Modeling Departure Time Adjustment Behavior Considering Travel Time Variability Using Adaptive Neuro-Fuzzy Inference System

Amr M. Wahaballa[1], Fumitaka Kurauchi[2], Akiyoshi Takagi[3] and Ayman M. Othman[4]

[1]Visiting Academics, Dept. of Civil Eng., Gifu University / PhD researcher, South Valley University, Egypt.
(1-1 Yanagido, Gifu City 501-1193,Japan)
E-mail: gif122@gifu-u.ac.jp
[2]Associate Professor, Dr. of Eng., Dept. of Civil Eng., Gifu University
(1-1 Yanagido, Gifu City 501-1193,Japan)
E-mail: kurauchi@gifu-u.ac.jp
[3]Professor, Dr. of Eng., Dept. of Civil Eng., Gifu University
(1-1 Yanagido, Gifu City 501-1193,Japan)
E-mail: a_takagi@gifu-u.ac.jp
[4]Associate Professor, Dr. of Eng., Dept. of Civil Engineering, South Valley University
(Abuelresh Kebly, Aswan 81542, Egypt)
E-mail: ay_othman@mail.com

In this paper, a departure time choice model is developed, taking into account that drivers face an uncertain travel time due to opening a new expressway. A departure time choice model considering travel time variability is estimated by applying the Adaptive Neuro-Fuzzy Inference System (ANFIS). This paper attempt to study departure time choice behavior as a result of travel time reliability improvement based on the actual traveler behavior collected by ETC. To investigate the effectiveness of ANFIS model, the strengths and weaknesses of the developed model are examined by comparing the predicted departure time with the actual values. An evaluation of the model indicates that ANFIS model is a good model for representing departure time choice adjustment.

Key words : *Departure time choice behavior, Travel time reliability, Travel time variability, Adaptive Neuro-Fuzzy Inference System (ANFIS).*

1. INTRODUCTION

Travel choice behavior have been addressed in various researches. However, existing models set limits to examine non-linearity occurred by variety of human conscious structure and process of decision-making[1)]. Recently, intelligence system approaches such as neural network and neuro-fuzzy methods have been used successfully for different transportation models[1)-2)-3)].

Van Lint, and van Zuylen [2)] developed a two layer feed forward neural network model summarizes the day to day travel time distribution for different time of day and day of the week. Lee, et. al[1)] linked Artificial Neural Network (ANN) with Genetic Algorithm (GA) to perform road choice behavioral model based on stated preference survey. In the area of mode choice modeling, Tortum, et. al [3)] compare results of ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) models to regression model to model fright transport mode choice and concluded that ANN and ANFIS models are more successful in modeling mode choice behavior of intercity freight transport compared to the classical models.

In a previous research by the authors[4)], travelers were changed their departure time significantly after opening Shin-Meishin expressway. In this paper we attempt to model traveler's departure time adjustment behavior after opening a new expressway (Shin- Meishin expressway) using ANFIS based on Electronic Toll Collection (ETC) data. Our analysis is based on the assumption that travelers' behavior due to reliability improvement is related to their change in departure time.

This paper is structured as follows. In the next section, neuro-fuzzy system will be reviewed. In section 3 and section 4 we will describe study site and data used for this study. Thereafter, in section 5, model will be developed. Then, in section 6 model results will be discussed. Finally, section 7 concludes.

2. NEURO-FUZZY NETWORK

Intelligent systems possess human-like expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions[5]. Neuro-Fuzzy is among the most successful intelligent systems techniques. A neuro-fuzzy network consists of two parts; neural network and fuzzy system. Composition of these two parts would lead to a neuro-fuzzy network which enables the information that is stored in trained networks to be expressed in the form of a fuzzy rule base[6].

(1) Artificial neural networks

Artificial neural network looks like human brain neuron cells. These neurons are working as a neural cell able to receive and send information. In general, a simple form of an artificial neural network is shown in **Fig.1**. Input data are entered as a standardized parameter *p*, and then input information are multiplied by a weight and added to a bias *b*. Then the calculated value is put in a function *f* and after that the neuron outputs form a column vector (a) which follows the same procedures via the next hidden layer (i.e. outputs of every layer could be considered as inputs for next layer).

