DESIGN OF A RECURRENT NEURAL NETWORK FOR ANALYZING ROUTE-CHOICE BEHAVIOR IN THE PRESENCE OF AN INFORMATION SYSTEM

P.D. Reddy and K.M. Vaughn
University of California at Davis
Davis, CA

M.A. Abdel-Aty and P.P. Jovanis
University of California at Davis
Davis, CA

Ryuichi Kitamura
Kyoto University
Kyoto, Japan

ABSTRACT

As a cost-effective alternative to field studies, computer simulation is an often-used methodology to study travel behavior. In this study, a PC-based computer simulation was used to study the effects of information on drivers' route choice and learning. Building on a prior stage of simulation efforts, a new set of experiments was developed with an expanded traffic network and various levels of information given to subjects. This framework allows one to investigate both en route and pre-trip route-choice behavior and capture the effect of different levels of information on drivers' learning and adaptive processes.

The experiments were conducted in two generations (stages). In the first-generation experiments, a simple, two-route-alternative traffic network was developed. Experiments conducted with this network provided the authors with a set of extensive comments from participants. These insights were modeled using object-oriented programming techniques to produce a better subsequent design. Data from the first-generation experiments were analyzed using neural network techniques, and the neural network was trained using the back-propagation method. The second-generation experiments used a multiple-route, expanded network with varying levels of information. Data obtained in this stage are being analyzed using recurrent neural networks. This paper describes the redesign of the network simulation with the experience gained in the first-generation experiments. The paper also analyzes data obtained from the experiment.

Design of the network simulation involved the following steps: Requirements analysis, data base design, specifications of user-computer interface, design of shortest-path module, software development, and prototype testing and refinement. The simulator was developed using an object-oriented programming language, C++. A recurrent neural network has been built for modeling of the data obtained in the second generation experiments. This neural network will be used to predict subjects' choices of whether or not to follow the system-provided advice, depending on their past experience. An important feature of this neural network is that decisions at previous nodes will be used as an input for the neural network at subsequent nodes. This allows one to model participants' route-choice behavior at every node that approximates a traffic intersection.

INTRODUCTION

Recently, there has been much interest in developing advanced traveler information systems (ATIS) to aid drivers make more informed route choices and alleviate traffic congestion. Important issues in implementing such systems include understanding how the ATIS will affect driver behavior, how drivers adopt and learn to use the ATIS, and how these changes impact the network.

Several methods have been used to study drivers' route-choice behavior in the context of ATIS. These methods, as summarized by Abdel-Aty et al,[1] include: Field experiments, route-choice surveys, interactive computer simulation games, route-choice simulation and modeling, and stated preference approaches. Although significant advances have been made in these studies, their results also have suggested that more theoretical and empirical investigations remain to be carried out in order to gain a basic understanding of drivers' route-choice behavior in the presence of information.

Research being performed at the University of California at Davis is investigating various impacts of ATIS on drivers' route-choice behavior. The goals of the project are to understand how people will adopt an ATIS, learn how to use it, and devise rules for trip planning. The research efforts described in this paper cover only a part of the larger project. Vaughn et al[2] describe the experimental design of the driving simulator in detail. This paper more briefly describes the experimental design of the driving simulator and the application of recurrent neural networks in the case of drivers' route choices.

Route choice in a real-traffic environment is very complex, and little experimental evidence exists as to how drivers process information and select routes.[1, 3] Therefore, it was decided to analyze route-choice behavior in a simpler, less complicated environment. It was felt that this would allow the effects of various factors on route-choice behavior to be adequately controlled and analyzed. The success or failure of ATIS will be highly dependent on the quality of advice that can be delivered to drivers. If a system consistently provides bad information, drivers soon will begin to ignore the advice and route-choice patterns will remain unchanged. If accurate information is consistently provided, drivers will most likely perceive a benefit from following the advice and adapt their behavior to the advice. However, providing and maintaining highly accurate information is expensive and not always possible. How do drivers perceive the provided information? If such thresholds do exist, are they consistent for all drivers, or do different types of drivers have different thresholds? Under what conditions and how rapidly? In this study, recurrent neural networks are used to:

1. Model the drivers' decision processes based on the information provided

2. To investigate with relation to driver and network characteristics, how much of the previous experience is remembered in presen route choices

LIMITATIONS OF FIRST-GENERATION ROUTE-CHOICE EXPERIMENTS

The first-generation of experiments used an interactive PC-based route-choice simulation to investigate drivers' learning and pre-trip route choice behavior under ATIS. For more information on experimental design, analysis, results and neural network applications of this work, one can refer to previous publications.[2-6] Even though there are many limitations to the first-generation experiments, it provided valuable results as well as suggestions for survey design and for simulation design that were not available in the literature at that time. That experience also provided knowledge useful for conducting lab experiments. Some of the limitations of the previous experiment are listed below.

1. *Network.* In the first generation experiments, the simulated network was a simple two-link and one-decision-point road network.

2. *Information content.* The level of information provided to the subjects was minimal. There was no information about accidents and congestion levels, which are important for ATIS users.

3. *En route information.* Navigation information to drivers was not included.

4. *Delay assignment.* Delays assigned to links were calculated using the relative ratio between freeway and side road. In a realistic network, however, the delays are distributed among the network links in a random fashion or based on type of road (e.g., freeway, neighborhood road, etc.)

5. *Sample characteristics.* The subjects used in the study were students at the University of California, Davis. The experiments were intended to examine the feasibility of the artificial simulator. A more representative population of drivers or commuters would have given more realistic information.

6. *Perception updating strategy.* The results were limited to a particular perception-updating strategy. Past results suggest the importance of perception-updating strategies and experience factors. It was assumed in the previous study that all variables were updated through one experience factor and that the experience factor was the same for all drivers. However, because of the difference in drivers' abilities to combine and process information on 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 required to associate different sets of experience factors with different drivers and different values of the experience factor's variables with the same driver.

7. *Experience factor*. The experience factor was not a continuous term. It varied by steps of 0.2 in the experiment. The basic aim of further-generation experiments is to include past experience as a continuous term using neural networks.

8. *Age*. Driver age was not included in the input list because all the subjects belonged to the same age group.

9. *Trials*: Individual decisionmaking was measured between days, as opposed to during a single trip. Measuring drivers' behavior in a single trip is a major attribute to the success of trip information systems.

10. *Model performance*. Conclusions concerning route-choice behavior presume that the neural network model correctly represented driver route-choice decisionmaking processes. The reliability of the results, however, depends on the model specification itself. A more hybrid neural network model would be needed to reliably analyze driver route-choice behavior in the presence of ATIS.

