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Research Article

Determination of Bus Crowding Coefficient Based on Passenger Flow Forecasting

Zhongyi Zuo,[1] Wei Yin,[1] Guangchuan Yang,[2] Yunqi Zhang,[1] Jiawen Yin,[1] and Hongsheng Ge[3]

[1] *School of Traffic & Transportation Engineering, Dalian Jiaotong University, Dalian 116028, China*
[2] *Department of Civil and Architectural Engineering, University of Wyoming, Laramie, WY 82071, USA*
[3] *College of Mechanical Engineering, Dalian Jiaotong University, Dalian 116028, China*

Correspondence should be addressed to Zhongyi Zuo; zuozy@djtu.edu.cn

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To improve bus passengers' degree of comfort, it is necessary to determine the real-time crowd coefficient in the bus. With this concern, this paper employed the RBF Neural Networks approach to predict the number of passengers in the bus based on historical data. To minimize the impact of the randomness of passenger flow on the determination of bus crowd coefficient, a cloud model-based bus crowd coefficient identification method was proposed. This paper first selected the performance measurements for determining bus crowd coefficient and calculated the digital characteristics of the cloud model based on the boundary values of the selected performance measures under six Levels-of-Service (LOSs). Then the subclouds obtained under the six LOSs were synthesized into a standard cloud. According to the predicted number of passengers in the bus, the passenger density and loading frequency were calculated, which were imported into the cloud generator to set up the bus crowd coefficient identification model. By calculating the crowd degrees of identification cloud and template cloud at each site, this paper determined the crowed coefficient of each bus station. Finally, this paper took the bus line No. 10 in Dalian city as case study to verify the proposed model. It was found that the crowd coefficients of the selected route ranged from 60.265 to 109.825, and the corresponding LOSs ranged between C and F. The method of discriminating bus crowding coefficient can not only effectively determine the congestion coefficient, but also effectively avoid the fuzziness and randomness of the crowding coefficient judgment in the bus, which has strong theoretical and practical significance.

1. Introduction

With the development of urbanization and the rapid growth of urban population, traffic congestion problems have seriously restricted the nation's economic development and affected people's daily lives. In the process of development, we should give priority to the development of public transportation and improve the service quality and travel environment of public transportation. Developing public transportation vigorously is an important way to alleviate road traffic congestion [1]. At present, we usually use standing-passenger density and loading frequency to judge the bus congestion coefficient in the domestic and foreign countries. The standing-passenger density can not only affect the passengers' stress, but also seriously affect the personal safety of the passengers in the bus if the standing-passenger density exceeds the normal values. Lu et al. [2] analyzed the crowded people and found that, in the case of high standing-passenger density, there is a large squeeze force between the passenger and the passenger. In addition, the accumulation and spread of the force ar prone to causing traffic accidents. Ran et al. [3] explored the population density and found that the limit of the density of the Chinese population was 9 m^{-2} when the crowded accident occurred according to the individual physiological size. Liu et al. [4] analyzed the various warning indicators and optimized the population density as warning indicator of the degree of crowding in the bus. At last, she proposed the recommended value of the population density according to different situations. Chen et al. [5] used survey, simulation, and other means to select passenger flow density

as a parameter indicator and passenger flow as a weight to construct a passenger flow congestion index suitable for assessing the degree of congestion, and the congestion index is at [0, 1]. He et al. [6] proposed the fact that the congestion degree is the time characteristic of pedestrians gathering in response to passenger evacuation and can respond to the comfort during passenger evacuation, which is determined by the number of passengers per unit area. Jiang et al. [7] used the standing-passenger density to describe the congestion degree and adopted the RP_SP method to establish a crowding degree grading system based on standing-passenger density. Xu [8] used the service level based on personal space demand to measure the congestion level of pedestrian facilities and established a crowd perception function based on neuron model. At last the paper proposed a congestion perception information representation method based on spatial environment information representation. In addition, some scholars used image processing technology for passenger flow statistics and the method had also achieved certain development. In 2008, in order to achieve passenger area detection function, Yu et al. [9] proposed a new foreground/background edge model (FBEM) detection method, which traversed all the pixels in the video image and counted statistics and learning to obtain the background area and foreground area within the image. In 2014, Tian [10] used the background difference algorithm and the closed contour fitting moving target detection algorithm in the video detection process to extract the passenger contour by using the morphological processing method, and she also used the head and shoulder classifier to count the passenger movement direction trajectory to realize the passenger detection function. In 2010, Chen [11] performed passenger edge detection in the RGB color space and then used the Hough transform to calibrate the passenger's head area. Finally, the MeanShift's target tracking was used to complete the bus passenger movement target count. In 2013, Hou [12] extracted the passenger's head area by using information such as Hough circle detection and confidence gray interval and combined with the CamShift target tracking algorithm predicted by Kalman filtering. At the same time, the images collected by the upper and lower door cameras are analyzed to calculate the passengers.

