jiaozuo 454003, China; 18403909837@163.com (M.W.); zhe991027@163.com (Z.Z.); 15236446375@163.com (Y.Z.)

² Jiaozuo Engineering Research Center of Road Traffic and Transportation, Henan Polytechnic University, Jiaozuo 454003, China

* Correspondence: guobaohua@139.com

Abstract: In order to enhance passenger willingness to choose buses for commuting and to reduce the operating costs and tailpipe emissions of bus companies, a bus scheduling model is established. The model aims to minimize the sum of the operating costs of the bus company, the costs associated with the loss of passengers' interest, and the cost of tailpipe emissions. It considers constraints such as maintaining an average load factor of the buses above 60%, ensuring a departure interval of greater than 5 min during non-peak hours and less than 30 min during peak hours, and limiting the maximum number of buses allocated to a route. The passenger flow is divided into peak hours and nonpeak hours according to the survey of passenger flow during each period of a bus operation on a route in Nanjing City, China. A genetic algorithm is employed to solve the proposed bus scheduling model and determine the total costs during peak and non-peak hours. After designing the parameters of the genetic algorithm, optimal departure intervals and bus numbers for a day's operation cycle on a given route are calculated using a weighting method.

Keywords: genetic algorithm; bus scheduling; optimization design; green transportation



Citation: Wang, M.; Guo, B.; Zhang, Z.; Zhang, Y. Research on Bus Scheduling Optimization Considering Exhaust Emission Based on Genetic Algorithm: Taking a Route in Nanjing City as an Example. *Appl. Sci.* **2024**, *14*, 4126. <https://doi.org/10.3390/app14104126>

Academic Editor: Kuo-Ching Ying

Received: 3 April 2024

Revised: 11 May 2024

Accepted: 12 May 2024

Published: 13 May 2024



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1. Introduction

China's urbanization rate was 7.3% in 1949 [1], and after 74 years of steady development and ongoing urbanization promotion, it reached 64.6% in 2023. Rapid economic growth and a steady pace of urbanization contribute to the annual increase in the number of individual private automobiles. Insufficient development of transportation infrastructure, inadequate road networks, and a surge in private motor vehicles are the primary factors contributing to traffic congestion in most major cities across China. In addition to affecting economic growth, traffic congestion also has a negative impact on the daily lives of urban residents. Traffic congestion is a significant problem in approximately two-thirds of Chinese cities [2,3]. This is due to the underdeveloped public transportation infrastructure, low public transportation usage, and a noticeable mismatch between the supply and demand of transportation. The rapid growth of urbanization and motorization has made traffic and parking in cities more stressful. This has also significantly impacted the living environment, which will likely limit overall societal sustainability. The resulting traffic issues have become a pressing social problem that cannot be overlooked [4].

As an important branch of public transportation, the public transportation system has the advantages of low pollution, large passenger capacity, and economic convenience. It is an important measure for the development of public transportation to vigorously develop public transportation. An important factor affecting the development of buses is bus passenger flow. The size of passenger flow determines whether the bus company is profitable and whether the public recognizes public transportation. In order to effectively

attract passenger flow, it is necessary to improve the service quality of buses. The measures that can be taken include: compiling a reasonable bus operation time interval that can effectively reduce the waiting time of passengers, building bus lanes that can shorten the driving time of buses, and setting up bus stops reasonably.

Reasonable bus scheduling can not only improve the service quality of public transport but also improve the punctuality, efficiency, attractiveness, and comfort of public transport so as to attract more people to use public transport. The basis of the operation organization is to prepare the scheduling plan, and the departure interval is the core of the operation organization. A bus timetable is the key element for bus companies to provide high-quality services to passengers. Buses operate on this line, which directly affects passengers' travel and the benefits of bus companies. Under the premise of considering the concept of green transportation, this paper establishes a bus scheduling model with the minimum sum of the bus company operating cost, passenger interest loss, and exhaust emission cost as the optimization objective function. The genetic algorithm is used to solve the example. According to the passenger flow situation of a certain line in Nanjing at each time of the day, the design of the bus dispatching model is realized. The example is solved to obtain a line with the optimal bus running time interval and the least number of bus assignments. Studies have shown that reasonable bus scheduling can improve passengers' willingness to choose bus commuting, reducing operating costs and exhaust emissions of bus companies.

The structure of the article is as follows: The first chapter introduces the research background and significance of the article; the second chapter reads, summarizes, analyzes, and synthesizes the relevant literature, and summarizes the current research status, research progress, existing problems, and future research directions in the current research field. In the third chapter, in order to simplify the problem, the model is assumed, and then a bus scheduling model with the minimum sum of the operating cost of the bus company, the loss of passenger benefits, and the cost of exhaust emissions as the optimization objective function is established. The fourth chapter introduces the parameters and solving steps of the genetic algorithm. In the fifth chapter, taking a line in Nanjing as an example, on the basis of the input parameters of the above model, the optimal departure interval and the number of departures in the one-day operation cycle of the line are obtained. The cost before and after optimization is compared and analyzed, and the feasibility of the model in bus dispatching is verified. The sixth part discusses the key problems to be solved in bus dispatching. The seventh part summarizes the article and puts forward the shortcomings and prospects of the article.

