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Intelligent Bus Scheduling Control Based on On-Board Bus Controller and Simulated Annealing Genetic Algorithm

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Abstract: The stable and fast service of a bus network is one of the important indicators of the service quality and management level of urban public transport. With the continuous expansion of cities, the bus network complexity has been increasing accordingly. The application of new technologies such as self-driving buses has made the bus network more complex and its vulnerability more obvious. Therefore, how to collect information on passenger flow, traffic flow, and transport distribution using intelligent means, and how to establish an effective intelligent bus scheduling control method have been important questions surrounding the improvement of the level of urban bus operation. To address this challenge, this paper proposes the design method of a bus controller based on data collection and the edge computing requirements of autonomous driving buses; and installs them widely on buses. In addition, an intelligent bus control scheduling method based on the simulated annealing genetic algorithm was developed according to the current scheduling requirements. The proposed method combines the strong local search ability of the simulated annealing algorithm, which prevents the search process from falling into a local optimum, and the strong search ability of the genetic algorithm in the overall search process, leading an intelligent bus control scheduling method based on the simulated annealing genetic algorithm. The proposed method was verified by experiments on the optimal scheduling of multi-destination public transport as an example, we verified the research method, and finally, simulated it using historical data. There is good model prediction of the experimental results. Therefore, the intelligent traffic control can be realized through efficient bus scheduling, thus improving the robustness of the bus network operation.

Keywords: bus network; on-board controller; intelligent scheduling; edge computing; simulated annealing genetic algorithm

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1. Introduction

Due to the characteristics of large capacity, fast speed, punctuality, along with safety, and environmental protection, urban buses have developed rapidly both in China and worldwide in recent years [1]. The passenger flow of public transport, including buses, subways, and passenger ships, has been one of the most crucial factors affecting the public transport operation in urban public transport. Therefore, the bus passenger flow analysis has become an important market research tool, as well as an important basis for urban transportation system planning and construction, and an important means of business analysis for passenger computing companies [2–4]. By systematically analyzing the distribution characteristics and changing patterns of the passenger flow mastering the corresponding changing patterns, an important reference for management decision-makers can be provided [5]. Xu et al. [6] proposed a subway passenger flow prediction method based on temporal and spatial characteristics, taking the influence of time and space as the influencing factor of prediction, and using linear regression to predict subway passenger flow. Yang et al. [7] developed a method for the short-term passenger flow prediction of urban rail transit based on a backpropagation neural network model, considering influence factors such as weather conditions and date. Mo et al. [8] presented a neural network-based real-time bus line passenger flow prediction model, which uses the passenger flow, date, time, and weather conditions as input parameters and the real-time passenger flow prediction as an output parameter, and they analyzed the bus passenger flow through multi-dimensional analysis.

One of the main purposes of the bus passenger flow analysis is to provide various intelligent algorithms for bus scheduling, thereby improving the level of bus operation management. The core problem of intelligent bus scheduling is timetable optimization, which has been a common research topic. The influencing factors of intelligent bus scheduling include the bus model [9], number of vehicles [10], and passenger transfer [11]. However, most of the existing bus scheduling optimization methods have been developed based on certain assumptions, such as fixed inter-station running time [12], fixed demand of passengers in each group of origin-destinations (ODs) [12], and fixed frequency [13], which conflict with the actual management. In addition, continuous investment in customized buses [14–16], the promotion of multiple payment methods [17–19], and the application of autonomous driving [20–23], combined with various neural networks and route planning methods [24–26], have increased the complexity of statistical analysis of bus passenger flow and have put higher requirements for the optimization of intelligent bus scheduling methods.

To improve the accuracy of passenger flow statistical analysis, this paper proposes an on-board bus controller suitable for the current situation. In addition, based on the requirements for complex multi-source bus operation data, an intelligent bus scheduling method based on a simulated annealing genetic algorithm is proposed. The statistical analysis results of bus passenger flow data show that the limited bus network and vehicle resources can be reasonably allocated. Moreover, the travel needs of various passengers can be met at reduced manpower, material resources, and funds, which can significantly reduce the operating cost of bus companies and adjust the balance between supply and demand. In this way, more passengers will be motivated to use buses as a means of transport, which is beneficial for both bus enterprises and passengers.