To improve the simulation and overcome some of the limitations, a second generation of experiments was developed and a new modeling technique using recurrent neural networks was introduced.

EXPERIMENTAL DESIGN

Simulation

This simulation is developed as an interactive program running on a PC platform. The screen displayed to subjects is composed of three main windows: A network window, an information window, and an instruction window (Figure 1). The simulation is designed to be self-explanatory, with built-in instructions. The program also has an experimentation phase in which subjects are allowed to make preliminary trials and request help until they are familiar with the system before proceeding to the actual simulation. No data are collected in this experimentation phase, but the total length of time each subject spends experimenting with the system is recorded for comparison purposes. Also, an interface is provided to allow the experiment coordinator to set up the desired experimental conditions that will be in effect for the subject.

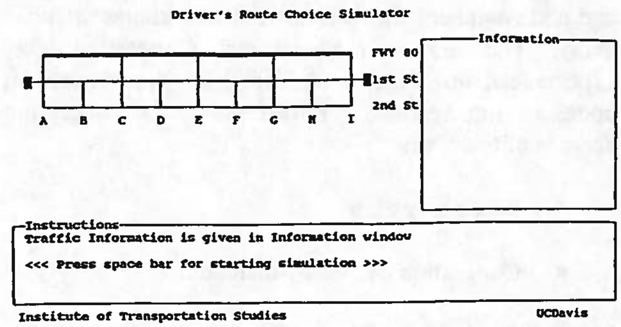

Figure 1. Screen display of driving simulator

Potential subjects are selected from the Sacramento area by random digit dialing. Approximately 100 subjects are recruited based on an initial screening. The subjects in this simulation are limited to commuters who travel to work five days per week. Included within the population of commuters are carpoolers (both drivers and passengers) and drivers of single-occupant vehicles. The sample is further segregated by such demographic criteria as gender, education, driving experience, and age. The screening criteria are presented in Vaughn et al.[2]

Road Network

The network window displays a hypothetical road network (Figure 2). The network comprises three primary routes from an origin to a destination. The primary routes are a freeway and two arterial routes. These primary routes are interconnected by series of surface streets creating a network of 34 roadway links and 23 intersections (or potential decision points). The links running from nodes 2 to 22 make up the freeway route, and the links running from nodes 3 to 23 and from 4 to 24 make up the two arterial routes.

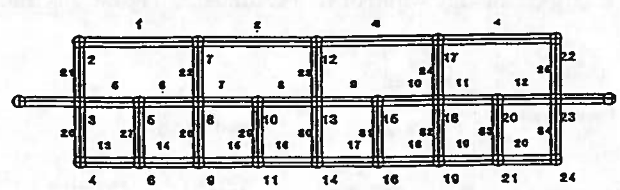

Figure 2. Simulated network

A simulated vehicle (cursor) moves through the network in response to decision inputs by the subject. Driver's decisions are input via the keyboard and indicate desired movements. The simulation currently uses a 1:30 time scale (2 seconds of simulated time = 60 seconds of real time).

Link Delay

Simulated network characteristics are pregenerated and stored in a network data file. This data file contains all of the network characteristics identified by travel day and node number. The primary network characteristic is delay. The delay is in two forms: Congestion delay experienced on a link and stop delay experienced at nodes or intersections. Furthermore, the congestion delay is of two types:

- Pure congestion
- Congestion caused by incidents.

Incident Delay

For this simulation, at least one incident occurs within the network on each simulated day. Also, incidents are more likely to occur on the freeway than on surface streets. For this simulation, the probability of an accident occurring on a given travel day is 1.0. This breaks down into the probability of the accident being on freeway or arterial links is 4/5 and the probability of it being on the surface streets is 1/5.

Stop Delay

From the first generation of experiments, the effects of stop delays were observed to have a significant effect on driver behavior.[4] In this experiment, a stop delay occurs as a result of stop signs or signalized intersections. In Figure 3, nodes 8, 9, 13, 14, 18, and 19 are signalized intersections; nodes 5, 6, 10, 11, 15, 16, 20, and 21 have stop signs only on the surface street approaches. Nodes 2, 7, 12, 17, and 22 represent freeway on/off ramps and are not assigned stop delay in the simulation. At stop sign locations, the vehicle tracking cursor will stop for an appropriate amount of time, but at signals, stops are only required when the light is red. Stop signs have been assigned a delay value of two seconds for right turns and

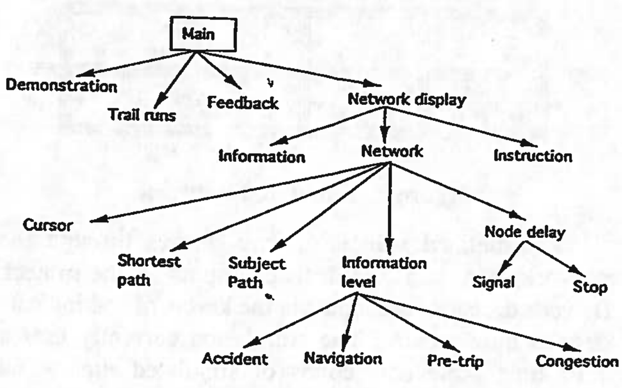

Figure 3. Object-oriented simulator design

three seconds for left turns. In the simulation, a 50-perecent probability of the light being encountered as red is used for every signal.

Within this controlled, simulated travel environment, experimental treatments were applied consisting of various levels of information. In addition, several blocking factors were considered, such as gender, age, and education. For complete details, see Vaughn et al.[2]

The simulation applies four information treatments and uses three blocking factors to make up the seven experimental treatments. The information treatments are labeled A through D, and the blocking factors are E through G. All treatments have two levels and are described below:

A. *Incident with description*. Red icon displayed at the location of a severe incident, yellow icon displayed at the location of a moderate incident. Also, the information window displays textually the location and classification of the incident. For example, "Severe accident on First Street between F St. and G St."

B. *En route guidance*. Arrows indicating advised turning movements and textual description of advice at every intersection.

C. *Pre-trip guidance*. Minimum path displayed at beginning of trip along with an estimate of the travel time on the path for that day.

D. *Congestion information*. Color-coded links for moderate and severely congested links, with green indicating normal congestion, yellow indicating moderate congestion, and red indicating severe congestion.

