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ROUTE CHOICE BEHAVIOR MODEL WITH GUIDANCE INFORMATION BASED ON FUZZY ANALYTIC HIERARCHY PROCESS

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Abstract. *Using modeling and simulation methods, a hierarchical structure model of origin-destination (OD) travel process of driver's route choice under guidance information is explored based on fuzzy analytic hierarchy process (FAHP) which is a fuzzy version of analytic hierarchy process (AHP). Firstly, a Logit model of driver's route choice is presented based on the Bayesian theory, and then combining it with dynamic route choice model based on decision field theory (DFT), a solution of NASH equilibrium game is given under complete dynamic information. Secondly, an FAHP was used to establish the hierarchical structural model of the OD travel process of driver's route choice. Finally, an example is given to demonstrate the optimal solution. The results show that driver preferences, behavior characteristics and route characteristics, the acceptance degree of guidance information, and avoiding difficult route are the key factors for driver's route choice.*

Keywords: Route choice, Fuzzy analytic hierarchy process, Preference, Bayesian theory

1. **Introduction.** There is a game relation between traffic managers and travelers in traffic guidance system because of the non-mandatory characteristics of traffic guidance, and the choice behavior of decision makers may be different in order to maximize their expected utility. The assumption of "completely rational person" in early route choice behavior models is an ideal situation which is very different from the reality. In order to make route choice models closer to the reality, some discrete choice models have been proposed.

These discrete models are mainly based on the expected utility theory of Neumann [1] and the extended version by Savage [2]. According to the theory, if the effect is used to describe the attraction degree of each alternative, each individual will choose the alternative with the highest expected utility value [3]. However, even if a small number of complex factors are added in the decision-making environment, there will be various obvious deviations between the actual behavior and the expected utility theory. For example, the famous Allais and Ellsberg paradox shows that the real individual behavior is a violation of the hypothesis of expected utility maximization which is the base of expected utility theory and subjective probability theory [4]. Therefore, researchers have been trying to find alternative theories to explain the decision-making behavior under uncertainty. One most famous theory is the prospect theory proposed by Kahneman and Tversky on the basis of Simon's bounded rationality in 1979 [5,6]. Kahneman and Tversky replaced the utility function in the expected utility theory with the value function, and converted the probability in the expected utility theory into the decision weight determined by decision weighting function. Bogers and Zuylen also found the similar evidence that when travelers are able to make a choice between a shorter but uncertain route and a longer but deterministic route, they tend to be risk-averse [7]. In addition, using the prospect theory to study the bounded rationality and decision-making, Shi and Jia found that travelers will choose the route with risks when their psychological expectations cannot be met [8]. This deviation and emergence of prospect theory are because the traveler route choice behavior is not only related to the influential factors in expected utility theory, but also related to the travelers' behavior decision after they received the guided route information.

Most existing route choice behavior models usually regard the drivers as one homogeneous class or classify the drivers accurately, then analyze them by mathematical methods, and establish a discrete model for driver route choice [9]. Thus, the uncertainty of the drivers' behavior decision cannot be expressed well. Specifically, Venigalla et al. used a data including 5,700 unique real routes to observe the influence of signals, turns and roadway classification on the route choice [10]. Xu et al. considered the bounded rationality and asymmetric preference into the route choice model [11]. Lou et al. observed the influence of the travelers' en-route switching behavior on the whole day-to-day network traffic flow [12]. Li and Huang introduced a regret aversion parameter to build a regret-theory-based stochastic route choice model [13]. Obviously, these considered factors are not specifically considered in classical route choice behavior models but take a real effect on the real-world travelers.

In addition, some researchers begin to consider the guidance information with the wide application of GPS navigation systems. Gao and Wang [14] early considered the guidance information and applied the decision field theory and Bayesian theory to developing a route choice behavior model. This work is a simulation study which does not consider the qualitative factors. In order to fix this shortage, we consider the route selection as a comprehensive evaluation problem of multiple feasible routes, and use an improved analytic hierarchy process (AHP) and fuzzy comprehensive evaluation method to explore the influence factors of route choice behavior for seeking the optimal solution of route selection. The influence factors considered in the work consist of psychological factors and behavior preference of individual travelers.