2. Autonomous Driving Bus On-Board Controller Design and Edge Computing

2.1. Autonomous Driving Bus On-Board Controller

Considering the requirements for openness, versatility, and high-end performance of an autonomous driving on-board controller, the self-controllable processor and chip are used to design a safe and reliable intelligent controller. Using the research system management control and hardware acceleration technology adopting autonomous processors, self-organizing communication design and collaborative communication optimization technology can provide a multi-level networking interconnection, complete regional communication coverage, and operation coordination.

This study designed the hardware circuit for high-end intelligent controllers, analyzed the differences in computing modes and computing power requirements in different application scenarios, designed a unified hardware architecture, and realized the collocation and collaborative management of heterogeneous computing power processors. In addition, the application optimization of processors with independent intellectual property rights was performed for better adaptation. A system bus architecture that supports multi-mode computer buses was designed to achieve fast access support for various sensors. Finally, this study also designed a multi-mode is adopted communication mode to achieve high-speed self-organizing communication.

An autonomous driving on-board controller has the characteristics of high computing power and low power consumption according to the application scenario. In application scenarios that require high computing power, such as obstacle avoidance and switching lanes, the main requirement is high computing power. This application is mainly related to buses running on various complex roads; in bus lanes, BRT (Bus Rapid Transit), and other relatively simple scenarios, the main requirement is low power consumption. The autonomous driving on-board controller was designed for a unified hardware architecture, and can invoke various processors and computing resources. To adapt to external sensors and intelligent devices for different applications, the computer bus coupling mechanism is used in the processor exterior to achieve control between the internal bus and external devices. Considering differences in transmission protocols and technologies of different applications, a variety of computer bus protocol adaptations were implemented in the controller. In addition, to meet the connection requirements of various external sensors and devices, several external interfaces were used, including the Ethernet, CAN bus, and serial port, and support time-sensitive network docking. The hardware block diagram of an autonomous processor-based on-board controller for autonomous vehicles is presented in Figure 1.

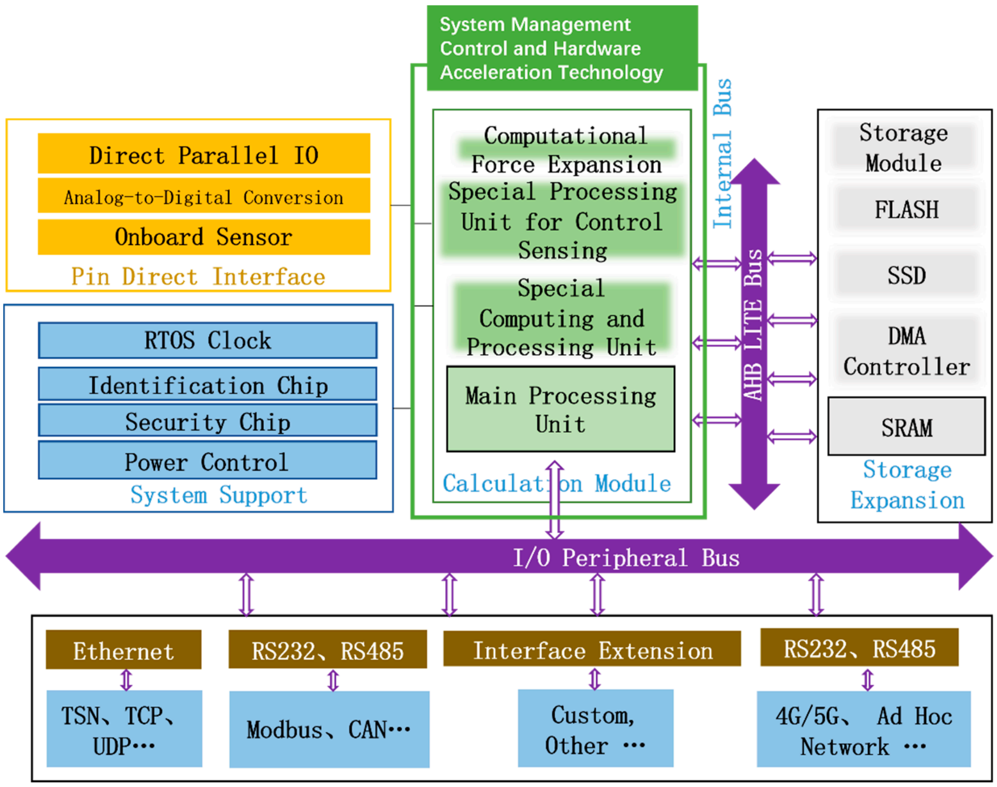


Figure 1. The hardware block diagram of the controller based on an autonomous processor.