The three blocking factors:

E. *Gender*. Male or female.

F. *Age*. Young (40 years old or less) or old (greater than 40).

G. *Education*. High (some college or more) or low (high school or less).

To investigate the effect of accuracy on decision and learning processes, the information provided within the simulation was not always 100-percent accurate. Within the simulation, the locational information of incidents, however, was provided at 100-percent accuracy. Route guidance/advice and congestion information was provided at 75-percent accuracy. This means that on 75 percent of the trial days, the guidance/advice or the congestion information provided to the subject was accurate, but on 25 percent of the trial days it was inaccurate.

DATA COLLECTION

In addition to the data recorded by the experiment coordinator, the simulation program recorded all of the subjects' decision inputs automatically and also stored their responses to all questions asked during both the initial interview survey and the simulation. A separate data file was created for each subject and assigned a file name that matched the subject ID number. Of the 100 completed simulations, 99 data files are useable, (one subject was inadvertently assigned an incorrect treatment combination). These 99 files have been broken into three separate data files, with increasing order of complexity. Data from the simulation now reside in a subject file, a daily file, and a decision file. This relational file structure was selected to support a phased schedule of analysis and to create a file structure that could be merged to support data analysis efforts. Decision data were used for the current analysis. The first two files are analyzed in a companion paper by Vaughn et al.[2]

From the total sample set, 49 subjects were selected for this analysis (Figure 4). All these subjects had navigation information displayed during their experiments.

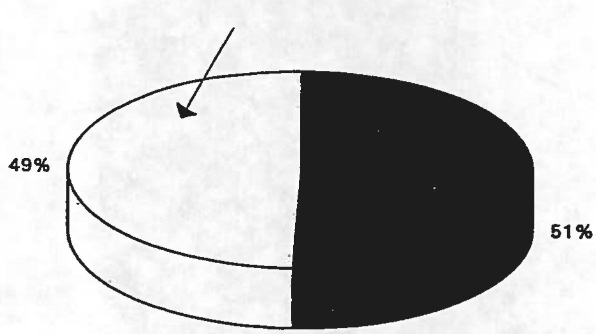

Figure 4. Part of the sample selected for node analyis

ANALYSIS OF SIMULATION DATA

Subjects conducted 20 days of trials. These 20 trials are divided into three segments:

- A first segment consisting of Days 1 to 6
- A middle segment consisting of Days 7 to 14
- A last segment consisting of Days 15 to 20.

The analysis is based mostly on these segments to observe changes in subjects' behavior from segment to segment. For subjects' socioeconomic and travel characteristics, one may refer to the companion paper by Vaughn et al.[2] The term "system's decisions" was defined to facilitate assessing the impact of the simulation on subjects. It is defined as the number of decision points (intersections) in the route suggested by the system as pre-trip information before the subject starts the simulation for the day. If user decision points exceed the system's decisions, it means that the subjects are trying different options and not just following the system's advice.

Figure 5 indicates that subjects made more decisions in the middle segment than in the first and last segments. This shows the usual phenomenon that when subjects are new to the network, they try to stick with a few familiar routes. When subjects become familiar, they try many options to evaluate the network and information system. So the number of decisions increases. In the last segment subjects are well experienced with the network and information system, which helps the subject to minimize the number of decisions. Here the number of decisions will reduce, but still exceed the system's decisions. In the figure, the distribution of decisions for each day are also listed. Figure 6 also supports the above argument. This figure explains the distribution of average decisions per day by the user shows how it compares with the average decisions given by the system.

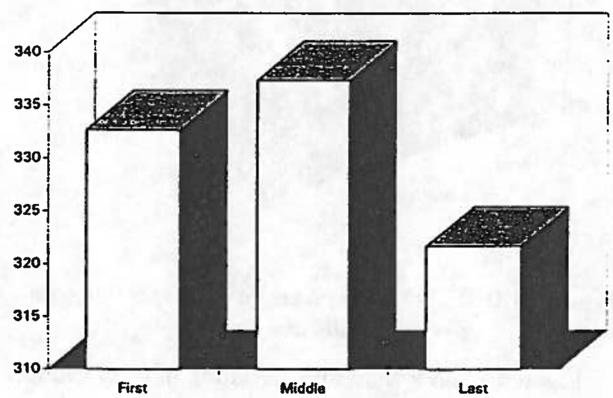

Figure 5. Distribution of number of decisions among segments

Figure 7 indicates that female subjects have made more decisions than male subjects. In the first segment, female subjects deviated more from the system's decisions than did male subjects. They made 11.35 percent more decisions than systems decisions compared with 7.62 percent for males. In the middle segment, female and male subjects made 2.07 percent and 1.78 percent more decisions respectively, and are close to following the system's decisions. In the last segment, subjects have increased their propensity to make more decisions than the system's decisions (female subjects, 10.33 percent more, and male subjects 7 percent more).

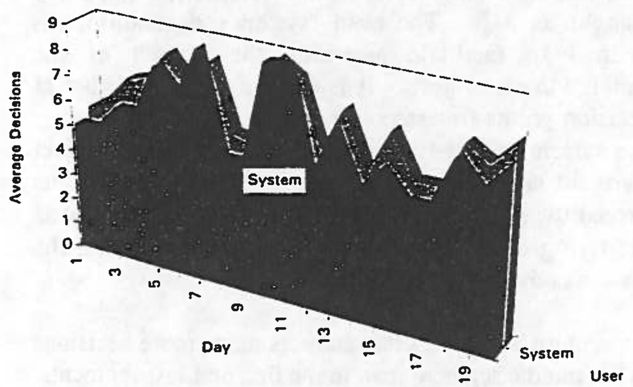

Figure 6. Distribution of average decisions per day between system and user

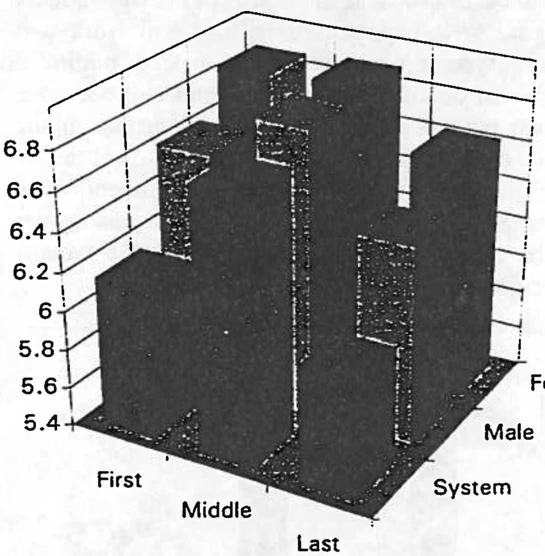

Figure 7. Distribution of average decisions between system, male, and female

Figures 8 and 9 shows the deviation of other groups from the system's decisions. Younger subjects have made more decisions than older subjects. Younger subjects made 10.37 percent more in the first segment, 3.41 percent more in the middle segment, and 11.33 percent more in the last segment than the system's decisions. In comparison, older subjects made 9.24 percent more in the first segment, 0.89 percent more in the middle segment, and 8.17 percent more in the last segment. Similarly, highly educated subjects have more deviation from the system's decisions than less-educated subjects. Highly educated subjects made 9.23 percent, 3.52 percent, and 11.83 percent more decisions in the first, middle, and last segments, respectively, and less-educated subjects made 10.21 percent, 0.74 percent, and 7.5 percent more decisions in the first, middle, and last segments, respectively. These results are discussed later in more detail later.

