ROUTE CHOICE BEHAVIOR MODEL CONSIDERING RANDOMNESS AND VAGUENESS UNCERTAINTY

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1 INTRODUCTION

In the analysis of choice behavior problem, the uncertainties that transportation researchers always encounter and feel uncomfortable can be divided into two different types (Lotan and Koutshopoulos, 1993): One is randomness due to the non-deterministic nature of choice behavior problems. Random utility models based on probability distribution have been employed to deal with the randomness. Another is vagueness due to the lack of familiarity with road networks and the linguistic information of the network attributes. Fuzzy models based on possibility distribution have been used to treat the vagueness. These two types of choice behavior models have been independently developed.

Some literatures in recent years have focused on the relationship between probability and fuzzy theories and considered both theories not as conflicting but as complementary rivals. Dubois and Prade (1993) presented some misunderstandings and gaps of the relationship between probability and fuzzy theories but also pointed out existing bridges. Teodorović (1999) insisted that probability and fuzzy theories should exist side by side, that it is possible to combine them, and that both have a very important role in explaining complex transportation processes. A more practical approach proposed by Mizutani and Akiyama (2000) is hybrid model based on random utility models and soft computing techniques, called fuzzy logit model, in order to describe various aspects of travel behavior effectively.

The purpose of this paper is to suggest a stepwise method for combining the randomness and the vagueness uncertainty that may exist simultaneously in driver perceptions. First, a latent class multinomial logit (LCML) model, one of random utility models, is developed to consider the heterogeneity among drivers. The heterogeneity means driver perceptions may differ at the individual level of familiarity with road networks. For instance, drivers familiar with road networks have distinct perceptions for the network attributes (travel time, congestion levels, etc) so they are very sensitive for the variations of the network attributes and their route choice behaviors more depend on the randomness than the vagueness uncertainty. On the other hand, drivers unfamiliar have indistinct perceptions so that they are not so sensitive for the variations and their choice behaviors more depend on the vagueness than the randomness uncertainty. It is noticeable however that the route choice behaviors of all drivers are not completely depend on only either of the uncertainties but partially depend on both since they may have both uncertainties simultaneously in their perceptions and
incorporate both in their route choice situation. Second, a fuzzy model based on possibility distribution is established to consider the vagueness of driver perceptions. The perceived levels of travel time of drivers and the linguistic information such as “light congestion” and “heavy congestion” for road networks are dealt in the fuzzy model. A specially designed questionnaire data was used to investigate the driver’s perceptions for possible travel times and possible increased travel times due to the congestions of each link. Finally, a combined model is established based on the estimation results of the LCML and the fuzzy models.

2 THE DATA

A questionnaire survey was carried out among drivers who used three commute routes, Dongbu-ro, Paldal-ro and Seobu-ro, in Chunju city, Korea, in 2001. The aims of the survey were to investigate the ordinary perceptions of drivers for the routes, the sensitivity of the linguistic expressions for the network attributes and the responsiveness for the variations of the network attributes. In the survey, the respondents were asked to answer possible travel times by three levels (short, moderate and long travel time) and possible increased travel times due to road congestion by two levels (light and a heavy congestion) for each link. To investigate driver’s responsiveness for the variations of the network attributes stated preference (SP) survey was undermined with 9 profiles per respondent. The factors set up in the SP profiles are travel times (25, 30, 35, 40), reliability of traffic information (±0, ±5, ±10), and congestion levels (no, light and heavy congestion). The response rate was 60.33% (724/1200).

