Research on road congestion analysis strategy based on combined weights of game perspective

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Abstract. In recent years, the vehicle carrying demand of urban roads has been growing, and in order to prevent road congestion, this paper conducts a road congestion analysis based on the game perspective of AHP-EWM combined weights, and the analysis shows that drivers have a great relationship with the congestion degree of roads when choosing routes in urban roads, so establishing a more perfect visualization of induced information can play a significant role in alleviating urban traffic congestion and guiding drivers to choose more appropriate roads.

Keywords: combined weights, game perspective, road congestion, Nash equilibrium.

1. Introduction

With the continuous improvement of people's living standards, a substantial increase in the ownership of cars has occurred.

According to the statistics of the Ministry of Public Security, by the end of March 2022, the number of motor vehicles in the country reached 402 million[1], so with the increasing demand of the people to travel by motor vehicles, the vehicle carrying demand of urban roads also grows, so in order to prevent the occurrence of congestion on urban roads, the causes of road congestion need to be analyzed in depth, so as to improve the capacity of roads.

Jun Wang[2] by widening and modifying specific urban roads, tidal lanes and variable lanes for the purpose of meeting the basic travel needs of practical and urban residents; Pengzhan Chen[3] et al. based on LSTM, using the vehicle distance information matrix as input, output the traffic congestion analysis results of this model, which can analyze the current road congestion situation of the user's vehicle in real time; Xubing Zhang[4] et al. use the existing road congestion time data to collect and model, and train the Hidden Markov Model to predict the road congestion time in the future period through algorithm calculation and analysis, and provide congestion time prediction for people's travel, and then propose the optimal path with the shortest time through the road at different times.

Based on the above research literature, this paper proposes a game perspective road congestion analysis model based on AHP-EWM combined weights, and then assigns weights to the factors affecting urban roads, analyzes the impact when drivers choose different routes, and proposes measures to reduce urban road congestion based on the results of the game perspective analysis.

2. AHP-EWM combination weights

2.1. AHP-OWA model

Assuming that there are n alternative routes from A to B, the main influencing factors for choosing a route include: the congestion level of the road ε_1, the road driving experience ε_2 and the distance from A to B ε_3. Now it is necessary to calculate the final chosen route scientifically based on each element. Therefore the hierarchy is constructed as shown in Figure 1.

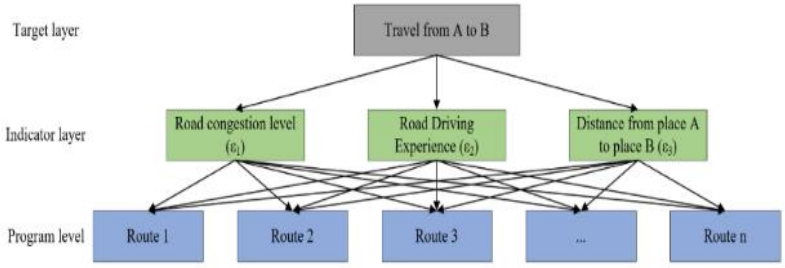


Figure 1. Hierarchy diagram

Ordered weighted vectors v_t:

$$v_s = \frac{C_{s-1}^t}{\sum_{t=0}^{s-1} C_{s-1}^t} = \frac{C_{s-1}^t}{2^{s-1}} \tag{1}$$

The absolute weight of the jth indicator $\overline{w_j}$:

$$\overline{w_j} = \sum_{t=0}^{s-1} v_t \, p_t \tag{2}$$

Subjective weight weights after OWA operator correction w_j:

$$w_j = \frac{\overline{w_j}}{\sum_{j=1}^{n} \overline{w_j}}, j = 1,2, \dots, n \tag{3}$$

2.2. EWM model

Cloud model is used to build cloud rubrics for f experts, and each language description corresponds to a cloud model $(\mathrm{Ex_p}, \mathrm{En_p}, \mathrm{Ee_p})(\mathrm{p} = 1,2, \cdots, \mathrm{f})$. The combined cloud rubric of qualitative indicators $(\mathrm{E_x}, \mathrm{E_n}, \mathrm{E_e})$ is obtained by combining the comments of f experts, Among them:

$$\mathrm{Ex} = \frac{\mathrm{Ex_1 En_1 + Ex_2 En_2 + \cdots + Ex_f En_f}}{\mathrm{En_1 + En_2 + \cdots + En_f}} \tag{4}$$

Where: the expected Ex in the cloud rubric for qualitative indicators is used as the final quantified value for qualitative indicators by the expert group.

