ADAPTIVE NEURO – FUZZY INFERENCE SYSTEM FOR MODELING THE TRANSPORT MODE CHOICE PROBLEM

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ABSTRACT
Developing precise travel behavior models is important for estimating traffic demand and consequently, for planning transportation systems. The objective of this study is to suggest a hybrid model, which combines a stochastic model with a neuro-fuzzy inference system. The model is applied for estimating travelers' behavior in the context of the transport mode choice problem. Particularly, the multinomial logit model with neuro-fuzzy utility functions is developed to investigate shopping travelers' preferences regarding the modes of bus, subway and automobile. The model is evaluated by comparing its results with the actual transport mode choices. The model showed good performance by estimating an expressive number of right choices during the validation process. Furthermore, the obtained probabilities of selecting a transport mode were coherent with the survey results. The results show that the model is able to describe the uncertainties concerning travelers' decisions on the time of transport mode choice.

RESUMO
O desenvolvimento de modelos de comportamento de viagem adequados é importante para a estimativa da demanda de tráfego e consequentemente, para o planejamento de sistemas de transporte. O objetivo deste estudo é propor a combinação de um modelo estocástico a um sistema inferencial *neuro-fuzzy*, que é aplicado na estimativa do comportamento de usuários durante o processo de escolha modal. Particularmente, o modelo logit multinomial, composto por funções utilidade *neuro-fuzzy*, é usado para investigar viagens de compras considerando os modos ônibus, metrô e automóvel. O modelo é avaliado comparando-se os resultados estimados aos resultados da pesquisa. Este mostrou bom desempenho durante o processo de validação, estimando corretamente uma parcela considerável da amostra, além de apresentar coerência na estimativa da probalibidade de seleção dos modos de transporte. Os resultados mostram que o modelo descreve corretamente as incertezas referentes às decisões dos usuários no momento da escolha do modo de transporte.

1. INTRODUCTION

Travel behavior models are valuable tools in the field of traffic demand estimation. These models provide information about travelers' preferences. This information is required in the design and planning, among other areas, of transportation systems. Since several decades, statistical models have been largely applied to solve traffic and transportation problems. However, researchers usually face difficulties to interpret the uncertainties inherent to the real-life choice behavior problems while using exclusively mathematical models (Teodorovic, 1999). Lee *et al.* (2003) point that the uncertainties regarding travelers' decisions are composed of two types, the randomness and the vagueness. The former is due to the non-deterministic nature of choice behavior while the later is due to the lack of familiarity with the choice alternatives. Therefore, the travel behavior model would correctly describe both kinds of uncertainties to be adequate.

In the last decades, several models have been suggested to deal with the different uncertainties. This new category of travel behavior models includes statistical methods and various techniques of soft computing, such as Fuzzy Logic (FL), Neural Network (NN) and Genetic Algorithm (GA). Among the stochastic models, the well-known logit models are effective tools. There are some studies in which new models, which can be called hybrid models, are presented with promising results (Akiyama *et al.*, 1999). Among the hybrid models, fuzzy reasoning is successfully applied to describe various aspects of travel behavior. However, few of these studies deal with adaptive learning approaches (Lee *et al.*, 2003; Mizutani and Akiyama, 2001). In these studies, the characteristics of the initial fuzzy inference systems are exclusively based on the designer's judgment, which is a disadvantageous characteristic as long as it deals with human behavior modeling. In this context, the neuro-fuzzy systems arise as an interesting option for reducing the errors regarding human judgment. Summarily, the main task of adaptive systems, such as neuro-fuzzy systems, is to find an appropriate architecture and a set of parameters which should be the best for modeling an unknown target system that is described by a set of input-output data pairs (Jang, 1997).

In this study, an adaptive neuro-fuzzy multinomial logit model is proposed. The overall structure is based on the logit model. However, the adaptive utility function is described by a neuro-fuzzy inference system. By using the neuro-fuzzy utility function into the discrete choice formulation, a better description of the combination of the vagueness uncertainty and the randomness uncertainty is expected. The model, which can be named neuro-fuzzy multinomial logit (NFML) model, is developed to the transport mode choice problem. The preferences of shopping travelers regarding the transport modes of bus, subway and automobile are investigated. The results of the estimation are evaluated and compared with the survey results, which show good performance of the proposed model.