2. Literature Review

The form of bus scheduling refers to the form of transportation organization adopted by bus companies in the operation scheduling plan. Domestic and foreign scholars consider the constraints of fleet size, vehicle full load rate, etc., construct a bus scheduling model that meets the interests of passengers or takes into account the interests of bus passengers and enterprises and uses mathematical programming, genetic algorithms, etc. The model is solved to obtain the optimal departure interval and departure timetable. Jiang et al. [5] discussed a large-scale multi-location electric bus scheduling problem considering vehicle-location constraints and partial charging strategy. To solve this problem, we establish a mixed-integer programming model and an efficient branch plus price (BP) algorithm. In the BP algorithm, we design a heuristic method to generate a good initial solution and use heuristic decisions in the label-setting algorithm to solve the pricing problem. Chang [6] developed a mathematical model for the optimization of radial bus networks with time-dependent supply and demand characteristics and obtained closed-form solutions for optimal route angles, frequency intervals at different periods, and station spacing at different locations to minimize the total cost. Due to the limited driving range and long charging time of electric buses, such models are not suitable for electric buses. Therefore, it is necessary to develop new mathematical models to consider the unique characteristics of electric buses. Alamatsaz et al. [7] proposed a comprehensive literature review to critically

review and classify the work done on these topics. This paper will compare the existing research in this field, highlighting the missing links and gaps in the papers considered, as well as the potential research that can be carried out in the future. Chakroborty [8] studied the optimization problem of optimal fleet size allocation and scheduling of a bus system considering interchange factors, applying a simple optimization method based on binary coded genetic algorithms (GA) to obtain optimal results with limited computational effort. Ibarra-Rojas [9] studied a bus network in Monterrey, Mexico, where priority is given to passenger transfers and almost uniform departure intervals are sought to avoid bunching of buses on different routes, and posed the problem of timetabling the network to maximize the number of synchronizations to facilitate the passenger transfers, and, applying a new heuristic algorithm for obtaining a high-quality solution, a two-layer planning model is developed, and the model is solved using a forbidden search algorithm. Wang et al. [10] created a two-layer planning model, which they solved using a prohibited search algorithm. The lower-level goal is to minimize the fixed cost of the firm's vehicles and the amount of vehicle idling, while the upper-level goal is to minimize vehicle congestion and passenger waiting times. Sunder et al. [11] used the suburban railway station as the study site and coordinated the frequency between suburban trains and public buses with the objective function of minimizing the interchange time between the two routes and the vehicle operating cost of the buses. Verma and Sunder [12] developed a combination optimization model to improve the schedules of urban rail and feeder bus operations. The model aimed to minimize total operating and user costs while considering load factor and waiting time constraints. Shrivastava et al. [13] developed an integrated model for suburban train and public bus operations in which a genetic algorithm is used to assign the optimally coordinated timetable for feeder buses based on the given suburban train timetable in a "scheduling sub-model". Avila-Torres et al. [14] developed a dual-objective fuzzy planning model to address traffic demand uncertainty. They considered factors like departure frequency, schedule, operating cost, and cycle synchronization. The model uses three evaluation indexes—confidence, fuzzy, and demand level—to assess bus, metro, and train scheduling, proving its value for transport operators. Yu et al. [15] studied the use of the symmetry principle to solve the problem of bus scheduling. By considering the symmetrical operation route of public transport vehicles, a new scheduling algorithm is proposed to simplify the complexity of the scheduling scheme and improve the scheduling efficiency. When there is a shortage of backup buses or a large area of disruption, it becomes unrealistic and challenging to develop a feasible and reasonable rescheduling plan for the remaining bus services. In response to this challenge, Deng et al. [16] proposed an innovative model that comprehensively considers service capabilities and regularity, aiming to minimize rescheduling costs through schedule adjustment and scheduling redistribution. Dynamic programming is used to fully consider the lag effect of interruption and the long-term optimal rescheduling scheme is realized. In order to solve the proposed model efficiently, the large neighborhood search algorithm is improved by combining the operation rules. Bie et al. [17] developed a vehicle scheduling method for electric bus (EB) lines, considering the random volatility of travel time and energy consumption. An optimization model is established with the goal of minimizing the expected travel departure time delay, the sum of energy consumption expectations, and bus procurement costs. Finally, a real bus line is taken as an example to verify the proposed method by Li et al. [18]. Considering the coordinated scheduling with EB, this paper proposes an optimization model for the joint restoration of post-disaster distribution systems. Using integer algebraic techniques, the repair problem with bus scheduling constraints is re-expressed as a mixed integer linear program, which can be processed by an off-the-shelf solver.

Bus vehicles are one of the main means of transport for urban residents to travel. With the growth in the number of bus routes and vehicles, bus exhaust emissions have gradually gained widespread attention in the academic community. Rabl [19] quantified the benefits of natural gas-fueled and diesel-fueled buses. The study showed that the environmental loss cost of diesel buses is higher than that of natural gas-fueled buses.

Zhang et al. [20] calculated the emissions of public transport diesel vehicles based on the year of engine purchase, model and fleet, etc., and analyzed various factors affecting the carbon smoke emissions of public transport diesel vehicles. Hu et al. [21] studied the power, fuel economy, and emissions of GTL diesel and regular diesel in in-service buses without engine adjustments. They found that GTL diesel can reduce both NO_x and particulate matter emissions, making it a promising clean fuel option for diesel engines. Their findings suggest that GTL diesel is a viable choice for reducing emissions from diesel engines. Alam et al. [22,23] simulated greenhouse gas emissions from buses on busy lanes and assessed how different fuels and driving conditions affect emissions. They also analyzed the impact of strategies such as bus signal priority, queue-cutting lanes, and bus stop relocation on bus emissions. Combining these strategies with TSP results in more noticeable emission reduction benefits. Additionally, they examined how factors such as network congestion, road type, passenger load, and fuel type individually and collectively affect transit greenhouse gas emissions. They found that, while increased bus ridership raises emissions, the impact of higher passenger loads on emissions per passenger varies depending on bus ridership levels. In their study of public transportation bus performance and emissions, Addo et al. [24] measured operational improvements (speed increases, idle reductions). The effectiveness of emission reduction techniques is largely dependent on the features of the buses and their drive cycles. Fan [25] evaluated the setting of bus lanes from the perspective of the traffic environment by studying the development of bus lanes and motor vehicle tailpipe emission models, establishing a quantitative method for the setting of bus lanes on motor vehicle fuel consumption and tailpipe emission. Example analyses show that the fuel consumption, CO₂, CO, HC (hydrocarbon), and NO_x emissions of road sections are reduced after the implementation of bus-only lanes.