For quantitative indicators, the very large indicators, interval-type indicators and very small indicators are standardized on the basis of the standardization processing method. Finally, the decision matrix X standardized with m evaluation units and n evaluation indicators for the evaluation index data is obtained as:

$$\mathrm{X} = \left(\mathrm{x_{ij}}\right)_{\mathrm{m \times n}} \tag{5}$$

$\mathrm{x_{ij}}$:The jth indicator of the ith evaluation unit.

The weight of the jth indicator value $\mathrm{x_{ij}}$ under the i-th evaluation unit $\mathrm{b_{ij}}$:

$$\mathrm{b_{ij}} = \frac{\mathrm{x_{ij}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{x_{ij}}} \tag{6}$$

The entropy value of the jth indicator $\mathrm{e_j}$:

$$\mathrm{e_j} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{b_{ij}} \ln \mathrm{b_{ij}}}{\ln \mathrm{m}} \tag{7}$$

Entropy weight of the jth indicator, i.e. objective weight vector $\mathrm{h_j}$:

$$\mathrm{h_j} = \frac{1-\mathrm{e_j}}{\sum_{\mathrm{j=1}}^{\mathrm{n}} (1-\mathrm{e_j})}, \mathrm{j} = 1,2, \cdots, \mathrm{n} \tag{8}$$

2.3. Combined weighting model

Using AHP to assign subjective weights to road congestion ε_1, road driving experience ε_2 and distance from A to B ε_3, and correct the weights by OWA operator, meanwhile, objective weights are

assigned to the indicators by EWM, and finally, the combined weights are assigned by linear weighting method, so that the influence of effective subjective extreme value deviation on the accuracy of the weights and the calculated weight values are reliable.

Portfolio weights W_j:

$$W_j = \alpha w_j + \beta h_j \tag{9}$$

Where $\alpha + \beta = 1$.

3. Game perspective road congestion analysis strategy model

3.1. Driver's route selection rules

If there are multiple routes available to drivers between A and B, then the average driver will choose a passing route based on the condition of the road (as shown in Figure 2). That is, assuming that the shortest route is the optimal choice when the road is not congested, as drivers continue to travel more and more, the traffic volume on the shortest route will increase significantly, thus leading to road congestion on the shortest route and making the time it takes drivers to get from A to B increase. When this happens, some drivers will generally change their route, choosing a route from A to B that is farther away but has less road driving experience or less congestion, so that eventually the vehicles driving on different routes from A to B will reach a certain relative balance.

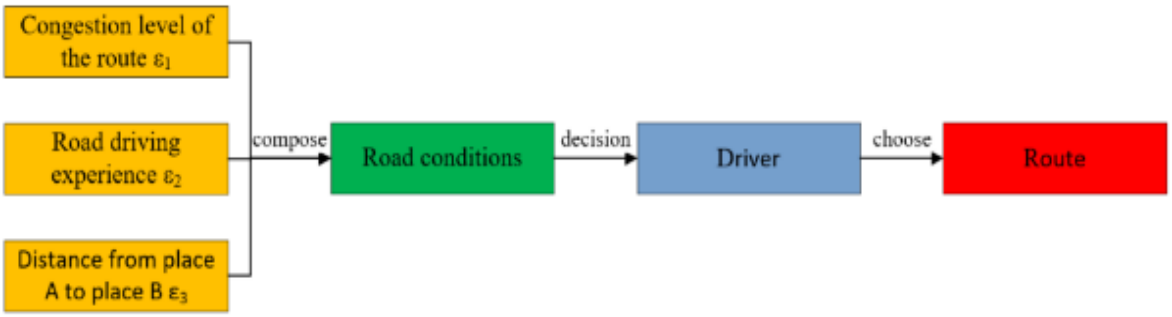


Figure 2. Components of route choice between travellers

3.2. Driver's route choice game model

Suppose that n drivers depart from A to B at the same time, that there are n access routes between A and B, and that m routes have different levels of congestion ε_1, road driving experience ε_2, and distance from A to B ε_3, as shown in Figure 3.

