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CALIFORNIA PATH PROGRAM  
INSTITUTE OF TRANSPORTATION STUDIES  
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# **EXPLORATION OF DRIVER ROUTE CHOICE WITH ADVANCED TRAVELER INFORMATION USING NEURAL NETWORK CONCEPTS**

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## **ABSTRACT**

A model of drivers' route choice behavior under advanced traveler information system (**ATIS**) is developed based on data collected from learning experiments using interactive computer simulation. The experiment subjected drivers to 32 simulated days in which they were to choose between a freeway or a side road. A neural network model is used as a convenient modeling technique in this initial phase of the analysis. The results indicated that most subjects made route choices based mainly on their recent experiences. Results also demonstrated that route choice behavior is related to the personal characteristics as well as the characteristics of the respective routes. Travel experiences had less effect on the choice of the side road compared to the freeway and the results indicate that the prediction accuracy of the model, the acceptance rate of advice, and the quality of advice are closely correlated. The model developed here was for advice consistently provided at a level of 75 percent accuracy. The paper concludes with a discussion of experimental limitations and suggestions for future research.

## **INTRODUCTION**

Recently, much interest has focused on the development of advanced traveler information systems (**ATIS**) as a "hi-tech" approach to aid the driver more informed route choices and to alleviating increasing levels of traffic congestion. An important issue in the implementation of these systems is to develop an understanding of how **ATIS** will affect drivers' behavior, how drivers will adopt and learn to use **ATIS** and how these changes will impact travel demand in the network. Several

methods have been used to study drivers' route choice behavior when influenced by **ATIS**. These methods, as summarized by Abdel-Aty et al. (1992), include: Field experiments (Catling and **McQueen**, 1991), route choice surveys (Khattak et al., 1992; Hatcher and Mahmassani, 1992), interactive computer simulation games (Bonsall and Parry, 1990, Krage and Mark, 1991;), route choice simulation and modeling (**Lotan** and Koutsopoulos, 1992; and Mahmassani and Chen, 1991) and stated preference approach (Haselkorn et al., 1991). Although significant advances have been made in these studies, results also suggest that more theoretical and empirical investigations need to be carried out in order to gain a basic understanding of drivers' choice behavior in the absence of information.

## COMPUTER-BASED SIMULATION EXPERIMENT

An experiment to investigate drivers' learning abilities and route choice behavior under **ATIS** was performed. The experiment developed through a collaborative effort between the Institute of Transportation Studies and the Psychology Department at UC Davis is carried out on an IBM compatible micro-computer using an interactive simulation program written in Turbo Pascal. The simulation experiment begins by presenting a set of instructions to the subject describing how the program operates. Subjects are instructed that their main task is to minimize their overall travel time by deciding when, and when not, to follow the advice provided by the transportation information system. Subjects are also told that their decision and response time, are being measured and that they should try to respond as quickly as they can. This experiment subjected drivers to 32 simulated days in which they were to choose one of two routes, either the freeway or a side road. The test subjects are told that they have purchased a new "Traffic Watch Device" which will provide **traffic** information prior to their route selection. The subjects are also told that the device will not always be accurate, but are not given any indication of its overall accuracy.

Upon completion of each trial, subjects were asked to rate their choice satisfaction, and to provide an estimate of their perceived travel time on their chosen route. Upon completion of 32 sequential simulated days, subjects were asked to rate their potential for purchasing a traffic information

device, their perceived accuracy of the device, and their own ability at selecting routes when compared to the information device. The data set used for this analysis was **based** on the choices made by 20 individuals. The simulation was run with 75 percent accuracy level and with feedback. A more detailed description of the route choice experiment can be found in a companion paper (Vaughn et al. 1992)

## NEURAL NETWORK CONCEPTS

Artificial neural networks have been widely studied for information processing. But recently there has been an increasing interest in application of neural network techniques to transportation engineering. In a recent conference held in California, different transportation application problems analyzed with neural networks have been reported including: classification and pattern recognition (Faghrin and Hua, **1992**), travel demand estimation (Yang et al., 1992; Shih-Miao Chin et al., **1992**), image processing (Bullock et al., 1992; Kaseko et al., **1992**), freeway incident detection (Richie et al., 1992) and driver route choice analysis (Dougherty and Joint, 1992). It is generally reported that the neural networks have the ability to accommodate complicated problems without the requirement of giving explicit equations correlating input/output data, and neural networks can generate reasonable results efficiently. The neural network approach utilizes an iterative data matching technique and is often confused with artificial intelligence (Berardinis 1992). This approach is being used as a quick and efficient method to analyze route choice behavior and as a comparative approach to conventional analysis methods (Vaughn et al. 1992).

Here, a neural network route choice model is constructed and used to analyze the driver route choice mechanisms under **ATIS**. UC Davis students were recruited to participate in the experiments. While the students participating in the experiment were quite diverse, they certainly are not intended to represent a broader population of drivers. The students were tested to evaluate the simulation game and conduct initial data analyses, some of which are **reported** here.

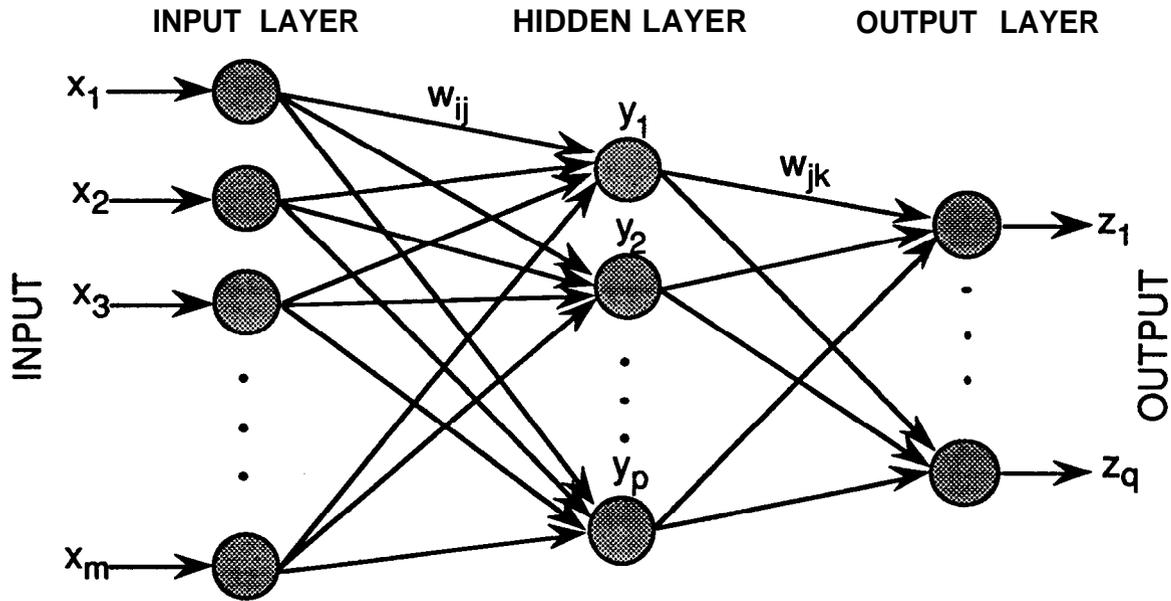


FIGURE1 A typical multi-layer feed-forward neural network.