2.2. Mobile Edge Computing

The mobile edge computing architecture of a bus controller relies on the edge-cloud coordination and communication infrastructure and services provided by the LTE/5G system installed on the on-board unit. However, with the application of AI and V2X, the vehicle control system of intelligent networked vehicles has become more complex. Load integration and methods have been used to simplify the control system, and integrate HMIs of different systems, ADAD, IVI, digital instruments, and HUD. The on-board information services are complex and run on the same hardware platform through virtualization technology. The schematic diagram of the hardware architecture of the on-board computing unit is presented in Figure 2. However, the load integration based on virtualization and hardware abstraction layer HAL makes it easier for the cloud to perform flexible business orchestration, deep learning model updating, and software and firmware upgrading for the vehicle driving system. The hardware architecture diagram of the on-board computing unit is shown below [22,23,27,28].

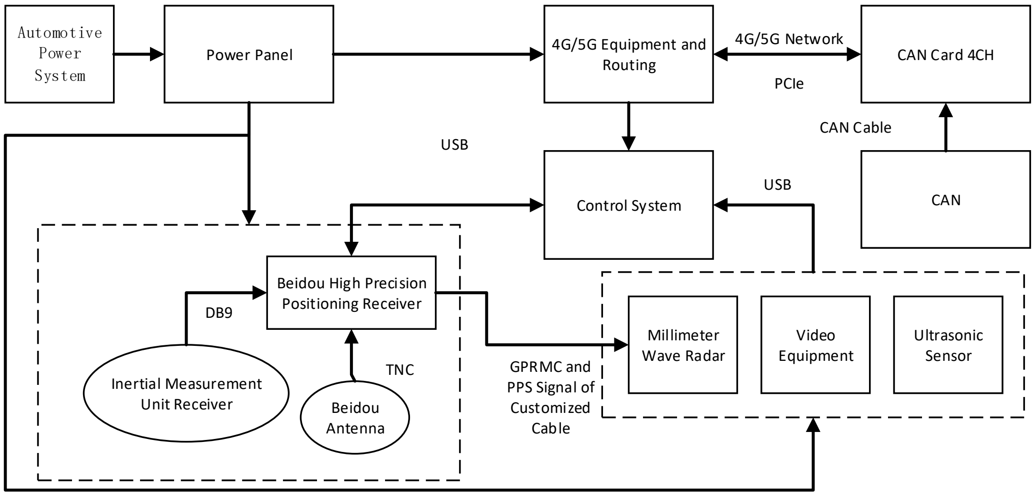


Figure 2. Hardware architecture of the on-board computing unit.

The management and control of intelligent and connected vehicles have very high requirements for the real-time response of a system. For instance, the braking time includes not only the vehicle control time, but also the response time of the entire system, including network cloud computing, processing the agreement between vehicles, vehicle system computing, and the time of each process, such as braking processing. Therefore, dividing the response time into intervals corresponding to functional modules of the edge computing platform in real-time can greatly shorten the computing time. In this way, the time required for the detection and precise positioning of surrounding targets, fusion and analysis of sensor data, and behavior and route planning will also be reduced. However, in the computing process, the ability to allocate network processing transactions based on data priorities needs to be improved.

3. Intelligent Bus Scheduling Control Based on Simulated Annealing Genetic Algorithm

3.1. Simulated Annealing Genetic Algorithm

The simulated annealing algorithm is a heuristic random search algorithm based on the iterative Monte Carlo method. It simulates the similarity between the thermal equilibrium problem of the solid material annealing process and the random search optimization problem to find or approximate the global optimum. This algorithm is a random search method technology established by direct and simple simulation. It has a strong local search ability, allowing the search process to avoid falling into local optima, but the overall search ability is poor, which is inconvenient for allowing the search process to enter the most promising area. Therefore, the entire search space cannot be performed well, and the convergence speed is slow, making the computational efficiency of the simulated annealing algorithm low.

A genetic algorithm is a random search algorithm that simulates the natural selection and evolution of biology. The random search algorithm obtains the optimal solution through individual selection, crossover and mutation, and continuous evolution. Its advantages are mainly manifested in intelligence, parallelism, universality, and global optimality. Furthermore, this algorithm does not require prior information. However, it has the disadvantage of an insufficient local search ability. Nevertheless, the ability to grasp the overall search process is strong.

