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Fuzzy Comprehensive Evaluation of APTS Dispatcher Working Level Based on Cloud Model

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Abstract: Many cities in China have built an advanced public transportation system (APTS) in recent years. These systems cannot carry out automated dispatches but rely on the dispatcher to ensure normal operations. Based on the theory of fuzzy comprehensive evaluation, this study created a hierarchical evaluation model to evaluate the work level of the dispatcher. Firstly, a hierarchical evaluation system was established based on the data of line complexity and dispatch workload provided by the APTS. Secondly, we assigned the weight of the evaluating indicator by combing an expert scoring method and the entropy weight method. We then transformed the quantitative data into qualitative evaluation data with a cloud model. Through a comparison with the standard cloud, the work level of an APTS dispatcher can be defined. The evaluation results for 12 cities in China showed that there was no obvious connection between the working level and bus company size, but the work level was always higher in large cities. We finally obtained the standard range of the evaluation indicator through cluster analysis. This method can be used as a reference to evaluate the work level of dispatchers in other cities, and can reflect the correlation between the work level and dispatching system construction, population and city size.

Keywords: advanced public transportation system; fuzzy comprehensive evaluation; cloud model; dis-patcher working level

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1. Introduction

With the rapid development of intelligent transportation, many cities have built an advanced public transportation system (APTS), which greatly improves public transport. However, the APTS in most cities is still controlled by human operators on the basis of real-time data, lacking the capacity for intelligent dispatch. Under such conditions, the service level of urban public transport is closely related to the work level of the dispatchers. Considering the management requirements of bus enterprises, it is necessary to evaluate the scheduling level of dispatchers.

Most of the existing studies on public transport evaluations can be roughly divided into the following three categories: service evaluation, network structure evaluation and network optimization evaluation, particularly the assessment of service level and quality [1–4]. Yu [5] set up a four-layer cruise passenger-oriented evaluation system and identified the weights of 21 criteria and the ranking of transport routes for cruise passengers in different age groups. The proposed evaluation system also provided suggestions for a one-day tour itinerary of cruise passengers in the hinterland by considering the berthing time of cruise ships and the commuting time of local residents. Celikbilek [6] conducted a grey decision model of the BWM, AHP and MOORA for improving the quality of public transportation systems. The public transportation system in the capital of Hungary, Budapest, was evaluated to check its efficiency and validate the proposed grey decision model. Lo [7] proposed a two-stage multi-criteria decision-making (MCDM) approach for sustainable supplier evaluation and transportation planning in multi-level SCNs. The multi-level framework assessed the service quality by combining subjective and objective factors.

For dispatch systems, some studies have examined the vehicle scheduling problem. Andrade-Michel [8] proposed an exact constraint programming model and compared it with a variable neighborhood search that incorporated the driver's reliability and the trip's importance. Wang [9] studied the relationship between bus dispatch and passenger traffic volume in order to shorten passenger waiting time. Shen [10] developed a new vehicle scheduling approach based on AVL data to realize high on-time probability and low cost, and Wu [11] compared the operation strategies in schedule design and summarized the most appropriate scheduling strategies in different situations. Other recent studies have focused on the working conditions and fatigue level of dispatchers, e.g., using physiological indicators, rest records and subjective ratings to assess the fatigue of railway dispatchers [12]. Indicators analyzed the relationships among working time, workload, fatigue level and the safety of railway dispatchers [13] or analyzed the risk of decreased operator performance in railway dispatchers [14]. In terms of public transportation dispatch, Han [15] addressed the crew scheduling problem for a mass rapid transit system by optimizing dispatcher task allocation in different situations to save labor costs. Mayas [16] surveyed dispatchers in German transport companies regarding their acceptance and expectations, and analyzed the fundamental requirements for dispatching systems. Shi [17] presented a comprehensive evaluation model of bus route optimization based on multi-source data including bus smart card transaction data, bus location data and static attribute data of the bus network by applying the analytic hierarchy process (AHP).

However, there are few studies on the evaluation of dispatchers, and most of these evaluations are for railway dispatchers, so this study intends to explore the scheduling level of APTS dispatchers in different cities.

As evaluation algorithms, fuzzy comprehensive evaluation is a commonly used method, which is often integrated with other models for risk evaluations [18,19] or performance evaluations [20]. However, the subjectivity and arbitrariness in the selection of its membership function always lead to the unreliability of the evaluation results. The cloud model belongs to the category of fuzzy comprehensive evaluation. It is a bidirectional cognitive model that can express qualitative and quantitative concepts and reflect the uncertainty of concepts in natural language [21]. It is not only explained by the classical probability model and fuzzy mathematics but also reflects the relationship between randomness and fuzziness. Besides, the ubiquity of normal distribution in real situations makes the cloud model have better universality, so this model has been widely used in decision analysis [22,23], ecological carrying capacity analysis [24], risk assessments [25], traffic congestion situation assessments [26] and other applications.

Evaluating the dispatcher's scheduling level can help public transport enterprises to formulate a dispatcher selection plan according to the evaluation results. Moreover, it can help enterprises to optimize the bus departure plan according to the evaluation results, thereby improving the bus service level. In addition, it can provide the urban traffic management department with important data to explore the development of public transport and residents' travel satisfaction.