Figure 1 shows the connection scheme of a typical multi-layer feed-forward network. This network consists of processing elements arranged in three layers: an input layer, a hidden layer and an output layer. Processing elements in adjacent layers are connected through connections  $w_{ij}$  and  $w_{jk}$ . The output emitted from each processing element is a function of the weighted outputs from the processing elements in the preceding layer. Mathematically,

$$y_j = f\left(\sum_{i=1}^m w_{ij}x_i + \theta_j\right) \quad (1)$$

where  $\theta_j$  is the threshold value for the  $j$ th processing element in the hidden layer,  $f$  is called an activation function which scales and smoothes the output. Usually, a logistic function is used:

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

In the same way, the output value of the processing elements in the output layer are computed as

$$z_k = f\left(\sum_{j=1}^p w_{jk}y_j + \theta_k\right) \quad (3)$$

where  $\theta_k$  is the threshold value of the  $k$ th processing element in the output layer.

Proper values of connection weights and thresholds can be estimated so that the squared errors between the network output and the desired output is minimize:

$$\min_w \sum_{k=1}^q (z_k - d_k)^2 \quad (4)$$

where  $d_k$  is the desired output (or “teacher signal”) of the  $k$ th processing element in the output layer.

A back-propagation algorithm implementing gradient descent in the output error is used for “training” the network. In this algorithm, connection weights are updated gradually in proportion to the difference between the estimated and actual output as follows (Rumelhart et al., 1986):

$$\delta w_{ik} = (d_k - z_k) z_k (1 - z_k) y_i \quad (5)$$

$$\delta w_{ij} = \sum_k^q (d_k - z_k) z_k (1 - z_k) w_{jk} x_i y_j (1 - y_j) \quad (6)$$

$$\Delta W(n) = \eta \delta W(n) + \alpha \Delta W(n-1) \quad (7)$$

$$W(n+1) = W(n) + \Delta W(n) \quad (8)$$

The  $\delta$  is the error,  $\Delta W$  is change in weight and  $n$  is the cycle number. The first term on the right hand side in (7) is a correction based on the current error;  $\eta$  is called the training rate, and  $0 < \eta < 1$ . The second term is the momentum term from the previous adjustment, and  $\alpha$  is referred to as the momentum rate, also  $0 < \alpha < 1$ .

Thresholds for each processing element in the hidden and the output layers are updated respectively by:

$$\delta \theta_k = (d_k - z_k) z_k (1 - z_k) \quad (9)$$

$$\delta \theta_j = \sum_{k=1}^q (d_k - z_k) z_k (1 - z_k) w_{jk} y_j (1 - y_j) \quad (10)$$

$$\Delta\theta(n)=\eta \delta\theta(n) + \alpha\Delta\theta(n-1) \quad (11)$$

$$\theta(n+1)=\theta(n) + \Delta\theta(n) \quad (12)$$

Training of the network starts with small random numbers assigned to all the weights and the thresholds. The training is terminated when either the maximum number of iterations is reached or the sum of squared output errors is reduced to an acceptable value. Figure 2 shows the training process with a back-propagation algorithm (Rumelhart et al., 1986).

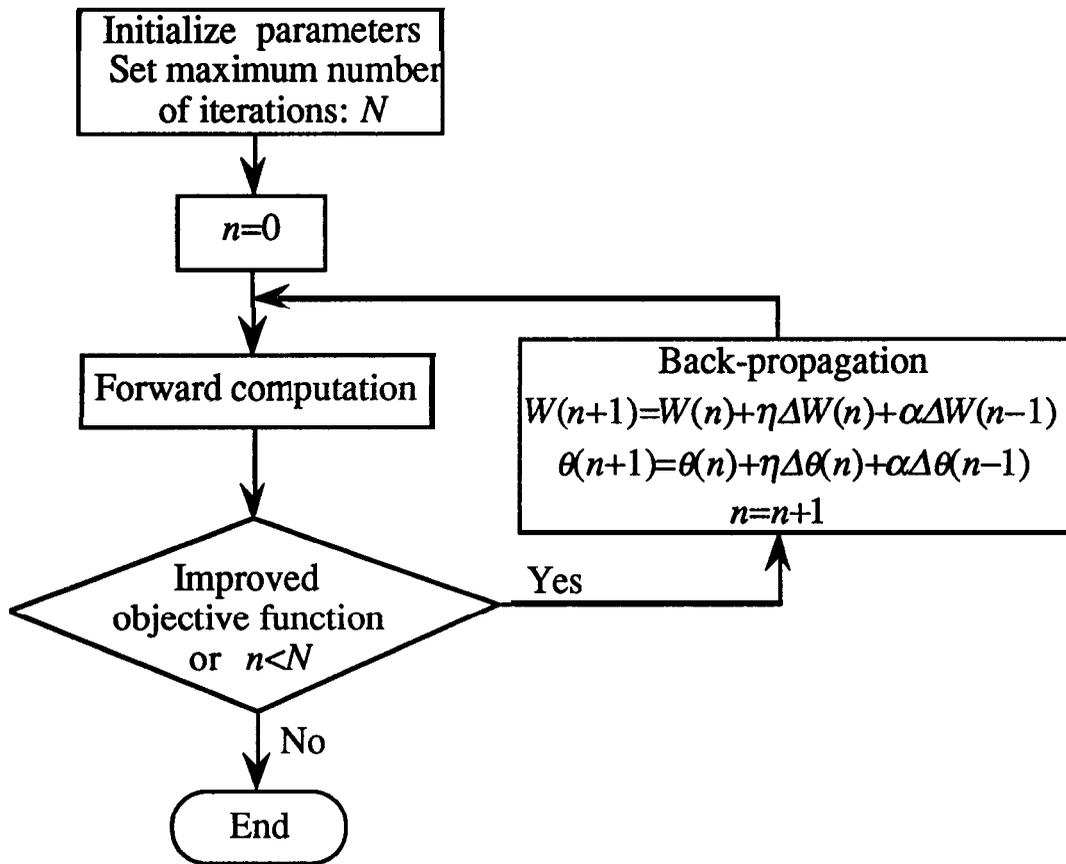


FIGURE 2 Flow chart of a back-propagation training algorithm (Rumelhart et al., 1986).

