

Research Article

Assessing the Impacts of Autonomous Bus-on-Demand Based on Agent-Based Simulation: A Case Study of Fuyang, Zhejiang, China

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Received 3 February 2020; Revised 13 October 2020; Accepted 7 November 2020; Published 23 November 2020

Academic Editor: Prakash Ranjitkar

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This paper envisions and assesses the performance of an autonomous bus-on-demand (ABoD) system. We take Fuyang, Zhejiang, China, as the study area to investigate the spatiotemporal distribution of bus travel demand during workdays, and we propose replacing inefficient bus routes with the ABoD system. Agent-based models with various bus dispatching and operation control strategies are constructed to evaluate the performance of the ABoD system. The behaviors and interactions of the agents, passengers, autonomous buses, and a control center are designed. After the verification of the simulated bus travel demand with real-world demand, a series of scenarios with various ABoD operation strategies are simulated. The simulation results show that, in comparison with both current fixed-schedule bus services and the optimized bus dispatching strategies, the ABoD system occupies fewer road resources and utilizes bus vehicles more efficiently. Besides, the system is adaptive to the sudden surge in bus travel demand and is economically sustainable.

1. Introduction

The concept of a demand-responsive public transit system has been proposed and experimented with Daganzo [1] and Wilson and Hendrickson [2]. Decades of effort have been invested in designing and operating these on-demand public transit services. Ceder and Wilson [3] constructed a bus network planning model based on real demand to minimize time consumption. Dial [4] designed a dial-a-ride transit system for passengers to book vehicles by phone in advance, which can be regarded as the precursor of modern mobility-on-demand services, such as Uber and Didi. Adebisi and Hurdle [5] showed that demand-responsive bus services are suitable for low ridership, low density, and scattered demand. Chang and Schonfeld [6] designed a flexible route bus subscription system to provide feeder services to a single destination, to minimize total cost in comparison with fixed-route conventional bus systems. Quadrifoglio et al. [7] examined the impact on oil productivity of demand-responsive transit systems and concluded that the same demand can be satisfied employing fewer vehicles. However, due to the constraints

of information and communication technology (ICT) and labor costs, demand-responsive public transit services have seldom been successfully implemented.

In recent years, thanks to the rapid development of ICT and significant progress in autonomous driving technologies, autonomous bus-on-demand (ABoD) services are expected to manifest [8]. Although a few studies have envisioned various proposals for on-demand bus systems [9, 10], the majority of works on the potential application of autonomous technologies treat autonomous vehicles (AVs) primarily as personal vehicles [11–13]. And some works look into the fact that how AVs can be embedded into public transit systems. Vakayil et al. [14] explore a hybrid transit system with on-demand AVs as an additional service to improve metro connectivity. Shen et al. [15] propose the integration of shared AVs into public transportation systems for the first-mile service in Singapore. However, only a few studies have focused on the feasibility of an ABoD system replacing traditional bus services completely. Winter et al. [16] design an automated demand-responsive transport system suitable for areas with intensive demand, which offers a direct connection between pick-up and drop-off

locations without any detours or intermediate stops. Navidi et al. [17] demonstrate that replacing traditional public transport with demand-responsive transport can decrease passengers' perceived travel times without any extra costs, under certain circumstances. Nonetheless, these studies mainly focus on demand-responsive transit services between two locations, whereas strategies for on-demand operation between multiple stops are seldom discussed.

In this study, we envision a real-time ABoD system servicing multiple intermediate bus stops. The new system is compared with the current fixed-schedule and fixed-route bus services. We assess the impacts of the envisioned ABoD system under various scenarios via agent-based simulation, which has advantages over mathematical approaches, as it can provide insight into the operation of a system under different scenarios [18].

This paper is organized as follows. In the second section, we conduct a descriptive analysis to investigate current bus travel demand in our study area, Fuyang, Zhejiang China, based on mobile payment records. In the third section, we elaborate on the agent-based modeling framework and the behaviors of the agents and their interactions, including passengers, autonomous buses, and the control center. In the subsequent section, after the verification of the consistency of the random bus travel origin-destination (OD) matrix with real-world data to ensure the reliability of the simulation results, we simulate the scenarios with various ABoD operation strategies and compare this with the current conventional bus services to evaluate whether the ABoD is competent in improving the quality of bus services in Fuyang. In the final section, discussions and conclusions are offered.

2. A Descriptive Analysis of Bus Travel Demand in Fuyang, Zhejiang

We select Fuyang, a prefecture-level city of Zhejiang, China, for our case study. Fuyang city, classified as a small city in China, had a population of approximately 742,000 in 2018. We collect data from DTChuxing, a company that promotes data fusion innovation in the urban public transport sector. The datasets include the boarding time and bus stop of each passenger who pays via IC Card or mobile phone. The period of the data incorporated in this study spans September 2018, consisting of 20 workdays and 10 weekends. In this study, we focus on bus travel demand during workdays. It is worth mentioning that the number of passengers using either IC Card or mobile phone accounts for 50% of total bus travel demand, whereas the remainder of passengers pays with cash [19]. Thus, we empirically scale up the number of passengers uniformly to synthesize aggregate bus travel demand in Fuyang.

The average bus travel demand during workdays in September 2018 is shown in Figure 1. As outlined in Figure 1(a), the number of passengers varies with the nature of land use. For example, bus stops close to railway stations or hospitals attract more passengers. In addition, bus travel demand varies largely by bus route. As outlined in Figure 1(b), the busiest bus lines carry more than 5,000

passengers a day, whereas some other routes transport less than 1,000. These inefficient bus routes are more financially unsustainable for operators (i.e., black bar: Bus Line 622). Thus, in this work, we envision an ABoD system to replace these routes, and we assess the performance of the new system.

The descriptive analysis above demonstrates that one of the greatest challenges faced in Fuyang, as in many small Chinese cities, is the imbalance of transit supply and demand, where the bus supply normally exceeds the demand, which leads to the low utilization of buses and, possibly, great financial deficits. Meanwhile, the development of ICT and driverless technology offers new possibilities to operate ABoD services. A variety of autonomous bus services have been opened for trial operation. For instance, in Dubai, UAE, the Next Future Transportation Inc. deployed a modular autonomous bus—with 6 seats and a capacity of 10 passengers—that can be joined onto or detached from the other bus modules (see <https://www.next-future-mobility.com>).

In this paper, we take Bus Line 622 as an example to demonstrate the impacts of the ABoD system. Currently, the bus service operates from 6 a.m. to 8 p.m., with a fixed departure interval of 10 minutes. The vehicles with 26 seats are employed in operation with a capacity of 45 passengers. The route travels across Fuyang city center, with 14 stops, including a number of important points-of-interest, such as the First Hospital of Fuyang and Fuyang West Station. Figure 2(a) outlines the detailed routes of this bus line, and the average number of passengers boarding the buses at each stop is also visualized. As shown in the figure, the spatial distribution of bus travel demand is not uniform across the route. Some bus stops attract over 100 passengers, while others have fewer than ten passengers during workdays.

The temporal distribution of travel demand is shown in Figure 2(b). The average travel demand of Bus Line 622 during workdays is measured in 30-minute intervals. Observable morning and evening peak hours exist for this bus line, with around 200 passengers boarding during morning peak hours, whereas passengers during off-peak hours are few.

3. An Autonomous Bus-on-Demand System: Design and Operation

We construct an agent-based model to evaluate the performance of the ABoD system from three perspectives: operator, passenger, and road resources. We compare the ABoD with traditional bus systems under various travel demand scenarios. The model is coded in Java in the AnyLogic platform, with an integrated GIS environment.