Artificial neural network consists of one or more hidden layers and each layer includes several neurons. After the last hidden layer, final single or multiple outputs will be formed. As shown in **Fig.1**, multiple hidden layers uses layer weight (LW) matrices as well as input weight (IW) matrices. The network shown in **Fig.1** has *R* inputs, S^1 neurons in the first layer, S^2 neurons in the second layer, etc. different layers may have different numbers of neurons. A constant input 1 is fed to the bias for each neuron. The expression for (a) is calculated as follows.

$$a = f\,(W_P + b) \quad (1)$$

$$a^1 = f^1\,(IW^{1,1}{}_P + b^1) \quad (2)$$

$$a^2 = f^2\,(LW^{2,1}{}_a{}^1 + b^2) \quad (3)$$

$$a^3 = f^3\,(LW^{3,2}{}_a{}^2 + b^3) \quad (4)$$

At the end the formed output is compared with the target value, and then the error will be calculated and spread through the variable values (w and b) of the network. This process is called network training and it will be continued while the error amount is near to zero or a certain value specified by developer[7].

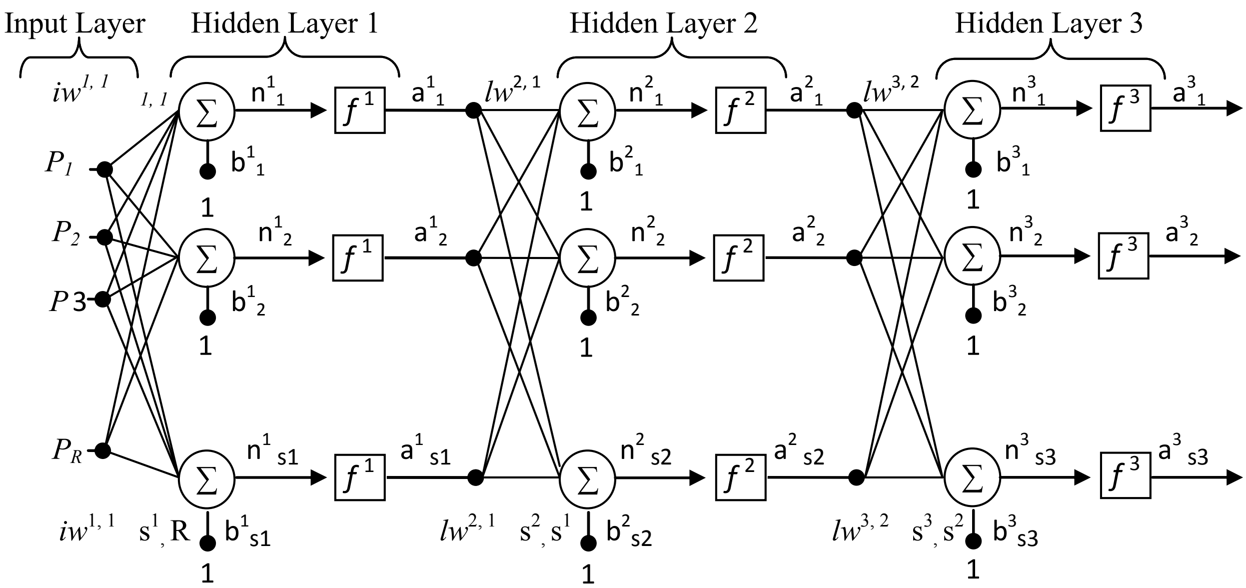

Fig.1 General form of artificial neural network

(2) Adaptive neuro-fuzzy inference system (ANFIS)

Fuzzy modeling is generating a fuzzy inference system that can predict and explain the behavior of an unknown complex problem described by a set of sample data[8]. A fuzzy inference system utilizes fuzzy if-then rules to model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. The most important fuzzy inference system is Sugeno fuzzy model[9].

