Title
Design of an Artificial Simulator for Analyzing Route Choice Behavior in the Presence of Information System

Permalink
https://escholarship.org/uc/item/93x4h7pp

Authors
Yang, Reddy H
Vaughn, K M
Abdel-Aty, M A
et al.

Publication Date
1995-07-01
Design of an Artificial Simulator for Analyzing Route Choice Behavior in the Presence of Information System

P. D. V. G. REDDY, H. YANG,
K. M. VAUGHN and M. A. ABDEL-ATY
Institute of Transportation Studies, University of California at Davis
Davis, CA 95616, U.S.A.

R. KITAMURA
Department of Transportation Engineering
Kyoto University, Kyoto 606, Japan

P. P. JOVANIS
Institute of Transportation Studies, University of California at Davis
Davis, CA 95616, U.S.A.

Abstract—Computer simulation is often-used methodology to study travel behavior as a cost effective alternative to field studies. In this study, we utilize PC-based computer simulation to study the effects of information on route choice and learning. Building on the efforts of a prior stage of simulation, further experiments that utilize an expanded traffic network and provide various levels of information to subjects, have been designed. This framework allows us to investigate both pretrip and en route route-choice behavior, and capture the effect of different levels of information of drivers’ learning and adaptive processes that are being undertaken in these experiments.

The experiments were designed in two stages. In the first stage, a simple, two route-alternative traffic network was developed. Experiments conducted with this network provided extensive comments from participants, which were modeled using object-oriented programming techniques to produce a better subsequent design. The data from the first stage was analyzed using neural network techniques and the network was trained using back-propagation. The second stage of experiments utilized a multiple-route, expanded network with pretrip and/or en route information, and varying levels of information. The data obtained in this stage is being analyzed using recurrent neural networks. This paper describes the design and analysis of the first stage of experiments, and the redesign of the network simulation using experience gained in the first stage.

The design of the network simulation involved the following steps: requirements analysis, database 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++. The object-oriented features included inheritance, class hierarchy, message passing and concurrency. A recurrent neural network has been built for future modeling of the data obtained in the second stage of experiments. This neural network will be used to predict subjects’ choices of whether or not to follow the system-provided advice, depending on past experience. An important feature of the neural network is that the decisions at previous nodes, will be used as an input at subsequent nodes. This allows us to model participants route choice behavior at every node, that is at every decision point.

Keywords—Class hierarchy, Recurrent neural networks, Drivers’ route choice, Decision points, Experience factor.

The authors wish to thank N. Kroll, R. Post, and B. Oppy from the Psychology Department of U.C. Davis for developing the first stage of route choice simulation software and carrying out the experiments. The funding provided by PATH and the California Department of Transportation is gratefully acknowledged.

Typeset by AMS-TEX
INTRODUCTION

Recently, there has been much interest in developing advanced traveler information systems (ATIS) as a way to aid drivers make more informed route choices and alleviate traffic congestion. An important issue in implementing such systems requires understanding how the ATIS will affect driver behavior, how drivers adopt and learn to use the ATIS, and how these changes will impact the network. Several methods have been used to study driver's route choice behavior when influenced by 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 have also 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.

Current research being performed at the University of California at Davis is investigating the impact of ATIS on travel demand. The goals of the project are to understand how people will adopt an ATIS, learn how to use it, devise rules for travel planning and how all these relate to travel demand. The research efforts described in this paper and in a companion paper [2] covers only a part of this larger project. Vaughn et al. [2] describe the experimental design of the driving simulator. This effort is the first step in the process of obtaining a basic understanding of the factors which influence route choice and how ATIS will affect drivers' route choice behavior over time.

Route choice in a real traffic environment is very complex, and little experimental evidence exists of how drivers process information and select routes [1]. Therefore, it was decided to analyze route choice behavior in a simplistic, less complicated environment. It was felt that this would allow us to adequately control and analyze the effects of various factors on route choice behavior. One factor that is of utmost importance to any analysis of driver behavior influenced by ATIS, is the accuracy of information. The success or failure of ATIS will be highly dependent on the accuracy and quality of advice that can be delivered to drivers. If a system consistently provides bad information, drivers will soon 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 accuracy of provided information? Is there an accuracy threshold below which drivers perceive no benefit from following advice? If such thresholds do exist, are they consistent for all drivers, or do different types of drivers have different thresholds? Can drivers perceive the accuracy of information, and under what conditions and how rapidly? All of these questions need to be addressed in order to maximize the potential of ATIS. In the first stage of experiments, we did not introduce any variables related to information content and experience. Information content is defined as the level of information to be provided to drivers. Driving history refers to drivers' experience with the information system. In the second stage of experiments, the extent to which drivers need information, and how much of the previous experience will be remembered in his present route choices is investigated, with relation to driver characteristics.

FIRST STAGE OF ROUTE CHOICE EXPERIMENTS

The first stage of experiments used an interactive PC-based route choice simulation to investigate drivers' learning and prettrip route choice behavior under ATIS. A set of instructions were given to the subject describing the operation of the simulation. The subjects were told that they were to purchase a new "Traffic Watch Device" which would provide them with traffic information prior to selecting their route. The subjects were also told that the device was not always accurate, but were not given any indication of its overall accuracy. Before beginning the
simulation, the subjects were shown examples of the fastest and slowest possible times on each of the routes, and were allowed to repeat the examples as often as necessary to become familiar with the system. Subjects were instructed that their main task was to minimize their overall travel time by deciding when, and when not, to follow the advice provided by the traffic information system. Subjects were also told that their decision and response times are being measured, and that they should try to respond as quickly as possible.

At the beginning of the simulation, subjects were presented with a screen indicating the trial day number and instructed to position their hands on the computer keyboard, and press the space bar when they are ready to receive advice. On pressing the space bar, the advice for that day is presented along with a simulated freeway link, a side road link and an origin and destination. The advice given was either “Take the Freeway, traffic is moving smoothly,” or “Take the side road, there is a problem on the Freeway.” The display was simple and is shown in Figure 1.

