# DEVELOPMENT OF DYNAMIC ROUTE CHOICE BEHAVIORAL APPLIED INTELLIGENT SYSTEM THEORY

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**Abstract:** The purposes of this paper are drivers' route choice behavior models based on artificial neural network theory to analyze the variation of drivers' preference as the change of their social-economic characteristics. In this paper, artificial neural network theory is applied to effectively incorporate the non-linearity of decision-making process, which was difficult to deal in tradition. To improve the cross-section model and establish the importance of the dynamic model, the artificial neural network theory is introduced in the dynamic route choice model of this paper. At the result of analysis, we find that the fit-ratio of the artificial neural network model of this paper is higher than it of the existed multinomial logit model and applied fuzzy inference model.

Key Words: Multinomial Logit, Neural Network, Fuzzy Inference, Dynamic Theory

# **1. INTRODUCTION**

There have been various researches on the traffic behavior to find out the process of decision making of drivers. However, existing models set limits to examine non-linearity, ambiguity and the errors, which are occurred by variety of space-time contained in human conscious structure and process of decision-making. Especially, although it is true that driving experiences and such external factors as various information's on traffic situation affect a driver's route choice behavior, there must be some limits to explain the traffic status clearly taking into accounts the reality of our society that has a lot of traffic problems to be solved. To examine drivers' traffic behavior closely and clearly is most important for resolving the traffic problems caused by the future social structure and changes in road situation and suggesting desirable directions in order to improve the road situation. Artificial Neural Network Theory, which has the same structure as human conscious structure, is a very useful

theory to minimize the errors with repetitive learning processes. It is being utilized widely to solve various problems occurred in the field of engineering currently. Thus, in this paper, more elaborate route choice behavior model is established considering non-linearity and ambiguity contained in the decision making process of drivers through several researches on traffic behavior models applied with artificial neural network theory. To take the dynamic human behaviors into consideration, dynamic route choice behavior model was made with the state-dependency and panel survey data on state preference.

In this paper, through this dynamic route choice behavior model, artificial neural network theory is proved to be effective and feasibility of application of the theory in the field of traffic is confirmed. In this paper, to give consideration to non-linearity, ambiguity and interdependence of dynamic route choice behavior model applied with artificial neural network theory, Jeonju City that is establishing the Traffic Information System was selected as a research subject. And for Jeonju City, 3 times of panel surveys were conducted every two months (Feb. 2001: Wave 1 / April: Wave 2 / June: Wave 3) to collect panel data on the route preference of road users who had been given with traffic information. Traditional multinomial logit model and fuzzy inference model were established and compared with each other to confirm the effectiveness and application feasibility of artificial neural network dynamic route choice behavior model based on the survey data. Especially, to demonstrate route choice behaviors of drivers according to state-dependence, static model and dynamic model were established for the comparison of each model's fit-ratio. The following is the logical conclusion of the comparison between traditional multinomial logit model, fuzzy inference model and artificial neural network model: first, artificial neural network model recorded the highest mark in the hit ratio and feasibility of artificial neural network theory which can be used effectively in learning and revision was confirmed applicable. Second, MSE of artificial neural network model was calculated lower than those of other models and effectiveness of artificial neural network model was confirmed. Third, dynamic artificial neural network model considering state-dependence was proved to record higher mark in fit-ratio and more effective than static model. Based on the results above, dynamic traffic behavior model using artificial neural network theory is proved to be effective and feasible.

## 2. APPLICATION OF NEURAL NETWORK THEORY TO ROUTE CHOICE

## **2.1 Artificial Neural Network**

Artificial neural network consists of these artificial Neurons, as it is the model of human brain's structures for special functions and missions. A procedure of learning process is called learning algorithm and functions to adjust the weight of neural network to achieve targets. Among several good points of neural network, only three good points can fit in with this research, that is, non-linearity, mapping between input and output, and adaptively. First, neural network may be linear or non-linear. However, neural network formed by mutual connectivity's between non-linear Neurons has non-linearity, which ranges in the whole neural network. Considering a situation that non-linearity is contained in a phenomenon itself like a driver's route choice in time of providing information, it is much more important to develop a model to show non-linearity in neural network. Second. Neural network performs learning process through the mapping between input and output. That is, learning method known as 'supervised learning' adjusts the weight by applying training materials to neural network. Each applied material contains unique input signals and corresponding responses. Training of neural network is performed repeatedly until difference between targeted response and the response from neural network is minimized and the weight reaches a stable status with no more changes. Lastly, neural network can adjust the weight to adapt itself to the circumstances. Especially, a neural network, which was trained to perform its functions in certain circumstances, can be retrained easily to handle small changes in environmental elements. Neural network, a mutual connection of nodes that can perform mathematical operation, can be operated according to proper learning rules. That is, each node performs the mathematical operation with Combination Function and Transfer (Activation) Function. Signals input to actual nodes are the sum up of the values with weights as provided in the following formula (1).