In light of the analysis above, the main contributions of this study can be summarized as follows:

(1) It selects the data indices related to dispatchers from an APTS, focusing on the complexity of lines and the workload of dispatchers, and establishes an evaluation system for dispatchers' work level by AHP.
(2) The proposed hybrid weight method can reduce the subjective tendency of artificial evaluations of dispatchers in conventional mode, as it can combine subjective factors and objective factors to ensure the objectivity of the evaluation results.
(3) Based on the fuzzy evaluation theory, we introduced the cloud model to realize the conversion between quantitative data and a qualitative evaluation through a cloud generator to evaluate the actual work levels of dispatchers in different cities.
(4) Based on the evaluation results, we determined the characteristics and standard cloud of dispatchers' work levels in different cities, which would be convenient for urban

public transport enterprises and traffic management departments to quickly judge the dispatcher's work level.

The rest of this article is organized as follows. In Section 2, we introduce the theory relating to the cloud model. In Section 3, we establish a hierarchy evaluation system based on the daily average statistical data of dispatchers from the APTS. We then obtain the dispatchers' work level by using the cloud model. Section 4 presents and classifies the analysis results and determines the characteristics and standard cloud of the dispatchers' work level.

2. Methodology

The cloud model can fully reflect the whole process of human cognition, overcome the deficiencies of other methods in cognition and be flexibly expanded and compressed in the domain to effectively reduce the subjectivity, improve the validity and reliability of the results, and have universality for the mutual transformation between qualitative and quantitative data. In this section, the cloud model is combined with the AHP method to establish an evaluation model for the work level of APTS dispatchers, and the effectiveness of the model is verified.

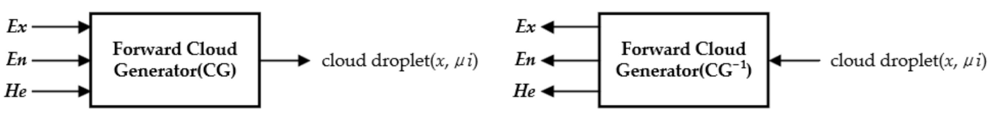
2.1. Cloud Model

The cloud model can be defined as follows: assuming that *U* is the quantitative domain of the exact numerical representation, $x \in U$, and the qualitative concept of the definition space *U* is *T*, the distribution of the mapping of *T* from the interval $U \rightarrow [0,1]$ in the quantity domain space is a cloud if the membership degree $C_T(x) \in [0,1]$ of the element ($x \in X$) corresponding to T has random numbers with a stable distribution, as shown in Formula (1):

$$C_T(x), U \rightarrow [0,1], \forall x \in X(X \in U), x \rightarrow C_T(x) \quad (1)$$

The cloud can be characterized by three digital parameters: the mean value (*Ex*), entropy (*En*) and hyperentropy (*He*). Ex reflects the central position of the cloud, En reflects the uncertainty and ambiguity of the qualitative concept, and He reflects the uncertainty of entropy, describing the degree of association between ambiguity and randomness, which can reflect the degree of dispersion and thickness of the cloud. There are two types of cloud model algorithms: the forward cloud generator and the backward cloud generator.

The forward cloud generator (CG) is shown in Figure 1a. It can generate a certain number of cloud drops based on the cloud parameters, so the cloud parameters in the qualitative field can be converted to cloud droplets in the quantitative field. In this study, it converted the dispatchers' work level classifications into a visual cloud map to characterize the distribution of the cloud, which can be used as a standard reference for scheduling evaluations.



(**a**) (**b**)

Figure 1. The process of the cloud generator: (**a**) the forward cloud generator; (**b**) the backward cloud generator.

The process of the forward cloud generator algorithm can be divided into four steps:

(1) Set the entropy *En* as the expected value and the hyper-entropy He as the standard deviation, so a normally distributed random number *En′* can be generated that satisfies Formula (2). Next, generate a normally distributed random number *x* with *Ex* as the expected value and *En* as the standard deviation that satisfies Formula (3).

$$En' = N \sim (En, He) \quad (2)$$

$$x = N \sim (Ex, En') \quad (3)$$

In this study, *Ex* is the scheduling level of dispatchers; *En* and *He* are the parameters corresponding to the scheduling level.

(2) Calculate the membership of the cloud droplet as shown in Formula (4).

$$\mu(x) = exp(-(x - Ex)^2/2En'^2) \quad (4)$$

(3) Set x as a cloud droplet with the membership degree $\mu(x)$.

(4) Determine the number of cloud droplets M, then repeat the steps mentioned above until M droplets have been generated.

Correspondingly, the backward cloud generator (CG^{-1}) calculates the digital characteristics of the cloud based on actual data to realize the conversion from quantitative to qualitative concepts. This is the inverse process of the forward cloud generator algorithm. In this study, the main purpose of the backward cloud algorithm was to convert the evaluation data from a survey of experts into cloud parameters. Therefore, the second algorithm with a simple process was selected, and the algorithm is shown in Figure 2.

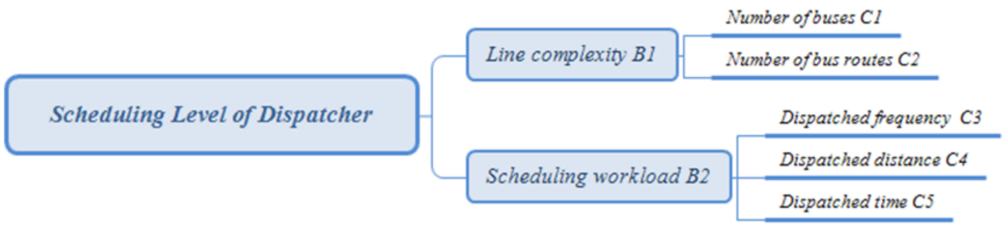


Figure 2. Hierarchical chart of the evaluation indicators.

The process of the backward cloud generator algorithm can be divided into five steps:

(1) Calculate the mean value *Ex* and the variance S^2 of the cloud drop sample from the basic data of the dispatchers' scheduling level.