2. BASIC STRUCTURE OF LOGIT MODELS

Logit models, based on random utility theory, are well established as discrete choice models. By adopting this model, the basic assumption is that a traveler will select the transportation mode which provides the maximum utility in the economic sense (Ben-Akiva and Lerman, 1985). The utility of an alternative *i* for a person *n* is described in the following equation:

$$U_{in} = V_{in} + \varepsilon_{in}, \tag{1}$$

where V_{in}, usually described by a linear function, is the deterministic term of the utility of alternative *i*, while the second term (ε_{in}) is the random variable for the utility. By following the choice theory, the probability of selecting an alternative *i*, in a multinomial process, is given by:

$$P_{in} = \Pr(U_{in} \geq U_{jn}), \forall j \in C_n, j \neq i \tag{2}$$

$$P_{in} = 1 \Big/ 1 + \sum_j \exp^{\mu(Vin - Vjn)}, \tag{3}$$

where C_n is the set of alternatives. The least squares method can be applied for estimating the parameters of logit models (Ben-Akiva and Lerman, 1985). Moreover, the least squares method proves to be an essential tool for constructing linear mathematical models, which can be extended to non-linear models as well (Jang, 1997). Thus, this method provides important mathematical basis for solving neuro-fuzzy modeling problems (Yager and Filev, 1994). In general, the model parameters are estimated by minimizing:

$$Q = \sum_{n=1}^{N} \sum_{i \in C_n} (y_{in} - P_{in})^2 \tag{4}$$

with respects to the parameters, where N is the number of samples. In this equation, y_{in} is equal to 1 if person n selects alternative i, 0 otherwise.

3. THE DATA

A questionnaire survey was carried out by targeting shopping travelers who live in the district of Shin-Sapporo, Sapporo – Japan. In this study, shopping travelers are focused because of the intrinsic high level of uncertainty regarding the transport mode choice behavior on the time of shopping trips. The travelers' preferences regarding the transport modes of bus, subway and private automobile, which are available for the respondents, were investigated. Specifically, two commercial zones in the downtown of Sapporo city were assumed as destination areas.

The objectives of the survey were to explore the factors which influence the transport mode choice, to find out the actual preferences of transport mode, and to find out the response to changes in the characteristics of the modes. The questionnaire consisted of two parts, in which the first part included fourteen short questions, while the second part included 6 profiles of stated preference (SP) survey aimed to capture travelers' response for variations on the attributes.

Primarily, the factors included in the SP profiles are travel time, walking time, waiting time and cost. The attributes were organized by profile as showed in Figure 1. In this study, only the attribute Time-in-Vehicle (TV) was included in the NFML model. A summary of the levels of this attribute is presented in Table 1. The levels of the variables were selected in order to correspond to the reality of the study area. Therefore, the real values of time-in-vehicle were included, as well as, possible lower and higher values.

One thousand questionnaires were randomly distributed. From these, 192 were returned giving a recovery rate of 19.2 percent. The final valid sample size was composed of 160 questionnaires since 32 were incomplete or filled out by incorrect answers. Although the number of questions was kept at minimum to increase the willingness of respondents, the response rate was considered to be low.

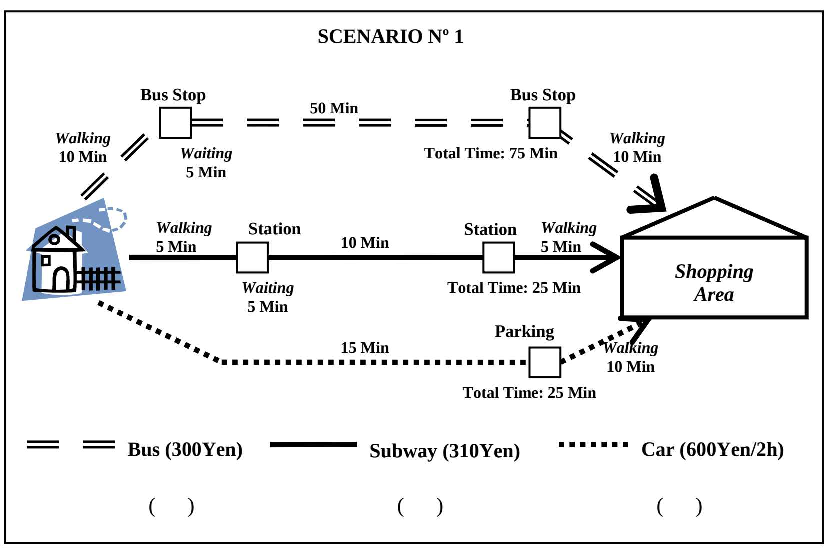

Figure 1: Example of Profile Included in the SP Survey

Table 1: Levels of the attribute Time-in-Vehicle included in the Survey

Transport Mode	Levels of Variable TV (min.)
Bus	20, 35, 50
Subway	10, 20, 30
Car	15, 30, 45