$$s_j = \sum_{i=0}^m (w_{ji} \cdot x_i) \tag{1}$$

 $w_{ii}$ : Connection weight,  $x_i$ : input Value

In the formula (1),  $s_j$ , actual input signal, passes through non-linear function called Transfer Function or Activation Function. The most widely used non-linear function is Sigmoid Function. In this research, unipolar Sigmoid Function was used. The following formula (2) provides the  $y_j$ , the results of  $s_j$  input.

$$y_j = f(s_j) = \frac{1}{1 + \exp(-s_j)}$$
 (2)

## 2.2 Learning Algorithm

Figure 1 provides the multi-layer neural network used in this research. This multi-layer neural network consists of input layer, hidden layer and output layer. Learning algorithm used in this research is the Back Propagation Algorithm (BPA) with the Steepest Descent Method using Momentum Constant and Adaptive Learning Rate. For Activation Function here, unipolar Sigmoid Function and Linear Function were used. To increase the effectiveness in the training, the Early Stopped Training Approach was used. The following methods and algorithms were used in this research.



Figure 1. The Multi-Layer Neural Network

## **3. APPLICATION OF MODELING**

In this research, the existing Multinomial Logit Model, Fuzzy Inference System Model and Neural Network System Model were compared with each other to measure the goodness of ratio of models in the development of intelligent model. Moreover, models were divided into the categories of static model and dynamic model respectively for modeling.

## 3.1 Summary on the Survey Data

In this research, road users' route preference related data based on the provided traffic information was used with the subject of Jeonju City where traffic information system is under establishment in order to analyze the drivers' behaviors according to the travel time information providing. In the figure 2, the concept map of the subject area of this research is provided. The selected main subject routes are Kirin-Ro, Paldal-Ro and Cheonbyeon-Ro connected to the office of provincial government via the center of the Jeonju City.



Figure 2. Concept map of the survey area

The 3rd route, which is one of the research subjects, is marked in the Table 1. The travel time during the peak time and normal time was almost the same on the 3 roads in the Table 1. In addition, a survey was performed on the similar road situations to measure the effect of traffic information provision.

Survey Contents	Kirin-Ro	Paldal-Ro	Cheonbyeon-Ro
Road length	4.8Km	3.4Km	4.2Km
Travel Time (Peak Time)	17(min)	17(min)	15(min)
Travel Time (Ordinary Time)	14(min)	11(min)	10(min)
Signalized Intersection	13	10	9
Non-Signalized Intersection	2	1	5
Number of Lane (One way)	2	3	4
Number of Horizontal Curve	2	2	4
Number of Vertical Alignment	3	0	2

Table 1. Road Situation

To examine drivers' reactions to provided information, drivers who commute from their home located in Jeonju City to their workplace in the center of the city were selected as the subjects of this research because business related functions are concentrated in the heart of the city and it takes relatively more time for commuting in the center of the city than in the noncenter of the city area. Moreover, during short time, the traffic in the time period of commuting is most crowded and concentrated than any other time period. As a research method, preference survey was adopted. The outline of this survey is provided in the Table 2.

Investigation Object	Driving Commuters in Jeonju city, Korea				
	Personal Information, Estimated travel time,				
Survey Items	Normal Commuting Route in the Morning,				
	Preference Route, SP questions				
Survey Period	Wave 1	Wave 2	Wave 3		
Number of Questionnaires	1,100	464	246		
Number of used Questionnaires (%)	464(42.18%)	246(53.02%)	188(76.42%)		
Number of used Questionnaires(SP)	4,173	2,214	1,692		

Table 2. Survey Outline

For each number of questions on the SP survey, orthogonal array table of test plan to guarantee research subjects with orthogonality between properties of hypothetical alternatives and to let them avoid multicollinearity using level values by routes mentioned in the Table 3. In this research, the orthogonal array table of  $L_9(3^4)$  in which 4 factors can be arrayed was used in the 9 test times to condense all the conditions to 9 kinds of traffic conditions. Nine kinds of cards were provided as travel time related information to a respondent. To analyze the adaptation process in time of wave progressing, repetitive surveys were executed with the same level values without change in the level value.