The ABoD system primarily consists of three types of agents: passenger, control center, and autonomous bus. In this study, we model the behaviors and interactions among the three types of agents in the system, as illustrated in Figure 3. The control center collects travel demand information from passengers and determines departure intervals and bus operation strategies. Meanwhile, passengers can receive real-time bus information. When the departure

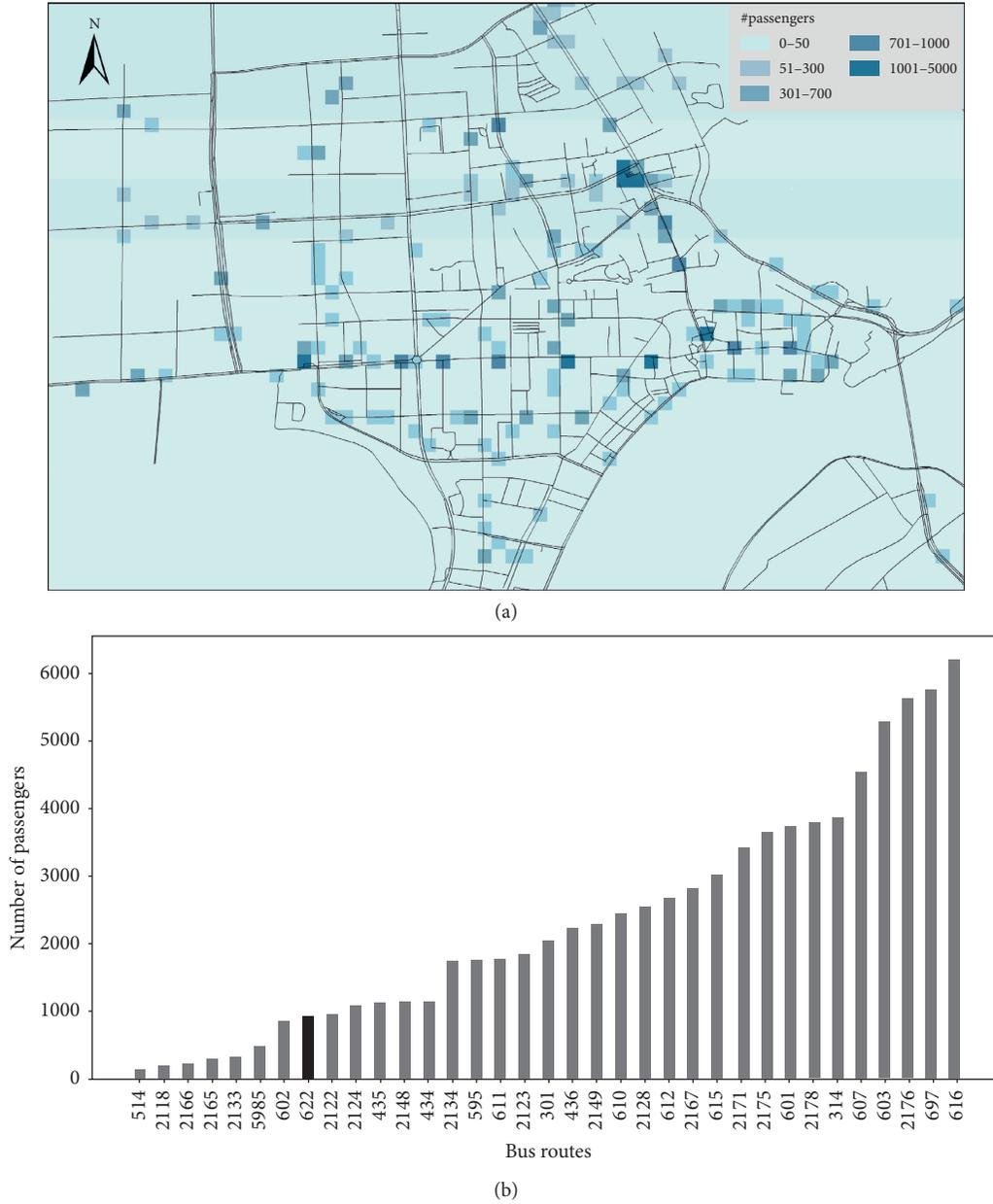


FIGURE 1: Bus travel demand in Fuyang, Zhejiang, China. (a) Spatial distribution of bus travel demand in Fuyang. (b) Bus travel demand by route.

threshold is met, the control center instructs the autonomous buses to depart and continuously receives bus travel information. If necessary, the autonomous buses skip intermediate stops, according to instructions from the control center.

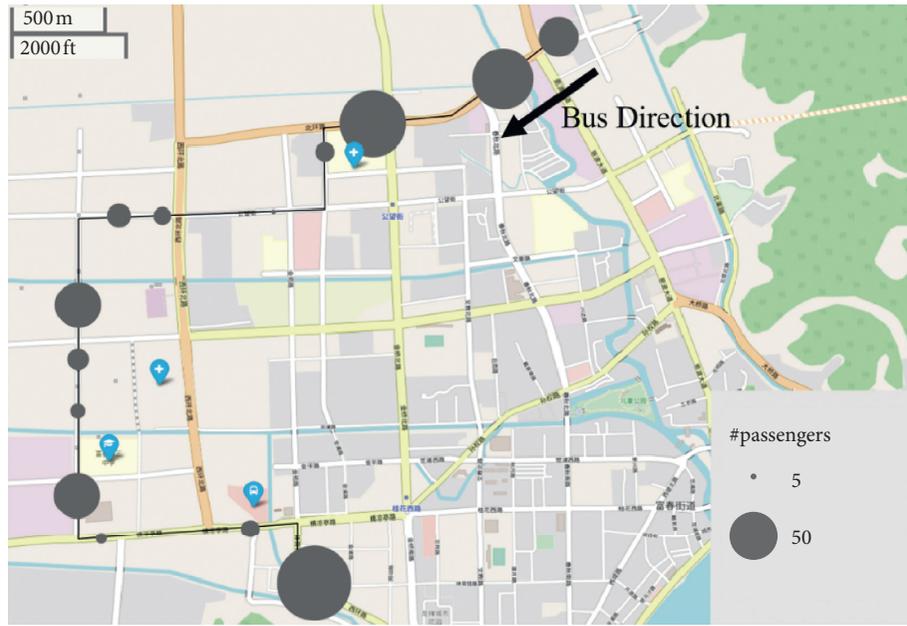
Figure 4 describes the detailed designs of the ABoD system, which are elaborated in the following subsections. In the figure, rounded rectangles refer to the agents; ovals refer to locations; rectangles refer to agents' behaviors.

3.1. Passengers. Passengers send their real-time travel demand information to the control center and walk to the bus stop to wait for the bus. In the simulation, the incidence of

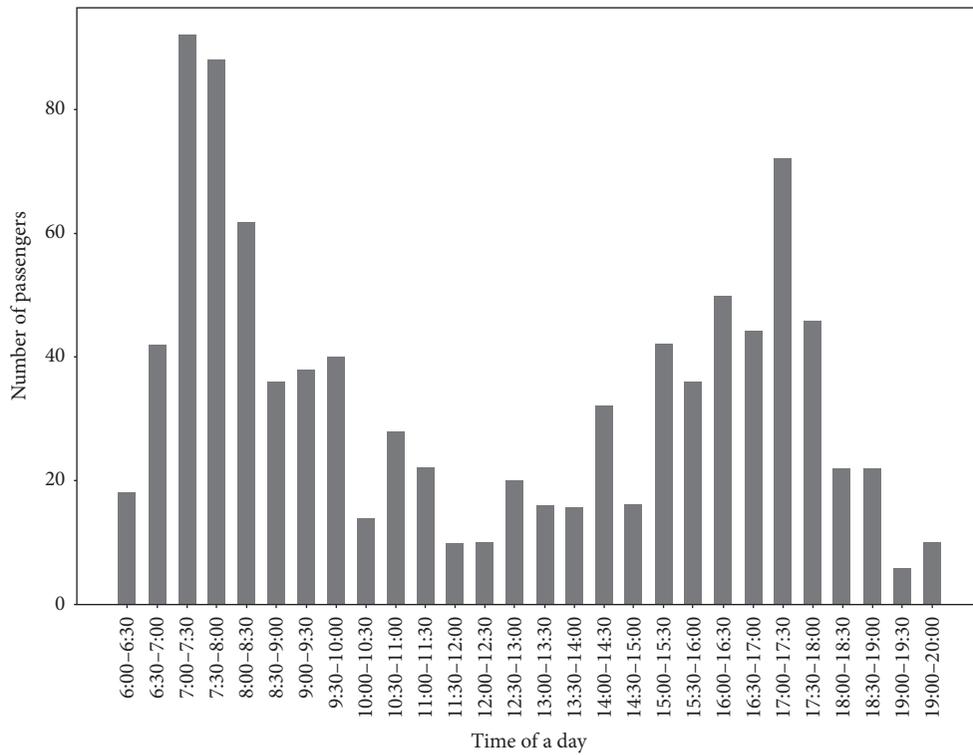
passengers follows the real-world statistics of boarding time in each second. Due to the lack of alighting information, we firstly derivate the OD matrix of bus travel in morning and evening peak hours based on the following model, in which the initialized OD matrix can be expressed as in the following equation [20, 21]:

$$\begin{cases} OD_{ij} = \frac{A_i}{\sum_{k=1}^m A_k} \times \frac{p(j-i)}{\sum_{w=1}^{j-1} p(w)} \times \sum_{z=1}^m O_z, & \text{if } i < j, \\ OD_{ij} = 0, & \text{if } i \geq j, \end{cases} \quad (1)$$

where OD_{ij} is the number of passengers from bus stop i to j during morning peak hours; m is the number of bus stops



(a)



(b)

FIGURE 2: Demand for Bus Line 622. (a) Spatial distribution of bus travel demand. (b) Temporal distribution of bus travel demand.

along the bus route; $\sum_{z=1}^m O_z$ represents the total number of passengers boarding the bus at all stops during morning peak hours; A_i is the number of passengers boarding the bus at stop i in the evening peak in the opposite direction; and $p(j-i)/\sum_{w=1}^{j-1} p(w)$ represents the probability that the

passengers get off at stop j coming from stop i . We also assume that the number of bus stops a passenger passes by follows the Poisson distribution [22].