The ANFIS uses fuzzy logic to account for a hidden imprecision in data and to make accurate mapping accordingly[10)-11)]. This is done by fuzzification of the input through membership functions, where a curved relationship maps the input value within the interval of [0–1]. The parameters associated with input as well as output membership functions are trained using back-propagation and/or least squares. The back-propagation learning rule is exactly the same as that used in the common feed-forward neural-networks[12]. In ANFIS, fuzzy rules or conditional (if-then) statements are determined in order to train the system. Selection of the structure of fuzzy inference system (FIS) includes selecting relevant input variables, determining the number of fuzzy rules and determining the type and number of membership functions[13]. For Sugeno fuzzy model, a typical rule set can be expressed as[14]:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x+q_1y+r_1$ (5)

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x+q_2y+r_2$ (6)

Where A_1, A_2 and B_1, B_2 are the membership functions for inputs x and y, respectively; p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. **Fig.2** (a) and (b) illustrates the fuzzy reasoning mechanism and the corresponding ANFIS architecture, respectively.

As shown in the figure, in the same layer, node functions should by similar. Noting that O^j_i denotes the output of the ith node in layer j, the functioning of the ANFIS is as follows[3]:

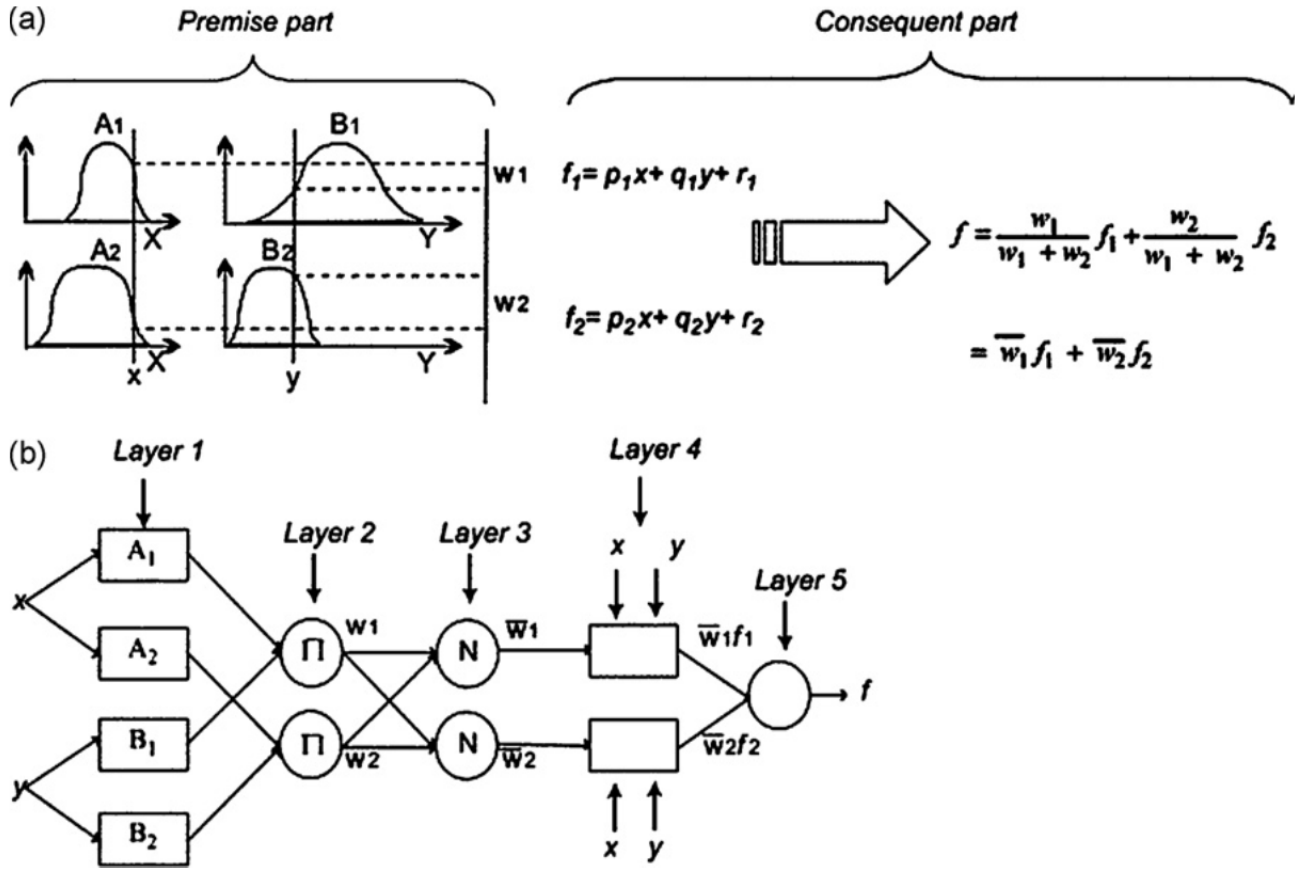

Fig.2 (a) Sugeno's fuzzy if then rule and fuzzy reasoning mechanism; (b) equivalent ANFIS architecture.