While public transport enterprises are committed to providing efficient traveling services to passengers with less economic costs, they bear the social responsibility of reducing transport emissions. Some studies have found that reasonable bus scheduling is conducive to reducing bus tailpipe emissions [26]. Currently, few scholars have considered bus tailpipe emissions as the optimization objective of the scheduling strategy in their studies on bus scheduling optimization. A demand-responsive bus scheduling optimization model was put forward by Dessouky et al. [27]. Three objectives were chosen: bus emissions, operating costs, and service level. The objective of the model was to identify a scheduling strategy that would reduce bus exhaust emissions significantly, albeit somewhat at the expense of operating costs and passenger travel time. In order to cut down operational expenses and vehicle emissions while purchasing fresh buses under a restricted budget and adhering to strict bus travel timetables, Li and Head [28] looked into the bus scheduling challenge. Taking into consideration the variations in the importance of the bus-stopping scheme and the frequency of departure in the optimization process, Jin et al. [29] established a combined skip-stop and inter-area bus scheduling model to minimize the total cost of passenger time, the total cost of bus operation, and the cost of tailpipe emission. It, additionally, suggested a dynamic probabilistic genetic algorithm for optimization with probability varying with the number of iterations to solve for the optimal stopping scheme, along with the frequency of departure. The research on optimizing the combination scheduling of large station express buses aims to propose an optimal scheduling program that satisfies passenger, enterprise, and environmental requirements. Wei [30] prioritizes minimizing passenger time costs and enterprise operating costs as the primary objectives, while considering reducing bus exhaust emissions as a secondary objective. Taking the reduction of bus exhaust emissions as one of the model optimization objectives, Han [31] studied the combination of two full buses, inter-area buses, buses with big stops, and express buses, considering the benefits to passengers and bus companies, and solved the two models by using genetic algorithms.

This work investigates bus scheduling optimization, taking into account bus exhaust emissions and drawing inspiration from previous studies on bus exhaust emissions and scheduling. However, the existing research still has the following problems:

- (1) The full-vehicle scheduling models in the literature are proposed mostly by taking the travel time cost of passengers and the operating cost of public transport enterprises as the optimization objectives, and there are very few researches that have taken bus exhaust emissions into account in the optimal design of scheduling strategies.
- (2) The proposed scheduling model in the literature has not considered the impact of passenger travel choice behavior on passenger flow distribution and the constraints on the number of buses allocated to a route.
- (3) Unbalanced dispatching strategies are adopted in most previous studies, but unbalanced scheduling schemes obtained by using intelligent algorithms are not only detrimental to the schedulers' designation of the scheduling plan but also prolong the waiting time of some passengers.

This paper uses Nanjing's segmented IC card data as the main database. It employs a balanced dispatching strategy and aims to minimize the total cost of passenger travel time, bus operation, and exhaust emissions. The bus scheduling model considers constraints such as bus service level, average full load rate, and allocated number of buses per route. It is solved using a genetic algorithm. The benefits of the scheduling scheme considering bus exhaust emission and the original schedule made according to manual experience are compared to verify the advantages and stability of the constructed scheduling model considering bus exhaust emission.

3. Model Hypothesis and Construction

By planning a sufficient number of departures and adjusting the intervals between them, the vehicle scheduling model aims to reduce the cost of passenger journey time, the operational expenses of the bus company, and the emissions produced by the buses. Assume the following [32]:

- (1) The types of bus vehicles are the same and the passenger load is equal;
- (2) The situation where buses are delayed due to other uncontrollable factors such as weather is not considered;
- (3) Passengers do not have to wait for the bus twice; that is, passengers can take the bus immediately after arriving at the station, without waiting for the second vehicle to arrive;
- (4) Passenger transfers are not considered;
- (5) The vehicle operates according to only one mode of operation during the day's operating cycle;
- (6) Passenger arrival rates follow a uniform distribution throughout the vehicle's operating time;
- (7) All vehicles on the route operate according to the departure schedule.

To address the costs associated with operating bus companies, passenger waiting times, and tailpipe emissions, this study develops a bus scheduling model based on passenger flow.

3.1. Model Parameters

Table 1 summarizes the main model parameters and their definitions.

Table 1. Definition of variables for models.

Parameter	Definition
K_{np}	Number of total nonpeak hours
K_p	Number of total peak hours
T_p	The length of bus operating time during the k -th peak hour
T_{np}	The length of bus operating time during the k -th nonpeak hour
μ_{kj}	The arrival rate of passengers at the station j during peak hours
v_{kj}	The arrival rate of passengers at the station j during nonpeak hours
J	The total number of bus stops along the route
Δt_p	The interval between bus departures during peak hours
Δt_{np}	The interval between bus departures during nonpeak hours
C_{pp}	The total waiting time cost for passengers during peak hours
C_{pnp}	The total waiting time cost for passengers during nonpeak hours
y	The amount that passengers are paid per minute, EUR/min
D_p	The cost loss weighting factor for passengers waiting for buses during peak hours
D_{np}	The cost loss weighting factor for passengers waiting for buses during nonpeak hours
n_p	The departure number during peak hours
n_{np}	The departure number during nonpeak hours
T_i	The traveling time of the vehicle in the i period
C_{bp}	The operating costs of bus companies during peak hours
C_{bnp}	The operating costs of bus companies during nonpeak hours
S	The total length of the route, km
m	The cost per kilometer on the route, yuan
Z_{ipp}	The mass of pollutant i emitted from the exhaust of buses during peak hours
Z_{inp}	The mass of pollutant i emitted from the exhaust of buses during nonpeak hours
EF_{iq}	The emission factor corresponding to pollutant i emitted by buses, g/km
λ_i	The weighting factor of pollutant i emitted by buses
V_q	The planned running speed of the vehicle, m/s.
u_i	The impact cost of emitted pollutant i , yuan/g
α_p	Weighting factor assigned to passenger waiting time cost during peak hours
α_{np}	Weighting factor assigned to passenger waiting time cost during nonpeak hours
β_p	Weighting factor assigned to public transportation enterprises operating cost during peak hours
β_{np}	Weighting factor assigned to public transportation enterprises operating cost during nonpeak hours
γ_p	Weighting factor assigned to public transportation tailpipe emission cost during peak hours
γ_{np}	Weighting factor assigned to public transportation tailpipe emission cost during nonpeak hours
ω_1	Weighting factor assigned to the total cost of the passenger during peak hours
ω_2	Weighting factor assigned to the total cost of the passenger during nonpeak hours