In this work, the two mentioned algorithms were combined. Namely, the genetic algorithm was integrated into the operation of the simulated annealing algorithm, which not only accelerates the convergence speed of the algorithm, but also avoids falling into local optima. Therefore, in the process of searching for an optimal solution, the simulated annealing method not only accepts improved solutions, but a random acceptance criterion called the Metropolis criterion is used to accept deteriorating solutions to a limited extent. The probability of accepting a deteriorating solution gradually tends to zero, which makes it possible for the algorithm to jump out of the local extreme region and find the global optimal solution. Moreover, in this way, the convergence of the algorithm is guaranteed and the multi-objective optimization solution is realized.

In the prediction process of the genetic algorithm, the judgment of the simulated annealing algorithm is added to prevent the genetic algorithm from falling into a local optimum during the prediction process, thus preventing the final output result from differing from the global optimal scheduling result. In the process of intelligent prediction of shift scheduling by the genetic algorithm, due to the completely random process of new shift scheduling individuals generated by mutation, the algorithm can easily fall into a local optimum, which can result in gradient disappearance. However, the introduction of the simulated annealing algorithm can correct the mutation probability in the iterative process, thus solving the problem of gradient disappearance and ensuring the global optimal solution is found. The mutation probability correction function is given by [29,30]:

$$P_i = \begin{cases} \varepsilon - \frac{E(i+1)-E(i)}{T_i}, E(i+1) \geq E(i), i = 0, 1, \cdots, n \\ 1\,, E(i+1) < E(i), i = 0, 1, \cdots, n \end{cases}$$
$$T_i = \frac{T_i(0)}{\lg(1+i)}, i = 0, 1, \cdots, n$$

where P_i is the jumping probability of the simulated annealing algorithm; T_i is the current temperature; $E(i)$ is the current energy; ε is a random value in the interval $[0, 1)$; $T_i(0)$ is the initial temperature; n is the number of iterations.

The solution process of the simulated annealing algorithm includes the following steps:

Step 1: Set the population size, the number of iterations, the probability of crossover and mutation, and the initial temperature, and randomly generate the initial solution x_0;

Step 2: Initialize the annealing temperature $T_i(0)$;

Step 3: At temperature T_i execute the following operations:

(1) Generate a new feasible solution x', where x' represents the neighborhood solution of the final solution x;

(2) Calculate the difference between functions $f(x')$ and $f(x)$: $\Delta f = f(x') - f(x)$;

(3) Using the probability of $\min\{1, \exp(-\Delta f/T_i)\} > random[0, 1]$, accept the new solution, where $random[0, 1]$ is a random number in the interval of $[0, 1]$. If the equilibrium temperature T_i is reached, proceed to Step 4; otherwise, repeat Step 3;

Step 4: Decrease the temperature according to the decreasing function defined by:

$$T_{i+1} = \alpha \frac{T_i}{\lg(1+i)}, \alpha \in [0, 1]$$

Step 5: If the convergence criterion is satisfied, the annealing process terminates; otherwise, the algorithm proceeds to Step 3.

Based on the above steps of the simulated annealing process, the annealing temperature controls the solution process to the optimal direction of the minimum value. At the same time, it accepts inferior solutions with a probability, $\exp(-\Delta f/T_i)$ so that the algorithm can jump out of the local extreme points. As long as the initial temperature is high enough and the annealing process is slow enough, the algorithm can converge to the global optimal solution.

3.2. Intelligent Bus Scheduling Control Method

Vehicle scheduling and dispatching denote the key to the operation of public transport enterprises. After a multi-dimensional and refined analysis of bus passenger flow vehicles, stations, routes, and vehicle arrival predictions, the 5G, artificial intelligence, simulation, and other technologies were comprehensively applied to simulate the whole process of scheduling the vehicles on a route. At the same time, a rationality evaluation index system was established to verify the optimal scheduling scheme that matches the passenger flow and transport capacity, thereby realizing automatic bus scheduling, dispatching, and intelligent scheduling.