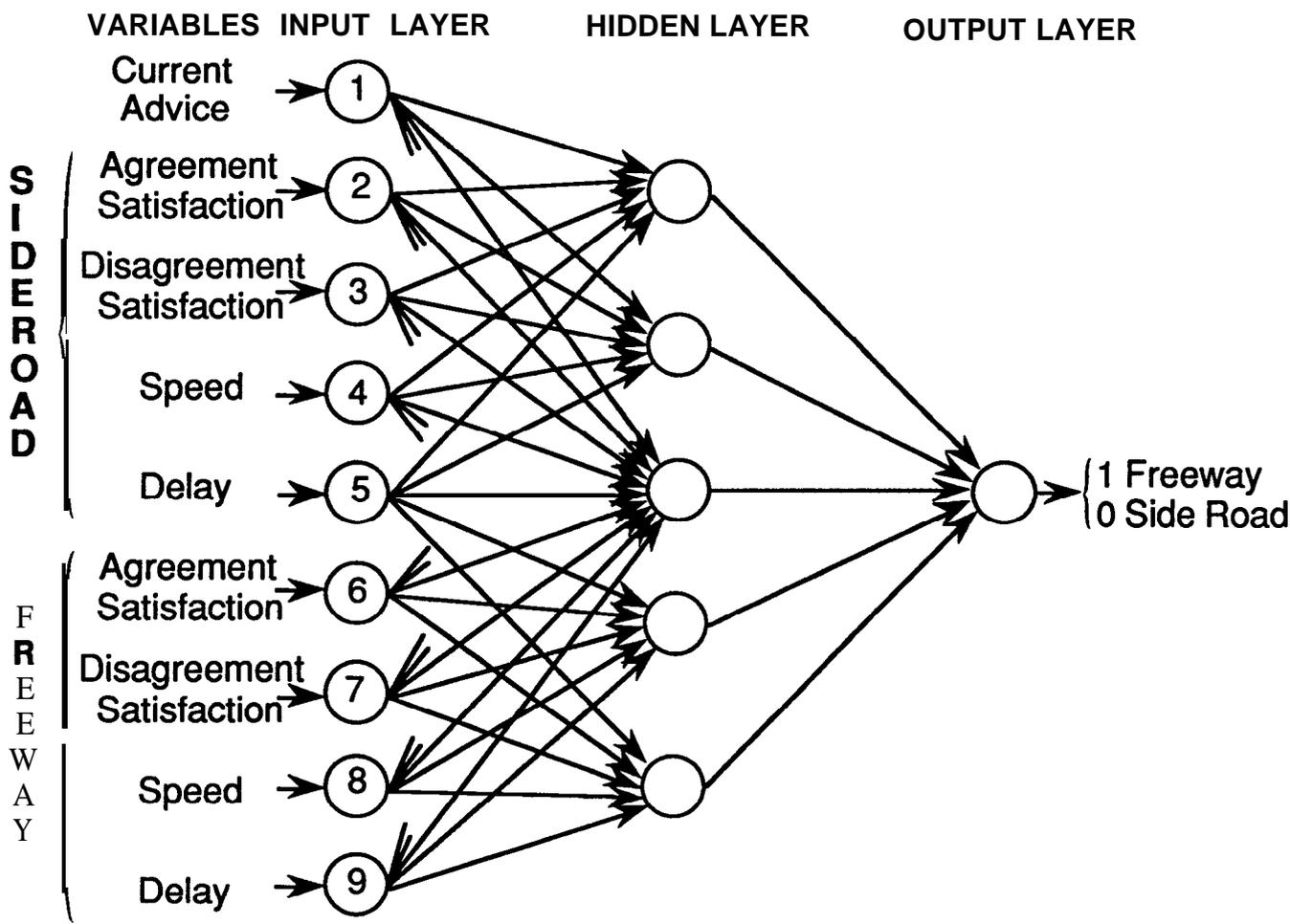


FIGURE 3 A three-layer neural network model for route choice analysis.

### NEURAL NETWORK ROUTE CHOICE MODEL

#### Structure of neural network

The neural network used in this study consists of the input layer, a hidden layer and the output layer as shown in Figure 3. There are 9 processing elements in the input layer which feeds various pieces of information to the network. A single processing element in the output layer is used to indicate a choice between freeway and side road. During the training of the neural network, the desired output is set to be 1 if the freeway is chosen and 0 otherwise. During the testing or

prediction, the freeway is estimated to be chosen if the output value is greater than or equal to 0.5, and the side road is estimated to be chosen if the output value is less than 0.5.

In the model, two pieces of information, the route advice provided by the information system and the drivers' perceptions of travel conditions on the freeway and side road, are considered to be important in the route choice decision. To reflect the fact that the drivers' perception and knowledge are based on experience accumulated from day to day, weighted cumulative averages are used as input variables of the analysis. The input variables to the model are defined as follows:

- $x_1$ : Current advice: 1 If the freeway is recommended by the information system and 0 if the side road is recommended
- $x_2$ : Weighted agreement satisfaction on the side road: A weighted sum of the drivers' level of satisfaction with the choices made in previous days when they followed the advice to take the side road.
- $x_3$ : Weighted disagreement satisfaction on the side road: A weighted sum of the drivers' level of satisfaction with the choices made in previous days when they did not follow the advice to take the side road.
- $x_4$ : Weighted speed on the side road: A weighted sum of the driver's estimate of his/her perceived speeds on the side road chosen in previous days.
- $x_5$ : Weighted delay on the side road: A weighted sum of delays on the side road in previous days.
- $x_6$ : Weighted agreement satisfaction on the freeway.
- $x_7$ : Weighted disagreement satisfaction on the freeway.
- $x_8$ : Weighted speed on the freeway.

$x_9$ : Weighted delay on the freeway.

Note that the neural network shown in Figure 3 is designed for the analysis of individual route choice behavior. If the route choice behaviors of a group of drivers are to be analyzed, a drivers individual attributes should be taken into account. The set of variables is thus extended to include two new input variables  $x_{10}$  and  $x_{11}$  defined as:

$x_{10}$ : Driving frequency.

$x_{11}$ : Individual's gender: 1 if the driver is male and 0 if female.

The driver's age category can be used as an input variable, but it is not considered here because most of the subjects in this experiment are college students at UC Davis.

In the above input variable,  $x_1$  reflects the effect of advice provided by the information system;  $x_2$  through  $x_5$  represent the effects of the driver's previous travel experiences on the side road, and  $x_6$  through  $x_9$  on the freeway;  $x_{10}$  and  $x_{11}$  reflect the influence of personal characteristics on the route choices.

All values taken by variables  $x$  will be normalized to be between 0 and 1 using a logistic function and then transmitted to the hidden layer in the neural network

#### Measure of travel experience

Subjects were asked to indicate their levels of satisfaction with the choice made and estimate their perceived speed on their chosen route after each simulation run: A five-stage rating on choice and speed, ranking from -2 to +2 was adopted where a negative number implies a bad experience. If one of the routes was not used by the driver on some day, then the corresponding evaluation values were set to be zero, which means that no new knowledge or experience about the unused route was acquired. In the same way, driving frequency of the subjects was also measured. The scales are summarized in the next page:

-2	-1	0	1	2
Incorrect choice	Probably incorrect	Don't know	Probably <b>correct</b>	correct choice

Evaluation of choice

-2	-1	0	1	2
Incredibly slow	Fairly slow	Moderate	Reasonably fast	Fastest possible

Evaluation of speed

-2	-1	0	1	2
Do not drive	Drive infrequently	Never commuted but drive frequently	Do not now but formerly commuted	Currently commute

Evaluation of driving frequency

In the simulation experiments, delays on the routes were randomly generated to be 1 through 5 units on the freeway and 2 through 6 units on the side road. These values were also transformed linearly into values between -2 and 2.

The vectors of previous travel experience evaluated above need to be combined by a perception updating strategy to constitute the vector  $\mathbf{x}$  of the driver's current perception of travel conditions on the freeway and side road. But, no matter what strategy is adopted, the final combination values should be fit into the same evaluation scale  $[-2, 2]$  in order for the values to be meaningful.

### Perception updating strategy

Variables  $\mathbf{x}_2$  through  $\mathbf{x}_9$  represent the drivers' knowledge or perception of travel conditions on the side roads and freeway. This perception comes from the travel experience accumulated **from** day to day, and hence must be updated in choice sequences by historical experience. In general, a perception updating strategy reflects a learning process and may be different across drivers.