Some scholars employed video image processing technology to count the number of people in the bus, and they have achieved certain achievements. For instance, Mukherjee et al. [13] used the Hough circle to extract the passenger's head geometry and count the passengers by the number of blocks that match the set feature. In 2012, Garcia-Bunster et al. [14] corrected the viewing angle of the image and combined it with the standard linear regression model and linear discriminant parameters to find the mapping between the optimal area measurement and the count. Finally, they applied this method to queued passenger counts. In 2013, Daley et al. [15] used the infrared light of the appropriate wavelength to detect the passenger situation in the seating area and the passage area of the vehicle and realized the counting function of the passengers in the bus according to the geometric distribution of the vehicle and the passenger. Mudoi et al. [16] used the background difference method to extract the target region in the video image, and combined with the neural network algorithm. They used the neural network algorithm to train the results to identify the object in the color and shape characteristics of the target. In 2013, Miklasz et al. [17] used facial recognition algorithm combined with passenger flow optical analysis technology to realize the statistics of passenger flow technology in the car, and the results in the experiment proved that the method has very high statistical accuracy. In 2000, Feng et al. proposed Discrete Representation Method (DRM), which is to analyze the sequence of object trigger points by analyzing discrete targets and object centerlines. This method solved the problem of overlapping objects in passenger counting research [18]. In 2008, Yahiaoui et al. simulated the stereo surveillance video sequence on the bus and the algorithm achieved 99% accuracy by passenger counting experiment [19].

The above research mainly determines the bus crowding coefficient from the two aspects, namely, standing-passenger density and the actual number of people in the bus. The discriminant index is single and has certain fuzziness and randomness. In view of this, this paper proposes a method for judging the bus crowding coefficient based on passenger flow data by using the cloud model. And this method combines the standing-passenger density and loading frequency to identify the crowding coefficient. The method of cloud model can not only avoid fuzziness and randomness of traditional method but also has a strong practical effect.

The remainder of this paper is organized as follows: Section 2 discusses the model to predict the number of passengers in the bus at each bus station. Section 3 introduces the method of bus crowding coefficient based on passenger flow forecast. In this part, we introduced the cloud model to discriminate bus crowding coefficient. Section 4 provides an experimental evaluation of the proposed enhancements. Finally, conclusions of this research are presented in Section 5.

2. Model Development

2.1. Prediction of Passenger Flow Based on RBF Neural Network. The training method of RBF neural network is simple and efficient. Besides, it has good function approximation ability, classification learning ability, and high convergence speed. The RBF neural network can deal with various intrinsic and difficult to analyze complex system regularity problems. Compared with traditional prediction methods, the use of RBF neural network for passenger flow prediction has the following advantages.

(1) Self-Learning Ability. The RBF neural network can adapt to the randomness and nonlinearity of passenger flow changes between stations on public transport lines through continuous training of data. And it has strong nonlinear processing ability. It also makes up for the shortcomings of traditional forecasting methods in solving nonlinear and time-varying problems.

(2) Adaptive and Self-Organizing Ability. The RBF neural network can automatically adjust network parameters according

to input and output samples, and it establishes a good input-output mapping relationship to achieve the prediction function.

(3) Fault Tolerance and Self-Repairing Ability. The RBF neural network can give correct answers to incomplete information and the system can still be in good condition when some internal faults occur. Therefore, when forecasting the number of passengers in a bus, it only provides the data of passenger flow on and off the bus to train the neural network. And the information of the distribution matrix is obtained and stored in the network. The actual situation can be predicted accurately without relying on the determined distribution matrix.

(i) Algorithm Design. This paper uses a three-layer neural network to predict the number of passengers in the bus. It surveyed the number of people in the bus on No. 10 in Dalian City from Monday to Friday in three weeks. Specific steps are described as follows.

Step 1. Collect historical passenger flow data via the Information Collection System. Then, we selected the number of passengers in the bus under normal operating conditions as the sample data. The data were divided into two subdatasets: training dataset and prediction dataset. The number of people in early rush hour in previous two weeks was trained as training dataset, and the prediction dataset was the number in early rush hour on the third Friday.

Step 2. To avoid the potential prediction errors that might be caused by the sample size of the collect datasets, the original data need to be normalized prior to prediction.

Step 3. Construct the passenger flow prediction model. The historical data of number of passengers in the bus, under various weather conditions, holidays, and weeks are selected as input variables to train the neural network and construct a predictive model.

Step 4. Apply the trained neural network model to predict the number of passengers in the bus at a certain time in the future.

Step e. Analyze prediction errors.

(ii) Evaluation Indicators. In order to evaluate the predict results of bus passenger traffic, this paper introduced a predictive result evaluation index. Specifically, predication errors were calculated by comparing the difference between the predicted value Y_{sim} and the actual value $Y_{real.}$ There are four indicators for verifying the difference. Among them, the mean average error represents the deviation level between the predicted value and the actual value, and the smaller the error value is, the closer the predicted value is to the true value. The mean average relative error is a commonly used indicator for evaluating prediction results. When mean average relative error is between 20% and 50%, the prediction result is proved to be feasible.

(a) Mean Average Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{sim} - Y_{real}\right| \tag{1}$$

(b) Mean Square Error

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{sim} - Y_{real}\right)^2}{n}} \tag{2}$$

(c) Mean Average Relative Error

$$MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_{sim} - Y_{real}\right|}{Y_{real}} \tag{3}$$

(d) Mean Square Relative Error

$$MSRE = \sqrt{\frac{\sum_{i=1}^{n}\left(\left(Y_{sim} - Y_{real}\right)/Y_{real}\right)^2}{n}} \tag{4}$$

3. Determination of Bus Crowding Coefficient

3.1. Measurement of Passengers' Crowding Coefficient. The purpose of determining the crowding coefficient in the bus is to timely and reliably identify the passenger crowd in the bus, so as efficient measures could be applied to reduce the potential safety hazards to passengers and improve passengers' comfort. It has been a common practice that existing research methods use fuzziness and randomness for dividing the crowding states in buses. Therefore, it is of great significance to use a reasonable method to divide the crowded state in the bus. In this paper, the standing-passenger density and loading frequency were used to determine the crowding factor in the bus, as shown in Tables 1 and 2.