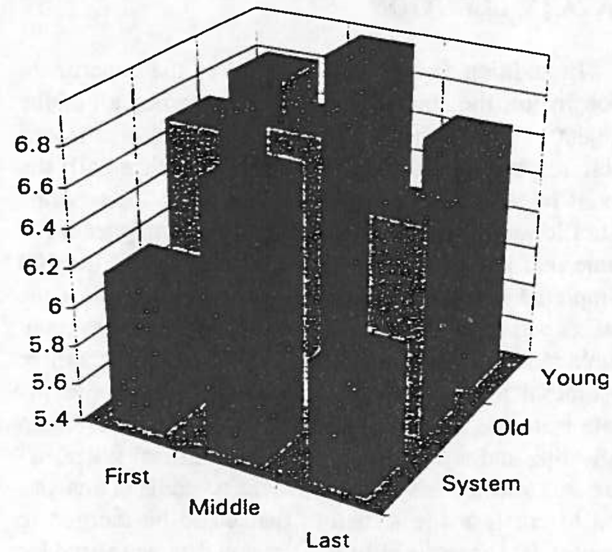

Figure 8. Distribution of average decisions between system, old, and young

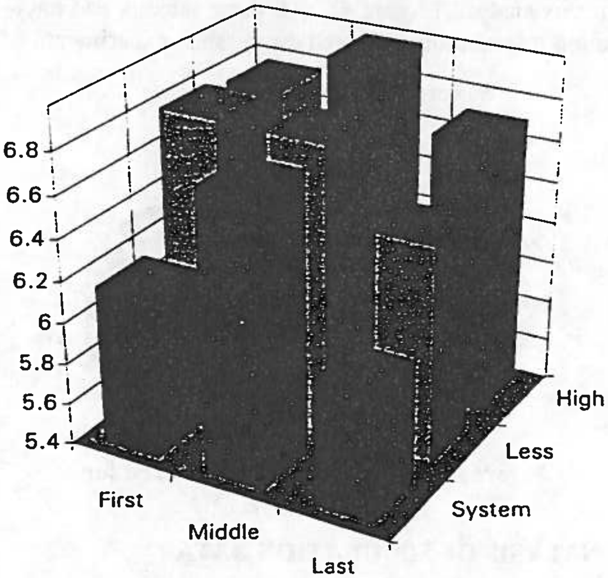

Figure 9. Distribution of average decisions between system, less educated and high educated

Figure 10 gives overall decision patterns of each group of subjects in the simulation experiments. In general, subjects make 6.81 percent more decisions than the number of the system's decisions. Male subjects

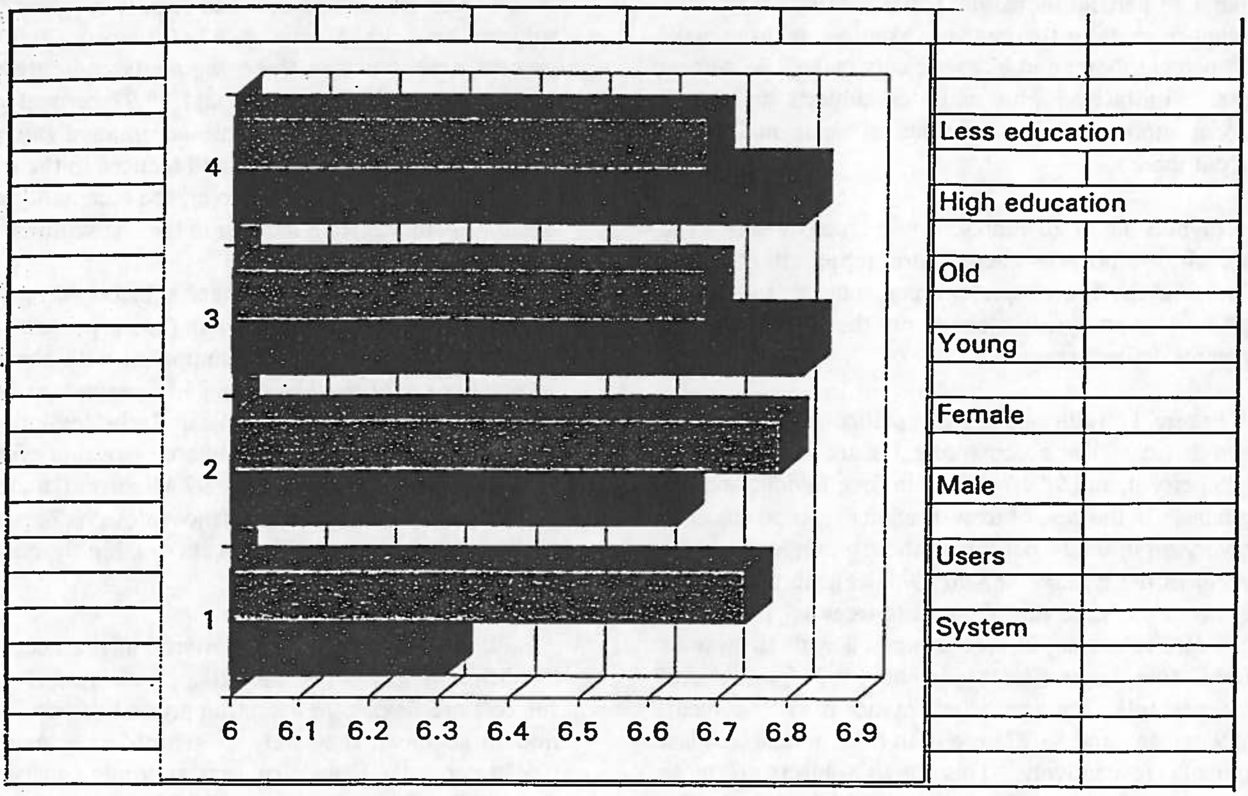

Figure 10. Comparison of average decisions per day in different subject groups

Segment	Total	Accepted
	Total acceptancy	
First	1949	1724
Middle	2545	2323
Last	1910	1722
	Freeway acceptancy	
First	657	629
Middle	794	771
Last	597	579
	Ramp acceptancy	
First	278	207
Middle	247	200
Last	200	155
	Artirial acceptancy	
First	1014	888
Middle	1504	1352
Last	1113	988