3 MODELING FRAMEWORK

The methodological procedure of the combined model can be summarized as shown in Fig.1. The LCML model is established by using EM algorithm to consider the heterogeneity among drivers (McLachlan and Krishnan, 1997). Specially, the drivers are classified into $S$ latent classes with the expected probability to belong each latent class. By comparing the sensitivity for the network attributes through latent classes, it is known whether the drivers of a certain latent class have more distinct or more indistinct perceptions for the road networks. Since the route choice behaviors of all drivers are assumed to partially depend on both uncertainties, the only difference through latent classes is which latent class has a more randomness or a more vagueness character. The fuzzy model is established to model the vagueness uncertainty due to the indistinct perceptions and the linguistic information for each link. Since the expected probability calculated from EM algorithm means the membership degree of a driver to join each latent class, the probability is regarded as the index representing the relationship between the randomness and the vagueness uncertainty in driver perceptions. The combined model therefore will be established by weighting the expected probability to the probabilities that are estimated from the LCML and the fuzzy models.
Drivers

Latent Class Multinomial Logit Model

Expected Probability to join each latent class: $z_{nis}$

EM Algorithm

Randomness Vagueness

Latent Class 1 Latent Class 2 $\cdots$ Latent Class S

Combined Model

Figure 1. Stepwise method for the combined model

3.1 Latent class multinomial logit model

The mathematical framework of the LCML model will be briefly presented. For more detailed explanation refer the reference paper (Lee et al, 2001). The $S$ LCML model has the form

$$P_n(\phi) = \sum_{s \in S} \pi_s P_{nis}(i; \beta_s) \quad \text{where,} \quad P_{nis}(i; \beta_s) = \exp(c_{js} + \beta_s x_{ni}) / \sum_{j \in J} \exp(c_{js} + \beta_s x_{nj}).$$

(1)

$\phi = (\pi_1, \pi_2, \ldots, \pi_{S-1}, \beta_s)$ is the vector containing the unknown parameters. $\pi_s$ is mixing proportions of $s$ latent classes. $P_{nis}(i; \beta_s)$ is the probability that driver $n$ belonging to latent class $s$ chooses route $i$. $c_{js}$ are the intrinsic preferences and $\beta_s$ is the parameter vector associated with the vector of explanatory variables $x_{ni}$. Each latent class consists of a number of drivers that are assumed to be homogenous with respect to their preferences as well as their responsiveness to road network attributes. Latent classes, however, differ in both preferences and responsiveness to network attributes. Since the likelihood equation of Eq.1 does not yield an explicit solution for $\phi$, the EM algorithm is employed to estimate the LCML model. The EM algorithm comprises two steps. In the expectation step, expected values of the latent are computed using a set of starting values for the model parameters $(\pi_s, \beta_s)$. The expected probability $(Z_{nis})$ that a driver $n$ belongs to latent class $s$ is $Z_{nis} = \pi_s P_{nis}(i; \beta_s) / \sum_{s \in S} \pi_s P_{nis}(i; \beta_s)$. The expectation step is then followed by the maximization step. The log likelihood function is

$$\log L(\phi) = \log \left( \prod_{n=1}^{N} \sum_{s=1}^{S} \pi_s^{z_{nis}} P_{nis}(i; \beta_s) \right) = \sum_{n=1}^{N} \sum_{s=1}^{S} z_{nis} \log \pi_s + \sum_{n=1}^{N} \sum_{s=1}^{S} z_{nis} \log P_{nis}(i; \beta_s)$$

(2)

In the maximization step, the log likelihood function is maximized with respect to the model parameters $(\pi_s, \beta_s)$ and then the estimated parameters replace the initial values to update the expected probability $(z_{nis})$. The two steps are repeated until the estimates $(\pi_s, \beta_s)$ achieve convergence. The Bayesian Information Criterion is used to decide the number of latent classes.
3.2 Fuzzy model

The general rule form of the fuzzy model is $R^k: \text{if } x \text{ (or } y) \text{ is } A_k \text{ (or } B_k) \text{, then } z = C_k, k = 1,...,K$. Where $x$, $y$ and $z$ are linguistic variables representing the input and the control variable, respectively. $A_k$, $B_k$ and $C_k$ are the linguistic predicates of the linguistic variables $x$, $y$ and $z$ in the universes of discourse $U$, $V$ and $W$ respectively. $k$ is the number of fuzzy rules. In the paper, $A_k$ and $B_k$ characterize possible travel times and possible increased travel times due to a traffic congestion (Fig. 2). The initial membership functions of the network attributes are set up by using mean and standard deviation of collected data and then calibrated to approach the optimal membership function range.