It can be seen from Tables 1 and 2 that when the service level in the bus is between A and C, the passengers can move freely in the bus and there is a large comfortable space without crowding. When the service level is worse than E, there is obvious crowd in the bus. Under this situation, it is necessary for the bus dispatchers to take corresponding countermeasures to reduce the crowdedness in the bus, such as the shuttle buses. Therefore, this paper uses the aforementioned service indicators (i.e., standing-passenger density and loading frequency) to determine the degree of crowdedness in the bus

3.2. Method for Determining Bus Crowding Coefficient. In order to overcome the fuzziness and randomness of discriminating bus crowding coefficient, this paper uses the cloud model to judge the crowding coefficient in the bus. The cloud model [21] combines the fuzziness in fuzzy theory with the randomness in probability statistics and it was first proposed by Academician De Yi Li and applied to the field of artificial intelligence [22]. Because the cloud model can overcome the fuzziness and randomness very well, the discriminant of the traffic flow state also has time-varying, discrete, fuzzy, and nonlinear. So it is also meaningful to apply the cloud model in the traffic field. The cloud model is used to determine the congestion coefficient in the bus, which further expands the application of the cloud model in the transportation field.

Table 1: Passenger standing density evaluation standards.

Service level	Comfort level	Standing-passenger density (people/m^2)	Description
A	Very Comfortable	3	Satisfy the passengers' psychological comfort requirements and the comfort space is just in contact.
B	Comfortable	5	Passengers can move slightly in the vehicle to meet body comfort requirements and the passenger's body will come into contact.
C	Generally Crowded	6	Passenger's body can maintain a standing position, and the passengers can be in contact with each other without squeezing, which can satisfy the basic space.
D	Crowded	7	Passenger's body remains squeezed and have a sense of crowding, but there is no safety issue.
E	Very Crowded	7.5	Passengers squeeze each other and feel uncomfortable. They may cause safety problems.
F	Unbearable	9	Passengers need to break through the seat area and squeeze into the seat area. It is extremely crowded and unbearable. In addition, boarding and alighting bus become difficult. It is an extreme situation.

Table 2: Classification of crowding service quality [20].

QOS	Loading Frequency	Description
A	0~0.5	Passengers can randomly choose seats
B	0.5~0.8	Passengers can appropriately choose seats.
C	0.8~1.0	All passengers have seats but they are less selective
D	1.0~1.25	They are 20% passengers need to stand, but passengers still have personal space
E	1.25~1.5	There are only 1/3 passengers need to stand, some of them have contact, and there is pressure.
F	>1.5	Passengers are obviously crowded and have a strong sense of oppression

Table 3: Definition of the digital eigenvalues of the cloud.

Eigenvalues	Definition
Ex	The central value of the spatial distribution of cloud drops
En	Fuzzy measure of qualitative concept
He	Uncertainty measure of entropy

3.3. The Process of Establishing Cloud Model

(1) Definition of Cloud Model

Definition 1. Set U as a quantitative domain and express by an exact numerical value. Set C as a qualitative concept and C $\in$ U. If the quantitative value x$\in$U, x is a random implementation of C, and the certainty of x to C is a random number $\mu(x) : U \longrightarrow [0,1], \forall x \in U, x \longrightarrow \mu(x)$ with a stable tendency. Then the distribution of x on the domain C is defined as cloud, and each x is a cloud drop [23]. The digital characteristics of the cloud are usually embodied in three aspects, namely, expected value, entropy, and hyper-entropy, respectively. The specific definitions are shown in Table 3.

Definition 2. If x satisfies x~NORM (Ex, En$'$), En$'$ ~ NORM (En, He^2) and the certainty of x to C satisfies

$$\mu(x) = \exp \frac{-(x - Ex)^2}{2(En')^2} \tag{5}$$

So the distribution of x on the domain U is called a normal cloud [24]. The implementation algorithm of the forward normal cloud generator is described as follows [25].

Step a. Generate a normal random number $En_i{}'$ with En as the expectation and He^2 as the variance.

Step b. Generate a normal random number x_i with Ex as the expectation and $En_i{}'$ as the variance.

Step c. Calculate $\mu_i(x) = \exp(-(x_i - Ex)^2/2(En_i{}')^2)$.

Steps (a) to step (c) are iterated until predetermined n cloud drops are produced.

Definition 3. There are n subclouds with the same properties in the domain.

There are n subclouds with the same properties in the domain, namely, $C_1(Ex_1, En_1, He_1), C_2(Ex_2, En_2, He_2), \ldots C_n(Ex_n, En_n, He_n)$. Then the process of subcloud synthesis of the parent cloud is represented by "$\circ$" [15], namely, $C = C_1 \circ C_2 \circ \cdots \cdot C_n$. If each subcloud has a certain weight, a formula for the expected value, entropy, and hyperentropy of the parent cloud is

Table 4: Index of each indicator.

Service level	A	B	C	D	E	F
Standing-passenger density (passenger /m^2)	3	4	5	6	7	
Boarding frequency	0.5	0.8	1.0	1.25	1.5	

$$Ex = \frac{\sum_{i=1}^{n}(En_i \times Ex_i \times \omega_i)}{\sum_{i=1}^{n}(En_i \times \omega_i)},$$
$$En = \sum_{i=1}^{n}(En_i \times \omega_i), \quad (6)$$
$$He = \frac{\sum_{i=1}^{n}(En_i \times He_i \times \omega_i)}{\sum_{i=1}^{n}(En_i \times \omega_i)}$$

(2) Select Metrics. According to Tables 1 and 2, this paper selected standing-passenger density and boarding frequency as indicators for judging the crowd coefficient in the bus. In order to reduce the singularity of the evaluation index, the same weight was given to each indicator when determining the crowd coefficient in the bus, that is, $\omega_1 = \omega_2 = 1/2$, as shown in Table 4.