In this paper, we firstly establish a Logit model for driver route choice using Bayesian theory, then combine it with dynamic route choice model based on decision field theory (DFT), and give the NASH equilibrium solution of the game under the complete information dynamic game. Secondly, we use an improved AHP and fuzzy AHP to establish the hierarchical structural model of driver route choice of origin-destination (OD) travel process. Finally, an example is used to perform numerical tests.

The rest of the work is organized as follows. Section 2 presents a game model for the driver route choice. In Section 3, we analyze the influence factors of route choice.

Then, Section 4 presents the FAHP based method and give an application case. Section 5 concludes the work with future directions.

2. **Game Analysis on Driver Route Choice.** When a policy is given by the road manager, driver and guidance information constitute a Stackelberg game process. The driver's behavior is random, rational, and non-cooperative. Under the condition of ensuring the optimal system, the driver will not change his strategy when the system reaches the Nash equilibrium.

American psychologist Burrhus Frederic Skinner (1904-1990) believes that behavior is the response of learners to environmental stimulation [7]. According to this view, route selection behavior is a response to guidance information. We divide the impact factors of route selection into three categories: driver behavior characteristics, route characteristics, and driver preference. The schematic diagram of driver's route selection under guidance information is as Figure 1 shows.

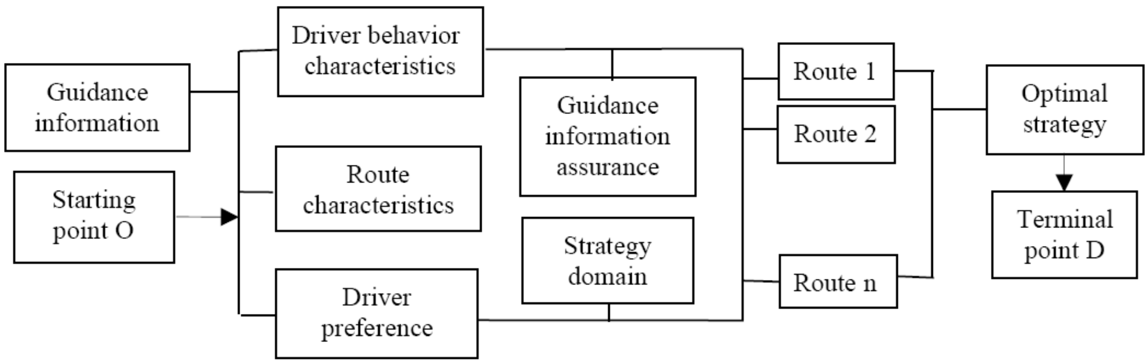

FIGURE 1. Schematic diagram of driver's route selection

The road manager first gives the guidance information; the driver estimates its credibility $\lambda_i(x_i)$ based on the guidance issued by the manager and selects an optimal strategy $S_U^* = R_u S_M$ from strategy domain S_U^M. The expression of $\lambda_i(x_i)$ is as follows:

$$\lambda_i(x_i) = \alpha e^{-\gamma\left(\frac{x_i}{\sigma}\right)^2} \theta\left(x_i^0 - x_i\right) + \beta\theta\left(x_i - x_i^0\right), \; x_i^0 < \sqrt{\frac{1}{2\gamma}} \tag{1}$$

where α, γ, σ, θ are the parameters that need to be determined for each grade, β is the minimum degree of certainty, x_i is the traffic volume of the section i, and x_i^0 is the critical traffic volume of the section i.

According to the Logit route selection model in the Bayesian theory, the probability of driver selecting route i is p_i^k:

$$p_i^k = \frac{\exp[-\theta_i(x_1, x_2, \ldots, x_n)]}{\sum\limits_i \exp\left[-\theta_i(x_1, x_2, \ldots, x_n) \cdot c_i^{OD}\right]} \tag{2}$$

where route parameters $\theta_i(x_1, x_2, \ldots, x_n) \succ 0$ $(i = 1, 2, \ldots, n)$ include road condition, congestion level, travel destination, route preference, driving experience, credibility of guidance information, etc. and c_i^{OD} is the impedance on the route.