Primary Factor	Level				
Current Route	Kirin-Ro / Paldal-Ro / Cheonbyeon-Ro				
	Kirin-Ro	10 min	20 min	30 min	
Travel time Information	Paldal-Ro	15 min	25 min	35 min	
	Cheonbyeon-Ro	10 min	20 min	30 min	

Table 3. Primary Factor and Level of Profile

SP survey was executed in the method that a researcher visits the work places, distributes survey papers and recollect them by means of self-administered survey method including such survey items as private features, normal commuting route, preference route, frequency of usage by routes in a week, expected travel time and SP questions.

## 3.2 Individual attributes and Statistical Analysis

We survey the basic items such as sex, age, education degree, occupation, driving career, monthly income of household, because a driver's choice behavior becomes different to individual attribute. Figure 3 shows number of sample and composition ratio for each attribute of drivers to response questionnaire.



Figure 3. Composition Ratio for Individual Attribute

#### **3.3 Route Choice Multinomial Logit Model**

Basic formula of disaggregate model can be explained with the basic theory of Random Utility Theory. Preference or (Utility:  $U_j$ ) of j (Optional choice) depends on  $(X_j)$  (the property of the choice) and  $(S_j)$  (a person's social and economic properties. In a word, it is impossible to observe the whole factors. Thus, according to the approach of Random Utility Theory, utility value fluctuates in probability. To put it concretely, in the Multinomial Logit Model, when  $A_n$  (group of choices) is provided to a person n, the choice probability is provided in the following formula (3).

$$p_{in} = \frac{e^{\lambda V_{in}}}{\sum_{j \in A_n} e^{\lambda V_{jn}}} = \frac{1}{\sum_{j \in A_n} e^{\lambda (V_{jn} - V_{in})}}, (i \in A_n)$$
(3)

 $A_n$ : Cardinal number, (a person)'s choice

 $p_{in}$ : Probability that (a person) chooses choice  $i(i = 1, \dots, i_n)$ 

 $V_{in}$ : Invariable item of utility accepted in the choice *i* by *n* (a person)

 $\lambda$ : Coefficient representing the dispersion of Utility invariable items

In the formula (3), it has to be noted that the number of choices is more than 3 in the MNL model and that group of choices has nothing to do with changes in each person. Variables used in the establishment of MNL model are travel time and travel experiences. For the properties of each variable, drivers preferred the shortest route with the shortest travel time and tended to choose a route with more usage experiences.

#### 3.4 Fuzzy Inference System Model

Fuzzy theory was introduced for the first time by Professor Lofti A. Zadeh, in the University of California at Berkeley in 1965 and has been researched and applied actively in Japan and the Europe. It handles the vagueness of a concept, which is not limited with certain boundaries as a kind of inference of inducing a proposition from several fuzzy propositions. It has attracted public attentions that the inference performed by fuzzy theory is very similar to that performed by human brain. Moreover, this theory plays an important role in such fields

as fuzzy control, expert system and decision-making. The concept of Fuzzy Induction Method is provided in the Figure 4. Typical form of general rules for Fuzzy inference is IF  $A_i$  THEN  $B_i$ . The result of  $B^*$  is obtained through the concurrence of *i* (all the rules including the  $A_i$ ) and  $A^*$  (input value). Inference structure helps the input value to be applied for each rule and induces an approximate value although the present input value does not match with the standard input value required by the rules. The return value is the compound of all the  $B_i^*$ . In the end, for the return values of all the rules, attraction level of alternative routes is calculated through defuzzification and the drivers' final route decision is inferred. Moreover, in time of inference, flexibility was applied to the information processing in the decision-making using the approximate reasoning.