Layer 1: Each node in this layer generates membership grades of an input variable. The output. of the ith node might be:

$$O_i^1 = \mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{7}$$

Where x (or y) is the input to the node; A_i (or B_i) is a fuzzy set associated with this node, and a_i, b_i, c_i are the parameters set that changes the shapes of the membership function, the a generalized bell function is assumed here. Parameters in this layer are referred to as the "premise parameters".

Layer 2: Each node in this layer multiplies the incoming signals, denoted as π, and the output O^1_i that represents the firing strength of a rule is computed as[3)]:

$$O_i^2 = w_i = \mu A_i(x) x \mu B_i(y), \qquad i = 1,2 \tag{8}$$

Layer 3: The ith node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths (normalized firing strengths)[3)]:

$$O_i^3 = \acute{w}_i = \frac{w_i}{w_1+w_2}, \qquad i = 1,2 \tag{9}$$

Layer 4: Every node i in this layer is a square node with a node function[3)]

$$O_i^4 = \acute{w}_i f_i = \acute{w}_i (p_i x + q_i y + r) \tag{10}$$

Where $\acute{w}_i$ is the output of layer 3, and is the parameter set. Parameters in this layer will be referred to as "consequent parameters".

Layer 5: The single node in this layer is a circle node labeled R that computes the ''overall output" as the summation of all incoming signals, i.e.

$$O_i^5 = \text{overall output} = \sum_i \acute{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{11}$$

Therefore, an adaptive network is presented in **Fig.2** (b), which is functionally equivalent to a fuzzy inference system in **Fig.2** (a). From the ANFIS architecture in **Fig.2**, it is observed that given the values of premise parameters, the overall output f can be expressed as a linear combination of the consequent parameters[3)].

3. RESEARCH NETWORK

The Meishin expressway is a major intercity expressways in Japan. The new expressway (the Shin-Meishin expressway) has operated in February 23, 2008. **Fig.3** illustrates the network used for this research. As shown in **Fig.3**, the Shin-Meishin expressway provides an alternative to users traveling from locations east of the Toyokawa Interchange (IC) to locations west of the Seta IC. Travelers who travel from locations east of the Toyokawa IC to areas west of the Seta IC may take the Shin-Meishin expressway due to the shorter distance. Therefore, the changes in travelers' departure time choice were modeled. All ETC entrance gates east of the Toyokawa IC and ETC exit gates west of the Seta IC are studied to model travelers' departure time choice behavior.

Fig.3 Research network

4. DATA

Modeling the effect of improvements in the travel time reliability depends upon accurate and sufficient data of departure time and travel time. Because more than 85% of cars in Japan are now equipped with ETC devices, it is now possible to acquire actual behavior of individual traveler based on his/her ETC card data.

By regarding the entry time of individual to the highway as departure time, this can be used to model traveler's departure time choice behavior. ETC data observed on Meishin expressway in the year before the opening of Shin-Meishin expressway (2007) and the year after opening it (2008) was used for calculating the average, median travel time and several indices representing travel time reliability.

The data for the period from January, 1st, 2008 to February 23rd, 2008 are excluded from 2008 data because the new Shin-Meishin expressway was not in operation during this period. Most frequent travelers used the selected IC pairs during that period are assumed to represent the departure time choice behavior of all car drivers using this road due to their experience about the travel time variations of each route. The travelers selected to study their behavior were who made at least two trips per month at the same time of day in 2007 and 2008. Their behavior was analyzed to observe changing their departure time toward improving travel time reliability for the morning commuting peak period (6~9.59), Day time (10~16.59), afternoon peak period (17~21.59), and evening time (22~5.59). ETC data was used as learning data to learn the neuro-fuzzy model. All learning data was normalized, where the mean and standard deviation is [0, 1].