(3) Determine the Digital Characteristics of the Cloud. Assume that the threshold vector of a metric is $X = (x_1, x_2, x_3, x_4, x_5)$, because it needs to be implemented in the same domain when synthesizing with the cloud model. When solving the digital features of the cloud, the index value needs to be standardized, and the interval is $[0, 1]$.

The standardized treatment formula for the larger the better indicator is

$$x_j^* = \frac{x_j - \min\{x_j\}}{\max\{x_j\} - \min\{x_j\}} \quad (j = 1, 2, 3, 4, 5) \quad (7)$$

The standardized treatment formula for the smaller the better indicator is

$$x_j^* = \frac{\max\{x_j\} - x_j}{\max\{x_j\} - \min\{x_j\}} \quad (j = 1, 2, 3, 4, 5) \quad (8)$$

where $\max\{x_j\}$ and $\min\{x_j\}$ are the maximum and minimum values of the jth threshold, respectively, and x_j^* is the normalized value of x_j.

In addition, the service levels A and F are represented by a half-liter normal cloud and a semifalling normal cloud, respectively. Their numerical characteristics are Ex_{x1} and Ex_{x6}, and the entropies are En_{x1} and En_{x6}. The calculation formulas are described as follows:

$$Ex_{x1} = x_1^*,$$
$$\mathrm{En}_{x1} = \mathrm{En}_{x2}$$
$$Ex_{x6} = x_5{}^*, \quad (9)$$
$$\mathrm{En}_{x6} = \mathrm{En}_{x5}$$
$$He = 0.01$$

The service levels B, C, D, and E are represented by a full normal cloud, and the eigenvalue calculation formula is

$$Ex_{xj} = \frac{(x_{j-1}^* + x_j^*)}{2}$$
$$En_{xj} = \frac{(x_{j-1}^* - x_j^*)}{6}, \quad (j = 2, 3, 4, 5) \quad (10)$$
$$He = 0.01$$

(4) Establish an Identified Cloud Model. The specific process is interpreted as follows.

Step a. Enter the digital characteristics of the service levels of the passengers occupying space indicators in the bus and combining with the forward normal cloud generator algorithm. This paper employed MATLAB software to establish a forward normal cloud generator CG_{rj} with metrics.

Step b. The actual values of collected number of passengers in the bus were normalized and recorded as r'. For the index values, if r is smaller than the $\min\{r_j\}$, the normalized result is 0; if r is greater than $\max\{r_j\}$, the normalized result is 1.

Step c. Substitute r' into the forward normal cloud generator CG_{r1}, CG_{r2}, CG_{r3}, CG_{r4}, CG_{r5}, and CG_{r6}. The output values μ_{r1}, μ_{r2}, μ_{r3}, μ_{r4}, μ_{r5}, and μ_{r6} of each cloud generator indicate the extent to which the input parameter r' belongs to R_j. Since the output value has a certain randomness, the output value μ_{rj} needs to be normalized to obtain the weight ω_{Rj} of R_j.

$$\omega_{Rj} = \frac{\mu_{rj}}{\sum_{j=1}^{6}\mu_{rj}} \quad (11)$$

(5) Calculate Similarity of Identified Cloud and Standard Cloud. Similarity refers to the degree of membership β_i of the cloud drops x_i $(i = 1, 2, \ldots, N)$ generated by the identified cloud U' and each standard cloud U_j. The calculation process is listed as follows.

Step a. In identified cloud U', generate a normal random number with **En** as the expected value and **He^2** as the variance, namely, $En_i = NORM(En, He^2)$.

Step b. In identified cloud U', generate a normal random number with Ex as the expected value and En_i^2 as the variance, namely, $x_i = NORM(Ex, En^2)$.

Step c. In standard cloud U_j, generate a normal random number with En_j as the expected value and He_j^2 as the variance, namely, $En_j = NORM(En_j, He_j^2)$.

Table 5: Congestion range corresponding to the six service levels.

Service Level	Congestion γ
(A) Very Comfortable	$\gamma < 30$
(B) Comfortable	$30 \le \gamma < 50$
(C) Generally Crowded	$50 \le \gamma < 70$
(D) Crowded	$70 \le \gamma < 90$
(E) Severely Crowded	$90 \le \gamma < 110$
(F) Unbearable	$\gamma > 110$

Step d. Calculate the membership of ath service level, namely, $\beta_{\mathrm{ij}} = \exp(-(\mathrm{x}_i - Ex_j)^2/2En_j{}^2)$.

Step e. Iterate Steps a-d until the required cloud drops **N** are generated.

Step f. The similarity between the identified cloud U′ and the each standard cloud is

$$\delta_j = \frac{1}{N}\sum_{i=1}^{N}\beta_{\mathrm{ij}} \tag{12}$$

Step g. Normalize j to get the degree to which the identified cloud belongs to the jth service level, namely,

$$\lambda_j = \frac{\delta_j}{\sum_{j=1}^{6}\delta_{\mathrm{j}}} \tag{13}$$

The more the cloud drops x_i generated by the identified cloud U' fall within the range of a standard cloud U_j, the larger the δ_j value as well as the λ_j value. This situation indicates that the closer the identified state is to the fth service level.