3.2. Model Construction

3.2.1. Passenger Waiting Time Cost

The total time cost of the passenger in a cycle of the vehicle traveling is determined as below. According to the survey, the monthly income per capita of Nanjing inhabitants in 2023 was 6500 yuan. Each month is considered to have 30 days, during which individuals have 8 days of double rest. Additionally, within the 22 working days of the month, people work for 8 h each day. Equations (1)–(3) provides the total time cost of the passenger, and the level of pay per minute is y . On May 2024, 1 yuan was equal to 0.13 euros or 0.14 US dollars.

$$y = \frac{6500}{22 \times 8 \times 60} = 0.0806 \text{ (EUR/min)} \quad (1)$$

$$C_{pp} = y \cdot D_p \sum_{k=1}^{K_p} \sum_{j=1}^J \frac{v_{kj} \Delta t_p T_p}{2} \quad (2)$$

$$C_{pnp} = y \cdot D_{np} \sum_{k=1}^{K_{np}} \sum_{j=1}^J \frac{\mu_{kj} \Delta t_{np} T_{np}}{2} \quad (3)$$

3.2.2. Bus Companies' Operating Costs

Bus companies' operational costs are influenced by a variety of factors, including the cost of hiring drivers and the cost of buying and maintaining buses. In this paper, we only

take into account the variable costs of buses operating on the entire route [33]. For buses, the cost of gasoline used per kilometer is 4 yuan.

Equations (4)–(7) are used to determine the overall operating costs of the bus company, as well as the number of departures in a trip cycle.

$$n_p = \frac{T_i}{\Delta t_p} \quad (4)$$

$$n_{np} = \frac{T_i}{\Delta t_{np}} \quad (5)$$

$$C_{bp} = S \times m \times n_p \quad (6)$$

$$C_{bnp} = S \times m \times n_{np} \quad (7)$$

3.2.3. Bus Companies' Exhaust Emission Costs

The operation of a bus on a route is roughly divided into two parts: one part is the vehicle traveling at a constant speed between stops and the other part is the process of the vehicle stopping at stops. Researches have indicated that car tailpipe pollutant emissions vary depending on driving conditions. Emissions between stops occur during uniform speed, while emissions during stops are associated with acceleration and deceleration. Here, we only consider the size of vehicle emissions between stations to account for lower during-stop emissions. The primary pollutants from public bus exhaust are CO, NO_x, PM, and HC. Impact cost modeling is proposed to estimate vehicle exhaust emissions based on pollutants released from public bus exhaust, allowing for the assessment of the social impact cost of these tailpipe emissions [30].

Equations (8) and (9) can be used to estimate the emission of each type of pollutant from public buses. The emission of each type of pollutant is mostly related to the emission factor, the number of departures, and the length of the route. Buses in a city often operate at a speed of 20 to 30 km/h, hence in this study, V_q is set as 30 km/h.

$$Z_{ipp} = \lambda_i \cdot EF_{iq} \cdot S \cdot n_p \cdot V_q \quad (8)$$

$$Z_{inp} = \lambda_i \cdot EF_{iq} \cdot S \cdot n_{np} \cdot V_q \quad (9)$$

Bus tailpipe emissions were estimated based on the bus VSP measurement method [34] after collecting the National IV standard emission data regarding operating conditions [35] for a single-deck, single-engine CNG (compressed natural gas) bus and the vehicle's average traveling speed. The emission factor of each type of pollutant for the vehicle is displayed in Table 2, which is derived from a large number of bus emission data and operating condition data. Table 3 displays the weighting factors for each type of pollutant. The method of determining the weight factor is the expert evaluation method. The importance of each index is evaluated and arranged by experts and then converted into a weight coefficient.

Table 2. Emission factors for each pollutant.

Forms of Dispatch	NO _x (g/km)	HC (g/km)	CO (g/km)	PM (g/km)
Full journey bus	8.2560	2.0996	5.3981	0.1054

Table 3. Weighting factors for each type of pollutant.

Pollutant Type	Weighting Factor	Value
NO _x	λ_1	0.3
HC	λ_2	0.1
CO	λ_3	0.3
PM	λ_4	0.3

The total cost of tailpipe emissions is:

$$C_{ep} = \sum_{i=1}^4 u_i Z_{ipp} \quad (10)$$

$$C_{enp} = \sum_{i=1}^4 u_i Z_{inp} \quad (11)$$

The World Resources Institute provided a methodological guide for estimating transportation emission inventories and their corresponding social costs in the “Assessment of Transportation Emission Inventories and Corresponding Social Costs” project study [36]. The guide covers pollutants and greenhouse gases emitted by 18 different transportation modes. It is designed for use in developing nations and cities with limited statistical systems and poor data availability and quality. According to the guideline, social costs refer to the external expenses linked to transportation emissions, primarily focusing on their effects on public health. The initial assessment of social costs involves utilizing knowledge from various sources such as models, surveys, epidemiology, statistics, and socio-economic analysis, employing IPA (Importance and Performance Analysis) as the framework and adopting a top-down approach through meta-analysis of social impact costs. Ultimately, the localization value of social impact costs for each emission in China, including environmental damage costs and health value localization, is determined based on additional social impact costs identified through China’s measured data, as shown in Table 4.

Table 4. Impact costs of emitting pollutants.