![Traffic decisions](image)

**Figure 1.** Screen display of first stage simulator.

When the subject selects a route by using arrowkeys, a red blinking cursor (depicted by the shaded box on the freeway link) moves across the screen from origin to destination. The speed at which the cursor moves represents the average travel speed on that link for that travel day. The double line in the Figure 1 represents the freeway, while the single line represents the side road. Upon completion of each trial the subjects were asked to rate their satisfaction with choice (one of Correct, Probably Correct, Don’t Know, Probably Incorrect, Incorrect), and provide an estimate of their travel time on the chosen route (one of Fastest Possible, Reasonably Fast, Moderate, Fairly Slow, Incredibly Slow).

The simulation was developed such that various treatments could be applied and then data collected under these different conditions. The treatments which were applied to the simulation are accuracy (the accuracy of the advice provided to subjects was either 60%, 75% or 90%), Stops (a simulated stop on the side road route), rationale (justification statement as to why the subject should follow the advice), feedback (provided at the end of each trial in the form of actual simulated travel times on the two routes for that trial), freeway (identification of the routes as Freeway and Side Road as opposed to simply routes), and side road (display with two road links as shown in Figure 1 or with no network display provided), and travel time by a blinking cursor located in the center of the screen.

Three separate experiments were carried out to collect data under various conditions. The three experiments and the conditions under which the simulation has been run to date are shown in Table 1. The first experiment was used to investigate accuracy requirements of ATIS. The experiment was structured to provide three levels of information accuracy. Three separate groups of 23, 25 and 29 subjects experienced the simulation at the levels of accuracy. In the second and third experiments, the information accuracy was held constant at 75 percent while other experimental conditions were varied. This report provides an initial analysis of the data collected in the first experiment utilizing three of the sixteen possible initial conditions shown in Table 1 (conditions 1, 2 and 3). For each condition, 10 subjects were selected for analysis purpose.
Table 1. Experimental treatments.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Condition</th>
<th>Treatment Number</th>
<th>Number of Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1    2    3    4    5    6</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>60%   no yes yes yes yes</td>
<td>23</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>75%   no yes yes yes yes</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>90%   no yes yes yes yes</td>
<td>29</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>75%   yes yes yes yes yes</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>75%   yes yes yes yes yes</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>75%   yes yes no yes yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>75%   no yes yes yes yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>75%   no no yes yes yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>75%   no yes no yes yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>75%   no yes yes no yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>11</td>
<td>75%   no no yes no yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>12</td>
<td>75%   no no no yes yes</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>13</td>
<td>75%   no no yes no no</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>14</td>
<td>75%   no no no no no</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>75%   yes no yes no no</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
<td>75%   yes no no no no</td>
<td>20</td>
</tr>
</tbody>
</table>

A forthcoming paper will address the second and third experiment and the effects of varying conditions.

All of the experiments subjected the drivers to 32 simulated days in which they were to choose one of the two possible routes. For each travel day, an amount of delay was randomly assigned to each of the two routes. The units of delay assigned to a particular route were proportional to the travel time experienced on the route. The delay was distributed over the 32 trials such that the mean delay for each route was equal but the variance differed. In this manner, routes with potentially faster travel times but with a greater amount of uncertainty (as one might expect on a freeway) can be compared to routes with slower travel times but with a greater amount of certainty (similar to surface street routes). Upon completion of 32 sequential simulated days, subjects were asked to rate their potential for purchasing such a traffic information device, their perceived accuracy of the device, and their own ability at selecting routes when compared to the information device.

This first stage of the experiment was used to determine what is needed in a real simulation. The computer program automatically recorded and stored data from each subject for 32 sequential trials. The variables recorded by the program are the advised route, relative delay between the routes, delay on the freeway, delay on the side road, route chosen by the subject, individual's level of satisfaction, individual's estimate of their perceived speed, decision time, individual's gender, driving frequency, potential usage of information system, perceived accuracy of the information system, personal ability, accuracy level, and trial number. Test subjects were all undergraduate students in the Psychology Department at the University of California at Davis. The variables selected from the past literature and personal experience were introduced into this first stage of experiments. The variables created from the original dataset are trial block, agreement, average acceptance rate, and accuracy of the advice given on the previous trial.
Artificial neural networks have been widely used to model information processing. There is an increasing interest in application of neural network techniques to transportation engineering. They include classification and pattern recognition, travel demand estimation, image processing [3,4], freeway incident detection [5], and driver route choice analysis [6]. The neural network approach utilizes an iterative data matching technique and is generally reported to have the ability to accommodate complicated problems without requiring explicit equations correlating input/output data, and effectively generate reasonable results. This approach is being used by the authors as a quick and efficient method to analyze route choice behavior in comparison to conventional analysis methods [2].

In this study, a neural network model is constructed to analyze driver route choice mechanisms under ATIS. 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. The output emitted from each processing element (node) is a function of the weighted outputs from the processing elements (nodes) in the preceding layer. For more information about the theory of neural networks, see [7,8].

A back-propagation gradient descent optimization algorithm to 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. Training of the network starts with small random numbers assigned to all the weights and thresholds. The training is terminated when either the maximum number of iterations is reached or the sum of squared output errors is reduced to 0.0001. Figure 2 shows the training process with a back-propagation algorithm [8].

![Flow chart of a back-propagation training algorithm](image)

**Figure 2. Flow chart of a back-propagation training algorithm [8].**

### NEURAL NETWORK ROUTE CHOICE MODEL

**Structure of Neural Network**

The neural network used in this study consisted of an input layer, a hidden layer and an output layer, as shown in Figure 3. There are 9 processing elements in the input layer. A single processing element in the output layer is used to indicate drivers' acceptance or nonacceptance of advice given by the information system. During the training of the neural network, the desired output is set to 1 if accepted and 0 otherwise. During the testing or prediction phases, the advice is accepted if the output value is greater or equal to 0.5, and not accepted if the output value is less than 0.5.
In the model are 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. To reflect the fact that the driver's perception and knowledge are also based on experience accumulated from preceding days, weighted cumulative averages are used as input variables. The following input nodes were defined:

- $x_1$: 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 driver's level of satisfaction with choices made on 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 driver's level of satisfaction with choices made on 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 their perceived speeds on the side road chosen on 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 behavior of a group of drivers is to be analyzed, then drivers' individual attributes should be taken into account. The set of variables is thus extended to include two new input variables $x_{10}$ and $x_{11}$. Driving frequency and Driver's gender.