By introducing the simulated annealing genetic algorithm, the number of vehicles operating in different areas, times, and lines can be reasonably configured. The driving operation plan is automatically arranged and the shift interval is planned to ensure an optimal riding environment and the highest operating efficiency. For small and special-service routes with long shift intervals, the departure time shall be announced according to the travel operation plan, and the buses will automatically depart at fixed times and places. For routes with a large passenger flow and many uncertain factors in road traffic, the turnaround time is calculated based on the bus passenger flow prediction, real-time scheduling is adopted, and a simulated annealing genetic algorithm is used for dynamic adjustment to achieve the best matching of capacity and passenger flow. This method effectively improves the bus scheduling, efficiency, the matching between the departure schedule and the passenger flow demand, and the utilization rate of bus vehicles. It also reduces the operating cost of public transport enterprises, and improves their operation and management capabilities. Further, it promotes the maximum effectiveness of route resources, improves the quality and reliability of public transport services, and enhances passenger comfort and information service capabilities.

4. Results and Analysis

The business data collected on the bus routes in Guangzhou in August 2021 were used to construct the database for testing the proposed method. The real-time calculation and verification were performed using 4.3229 million trip records collected on 18 August 2021. In the calculation process, to ensure real-time efficiency, the distributed storage and calculation of the travel chain information on different vehicle payment methods (e.g., bus card, QR code, and UnionPay) were used to obtain the passenger OD. Based on the bus running routes and bus positioning information on a given day, and considering the real-time traffic operation conditions, an index library of bus network capacity and full capacity operation rate was constructed to form the final test library.

The accuracy of the proposed method was evaluated using the actual bus route operation indicators and scheduling timetable as test data. The traffic simulation method and the intelligent bus scheduling control method based on the simulated annealing genetic algorithm, were applied on the accurate data, such as the full capacity rate of the vehicle.

The all-day bus operation plan selected for testing was used as an analysis object, and the algorithm was verified by simulating and optimizing the actual data and comparing the simulation results with the real data.

In practical applications, bus operators commonly set the minimum deviation in the given timetable, waiting time of passengers, bus operating cost, minimum carpooling cost, and the shortest route as a goal to realize bus scheduling. This study sets the waiting time of passengers as a goal and combines the bus schedule optimization, multi-mode combined scheduling, carpooling mitigation, passenger flow evacuation, uncertain-demand scenarios, and the proposed algorithm. The impact of carpooling, surges in passenger flow, random passenger flow, passengers' personalized choices of different transportation modes, passenger flow evacuation, and other scenarios are considered in order to solve the bus scheduling problems in different scenarios.

To verify the effectiveness of the bus scheduling for the bus line network management, one of the bus lines was selected as a simulation structure for analysis. The operation of a bus line during the morning rush hour from 8:30 to 9:00 was randomly selected for direct analysis. The bus line has a total of 21 stations. The number of waiting passengers at the same main bus station in this period was used as the main analysis object. The travel demand of passengers at parts of the main stations of the selected bus line at 8:30 on the day considered in the analysis using the travel demand thermodynamic diagram is presented in Figure 3. The dispatching results comparison by average waiting time of passengers compared the intelligent bus scheduling method and the traditional manual scheduling method is shown in Figure 4.

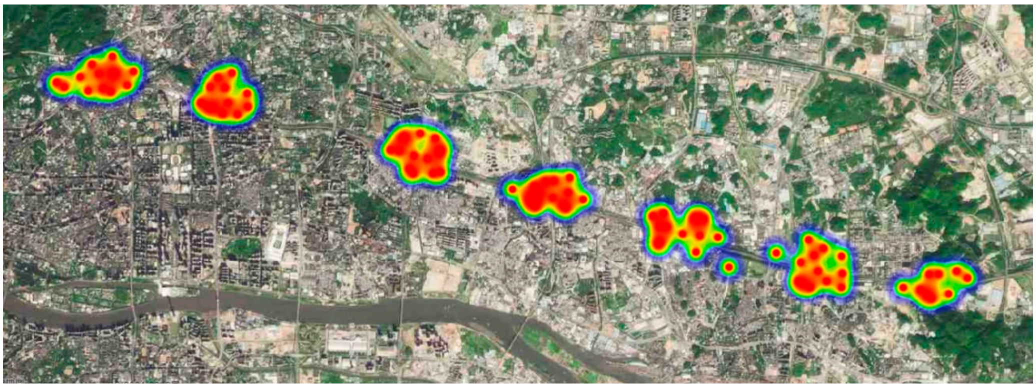
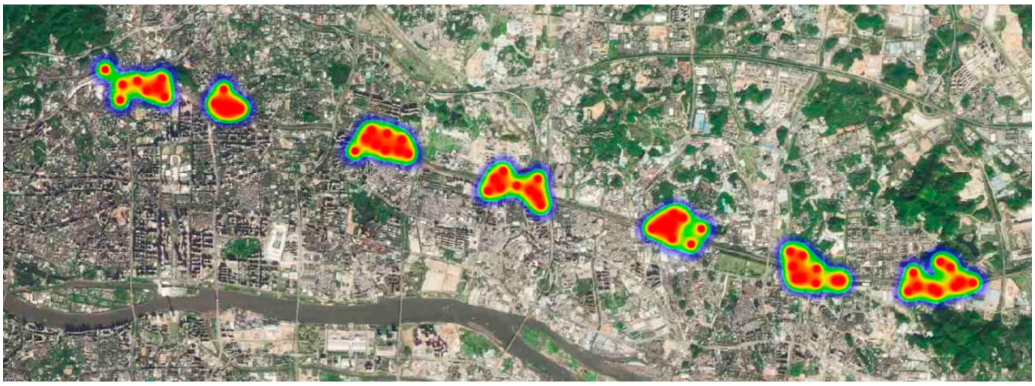