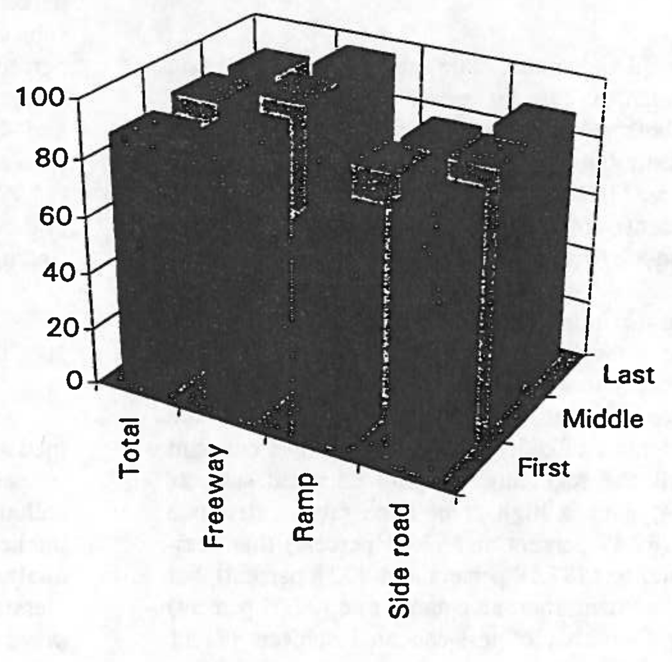

Figure 11. Distribution of acceptancy rate for different road type advice

make 5.23 percent more, and female subjects make 7.61 percent more than the system. Younger subjects make 8.08 percent more, and older subjects make 5.86 percent more. Similarly, highly educated subjects make 8.08 percent more, and less-educated subjects make 5.86 percent more.

Figures 11 to 20 represent two types of data. The table shown next to each figure represents absolute values, and the figure represents percentages. In all these figures, the analysis is based on the three different segments defined earlier.

Figure 11 indicates the acceptance rate of system-given advice. The acceptance rates are 88.46 percent, 91.25 percent, and 90.16 percent in first, middle, and last segments. In the case of freeway advice, acceptance rates are very high, 95.74 percent in the first segment, 97.10 percent in the middle, and 96.99 percent in the last. If the advice is "take ramp" towards freeway, the acceptance rate is not significant compared with freeway or arterial acceptance (74.46 percent, 80.97 percent and 77.50 percent). The arterial acceptance is 87.57 percent, 89.89 percent, and 88.77 percent in first, middle, and last segments, respectively. This shows subjects are more receptive to freeway advice than arterial advice. The small percentage of acceptance for ramp advice shows that subjects are most open to using either freeways or arterials before they start the trip. In other words, switching between freeway and arterial is not that common.

Figure 12 shows that male subjects' acceptance rate is higher than the rate for female subjects. In the first segment, both subjects have the same acceptance rate (88.4 percent), but in the middle and last segments, male subjects have higher acceptance rates (92.67 percent and 90.90 percent) compared with female subjects (90.46 percent and 89.77 percent).

Figure 13 indicates that older subjects have high acceptance rates (91.01 percent, 91.72 percent, and 91.21 percent) than younger subjects (85.56 percent, 90.76 percent, and 88.78 percent), and that the acceptance rates of older subjects are almost constant through all the segments. Highly educated subjects (Figure 14) have a high acceptance rate in first two segments (89.49 percent and 92.03 percent) than less-educated subjects (87.59 percent and 90.58 percent), but in the last segment, their acceptance rate (89.05 percent) is smaller than that of less-educated subjects (91.11 percent).

Figure 15 to 17 show the freeway acceptance in each group of subjects. In Figure 15, male subjects are more receptive to freeway advice than female subjects. Male subjects have 96.55 percent, 97.40 percent, and 98.40 percent acceptance in three segments compared with 95.20 percent, 96.91 percent, and 95.97 percent acceptance for females. The female acceptance rate is increased in the middle segment and reduced in the last. In the case of male subjects, however, the acceptance rate is linearly increased from the first to the last segments.

Figure 16 indicates younger subjects have higher and more variable acceptance rate (95.90 percent, 97.42 percent, and 97.06 percent) compared with the stable acceptance rates (96.42 percent, 96.85 percent, and 96.92 percent) of older subjects. Similarly less-educated subjects have higher and more variable freeway acceptance rates (94.83 percent, 97.44 percent, and 97.14 percent) than the stable acceptance rates (96.76 percent, 96.70 percent, and 96.81 percent) of highly educated subjects.

Figures 18 to 20 show the arterial advice acceptance by different groups of subjects. In Figure 18 male subjects are flexible in accepting arterial advice. In the middle segment, they were at a high acceptance rate (96.36 percent). Female subjects are more consistent in the middle and last segments (87.71 percent and 87.42 percent) than in the first (85.50 percent).

In the case of younger subjects (Figure 19), the arterial advice is less acceptable (81.60 percent, 87.97 percent, and 84.74 percent) than it is for stable older subjects (88.44 percent, 89.31 percent, and 88.76 percent). Highly educated subjects are very flexible in accepting arterial advice (85.64 percent, 90.15 percent, and 85.34 percent) when compared with the linearly increased acceptance rates of less-educated subjects (84.79 percent, 87.23 percent, and 88.43 percent). Most of the results are supported by previous experiments and findings reported in companion papers.