The category of Driver age could also be used as an input variable, but is not considered here because most of the subjects in this experiment were young students at U.C. Davis. Among the input variables considered above, $x_1$ reflects the effect of advice provided by the information system; $x_2$ through $x_5$ represent the effect of the driver's previous travel experiences on the side road, and $x_6$ through $x_9$ on the freeway; and $x_{10}$ and $x_{11}$ reflect the influence of personal
characteristics on route choice. All the values taken by variables \( x \) were normalized to range from 0 to 1 using a logistic function, and then be transmitted to the hidden layer in the neural network.

**Measure of Travel Experience**

Subjects were asked to indicate their satisfaction with the choice made and their perceived speed on the chosen route after each simulation run. A five-point rating scale is adopted for choice and speed ranging from \(-2\) to \(+2\), where a negative number implies a bad experience. Moreover, if one of the routes was not used by the drivers on a particular day (no rating was provided on that route), then the corresponding rating was at zero, which means that no new knowledge or experience about the unused route was acquired. In the same way, the driving frequency of subjects was also measured.

In the simulation experiments, delays on the routes were randomly generated to range from 1 to 5 units on the freeway, and 2 to 6 units on the side road. These values were also transformed linearly into values between \(-2\) and \(2\). The vectors of previous travel experience rated above need to be combined by some perception updating strategy to constitute the vector \( X \) of the driver’s current perception of travel conditions on the freeway and side road. However, no matter what updating strategy is adopted, the final values should fit into the same evaluation interval \([-2, 2]\) in order for the values to be meaningful.

**Perception Updating Strategy**

Variables \( x_2 \) through \( x_9 \) represent the driver’s 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 combining historical information and experience. In general, a perception updating strategy reflects a learning process which may differ across drivers.

Suppose, at the beginning of day \( w \) the driver constructs his updated historical perception \( x \) of travel conditions. This update is a function of previous historical perceptions and his personal travel experience on day \((w-1)\) [9]. The following updating strategy is considered in this study:

\[
x(w) = (1 - \lambda)x(w - 1) + \lambda u(w - 1), \quad 0 \leq \lambda \leq 1,
\]

where:

- \( u(w - 1) \): a vector of the driver’s evaluations on his travel on the previous day,
- \( x(w - 1) \): a vector of the driver’s previous historical perception of road conditions,
- \( \lambda \): a positive parameter called experience factor which reflects the relative impact of the previous day’s experience, and the accumulated historical knowledge on the individual’s perception.

With this recursive formula, the weights assigned to the evaluation vector \( u \) of travel experiences for previous days can be easily shown as:

\[
x(w) = (1 - \lambda)^{w-1}u(0) + (1 - \lambda)^{w-2}\lambda u(1) + (1 - \lambda)\lambda u(w - 2) + \lambda u(w - 1).
\]

Therefore, the earlier the day, the smaller the weight, which reflects the relative impact of travel experiences on different days to the present day travel condition perception. If \( \lambda = 1 \), then only the most recent experience of on the previous day is taken into account in today's route choice. If \( \lambda = 0 \), the driver does not update his information.
RESULTS AND ANALYSIS

Neural Network Performance

Before examining an individual's dynamic route choice in detail, we report the results of validation experiments on the performance of the neural network model. Thirty-two days' route choices made by one individual in the simulation experiments were used to train the basic neural network in Figure 3. In each training cycle, the training vectors are 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 to investigate its effect on the performance of the network. During the training, the values of learning and momentum rates \( \eta \) and \( \alpha \) were set at 0.2 and 0.9, respectively, and kept constant. Moreover, the experience factor \( \lambda \) in the perception updating formula was chosen to be 0.8.

Figure 4a shows the changes in 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 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 $\lambda = 0.8$.

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 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 results of testing with an extended neural network model for route choice analysis of a group of drivers. In this test, a total of 320 route choices for 10 subjects were used to train the network. It is observed that networks with a different number of hidden processing elements show varying performances. Networks with 5 and 7 hidden processing elements, respectively, have better performance, but the latter exhibits a little fluctuation in the training process. After convergence, the neural networks had an overall replication rate of about 90%. Table 2 presents replication results with respect to road type for a 7 hidden processing
Table 2. Replication of route choices by a neural network model with 7 hidden processing elements after 2000 cycles of training.

<table>
<thead>
<tr>
<th>Actual Choices</th>
<th>Predicted Choices</th>
<th>Total Number</th>
<th>Replication</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freeway</td>
<td>171</td>
<td>16</td>
<td>187</td>
</tr>
<tr>
<td>Side Road</td>
<td>7</td>
<td>126</td>
<td>133</td>
</tr>
</tbody>
</table>

Average Replication Rate = \((171 + 126)/320 \times 100\% = 92.81\%\)

Figure 6. Conceptual framework for route choices with experiment.

element, network after 2000 cycles of training. It should be pointed out that, although the above results can be considered excellent, further improvements on the performance of the neural network route choice model can be made by improving the perception updating strategy, especially in determining the experience factor \(\lambda\).

Route Choice Behavior

The above results suggest that the neural network model can be used to reliably predict route choice. In general, route choice behavior, even in the presence or absence of ATIS, differs considerably from driver to driver, since drivers have different abilities in combining and processing information concerning road conditions; in forecasting future travel conditions with available information; in their previous experience; and, in developing heuristic decision procedures. Here, we roughly classify the route choice behavior with ATIS experience into three types as shown in Figure 6, based on the model’s replication or prediction results.