(2) Obtain the entropy of the cloud drop sample as shown in Formula (5).

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{N}\sum_{1}^{N}|x_i - Ex| \quad (5)$$

where N is the volume of the sample data and x_i is the value of Sample i.

(3) If the relationship between S^2 and E_n satisfies Formula (6), proceed to Step 5; otherwise, proceed to step 4.

$$S^2 - E_n^2 \geq 0 \quad (6)$$

(4) Delete the s sample points closest to the mean value E_n. If $N \leq 100$, then define s = 1; otherwise, define s = 0.01 × N. Let the new volume of the sample data be N' = 0.99 × N; then, calculate the variance value.

(5) Calculating the hyperentropy of the cloud as shown in Formula (7). The three parameters of the cloud can then be obtained.

$$H_e = \sqrt{S^2 - E_n^2} \quad (7)$$

2.2. Weighted Comprehensive Algorism

There are two kinds of methods for assigning the weight: the subjective weighted algorism and the objective weighted algorism [27]. The weight assigned by the subjective method can reflect the intention of researchers and have strong explanatory properties. Still, it usually fails to reflect the actual evaluation data and can be easily restricted by the experience of the researchers, which implies obviously subjective arbitrariness. The weight assigned by the objective method is closely related to the actual data, but it is easily affected by abnormal values in the dataset.

To improve the rationality of the evaluation results, this study combined AHP with the entropy weight method to calculate the comprehensive weight of the evaluation index to make up for the defects of individual algorithms.

2.2.1. Subjective Weight

The analytic hierarchy process (AHP) is a commonly used subjective method of assigning weights to evaluation indices through the working experience of experts. In our study, we chose the Saaty Scaling Law [28] to determine the importance of different indicators, as shown in Table 1.

Table 1. Interpretation of judgment matrix.

Value	Interpretation of Pairwise Comparison
1	Indicators are equally important
3	The former indicator is slightly more important than the latter
5	The former indicator is more important than the latter
7	The former indicator is strongly more important than the latter
9	The former indicator is absolutely more important than the latter
2, 4, 6, 8	The importance of the former and the latter is between adjacent judgment values
Reciprocity	If the importance ratio of the former to the latter is p, then the latter to the former is $1/p$

It was necessary to invite some experts to compare the importance of each indicator in the hierarchical model so we could construct the importance judgment matrix $A_{m\times n}$. All values on the diagonal of the matrix are 1, and the importance scale value of diagonal symmetry satisfies the condition shown in Formula (8).

$$a_{ij} = 1/a_{ij} \tag{8}$$

The scores of different experts are independent, so it was necessary to conduct a consistency check to avoid contradictions in the results of the judgment indicators. The consistency index CI and the consistency ratio CR are shown in Formula (9).

$$\begin{cases} CI = \frac{\lambda_{\max} - n}{n-1} \\ CR = \frac{CI}{RI} \end{cases} \tag{9}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix $A_{m\times n}$ and RI is the random index.

After the consistency test, the eigenvectors need to be normalized to the weights of the corresponding row elements. We set W_k^{I} as the integrated weight vector of the layer k element relative to the final evaluation and the weight vector of the element n_{k-1} of the layer $k-1$ relative to the final evaluation target was $W_{k-1}^{\mathrm{I}} = \left(w_{k-1,1}^{I}, w_{k-1,2}^{I}, w_{k-1,3}^{I}\right)^T$. We also set the elements n_k on the layer k corresponding to the single-layer weight vector of the attribute j on the layer $k-1$ as $P_j^k = \left(P_{1j}^k, P_{2j}^k, \ldots, P_{nj}^k\right)^T$, where the importance degree of the evaluation index of the layer k that is not affected by the attribute j can be assigned a value of 0. $P^k = (P_1^k, P_2^k, \ldots, P_n^k)$ is a $n_{k-1} \times n_k$ matrix, which represents the weight vector of each element of the layer k to each element on the layer $k-1$, and the formula of W^I is as follows:

$$W^I = P^k \times W^I_{k-1} = P^k \times P^{k-1} \times \ldots P^3 W^I_2 \tag{10}$$

where W^I_2 is the weight vector of each element on the second layer relative to the first layer.

2.2.2. Objective Weight

The entropy weight method (EWM) is a type of objective weight method. The process of this method is as follows:

(1) Data standardization: The matrix $X_{m\times n} = \{X_1, X_2, \ldots X_n\}$ is set according to m evaluation objects and n evaluation indices, where x_{ij} denotes the real data of the evaluation index i. The value of the respective indicators can be converted to the standardized data y_{ij}, as shown in Formula (11), and then the standardized matrix $Y_{m\times n}$ can be obtained.

$$y_{ij} = \frac{x_{ij} - \min X_j}{\max X_j - \min X_j} \tag{11}$$

where X_j denotes the jth column vector of the matrix $X_{m\times n}$.

(2) The information entropy of the evaluation index is calculated. According to the definition of information entropy, the entropy can be calculated through Formula (12).

$$\begin{cases} E_j = \frac{-\sum_{i=1}^{m} \ln f_{ij}}{\ln m} \\ f_{ij} = y_{ij} / \sum_{i=1}^{m} (1 + y_{ij}) \end{cases} \tag{12}$$

If f_{ij} = 0, then define $\lim\limits_{f_{ij}=0} f_{ij} \times \ln f_{ij} = 0$.