5. MODEL DEVELOPMENT

Departure time adjustment due to the opening of the new expressway is approximated based on actual traveler behavior during a year before opening Shin-Meishin expressway and a year after that. The difference between average departure time in 2007 and 2008 of a certain traveler was related to the difference in his/her average travel time, the difference in variance or the difference in standard deviation between 2007 and 2008 for that traveler at that time of day. The free flow travel time was included to represent and determine using of old Meishin expressway or using the Shin-Meshin expressway and calculated as the minimum average travel time of any traveler between each IC pair at a certain time period. Traveler who has average travel time greater than three times the free flow travel time or his difference in departure time exceeds one third of the free flow travel time is reasonably considered outlier observation and excluded from modeling dataset. The structure of the model is as follows:

$$\Delta \text{ Departure time} = f\,(\Delta\mu,\ \Delta V \text{ (or } \Delta\sigma),\ \Delta FFTT,\ TOD) \qquad (12)$$

Where:

$\Delta\mu$ is the change in mean travel time,

ΔV is the change in variance of travel time,

$\Delta\sigma$ is the change in standard deviation of travel time,

$\Delta FFTT$ is the change in free flow travel time, and

TOD is time of day (categorical value).

The independent variables (inputs) and the dependent variables (outputs) both are normalized. In search of best fitting, data sets used for training and testing are divided randomly. Several ANFIS models tried by changing the type and the number of membership functions for each of input variables in addition to try least square and hybrid functions and adjusting other parameters.

6. RESULTS

Based on trial and error approach, the number and type of membership functions for each input parameters ($\Delta\mu$, ΔV or $\Delta\sigma$, $\Delta FFTT$, and TOD) were set.

The parameters are trained using least squares algorithm individually or combined with back-propagation algorithm (hybrid). Fuzzy rules used is (if-and), and the number of epochs are changed reasonably to prevent over-fitting or under-estimation. In addition, other characteristics of ANFIS such as data range are adjusted toward best model. The previous steps are generated for standard deviation and variance to find which of them give best fit model. It is worth noting that, in the presented results, using difference in variance instead of difference in standard deviation gives best fit model. It is noted also that Gaussian membership function had better results than other membership functions.

The structure of best ANFIS model used here is shown in **Fig.4**. Seventy five percent of the data were used on training and the remained twenty five percent were used for the testing. The fitting of estimated values of departure time change to real values can statistically be approved though root mean square error (RMSE) values. The matching between data used for training the model and the data resulted from Fuzzy Inference System (FIS) model is an indication of fitness. In other words the smaller the dispersion between actual data and predicted data indicates the excellence of the model to represent actual data. **Fig.5** shows the fitting between training data and corresponding data predicted by ANFIS model. Also, **Fig.6** presents the goodness of the model through plotting the actual data used for testing the model together with predicted data. It is concluded that ANFIS model showed higher adaptation rate reflected by matching of predicted values with real values.

ANFIS model results can be used to give an overview of travelers' departure time adjustment behavior due to travel time and travel time reliability improvements. Based on the developed model, **Fig.7** summarizes the behavior of travelers to adjust their departure time (output) as a result of the change in travel time (input1) and the change in variance (input2). It can be seen from **Fig.7** that travelers tends to change their departure time according to reliability improvement.