RECURRENT NEURAL NETWORKS

Artificial neural networks have been widely used to model information processing. There is an increasing interest in the application of hybrid neural network techniques to transportation engineering. In recent publications, different transportation applications are analyzed with simple neural networks. They include classification and pattern recognition,[5] image processing,[7, 8] freeway-incident detection,[9] and driver route-choice analysis.[3] This approach is being used by the authors as a quick and efficient method to analyze route-choice behavior vis-a-vis conventional analysis methods.[4]

Male given adv. acceptancy		
Segment	Given	Accepted
First	726	642
Middle	941	872
Last	649	590
Female given adv. acceptancy		
Segment	Given	Accepted
First	1223	1082
Middle	1604	1451
Last	1261	1132

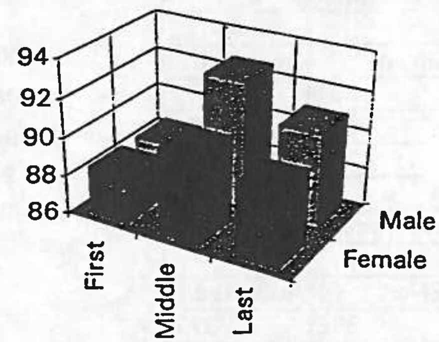

Figure 12. Gender distribution of system's advice acceptance

Young given adv. acceptancy		
Segment	Given	Accepted
First	914	782
Middle	1180	1071
Last	829	736
Old given adv. acceptancy		
Segment	Given	Accepted
First	1035	942
Middle	1365	1252
Last	1081	986

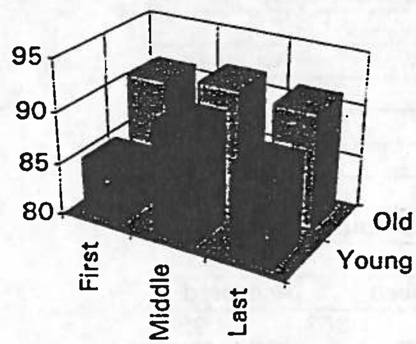

Figure 13. Age distribution of system's advice acceptance

High education adv. acceptancy		
Segment	Given	Accepted
First	894	800
Middle	1229	1131
Last	886	789
Low education adv. acceptancy		
Segment	Given	Accepted
First	1055	924
Middle	1316	1192
Last	1024	933

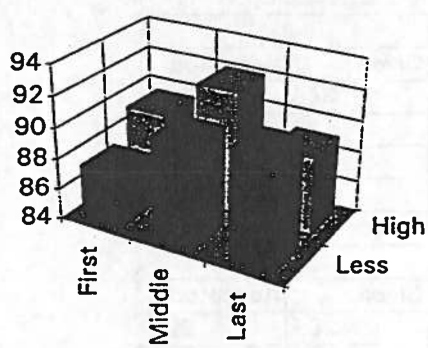

Figure 14. Education level of system's advice acceptance

Male freeway acceptancy		
Segment	Given	Accepted
First	261	252
Middle	308	300
Last	250	246
Female freeway acceptancy		
Segment	Given	Accepted
First	396	377
Middle	486	471
Last	347	333

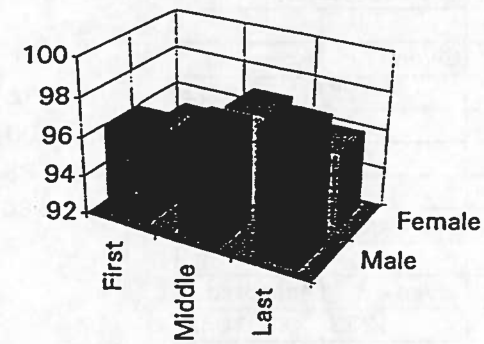

Figure 15. Gender distribution of freeway advice acceptance

Young freeway acceptancy		
Segment	Given	Accepted
First	294	279
Middle	349	340
Last	272	264
Old freeway acceptancy		
Segment	Given	Accepted
First	363	350
Middle	445	431
Last	325	315

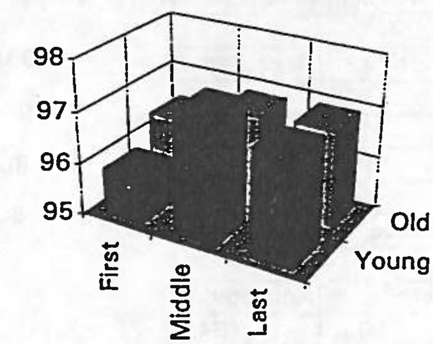

Figure 16. Age distribution of freeway advice acceptance

High education acceptancy		
Segment	Given	Accepted
First	348	330
Middle	430	419
Last	315	306
Low education acceptancy		
Segment	Given	Accepted
First	309	299
Middle	364	352
Last	282	273

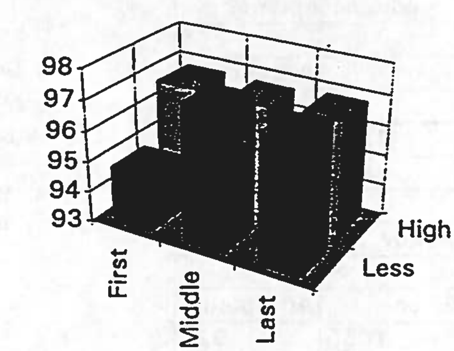

Figure 17. Education level of freeway advice acceptance

Male artirial acceptancy		
Segment	Given	Accepted
First	461	390
Middle	633	572
Last	399	344

Female artirial acceptancy		
Segment	Given	Accepted
First	821	702
Middle	1115	978
Last	914	799

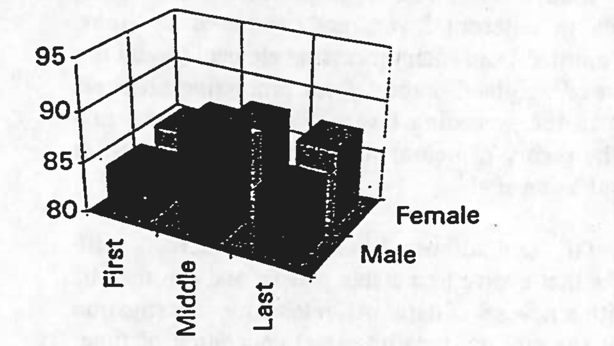

Figure 18. Gender distribution of arterial advice acceptance

Young artirial acceptancy		
Segment	Given	Accepted
First	616	503
Middle	831	731
Last	557	472

Old artirial acceptancy		
Segment	Given	Accepted
First	666	589
Middle	917	819
Last	756	671

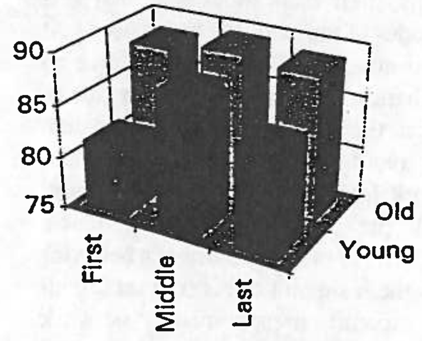

Figure 19. Age distribution of arterial advice acceptance

High education acceptancy		
Segment	Given	Accepted
First	585	501
Middle	863	778
Last	604	516