For such a complete information dynamic game, its equilibrium solution is a refined sub game of NASH equilibrium, so the decision-making problem of drivers becomes the optimization problem of the income of drivers, and we can describe it using the following formula:

$$u_U(S_M, S_U) \Leftrightarrow J_U\left(\tau_1^G, \ldots, \tau_i^G, \ldots; \hat{P}_1, \ldots, \hat{P}_i, \ldots\right) \tag{3}$$

where τ_i^G is the travel time when the manager selects to release the route i, and $\hat{P}_i$ is the selection probability of route i for drivers, which is based on the perception of travel time. Based on the decision field theory, the above optimization problem becomes to seek the optimal solution:

$$\max_{S_U \in P} u_U(S_M, S_U) \Leftrightarrow J_U\left(\tau_1^G, \ldots, \tau_i^G, \ldots; \hat{P}_1, \ldots, \hat{P}_i, \ldots\right) \tag{4}$$

$$S_U^* = R_u(S_M) \tag{5}$$

By $S_U^* = R_u(S_M)$, we can get the optimal route selection.

3. **Influence Factors of Route Choice.** Route selection is a complex system problem, which is affected by many interrelated and mutually restricted factors. Under guidance information, the route choice behavior is related to many factors such as individual attributes, road network layout, travel distance, and travel cost.

Considering the various factors that influence driver route choice, we select behavior characteristics, route characteristics and driver preferences as criterion layer indicators of route choice. Thus, we set $X = \{X_1, X_2, X_3\}$ as a vector of factors affecting route selection, where $X_i = \sum_j \varepsilon_{ij} x_{ij}$, x_{ij} represents one sub-factor of X_i $(i = 1, 2, 3)$, and ε_{ij} is the weight of sub-factor x_{ij}. The details of $\{x_{ij}\}$ are as follows.

1) Behavior characteristics X_1

Criterion indicator $X_1 = \{x_{11}, x_{12}, x_{13}\}$ includes driver character x_{11} (radical, stable or conservative), travel experience x_{12} (driving years, mileage ride, and route familiarity), and the acceptability of guidance information x_{13}.

2) Route characteristics X_2

$X_2 = \{x_{21}, x_{22}, x_{23}, x_{24}\}$ include route distance x_{21}, road grade x_{22} (the road conditions at intersections, control mode, driving freedom and comfortable level), the road traffic condition x_{23} (road network layout, road network density and the degree of congestion), and the road toll x_{24} (fast road or high-speed road, etc.).

3) Driver preferences X_3

$X_3 = \{x_{31}, x_{32}, x_{33}, x_{34}, x_{35}, x_{36}, x_{37}\}$ include the shortest route x_{31}, the shortest time x_{32}, avoiding congestion x_{33}, avoiding charges x_{34}, avoiding difficult route x_{35}, the landscape along x_{36}, and travel purposes x_{37}.

Some evaluation indicators such as travel time and congestion degree are dynamic indexes, and some such as driving distance, tolls and landscape are static. Therefore, priority selection score S_U^M that driver gives route to alternative route under guidance information can be determined by:

$$S_U^M = W_A X = \sum_{i=1}^{3} \delta_{Ai} X_i = \sum_{i=1}^{3} \delta_{Ai} \sum_j \varepsilon_{ij} x_{ij} \tag{6}$$

where δ_{Ai} $(i = 1, 2, 3)$ is the weight of one factor under the three categories, $W_A = (\delta_{A1}, \delta_{A2}, \delta_{A3})$, $X = (X_1, X_2, X_3)$ and $X_i = \sum_j \varepsilon_{ij} x_{ij}$.

Accuracy of the calculated S_U^M depends on the method and correctness of determining the weights W_A and ε_{ij}. If W_A and ε_{ij} are determined rationally, S_U^M will be correct and fit the fact, vice versa. Then the key in the model is to develop a method to rationally estimate W_A and ε_{ij}. Moreover, it can be seen that there are many descriptive factors in X. Then, after developing a weight determining method, it is also necessary to have a method to quantify these descriptive factors. Here AHP is used to deal with both of them. Because driver's route choice is a bounded rational behavior decision of human brain, which is fuzzy and uncertain, so we use a fuzzy analytic hierarchy process to describe it.