Pollutant Type	Social Impact Cost	Value (EUR/g)
NO _x	u_1	0.00660819393
HC	u_2	0.00260746317
CO	u_3	0.00171559726
PM	u_4	0.05477157634

3.2.4. Constraints

Considering the interests of bus companies, in actual bus operations, the number of people inside the bus should not be too small. Considering the comfort of passengers, the bus should not be too crowded during operation [37]. This paper takes the average full load rate of buses not less than 60% as the constraint condition of the objective function.

$$\frac{\sum_{j=1}^J (\mu_{kj} + v_{kj})}{R \times \left(\frac{T_p}{\Delta t_p} + \frac{T_{np}}{\Delta t_{np}} \right)} \geq 60\% \quad (12)$$

The departure interval constraints during peak and nonpeak hours of public transportation operation are set as follows:

$$5 \leq \Delta t_{np}, \Delta t_p \leq 30 \quad (13)$$

For multi-objective optimization problems, assigning a weighting factor to each sub-objective function determines the importance level of that particular sub-objective in the overall optimization process. These weighting factors are determined using expert experience by comparing the importance levels of passenger waiting time cost, bus company operating cost, and bus exhaust emission cost in the optimization problem.

These three optimization objectives are conflicting, and it is not possible to reach a minimum value at the same time, so it is necessary to find a balance point for the best situation. Weighting these three functions into one objective function is to merge the three costs into one cost. The objective function is the sum cost of passenger waiting time, the operating cost of public transportation enterprises, and the cost of exhaust emissions.

The public transportation problem is a very complex multi-objective optimization problem. When solving this problem, the weighting method is used to give different

weighting functions to the waiting time costs of passengers, the operating costs of the public transportation company, and the exhaust emission costs. The multiple functions are transformed into one objective function. Therefore, the simplified function is:

$$F_p = \alpha_p \cdot C_{pp} + \beta_p \cdot C_{bp} + \gamma_p \cdot C_{ep} \quad (14)$$

$$F_{np} = \alpha_{np} \cdot C_{pnp} + \beta_{np} \cdot C_{bnp} + \gamma_{np} \cdot C_{enp} \quad (15)$$

$$F(\min) = \omega_1 \cdot F_p + \omega_2 \cdot F_{np} \quad (16)$$

4. Solution Algorithms

4.1. Principle of Genetic Algorithms

A genetic algorithm (GA) is a kind of evolutionary algorithm that is modeled after the evolutionary law of “natural selection and survival of the fittest” in the biological world as the basic principle of evolutionary algorithms, which was initially proposed by Prof. Holland in 1967 [38]. In the course of natural evolution, organisms become changeable, hereditary, and environment-adapted. This implies that only species possessing superior qualities and greater adaptability to their natural surroundings will be able to endure and procreate, while those lacking superior qualities will ultimately become extinct. Genetic algorithms, which simulate the above phenomenon of natural evolution, map the search space to the gene space, i.e., each possible solution gene is encoded as a chromosome. Genetic algorithms generate an initial population at random and then, through replication, crossover, mutation, and other operations, increase an individual’s degree of adaptability. This allows the group of individuals to perform increasingly better searches in the search space, and so on. Generation by generation, the evolution continues until it eventually converges in a group of the best-adapted individuals, at which point it finds the optimal solution to the problem.

4.2. The Procedure of the Algorithm

The selection of the operational methods and the values of the parameters are as follows:

- (1) Initial population: the size of the population for each generation is Pop Size = 100.
- (2) Coding: in this paper, the method of real number coding is used; in this coding method, each gene of the chromosome is the real value of the decision variable.
- (3) Fitness function: to use the transformation method shown in Equation (17), the problem of minimizing the sum of the time cost of passenger travel, the operating cost of public transportation companies, and the cost of bus exhaust emissions is studied:

$$fit(f(x)) = \frac{1}{F(\min)} \quad (17)$$

- (4) Selection of the operator: a 1-to-1 substitution mechanism is adopted to ensure that the population size is diversified. The substitution phenomenon occurs only when the descendants appear stronger than their parents. In this paper, an elite retention strategy is used to select a specified number of best solutions to replace the worst solutions after each iteration, where the number and probability are calculated according to the iteration progress.
- (5) Crossover operator: the crossover probability in this paper takes the value of $P_c = 0.9$.
- (6) Variation operator: the existing research results show that the range of the value of the variation probability is generally between 0.001 and 0.1. In this paper, the value is taken as $P_m = 0.01$ during the algorithm design process.
- (7) Algorithm termination condition: the termination condition of the algorithm is the maximum number of iterations Max Gen = 300.

The algorithm flowchart, shown in Figure 1, first initializes the population through the following steps: assigning model data, algorithm parameter setting, and encoding. Then, genetic operations are conducted on the population to decode the departure intervals and

quantities for each time period using crossover and mutation. Based on the established model, the total waiting cost for passengers, operating cost of public transportation enterprises, and exhaust emission cost are calculated. Following the verification of model constraints, the fitness of chromosome individuals is determined and selection is made. This process is iterated continuously, with selection, crossover, and mutation operations, while assessing real-time fitness results of chromosome individuals. If optimal fitness results are achieved, the genetic algorithm terminates and outputs the results. However, if individual chromosome fitness results are not optimal, the algorithm continues selecting, crossing, and mutating chromosomes until the optimal result is obtained.