(6) Determination of Bus Crowding Coefficient. This paper uses the maximum value determination method to determine the crowd level in the bus. This method determines the service level corresponding to the state to be recognized in the vehicle by using the maximum degree of possibility. It is difficult to judge the degree of crowding in the bus by this method. The in-vehicle environment with different crowding levels directly affects the behavior of passengers in the bus. Therefore, this paper introduces the crowdedness of passengers in the bus. The calculation formula is as follows:

$$\gamma = \sum_{j=1}^{6}\lambda_j \times \xi_j \tag{14}$$

In the formula, the values of ξ_j represent different crowd coefficients of the service levels, and the crowd coefficients of between A and F were set to 20, 40, 60, 80, 100, and 120, respectively. The larger the congestion γ in the bus, the more crowded the lower service level in the bus.

The crowd range corresponding to the six service levels is shown in Table 5.

4. Case Study

This research selected the Dalian Bus Line No. 10 as a case study to verify the accuracy of the proposed model. The Dalian Bus Line No. 10 is a regular bus route. Typically, there are 40 seats on a bus; in addition to these fixed seats, the total effective standing area in the bus is about 6m^2, making the total capacity up to about 100 passenger per vehicle. This route starts from Shahekou Railway Station to Lily Villa, with a total mileage of 16_km and the regular operation hours from 6:00 to 21:00. There are 29 stations for the inbound direction (i.e., from Shahekou Railway Station to Lily Villa) and 27 stations for the outbound direction (i.e., from Lily Villa to Shahekou Railway Station). Among them, it was found that stations 4, 7, 10, 11, and 15 were the most passenger intensive stations. A manual survey about the number of passengers getting on and off the bus at each station was conducted in the morning peak hours (i.e., 7:00 to 8:00).

4.1. Passenger Flow Forecast in the Bus. This paper investigated the passenger flow of bus line No. 10 during a working day morning peak hours. The data are shown in Figure 1 (inbound direction) and Figure 2 (outbound direction).

To use the RBF neural network algorithm for predicting the number of passengers in the bus, a prerequisite step is to normalize the data, described as follows:

$$y = (y_{\max} - y_{\min}) \times \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} + y_{\min} \tag{15}$$

where x and y represent the values before and after normalization, respectively; min and max represent the minimum and maximum values in the sample data, respectively. The normalized data are shown in Table 6.

The number of passengers in the bus was predicted by the RBF neural network algorithm, as shown in Figure 3.

Then, the predicted number of passengers was compared with the actual data; the following criteria, including MAE, MSE, MARE, and MSRE (see (1) to (4)), were employed for identifying the differences, as shown in Table 7.

By analyzing the evaluation results, it was found that the MAE=2.206 and MARE=0.249, indicating that the predictions were closed to field data.

4.2. Determination of Bus Crowding Coefficient Based on Cloud Model. According to (7) to (10), the subclouds of each evaluation indicator in the bus were calculated, as shown in Table 8.

The numerical characteristics of the standard cloud in the bus are calculated using (6), as shown in Table 9.

Based on the algorithm of the forward cloud generator that generated 5000 cloud drops and using MATLAB as simulation software, the standard cloud pattern formed is shown in Figure 4. In the figure, the green dots represent LOS A and the red dots represent LOS-F.

This section selected a section of the bus route (bus stations 8 to 15) to demonstrate how to convert the predicted number of passengers boarding at a bus station to a corresponding boarding frequency as well as the in-vehicle standing-passenger density, as shown in Table 10.

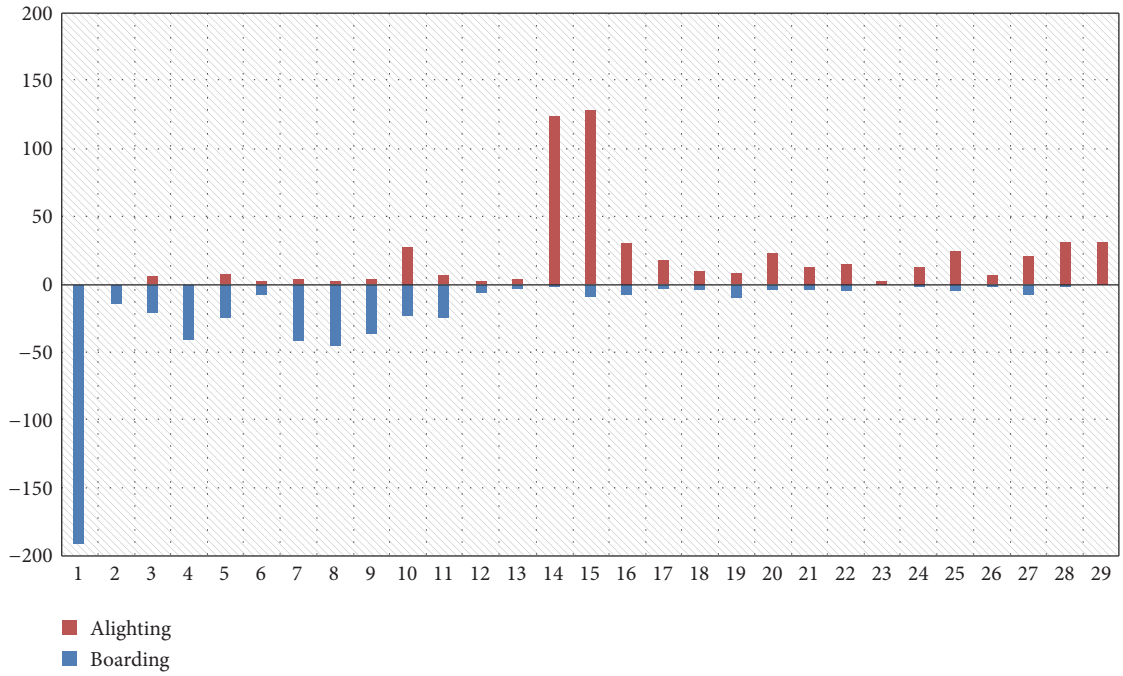

Figure 1: Boarding and alighting data of inbound direction.