Figure 4. Fuzzy Inference Process

To find out the application of route choice behavior model with Fuzzy Inference System Theory, the following drivers' recognition concepts of travel time and travel experiences for each route are assumed:

For Kirin-Ro  $= A_1 = 15$  min. (fast), 30 min. (slow), 18 min. (normal), around 5 times For Paldal-Ro  $= A_2 = 20$  min. (fast), 40 min. (slow), 25 min. (normal), around 3 times For Cheonbyeon-Ro  $= A_3 = 30$  min. (fast), 45 min. (slow), 60 min. (normal), around 1 time The following result is induced through the application of fuzziness to each rule and the calculation of attraction level for each alternative route by Defuzzification:

 $z^{1}$ (Kirin - Ro) = 0.5161,  $z^{2}$ (Paldal - Ro) = 0.2766,  $z^{3}$ (Cheonbyeon - Ro) = 0.2073

Thus, this driver prefers the Kirin-Ro and chooses it. The methods exemplified above are based on the calculation by Min-Max Centroid Method among various Fuzzy Inference System Methods. In addition, for the range and overlapping level of membership function for each variable, the average value of each data and 50% overlapping level were used based on the experts' experience. In this way, Route Choice Behavior Model by Fuzzy Inference was inferred.

# 3.5 Neural Network System Model

In this research, artificial neural network theory, which is known to be able to realize the human intelligence system of decision-making artificially, was applied to establish the route choice model as the existing researches had a lot of difficulties in handling complexity and uncertainty contained in the human conscious structure and decision-making process. In

addition, panel data was used as Learning Data to teach neural network model and all the learning data was converged to Pre-process Normalization, that is, normalized data of [0,1] (the average value and the standard deviation) which is converged again to the actual value afterwards through Post-process. Error Back Propagation Algorithm, which is widely used for teaching of neural network model, was applied to analyze the indexes of each model. And through the comparison between the predicted value and actually measured value, hit ratio was calculated. Neural network system model was established with the application of each variable. Providing that the number of Node in the input layer is n, the number of node in the hidden layer is changed from n to 6n to sort optimal neural network model. In addition, for every 10,000 time of repetition, trials were performed by models to analyze the learning effect according to the number of processing elements in the hidden layer. For the period of more than 10,000 times, the training was repeated to the maximum repetition times and the level of generalization and effectiveness of the model was decreased while for the period of around 10,000 times, the best result was obtained. Accordingly, in this research, the repetition times for the model were fixed to 10,000 times. In the training for correction of neural network, Momentum-Adaptive Learning Rate was used to prevent the convergence of errors to Local Minima in time of application of the algorithm and to increase the effectiveness of learning. Momentum constant and the initial learning rate were obtained through the analysis on sensitivity. In all the models, 0.4 was used collectively. The standard of evaluation on the models gained through a set of processes was examined with both graphic standard and numerical standard. As a graphic standard, simulated value and measured value for Training and Verification were illustrated on the dispersion for evaluation.

## 3.6 Comparison and Study on the Assumed Route Choice Models

To compare the three models for RP and SP data, hit ratio of MNL model, average *Pi* value of Fuzzy Inference System Model and *MSE* (Mean Square Error) of Neural Network System Model were used as the indexes of effectiveness. Average *Pi* value represents the appropriateness of route choice results as provided in the following formula (4).

$$Pi(average) = \frac{\sum_{i}^{n} |R_i - P_i|}{n}$$
(4)

*n* : Number of Data,  $R_i$  : Actually Measured Value,  $p_i$  : Predicted Value

Where  $R_i = \begin{pmatrix} 1 & \text{if a route is chosen} \\ 0 & \text{otherwise} \end{pmatrix}$  and Pi is proposition of drivers choosing an alternate route. Moreover, *MSE* (Mean Square Error) was used to show the global goodness and to evaluate the performance of general neural network as provided in the following formula (5). If the value of *MSE* is 0, observed value matches with predicted value perfectly.

$$MSE = \frac{\sum_{i=1}^{n} (obs_i - \exp_i)}{n}$$
(5)