4. **An FAHP Based Method and Application Case.** Fuzzy analytic hierarchy process (FAHP) was proposed by Professor T. L. Satty in the end of 1970s [9]. FAHP's basic idea is to divide a complicated problem into sub-factors, group them into several layers according to their subordinate relationship, construct a hierarchy structure and synthetic judgment matrix based on the relative importance of factors in each layer determined by expert questionnaire, and then calculate the weight vector of each judgment matrix using Eigenvector method.

4.1. **Hierarchical structure frame.** AHP structure in this study is illustrated in Figure 2. On the top of frame, there is the goal layer A, and then come criteria layer C_1 and index layer C_2; at the bottom of frame, there are the alternative routes.

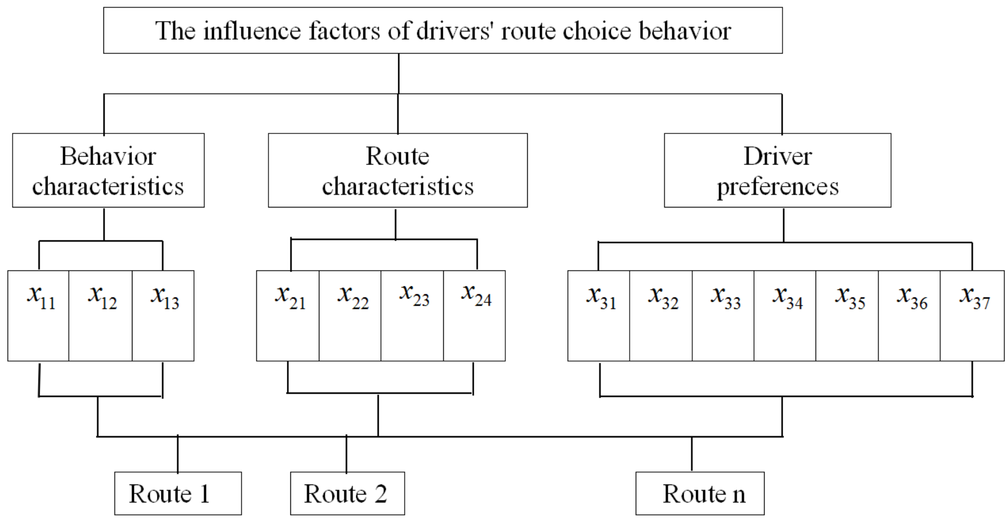

Figure 2. AHP frame for the influence factor of drivers' route choice behavior

4.2. **The judgment matrix.** Using the Eigenvector method to calculate the weight vector of the judgment matrix, it is found that exclusive integrated judgment matrix gets lost and system errors tend to be produced. In order to avoid these errors, questionnaire designed for this study combines with the merits of fuzzy evaluation and AHP.

Firstly, index values in each layer in the framework are given based on the fuzzy judgment questionnaire, and then judgment matrix of AHP is given based on the comparison table. For example, two questionnaires for three indexes in the second layer are designed and distributed in two times. In the first round, 15 questionnaires are distributed and 11 useful questionnaires were received. In the second round, in order to obtain the judgment matrix of AHP based on the results of the first round and the weight matrix of indexes, 21 copies of questionnaire sheets are distributed and 14 of useful questionnaires are received. Among them, 78.6% of experts agreed with the results in Table 1. It means that AHP judgment matrix constructed based on weight ratio matrix is accepted by experts. Based on the expert's suggestion and the consistency test's requirement, this study adjusts the results slightly. The adjustment rule is that if the difference between the weight ratio and

Table 1. The weight ratio in the AHP method

Weight Ratio	0.95-1.05	1.05-1.15	1.15-1.25	1.25-1.35	1.35-1.45	1.45-1.55	1.55-1.65	1.65-1.75	1.75-1.85

standard value in Table 1 is less than 0.02, we add ± 1 to the adjusted value to satisfy the requirement of consistency test.