(3) Computing the weight matrix of the evaluation index. The weight coefficient reflects the volume of the index information. The larger the entropy weight, the greater the effect of the index on comprehensive decision-making. This intuitively and effectively reflects the degree of difference between the indices, and the entropy weight can be calculated as shown in Formula (13).

$$\begin{cases} w_j^I = \frac{1-E_j}{n-\sum_{j=1}^{n} E_j} \\ \sum_{j=1}^{n} w_j^{II} = 1 \end{cases} \tag{13}$$

The weight cloud vector of the evaluation index $W^{II} = \{w_1^{II}, w_2^{II}, \ldots w_n^{II}\}^T$ can then be calculated using the backward cloud generator algorithm.

2.2.3. Weighted Combination

According to Formula (14), the weight of the dispatchers' scheduling indicators given by AHP and EWM can be integrated, so the mixed weight matrix $W = \{w_1, w_2, \ldots w_n\}^T$ that considers both subjective and objective factors can be obtained.

$$w_{ij} = \frac{w_i^I w_i^{II}}{\sum_{i=1}^{n} w_i^I w_i^{II}} \tag{14}$$

2.3. Hierarchical Evaluation System of Dispatcher's Work Level

This study established an evaluation system of the APTS dispatchers' working level via fuzzy comprehensive theory for the first time. The evaluation process includes four steps: establishing the evaluation system, calculating the comprehensive weight of the evaluation indices (constructing the cloud judgment model matrix and calculating the weight vector of the evaluation indices), constructing the fuzzy evaluation matrix and finally analyzing the evaluation results.

2.3.1. Construction of the Hierarchical Evaluation System

The evaluation indicators and the establishment of the evaluation system should be scientific, comprehensive and feasible. For the scheduling level of dispatchers, the qualitative field can be divided into four grades: IV—qualified; III—medium; II—good; I—excellent. Therefore, the evaluation set can be defined as V = {IV, III, II, I}.

Next, based on the ATPS data, the line complexity (B1) and scheduling workload (B2) can be set as the main evaluating factors, and the corresponding evaluation factor set can be defined as U = {number of buses (C1), number of bus routes (C2), dispatch frequency (C3), dispatch distance (C4), dispatch time (C5)}, as shown in Figure 2. The relationships among the different indicators are shown in Figure 2. The meanings of these indicators are shown in Table 2.

Table 2. Index system of evaluating APTS dispatchers' scheduling level for urban public transportation.

Main Factor	Index	Index Meaning
Line complexity	Number of buses	Average number of buses available to dispatchers.
	Number of bus routes	Average number of bus lines available to dispatchers.
Scheduling workload	Dispatched frequency	The count number of times the bus runs one round trip.
	Dispatched distance	Average running distance of the bus operated by the dispatcher during working hours.
	Dispatched time	Cumulative travel time of the buses operated by the dispatcher.

The frequency of buses is related to the departure lines and methods, as well as the traffic conditions. The departure pattern is divided into planned departures and sequenced departures.

2.3.2. Fuzzy Evaluation Cloud Model

The cloud model has a clear bilateral constraint relationship when transforming the quantitative concept to the qualitative description [29], that is, when generating cloud parameters according to the qualitative evaluation level. This mainly depends on the range boundary corresponding to each grade; therefore, once the boundaries of the qualitative domain (comment level) have been determined, the cloud parameters of the different rating levels can be obtained, as shown in Formula (15).

$$\begin{cases} Ex = \frac{C_{\min} + C_{\max}}{2} \\ En = \frac{C_{\max} - C_{\min}}{6} \\ He = \lambda \end{cases} \tag{15}$$

where $C_{\max}$ and $C_{\min}$ denote the upper and lower limits of the numerical interval of the evaluation level, and λ denotes a constant which can be defined by the degree of ambiguity of the comment concept.

The value of λ should satisfy the condition shown in Formula (16) in order to avoid the generated cloud being too fuzzy.

$$0 < \lambda < \frac{En}{3} \tag{16}$$

In this study, the daily average dispatch data were selected as the basic data for experts to evaluate the scheduling level of dispatchers, and k experts were invited to evaluate the indicator set $U = \{u_1, u_2, \ldots u_m\}$. We obtained the evaluation result set $V = \{v_1, v_2, \ldots v_m\}$, where $V_i = \left\{C_i^1, C_i^2, \ldots C_i^k\right\}^T$, and C_i^j is the cloud model obtained by the index k evaluated by Expert j. According to the synthetic cloud algorithm, the mixed cloud model of factor

u_i of Expert k can be obtained, which can be expressed as $C_i(Ex_i, En_i, He_i)$, and thus, the evaluating cloud matrix $V = [C_1, C_2, \ldots C_m]$ was obtained.

2.4. Assessment of Dispatcher's Work Level

According to the weight matrix W and the comprehensive evaluation cloud matrix V, the process of evaluating the dispatchers' work level based on cloud model theory can be expressed as given in Formula (17)

$$Z = C \times V = C(Ex, En, He) \tag{17}$$

Since the calculation process involves a hybrid operation of cloud parameters and conventional parameters, according to the calculation rules of the cloud model, combined with the fuzzy operation law, the specific calculation process of each cloud parameter is as shown in Formula (18) [21].

$$\begin{cases} Ex = \sum_{i=1}^{m} Ex_i w_i \\ En = \sqrt{\sum_{i=1}^{m} En_i{}^2 w_i} \\ He = \sum_{i=1}^{m} He_i w_i \end{cases} \tag{18}$$

According to the cloud parameters above, the forward cloud generator algorithm can generate a certain number of cloud drops to form the result cloud. We can then compare this with the comment cloud to obtain the working level of APTS dispatchers. Since the weights used in the cloud model combine subjective and objective factors, the evaluation results are more objective than relying solely on artificial scoring.