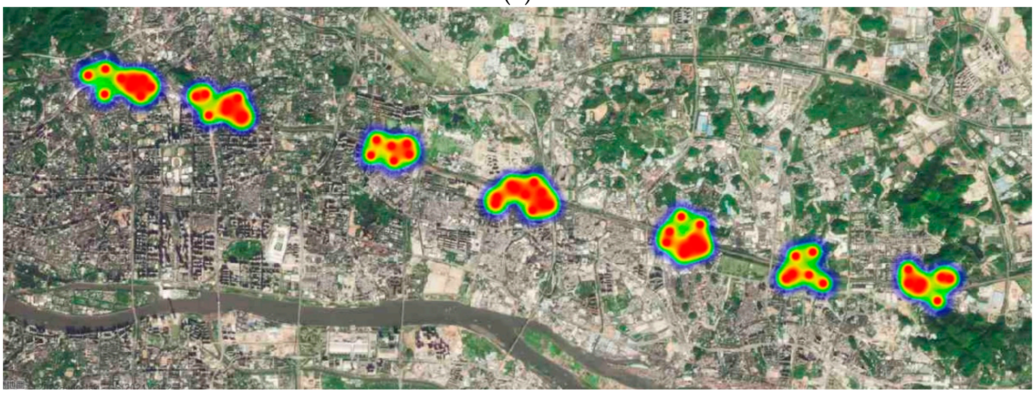
Figure 3. Thermodynamic diagram of the passenger travel demand at the major stations at 8:30.

Figure 4. Dispatching results comparison by average waiting time of passengers.

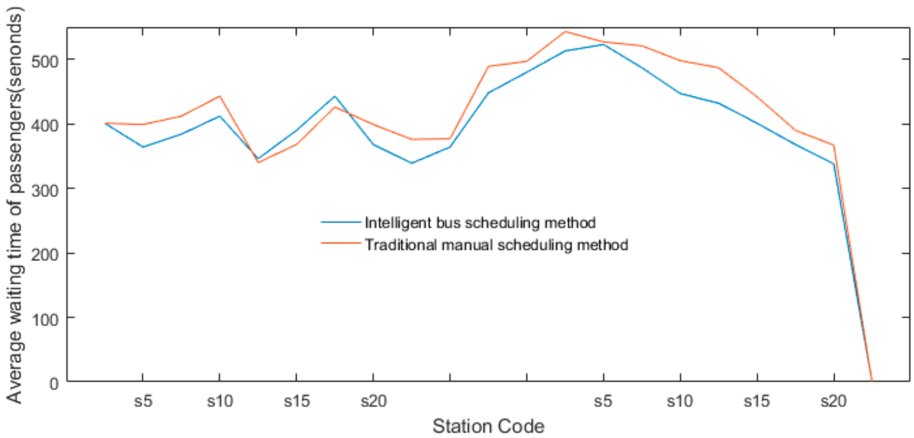
The statistical interval was set to 15 min. The thermodynamic diagrams of the passenger travel demand at the main stations at 8:45 obtained by the traditional bus scheduling method and the proposed method are presented in Figure 5a,b, respectively. The dispatching results comparison by average waiting time of passengers compared the intelligent bus scheduling method and the traditional manual scheduling method, and is shown in Figure 5c, corresponding to Figure 5a,b.