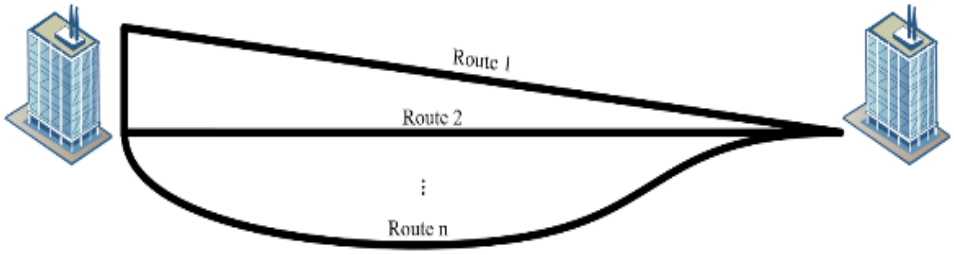


Figure 3. n-driver passage path

To facilitate the analysis of the game model, assume that all n drivers are rational and that the game is static. If the gain from A to B is W, the time loss gained by driving along route m is t_m, the gain when route m is congested is c_m, and the gain when the road experience is poor is u_m; assume that n=m, and that the number of drivers and routes are equal, and that the roads are not congested when n drivers take different routes separately, and that road congestion occurs when n drivers choose the same route, so the payoff table is shown in Table 1 is shown (only one of the results is shown)[6].

Table 1. Driver's game payoff table

		Route				
		1	**2**	**3**	⋯	**m**
Drivers	**1**	$a-t_1-u_1$	$a-t_2-c_2-u_2$	$a-t_3-c_3-u_3$	⋯	$a-t_m-c_m-u_m$
	2	$a-t_1-c_1-u_1$	$a-t_2-u_2$	$a-t_3-u_3$	⋯	$a-t_m-c_m-u_m$
	3	$a-t_1-c_1-u_1$	$a-t_2-c_2-u_2$	$a-t_3-c_3-u_3$	⋯	$a-t_m-c_m-u_m$
	⋮	⋮	⋮	⋮	⋯	⋮
	n	$a-t_1-c_1-u_1$	$a-t_2-c_2-u_2$	$a-t_3-c_3-u_3$	⋯	$a-t_m-u_m$

It follows from the payoff table that the purely curative Nash equilibrium is $(route\ x, route\ y, \cdots route\ e), \ldots (route\ e, route\ x, \cdots route\ y)$. A total of A_n^n routes are available (where the choice of route varies), This means that when driver 1 chooses route 1, the other n-1 drivers do not choose route 1, which satisfies the hawk and dove game in game theory-"you go in, I go out, you go in". In the game theory-hawk and pigeon game, if all n drivers want to get the maximum benefit they can get, they need to trust and cooperate with each other and choose a different route from the other drivers from A to B. This situation requires the n drivers to know each other's movements and thus choose a different route from them.

According to the n-driver payoff table, combined with the mixed-strategy Nash equilibrium case: let p_1 be the probability of driver 1 choosing route e, p_2 the probability of driver 2 choosing route x, and p_n the probability of driver n choosing route y (where the chosen route varies). Then: let p_1 be the probability of driver 1 choosing route e; p_2 be the probability of driver 2 choosing route x; ...; p_n be the probability of driver n choosing route y (assuming that the weight values obtained using the portfolio weighting analysis are equal to their probabilities), Then $1-p_1$ is the probability that driver 1 does not choose route e; $1-p_2$ is the probability that driver 2 does not choose route x; ...; $1-p_n$ is the probability that driver n does not choose route y.