**Type 1.** This is a subject for whom combination of the most recent and historical experiences are optimal (the optimal experience factor \(\lambda^*\) is around 0.5).

**Type 2.** Subjects of this type stress the importance of their most recent travel experience (the optimal experience factor \(\lambda^*\) nears 1.0).

**Type 3.** Subjects of this type make their route choices based not so much on their previous experiences, but (probably) based on the advice provided by the information system.

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

In keeping 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 30 subjects were used for training the extended neural network with 11 input variables (in total 30 x 32 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 480 data points in total for training and 480 data points for prediction. 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 training cycles was set at 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's 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 is 79.7% in Case A, and 73.8% in Case B. The average acceptance rate of advice is 79.7% for 10 subjects.

![Figure 7. Relationship between percentage of advice acceptance and percentage of correct prediction](image)

From the computation results of Case A (Figure 8), it can be observed that most of the route choice behavior fits into either Type 1 or Type 2. Based on the shape of the average curve, the optimal experience factor is around 0.8 (for more results, see [6]), 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 its smallest value at the optimal experience factor $\lambda^*$, and increases as $\lambda$ approaches 0 or 1. This means that there is a large difference in how subjects perceive past and recent experiences in making route choice decisions. In other words, personal characteristics generally have a great influence on an individual's route choice behavior. Moreover, the dispersion of replication rates at $\lambda = 0$ reflects differences among subjects in accepting advice.
Figure 8. Replication of route choice with varying experience factor.
LIMITATIONS OF THE EXPERIMENT

When conducting empirical investigations, the limitations of the experiments must be kept in mind. The most important limitations of this study are:

(1) The number of replications: The individual replication rates are greatly influenced by the number of route choices. In general, subjects tended to choose the freeway. In our experiment, the average proportion of choices between the freeway and side road is approximately 1.4:1.

(2) Perception updating strategy: The results presented in this paper are limited to a particular perception updating strategy. The results suggest the importance perception updating strategies and experience factors. Further studies should investigate different perception updating strategies, and individual route choice behavior models using different experience factors.

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

(4) Sample characteristics: The subjects used in the study were students at U.C. Davis. The experiments were intended to examine the feasibility of the neural network approach. Generalizations to the broader population of drivers require extensive experimentation.

(5) It is assumed in this study that all variables are updated through one experience factor and that experience factor is 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 with variables of the same driver.

(6) This analysis suggests that drivers are initially predisposed to following the route advice. The average agreement with advice over time shows that for the first few trials drivers accept the advice approximately 78 percent of the time independent of the accuracy level of advice being provided. The findings also suggest that drivers can perceive the level of information accuracy and that they do so rather rapidly. Within the first eight of thirty-two sequential trials, the average agreement with advice moved in the direction of the level of accuracy provided. At 75 and 90 percent level of accuracy, the average agreement with advice increased over the remaining 28 trials, while at the 60 percent level of accuracy, the average agreement declined from the initial rate to approximately 60 percent (system accuracy). These findings indicate the importance of the accuracy of information provided by ATIS, and show that drivers can quickly discern the level of accuracy being provided.

(7) In this stage of experiments, the delays assigned to links was calculated using the relative ratio between freeway and side road. However, in a realistic network the delays are distributed among the network links in a random fashion.

(8) Driver age is not included in the input list because all the subjects belonged to the same age group.

(9) The experience factor is not a continuous term. It varies by steps of 0.2 in the experiment. The next stage of experiments will include the experience effect into the neural network as a built in function.

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

This simulation will utilize 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 9). The program is designed to be self-explanatory, with built-in instructions. The program also has an experimentation phase where subjects are allowed to make preliminary trials on the system and request help until they reach a point of familiarity with the system, and then proceed to the actual simulation. No data is collected in this experimentation phase, but the total length of time each subject spends experimenting with the system is recorded for comparison purpose. Also, an interface is provided to allow the experimenter to set up the desired experimental conditions which will be in effect for the subject.

Subjects will be recruited from the Sacramento area by a telephone interview using a random digit dialing. Approximately 100 subjects will be recruited based on an initial screening. The subjects in this simulation will be limited to commuters who travel to work five days per week. Within the population of commuters, we included carpoolers (both drivers and passengers) and single-occupant vehicle drivers. The sample is further segregated by demographic criteria such as gender, education, driving experience, and age. The screening criteria are presented in flow chart form in Figures 10 and 11.

Road Network

The network window displays a hypothetical road network (Figure 12). 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 cross connected with a 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. While this network is still simplistic in comparison to the real traffic environment, it is a considerable step up in complexity from the two-link, two-node traffic network utilized in the first set of experiments, and the objective of this work is to obtain drivers' route choice behavior.

The network window will be animated, in that the simulated vehicle movements will take place on the network. A simulated vehicle (cursor) will move through the network in response to decision inputs by the subject. Driver's decisions will be input via the keyboard to indicate desired turning movements. The simulation is currently designed with a 1:30 time scale (1 minute real time = 2 seconds simulated time).
Figure 10. Subject recruitment—commuters.
Considering one of the freeway links, the program has been configured so that each freeway link is 10 pixels in length. The movement is generated by having the cursor move from pixel to pixel along the link. The time that the cursor stays at each pixel location is determined by the delay setting of the link. The current delay setting is in 1/1000 second increments. Thus, if the delay setting on a freeway link is 1000, then the cursor will move from pixel to pixel at a rate of one per second. Assuming one freeway link represents 5 miles, this gives us a 20 mile freeway segment and each pixel represents 0.5 miles. In the real world, assuming a travel speed of 30 mph, it would take 1 minute to traverse 0.5 miles. Thus with a 1:30 time scale, it takes 2 seconds to traverse the 0.5 mile pixel. Also, if the overall average freeway route speed were 30 mph, it would take 1 minute and 20 seconds to traverse the 4 freeway links.