The final results can be calculated according to the following equations:

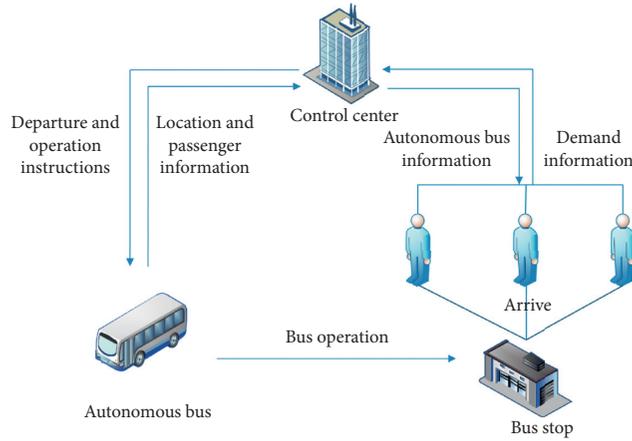


FIGURE 3: Autonomous bus-on-demand system.

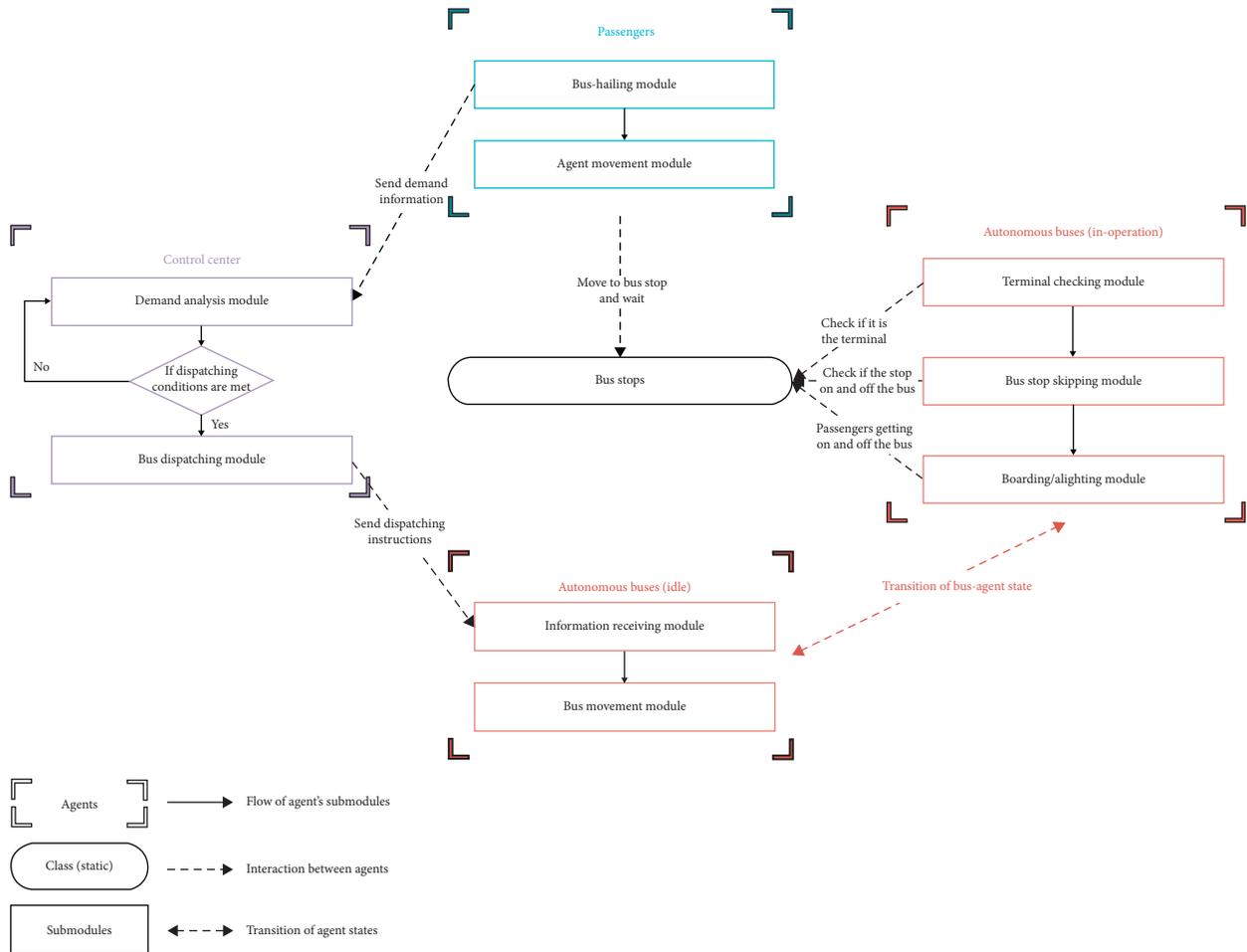


FIGURE 4: Agent-based simulation of passengers, control center, and autonomous buses.

$$OD_{ij}^{t+1} = \varepsilon_i \varepsilon_j OD_{ij}^t, \quad (2)$$

$$\varepsilon_i = \frac{O_i}{O_i^*}, \quad (3)$$

$$\varepsilon_j = \frac{D_j}{D_j^*}. \quad (4)$$

In step $t + 1$, OD_{ij}^{t+1} can be iterated according to (2). In (3), O_i refers to the number of passengers boarding the bus at

stop i , calculated by the OD matrix, OD_{ij}^t , at step t . Furthermore, O_i^* is calculated based on real-world data. The idea of (4) is similar to (3), but for the theoretical number of passengers getting off at stop j . The iteration terminates if the following condition is satisfied:

$$\frac{\max(\varepsilon_i \varepsilon_j) - \min(\varepsilon_i \varepsilon_j)}{((\max(\varepsilon_i \varepsilon_j) + \min(\varepsilon_i \varepsilon_j))/2)} \leq \sigma. \quad (5)$$

In (5), σ is a constant that determines the accuracy threshold, empirically set as 0.01 in this paper. Thus, the OD matrix for Bus Line 622 is obtained from 6:30 a.m. to 9:30 a.m., morning peak hours, and from 3:00 p.m. to 6:00 p.m., evening peak hours. The remaining bus travel demand is randomly allocated to off-peak hours. We assume that the passengers do not leave the queues.

3.2. Control Center. The behaviors of control center agents are illustrated in Figure 4. As the core of the ABoD system, the primary functions of the control center are information collection and the analysis of demand data, to control bus departure intervals and operation strategies. The control center determines departure intervals according to the algorithm integrated into Figure 5, based on real-time demand. The control center examines the total number of passengers that should be carried by the autonomous buses, including the number of passengers who are too late to board any bus in service and the number of passengers who are left behind during the constraints of bus capacity. The control center computes bus travel demand every minute, considering the following scenarios.

If the departure interval of the previous bus is less than the maximum departure interval, the number of autonomous buses sent out can be expressed as in the following equation:

$$n = E\left(\frac{\sum_{i=1}^m P_i}{c_{\max} S}\right) + E\left(\frac{(\sum_{i=1}^m P_i) \bmod (c_{\max} S)}{c_{\min} S}\right), \quad (6)$$

where $E(\bullet)$ means the function of taking the integer part of (\bullet) ; $\sum_{i=1}^m P_i$ represents the real-time demand of m stops, which is 14 in this paper; c_{\min} is the ratio of minimum departure condition; c_{\max} is the ratio of maximum departure condition; and S is the number of seats in an autonomous bus, which is six in this paper.

That is, if the real-time demand ranges between c_{\min} and c_{\max} , only one autonomous bus is needed. However, if the real-time demand is greater than c_{\max} , more than one autonomous bus could be required. In this case, n buses are dispatched together as a platoon. The value of n can be calculated using (6). Assuming that the maximum bus loading rate—the ratio of the maximum capacity of a bus to the number of seats—is R , the values of c_{\min} and c_{\max} should satisfy

$$c_{\min} < c_{\max}, \quad (7)$$

$$c_{\max} < R. \quad (8)$$

If demand reaches a very low level, where the departure interval from the previous bus is equal to the maximum allowed departure interval, a single autonomous bus is sent out regardless.

The maximum departure interval is set at 10 minutes, according to that of the current bus service. We also simulate the scenario of fixed-route, fixed-schedule bus services as the benchmark for comparative study.

3.3. Autonomous Buses. The behaviors of the autonomous buses are also illustrated in Figure 4. The autonomous bus's travel route mirrors that of Bus Line 622, calculated based on the routing service of OpenStreetMap. After receiving instructions from the control center, autonomous buses begin to service passengers from the origin stop, heading towards the terminal. To improve the efficiency of bus operations, autonomous buses may skip intermediate stop m , except for the following situations:

- (i) There is at least one passenger on the bus who needs to disembark at stop m .
- (ii) There is at least one passenger waiting at stop m for the autonomous bus, and the bus has enough room for the passengers to board, considering the number of passengers alighting at stop m .