3. Case Study

This chapter uses the relevant data of cities that have had APTS for more than two years. Firstly, the data of different cities are preliminarily compared and analyzed, which is the basis of city-level classification and paves the way for the evaluation of the dispatcher's work level. Secondly, by inviting experienced experts to score the relevant indicators and adjusting and testing the weights of different indicators after scoring, the mixed weights of various evaluation indicators are obtained. Finally, through the cloud model to quantify the indicators, the evaluation standard cloud is established, and the evaluation results of the dispatching level of twelve urban dispatchers are obtained and the results are analyzed.

3.1. Data Acquisition and Processing

All the data were collected from cities that have had an APTS for two years or more to ensure the stability and reliability of the research. These cities were Chengdu, Qingdao, Liaocheng, Changzhou, Yinchuan, Taizhou, Wuxi, Jining, Kunming, Urumqi, Yangzhou and Yangquan. At present, the scale of bus companies in these cities is different, so this study classified these cities into three categories according to the number of bus routes, vehicles and dispatchers. The classification standards are shown in Table 3.

Table 3. Standards of urban grade from the perspective of public transport.

City Level	Number of Bus Lines	Number of Buses	Number of Dispatchers
Category 1	>500	>10,000	>800
Category 2	[100, 500]	[1500, 10,000]	[100, 800]
Category 3	<100	<1500	<100

Since some cities (such as Chengdu, Qingdao, Kunming, etc.) have more than one bus company, this study only selected the data provided by the largest bus company in each city to ensure the representativeness of the data. According to the classification standard, the dispatching mode and related data of each city are shown in Table 4.

Table 4. Standards of urban grade from the perspective of public transport.

City Level	City	Departure Pattern	Bus Line	Bus	Dispatcher	Population [1] (Million)
1	Chengdu	planned	600	12,000	877	13.99
2	Wuxi	sequenced	170	2300	70	6.53
	Qingdao	sequenced	230	4800	483	7.91
	Kunming	sequenced	509	5712	192	5.60
	Yinchuan	planned	147	2231	69	1.84
	rumqi	planned	144	3322	237	2.68
	Changzhou	planned	269	2553	268	4.71
	Yangzhou	planned	153	1532	84	4.62
3	Yangquan	planned	10	750	23	1.40
	Taizhou	planned	149	1628	34	5.08
	Jining	planned	69	1319	22	8.38
	Liaocheng	planned	54	1300	10	6.04

[1] Demographic data are collected from the official websites of the city statistical bureau of 2015 and 2016.

The original dispatching dataset provided by the APTS is annual data from 2015 to 2016, which mainly include the following: employee ID, cumulative working hours of the dispatchers, cumulative number of dispatched vehicles, the number of dispatching lines, number of dispatching shifts, operating mileage and hours of the corresponding vehicles. Since the purpose of this research was to evaluate the dispatchers' work level in these cities and the data in the original dataset were all discrete data, the data needed to be averaged before all processes. Because of space limitations, the original data are not displayed in this article. The preprocessed data are shown in Table 5.

Table 5. Dispatcher data per capita.

City Level	City	Bus	Bus Line	Trip	Distance (Mile)	Travel Time (Hour)
1	Chengdu	42.69	2.43	211.17	3792.23	225.28
2	Wuxi	77.99	7.61	345.48	11,600.45	559.79
	Qingdao	40.57	2.47	119.45	3845.16	213.79
	Kunming	67.32	5.36	294.27	7037.1	409.31
	Yinchuan	56.47	4.51	265.51	4828.09	278.59
	Urumqi	38.83	1.45	182.35	2900.61	162.68
	Changzhou	24.03	2.72	186.48	3003.42	146.27
	Yangzhou	35.41	4.3	214.34	3943.01	172.62
3	Yangquan	34	5.62	89.62	1129.5	59.81
	Taizhou	61.15	10.79	544.6	10,619.02	408.64
	Jining	136.94	13.45	1146.71	18,367.66	877.73
	Liaocheng	97.14	8.2	823.77	11,268.69	654.75

According to Tables 4 and 5, it is obvious that most cities have adopted the scheduled departure mode, and the number of bus dispatchers and the number of bus routes in these cities are quite different.

3.2. Computing the Mixed Weight of Each Indicator

Based on the recommended value of the judgment matrix in Tables 1 and 2, we invited six experts and dispatching practitioners from the Huangdao Dispatching Center of Qingdao City to compare the importance of each factor in our three-layer hierarchical evaluation system, then create three types of 18 judgment matrices, which are the judgment matrix of Indicators B1 and B2, the matrix of Indicators C1 and C2, and the matrix of Indicators C3, C4 and C5.

Since the experts and practitioners are good at theoretical knowledge or actual scheduling operations, the matrices of the same type need to be given equal weight when aggregating the matrix of each evaluation object. The results of the comparison can be summarized for the indicator judgment matrix, as shown in Tables 6–8.

Table 6. B1–B2 importance judgment matrix.

	B1	**B2**
B1	1	5
B2	0.2	1

Table 7. C1–C2 importance judgment matrix.

	B1	**B2**
B1	1	5
B2	0.2	1

Table 8. C3–C5 importance judgment matrix.

	C3	**C4**	**C5**
C3	1	1.833	3.167
C4	0.545	1	1.024
C5	0.316	0.977	1

The consistency test was performed on these matrices of the experts according to Formula (9) to ensure the consistency of the judgment results. We carried out the consistency test on the matrix until the value of i was less than 0.1. The expert scoring results were, therefore, logical and were referred to in this study. Due to limited space being available, the details of the raw data of the experts' comparisons of the indicators have not been provided. The calculated weights of the evaluation indicators are shown in Table 9.

Table 9. Weight calculation results of the experts.