*n* : Number of Data,  $obs_i$  : Target value,  $exp_i$  : Output Value

$\overline{}$	MNL Model		FIS Model		NNS M	odel		
$\backslash$	Variable		Estimate	t-Value	Variable		Variable	
	Travel Time		-0.099	-2.186				
W A V	Troval	KR	0.307	6.647	Perceptions of Travel Time on the Three Alternatives			natives
	Experience	PR	0.178	8.458	(Fast, Medium, Late)			
		CR	0.255	3.890	Experience on the three alternatives (Few, Medium, Many)			
	Constant	KR	-0.236	-0.429				
E		PR	0.753	1.683				
1	Pi (average	Pi (average)		354	Pi (average)	0.283	Pi (average)	0.05
	MSE	875	0.4	102	MSE 0.371 MSE		0.015	
	Hit ratio (	%)	79	.10	Hit ratio (%) 79.79 Hit ratio (%)			93.90
w	Iravel 11m	e VD	-0.220	-0.445				
	Travel Experience		0.232	2.978	Perceptions of Travel Time on the Three Alternatives (Fast, Medium, Late) Experience on the three alternatives (Fay, Medium, Moany)			natives
		CD CD	0.102	1.302				
A		- VD	0.232	1.034				
V F	Constant		-0.203	0.421	(Few, Meuluin, Maily)			
2		РК	0.223	0.309			<u></u>	
4	Pi (average	)	0.5	83	Pi (average)	0.567	Pi (average)	0.168
	MSE	N7	0.7	//6	MSE	0.759	MSE	0.171
	Hit ratio (	%)	4/	.02	Hit ratio (%)	50.00	Hit ratio (%)	93.33
	Iravel 11m	e - 12 b	-0.449	0.059	<b>D</b> (*	¢т 1т		
***	Travel	- 70 - 70	0.525	2.005	Perceptio	ns of fravel 11me	e on the Inree Alteri	natives
Ŵ	Experience	CD.	0.411	1 257	г	(Fast, Meu	three alternatives	
v		- VD	1 263	1.357	(Few Medium Many)			
Ě	Constant	- PP	-0.653	-0.751		(1 0 %) 11100	(unity ivituity)	
ĩ	Pi (average	<b>.</b>	0.4	120	Pi (average) 0.360 Pi (average) 0.074			0.074
	MSE		Ŏ.5	521	MSE	0.458	MSE	0.025
	Hit ratio (%)		64 29		Hit ratio (%)	68.00	Hit ratio (%)	94 10

Table 4. Comparison of Estimated Driver's Route Choice Behavior Model (RP)

Table 5. Comparison of Estimated Driver's Route Choice Behavior Model (SP)

$\overline{}$		MNL	Model		FIS N	FIS Model		NNS Model	
	Variable		Estimate	t-Value	Variable		Variable		
	Travel Time		-0.140	-23.608					
	Traval	KR	0.345	2.199	Percepti	ons of Travel Time	e on the Three Alte	ernatives	
W	Experience	PR	-0.387	-0.255	-	(Fast, Medium, Late) Experience on the three alternatives			
A V		CR	0.579	3.366					
	Constant	KR	0.328	2.366		(Few, Med	ium, Many)		
E		<u>PR</u>	0.642	4.030					
1	Pi (average	9	0.4	12	Pi (average)	0.306	Pi (average)	0.232	
	MSE	n7	0.4	58	MSE 0.398 MSE		0.281		
	HIL FALLO (	<i>%</i> 0)	/3.58		HIL Fatio (%)	/5.12	HIL Fallo (%)	80.12	
W	Iravel 1ime		-0.148	-21.494					
	Travel Experience	KK ND	0.077	3./14	Perceptions of Travel Time on the Three Alternatives (Fast, Medium, Late) Experience on the three alternatives (Few, Medium, Many)			ernatives	
		rk CD	0.035	1.210					
A V		- VD	0.070	2.505				)	
ř	Constant	- 70	0.297	1.045					
2	Pi (average)		0.220	1.050	Pi (average) 2 0 276 Pi		Pi (average)	0.108	
_	MSE	2			MSE	0.363	MSE	0.241	
	Hit ratio (	<b>%</b> ]	75	.78	Hit ratio (%)	79.12	Hit ratio (%)	83.78	
	Travel Tim	ie	-0.179	-20.091	``´´				
	Traval	KR	0.086	2.248	Perceptions of Travel Time on the Three Alternat			ernatives	
W	Fynerience	("PR"	0.078	2.624	(Fast, Medium, Late) Experience on the three alternatives				
Α	Ехрегинее	CR	0.144	3.536			5		
V	Constant	KR	0.114	0.579		(Few, Medi	ium, Many)		
E		<u>PR</u>	0.151	0.653					
3	Pi (average)		0.3	<u>512</u>	Pi (average)	0.254	Pi (average)	0.175	
	MSE	A7	0.3	579	MSE	0.301	MSE	0.218	
	Hit ratio (%)		81	.49	Hit ratio (%)	82.12	Hit ratio (%)	84.32	