Suppose, the beginning of day  $w$  the driver constructs his updated historical perceptions  $\mathbf{x}$  of travel conditions. This update is a function of the previous historical perceptions and the personal experience observed in his travel on day  $(w-1)$  (Ben-Akiva, et al., 1992). The following updating strategy is considered in this study:

$$\mathbf{x}(w) = (1-\lambda)\mathbf{x}(w-1) + \lambda\mathbf{u}(w-1), 0 \leq \lambda \leq 1 \quad (13)$$

where

$\mathbf{u}(w-1)$ : a vector of drivers' evaluations on his travel on last day,

$\mathbf{x}(w-1)$ : a vector of drivers' previous historical perception of road conditions.

$\lambda$ : a positive parameter called experience factor which reflects the relative impact of the last day experience and the accumulated historical knowledge on the individual's perception updating.

With this recursive formula, the weights assigned to the evaluation vector  $\mathbf{u}$  of travel experiences in previous days can be easily shown as:

$$\mathbf{x}(w) = (1-\lambda)^{w-1}\lambda\mathbf{u}(0) + (1-\lambda)^{w-2}\lambda\mathbf{u}(1) + \dots + (1-\lambda)\lambda\mathbf{u}(w-2) + \lambda\mathbf{u}(w-1) \quad (14)$$

Therefore, the earlier the day, the smaller is the weight, which reflects the relative impact of previous travel experiences on different days to today's travel condition perception. If  $\lambda=1$ , then only the experience received on the last day (most recent) is taken into account in today's route choice. If  $\lambda=0$ , the driver does not update his information or knowledge from one day to another (because of this, this formulation is more general than the lagged formulation,  $\mathbf{x}(w) = \theta\mathbf{x}(w-1) + \mathbf{u}(w-1)$ ).

It is assumed in this study that all the variables are updated through one experience factor and this experience factor is the same for all the drivers. However, because of the difference in abilities of combing and processing various information about route conditions, drivers may give different

weights to the experience associated with travel on different days. Therefore, a more realistic representation of the updating process is to associate different sets of experience factors with different drivers, and different values of experience factors with different variables for the same driver.

Furthermore, the above simple updating strategy of linear combination is only one among many possible ways. For example, if the driver considers only the best and worst experiences of previous travel on a route, we get the following updating formula:

$$\mathbf{x}(\mathbf{w})_{\text{worst}} = \min \{ \mathbf{x}(\mathbf{w}-1), \mathbf{u}(\mathbf{w}-1) \} \quad (15)$$

$$\mathbf{x}(\mathbf{w})_{\text{best}} = \max \{ \mathbf{x}(\mathbf{w}-1), \mathbf{u}(\mathbf{w}-1) \} \quad (16)$$

Other methods such as Bayesian updating or fuzzy inference techniques may be used for perception updating, where confidence level or possibility distribution are employed to describe drivers' observation and perceptions about route conditions.

## RESULTS AND ANALYSIS

### Neural Network Performance

Before examining individual's dynamic travel behavior in detail, we report some results of the validation experiments on the performance of the neural network model.

Firstly, 32 "day-to-day" route choices made by one person in the computer-based simulation experiments were used for training the basic neural network in Figure 3. In each training cycle, the training vectors were presented to the network in sequential order from day 1 to day 32. The number of processing elements in the hidden layer was varied from 3 to 7 in investigating its effect on the performance of the network. During the training, the values of learning and momentum rates  $\eta$  and  $\alpha$  were set to be 0.2 and 0.9 respectively, and were kept constant. Moreover, the experience factor  $\lambda$  in the perception updating formula was chosen to be 0.8.

Figure 4a shows the changes of the sum of squared learning errors for an entire set of training vectors as training continues, with different numbers of processing elements in the hidden layer. Figure 4b indicates the corresponding results of training in terms of replication of all the 32 route choices. It can be seen that the first 50 cycles of training lead to a sharp reduction in the squared output errors. After 1000 cycles of training, no significant improvement effect was observed, the network parameters (connection weights and thresholds) were judged to be converged. The networks with 3 and 5 processing elements in the hidden layer had a replication rate of 96.9% (1 failure out of 32 training vectors) after about 900 cycles of training. This means that the neural network had adjusted its connection weights to fit on average 31 cases out of 32 route choices. It is observed that the number of processing elements in the hidden layer had little impact on the performance of the network.

Figures **5a** and **5b** show the testing results with an extended neural network model for route choice analysis of a group of drivers. In this test, a total number of 320 route choices for 10 subjects were used for training, It is observed that the networks with different numbers of hidden processing elements show different performances. The networks with 5 and 7 hidden processing elements respectively have **better** performance, but the latter exhibits fluctuation in the training process. After convergence, the neural networks had an overall replication rate of about 90%. Table 1 presents the replication results with respect to road type for the network with 7 hidden processing elements after 2000 cycles of training.

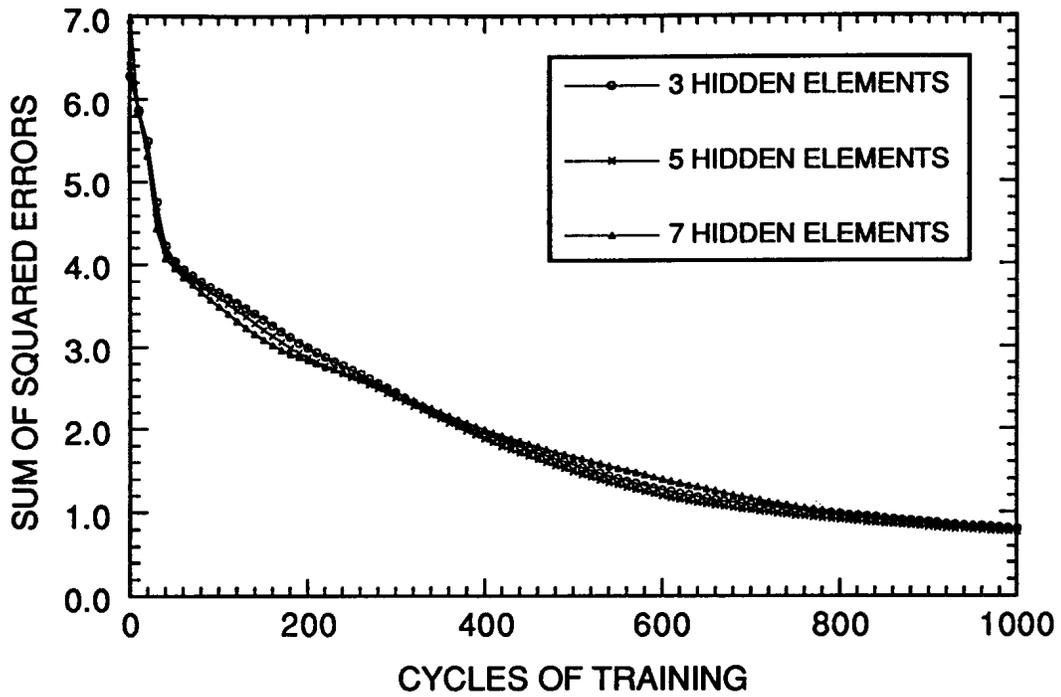


FIGURE 4a Changes of sum of squared learning errors across cycles of training for  $\lambda=0.8$ .