The autonomous bus stops if any of the above conditions are met. The specific operation strategy is shown in Figure 5. The autonomous bus receives instructions about whether to skip stop m from the control center before approaching the stop.

The operation details and assumptions about the autonomous buses are summarized as follows. The average speed of the bus is 20 km/h, according to morning peak-hour traffic conditions in Fuyang city center. The penalty of delay due to acceleration and deceleration at each stop is empirically set at 10 seconds, which is consistent with conventional buses. The average boarding or alighting time caused by each passenger is 1 second [23]. According to the technical specifications of the Next Future Transportation Inc., in the simulation, the bus can carry 10 passengers at maximum.

4. Simulation Results and Scenario Analysis

We examine the impacts of the ABoD system from the following perspectives:

- (1) Road resources: the concept of passenger car unit kilometers (PCU-km) is employed as the approximation for studying the occupation of road resources by autonomous or conventional buses [24]. The PCU-km is derived as the product of the vehicle kilometers traveled (VKT) and the passenger car equivalent (PCE) factor. According to the design code for urban road engineering in China [25], the PCE factor of a conventional bus is 2. If one autonomous bus or no more than three buses together

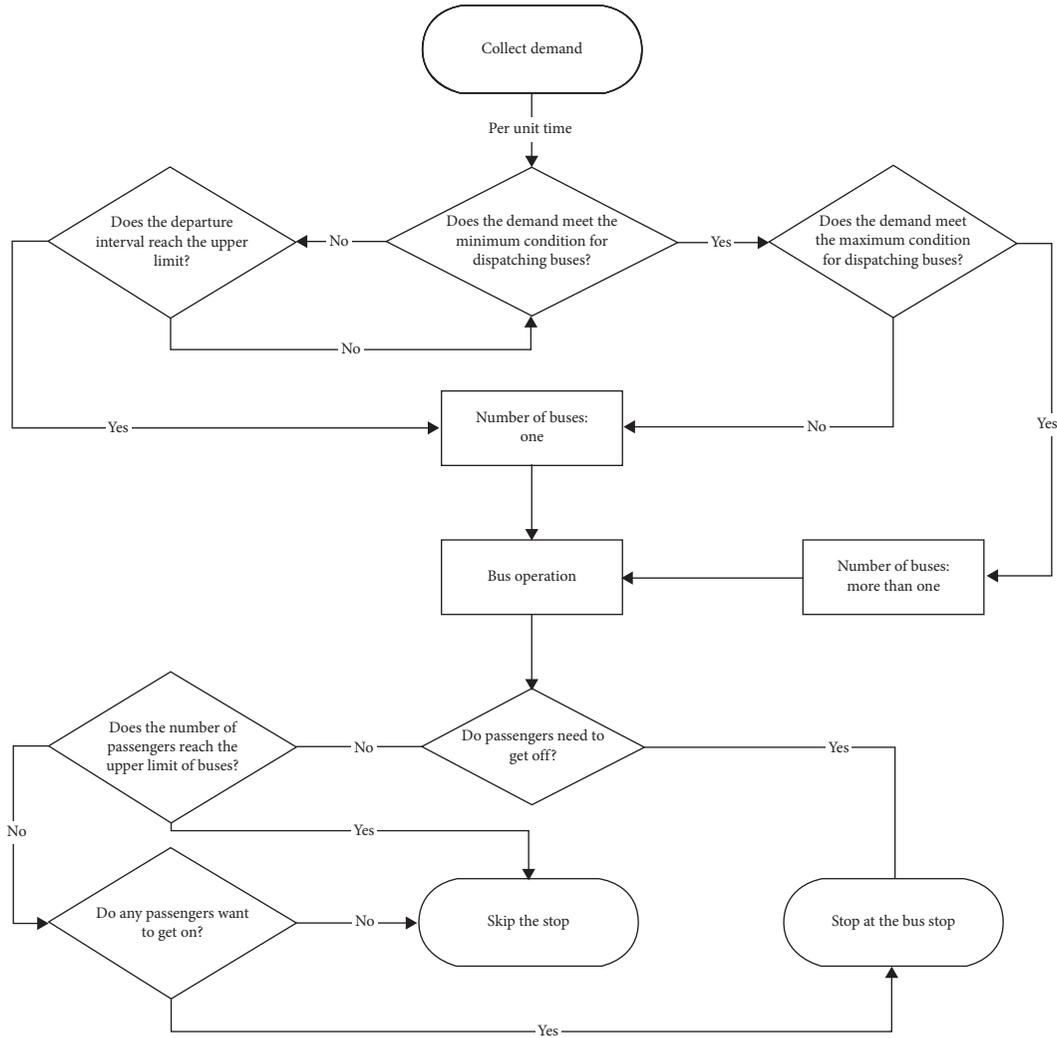


FIGURE 5: Algorithm of departure interval and bus operation.

as a platoon are dispatched, the PCE factor is 1. Otherwise, the PCE factor is set as 2.

- (2) Passenger: the waiting time of passengers is selected as the primary factor for evaluating bus service quality.
- (3) Bus operation: passenger load factor (PLF) is used to evaluate the efficiency of vehicle capacity utilization, which is the ratio of passenger-kilometers traveled to capacity-kilometers available, expressed as [26]

$$F = \frac{\sum_{i=1}^n p_i d_i}{\sum_{j=1}^u S_j^{\max} d_j}. \quad (9)$$

In the equation, $p_i d_i$ refers to the total kilometers traveled by passenger i ; and $S_j^{\max} d_j$ refers to the capacity-kilometers available for j -th bus.

4.1. Scenarios. Daily ABoD operation from 6:00 a.m. to 8:00 p.m. is simulated, where 1 second in the simulation equals one in the real world. We study the simulation results by varying the ranges of the following parameters, which are decisive in controlling the ABoD system. The ratio of minimum departure condition, c_{\min} , is set as 0.3, 0.6, or 0.9. The ratio of maximum departure condition, c_{\max} , is set as 1, 1.3, or 1.6. For comparative purposes, to simulate the performance of the current bus system, the departure interval is fixed at 10 minutes, while each bus vehicle dwells at each bus stop. In addition, we also shift the intervals of the conventional bus system to 5 and 8 minutes, to obtain more comprehensive results. From the perspective of bus travel demand, we also test the impact of various demand levels, ranging from one to ten multiples of current bus demand.

In each scenario, simulation results are the average of 100 runs. Based on actual bus travel demand, we randomize

the arrival time of each passenger according to Poisson distribution. To ensure the reliability of the results, it is necessary to control the error between the randomized travel OD matrix, M^* , and the real-world travel OD matrix, M . We choose the 2-Norm of matrix to assess error, expressed as [27]

$$\text{error} = \frac{\|M\|_2^* - \|M\|_2}{\|M\|_2}. \quad (10)$$

In the equation, $\|M\|_2$ refers to the 2-Norm of matrix M , and $\|M\|_2^*$ denotes the 2-Norm of matrix M^* . We empirically set the upper limit of error as 0.05, and the simulation result is adopted only if the simulation error does not exceed this limit.

Simulation results are shown in Figure 6, where each dot represents the average value of 100 simulation runs of each scenario. The solid lines refer to ABoD, and the dashed-dotted lines represent conventional buses. Each picture includes the simulation results of the ABoD system with various ratios of minimum departure condition c_{\min} , with the values of 0.3, 0.6, and 0.9, under conditions from one to ten multiples of current bus travel demand. For comparison, the simulation results of the conventional bus system with different fixed departure intervals (i.e., 5, 8, and 10 minutes) are also plotted in the figure. In addition, the x -coordinates of all figures refer to the multiples of bus travel demand. The figures in each row share the same vertical coordinates, but the ratios of maximum departure conditions differ, at 1, 1.3, and 1.6, respectively.

The figures in the first row show the impact on total PCU-km in each scenario. In the second row, the figures present the impacts on waiting time. Those in the bottom row show the impact on PLF.

In examining the figures in the first row, one can compare the impacts of the ABoD system with differing values for c_{\min} and c_{\max} and PCU-km of autonomous buses increases almost linearly, thanks to their demand-responsive nature. In terms of the ratio departure condition, c_{\min} and c_{\max} , larger ratios lead to greater PCU-km, particularly if the multiple of current demand is greater than 1. If bus travel demand is less than five multiples of the current demand, the total PCU-km of autonomous buses is still less than that of conventional bus services. These results show that, under current circumstances, the ABoD system occupies much fewer road resources than the current buses. Even if current bus travel demand were to grow, the performance of the on-demand-bus service would still surpass the current ones.