Five fuzzy inference rules are set up to model the decision-making process of drivers and to describe their preferences for a specific route.

- Rule 1) If possible travel time is short, then the preference of the route is High (HP)
- Rule 2) If possible travel time is moderate, then the preference of the route is Moderate (MP)
- Rule 3) If possible travel time is long, then the preference of the route is Low (LP)
- Rule 4) If congestion level is light, then the preference of the route is Moderate (MP)
- Rule 5) If congestion level is heavy, then the preference of the route is Low (LP)

The min-max composition is used to the fuzzy inference and the centroid of area (COA) method is applied for the defuzzification; COA: $z_n^j = \sum z \cdot \mu_{C^j}(z) / \sum \mu_{C^j}(z), \quad z \in Z$. In the paper, $z_n^j$ is assumed to correspond with the systematic components of random utility model so that the probability to choose alternative route $i$ can be written in Eq. 3

$$P_n^j(i) = \exp(z_n^i) / \sum \exp(z_n^j), \quad j = 1,...,J$$ (3)
3.3 Combined model

As mentioned in the previous section, the combined model is established by weighting the expected probability \( z_{nis} \) to the probabilities of the LCML and FR model, respectively. Therefore, the combined probability that driver \( n \) belonging to latent class \( s \) to choose alternative route \( i \), \( P^c_n(i) \), is written in Eq.4.

\[
P^c_n(i) = \sum_{s \in s} \pi_s \left( \left( \eta^c_n \right) \times P^c_n(i) + \left( \eta^f_n \right) \times P^f_n(i) \right)
\]

(4)

Where \( P^c_n(i) \) and \( P^f_n(i) \) is the probability the LCML model and the fuzzy model to choose alternative route \( i \), respectively. \( \eta^c_n \) and \( \eta^f_n \) are defined as following,

\[
\begin{cases}
\eta^c_n = 1 - z_{nis} \quad \text{and} \quad \eta^f_n = z_{nis} & \text{if a latent class \( s \) is more vagueness uncertainty} \\
\eta^c_n = z_{nis} \quad \text{and} \quad \eta^f_n = 1 - z_{nis} & \text{if a latent class \( s \) is more randomness uncertainty}
\end{cases}
\]

3.4 Route choice behavior models

Table 1 compares the BIC values of the estimated results from one to five LCML models to decide the optimal number of latent classes. The one LCML model corresponds to no heterogeneity of the data, that is MNL model. The three latent classes are most adequate to approximate the heterogeneity distribution, since it has the lowest BIC value.

<table>
<thead>
<tr>
<th>Num. Of class</th>
<th>Num. Of parameter</th>
<th>BIC value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S = 1 )</td>
<td>5</td>
<td>5730.1</td>
</tr>
<tr>
<td>( S = 2 )</td>
<td>11</td>
<td>5256.3</td>
</tr>
<tr>
<td>( S = 3 )</td>
<td>17</td>
<td>4797.5</td>
</tr>
<tr>
<td>( S = 4 )</td>
<td>23</td>
<td>4862.7</td>
</tr>
<tr>
<td>( S = 5 )</td>
<td>29</td>
<td>5133.5</td>
</tr>
</tbody>
</table>

The estimation results of the three LCML model \((S=3)\) and the fixed coefficient \((S=1)\) MNL model are summarized in Table 2.