	W_2^I	W_3^I		W^I
Weight	0.833	0.286	0	0.238
		0.714	0	0.595
	0.167	0	0.545	0.091
		0	0.25	0.042
		0	0.205	0.034
λmax	2	2	3.031	
I	0	0	0.015	

In Table 9, W_2^I is the weight of the indicator from the second layer to the first layer, and W_3^I is the weight of the indicator from the third layer to the second layer, where 0 means that this element is independent of the corresponding element in the upper layer.

The judgment matrices that passed the consistency test were substituted into the AHP, and we obtained the subjective weight W^I of each indicator. The objective weight W^I was obtained through the EWM with the original evaluation data from 12 cities according to Formulas (12) and (13). Finally, the composite weights combining W^I and W^{II} are shown in Table 10.

Table 10. Mixed weight of evaluation index.

Method	C1	C2	C3	C4	C5
AHP	0.238	0.595	0.091	0.042	0.034
EWM	0.190	0.188	0.266	0.184	0.172
Mixed weight	0.232	0.574	0.124	0.039	0.030

By comparing the difference in weight among the mixed weight, AHP and EWM, it was found that after the subjective weighting method (AHP) was corrected by the objective weighting method (EWM), the weight of Indicator C2 changed from 0.595 to 0.574, and the weight of Indicator C3 changed from 0.091 to 0.124. The other weights did not change significantly, indicating that the experts had an obvious subjective tendency to judge the importance of the number of bus routes (C2) and the dispatch frequency (C3), but they were relatively objective in measuring other indicators.

3.3. Fuzzy Evaluation Based on Cloud Model

The comment set V = {IV, III, II, I} can be quantified through the cloud theory according to Formula (15). We divided the judgment interval [0, 10] into four levels: IV [0, 2), III [2, 5), II [5, 8), I [8, 10]. Because the minimum value of En is 0.33 according to Formula (9), in order to satisfy the conditions of Formula (10), the value of λ can be defined as 0.1. The four cloud models of the comment set are (1,0.33,0.1), (3.5,0.5,0.1), (6.5,0.5,0.1) and (9,0.33,0.1). The cloud map obtained by the forward cloud generator is shown in Figure 3.

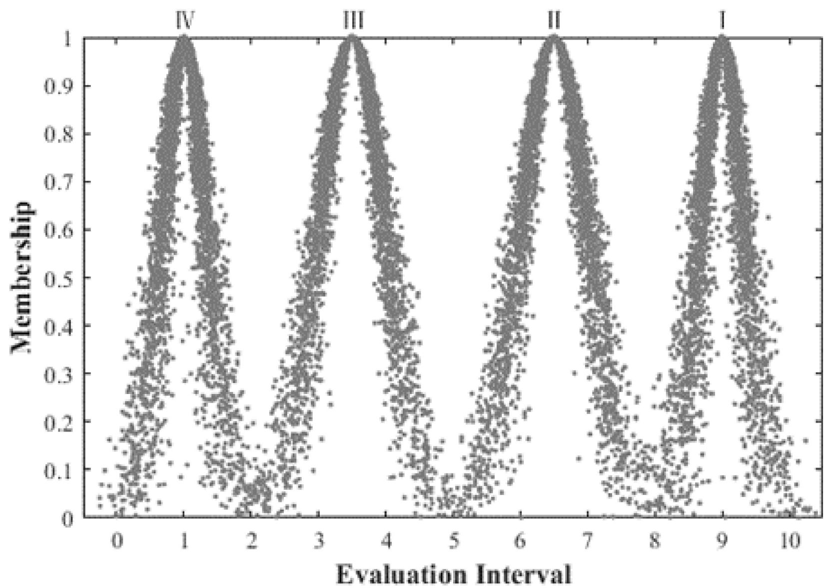


Figure 3. Cloud criterion of comment set.

On the basis of the average dispatching data of each city, the indicator level of the dispatchers in different cities was graded. Based on the mixed weights, the evaluation results were converted into cloud models according to the parameters of each comment level. Subsequently, the corresponding evaluation matrix of each indicator was generated by using the backward cloud generator algorithm.

According to Formulas (17) and (18), the evaluation results of the dispatchers' scheduling level in these 12 cities were as shown in Table 11.

Table 11. Evaluation results of APTS dispatchers' scheduling level.

Level	City	Dispatching Mode	Cloud Parameter	Evaluation Result
1	Chengdu	planned	(5.231, 0.793, 0.333)	II
2	Wuxi	sequenced	(7.244, 0.795, 0.201)	II
	Qingdao	sequenced	(3.142, 0.822, 0.309)	III
	Kunming	sequenced	(7.274, 0.852, 0.277)	II
	Yinchuan	planned	(4.829, 0.771, 0.536)	III
	Urumqi	planned	(3.488, 0.575, 0.251)	III
	Changzhou	planned	(3.805, 0.728, 0.284)	III
	Yangzhou	planned	(5.026, 0.789, 0.297)	II
3	Yangquan	planned	(4.265, 0.438, 0.357)	III
	Taizhou	planned	(6.620, 0.789, 0.252)	II
	Jining	planned	(8.070, 0.593, 0.401)	I
	Liaocheng	planned	(7.778, 0.760, 0.299)	II

As can be seen in Table 11, the dispatchers of Jining City, out of all 12 cities, had the best scheduling performance. Chengdu, Wuxi, Kunming, Yangzhou, Taizhou and Liaocheng belong to the second level, and Qingdao, Yinchuan, Urumqi, Changzhou and Yangquan belong to the third level.

In order to analyze the evaluation results more intuitively, we used the forward cloud generator method to transform the parameters of the result cloud into a normal cloud with the evaluation grade. The cloud maps are shown in Figure 4.