The figures in the second row indicate the average waiting time of each passenger under different scenarios. With greater bus travel demand, the average waiting time in the ABoD system decreases and tends to remain at the same level. However, in the scenario of the traditional bus system with 10-minute intervals, if demand exceeds five multiples of

the current demand, the average waiting time increases sharply, due to the constraints of bus capacity, and passengers are left behind. Compared with current bus services, passenger waiting time in the ABoD system is much lower, regardless of demand.

In the figures in the bottom row, we plot the PLF under different scenarios. Greater bus travel demand leads to an increased PLF, for both ABoD system and conventional buses. If the multiple of demand is less than or equal to ten, the PLF in ABoD is greater than that in the conventional bus system, indicating that it is reasonable to substitute ABoD for the current bus services.

In summary, with less than six multiples of current bus travel demand, the ABoD system presents as overwhelmingly advantageous, with less road resource occupation, shorter passenger waiting times, and more efficient utilization of vehicle capacity. In addition, the ratio of minimum departure condition, c_{\min} , and of maximum departure condition, c_{\max} , has little impact on the ABoD system with low demand. When the departure intervals of current conventional bus service decline to 5 or 8 minutes, despite shorter passenger waiting times, the total PCU-km of the conventional bus system becomes too large, meaning that, in this case, the fixed-schedule bus system occupies too many road resources compared with the ABoD system proposed in this study.

4.2. Number of Autonomous Buses. The average number of departed autonomous buses is counted every 30 minutes during a day with two multiplies of current demand. In Figure 7, the blue solid lines refer to the number of boarding passengers (i.e., demand), and the dashed-dotted lines represent the number of departed autonomous buses. In each figure, the ratio of minimum departure condition, c_{\min} , varies with the values of 0.3, 0.6, and 0.9, and the ratio of maximum departure condition, c_{\max} , is set as 1, 1.3, and 1.6. The ABoD system can adapt to changes in demand by adjusting bus dispatching strategies. In terms of the ratio of minimum departure condition, c_{\min} , larger ratios lead to smaller numbers of autonomous buses under the same conditions. However, the ratio of maximum departure condition has little impact on the control strategy of buses, due to insufficient demand.

4.3. Cost Analysis. The operating costs for conventional buses and autonomous buses are estimated as follows. For autonomous buses, the operating cost mainly includes energy cost, maintenance, vehicle repair, administrative cost, tax, and dispatching [28]. The operating cost follows a linear function of bus capacity. The operating cost for m bus units can be formed as [29, 30]

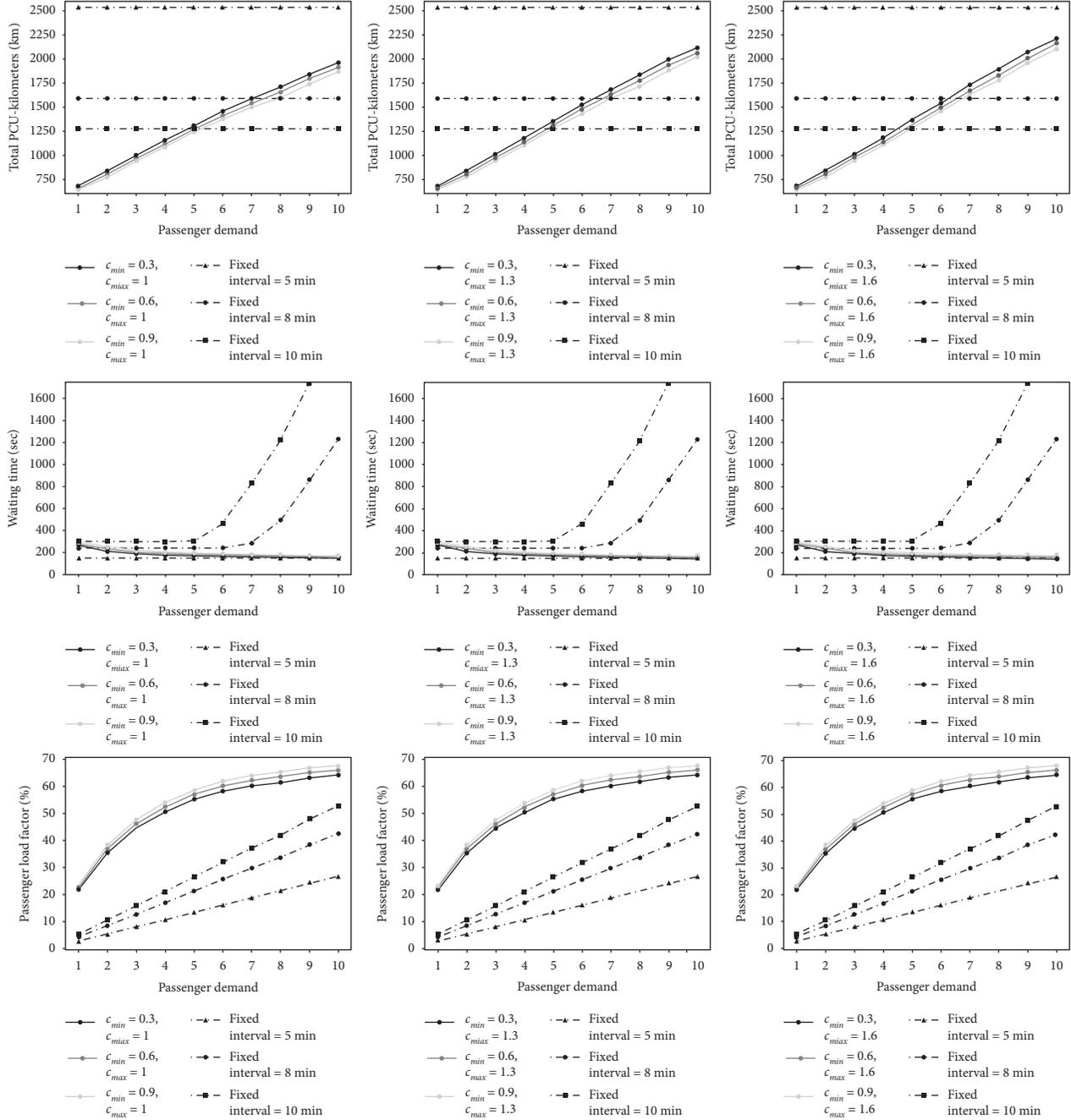


FIGURE 6: Simulation results.

$$f_a = C_a^F + C_a^A + C_a^V (mS_a^{\max})^\alpha, \quad (11)$$

where C_a^F means the fixed operating cost and C_a^A means dispatching cost, including the assembling and disassembling cost. C_a^V refers to the marginal operating cost, and S_a^{\max} is the capacity of an autonomous bus, which is 10 in this case. Parameter α ranges between 0 and 1 according to the cost to operate the autonomous buses. We assume that the saving of cost is greater with a larger bus fleet size as the buses are running with greater fuel economy when they are joined together.

For conventional buses, the labor cost is one of the major components of the total cost. Taking into account the labor cost, according to Dai et al. [29], the linear relationship between the operating cost and bus capacity still holds, expressed as

$$f_0 = C_0^F + C_0^V S_0^{\max}, \quad (12)$$

where S_0^{\max} stands for the capacity of a conventional bus, which is 45 in our study.

Based on the work of Dai et al. [29], for an autonomous bus, the fixed operating cost is \$14.49 per dispatch, the