A simple formula converts the link speeds to segment delay values:

\[
\text{link delay} = \text{pixel length(miles)} \times \text{time scale} \times \frac{60\text{sec}}{\text{min}} \times \frac{60\text{min}}{\text{hr}} \times \frac{1000}{\text{speed(in mph)}}
\]

\[
= 60000/\text{speed (mph)}
\]

For example, if a freeway link speed is 50 mph, then the delay assignment is 1200 or 1.2 seconds per pixel movement and the 5 mile link would be traversed in 12 seconds.

The objective of this simulation is to present the subjects with a sequence of travel days. To accomplish this, a series of network characteristics have been generated which will form the basis for the daily travel experiences encountered by subjects. Additionally, because the focus is on the effect of information, we also want to filter out as much variability due to the network as possible. To accomplish this, the sequentially generated travel days are dynamic across the sequence, but static from subject to subject. Thus, for example, the travel conditions experienced by subject #1 on travel day 6 will be the same as the travel conditions experienced by any other subject on travel day 6. Differences that will be experienced are choice-based in that with this network, subjects may not traverse (and therefore, experience) the exact same segments of the network, or they may traverse them in a different sequence, and therefore, may have fundamentally different experiences.

**Link Delay**

The simulated network characteristics will be pregenerated and stored in a network data file. This data file will contain all of the network characteristics identified by travel day and link or node number. The simulation program will then simply read this data file to create the travel environment for each day. A subroutine has been developed to create and write this file. An example of the file content is shown in Table 3. The primary network characteristic will be delay. The delay will be of two forms, congestion delay experienced on a link, and stop delay experienced at nodes or intersections. Additionally, the congestion delay will be of two types, pure congestion, and congestion caused by incidents.

On roadway links, the delay is assigned in inverse proportion to the travel speed on the link for that day. When an incident has been assigned to occur on a particular link, the delay assigned to that link will be elevated due to the incident.
Table 3.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link 1 to Link 34</td>
<td>Delay assignments for links 1 to 34</td>
</tr>
<tr>
<td>Node 2 to Node 24</td>
<td>Stop delay assignments for nodes 2 to 24</td>
</tr>
<tr>
<td>Incident Link</td>
<td>Link number on which random incident has occurred</td>
</tr>
<tr>
<td>Severity</td>
<td>Severity of incident (either moderate or severe)</td>
</tr>
<tr>
<td>Incident type</td>
<td>Random assignment of description of incident</td>
</tr>
</tbody>
</table>

The Normal distribution is selected to represent the speed distributions on a roadway links. For this simulation, the network characteristic subroutine creates normally distributed link speeds for each link in the network. The freeway links are $N(\mu = 35 \text{ mph}, \sigma = 10 \text{ mph})$, arterials are $N(\mu = 35 \text{ mph}, \sigma = 6 \text{ mph})$, and side streets are $N(\mu = 25 \text{ mph}, \sigma = 1 \text{ mph})$. This creates a scenario within the network where the three primary routes through the network have the same mean speed, but the variance in travel speed is much greater on the freeway than the arterials. The surface streets have lower mean speeds, but experience little variation. For the normal distribution, approximately 95% of the observations will be within $\pm 2\sigma$. This means that typical speeds will range from 15 to 55 mph on freeway links, 23 to 47 mph on arterials, and from 23 to 27 mph on surface streets. The speed distributions have been right truncated at the free flow or design speed of the links such that the maximum speed is 55 mph on freeway links, 45 mph on arterials and 30 mph on surface streets. The subroutine converts the speed assignments to units of delay, which the program uses to simulate movement in the network.

**Incident Delay**

For this simulation, it is assumed that at least one incident can be expected to occur within the network on each simulated day. It is also reasonable to assume that incidents are more likely to occur on the freeway and arterial links than on surface streets. For this simulation, we will assume that the probability of an accident occurring on a given travel day is 1.0, that the probability of the accident being on freeway or arterial links is 4/5, and the probability of being on the surface streets is 1/5. Then,

$$P(\text{incident on freeway route} \mid \text{it is on freeway or arterial}) = \frac{2}{3},$$

$$P(\text{incident on arterial route 1 or 2} \mid \text{it is on freeway or arterial}) = \frac{1}{3},$$

i.e., twice as likely to occur on the freeway as opposed to the arterials.

Then,

$$P(\text{incident is on a particular freeway link} \mid \text{incident on freeway route}) = \frac{1}{\text{(number of freeway links)}} = \frac{1}{4},$$

$$P(\text{incident is on a particular arterial link} \mid \text{incident on arterial route 1 or 2}) = \frac{1}{\text{(number of arterial links)}} = \frac{1}{16},$$

$$P(\text{incident is on a particular surface link} \mid \text{incident is on surface streets}) = \frac{1}{\text{(number of surface links)}} = \frac{1}{14}.$$
Total probability of the incident occurring on a specific freeway link $= \frac{1 \times 2 \times 4}{4 \times 3 \times 5} = \frac{2}{15}$.

Total probability of incident occurring on a specific arterial link $= \frac{1 \times 4}{16 \times 3 \times 5} = \frac{1}{60}$.

Total probability of the incident occurring on a specific surface link $= \frac{1 \times 1}{14 \times 5} = \frac{1}{70}$.

Incidents occurring on the network are randomly assigned to be either moderate or severe in nature. Links with incidents have their speed assignments reset to 15 mph for severe incidents and 20 mph for moderate incidents. For each incident, one of three incident types is also randomly assigned. Moderate incidents are assigned to be either Accident, Stalled Vehicle, or Maintenance, while severe incidents are assigned as Injury Accident, Truck Accident, or Maintenance Lane Closed.

Stop Delay

From the first stage of experiments, the effects of stop delay were observed to have a significant effect on driver behavior [2]. The compliance with advice was significantly lower in conditions where subjects experienced stop delay primarily due to subjects rejection of advice to take the route with stops. These results suggest significant behavioral differences in response to stop delay versus congestion (or moving delay). Within this simulation, we again incorporated the effects of stop delay in a more realistic manner. Additionally, because this is a simulated network, stops become a route (or link) specific attribute in addition to speed or incident delay.