Thus the expected payoff function for driver 1 is (assuming that there are 1, 2 drivers with routes 1, 2 travelling from A to B).

$$E_1 = P_1\begin{bmatrix} P_2(a-t_1-c_1-u_1) \\ +(1-P_2)(a-t_2-u_2) \end{bmatrix}$$
$$+(1-P_1)\begin{bmatrix} P_2(a-t_1-u_1) \\ +(1-P_2)(a-t_2-c_2-u_2) \end{bmatrix} \quad (10)$$

The expected payoff function for driver 2 is:

$$E_2 = P_2\begin{bmatrix} P_1(a-t_1-c_1-u_1) \\ +(1-P_1)(a-t_2-u_2) \end{bmatrix}$$
$$+(1-P_2)\begin{bmatrix} P_1(a-t_1-u_2) \\ +(1-P_1)(a-t_2-c_2-u_2) \end{bmatrix} \quad (11)$$

Due to the influence of the environment around the road, the width of the road, the smooth state of the road and other reasons, resulting in different road driving experience, therefore, for the convenience of calculation, let (10), (11) equal to 0, $u_m = 0$, resulting in:

$$P_1 = \frac{c_2}{c_1+c_2}, P_2 = \frac{c_1}{c_1+c_2} \quad (12)$$

Then the mixed strategy Nash equilibrium is:

$$\left(P_1 = \frac{c_2}{c_1+c_2}, P_2 = \frac{c_1}{c_1+c_2}\right) \quad (13)$$

4. Game perspective congestion analysis based on combined weights

4.1. Survey locations and routes

In this paper, we take the Najin Campus of Tibet University in Chengguan District of Lhasa City to the Hebalin Campus as an example to conduct a game perspective congestion analysis based on the combination of weights. Route 3 is 6.14 km long and is the furthest away, but less prone to congestion and has the best road driving experience.The route from the Najin Campus to the Hebalin Campus is shown in Figure 4:



Figure 4. The Najin campus is located at the Hebalin campus

4.2. Evaluation Indicator System and Quantitative Judgement Scale Correction

Based on the above modeling and example analysis, the following evaluation indicator system is shown in Figure 5:

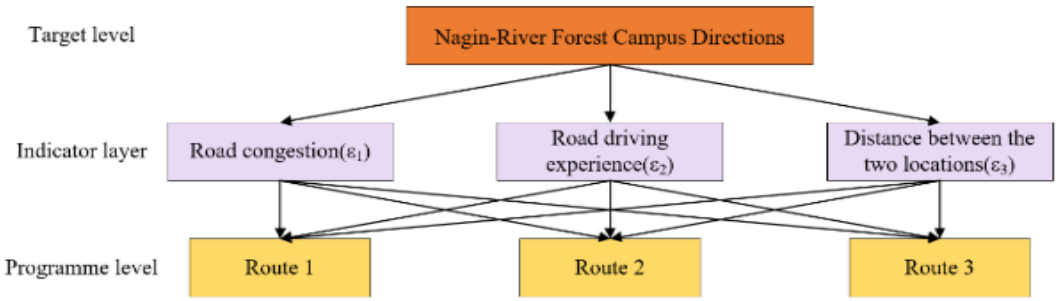


Figure 5. The congestion evaluation index system was established

This paper uses the 10/10-18/2 scale of Chenguang Zhang[5] et al. See Table 2.

Table 2. Correction of quantitative judgement scales for comparison between indicators

Degree of importance of factor i over factor j	**10/10-18/2 scale**	**1-9 scale**
Equally important	10/10(1)	1
Slightly more important	12/8(1.50)	3
Stronger importance	14/6(2.33)	5
Stronger importance	16/4(4.00)	7
Extremely important	18/2(9.00)	9
General	**(9+K)/(11-K)**	
The range of values of K	1~9	

4.3. Portfolio weighting analysis

In this paper, the subjective weights were calculated through the judgmental analysis of five highland transportation experts for the three routes travelling from the Nagin campus to the Hebbaling campus, and the correctness of the obtained matrix was proved by applying the consistency test, after which the weights of each route were calculated based on AHP-OWA; Also based on the entropy

weight method on the calculation of the indicator layer of the indicator entropy weight, and then obtain the objective weight of the line. Finally, according to the combined weight formula to determine the road congestion analysis indicator weights, where $\alpha = 0.7$, the results are shown in Table 3.