In Table 1, 9-rank important degree put forth by T. L. Saaty is used, it means that "same important" = 1, "a little more important" = 3, "more important" = 5, "much more important" = 7, "extremely important" = 9 when index i is used to compare with index j, while 2, 4, 6 and 8 represent the middle values between 1, 3, 5, 7 and 9. Relatively, if index j is used to compare with index i, its value is the reciprocal of the value when index i is used to compare with index j.

4.3. **Weight vector.** Finally, we obtained the results as shown in Table 2 which is a 3×3 judgment matrix of the second layer to objective layer and satisfies the consistency test.

TABLE 2. Relative importance of three criterion factors in route selection

	Behavior characteristics	Route characteristics	Driver preference
Behavior characteristics	1	2	1/2
Route characteristics	1/2	1	1/3
Driver preference	2	3	1
Eigenvector (RSW)	0.297	0.164	0.539

RSW in Table 2 means the weight vector of criterion layer C_1 to target layer A. Here, vector of Eigenvectors is $W_A = (\delta_{A1}, \delta_{A2}, \delta_{A3}) = (0.297, 0.164, 0.539)$ and $\lambda_A = 3.997$, $CR_A = 0.088 \prec 0.10$, so both of them can be obtained by AHP and satisfy the requirement of the consistency test. Repeating the above process, weight vector W_{Bi} $(i = 1, 2, 3)$ of the criterion layer C_2 to layer C_1 can be calculated and the results are as Tables 3-5 show.

TABLE 3. Behavior characteristics

	x_{11}	x_{12}	x_{13}
x_{11}	1	1/2	1/4
x_{12}	2	1	1/5
x_{13}	4	5	1
W_{B1}	0.131	0.193	0.676

TABLE 4. Route characteristics

	x_{21}	x_{22}	x_{23}	x_{24}
x_{21}	1	3	6	9
x_{22}	1/3	1	7	9
x_{23}	1/6	1/7	1	3
x_{24}	1/9	1/9	1/3	1
W_{B2}	0.539	0.335	0.086	0.041

In Tables 3 and 4, $W_{B1} = (\varepsilon_{11}, \varepsilon_{12}, \varepsilon_{13}) = (0.131, 0.193, 0.676)$, $\lambda_{B1} = 2.834$, $CR_{B1} = 0.09 \prec 0.10$ and $W_{B2} = (\varepsilon_{21}, \varepsilon_{22}, \varepsilon_{23}, \varepsilon_{24}) = (0.539, 0.335, 0.086, 0.041)$, $\lambda_{B2} = 4.304$, $CR_{B2} = 0.095 \prec 0.10$.

In Table 5, $W_{B3} = (\varepsilon_{31}, \varepsilon_{32}, \varepsilon_{33}, \varepsilon_{34}, \varepsilon_{35}, \varepsilon_{36}, \varepsilon_{37}) = (0.127, 0.173, 0.093, 0.076, 0.317, 0.218, 0.055)$, $\lambda_{B3} = 6.172$, and $CR_{B3} = 0.088 \prec 0.10$. By the result of $W_A = (\delta_{A1}, \delta_{A2}, \delta_{A3})$, the weight value of δ_{A3} is the largest and δ_{A2} is the smaller. These results show

TABLE 5. Driver preference

	x_{31}	x_{32}	x_{33}	x_{34}	x_{35}	x_{36}	x_{37}
x_{31}	1	1/2	4	1/3	1/4	6	5
x_{32}	2	1	5	1/4	1	8	4
x_{33}	1/4	3	1	1/6	1/5	1/2	1/2
x_{34}	4	4	6	1	2	8	4
x_{35}	4	1	5	1/2	1	4	8
x_{36}	1/6	1/8	2	1/8	1/4	1	1/3
x_{37}	1/5	1/4	2	1/4	1/8	3	1
W_{B3}	0.127	0.173	0.093	0.076	0.317	0.218	0.055

that driver preference has the greatest impact on the traveler's route choice and the route characteristic has less effect on it. Using the above model, if a route is given for evaluation and its attributes such as behavior characteristics X_1, route characteristics X_2 and driver preference X_3 are known, the value of S_U^M can be calculated using Formula (6).