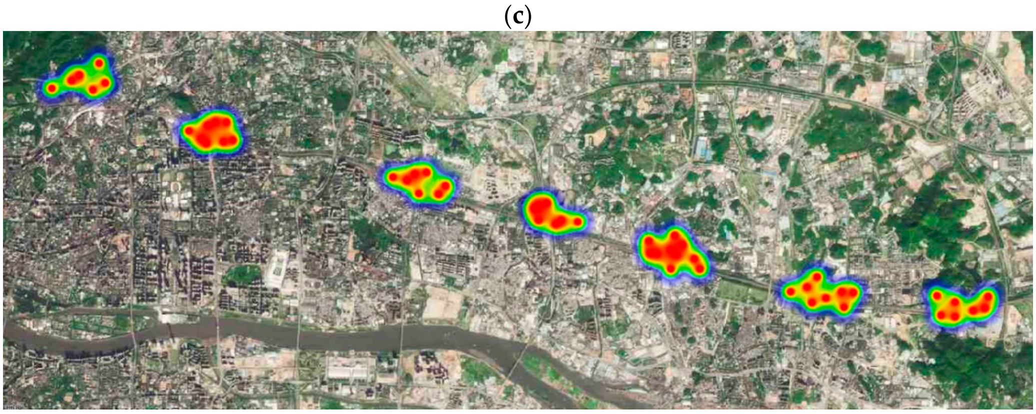
(**a**)



(**b**)

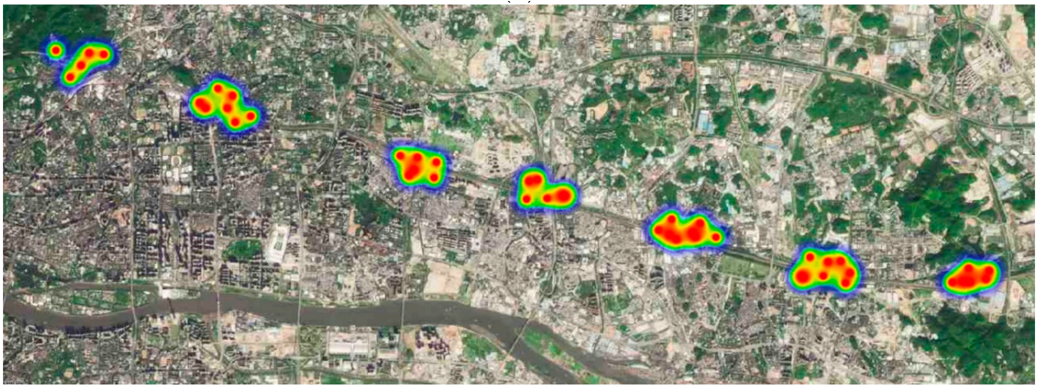


(**c**)

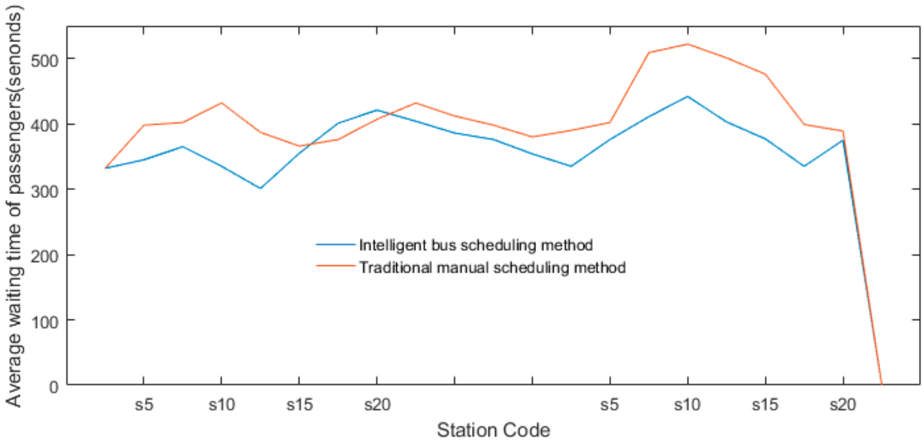


(**d**)

Figure 5. *Cont*.



(e)



(f)

Figure 5. (**a**) Travel thermodynamic diagram at 8:45 obtained by the traditional bus scheduling method. (**b**) Travel thermodynamic diagram at 8:45 obtained by the proposed bus scheduling method. (**c**) Dispatching results comparison by average waiting time of passengers. (**d**) Travel thermodynamic diagram at 9:00 obtained by the traditional bus scheduling method. (**e**) Travel thermodynamic diagram at 9:00 obtained by the proposed bus scheduling method. (**f**) Dispatching results comparison by average waiting time of passengers.