Stop delay will occur as a result of stop signs or signalized intersections. In Figure 12, nodes 8, 9, 13, 14, 18, and 19 are signalized intersections, and 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 2 seconds for right turn movements, and 3 seconds for left turn movements. Within the simulation, a 50% probability of the light being encountered as red is used for every signal. In this scenario, stop delay is mandatory at all stop signs, and stops at signals will be encountered approximately 50% of the time when traversing the network.

As currently envisioned, the network characteristic data file would be generated once for each trial day reflecting a static information situation. To move to a dynamic information system, several files could be generated for each trial day and the initial information provided would come from the first file. At some fixed time into the trial, the information could be refreshed or updated from the second file, likewise for a third file and so on, for whatever seems appropriate depending on the total travel time in the network and a reasonable refresh rate. Within a scenario of this type, we may want to update everything except incident information, and assume that incident durations will be longer than the total travel time in the network. This doesn't seem unreasonable as the network is not that large, but it may also be interesting to see the effects of clearing an incident.

Experimental Design

Within this controlled simulated travel environment, we wish to apply experimental treatments consisting of various types or levels of information. In addition, we may also wish to consider several blocking factors such as gender, age, driving experience, and education. We considered seven treatments each with two treatment levels. If enough subjects are available, then a complete factorial experiment could be performed. This design is known as a $2^7$ factorial design and requires 128 subjects for a single replication. In cases such as ours where a large number of treatment combinations are being considered, fractional factorial designs are often used to limit the data
requirements to a reasonable level. The disadvantage of the fractional factorial design is that not all factor level and interaction effects are estimable. By fractioning the design, certain factor effects and interactions could aliased or confounded with each other resulting in the inseparability of these effects. However, it is common that in experiments with high order interactions, the effects of these interactions are not significant. Thus the goal in a fractional factorial design is to try and alias the effects of interesting interactions (typically the main effects and two-way interactions) with higher order interaction terms which can reasonably be assumed to be insignificant.

However, if we perform a 1/8 replicate of the \(2^7\) design, it requires only 16 subjects and is considered a \(2^{7-3}\) fractional factorial. With this design, all main factor effects are aliased with three-way or higher interactions, and each two-way interaction is aliased with other two-way interactions. If it is reasonable to assume that all three-way and higher interactions are insignificant, then all of the main effects are estimable. In addition, 7 of the 21 two-way interactions are estimable if the effects of the 14 aliased two-way interactions can also be assumed to be negligible. Factorial experiments are typically used in production process environments where the variability between the units of analysis are generally small. In behavioral experiments where the experimental units are people, individual difference can be great due to differences in background, education, experience, etc. In this case, between subject variability can become large resulting in difficulty in detecting real differences between treatments. To deal with this problem, repeated observations are often required for each treatment combination. Assuming we can recruit and test at least 100 subjects, the \(2^{7-3}\) fractional factorial design would allow for 6 subjects within each treatment combination.

**Experimental Treatments**

With two levels for each factor, a full factorial design would require a minimum of \(2^7 = 128\) runs. A one-quarter fraction of this design can be used requiring a minimum of only 32 runs. If 3-way and higher interactions are assumed to be negligible, then all main effects are estimable and 15 of the 21 2-way interactions are also estimable. With three subjects per design block, 96 subjects are required.

The simulation will apply four information treatments and use 3 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 in the information window, display textually the location and classification of the incident, for example: “Severe injury accident on First Street between F St. and G St.”

B. En route Guidance: Graphical arrows indicating advised turning movements and textual description of advice.

C. Pretrip Guidance: Minimum path displayed at beginning of trip 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.

Three blocking factors:

E. Gender, male/female.
F. Age, young/old.
G. Education, high/low.
The design matrix for this one-quarter fractional factorial design is shown in Table 4 and will provide estimates of the following effects:

Estimable effects:

Aliased two-way interactions: CE = FG, CF = EG, CG = EF.

Accuracy Requirements

In order to investigate the effect of accuracy on the decision and learning process, the information provided within the simulation will not always be 100 percent accurate. This will allow us to investigate how subjects respond to receiving inaccurate information and what effect this may have on future decisions. The information content being provided to subjects is of three types: incident, guidance/advice, and congestion levels. It is a reasonable assumption that providing very accurate guidance/advice and congestion levels is much more difficult than providing incident location information. Guidance requires accurate estimates of link travel conditions. Errors are compounded across the network, and congestion can build up rapidly or dissipate between information updates. Incidents are static in nature, are more easily identified, and typically remain in the network for a significant length of time. While the effects of a particular incident may be difficult to predict, its location should be accurate. Within the simulation, the locational information of incidents will be provided at 100% accuracy. Route guidance/advice and congestion information will be provided at 75% accuracy. This definition means that on 75% of the trial days, the guidance/advice or the congestion information provided to the subject will be accurate, but on 25% of the trial days, it will be inaccurate.

Data Requirements

Data will be recorded as one record for each trial day with 20 records per subject. Data items recorded are trial Number, subject number, mini-survey (see the Appendix), treatment combination, system advice, driver decision, decision time, cumulative freeway distance, cumulative arterial distance, cumulative surface street distance, cumulative travel time, travel route, optimal route, performance measure, number of stops encountered on the subject’s route and the optimal route, amount of stop delay on the chosen route and the optimal route, and accuracy of advice provided. In the feedback, we will give a comparison between the optimal time and subject’s chosen travel time.

OBJECT ORIENTED PROGRAMMING DESIGN

In the second stage of the experiment, we simulated driver route choice in the network using object oriented design. An introduction to object oriented design can be found in many computer programming language books. The continuous simulation of events will provide data to analyze driver behavior at various levels of information.

The information level used in the simulation is predefined for each subject. The basic unit of time is a simulated minute. One simulated minute is equal to two seconds in real time. An object oriented solution to a problem requires that we map the problem space into a set of objects and operations in the solution space. The major components of the problem space are explained below.