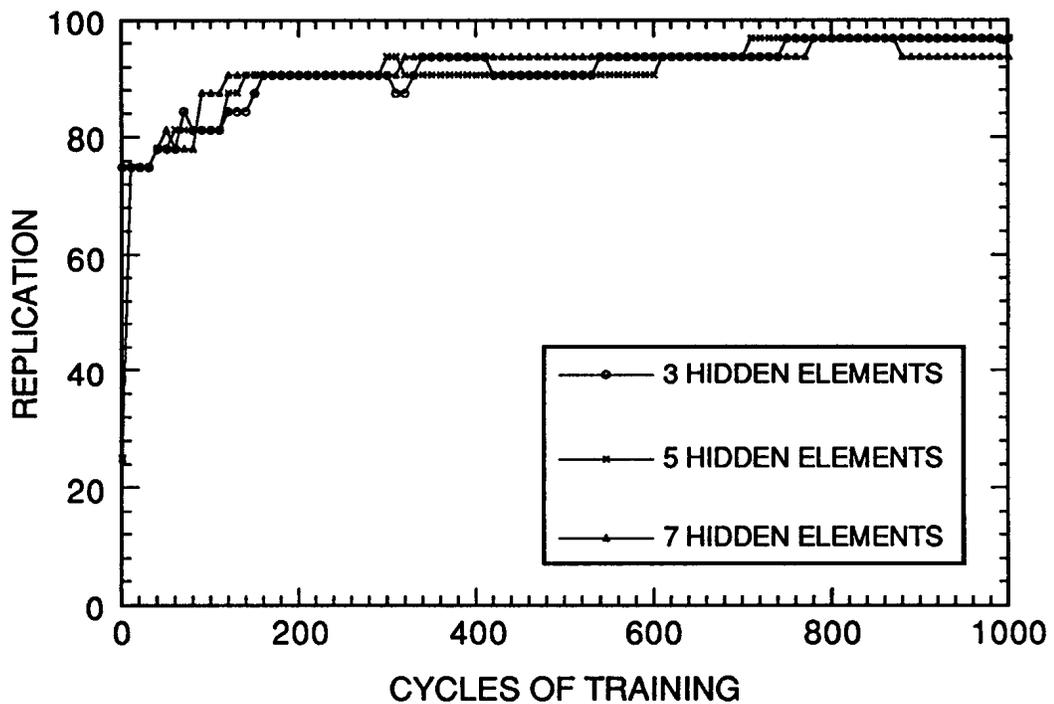


FIGURE 4b Changes of replication rate of route choices across cycles of training for  $\lambda=0.8$ .

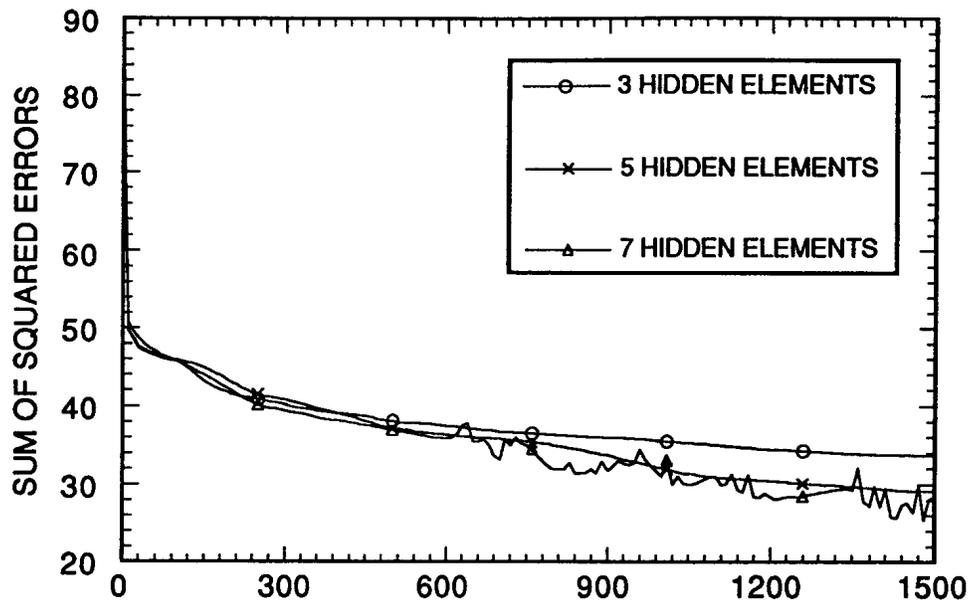


FIGURE 5a Changes of sum of squared learning errors across cycles of training for 10 subjects and  $\lambda=0.8$ .

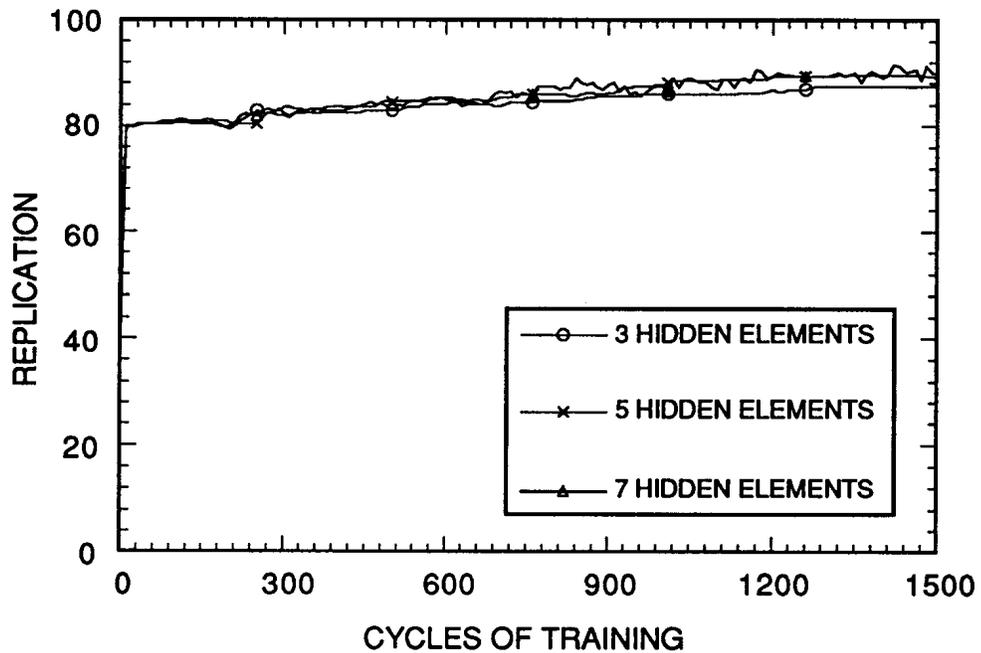


FIGURE 5b Changes of percentage success rate of recall across cycles of training for 10 subjects and  $\lambda=0.8$ .