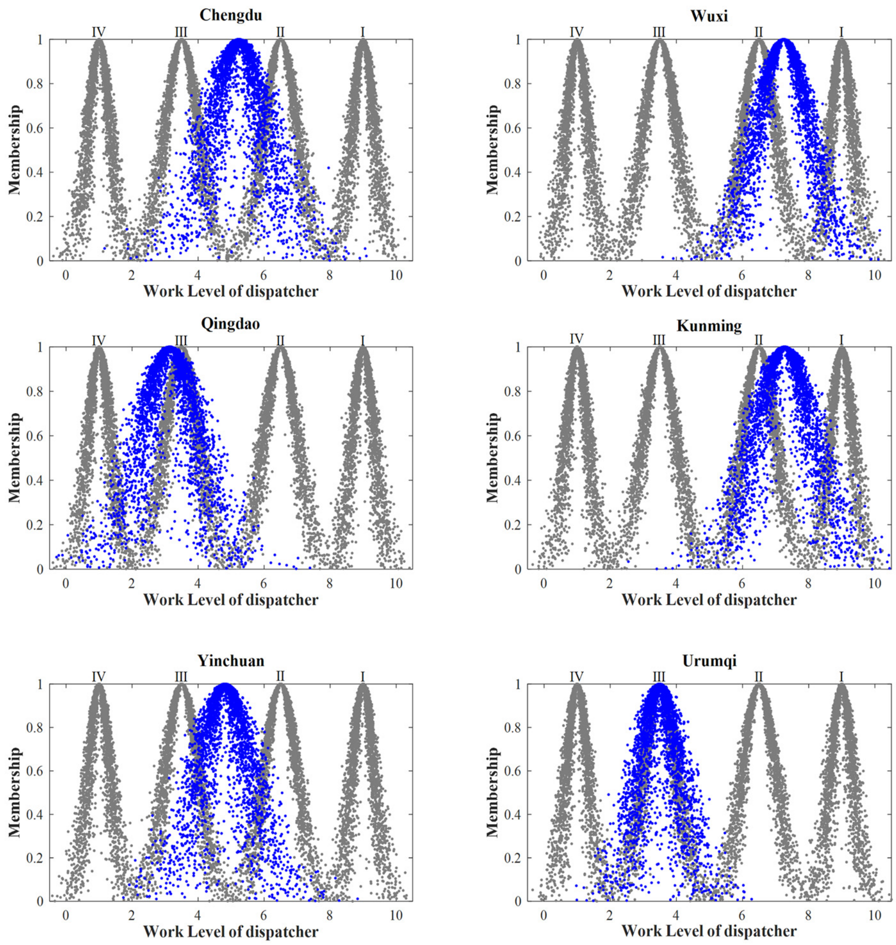


Figure 4. *Cont.*

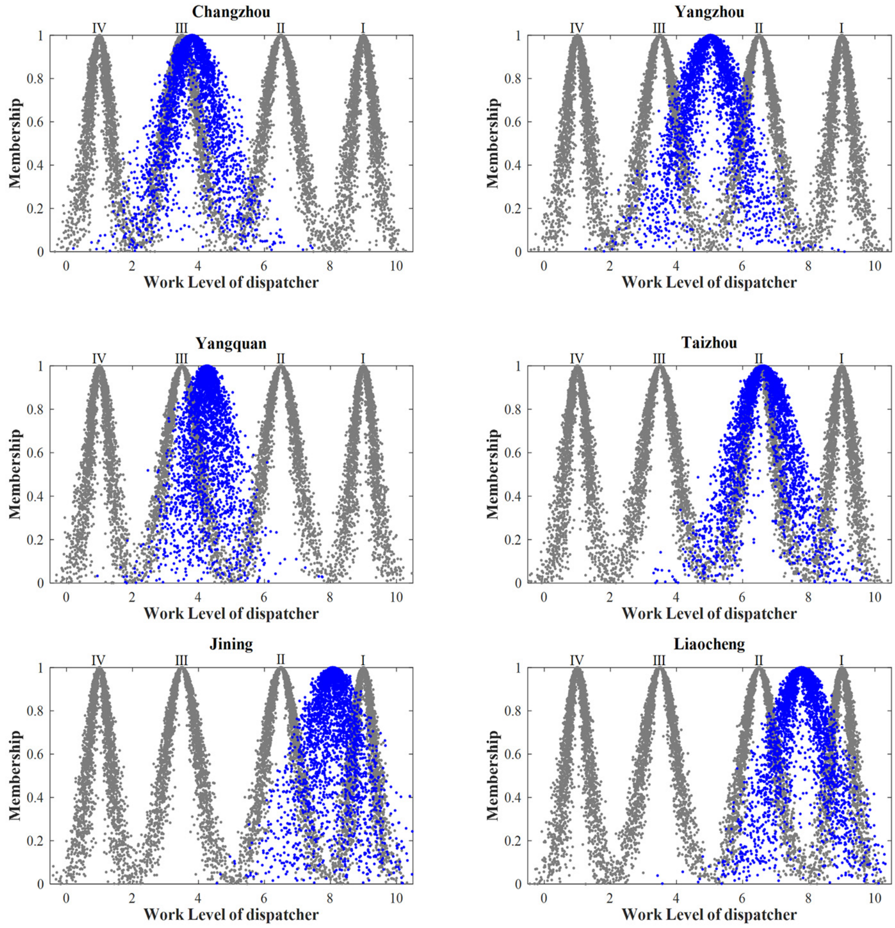


Figure 4. Cloud map of evaluation results.