The network entities are links, nodes, clock time, signals and stops, and the vehicle. Other entities are the: information and instruction windows, signal display and navigating arrow. These entities are defined as a friend classes to most of the other classes in the simulation. Each entity will be mapped to a class of abstract objects in the solution space. The class constructed in C++
Table 4. A $2^{7-2}$ fractional factorial design.

<table>
<thead>
<tr>
<th>Run</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>fg</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>a</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>b</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>abfg</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>cg</td>
</tr>
<tr>
<td>6</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>acf</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>bcf</td>
</tr>
<tr>
<td>8</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>abcg</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>d</td>
</tr>
<tr>
<td>10</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>adfg</td>
</tr>
<tr>
<td>11</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>bdfg</td>
</tr>
<tr>
<td>12</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>abd</td>
</tr>
<tr>
<td>13</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>cdf</td>
</tr>
<tr>
<td>14</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>acdg</td>
</tr>
<tr>
<td>15</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>bcdg</td>
</tr>
<tr>
<td>16</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>abcdf</td>
</tr>
<tr>
<td>17</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>ef</td>
</tr>
<tr>
<td>18</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>aeg</td>
</tr>
<tr>
<td>19</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>beg</td>
</tr>
<tr>
<td>20</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>abef</td>
</tr>
<tr>
<td>21</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>ce</td>
</tr>
<tr>
<td>22</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>acefg</td>
</tr>
<tr>
<td>23</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>bcefg</td>
</tr>
<tr>
<td>24</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>abce</td>
</tr>
<tr>
<td>25</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>deg</td>
</tr>
<tr>
<td>26</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>adef</td>
</tr>
<tr>
<td>27</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>bdef</td>
</tr>
<tr>
<td>28</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>abdeg</td>
</tr>
<tr>
<td>29</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>cdefg</td>
</tr>
<tr>
<td>30</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>acde</td>
</tr>
<tr>
<td>31</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>bcde</td>
</tr>
<tr>
<td>32</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>abcdefg</td>
</tr>
</tbody>
</table>

supports the encapsulation of data and the decomposition of problems into objects and operations. The class hierarchy is shown in Figure 13. We next discuss each of the classes and communication with other objects that make up the object-oriented solution space for this simulation.

The class ‘Main’ has four subclasses of demonstration, trial runs, network, and best information. The ‘Demonstration’ class has a single method of demonstrating how to use simulation. The ‘Trial runs’ will allow users to make as many as trial runs as necessary. The trial run has
a private data number for every trial each subject makes. The ‘Network’ class is a parent class for all simulation classes with a private data of number of nodes, links, decision points, origin, and destination. It also has private methods such as title screen, survey details, feedback, and post-experiment questions. The public methods that are defined for this class are a constructor that initializes all the classes in the simulation, a data reader from the file, and outputs to a data file. The class ‘Best info’ has a private method for evaluating different information systems and private data on how subjects rank information.

The cursor class contains an important feature associated with each subject’s arrival time in the system, and arrival and departure time at each node, as well as decision time. These time datums are part of the private section of the class. This private section also has the x and y coordinates of the present location. In the public section, this class stores the keyboard input which is accessed by many classes. We designated the shortest path, subject-path, event, navigation classes to be a friend of the class cursor, so that objects of these classes can access private data of class cursor. This is the only class which has no methods.

The class ‘Shortest path’ contains the following private data: a static array of links, a static array of nodes, subjects new location (node), previous node, previous link, total number of links, total number of nodes, least travel time, and cumulative delay at nodes. The private methods are finding the next node, shortest path, and total distance. The class ‘Time’ contains the private current time (computer clock time), methods get-time, set-time, and time conversion. The class ‘Signal’ contains an integer, available, that has the value 1 if the signal is red, and otherwise 0. A real value delay will be recorded if the signal is red. Class ‘Stop sign’ has all the data and methods same as signal class expect on or off data.

The class ‘Subject path’ has private data total number of links (at the beginning), current number of links, total travel time, cumulative travel time, cumulative delay at nodes, cumulative delay on links, reaction time at each node, number of decision points, number of acceptance, and not accepted points. This class has methods for counting number of links, decision points, and total reaction time. The ‘Congestion display’ class has private data array of links, link delays, and colors. It also have a method of painting network in different colors.

The class ‘Navigation’ has two subclasses: Navigation by arrow and Navigation by text. These two have same data and methods. But navigation by arrow method will display and animate arrow (graphics mode) and navigation by text display and animate text (text mode). These classes have private data of the next node and direction and have methods for finding next node, direction, and converting direction to display format. The ‘Pretrip’ class has private data shortest
path inherited from shortest path class stored in an array. This also has private method display shortest path and delete display of shortest path.

The 'Accident' class has the private data location coordinates, delay and link congestion level and private methods delay, accident display, and accident identifier. The accident display will indicate accident when subject made his first decision, if he assigned to that information configuration. If there is no accident information in his configuration file, then identifier function will display accident when he reached to a specific range from the accident. This phenomenon is included to simulate realistic conditions. If a person does not have any information about the accident, but he reaches that point, he observes the accident and delays his travel time.

The ability to sense the type of the object is crucial, and enables object-oriented programming languages to reduce the amount of programming necessary in large software applications. There are two advantages in using object oriented programming. First, the facility for data abstraction encourages the development of systems that, when modified, only require changes to relatively small parts of the system. Second, the facilities for polymorphism, dynamic binding, and inheritance enable a software developer to build a basic library of classes that can be reused with little extra effort for new applications.

**RECURRENT NEURAL NETWORKS**

We have so far been concerned with networks that evolve to a stable pattern, and then use them with a new set of data. Now interesting investigation involve the possibility of storing, recalling, and generating 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 personal characteristics and choice made at previous decision points. In this analysis, there is an input node which gets input from previous nodes of the previous neural network. At the beginning of the simulation, the driver will not have any past experience. So, 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 possible in the case of one day’s experience only. However, what happens if there is a need to evaluate drivers’ behavior from the first point to the last point of his trial with all his experience? Present methods do not consider this aspect of the problem. The other inadequacy of present methods include losing the initial decisions by not including them. This is a different type of problem than in similar data-trained networks. The other aspect of present systems is concerned strictly with supervised learning in feed-forward networks.