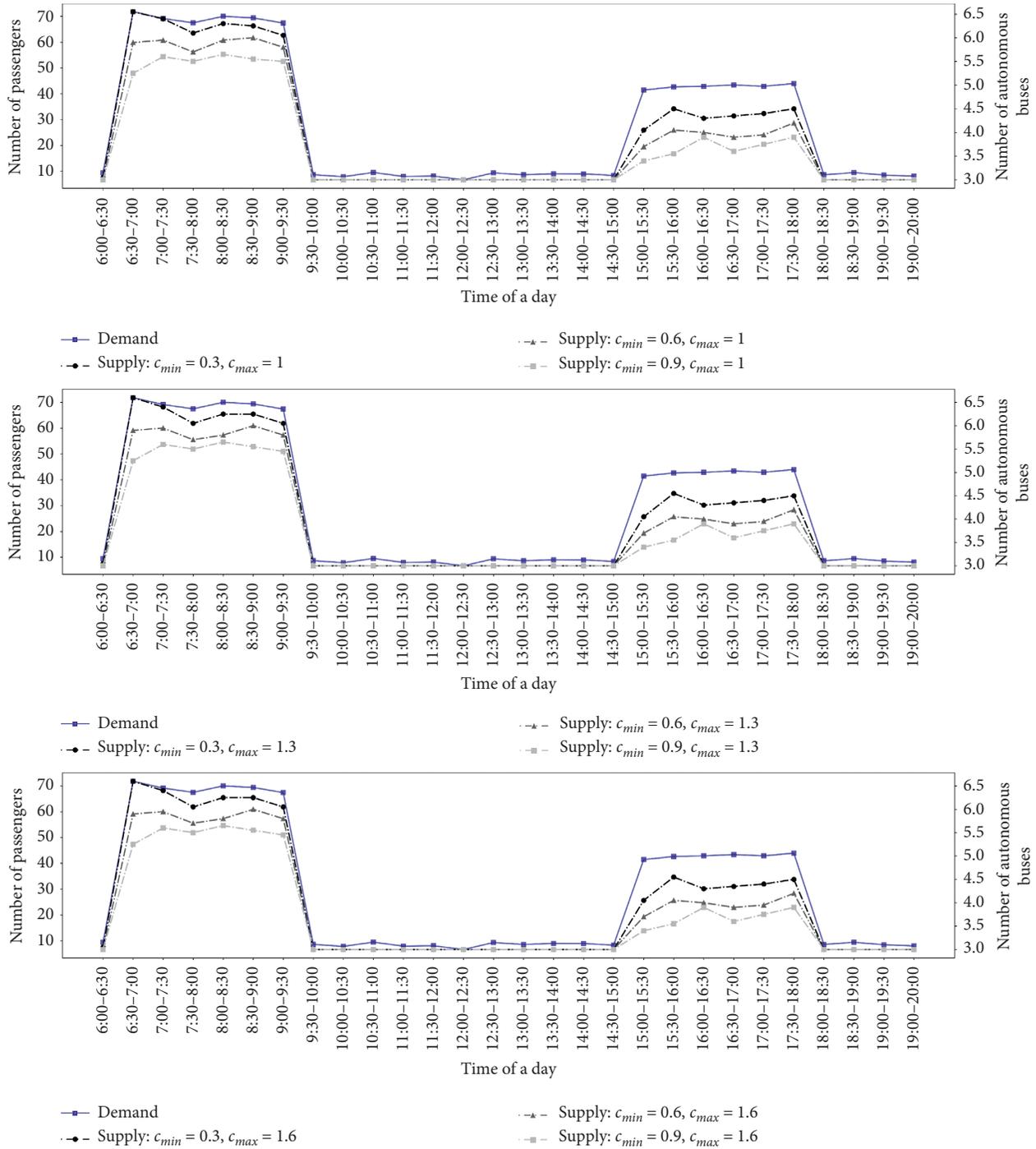


FIGURE 7: The variety of numbers of autonomous buses in a day.

marginal operating cost is \$0.45 per seat per dispatch, and the assembling and/or disassembling cost is \$1.07. For a conventional human-driven bus, the fixed operating cost is \$39.18 per dispatch; the marginal operating cost is \$0.45 per seat per dispatch. Parameter α is set as 0.9.

In addition to the operating cost, the generalized cost for passengers, including waiting time as bus stops and in-

vehicle travel time, is also taken into account [29]. The value of waiting time for each passenger is set as \$0.8 per minute according to the wage level of Fuyang, Zhejiang. Since the in-vehicle travel time is less sensitive, we set the value of in-vehicle travel time as \$0.2 per minute.

The comparison of cost between ABOD and conventional buses is illustrated in Figure 8. The total cost includes

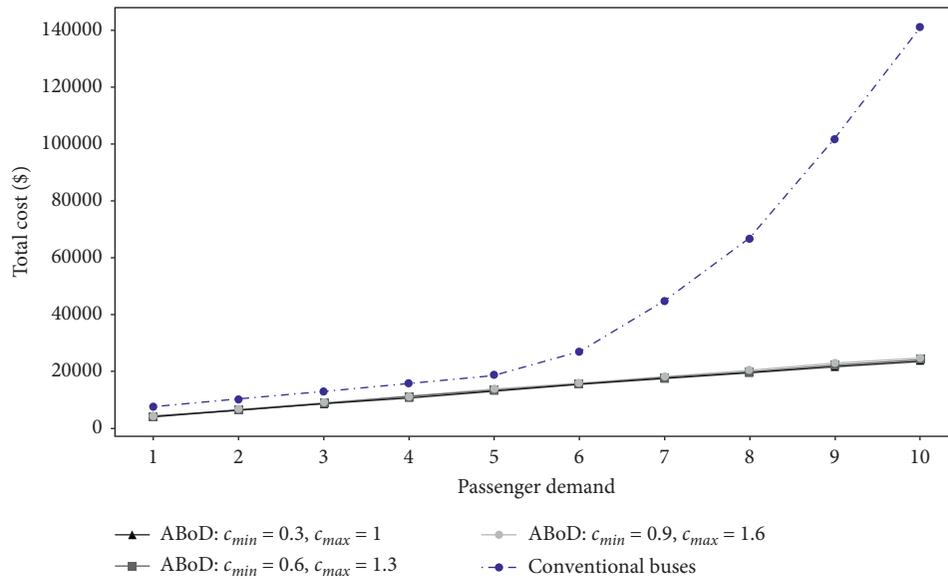


FIGURE 8: The total cost comparison between ABoD and conventional buses.

operating costs, passenger waiting time cost, and passenger travel time cost. In the figure, the ratios of departure condition of the ABoD system are set to combinations of 0.3 and 1, 0.6 and 1.3, and 0.9 and 1.6, respectively. The simulations show that no matter the ratio of departure condition is, the total costs vary only slightly. The total cost of conventional buses is always greater than that of the ABoD. If the travel demand exceeds five multiples of the current demand, the total cost of conventional buses increases sharply, while the cost of the ABoD increases almost linearly, which indicates that the ABoD system is more adaptive to the change in travel demand than the conventional buses.

4.4. Comparison with an Optimized Bus Dispatching Model.

In the section, we focus on the difference between ABoD and an optimized bus dispatching model. The optimal model is calculated based on Newell [31], which is elaborated in Appendix A. The total costs of the ABoD and optimization model under various passenger demands are shown in Figure 9. The excess cost ratio—defined as the ratio of excess cost to total cost of optimization model—is also plotted, represented by the red curve. The results show the total cost of ABoD compared to that of the optimized model. However, if current bus travel demand grows, the excess cost ratio decreases, meaning that the relative cost advantage of the optimization model over ABoD is shrinking.

The simulation results of the total PCU-Kilometers, waiting time, and passenger loads in the ABoD and the

optimized model are shown in Figure 10, in which the solid curves refer to the ABoD, and the blue dashed-dotted curves refer to the optimized model. Under the current level of travel demand, the passengers' waiting time of the ABoD is less than that of the optimized model thanks to the mechanism of maximum departure interval in ABoD. If travel demand increases, the passengers may wait for a longer time in the ABoD system. The longer waiting time is due to the fact that the ABoD system balances the waiting time against the PCU-Kilometers and loads of vehicles. As shown in the figures, with larger bus travel demand, the PCU-kilometers in the ABoD are much smaller while the loads are greater than in the optimized model. It shows that the ABoD system is potentially more beneficial to sustainable development for bus operators despite a relatively long waiting time.

In real life, bus travel demand can be affected by emergent incidents like large gathering events or the breakdown of the metro, which causes the outbreak of passenger flows. In this case, the adaptability of the bus system to the fluctuation of demand becomes essential. In this work, we simulate an emergent event (e.g., the metro breakdown) that results in the λ -multiples of current passenger demand from 7:00 a.m. to 9:00 a.m. The total costs of the ABoD and the optimized model with various demand multiples of λ are plotted in Figure 11. The blue dashed-dotted curve for the total cost of the optimization model grows faster than solid curves for ABoD. If λ becomes greater than 3, the ABoD is more dominant than the optimization model in total cost since the ABoD is more responsive to real-time passengers' demand.

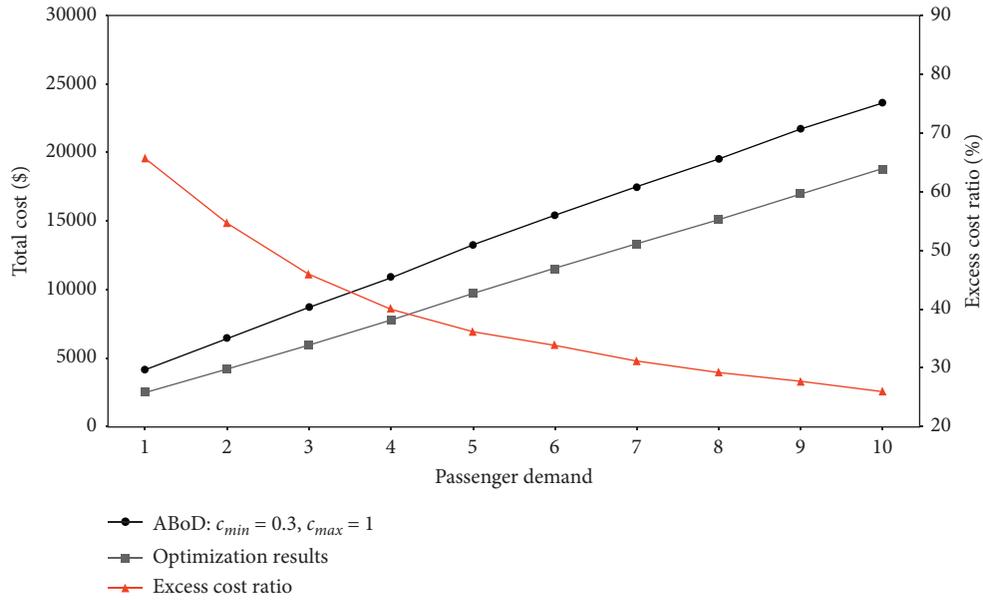


FIGURE 9: The total cost comparison between ABoD and optimization model.