In the model assumed with RP and SP data in the Table 4 and Table 5, the hit ratio of models with Fuzzy Inference is higher than that of MNL model and the average  $p_i$  value, which is the evaluation index of Fuzzy Model, is lower than that of MNL model. Moreover, the hit ratio of neural network theory model is much higher than those of MNL model or FIS model recording wave1=98.90%, wave2=93.33%, wave3=98.00% for RP data and wave1=80.12%, wave2=83.78%, wave3=84.32% for SP data. And the *MSE*, the evaluation index of neural network model was recorded much lower than those of MNL model or FIS model. Based on the results above, the hit ratio of neural network system theory model was the highest as a model for explanation of non-linearity contained in the decision-making process of drivers regarding route choice.

## 4. DYNAMIC ROUTE CHOICE BEHAVIOR MODEL

As preference is in the process of adaptation all the time, problems occur unavoidably in the existing cross section model, which assumes the equilibrium. Thus, dynamic model is necessary. The purpose of this research is to apply neural network theory, which has the highest hit ratio in the static models, to the state-dependency and to make dynamic model.

## **4.1 Outline of State-Dependent Model**

This model is based on the assumption that personal state is always in the process of adaptation. People have to adapt themselves to new circumstances as the surroundings or social/economic properties change. However, the adaptation is not done immediately but through the recognition of changed environmental information and experimental researches that is called 'Adaptation Process.' The trend of preference was marked in the following Figure 5.



Figure 5. The trend of preference in the cross section model

Figure 5 provides the preference on the vertical axis and the time on the horizontal axis. Supposing that a car is owned a person of the first generation now and that 2 cars are purchased by this generation, the existing cross section model provides the trend of preference illustrated in the Figure 5. In this figure, preference changes instantly according to the environmental changes. Preference Y(t-1) in time of (t-1) and Preference (t-1) in time of t are decided by  $X^2$  (the proposition that a generation owns two cars) disregarding other social/economic properties and traffic situation. Y(t-1) and Y(t) are in the static balance and time transferability can be secured in the stochastic model for each point of time. Moreover, preferences before and after the change of state are in the independent relationship. Thus, the assumption established by cross section model mentioned above is abandoned. The trend of preference in the dynamic model is provided in the following Figure 6 with the preference on the vertical axis and the time on the horizontal axis. Supposing that human beings have to go through adaptation for the changes of state, the trend of preference can be presented just like in the Figure 6. If the preference reaches to the state of balance,  $Y^*$  when the number of cars owned by one generation does not change from 1 to 2, the  $Y^*$  depends on the  $X^2$  establishing the following formula (6).



Figure 6. The trend of preference in the dynamic model

Y(t), the preference in the point of time, 't' is provided like below:

$$Y(t) = (1 - \beta)(Y^* - Y(t - 1)) + Y(t - 1) + \varepsilon = \beta Y(t - 1) + (1 - \beta)\alpha Y(t) + \varepsilon$$
(6)

In the formula (6) above, Y(t), the present preference depends on Y(t-1), the past preference. It is the State-Dependency. From this proposition, the following formula is established:

if 
$$\beta = 0.0$$
 then  $Y(t) = Y(t-1)$   
if  $\beta = 1.0$  then  $Y(t) = Y^*$  (7)

The formula above means that  $\beta$  is in the range between 0 and 1 and that the higher the value of  $\beta$  is, the smaller changes exist in the preference from t-1 to t. On the contrary, the closer  $\beta$  approaches 0, the more dependent Y(t-1) and Y(t) are with closer state of Y(t) towards balance, that is, the State-Dependency. For the dynamic modeling taking the effect of state-dependency into account, there are three known methods like following; First, the introduction of stochastic value into the model after respective optimization in each point of time; Second, the introduction of actually measured value exteriorly into the model for optimization; Lastly, execution of optimization simultaneously in multi-points of time. In this paper, the last method was utilized using neural network theory to optimize the multi-points of time through learning and establishing dynamic model. Moreover, dynamic neural network model was established using panel data in order to clarify the cause and effect between points of time in this research.