We now 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 constant input. In this work, we consider networks without the symmetry constraint; however, we address those that do reach a stable state.

The problem is investigated using simple sequences that are synchronously updated by connecting together a chain of neural networks. We will mainly explain how to design a sequential recurrent network. Instead of settling on a single network, we want the prediction to 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 14.

A similar idea was earlier proposed by Lapedes and Faber [10], in their ‘master-slave’ network, where the master network calculates the weights for slave. However, they had one master unit for each connection in the slave network, and made the master network calculate appropriate weights without using the slave for feedback. In our application, the starter will generate an output which 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 the single trial (day). For example, if we want to determine current decision using last three decisions, the required sequential network will have three starter and one recurrent neural network. The recurrent neural network will start functioning after three starters made their decision (Figure 15). From that point on, each decision
point replaces the oldest decision points by sequentially moving the decisions to the respective days. The arrows between $d_1 \ldots d_n$ shows this action of transformation.

These networks generate a temporal sequence of states, usually in a limit cycle. This naturally requires a recurrent network with asymmetric connections; neither a feed-forward network nor a network with symmetric connections will do, because they necessarily go to a stationary state. The desired sequence is embedded into the network by requirement.

The sequential networks are assigned three tasks. They are: 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 which is used by the next starter or recurrent network. We plan to use a simple backpropagation neural network for the starter network.

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 is 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 which are input to all the starter and master networks. In this case, personal characteristics are always static for all networks. Network characteristics will change from one decision point to another. The decision point nodes will transform these values.

**SUMMARY**

In this study, a neural network model is developed to predict driver’s 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 was first conducted to test the feasibility of the approach. The neural network model is found to reasonably predict 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 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. Using the experience in this experiment, a new simulator is being designed to include most of the realistic conditions. The initial test results show that the recurrent neural network is suitable for observing drivers’ route choice behavior using the past experience.
FUTURE RESEARCH

Future research will continue to expand the modeling efforts undertaken here and in a companion paper [6]. Specific topics include:

1. Investigation of information update strategies to determine which strategies are most representative of the way in which drivers learn from their experiences.
2. Extension of the modeling to a more complex and realistic simulated traffic network using multiple users after obtaining results.
3. Inclusion of mode choice and departure time choice into the experiment.

APPENDIX

At the beginning of the simulation, subjects will be asked several questions in the form of a computer prompted “mini-survey.” The initial list of questions for this survey is provided below:

1. Approximately how many miles is it from your home to your usual work place? ____ miles.
2. What time do you normally leave home for work? ____ (24:00 hr scale)
3. What time do you normally arrive at work? ____ (24:00 hr scale)
4. What is your normal work start time? ____ (24:00 hr scale)
5. Is your work start time fixed or is it flexible?
   1. Fixed.
   2. Flexible.
6. What is your primary method of travel to your usual work place?
   1. Drive alone (including motorcycle).
   2. Drive with one or more workers.
   3. Drive with one or more children.
   4. As a passenger in a car, truck or van.
   5. Other.
7. Do you listen to traffic reports before you leave home for work?
   1. No
   2. Yes, if yes then
   7.1. How often do you listen to traffic reports before you leave home?
       1. Only every now and then, or on special occasions
       2. On some days
       3. Most days
       4. Every day, or nearly every day
   7.2. Approximately how many times per month do you change your route to work based on these reports?
   7.3. Approximately how many times per month do you change your departure time for work based on these reports?
   7.4. Approximately how many times per month do you change your transportation mode for work based on these reports?
8. Do you listen to traffic reports while driving to work?
   1. No
   2. Yes, if yes then
   8.1. How often do you listen to traffic reports while driving?
       1. Only every now and then, or on special occasions
       2. On some days
       3. Most days
       4. Every day, or nearly every day
   8.2. Approximately how many times per month do you change your route to work based on these reports?
9. How accurate is the information you receive from traffic reports?
   1. Extremely accurate
   2. Very accurate
3. Somewhat accurate  
4. Not very accurate  
5. Not at all accurate

10. Approximately how many miles do you drive in a year?  
    1. Less than 5,000 miles  
    2. 5001 to 10,000 miles  
    3. 10,001 to 15,000 miles  
    4. 15,001 to 20,000 miles  
    5. More than 20,000 miles

11. What is your age?

12. What is your gender?  
    1. Male  
    2. Female

13. Do you live in a ...  
    1. Single family house  
    2. Apartment  
    3. Condominium or Townhouse  
    4. Duplex Unit  
    5. Mobile home  
    6. Hotel or Motel  
    7. Other

14. Do you own or rent?  
    1. Own  
    2. Rent  
    3. Don’t Know

15. Including yourself, how many people live in your household? Count all babies, relatives, roommates or others who regularly live with you.  
    Total # of persons ____.

16. Including yourself, how many of these household members are five years of age or older?  
    # of persons 5 or older ____.

17. Including yourself, how many of these household members are sixteen years of age or older?

18. Including yourself, how many of these household members are employed?

19. Which of the following best describes your relationship in your household?  
    1. Spouse with children in the home  
    2. Spouse with no children  
    3. Adult single with children in the home  
    4. Adult single with no children  
    5. Cohabitant  
    6. Child (family member under 18 years old)  
    7. Other relative  
    8. Roommate  
    9. Friend  
    10. Other

20. Which of the following best represents your education level?  
    1. Did not complete high school  
    2. High school graduate  
    3. Completed some college, including 2 year (AA)  
    4. College graduate

21. For statistical purposes, please indicate which income category best represents your last year’s total household income.  
    1. Less than $15,000  
    2. $15,000 to $25,000  
    3. $25,001 to $35,000  
    4. $35,001 to $45,000  
    5. $45,001 to $55,000
6. $55,001 to $75,000
7. $75,001 to $100,000
8. $100,001 to $150,000
9. More than $150,000

REFERENCES