TABLE 1 Replication of route choices by a neural network model with 7 hidden processing elements after 2000 cycles of training

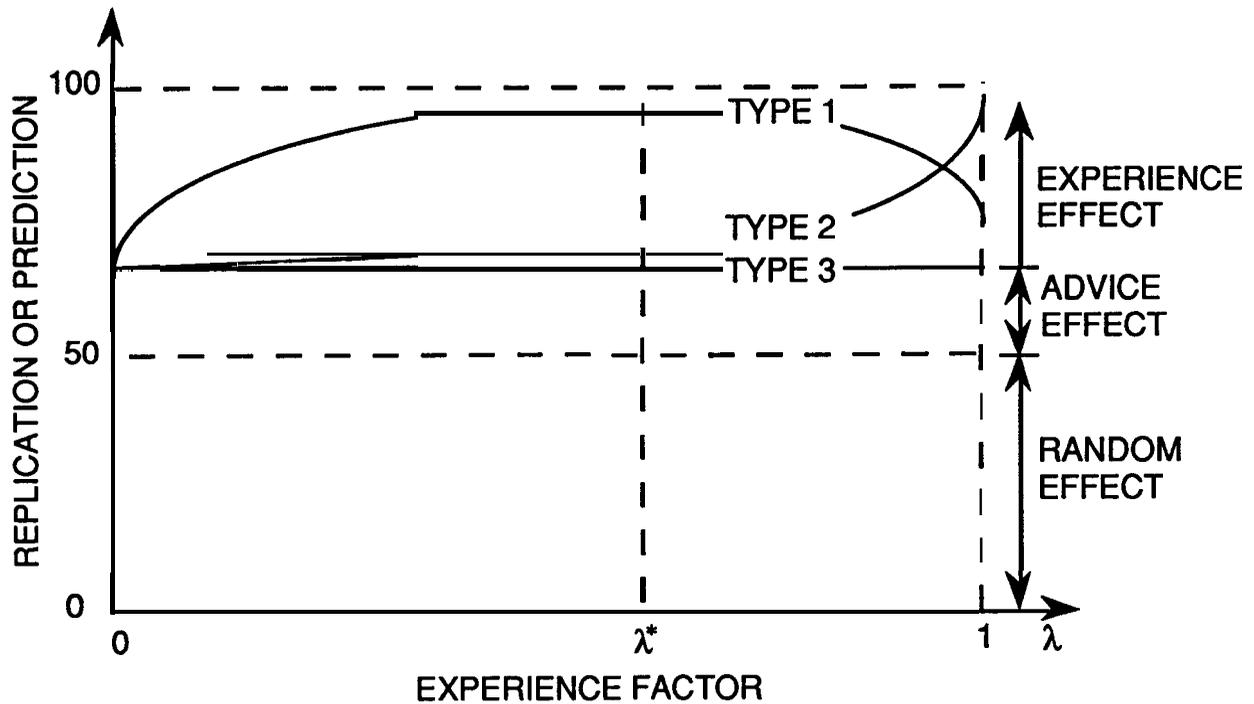
		Predicted Choices		Total Number	Replication
		Freeway	Side Road		
Actual Choices	Freeway	171	16	187	91.4%
	Side Road	7	126	133	94.7%
Average Replication Rate = $(171+126)/320 \times 100\% = 92.8\%$					

It should be pointed out that, though the above results can be considered to be excellent, further improvement on the performance of the neural network route choice model can be made by properly improving the perception updating strategy, especially the setting of the experience factor  $\lambda$ .

#### Route Choice Behavior

The above analysis suggests that the constructed neural network model can be **used** to reliably predict route choices. In general, route choice behavior, even in the presence or absence of **ATIS** is considerably different from driver to driver, since drivers have different abilities: in combining and processing a variety of information concerning road conditions; in performing travel forecasts with available information; in previous experience; and, in developing heuristic decision procedures (Ben-Akiva et al., 1992; **Ida**, et al., 1992). Here, we roughly classify the route choice behavior with **ATIS** experience into the three types shown in Figure 6, based on the model's replication or prediction results.

**TYPE 1:** This is the type of subject for whom a combination of the most recent and historical experience is optimal (the optimal experience factor  $\lambda^*$  is around 0.5).



**FIGURE 6 A conceptual framework for route choices with ADIS experience.**

TYPE 2: Subjects in this type stress the importance of most recent travel experience (the optimal experience factor  $\lambda^*$  nears 1.0).

TYPE 3: Subjects of this type make their route choices are not based much on their previous experiences, but (probably) resorting to the route advice provided by the information system.

The above classification is based on the shape of the curves representing the model's replication or prediction results with respect to the experience factor  $\lambda$ . Drivers can be subclassified into groups according to their acceptance/rejection of advice based on the value of replication or prediction accuracy at  $\lambda=0$ .

In line with the above classification, individual route choice behavior in the simulation experiment was studied with the neural network model by investigating the replication or prediction results with different experience factors. Two cases of computation were conducted.

CASE A: All the data from a total of 10 subjects were used for training the extended neural network with 11 input variables (in total 10x32 input vectors). The replication rates were then computed with different experience factors  $\lambda$  varying from 0.0 to 1.0 by steps of 0.2.

CASE B: In this case, the route choice data were divided into two groups. For each subject, 16 cases out of 32 “day-to-day” route choices were randomly chosen for training the neural network model and the remaining 16 cases were used for prediction. Therefore, there are 160 data points in total for training and 160 data points for prediction.

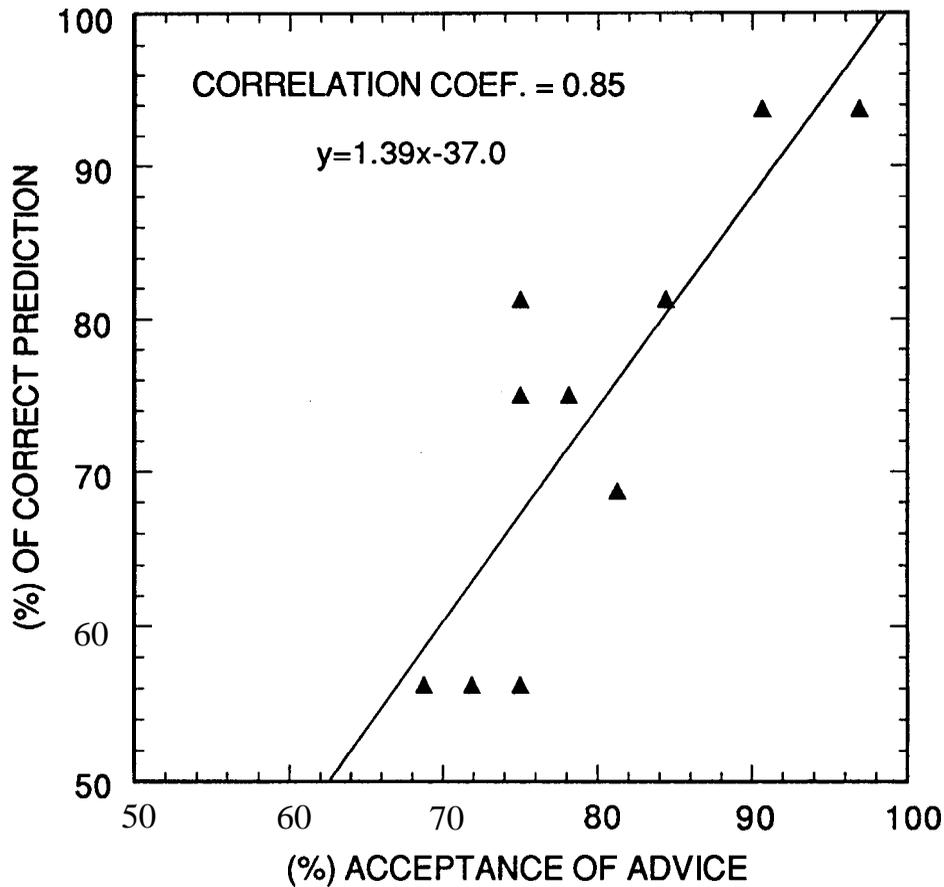


FIGURE 7 Relationship between acceptance of advice and percentage of correct prediction with zero experience factor.