3.1. Characteristics of the Data Sample

In the data sample, 58 percent of the respondents were females and 42 percent were males. The highest percentage of respondents was in the category of 33 to 44 years old contributing in 36 percent of the total, followed by 32 percent within 45 to 60 years old range. The remaining was distributed as 19 percent for respondents exceeding 60 years old and 13 percent within 18 to 29 years range. The questionnaire was addressed to adult people, i.e., there are no children less than 18 years old included in the samples. Vehicle availability is also a classic explanatory variable for mode choice. In the data sample, 21 percent of the respondents do not own automobile, 71 percent of the respondents own one vehicle and 9 percent of them own two or more automobiles.

Among all hypothetical scenarios, subway was the most favorite mode as it was chosen by 63 percent of the respondents, followed by 29 percent of respondents who choose private automobile, while bus was the least preferred mode chosen by only 8 percent of the respondents. However, it is important to highlight the influence of stated preference exercises in the respondents' answers, which can be different from their choice in the real life.

4. FRAMEWORK OF THE NEURO-FUZZY MULTINOMIAL LOGIT MODEL

The methodological procedure of the NFML model is summarized in Figure 2. The neuro-fuzzy utility functions were estimated by using the optimization algorithm proposed by the Fuzzy Logic Toolbox (Version 2) of the software Matlab 7.0 (Matlab, 2001) by trial and error manner. In the adaptive neuro-fuzzy optimization process, the named hybrid learning rule was applied for identifying the output parameters. The hybrid learning rule combines steepest descent (SD) and least squares estimator (LSE) for identifying the parameters of the consequent part of the inferential rules (Jang, 1997). Specifically, three independent first-order Sugeno fuzzy inference systems were developed and trained to describe the utilities of modes bus, subway and automobile. Each FIS is composed of four input (TV_{bus}, TV_{sub}, TV_{auto}, Car) and one output [Utility of mode – U_i, $\forall\ i \in$ (bus, subway, auto)). The FISs were trained by using 80% of the eligible data (768 input-output pairs). The remaining 20% input-output pairs (192 pairs) were used as holdout data for verifying the model. Since the mode choice behavior of all travelers is assumed to partially depend on the characteristics of the three modes, the set of input variables and the fuzzy rules were the same for the three FISs.

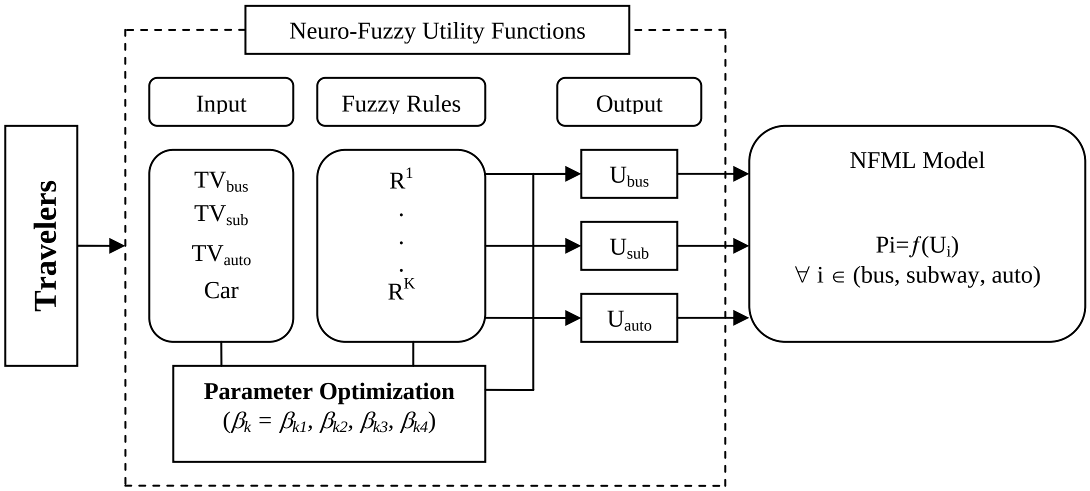

Figure 2: Sequential Procedure of the NFML Model

The general rule form of the fuzzy inference model is:

$$R^k : If\ TV_{bus}\ is\ A_k\ and\ TV_{sub}\ is\ B_k\ and\ TV_{\mathrm{auto}}\ is\ C_k\ and\ Car\ is\ D_k,\ \ldots$$
$$\ldots\ then\ z_k = \delta_{k1}x_1 + \delta_{k2}x_2 + \delta_{k3}x_3 + \delta_{k4}x_4 + \alpha_k,\ k = 1,\ldots K \qquad (5)$$

where TV_{bus}, TV_{sub}, TV_{auto} *and Car* are linguistic variables corresponding to the input variables; z_k is the control variable, which is a crisp function to be used for Sugeno fuzzy models; A_k, B_k, C_k and D_k are the linguistic predicates of the input linguistic variables; and K is the number of fuzzy rules. In this study, A_k, B_k, and C_k characterize possible time-in-vehicle by bus, subway and automobile, respectively, while D_k characterizes the possibility of owning a car. Figure 3 illustrates the membership functions of the antecedent terms of the fuzzy rules.

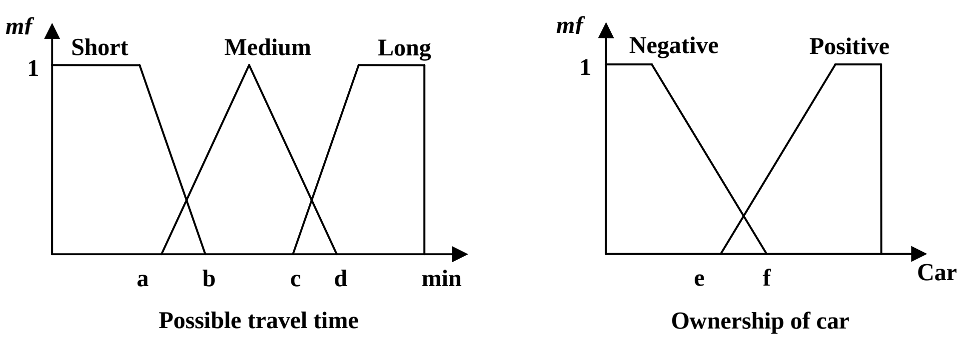

Figure 3: Membership Functions of Antecedent Terms of Fuzzy Rules

The parameters of the antecedent part of the fuzzy inference rules were set up based on the evaluation of the characteristics of the input data set. As a process used by adaptive neuro-fuzzy inference systems, the initial values of the antecedent parameters can be defined in a way that the centers of the MFs are equally spaced along the range of each input variable (Jang and Mizutani, 1997). Then, the parameters of the membership functions, i.e. δ_{k1}, δ_{k2}, δ_{k3}, δ_{k4} and α_k, are optimized to approach the final membership range.

In the NFML model, a total of 54 fuzzy inference rules (3x3x3x2 linguistic values) were automatically generated to model the decision-making process of travelers. Figure 4 illustrates a summarized example (for 2 rules and 2 input variables) of the fuzzy inferential system used for estimating the neuro-fuzzy utility functions.