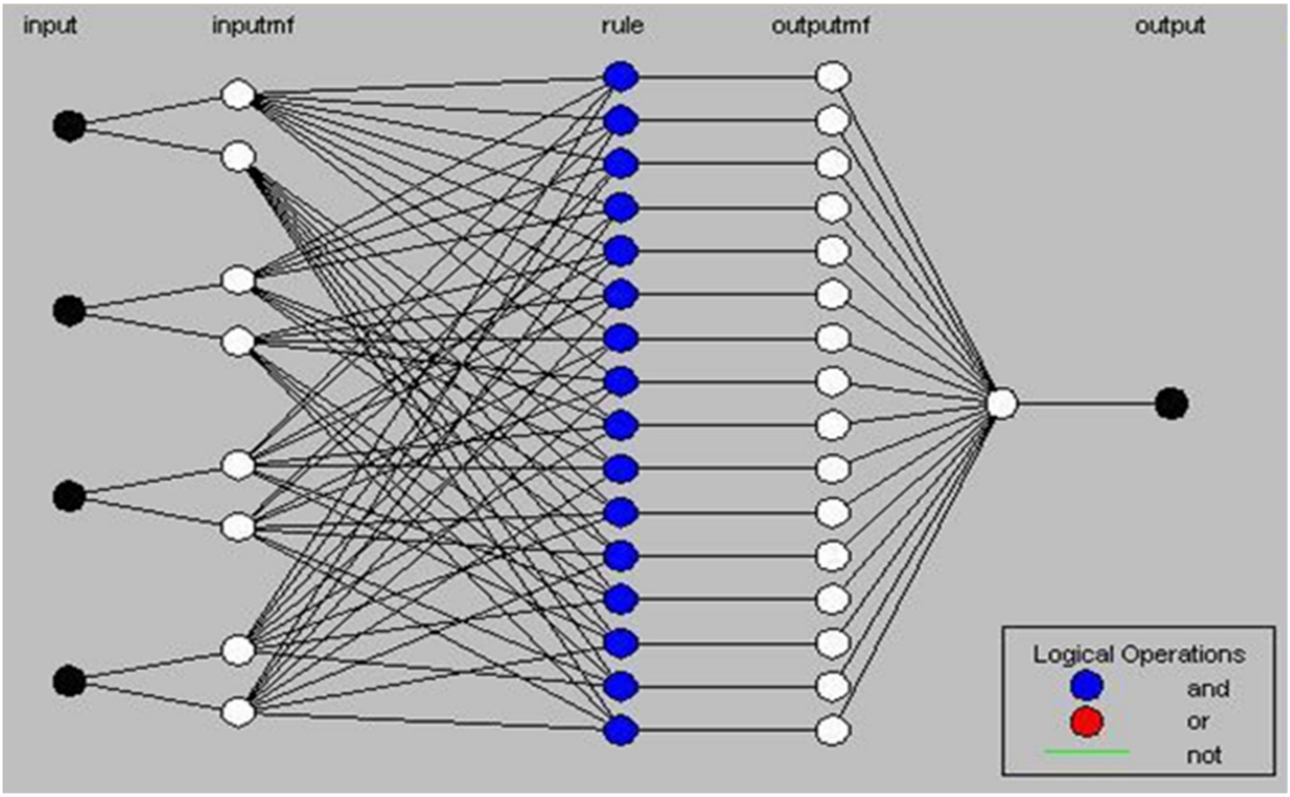

Fig.4 Structure adaptive neuro-fuzzy inference system model developed.

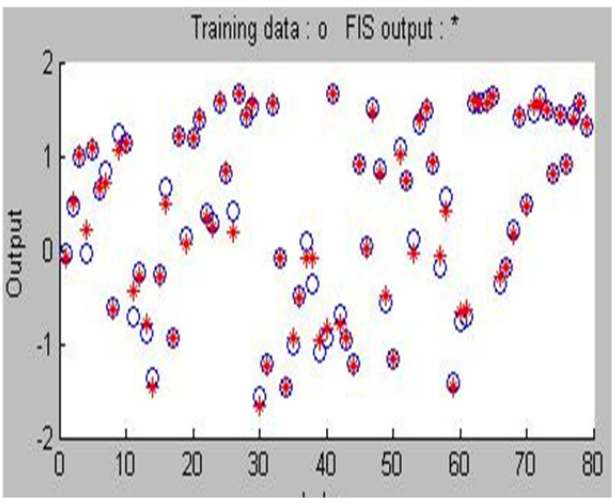

Fig.5 Fitting of actual data used for training with the values predicted by ANFIS model

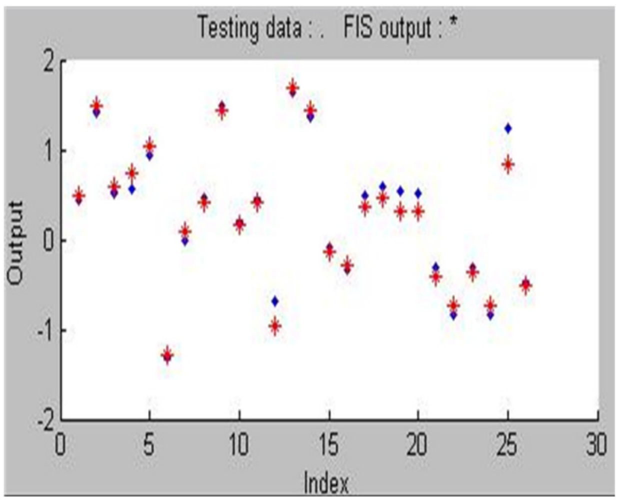

Fig.6 Fitting of actual data used for testing with the values predicted by ANFIS model