Table 3. Results of the weighting of the Nagin-River Dam forest route combination

Target level	Programme level	Subjective weighting (SW)		Objective Weighting (OW)	Combination Weights (CW)
		AHP	OWA	EWM	
Nalgene-Hebbaling Campus	Route 1	0.6250	0.6342	0.274	0.52614
	Route 2	0.2385	0.2310	0.529	0.32040
	Route 3	0.1365	0.1348	0.197	0.15346

Subjective weights: the judgment matrix has a maximum eigenvalue of 3.0183, a CI of 0.0091, a RI of 0.525 and a CR of 0.0174, and the consistency validation passes. Objective weights: information entropy values for routes 1, 2 and 3 are: 0.482, 0.002 and 0.628 respectively. According to the results of the weighting analysis, the weight of Route 1 is greater than that of Route 2 and Route 3 and the weight is greater than 0.5, which proves that most drivers will prefer Route 1 in route selection. This requires a game perspective road congestion analysis strategy model to be solved.

4.4. Game analysis of drivers' route choice

An analysis can be made on the basis of the table of benefits of the driver's choice of route (Table 1).

(1) Under the pure strategy Nash equilibrium constraint:

1) 3 drivers travelling from the Nagin campus to the Hebbaling campus need adequate traffic calming information when travelling, e.g. drivers need to be aware of each other's route options;

2) When three drivers travel from the Nagin campus to the Hebalin campus, two of them must choose route 1, i.e. when driver 1 chooses route 1, drivers 2 and 3 must not choose route 1, otherwise there will be a problem of small gains. Similarly, when driver 2 chooses route 1, drivers 1 and 3 cannot choose route 1 in order to maximise their own benefits.

(2) Under the mixed strategy Nash equilibrium constraint:

According to the combination weight analysis it can be obtained that drivers have a strong relationship with the congestion level of the route when they choose the route. When route 1, which is the closest route in terms of driving distance from Najin Campus to Hebbaling Campus, is congested, drivers will choose route 2 or 3, which is further away, and when route 2 is congested, drivers will choose route 1 or 3, and similarly, when route 3 is congested, drivers will choose 1 or 2.

5. Concluding remarks

The analysis of road congestion from the game perspective of combined weights shows that the driver's choice of route on an urban road has a strong relationship with the congestion level of the road, and has little to do with the increase in route length, road driving experience, etc. Therefore, the establishment of a better visualisation of guidance information can play a significant role in alleviating urban traffic congestion and guiding drivers to choose a more appropriate road.

References

[1] Ministry of Public Security Traffic Management Bureau. Ministry of Public Security: The number of motor vehicles nationwide reached 402 million by the end of March 2022 [M/CD]. (2022-4-13/2022-6-1) https://finance.sina.com.cn/tech/2022-04-13/doc-imcwipii4107268.shtml.

[2] Wang J. Research on micro-transformation of congested sections of urban roads [J]. Science and Technology Information, 2022, 20(05): 49-51. doi: 10.16661/j.cnki.1672-3791.2112-5042-6706.

[3] Chen PZ, Yu JJ. Research on road congestion analysis model based on LSTM[J]. Measurement and Control Technology, 2021, 40(08): 58-63. DOI: 10.19708/j.ckjs.2021.08.011.

[4] Zhang Xubing,Xie Yufei. Hidden Markov model for road congestion time prediction [J/OL]. Computer Engineering and Applications:1-8 [2022-06-01]. http://kns.cnki.net/kcms/detail/11.2127.TP.20210720.1721.007.html

[5] Zhang, Chen-Guang, Wu, Ze-Ning. Analysis and improvement of hierarchical analysis (AHP) proportional scaling [J]. Journal of Zhengzhou University of Technology, 2000(02): 85-87.

[6] Xie P. Y., Su G. Y., Song Y. P.. Analysis of urban traffic congestion countermeasures from the perspective of game theory [J]. Logistics Science and Technology, 2017, 40(08): 89-91+103. DOI: 10.13714/j.cnki.1002-3100.2017.08.024.