In both cases, the number of processing elements in the hidden layer was 3; **parameters  $\eta=0.2$  and  $\alpha=0.9$** , the maximum number of cycles of training was set to **be 1500**.

We first examine the extreme situation of  $\lambda =0$ , where subjects do not update their perception or knowledge from one day to another. In this situation, the neural network model predicts driver route choice based solely on the acceptance/rejection of route advice provided by the information system and personal characteristics. Therefore, driver compliance with route guidance advice can be observed from the replication rate or prediction accuracy at  $\lambda =0$ . In fact, in Case A with all route choices used for training, the neural network model gave the same replication rates of route choices as the acceptance rates of advice for each subject, indicating that the model predicts that subjects will follow the advised route. In Case B with **half** of the route choices used for training and testing respectively, it is found that the percentage of correct prediction has a strong relationship with the percentage acceptance of advice, as shown in Figure 7. The average replication rate 79.7% in Case A and the average correct prediction 73.8% in Case B, the average acceptance rate of advice 79.7% for 10 subjects, and the quality of advice 75% are found to be in about the same order.

Computation results for Case A are shown in Figures 8 through 10. It can be observed that most of the driver route choice behaviors fit into either Type 1 or Type 2. Based upon the shape of the average curve, the optimal experience factor  $\lambda$  is around 0.8 (see Figure 8), which implies that most subjects made route choices based mainly on their recent experiences. It is interesting to see that the dispersion of replication rates across subjects has a smallest value at the optimal experience factor  $\lambda^*$ , and becomes larger as  $\lambda$  approaches 0 or 1. This means that there is a large difference among subjects in how to recognize past and recent experience in making route choice decisions. In other words, personal characteristics generally had great influence on individual route choice behavior. Moreover, the dispersion of replication rates at  $\lambda=0$  reflects the difference among subjects in accepting advice.

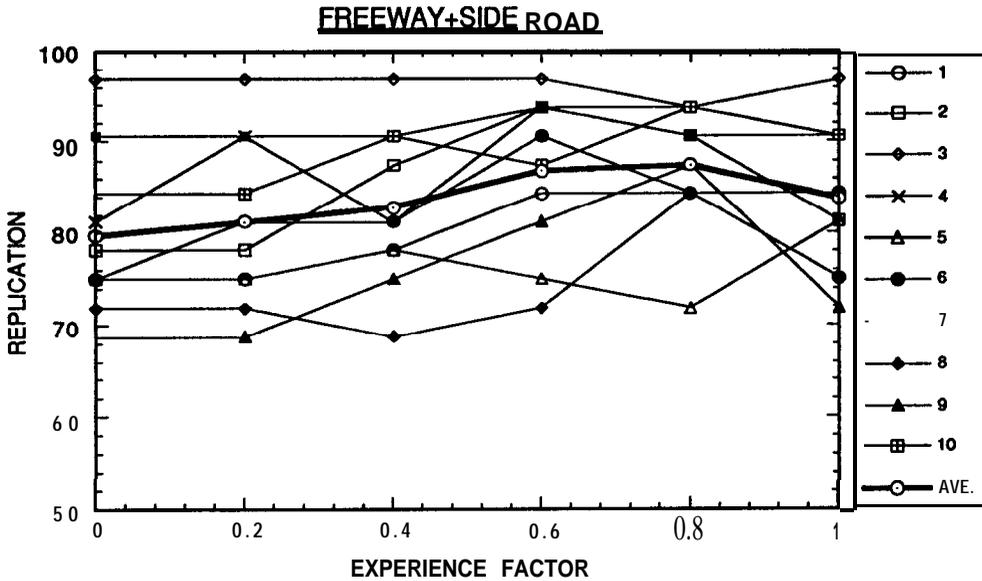


FIGURE 8 Replication of route choices with varying experience factor - Freeway and Side road choice combined.

From Figures 9 and 10, it can be seen that route choice behavior is related to the characteristics of the respective routes. It seems that in choosing the freeway, subjects integrate their past and recent experiences in ways consistent with our hypotheses. However, most of the replication rate curves for the side road, shown in Figure 10, exhibit no patterns similar to the hypotheses in Figure 6. It seems that travel experience has less effect on the choice of side road compared with the freeway.

Prediction results by the neural network route choice model in Case B are individually shown in Figures 1 la-d for four typical cases. It can be easily seen that subjects have different optimal experience factors and the same subject has a different optimal experience factors for the freeway and side road. These results demonstrate empirically that subjects have different abilities to remember previous route choices. They also update their knowledge or perceptions in different ways. There is an extensive diversity and variety of dynamic route choice behaviors across different subjects and across different types of road. In practice, it may be difficult to use a unified simple approach to describe driver route choice behavior. Similar findings on the differences between drivers, but not within drivers, have also been reported (Haselkom, et al. 1991, Stephanedes & Kwon 1989).

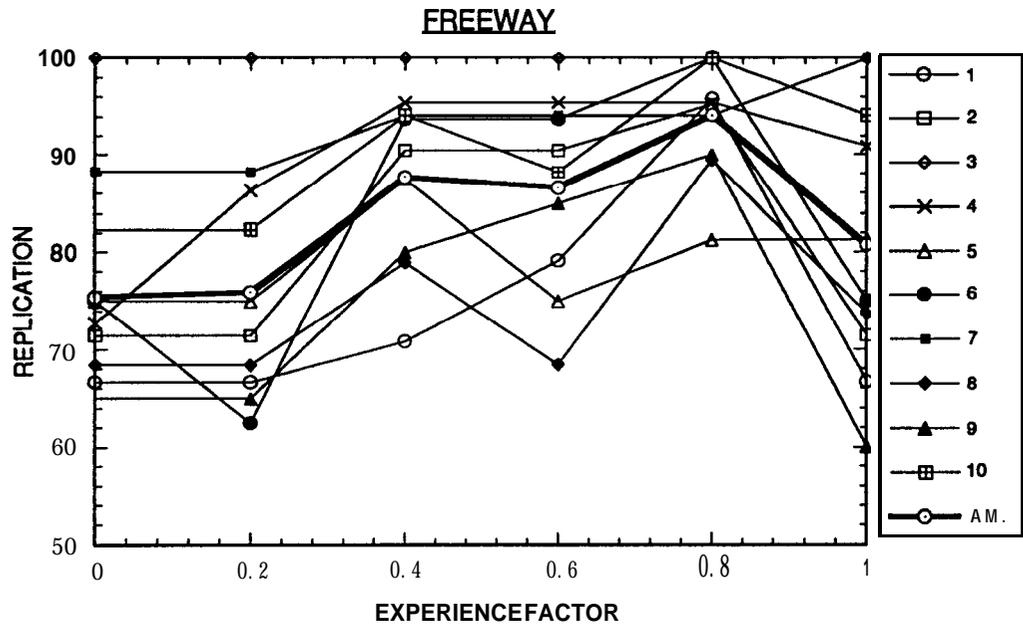


FIGURE 9 Replication of route choices with varying experience factor.