## 4.2 Dynamic Neural Network Model Taking the State-Dependency into Account

In this research, the models illustrated in the Figure 7 and 8 were established to form the models taking the state-dependency into account using neural network theory. It is assumed that the choice of the previous point of time (wave t-1) affects the choice of the present point of time (wave t) in the dynamic neural network model and that the influence of the state-dependency is consistent all the time regardless of the length of time passed from the initial panel research time. In this research, the serial lag correlation by error terms was not

taken into consideration to simplify this problem. It has to be noted that the previous choice of the initial panel research time (wave 1) is not considered for the modeling.



Figure 7. The 2 times point NNmodel

Figure 8. The 3 time point NNmodel

## 4.2.1 Two-time Neural Network Model Taking the State-Dependency into Account

The results of the 2 time point model taking the state-dependency into account is provided in the following Table 6. For RP data, the explanatory variable applied to the model is the answer data of the respondents for the items of fast, normal and late of travel time on the Kirin-Ro, Paldal-Ro and Cheonbyeon-Ro as travel time variables; the usage frequency of Kirin-Ro, Paldal-Ro and Cheonbyeon-Ro respectively as private property variables while the choice result of t-1 was used in the Model 1 and Model 2 and that of t-2 was used in the Model 3. For SP data, travel time on the Kirin-Ro, Paldal-Ro and Cheonbyeon-Ro as travel time variables; the usage frequency of Kirin-Ro, Paldal-Ro and Cheonbyeon-Ro respectively as private property variables while the choice result of t-1 was used in the Model 1 and Model 2 and that of t-2 was used in the Model 3. State-dependency model including the past preference data in the present traffic conditions is provided in the Table 6. Among the models using RP panel data, Model 1 is established with the present travel time information based on the Wave2 as the present point of time, the present travel experiences and the choice results of Wave 1 as an explanatory variable; Model 2 is established with the present travel time information based on the Wave 3 as the present point of time, the present travel experiences and the choice results of Wave 2 as an explanatory variable; and Model 3 is established with the present travel time information based on the Wave 3 as the present point of time, the present travel experiences and the choice results of Wave 1 as an explanatory variable. In addition, among the models using SP panel data, Model 4 is established with the present travel time information based on the Wave 2 as the present point of time, the present travel experiences and the choice results of Wave 1 as an explanatory variable; Model 5 is established with the present travel time information based on the Wave 3 as the present point of time, the present travel experiences and the choice results of Wave 2 as an explanatory variable; and Model 6 is established with the present travel time information based on the Wave 3 as the present point of time, the present travel experiences and the choice results of Wave 1 as an explanatory variable. To find out the state-dependency of the models above, comparison between the models was performed with MSE and hit ratio.

The results of comparison between the Model 1 and Model 2, the *MSE* and hit ratio of Model 2 was recorded slightly higher than those of Model 1 showing that Model 2 has more influence on the choice results of t-1 than Model 1. The *MSE* and hit ratio of Model 3 was recorded lower than those of Model 1 and Model 2 showing that the route choice result of t-1 has more influence on the point of time 't' rather than t-2. The *MSE* and hit ratio of Model 5 was recorded slightly higher than those of Model 4 showing that Model 5 has more influence on the choice results of t-1 than Model 4. The *MSE* and hit ratio of Model 6 was recorded lower than those of Model 4 and Model 5 showing that the route choice result of t-1 has more influence on the point of time 't' rather than t-2. For Model 1  $\sim$  Model 6, the values of *MSE* and hit ratio of all of them were recorded significantly high. It means that the present route choice behavior and preference route have more influence on the present route choice behavior as well as the current traffic conditions.

The 2-time point model taking the state-dependency (RP)								
MOD	DEL 1	MOI	DEL2	MODEL 3				
(Wave1-	→Wave2)	(Wave2-	→Wave3)	$(Wave1 \rightarrow Wave3)$				
Vari	Variable Variable			Variable				
Perce	ptions of Travel	Time on the th	ree alternatives	(Fast, Medium,	Late)			
	<sup>•</sup> Experience or	the three altern	natives (Few. M	edium. Manv)	,			
	I	Choice Result of	of (Wave $t-1$ )	,, <b>,</b> , , , , , , , , , , , , , , , , ,				
MSE	MSE   0.068   MSE   0.06		0.066	- MSE	0.110			
Hit ratio (%) 96.00		Hit ratio (%) 96.67 Hit ratio (		Hit ratio (%)	94.00			
	The 2-time point model taking the state-dependency (SP)							
MODEL 4		MOD	DEL 5	MOD	DEL6			
$(Wave1 \rightarrow Wave2)$		(Wave2-	→Wave3)	$(Wave1 \rightarrow Wave3)$				
Perce	ptions of Travel	Time on the th	ree alternatives	(Fast, Medium,	Late)			
Experience on the three alternatives (Few, Medium, Many)								
Choice Result of (Wave )								
MSE	0.197	MSE	0.196	MSE	0.214			
Hit ratio (%)	84.48	Hit ratio (%)	84.50	Hit ratio (%)	82.16			