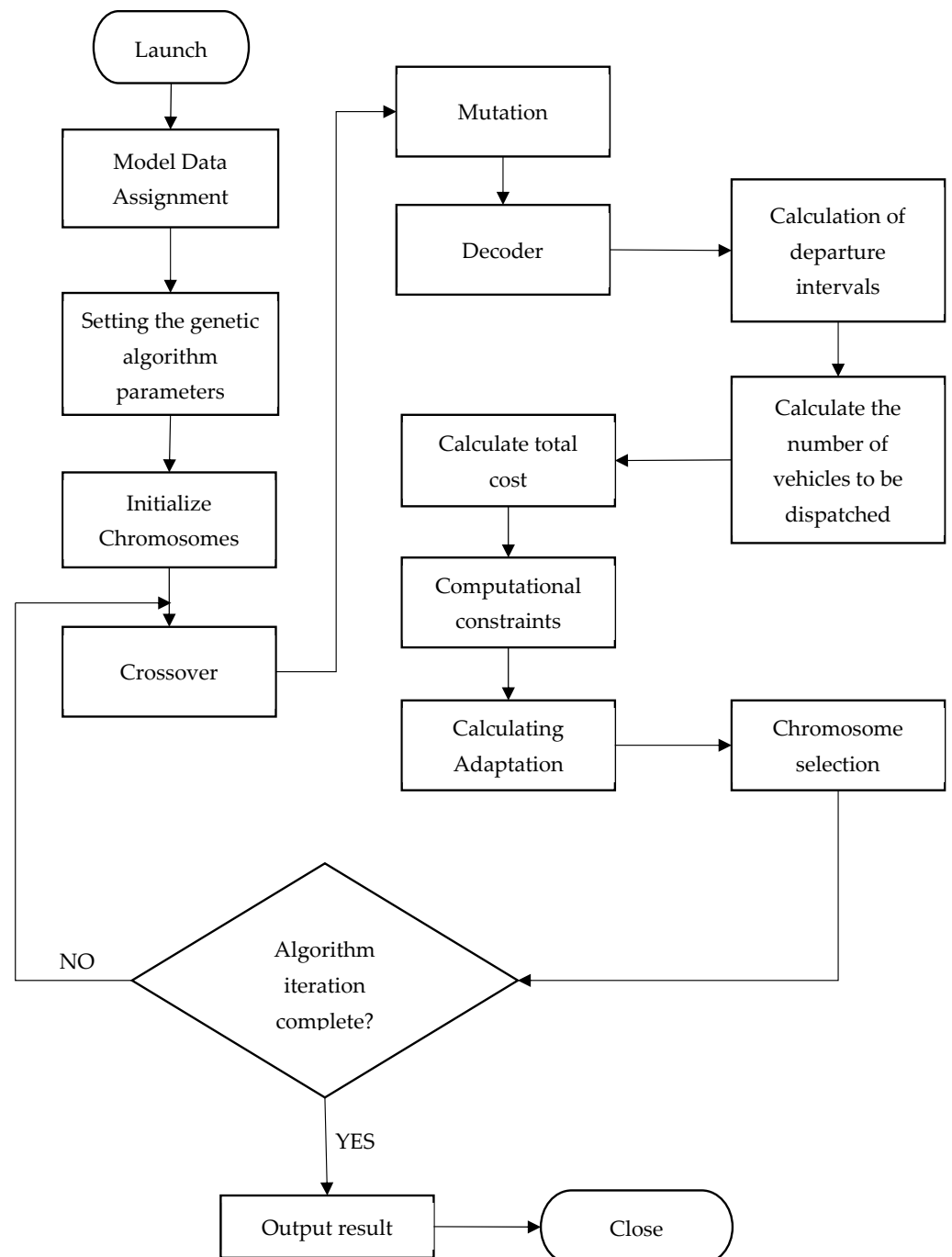


Figure 1. Flowchart of the genetic algorithm.

5. Case Study

5.1. Overview of a Particular Bus Route in Nanjing

Taking the departure frequency of a bus route in Nanjing as the research object, the departure schedule of the line is optimized considering the bus operating cost and the convenience of citizens. The bus passenger flow of this route during each period is shown in Table 5. The bus line is 21.4 km long, has 32 stations, with a fixed departure time interval of 15 min, the implementation of a uniform fare (2 yuan/person), and a line operation time of 6:30 a.m. to 10:30 p.m. (a total of 16 h).

Table 5. Passenger flow in each time period.

Number	Time Period	Passenger Flow (Person)
1	6:30–7:30	274
2	7:30–8:30	486
3	8:30–9:30	301
4	9:30–10:30	224
5	10:30–11:30	191
6	11:30–12:30	260
7	12:30–1:30	337
8	1:30–2:30	212
9	2:30–3:30	197
10	3:30–4:30	256
11	4:30–5:30	324
12	5:30–6:30	508
13	6:30–7:30	318
14	7:30–8:30	250
15	8:30–9:30	175
16	9:30–10:30	125

From Table 5, it can be seen that the peak hours of this route in Nanjing include the morning peak hour from 7:30 a.m. to 8:30 a.m., the noon peak hour from 12:30 a.m. to 1:30 p.m., and the evening peak hour from 5:30 p.m. to 6:30 p.m. The nonpeak hours refer to other time periods. The division of operating time periods is shown in Table 6.

Table 6. Division of operating time periods.

No.	Time Period	Peak Type	Duration (in min)
1	6:30–7:30	Nonpeak hour	60
2	7:30–8:30	Peak hour	60
3	8:30–12:30	Nonpeak hour	240
4	12:30–1:30	Peak hour	60
5	1:30–5:30	Nonpeak hour	240
6	5:30–6:30	Peak hour	60
7	6:30–10:30	Nonpeak hour	240

According to the established mathematical model of public transportation scheduling, in order to reduce residents' travel costs, enhance the attractiveness of public transportation, and adjust the travel structure, the weight coefficient is set, as shown in Table 7.