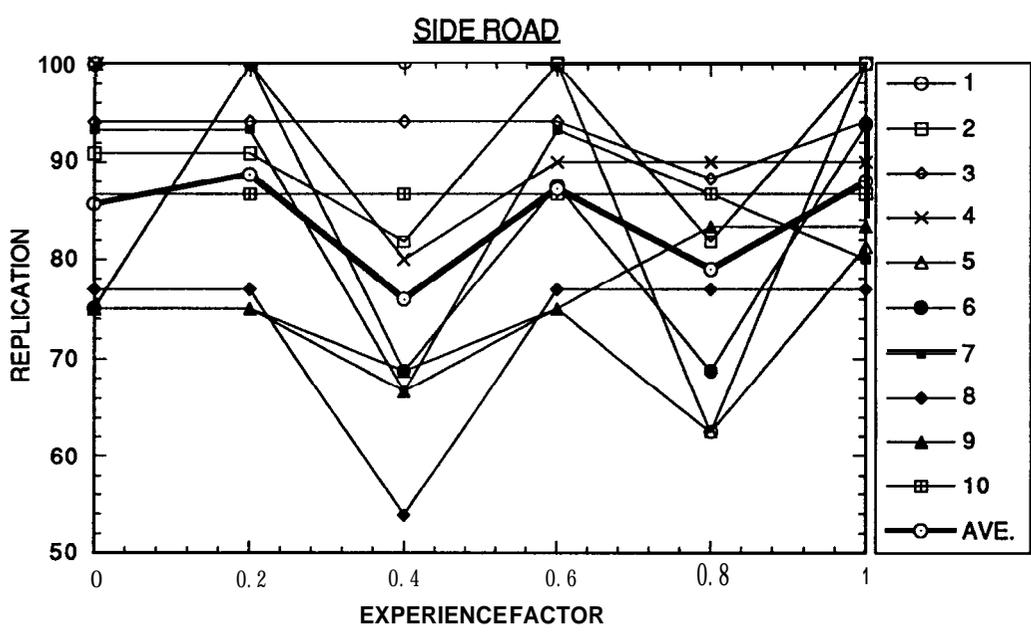
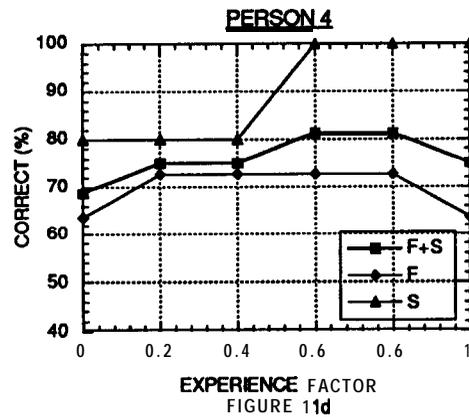
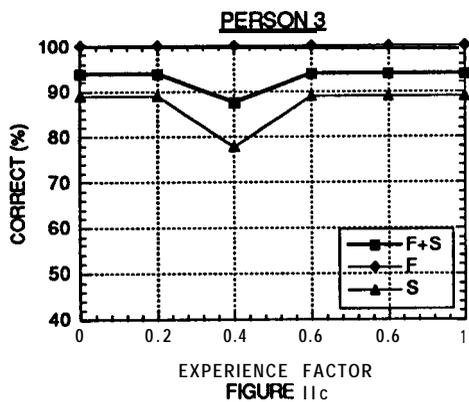
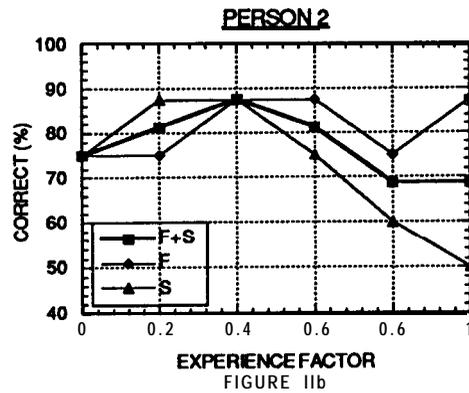
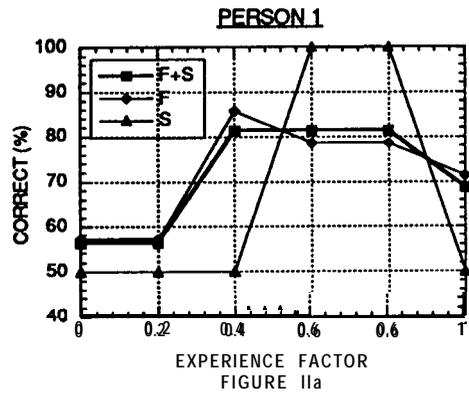


FIGURE 10 Replication of route choices with varying experience factor.



## LIMITATIONS OF THE EXPERIMENT:

In the conduct of empirical investigations, the limitations of the experiments must be kept in mind. Among the more important regarding this study are:

1) The number of replications: The individual replication rates are **greatly** influenced by the number of route choices. In general, subjects tend to choose the freeway. In our experiment, the average proportion of choices between the freeway and side road is approximately 1.4:1. The average number of choices of side road for a subject in the 32 sequential trials is thus 13. Giving one wrong prediction will lead to 7.7% variation in the replication rate. This perhaps explains, to some extent, why the replication curves for the side road shown in Figure 10 do not exhibit an anticipated pattern. It appears that an increase in the number of sequential route choices for each subject beyond 32 is needed to obtain more stable choice patterns for the side road.

2) Perception updating strategy: The results presented in this paper are limited to a particular perception updating strategy. The results suggest the need to carefully consider perception updating strategies and experience factors. Further studies should include investigation of different perception updating strategies and construction of a specific individual route choice behavior model using different experience factors.

3) Model performance: The conclusions concerning route choice behaviors presume that the neural network route choice model has a correct representation of driver route choice behaviors. The reliability of the results, however, depends highly on the reliability of the model itself. Further theoretical and empirical investigation on the performance of the neural network model should be conducted in order to reliably analyze driver route choice behavior in the presence of **ATIS**.

4) Sample characteristics: The subjects used in the study are drawn from UC Davis students. The testing is intended to examine the feasibility of the neural network approach. Generalizations to the broader population of drivers or commuters require more extensive experimentation.

#### SUMMARY:

In this study a neural network model is developed to predict drivers' route choice behavior under **ATIS**. The data used for analysis was collected from learning experiments carried out at the University of California at Davis using an interactive computer simulation. A series of validation experiments with different route choice structures is first conducted to test the feasibility of the approach. The neural network model is found to reasonably predict drivers' route choice. The constructed neural network model is then employed to explore the specific driver route choice mechanism under **ATIS**. The manner in which drivers update their perception of travel conditions was investigated, including the relative impact of the previous travel experiences on different days and the route advice provided by the information system.

It was found that most subjects make route choices based mainly on their recent experiences. This may indicate that drivers short term acceptance of advice is a function of their experiences, and if

they are given poor information they are unlikely to follow the system advice in immediately subsequent trips. Over time, however, they may return to following system advice if the system performs well. Route choice behavior was also related to the characteristics of the respective routes and varied significantly from driver to driver. The choice to use the freeway seems to be reasonably modeled by our approach, and indicates a significant use of **recent** travel experiences in updated choices with information. Choices to use the side road do not fit hypothesized behaviors, but this may be partially a function of sample size limitations. There appears to be significant differences both between and within subjects regarding the choice to use the freeway or surface street; more refined models need to be tested in this area.

#### FUTURE RESEARCH:

Future research will continue to expand the modeling efforts undertaken here and in a companion paper (Vaughn et al. 1992). Specific topics include:

- 1) Investigation of information update strategies to determine which strategies are most representative of the ways in which drivers learn **from their experiences**.
- 2) Extension of the modeling framework to a more complex and realistic simulated transportation network
- 3) Inclusion of mode choice and departure time choice in the experimental design

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