4.4. **Application case.** We tested 5 feasible traffic guidance routes which are from Dalian Railway Station to Zhoushuizi International Airport using the model proposed in this study. After data normalization, we calculate these five routes' score values of criterion layer C_1 using Formula (5). The results are as shown in Table 6 and the final score vector is as follows: $S_U^M = (0.3164, 0.2656, 0.3430, 0.3406, 0.3539)$.

TABLE 6. The score value of criterion layer

	Route 1	Route 2	Route 3	Route 4	Route 5
X_1	0.3	0.2	0.5	0.2	0.3
X_2	0.4	0.6	0.2	0.4	0.3
X_3	0.3	0.2	0.3	0.4	0.4

Thus, we know that the route priority order is: route 5, route 3, route 4, route 1, route 2 and the optimum choice is route 5. Optimum solution $S_U^* = 0.3539$ means that route 5 is the best route for the driver; route 3 and route 4 are next. The result of the numerical test is consistent with the actual traffic status of these five routes.

5. **Conclusions.** We use an improved fuzzy analytic hierarchy process and dynamic route choice model to search for the optimal solution of driver's route choice under traffic guidance condition. Thus, multiple fuzzy indexes of vague evaluation objects can be expressed by accurate mathematical means, and we obtain scientific and reasonable results which are close to the actual quantitative evaluation. The result shows that driver preferences, behavior characteristics and route characteristics are the key factors of route choice, and the acceptability of guidance information and avoiding difficult route are the most important sub indexes. In the future, we will apply the proposed method into more road networks and try to develop a real-time application software.

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REFERENCES

[1] J. V. Neumann, Zur Theorie der Gesellschaftsspiele, *Mathematische Annalen*, vol.100, no.1, pp.295-300, 1928.

[2] L. J. Savage, *The Foundations of Statistics*, Dover, New York, 1954.

[3] E. Avineri and J. N. Prashker, Sensitivity to uncertainty: Travelers' learning perspective, *The 13th Mini-EURO Conference, Handling Uncertainty in the Analysis of Traffic and Transportation Systems*, Bari, Italy, 2002.

[4] E. Avineri, A cumulative prospect theory approach to passengers behavior modeling: Waiting time paradox revisited, *Journal of Intelligent Transportation Systems*, vol.8, no.4, pp.195-204, 2004.

[5] D. Kahneman and A. Tversky, Prospect theory: An analysis of decisions under risk, *Econometrica*, vol.47, no.2, pp.313-327, 1979.

[6] H. A. Simon, A behavioral model of rational choice, *Quarterly Journal of Economics*, vol.69, no.1, pp.99-118, 1955.

[7] E. A. I. Bogers and H. J. van Zuylen, The importance of reliability in route choices in freight transport for various actors on various levels, *Proc. of European Transport Conference*, Strasbourg, France, 2004.

[8] G. Shi and F. Jia, Prospect theory based dynamic route choice model, *Shandong Science*, vol.29, no.5, pp.111-123, 2016.

[9] H. Gao and B. Zhang, VMS location model and simulation based on the one-way traffic organization, *Transportation Systems Engineering and Information*, vol.16, no.6, pp.54-59, 2016.

[10] M. Venigalla, X. Zhou and S. J. Zhu, Psychology of route choice in familiar networks: Minimizing turns and embracing signals, *Journal of Urban Planning and Development*, vol.143, no.2, 2017.

[11] H. L. Xu, H. Yang, J. Zhou and Y. F. Yin, A route choice model with context-dependent value of time, *Transportation Science*, vol.51, no.2, pp.536-548, 2017.

[12] X. M. Lou, L. Cheng and Z. M. Chu, Modelling travellers' en-route path switching in a day-to-day dynamical system, *Transportmetrica B: Transport Dynamics*, vol.5, no.1, pp.17-41, 2017.

[13] M. Li and H. J. Huang, A regret theory-based route choice model, *Transportmetrica A: Transport Science*, vol.13, no.3, pp.250-272, 2017.

[14] F. Gao and M. Wang, Route choice behavior model with guidance information, *Journal of Transportation Systems Engineering and Information Technology*, vol.10, no.6, pp.64-69, 2010.