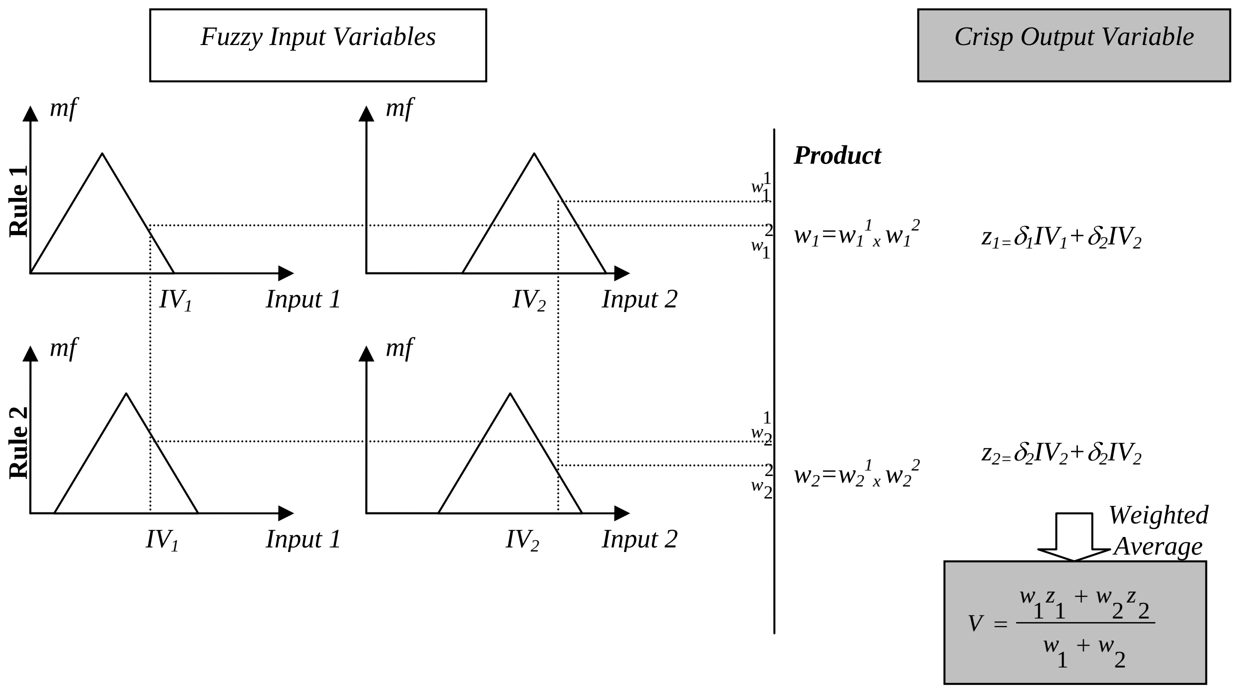

Figure 4: Inferential System used for estimating the Neuro-Fuzzy Utility Functions

The weighted average ($\overline{\mathrm{WA}}$) method is applied for the defuzzification (Equation 6) in order to define V_{in}. In this study, V_{in} is assumed to correspond to the systematic components of the random utility model. In this case, the probability of individual *n* select mode *i* in the choice set C_n can be written as in Equation 7.

$$\overline{\mathrm{WA}}: V_{in} = \sum_{k=1}^{K} w_k z_k \Big/ \sum_{k=1}^{K} w_k, \ \ \forall\, i \in \ (bus, sub, auto) \tag{6}$$

$$P_{in} = 1 \Big/ 1 + \sum_j \exp^{\Delta Zij}, (\forall j \neq i) \tag{7}$$

$$\Delta V_{in} = (V_{in} - V_{jn})$$

5. MODEL BEHAVIOR EVALUATION

Initially, the estimated results per transport mode were compared with the observed results, which are detailed in Table 2. The fitness of the model is defined as the proportion of samples correctly predicted. The NFML model succeeded in estimating 148 samples from the total of 192 data pairs, which provided approximately 77% of fitness for the model. It was clear that the model presented good performance, especially by estimating the choices of the modes subway and automobile. However, the number of correct predictions regarding the mode bus was considered to be low. This error can be a result of the low percentage of selection of this mode among the training data samples. Thus it is expected that the use of a larger training data set could reduce the error in the prediction of mode bus. As a consequence, lower error could be expected for the estimation of the other two modes.

Table 2: The Estimation Results by the NFL Model

Mode		Estimation			Total
		Bus	Subway	Automobile	
Observation	Bus	6	8	7	21
	Subway	6	114	11	131
	Automobile	5	7	28	40
Total		17	129	46	192
Number of samples estimated correctly					148
Fitness ratio (%)					77.08

Next, the probabilities of selecting a transport mode were estimated and compared with survey results. Figure $5_{(a)}$ summarizes the utility functions obtained for the three modes. These results show higher preference by the mode subway (Figure $5_{(b)}$). It is observed that the probability of selecting mode subway was underestimated while the probabilities of selecting modes bus and subway were overestimated if compared with actual choices. Despite this difference, the model demonstrated good performance.