Table 6. The results of the 2-time point model taking the state-dependency

# **4.2.2** Establishment of General Model of 3 Point of Time of Neural Network System Taking the State-Dependency into Account

In this research, the result of the establishment of the 3 point of time general model taking the state-dependency into account was provided in the Figure 7 which is the state-dependency model including the past preference result in the present traffic conditions. Model 7 that used the RP panel data was established with the present travel time information, the present travel experiences, the choice results of Wave 1 and Wave 2 as the explanatory variable, based on the Wave 3 as the present point of time. And Model 8 that used the SP panel data was established with the present travel time information, the present travel experiences, the choice results of Wave 1 and Wave 2 as the explanatory variable, based on the Wave 3 as the present point of time followed by the comparison between MSE and hit ratio, the effectiveness indexes of neural network model to find out the state-dependency of models. The MSE and hit ratio of Model 7 was recorded slightly higher than those of Model 1~Model 3 showing the proposition that they can have more influence on the models that use the choice results of and as simultaneous explanatory variables than those that use the choice results of or as respective explanatory variables. And the MSE and hit ratio of Model 8 was recorded slightly higher than those of Model 4~Model 6 showing the proposition that they can have more influence on the models that use the choice results of and as simultaneous explanatory variables than those that use the choice results of or as respective explanatory variables. In addition, the result of establishing the 3 point of time general model taking the statedependency into account with neural network was recorded very high to form a reasonable model.

The 3-point of time general model taking the state-dependency					
MODEL 7 (RP) MODEL 8(SP)					
$(Wave1 \rightarrow Wa)$	$ve2 \rightarrow Wave3)$	$(Wave1 \rightarrow Wave2 \rightarrow Wave3)$			
Variable Variable					
Perceptions of Travel Time on the three alternatives (Fast, Medium, Late)					
Experience on the three alternatives (Few, Medium, Many)					
Choice Result of (Wave $t-1$ )					
MSE 0.04 MSE 0.165					
Hit ratio (%)	97.33	Hit ratio (%)	86.07		

Figure 7. The 3-point of time general model taking the state-dependency

## **5. CONCLUSION**

In this research, the Fuzzy Theory and Neural Network Theory were used to understand the drivers' route choice behaviors clearly under the provision of travel time related information as the existing researches had a lot of difficulties in handling many errors generated by non-linearity and time and space diversity contained in the human consciousness and decision-making process. Thus, the route choice behavior model was established with neural network

theory in order to make a model considering a lot of errors generated by non-linearity and time and space related diversity in this research. As the result of the modeling above, the hit ratio of the route choice behavior model recorded much higher than that of exist the Logit Model and Fuzzy Theory Model showing its rationality. More than anything else, for the 3 approach routes towards the center of Jeonju City, dynamic neural network model was established with the route preference panel data based on the travel time information provision in order to examine the factors that influence the route choice of road users. The examination results are provided in the following paragraph:

First, through the modeling of route choice behavior, the fact was found out that users consider the road travel experience as well as travel time information.

Second, the neural network model was proved to be reasonable with higher hit ratio than MNL model through the establishment of neural network model that can be applied with learning and revision to increase the effectiveness.

Third, according to the evaluation results on the appropriateness of general models, neural network model recorded higher marks in MSE and hit ratio showing its reasonableness.

Lastly, according to the evaluation results on the validity with the concept of statedependency in the dynamic neural network model, a model that considered the statedependency recorded higher mark in the appropriateness than a model that didn't do it. Thus, it was proved to be proper to introduce state-dependency to dynamic model.

The future research task is to combine Fuzzy-Neuro Theory, DNA Theory and Chaos Theory with existing research results, to simulate this model for the application of it in the actual traffic situation and to predict the traffic volume on each route.

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