Low education acceptancy		
Segment	Given	Accepted
First	697	591
Middle	885	772
Last	709	627

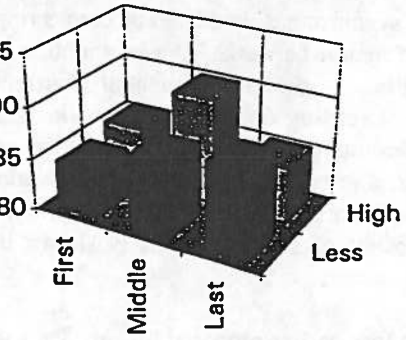

Figure 20. Education level of arterial advice acceptance

In this study, the neural 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 by links. Output emitted from each processing element (node) is a function of weighted outputs from processing elements (nodes) in the preceding layer. For more information about the theory of neural networks, see Rumelhart et al.[10] and Yang et al.[3]

So far, the authors have been concerned with networks that evolve to a stable pattern and can then be used with a new set of data. An interesting investigation involves the storing, recalling, and generating of time-related networks. The present problem is to include previous route choices in predicting the present route choice. In other words, the driver is located at an intersection in the network with system advice, and it is to be investigated whether the driver will accept the advice or not, depending upon his/her personal characteristics and choices made at previous decision points. In this analysis, there is an input node that gets input from previous nodes of the neural network used. At the beginning of the simulation, the driver will have no past experience, and hence, there is no input for one of the nodes. This makes the problem more complicated. Present methods will avoid the first decision point and train the neural network from the second decision point. This is only possible in the case of one day's experience. However, if there is a need to evaluate a driver's behavior from the first point to the last point of his trial taking all his experience into account, present neural network models are inadequate. One must turn to supervised learning in more general networks, with connections allowed both ways between a pair of units, and even within a unit itself. These are usually called recurrent networks. These networks do not necessarily settle down to a stable state, even with one time input.

Here the problem is investigated using simple sequences that are synchronously updated by connecting together a chain of neural networks. An explanation is in order regarding how to design a sequential recurrent network. Instead of settling on a single network, it is desired that predictions go through a predetermined sequence usually in a nonclosed cycle. These networks can recognize sequences, or learn sequences incrementally. The design of such networks is shown in Figure 21.

A similar idea was earlier proposed by Lapedes and Faber.[11] in their "master-slave" network, wherein the master network calculates weights for the slave. However, they had one master unit for each connection in the slave network and made the master network

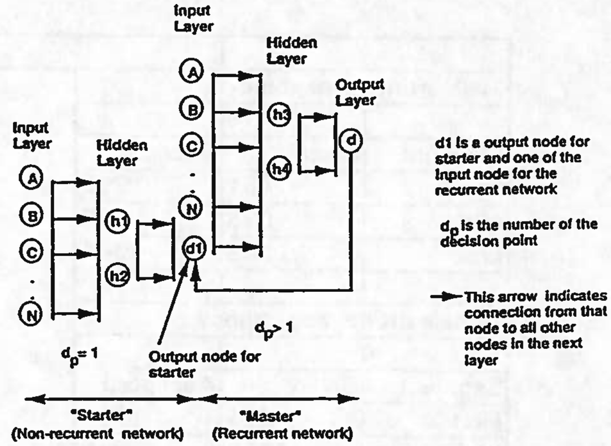

Figure 21. Recurrent network for single-day history

calculate appropriate weights without using the slave for feedback. In the present application, the starter will generate an output that is the input for one node in the recurrent neural network. This node takes an input value from the previous decision point output. Once all the input nodes are filled with values, the recurrent network starts functioning until the end of a single trial (day). For example, if one wants to determine a current decision using the last three decisions, the required sequential neural network will have three starter and one recurrent neural networks. The recurrent neural network will start functioning after three starters make their decision (Figure 22). From that point on, each decision point replaces the oldest decision points by sequentially moving decisions to the respective nodes. The arrows between $d_1 \ldots d_n$ show this action of transformation.

Recurrent networks are assigned three tasks: Sequence recognition, sequence reproduction, and temporal association. In the sequence-recognition task, the network is required to produce a particular output pattern when a specific input sequence is seen. This is appropriate in the case of starter neural networks. They just output a value that is used by the next starter or recurrent network. Use of a simple back-propagation training algorithm is planned for the starter networks.

In the second task, sequence reproduction, the network must be able to generate the rest of a sequence itself when it has all input values satisfied. The master network has to generate an output when the output signal reaches the input node, and the transformation of previous experiences is done with respect to their assigned nodes in the network. This is sometimes known as auto association or pattern completion of dynamic patterns. It would be appropriate for learning a set of decisions from the data collected. In other words, if there are data available about personal characteristics and network characteristics, it is easy to define what the decision pattern is going to be.

The last task, temporal association, includes a static group of input nodes that are input to all the starter and master networks. In this case, personal characteristics are always static for all neural networks. Neural network characteristics will change from one decision point to another.

Training

In this paper, some of the validation results were reported regarding performance of the neural network model. First, a neural network was trained with one back-node experience. In the training cycle, the training vectors are presented to the neural network in sequential order from first node of choice to last node of choice. The number of processing elements in the hidden layer was varied from three to seven in investigating the effect on network performance. During the training, the values of learning and momentum rates were set to be 0.2 and 0.9 respectively, and were kept constant. It can be seen that the first 500 cycles of training lead to a sharp reduction in the squared output errors. After 9,000 cycles of training, no significant improvement was observed, but training continued up to 10,000 cycles. At this point, one can plan on extending the network design to train daily route-choice decision patterns of single drivers and groups of drivers. Once a neural network has been stabilized, it is desirable to conduct further analysis of modeling drivers' route choice behavior.