(a) Values of mode utility functions

	Ut(bus)	*Ut(subway)*	*Ut(auto)*
Utility	-1.090	0.538	0.197

(b) Estimated probabilities of selecting transport mode

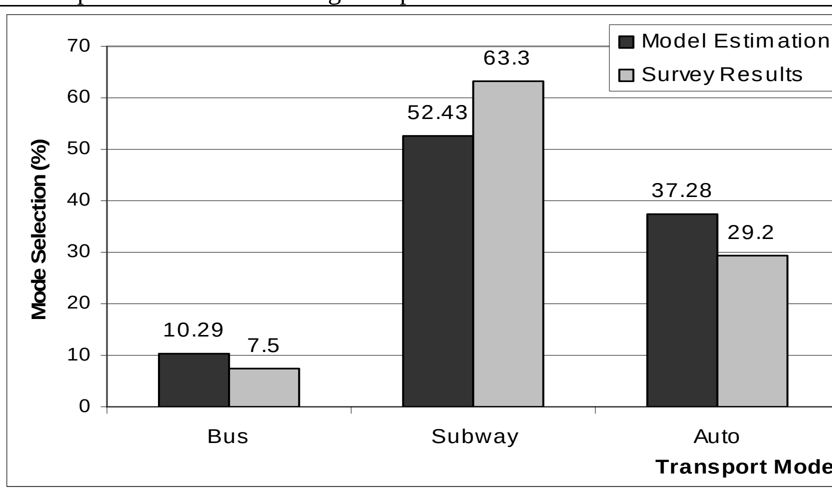

Figure 5: Model Estimation X Survey Results

Finally, by assuming that time-in-vehicle is a function of service frequency, a sensitivity analysis was performed in order to demonstrate the influence of time variations of mode subway on the probabilities of selecting a transport mode (Figure 6). By this figure, it is observed that whenever the travel time of subway increases, the probability of selecting this mode decreases while the probabilities of selecting the modes automobile and bus increase. Furthermore, Figure 6 shows that after a certain travel time (approximately 27 minutes) the probability of selecting mode automobile becomes higher than the probability of selecting mode subway. This result demonstrates that travelers shift to other modes, especially to the mode automobile, whenever the travel time by subway becomes longer.

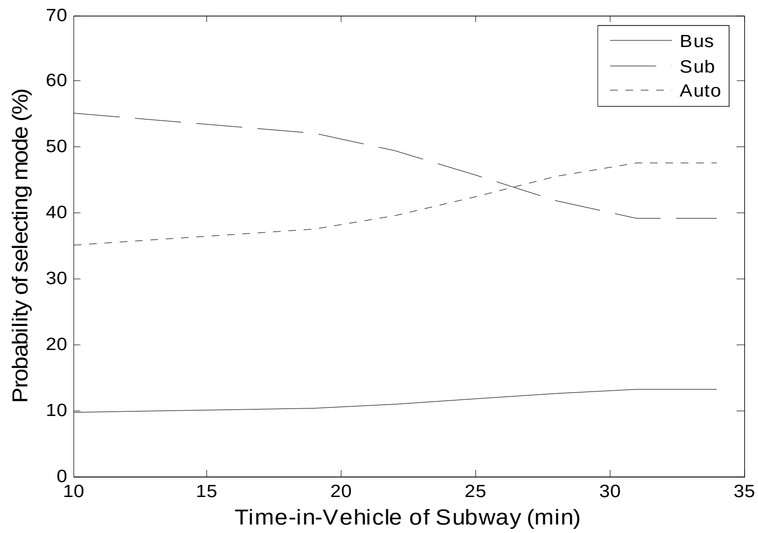

Figure 6: Effect of Variation of Travel Time by Subway on the Transport Mode Choice

6. CONCLUSION

A multinomial logit model with adaptive neuro-fuzzy utility functions for the mode choice problem was suggested in this paper. The NFML model, which is structurally based on the multinomial logit model, has incorporated fuzzy input variables to describe the vagueness uncertainty inherent to the decision making process of shopping trip makers. Furthermore, the model has described the vagueness by adopting fuzzy inference rules with linear crisp outputs. On the other hand, the randomness is well described by the logit structure of the model. The results showed that the parameters of the consequent linear functions were effectively estimated by using the hybrid learning rule, which combines steepest descent and least-squares estimator.

The results showed good performance of the model. The trained networks were used to estimate transport mode choice in the validation data set, which showed reasonable rate of right answers. Particularly, promising results were obtained for the estimation of modes subway and automobile. However, the model has not presented good performance by estimating selection of mode bus. For further studies, it has been planned to improve the training data set in order to deal with this problem. In addition, the probabilities of mode selection demonstrated quite good performance of the model. Although the probability of selecting mode subway was underestimated and the probabilities of selecting modes bus and subway were overestimated, the results seem to be reliable if compared to the survey results. Finally, the influence of variations of time by subway on the probability of selecting a transport mode was evaluated, which showed the high influence of the travel time by subway on the transport mode choice.

For further studies, other important variables should be incorporated to the model, such as travel cost and access time. By attempting to improve the explanatory power of the implication rules, different inferential strategies could be examined. Moreover, the neuro-fuzzy multinomial logit model should be applied to other complex discrete choice problems in order to acquire further knowledge about different aspects of travel behavior.

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