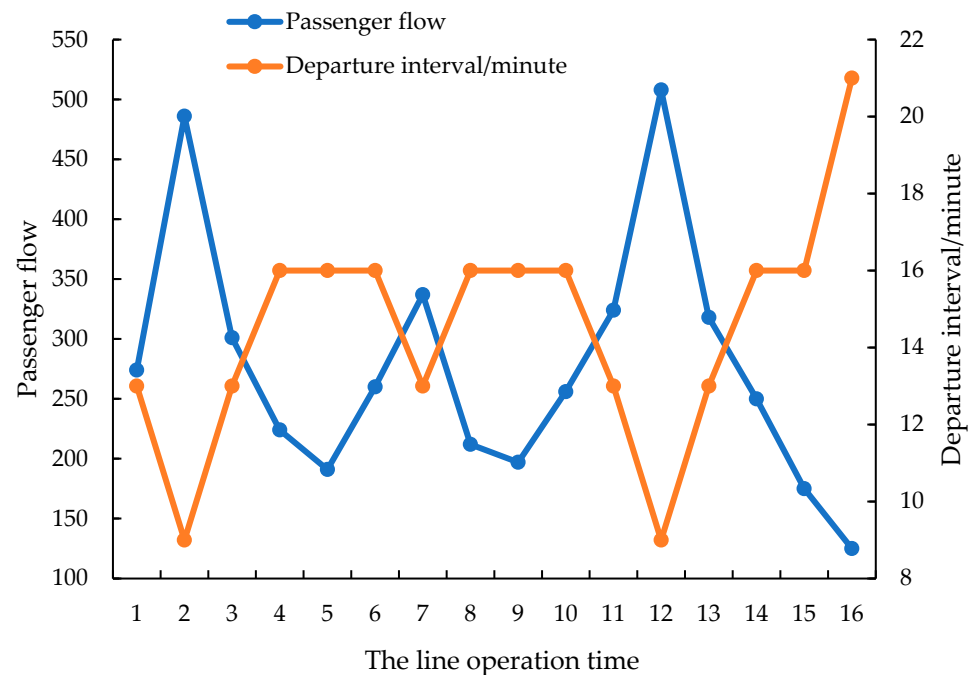
The weight coefficient is determined by the analytic hierarchy process (AHP): the hierarchical structure model is used to compare the relative importance of each index, and the weight coefficient is calculated.

Table 7. Model-related parameters.

Formula	Weighting Factor	Value
Formula (16)	ω_1	0.6
	ω_2	0.4
Formula (14)	α_p	0.6
	β_p	0.3
	γ_p	0.1
	α_{np}	0.5
Formula (15)	β_{np}	0.4
	γ_{np}	0.1

5.2. Calculation Results and Analysis

Figures 2 and 3 display the relationship between the departure interval and time period number and the relationship between the objective function values and the number of iterations, respectively. According to Figure 2, the average bus departure interval and the total number of bus departures during peak and nonpeak hours of the study route can be obtained, as shown in Table 8.

**Figure 2.** The relationship between the departure interval and time period number.

The original departure interval of this route was 15 min per trip. According to the operating time of the route, it can be inferred that the original total number of departures per day was 64. The passenger waiting time cost, the bus company's operating cost, and the bus company's exhaust emission cost can be calculated based on the established model before and after optimization, as shown in Table 9. The passenger waiting time cost was reduced by 8.49%, the bus company's operating cost was reduced by 3.13%, and the bus company's exhaust emission cost was reduced by 3.14%. The optimized departure schedule can improve passenger satisfaction and enhance the operational benefits and environmental protection effects of bus company and is conducive to the sustainable development of public transportation enterprises.

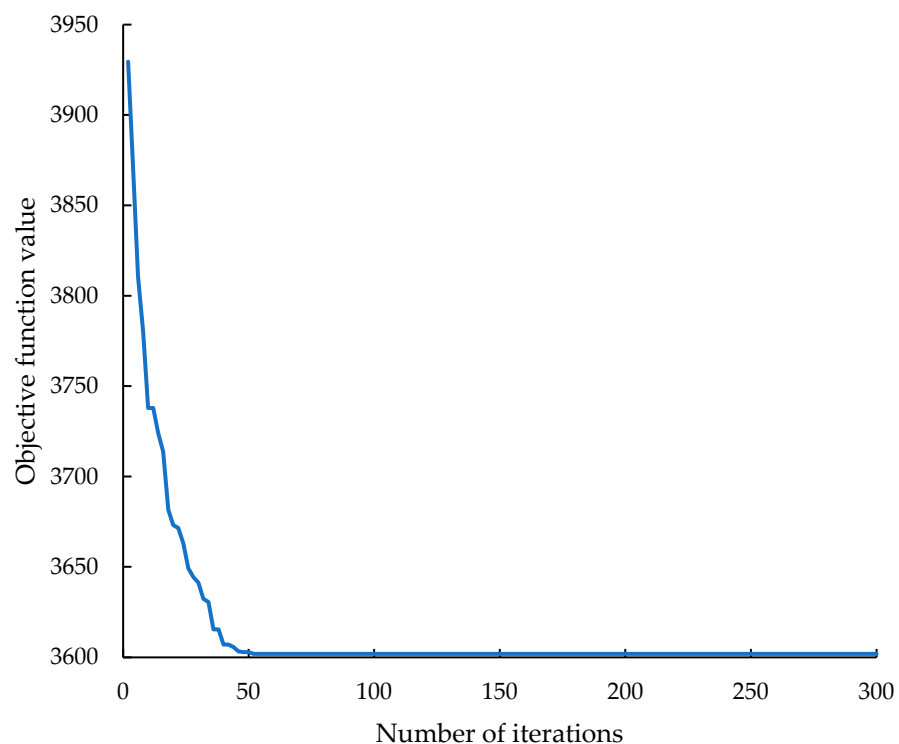


Figure 3. The relationship between the objective function values and the number of iterations.

Table 8. The average bus departure interval and the total departure number.

Time	Average Bus Departure Interval (min)	Total Number of Bus Departures
Nonpeak hour	21	42
Peak hour	12	16

Table 9. Cost comparison.

	Passenger Waiting Time Cost (EUR/d)	Bus Company's Operating Cost (EUR/d)	Bus Company's Exhaust Emission Cost (EUR/d)
Pre-optimization	1736.00	712.19	879.00
Optimal bus departure plan	1588.42	689.94	825.64
Reduce percentage	8.49%	3.13%	3.14%

Due to the differences in people's lives and work and rest situations, the actual departure intervals are usually multiples of 5 for the sake of practical scheduling, and the schedule of departures is generally constant throughout the day. According to the number of people at each station in each time slot, the corresponding departure interval and number of departures are adjusted to obtain the sub-optimal departure interval and number of departures, as shown in Table 10. The total number of trips is 59.