The thermodynamic diagrams of the passenger travel demand at the main stations at 9:00 obtained by the traditional bus scheduling method and the proposed method are presented in Figure 5d,e, respectively. The dispatching results comparison by average waiting time of passengers compared the intelligent bus scheduling method and the traditional manual scheduling method and is shown in Figure 5f, corresponding to Figure 5d,e.

The thermodynamic diagram of the passenger travel demand and the dispatching results at the main stations in the analyzed interval shows that the overall average wait time of passengers decreased. It also shows that the thermodynamic diagrams obtained by the proposed method were slightly weaker than those obtained by the traditional bus scheduling method. This indicates that the bus capacity scheduling was improved to a certain extent by using the proposed method. This improvement in the bus capacity scheduling reduced the number of waiting passengers.

According to the simulation results in the period of 8:30–8:45, by using the proposed method, the passenger transportation volume can be increased by 13.23% compared to the traditional bus scheduling method under the same transportation capacity. Furthermore, by using the proposed method, the transportation capacity was reduced by 11.68% under the same passenger volume. In addition, in the period of 8:45–9:00, by using the proposed method, the passenger transportation volume increased by 12.12% under the same transportation capacity, whereas the transportation capacity decreased by 10.81% under the same passenger volume.

According to the simulation results of the same route throughout the day, compared to the traditional bus scheduling method, the passenger transportation volume increased by 9.31% by using the proposed method, whereas the transportation capacity was reduced by 8.52% under the same passenger volume.

Considering the public welfare of public transport, the bus network planning considered indicators such as bus coverage and repetition rate. The overall results of the proposed method for the bus network from 8:30 to 8:45 showed an increase in the passenger transportation volume by 6.98% under the same transport capacity, whereas the transportation capacity was reduced by 6.53% under the same passenger volume. Similarly, the overall results from 8:45 to 9:00 showed an increase in the passenger capacity by 7.25%, whereas the transportation capacity was reduced by 6.76% under the same passenger volume.

According to the results of the operating hours throughout the day, by using the proposed method, the passenger traffic increased by 9.01% under the same capacity. On the other hand, the transportation capacity was reduced by 8.34% under the same passenger volume.

Overall, the results demonstrated that during the morning and evening peak hours, the efficiency of intelligent scheduling and control of the transportation capacity was more obvious for the routes near the city center than those in the suburbs and that in the early morning and at night, they did not significantly improve.

5. Discussion and Conclusions

In this paper, according to the data acquisition and edge computing requirements of autonomous driving buses, the design method of an on-board bus controller was proposed. On this basis, an intelligent bus control scheduling method based on the simulated annealing genetic algorithm was developed. The proposed method is verified by experiments on the optimal scheduling of multi-destination buses. The experimental results show that compared to the traditional bus scheduling method, the thermodynamic diagram of the passenger travel demand at the main stations obtained by the proposed method is slightly weaker. This indicates that by applying the proposed method, the bus capacity scheduling can be improved, thereby reducing the number of waiting passengers. The statistical results demonstrate that the efficiency of intelligent scheduling of transportation capacity during the morning and evening peak hours is better for the routes near the city center than for those in the suburbs. Consequently, the proposed method in this paper can effectively improve the efficiency of intelligent bus scheduling.

Although the proposed method can improve the bus optimization scheduling problem, this study has certain limitations. Namely, in the intelligent bus scheduling control, this study considers the running time between stations, the number of passengers, road congestion, and other influencing factors of bus operation. In future work, more practical factors should be considered when solving the bus optimization and scheduling problem, such as the influence of traffic lights and collinear bus transport. In addition, when studying intelligent bus scheduling and control, public welfare should also be considered, as well as many other aspects, including the passenger waiting time and bus operation cost and benefit. Furthermore, when selecting the analysis object, more consideration should be given to the routes with high travel demand and less consideration should be given to inclusive routes. These factors need further analysis and optimization in future research.

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Data Availability Statement: The original data used to support the findings of this study are restricted by the relevant law-enforcement departments in order to protect vehicle information privacy and law enforcement basis. Data are available from relevant law-enforcement departments for researchers who meet the criteria for access to confidential data.

Conflicts of Interest: Authors declare that they have no conflict of interest.

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