Table 1. Comparison of BIC values

Table 2. Summary of the latent class multinomial logit models

<table>
<thead>
<tr>
<th>Variables</th>
<th>LCML (S=3)</th>
<th>LCML (S=1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Latent class 1</td>
<td>Latent class 2</td>
</tr>
<tr>
<td></td>
<td>( \pi_1 = 0.4112 )</td>
<td>( \pi_2 = 0.3960 )</td>
</tr>
<tr>
<td>Dongbu-ro constant</td>
<td>-0.121 (-0.469)</td>
<td>-0.334 (-0.942)</td>
</tr>
<tr>
<td>Paldal-ro constant</td>
<td>0.097 (0.484)</td>
<td>-1.639 (-3.435)</td>
</tr>
<tr>
<td>Travel time</td>
<td>-0.091 (-2.376)</td>
<td>-0.120 (-2.075)</td>
</tr>
<tr>
<td>Reliability</td>
<td>-0.034 (-1.201)</td>
<td>-0.026 (-0.673)</td>
</tr>
<tr>
<td>Congestion level</td>
<td>0.343 (-2.235)</td>
<td>-1.094 (-4.474)</td>
</tr>
<tr>
<td></td>
<td>(no,light,heavy=0,1,2)</td>
<td>(no,light,heavy=0,1,2)</td>
</tr>
<tr>
<td>Num. Of sample</td>
<td>2842</td>
<td>2842</td>
</tr>
<tr>
<td>( L(0) / L(\beta) )</td>
<td>-3122.3 / -2331.1</td>
<td>-3122.3 / -2854.7</td>
</tr>
<tr>
<td>( \rho^2 / \bar{\rho}^2 )</td>
<td>0.253 / 0.248</td>
<td>0.086 / 0.084</td>
</tr>
</tbody>
</table>

Note) **: Significant at the 0.01 confidence level. *: Significant at the 0.05 confidence level
The parameters of all attributes have the expected signs. By comparing the indices $\rho^2$ of the two models, it is clear that the three LCML model can improve the fixed coefficient MNL model by considering the heterogeneity among drivers. In addition, the coefficients of each latent class show that the drivers of latent class 3 are most sensitive with “shorter travel time” and “higher reliability” attributes, and in the case of latent class 2 are most sensitive with “lower congestion level” attribute, while the drivers of latent class 1 are not so sensitive for the network attributes comparing with those of latent class 2 and 3. Therefore, it is assumed that the drivers belong to latent class 1 have indistinct perceptions for the road network and their choice behaviors depend on more vagueness uncertainty. Conversely, the drivers belong to latent class 2 and 3 are regarded that they have distinct perceptions so that their route choice behaviors depend on more randomness uncertainty.

For modelling the vagueness uncertainty, the fuzzy model is established by considering the ordinary perceived levels of possible travel times and possible increased travel times due to the congestions of each link. Especially, the linguistic information for the congestion levels of each link are incorporated with the ordinary perceived levels of the possible increased travel time of the link in the combined model. The estimation results of the combined model are summarized in Table 3. By comparing the log likelihood values between the LCML and the combined models ($\chi^2_{0.01} (D.F=5)=15.086<-2(-2331.1+1994.1)=674$), the combined model effectively incorporating the randomness and the vagueness uncertainty can enhance the explanatory power of the LCML model. Hence, the accuracy of the route choice behavior models can be enhanced from the combined model.

<table>
<thead>
<tr>
<th>Table 3. Summary of the combined model</th>
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</thead>
<tbody>
<tr>
<td><strong>Combined model</strong></td>
</tr>
<tr>
<td>Variables</td>
</tr>
<tr>
<td>Num. Of sample</td>
</tr>
<tr>
<td>$L(0) / L(\beta)$</td>
</tr>
<tr>
<td>$\rho^2 / \bar{\rho}^2$</td>
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</table>

4 CONCLUSIONS

A stepwise method for the combined model considering the randomness and the vagueness uncertainty simultaneously is proposed in this paper. The remarkable results are summarized as follows: First, LCML model can enhance MNL model by considering the heterogeneity among drivers. Second, the combined model is able to improve the explanatory power of the LCML model by effectively incorporating the randomness and the vagueness uncertainty of driver perceptions. Finally, to overcome the complexity of the stepwise procedure, a simultaneous method for the combined model should be explored in the future.
REFERENCES