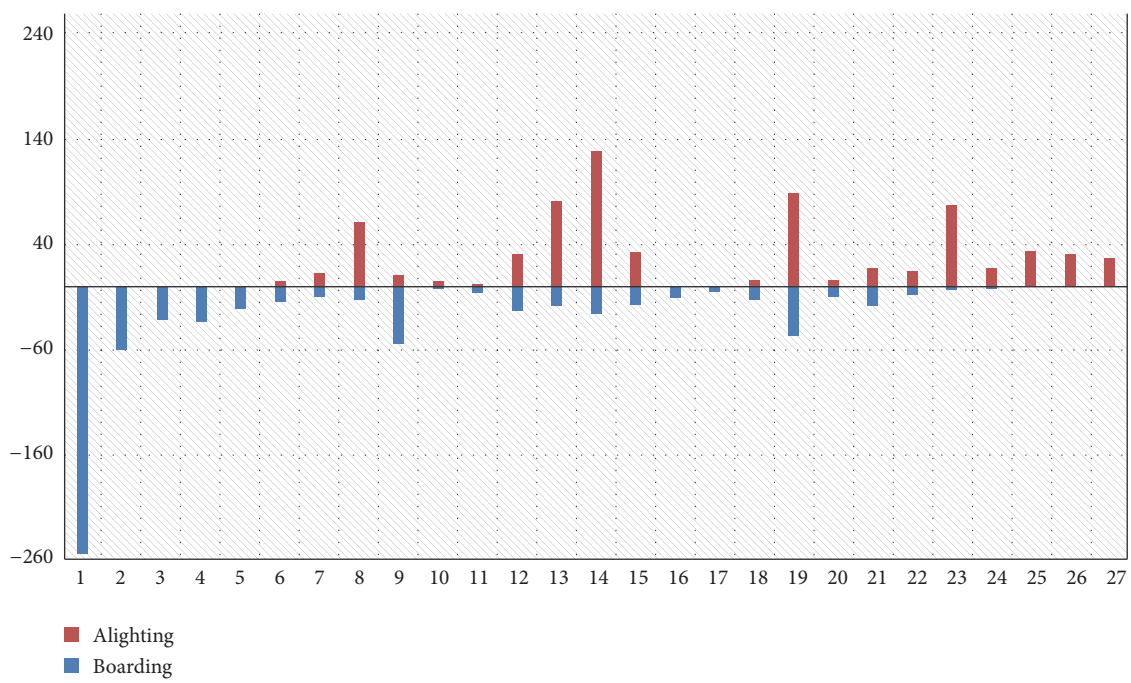

Figure 2: Boarding and alighting data of outbound direction.

The data presented in Table 10 were imported into (12) to (14) to calculate the similarity, possible degree, and congestion degree of the selected bus stations, as shown in Table 11.

Eventually, this paper combined with the implementation algorithm of the forward normal cloud generator based on 5000 cloud drops. The identified cloud patterns of each site are shown in Figure 5.

Based on the estimated congestion degrees, the service levels of this bus line at each station were determined, as shown in Figure 6.

Through simulation, it is found that using the cloud model algorithm to determine the crowding coefficient in the bus is a feasible method. According to the estimated congestion degree values presented in Table 8 and the determined service levels of the bus in Figure 6, it can be concluded that

Table 6: Normalized data in the prediction model (a part of data).

	1	2	3	4	5	6	7	8	9	10	11	12
1	-0.3556	-0.3333	-0.2444	-0.2000	-0.1111	-0.0667	0.1556	0.1556	0.3778	0.4222	0.3111	0.3111
2	0.3111	0.3111	-0.1333	-0.3111	-0.4000	-0.4667	-0.5333	-0.5333	-0.6444	-0.6889	-0.7333	-0.7333
3	-0.7556	-0.9111	-0.8889	-0.9333	-1	-0.3556	-0.3111	-0.2	-0.0677	-0.0889	0	0.0222
4	0.1778	0.6000	0.7111	0.6889	0.6889	0.6889	0.0667	-0.4667	-0.5778	-0.6667	-0.6889	-0.7111
5	-0.7111	-0.7333	-0.7778	-0.7778	-0.8222	-0.9111	-0.9333	-0.9556	-1	-0.2222	-0.1778	0.0667
6	0.1556	0.1333	0.2444	0.6889	0.9111	0.8889	0.9333	0.9778	1	0.9333	1	-1

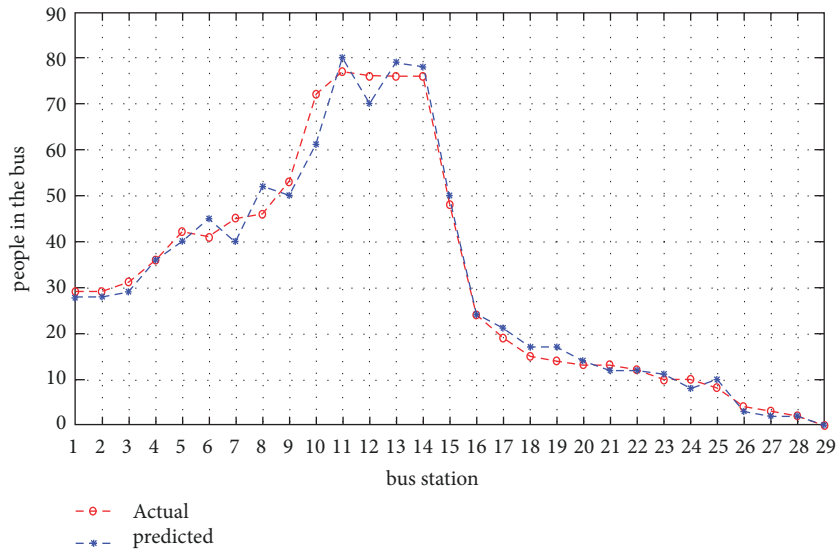

Figure 3: Prediction value of RBF neural network.