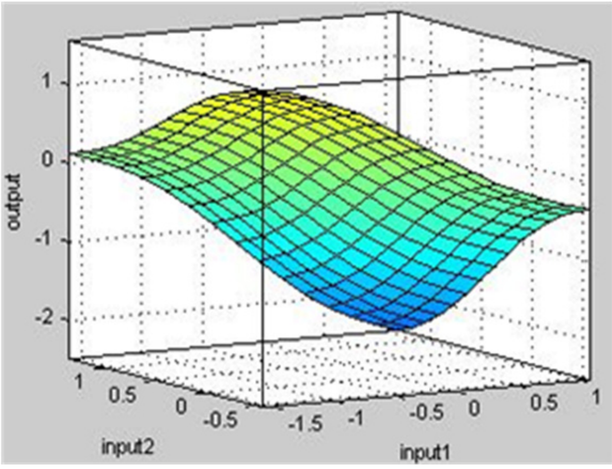

Fig.7 adjusted departure time (output) as a result of the change in travel time (input1), and variance (input2)

ACKNOWLEDGMENT

The data used in this study have been provided from NEXCO-West, Japan. We also thank the Institute of Systems Science Research for the ETC data handling.

REFERENCES

1) Lee, S., Kim, Y., Namgung, M., and Kim, J.: Development of route choice behavior model using linkage of neural network and genetic algorithm with trip information. *KSCE Journal of Civil Engineering*,Vol. 9 (4), pp. 321-327, 2005.
2) Van Lint, J.W.C., and van Zuylen H.J.: Monitoring and predicting freeway travel time reliability. *Transportation Research Record*, Vol. 1917, pp. 54-62, 2006.
3) Tortum, A., Yayla, N., Gokdag, M.: The modeling of mode choices of intercity freight transportation with the artificial neural networks and adaptive neuro-fuzzy inference system. *Expert Systems with Applications*, Vol. 36, pp. 6199–6217, 2009.
4) Wahaballa, A.M., Kurauchi, F., Takagi, A., and Othman, A.M.: Analysis of travelers' departure time choice behavior and travel time uncertainty recognition. *Journal of Al Azhar University Engineering Sector, JAUES*, Vol. 5(1), pp. 686-712, 2010.
5) Donald, A. W.: A guide to expert systems. Reading. MA: Addison-Wesley, 1986.
6) Zounemat-Kermani, M., Teshnehlab, M.: Using adaptive neuro-fuzzy inference system for hydrological time series prediction. *Journal of Applied Soft Computing*, Vol. 8, 928–936, 2008.
7) Flood, I., Kartam, N.: Neural networks in civil engineering I: principles and understanding. *Journal of Computer in Civil. Eng., ASCE,* Vol. 8 (2), 131–148, 1994.
8) Jang, J. S. R., Sun, C. T., and Mizutani, E.: Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence. London: Prentice Hall International (UK), 1997.
9) Takagi, T., and Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 15, 116–132, 1985.
10) Jantzen , J., “NeuroFuzzy Modelling”, Technical University of Denmark, 2005.
11) Wolkenhauer , O.: Fuzzy mathematics in systems theory and data analysis. John Wiley & Sons, Inc., 2001.
12) Rumelhart, D. E., Hinton, G. E., and William, R. J.: Learning internal representations by error propagation. In D. E. Rumelhart & James L. McClelland (Eds.), Parallel distributed processing: *Explorations in the microstructure of cognition*, Vol. 1–8, pp. 318–362, The MIT Press, 1986.
13) Buckley, J. J., and Hayashi, Y.: Fuzzy neural networks. In: R. R. Yager & L. A. Zadeh (Eds.), *Fuzzy sets neural networks and soft computing*, New York: Van Nostrand Reinhold, pp. 233–249, 1994.
14) Sugeno, M., and Kang, G. T.: Structure identification of fuzzy model. *Fuzzy Sets and Systems*, Vol. 28, pp.15–33, 1988.