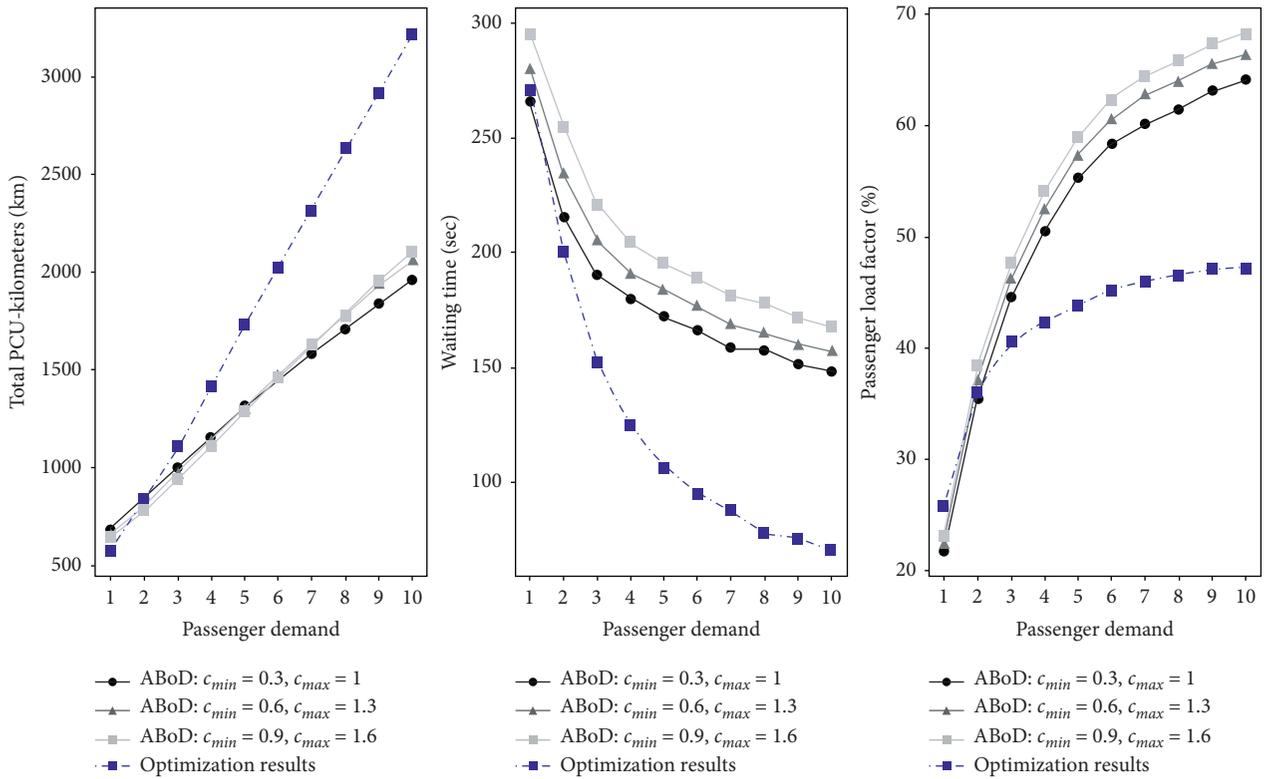


FIGURE 10: Simulation results of ABoD and optimization model.

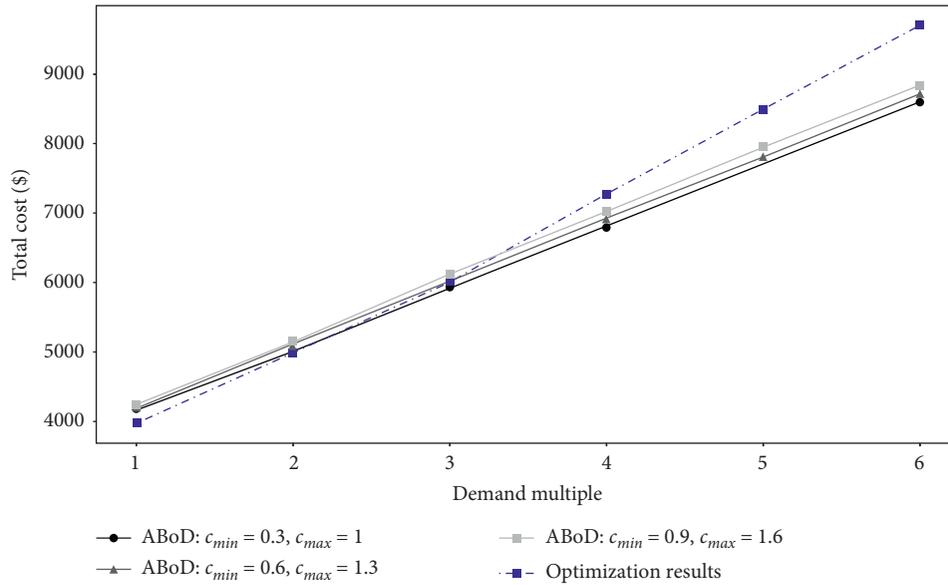


FIGURE 11: The impact of sudden passenger flow on ABoD and optimization model.

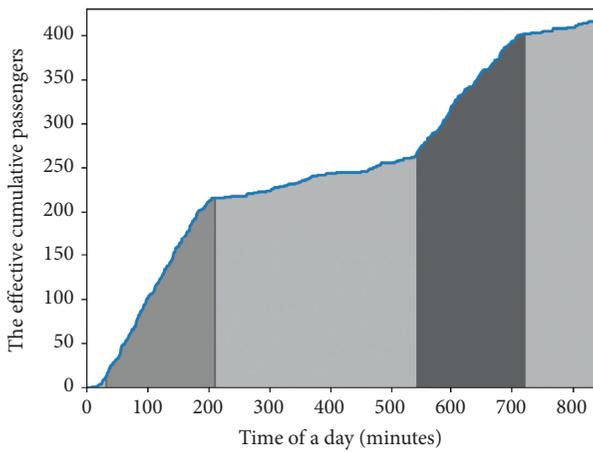


FIGURE 12: The effective cumulative passenger demand of Bus Line 622.

5. Conclusion and Discussion

This paper has presented a spatiotemporal analysis of current bus travel demand in Fuyang, a prefecture-level city in Zhejiang, China. Using Bus Line 622 as an example, we have envisioned an ABoD system with various bus dispatching and operation strategies. To evaluate the performance of the ABoD system, an agent-based model has been built that includes three primary types of agents: passengers, control center, and autonomous buses. To model bus travel demand, an OD matrix has been deduced, based on real-world payment data. We have investigated the impacts of the

ABoD system from the following perspectives: the occupation of road resources, passenger waiting time, and utilization of bus vehicles. Under a series of scenarios, with various bus dispatching rules and travel demands, we have compared the impacts of the ABoD system with those of both conventional fixed-schedule bus services and the optimized bus dispatching strategies. The simulation results show that the ABoD system performs better at levels below triple current demand. Using total PCU-km as an approximation of road resource occupation, the simulation has illustrated that the ABoD system is favorable in terms of saving road resources. The PLF in the ABoD system is greater, showing that vehicle capacity is utilized more efficiently. In addition, the ABoD system is adaptive to the sudden surge in bus travel demand and is economically sustainable.

Room for improvement exists that must be acknowledged here. Control strategies of departure intervals and bus operation in the current models are rule-based, which can be further improved with additional optimization algorithms. Other travel modes that may compete with buses can be incorporated into the model, and dynamic interactions between the supply and demand of autonomous buses should be considered as well.

In this paper, we use one bus line as an example to demonstrate the feasibility of implementing the envisioned ABoD system in small cities. For future work, we could examine the impacts of the entire bus network, considering supply-demand interactions. In addition, the constraints of bus fleet size may also lead to the empty travel of autonomous buses. The assessment of operational costs incurred by

the empty travel of buses and the repositioning of these empty buses could be another important direction for future studies. Finally, with additional types of agents, including other potential stakeholders involved in this system, the agent-based model can be extended to describe more complex realities with additional dimensions, such as modal competition and pricing strategies.