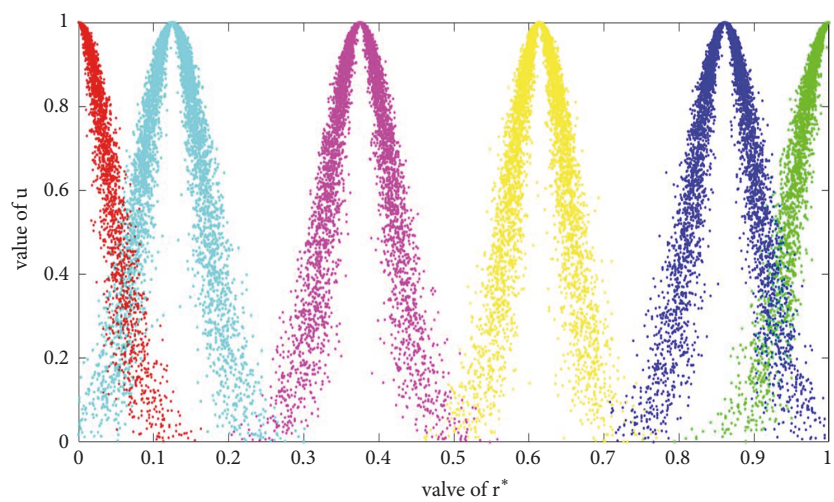

Figure 4: The standard cloud map of the bus.

the crowding level in the bus increases from Gaizhou Street to Zhilin Park, with the service level deteriorated from LOS-C to LOS-F. From Zhiyuan Park to Software Park, the crowding level in the bus has been decreased, and the service level changed from LOS-F to LOS-C.

5. Conclusion

(1) This paper employed the cloud model to combine the standing-passenger density with the loading frequency to determine the crowed coefficient. The method realized the change of the crowed coefficient from qualitative analysis to quantitative analysis.

(2) The cloud model can overcome the singularity of the index and ambiguity of the congestion state division, and it has certain adaptability in the congestion state division.

(3) Future research needs to make further exploration. It needs to cover a boarder range of bus routes that have different route lengths, numbers of stations, passenger demand levels, and vehicle capacities. In addition, it is necessary for future research to develop algorithms for applying the estimated crowding coefficient to the optimization of bus scheduling. According to the different congestion levels of bus stations, it is a new direction for future research to reasonably control the departure interval of vehicles and improve the service levels in the bus during peak hours.

Data Availability

The data used to support the findings of this study are included within the article. The data are shown in Figures 1 and 2. No external data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