The costs of the sub-optimal departure schedule are shown in Table 11. The passenger waiting time cost was reduced by 5.49%, the bus company's operating cost was reduced by 7.81%, and the bus company's exhaust emission cost was reduced by 7.82%. Compared with the optimal bus departure plan, the passenger cost reduction in the sub-optimal bus departure plan has been reduced and the reduction in the company's operating costs and pollutant emission costs has increased. Due to further consideration of the company's operating habits and passenger travel habits, the suboptimal solution is appropriate in actual operation and effectively reduces the overall cost of the public transportation system.

Table 10. Adjusted departure interval and departure number.

No.	Time Period	Departure Interval	Departure Number
1	6:30–7:30	15	4
2	7:30–8:30	10	6
3	8:30–9:30	15	4
4	9:30–10:30	20	3
5	10:30–11:30	20	3
6	11:30–12:30	20	3
7	12:30–1:30	15	4
8	1:30–2:30	20	3
9	2:30–3:30	20	3
10	3:30–4:30	20	3
11	4:30–5:30	15	4
12	5:30–6:30	10	6
13	6:30–7:30	15	4
14	7:30–8:30	20	3
15	8:30–9:30	20	3
16	9:30–10:30	20	3

Table 11. Cost comparison between optimal and suboptimal bus departure plan.

	Passenger Waiting Time Cost (EUR/d)	Bus Company's Operating Cost (EUR/d)	Bus Company's Exhaust Emission Cost (EUR/d)
Pre-optimization	1735.79	712.19	880.30
Sub-optimal bus departure plan	1640.42	656.55	811.53
Reduce percentage	5.49%	7.81%	7.82%

6. Discussion

The urban public transport scheduling problem is a very complex problem, and the calculation process is cumbersome and involves a wide range. In this paper, the influence of bus exhaust emissions is considered, and the bus dispatching model is established. Based on the green concept, the bus scheduling model is optimized to obtain a bus scheduling optimization model with the goal of minimizing the operating cost of the bus company, minimizing the loss of passenger benefits, and minimizing the cost of exhaust emissions. The optimal scheduling scheme of a line is obtained by solving an example.

In future scheduling research, the following factors can also be considered:

The number of operating vehicles, passenger waiting time, traffic venue distribution, bicycle ownership, GDP, resident population, urban road mileage, bus operation line length, number of civil motor vehicles, average fare, and other factors that may impact urban public transport. Discuss the interrelatedness of these factors and their cumulative impact on the efficiency and sustainability of public transport systems.

The integration of green concept in bus scheduling: explore the significance of incorporating environmental factors (such as bus exhaust emissions, and the impact of vehicle driving state on exhaust emissions) into the bus scheduling model. Exploring how to optimize the bus schedule based on the green principle can not only reduce environmental pollution but also helps bus companies save costs and improve the overall passenger experience.

The combination of multi-objective optimization methods: This paper expounds on the challenges brought by the multi-objective characteristics of the urban public transport scheduling problem, in which the key objectives are to minimize the operating cost, passenger travel cost, and environmental impact. In this paper, a single genetic algorithm is used to solve the model. In future research, the combination of genetic algorithm and optimization methods such as simulated annealing algorithm, ant colony algorithm, and particle swarm optimization algorithm can be considered to improve the effectiveness of solving these complex optimization problems and achieve a balanced solution considering various conflict objectives.

Verification analysis and practical application: This paper provides insights for the verification and analysis of passenger flow data in specific cities (such as Nanjing). How to verify the effectiveness of the proposed bus scheduling optimization model by discussing the results of this practical application. Future research directions should emphasize the practical relevance of research results and their implementation potential in different urban environments.

Potential Impacts on Urban Mobility and Sustainability: Discuss the broad implications of optimizing public transport scheduling, including its potential to improve urban mobility, ease traffic congestion, and promote the development of sustainable public transport systems. It is emphasized that optimizing the departure interval and departure frequency can improve the efficiency of bus operation, improving the overall quality of urban traffic services. By solving these key points, more optimized answers will be obtained in future public transport scheduling research.

7. Conclusions

There are many factors affecting urban public transport: public transport operating vehicles, passenger waiting time, distribution of transport venues, bicycle ownership, GDP, resident population, urban road mileage, length of conventional bus operation lines, civilian motor vehicle ownership, average public transport fares, etc. All have an impact on urban public transport and affect the operation of urban public transport. There is a certain relationship between the influencing factors of public transport scheduling. In this paper, the impact of bus tailpipe emission is considered to construct a bus scheduling model; the bus scheduling model is optimized based on the green concept, and the bus scheduling optimization model minimizes the operating cost of the bus company, minimizing the loss of passengers' interests, and minimizing the cost of tailpipe emission. The urban bus scheduling problem is a multi-objective function problem, which is solved using a genetic algorithm. The final example validation analysis, using the passenger flow data of a line in Nanjing city, is validated and analyzed, and the results show that the application of genetic algorithms to bus scheduling can be a good solution to the problems arising in scheduling. Reasonable departure intervals and the number of departures can improve the efficiency of bus operation, alleviate urban traffic congestion, and help to build a sustainable public transport system. Urban public transport scheduling problem is a very complex problem, the calculation process is cumbersome, involving more areas. The shortcomings of this paper are as follows: studying a single line without considering the overall scheduling of multiple lines; the number of passengers arriving at the bus station by default is evenly distributed, and the actual arrival rate of passengers is uneven; the bus is traveling at a constant speed—in the actual situation, it is easy to cause traffic jams and accidents; bus exhaust emissions at stops are not considered. In future research, we can further study the scheduling problem of double-line lines; based on real-time passenger flow information, vehicle operation information, etc., the bus dynamic scheduling problem can be studied. In this paper, a single genetic algorithm is used to solve multi-objective optimization problems. In future research, the tabu algorithm and simulated annealing algorithm can be introduced to design a hybrid genetic algorithm to solve scheduling problems.

Author Contributions: Methodology, M.W.; Software, M.W.; Validation, M.W.; Investigation, M.W.; Resources, B.G., Z.Z. and Y.Z.; Writing—original draft, M.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was financed by two grants from the Jiaozuo Engineering Research Center of Road Traffic and Transportation (JRTT2023003 and JRTT2023012).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available in the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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