SUMMARY

In this study, a neural network model is developed to predict a driver's route-choice behavior under ATIS. Data used for analysis were 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 was first conducted to test the feasibility of the approach. The neural network model is found to reasonably predict a driver's route choice. The constructed neural network model is then used 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

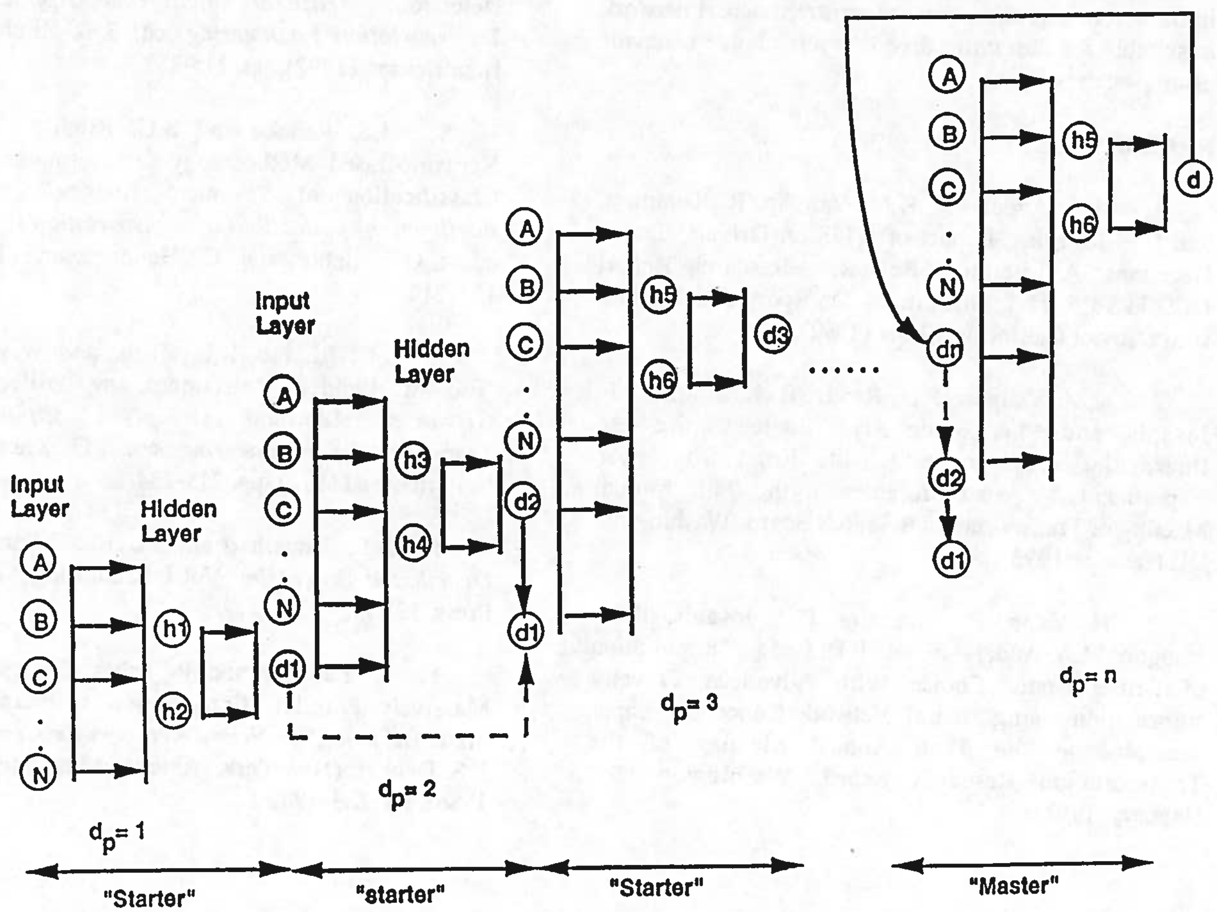

Figure 22. Recurrent network for n-days history

impact of 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 the 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 immediate subsequent trips. Over time, however, they may return to following system advice if the system performs well. Route-choice behavior also was 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 the author's 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 appear 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. Using the experience in this experiment, a new simulator is being designed to include most of the realistic conditions. Initial test results show that the recurrent neural network is suitable for observing drivers' route-choice behavior using past experience.

REFERENCES

1. M.A. Abdel-Aty, K.M. Vaughn, R. Kitamura, and P.P. Jovanis, "Impact of ATIS on Drivers' Travel Decisions: A Literature Review," Research Report UCD-ITS-RR-92-7, Institute of Transportation Studies, University of California, Davis (1992).

2. K.M. Vaughn, P.D. Reddy, R. Kitamura, P.P. Jovanis, and M.A. Abdel-Aty, "Route Choice and Information Use: Initial Results From Simulation Experiments," paper presented at the 74th Annual Meeting of Transportation Research Board, Washington, DC (January 1995).

3. H. Yang, R. Kitamura, P.P. Jovanis, K.M. Vaughn, M.A. Abdel-Aty, and P.D. Reddy, "Exploration of Driver Route Choice With Advanced Traveler Information Using Neural Network Concepts," paper presented at the 72nd Annual Meeting of the Transportation Research Board, Washington, DC (January, 1992).

4. K.M. Vaughn, M.A. Abdel-Aty, R. Kitamura, P.P. Jovanis, and H. Yang, "Experimental Analysis and Modeling of Sequential Route-Choice Behavior Under ATIS in a Simplistic Traffic Network," presented at the 72nd Annual Meeting of the Transportation Research Board, Washington, DC (January 1993).

5. P.D. Reddy, H. Yang, K.M. Vaughn, M.A. Abdel-Aty, R. Kitamura, and P.P. Jovanis, "Design of an Artificial Simulator for Analyzing Route-Choice Behavior in the Presence on the Information System," accepted for publication in *Journal of Computer Simulation and Applications* (1994).

6. P.D. Reddy, M. Weng, R. Kitamura, and P.P. Jovanis, "Rapid Prototyping of Transit Information System for Evaluation of Impacts on Solo Drivers' and Transit Users' Travel Decision," submitted for presentation at the 74th Annual Meeting of the Transportation Research Board, Washington, DC (January 1995).

7. D. Bullock, J. Garrett Jr., C. Hendrickson, and A. Pearce, "A Neural Network for Image-Based Vehicle Detection," *Artificial Intelligence Applications in Transportation Engineering*, ed. S.G. Ritchie and C. Hendrickson (1992), pp. 235-252.

8. M.S. Kaseko and S.G. Ritchie, "A Neural Network-Based Methodology for Automated Distress Classification of Pavement Images," *Artificial Intelligence Applications in Transportation Engineering*, ed. S.G. Ritchie and C. Hendrickson (1992), pp. 195-214.

9. S.G. Ritchie, R.L. Cheu, and W.W. Recker, "Freeway Incident Detection Using Artificial Neural Networks," *Artificial Intelligence Applications in Transportation Engineering*, ed. S.G. Ritchie and C. Hendrickson (1992), pp. 215-234.

10. D.E. Rumelhart and J.L. McClelland, *Parallel Distributed Processing* Vol.1 (Cambridge, MA: MIT Press, 1986).

11. A. Lapedes and P. Faber, "Programming a Massively Parallel, Computation Universal System: Static Behavior," in *Neural Networks for Computing*, ed. J. S. Denker, (New York: American Institute of Physics, 1986), pp. 283-298.