3.4. Result Analysis

In this section, the evaluation results of the cloud model are analyzed in detail in combination with the characteristics of the cities analyzed, such as population and traffic conditions, and the overall work level of urban dispatchers at different levels is regularly summarized. Finally, according to the above conclusions, the corresponding standards for judging the work level of dispatchers at different urban levels are defined.

3.4.1. Comparing Results

According to the population data released by the statistical bureaus listed in Table 4, cities with the same dispatcher levels have the following characteristics:

(1) Jining City has a population of less than 10 million, but the dispatchers' scheduling level was the best of all the cities. This is because the city has fewer dispatchers than other cities, and the dispatching mode is the planned departure mode. Moreover, the road structure of Jining City is relatively simple, which reduces the working difficulty of dispatching, so the work level is relatively high.

(2) The population of cities with Working Level II usually exceeds 5 million, and a larger population leads to a greater demand for public transportation for the residents. Therefore, the average workload of dispatchers is relatively large, and the dispatching level is higher.

(3) The population of cities with Working Level III is usually less than 5 million; most of these cities are inland cities. It is worth mentioning that a BRT system has been built in Yinchuan, Urumqi and Changzhou. Therefore, these cities are developing faster than other inland cities. Qingdao is a second-tier developed city in a coastal area. As the bus lines did not cover the entire urban area in 2016, and the layout of the urban

bus lines did not match the scale of the city, the workload of the APTS dispatchers was uneven and the work level was significantly lower than that of other cities.

Excluding individual cases, the dispatchers' work level is basically consistent with the city scale; that is, the dispatchers' scheduling level is relatively high in large-scale cities with a large population.

According to the standards of urban grade listed in Tables 3 and 11, these cities have the following characteristics:

(1) The overall working level of the dispatchers in the secondary cities, as shown in Table 11, is relatively low, but the distribution is relatively concentrated. This is because the scale of these cities is small, but the number of dispatchers is adequate. Thus, the work intensity of the dispatcher was reduced.
(2) The scale of bus companies in third-tier cities is small, and the dispatching systems are different; therefore, there are no uniform features in these cities.

3.4.2. Judgment Scale

According to the features above, we defined the corresponding criteria for judging the dispatchers' working level with different city scales. Taking the number of dispatched vehicles per capita as an example, the cluster analysis method was used to classify the number of dispatched vehicles per capita. The reference standard of the number of dispatched vehicles per capita can be obtained, as shown in Table 12.

Table 12. Standards of dispatched frequency per capita.

Level	Representative City	Departure Pattern	Standards (Time)		
			Low	Normal	High
1	Chengdu	planned	[50, 120)	[120, 310]	>310
2	Class A: Wuxi, Kunming	sequenced	[50, 230)	[230, 420]	>420
	Class B: Changzhou, Yangzhou	planned	[50, 110)	[110, 340]	>340
3	Taizhou	planned	[50, 300)	[300, 750]	>750

In order to meet the demand of the bus company, the standard reference of the work intensity can be divided into three levels: low, normal and high. Taking the evaluation data of each working level of the dispatcher as a reference, we used the reverse cloud generator to create the cloud parameter, as shown in Table 13. These parameters can be used as one of the assessment criteria for dispatchers' working level.

Table 13. Evaluation level of the normal cloud model.

Level	Cloud Parameters		
	Low	Normal	High
1	(95, 22, 5)	(235, 40, 5)	(370, 20, 5)
2-class A	(140, 37, 5)	(295, 44, 5)	(479, 36, 5)
2-class B	(80, 25, 5)	(225, 40, 5)	(340, 23, 5)
3	(175, 45, 8)	(425, 65, 8)	(715, 55, 8)

When researchers evaluate the work level of dispatchers in other cities, they can use the evaluation model established in this study to obtain the corresponding cloud parameters and compare the establishment of a cloud rule to evaluate the similarity between the cloud model and the evaluation model, as shown in Table 13. In assessments of the work level, the standard cloud closest to the cloud rule is the corresponding assessment level.

At present, the indicators of the public transportation evaluation systems in China are not uniform. In order to promote the continuous improvement of the evaluation system, each city should speed up the construction of the dispatching system with the support of the existing bus information collection technology and continuously improve the data collection and analysis ability. In addition, the salary level of dispatchers should be raised within a reasonable range to mobilize their working enthusiasm.

4. Conclusions

This research proposed the concept of assessing the work level of ATPS dispatchers to study the dispatchers' work intensity in a city and estimate whether the dispatchers' work intensity was significantly correlated with the level of urban transport development. Several important conclusions can be drawn from the results.

Firstly, from the perspective of the dispatchers' work level, the population of cities at Working Level II usually exceeds 5 million, but that of cities at Level III is usually less than 5 million, and the overall working level of the dispatchers in the secondary cities is relatively low.

Secondly, from the perspective of public transportation development, the working level of the dispatchers in the first-tier city is good, and the working level of dispatchers in the second-tier cities is excellent (e.g., Wuxi and Kunming) or good (e.g., Yangzhou). However, the working level of dispatchers in third-tier cities is difficult to determine.

Thirdly, from the perspective of the scale of the city, the dispatchers' work level is basically consistent with the city scale; that is, the dispatchers' scheduling level is relatively high in large-scale cities with a large population.

Since there is no complete system and data for evaluating dispatchers' scheduling levels, this study selected scoring scale standards that are easy for the public to accept. The interval corresponding to the evaluation level was artificially defined to evaluate the specific conditions of each city. Because of limited data, only a few cities could participate in the evaluation, and it was impossible to form a reference standard for complete cloud model evaluation data. If the APTS data of most cities in China could be collected in the future, statistical analysis of the cities will lead to a standard cloud for different cities.

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