Appendix

A. An Optimal Model for Bus Dispatching

To compare with the proposed ABoD model, we formulate the problem using the optimization methods based on Newell's work [31], which minimizes the operating costs and the passengers' delay. Along a bus line, $F_{ij}(t)$ stands for cumulative passenger demand at time t from point i to point j , i.e., the number of passengers boarding at point i at time t and alighting at point j . Thus, any cumulative passenger demand $F_{ij}(t)$ can be converted into an effective demand at time $t - \tau_i$ from the origin to point j , where τ_i stands for travel time from the origin to point j . $F(t)$ stands for the effective cumulative passenger demand from the origin at time t , which is expressed as

$$F(t) = \sum_{i,j} F_{ij}(t + \tau_i). \quad (\text{A.1})$$

Between time t_0 and time T , the sum of passenger waiting time can be approximately expressed as

$$W = \frac{1}{2n} \left[\int_{t_0}^T \sqrt{f(t)} dt \right]^2, \quad (\text{A.2})$$

where n is the number of dispatches; $f(t)$ is the derivative of $F(t)$. Regardless of the capacity of the vehicle, the optimal headways Δt with minimized total cost are expressed as

$$\Delta t = \sqrt{\frac{2a}{bf(t)}}. \quad (\text{A.3})$$

where a is the operating cost per dispatch and b is the value of passenger waiting time. Taking into account the constraint of vehicle capacity S^{\max} , the optimal headways Δt are expressed as

$$\Delta t = \min \left\{ \frac{S^{\max}}{f(t)}, \sqrt{\frac{2a}{bf(t)}} \right\}. \quad (\text{A.4})$$

In this case study, we adopt a staged optimization approach since the bus travel demand varies largely during peak and off-peak hours. As illustrated in Figure 12, the effective cumulative travel demand in one day can be divided into five stages. In each stage, the effective cumulative passenger demand $F(t)$ is approximated as a linear function of time t .

Data Availability

The data used to support the results of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that no conflicts of interest regarding the publication of this paper exist.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (71901164), the Natural Science Foundation of Shanghai (19ZR1460700), Shanghai Science and Technology Committee (19DZ1208700), and the Fundamental Research Funds for the Central Universities (22120180569). The corresponding author is sponsored by the Shanghai Pujiang Program (2019PJC107).

References

- [1] C. F. Daganzo, "An approximate analytic model of many-to-many demand responsive transportation systems," *Transportation Research*, vol. 12, no. 5, pp. 325–333, 1978.
- [2] N. H. M. Wilson and C. Hendrickson, "Performance models of flexibly routed transportation services," *Transportation Research Part B: Methodological*, vol. 14, no. 1-2, pp. 67–78, 1980.
- [3] A. Ceder and N. H. M. Wilson, "Bus network design," *Transportation Research Part B: Methodological*, vol. 20, no. 4, pp. 331–344, 1986.
- [4] R. B. Dial, "Autonomous dial-a-ride transit introductory overview," *Transportation Research Part C: Emerging Technologies*, vol. 3, no. 5, pp. 261–275, 1995.
- [5] O. Adebisi and V. F. Hurdle, "Comparing fixed-route and flexible-route strategies for intraurban bus transit," *Transportation Research Record*, vol. 854, pp. 37–43, 1982.
- [6] S. K. Chang and P. M. Schonfeld, "Optimization models for comparing conventional and subscription bus feeder services," *Transportation Science*, vol. 25, no. 4, pp. 281–298, 1991.
- [7] L. Quadrifoglio, M. M. Dessouky, and F. Ordonez, "A simulation study of demand responsive transit system design," *Transportation Research Part A: Policy and Practice*, vol. 42, no. 4, pp. 718–737, 2008.
- [8] R. Bishop, "Intelligent vehicle applications worldwide," *IEEE Intelligent Systems*, vol. 15, no. 1, pp. 78–81, 2000.
- [9] C. Csiszár and A. Zarkeshev, "Demand-capacity coordination method in autonomous public transportation," *Transportation Research Procedia*, vol. 27, pp. 784–790, 2017.
- [10] B. Wang, S. A. Ordonez Medina, and P. Fourie, "Simulation of autonomous transit on demand for fleet size and deployment strategy optimization," *Procedia Computer Science*, vol. 130, pp. 797–802, 2018.
- [11] W. Payre, J. Cestac, and P. Delhomme, "Intention to use a fully automated car: attitudes and a priori acceptability," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 27, no. Part B, pp. 252–263, 2014.

- [12] J. Shin, C. R. Bhat, D. You, V. M. Garikapati, and R. M. Pendyala, "Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types," *Transportation Research Part C: Emerging Technologies*, vol. 60, pp. 511–524, 2015.
- [13] M. Kyriakidis, R. Happee, and J. C. F. de Winter, "Public opinion on automated driving: results of an international questionnaire among 5000 respondents," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 32, pp. 127–140, 2015.
- [14] A. Vakayil, W. Gruel, and S. Samaranyake, "Integrating shared-vehicle mobility-on-demand systems with public transit," in *Proceedings of the Transportation Research Board 96th Annual Meeting*, Washington, DC, USA, January 2017.
- [15] Y. Shen, H. Zhang, and J. Zhao, "Integrating shared autonomous vehicle in public transportation system: a supply-side simulation of the first-mile service in Singapore," *Transportation Research Part A: Policy and Practice*, vol. 113, pp. 125–136, 2018.
- [16] K. Winter, O. Cats, G. H. d. A. Correia, and B. van Arem, "Designing an automated demand-responsive transport system: fleet size and performance analysis for a campus-train station service," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2542, no. 1, pp. 75–83, 2016.
- [17] Z. Navidi, N. Ronald, and S. Winter, "Comparison between ad-hoc demand responsive and conventional transit: a simulation study," *Public Transport*, vol. 10, no. 1, pp. 147–167, 2018.
- [18] N. Ronald, R. Thompson, and S. Winter, "Simulating demand-responsive transportation: a review of agent-based approaches," *Transport Reviews*, vol. 35, no. 4, pp. 404–421, 2015.
- [19] F. Hu, "Full coverage of mobile payment for all buses in Hangzhou," 2017, <http://zzhz.zjol.com.cn/system/2017/05/23/021520284.s.html>.
- [20] X. Zhou, X. Yang, and X. Wu, "Origin-destination matrix estimation method of public transportation flow based on data from bus integrated-circuit cards," *Journal of Tongji University (Nature Science)*, vol. 40, pp. 1027–1030, 2012.
- [21] J. Doblaz and F. G. Benitez, "An approach to estimating and updating origin—destination matrices based upon traffic counts preserving the prior structure of a survey matrix," *Transportation Research Part B: Methodological*, vol. 39, no. 7, pp. 565–591, 2005.
- [22] H. L. Dou, H. D. Liu, and X. G. Yang, "OD matrix estimation method of public transportation flow based on passenger boarding and alighting," *Computer and Communications*, vol. 25, no. 135, p. 79, 2007.
- [23] X. Chen, B. Hellinga, C. Chang, and L. Fu, "Optimization of headways with stop-skipping control: a case study of bus rapid transit system," *Journal of Advanced Transportation*, vol. 49, no. 3, p. 17, 2015.
- [24] Bureau of Infrastructure Transport and Regional Economics (BITRE), *Traffic and Congestion Cost Trends for Australian Capital Cities*, BITRE, Canberra, Australia, 2015.
- [25] Ministry of Housing and Urban-Rural Construction of the People's Republic of China, *Code for Design of Urban Road Engineering*, China Construction Industry Publishing House, Beijing, China, 2012.
- [26] "Load factor," http://web.mit.edu/airlinedata/www/Res_Glossary.html.
- [27] G. V. L. Golub and F. Charles, *Matrix Computations*, Johns Hopkins University Press, Baltimore, MA, USA, 3rd edition, 1996.
- [28] W. Zhang, E. Jenelius, and H. Badia, "Efficiency of semi-autonomous and fully autonomous bus services in trunk-and-branches networks," *Journal of Advanced Transportation*, vol. 2019, Article ID 7648735, 17 pages, 2019.
- [29] Z. Dai, X. C. Liu, X. Chen, and X. Ma, "Joint optimization of scheduling and capacity for mixed traffic with autonomous and human-driven buses: a dynamic programming approach," *Transportation Research Part C: Emerging Technologies*, vol. 114, pp. 598–619, 2020.
- [30] Z. Chen, X. Li, and X. Zhou, "Operational design for shuttle systems with modular vehicles under oversaturated traffic: discrete modeling method," *Transportation Research Part B: Methodological*, vol. 122, pp. 1–19, 2019.
- [31] G. F. Newell, "Dispatching policies for a transportation route," *Transportation Science*, vol. 5, no. 1, pp. 91–105, 1971.