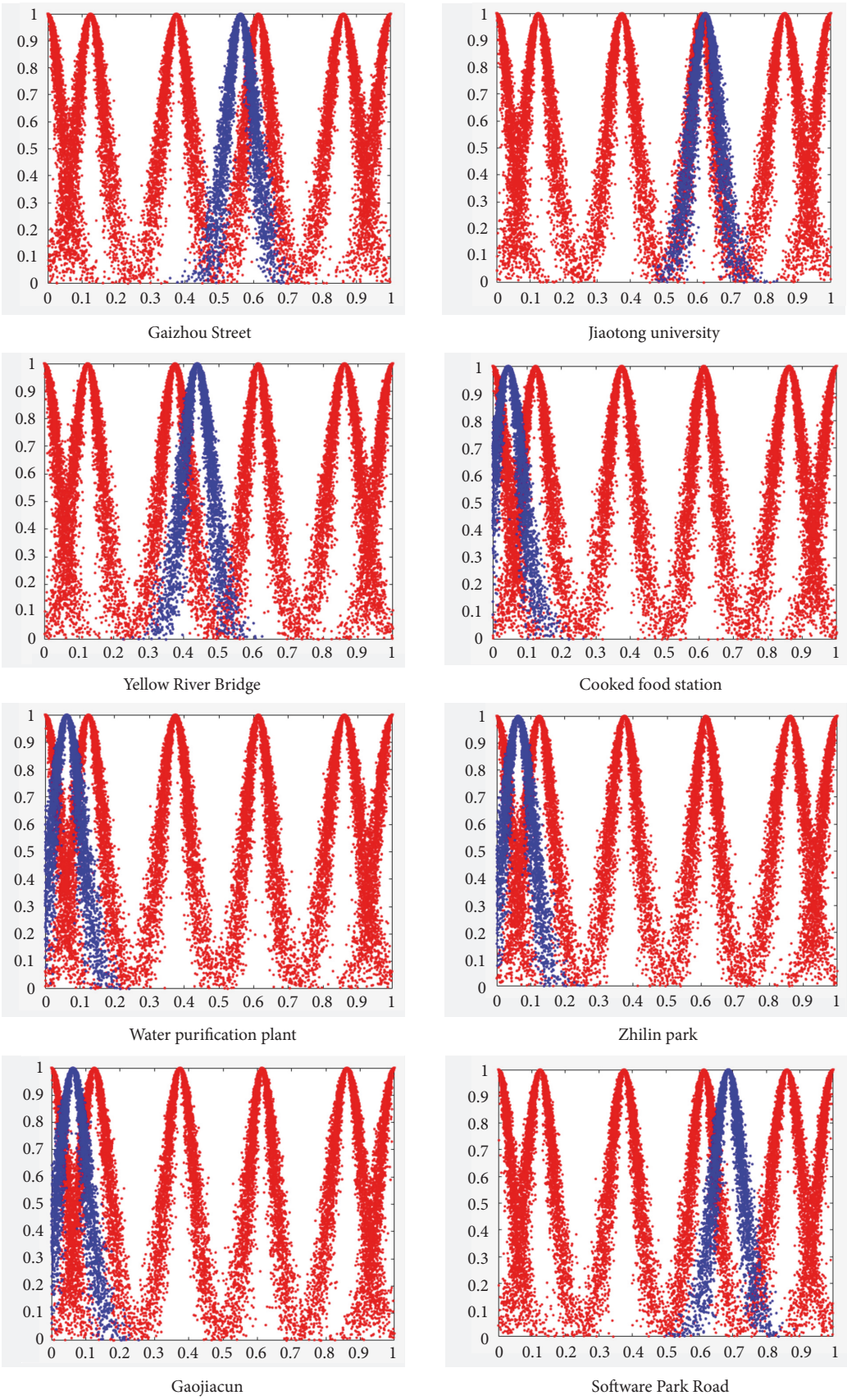

Figure 5: Identified cloud and template cloud within the bus.

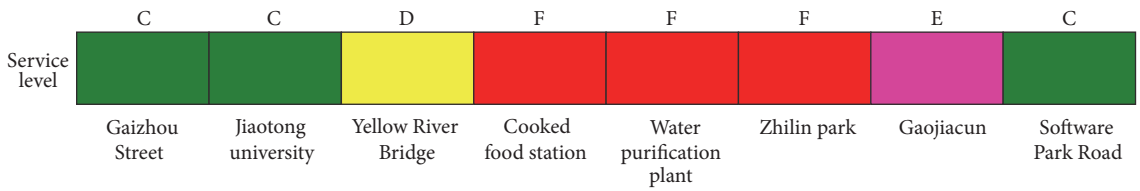

Figure 6: Division of service level within the bus.

Table 7: Performance evaluation results.

Evaluation Method	MAE	MSE	MARE	MSRE
Results	2.206	3.118	0.249	0.421

Table 8: In-vehicle congestion coefficient evaluation index cloud.

indicator 1	LOS	Ex	En	He	indicator 2	LOS	Ex	En	He
Standing-passenger Density	A	1	0.042	0.010	Loading Frequency	A	1	0.050	0.010
	B	0.875	0.042	0.010		B	0.85	0.050	0.010
	C	0.625	0.042	0.010		C	0.6	0.033	0.010
	D	0.375	0.042	0.010		D	0.375	0.042	0.010
	E	0.125	0.042	0.010		E	0.125	0.042	0.010
	F	0	0.042	0.010		F	0	0.042	0.010

Table 9: In-vehicle evaluation index standard cloud.

LOS	Ex	En	He
A	1	0.046	0.010
B	0.861	0.046	0.010
C	0.614	0.0375	0.010
D	0.375	0.042	0.010
E	0.125	0.042	0.010
F	0	0.042	0.010

Table 10: The load factor and standing-passenger density corresponding to the predicted number of people.

Station number	Station name	Loading Frequency	Standing-passenger Density
8	Gaizhou Street	1.3	2
9	Jiaotong University	1.25	1.7
10	Yellow River Bridge	1.525	3.5
11	Cooked food station	2.0	6.7
12	Water purification plant	1.975	6.5
13	Zhilin park	1.95	6.3
14	Gaojiacun	1.975	6.5
15	Software Park Road	1.25	1.7

Table 11: Similarity, possibility degree, and crowding degree of the selected bus stations.

Bus Station Number	Similarity	Possible Degree	Crowding Degree
8	[0.00, 0.00, 0.4284, 0.0065, 0.00, 0.00]	[0.00, 0.00, 0.985, 0.0148, 0.00, 0.000]	60.2645
9	[0.00, 0.0011, 0.6578, 0.00, 0.00, 0.00]	[0.00, 0.0017, 0.9979, 0.00, 0.00, 0.00]	59.9761
10	[0.00, 0.00, 0.0079, 0.3895, 0.00, 0.00]	[0.00, 0.00, 0.0200, 0.9800, 0.00, 0.00]	79.6019
11	[0.00, 0.00, 0.00, 0.00, 0.2721, 0.5259]	[0.00, 0.00, 0.00, 0.00, 0.3410, 0.6590]	113.18
12	[0.00, 0.00, 0.00, 0.00, 0.3937, 0.4005]	[0.00, 0.00, 0.00, 0.00, 0.4957, 0.5043]	110.059
13	[0.00, 0.00, 0.00, 0.00, 0.3951, 0.3978]	[0.00, 0.00, 0.00, 0.00, 0.4983, 0.5017]	110.034
14	[0.00, 0.00, 0.00, 0.00, 0.4043, 0.3904]	[0.00, 0.00, 0.00, 0.00, 0.5088, 0.4912]	109.825
15	[0.00, 0.000, 0.6631, 0.000, 0.00, 0.00]	[0.00, 0.0014, 0.9981, 0.00, 0.00, 0.00]	59.9800

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