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16. Abstract

The placement of guide signs and the display of dynamic massage signs greatly affect drivers' understanding of the network and therefore their route choices. Most existing dynamic traffic assignment models assume that drivers heading to a Major Traffic Generator (MTG) have sufficient knowledge of roadway networks. In this report, the concept of recognition level is defined to categorize drivers based on their unfamiliarity of the network and of the alternative routes between origins and destinations. Each catalog is assigned a specific utility function that is dependent on travel time, length of route and recognition parameters. Drivers' route choice behavior is determined by these specific utility functions. A sample network is first employed to test the feasibility of the proposed model, and the result complies with the specified travel patterns. After that, a real network near Downtown Houston is used to further test the proposed model. An experiment is conducted based on the information collected from an on-site survey and the on-line real-time traffic map from Houston TranStar. In order to validate the necessity of the proposed model, a control experiment is carried out with all parameters being set in the same way as the designed experiment except that drivers are assumed to be fully familiar with the network layout and alternative routes. Test results show that the proposed model can fit the real case very well. The developed algorithm and the assessment procedure results are not only awfully imperative in trailblazing guide signing for MTGs, but also indispensable in both the modern Route Guidance System (RGS) and the Advanced Traveler Information System (ATIS), which are important components of the Intelligent Transportation System (ITS).

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Dynamic Traffic Assignment Based Trailblazing Guide Signing for Major Traffic Generator

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ABSTRACT

Trailblazing guide signs, aiming to direct the traveling public to Major Traffic Generators (MTGs) which are normally located in the central core area of a town, can provide directional guidance on a particular road facility from other highways in the vicinity, and therefore, enhance mobility and infrastructure efficiency of the roadway system. Currently, there is no adequate quantitative analytical instrument on how these signs direct road users progressively along the right route, and what the distinction would be of impacts of unlike sign placement plans. On the other hand, most existing dynamic traffic assignment models assume that drivers heading to a MTG have sufficient knowledge of roadway networks. Past experiments have shown that drivers' familiarity with the network layout that could be based on past experiences or the proper guidance of trailblazing signs, is an essential component in route selections. In order to address this issue, the concept of recognition level is defined in this report to categorize drivers based on their unfamiliarity of the network and of the alternative routes between origins and destinations. Each catalog is assigned a specific utility function that is dependent on travel time, length of route and recognition parameters. Drivers' route choice behavior is determined by these specific utility functions. A sample network is first employed to test the feasibility of the proposed model, and the result complies with the specified travel patterns. After that, a real network near Downtown Houston is used to further test the proposed model. An experiment is conducted based on the information collected from an on-site survey and the on-line Real-Time Traffic Map from Houston TranStar. In order to validate the necessity of the proposed model, a control experiment is carried out with all parameters being set in the same way as the designed experiment, except that drivers are assumed to be fully familiar with the network layout and alternative routes. Test results show that the proposed model better fits the real case. The developed algorithm and the assessment procedure results are not only awfully imperative in trailblazing guide signing for MTGs, but also indispensable in both the modern Route Guidance System (RGS) and the Advanced Traveler Information System (ATIS), which are important components of the Intelligent Transportation System (ITS).

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EXECUTIVE SUMMARY

Drivers' information on roadway systems normally comes from either their daily driving experiences on the network as commuters, or the dynamic message signs and/or en-route guide signs including trailblazing guide signs. The trailblazing guide sign is a town sign that directs the traveling public to the central core area of the town, or to specific destinations or sites within or nearby the town center. This is accomplished by installing trailblazer assemblies at strategic locations of the network to indicate the direction to the nearest or most convenient point of access.

The placement of guide signs and the display of dynamic message signs greatly affect drivers' understandings of the network and, therefore, their route choices. Past experiments have shown that drivers' familiarity with the network layout is an essential component in route choices.

However, most existing DTA models can hardly be directly used in the process of the evaluation of the impacts of trailblazing guide signs on a network. The first reason is related to the assumption of network users. Traditional DTA models assume that all users have sufficient information of the network travel time and should choose a route that minimizes either their own travel time or other generalized cost. Other DTA models realize that network users may not have perfect information on travel time, and therefore focus on the modeling of the probability distribution of such perception errors.

The second reason is related to the sign performance. The popular research trend on Advanced Traveler Information Systems (ATIS) has resulted in a bunch of models considering the effects and performance of different types of information provided to travelers.

In this report, a new DTA model is developed with the consideration of drivers' unfamiliarity of network layouts, which can be used not only on sign performance evaluations, but also in ATIS and Intelligent Transportation System (ITS).

By this new model, the concept of recognition level is defined to categorize drivers based on their unfamiliarity of the network and of the alternative routes between origins and destinations. Each catalog is assigned a specific utility function that is dependent on travel time, length of route and recognition parameters. Drivers' route choice behavior is determined by these specific utility functions. A computer program in MATLAB is compiled to simulate drivers' route choices and path switching behaviors. A sample network is first employed to test the feasibility of the proposed model, and the result complies with the specified travel patterns. After that, a real network near Downtown Houston is used to further test the proposed model. An experiment is conducted based on the information collected from an on-site survey and the on-line real-time traffic map from Houston TranStar.

In order to validate the necessity of the proposed model, a control experiment is carried out with all parameters being set in the same way as the designed experiment except that drivers are assumed to be fully familiar with the network layout and alternative routes. Test results show that the proposed model better fits the real case.

The developed algorithm and the resulted assessment procedures are not only awfully imperative in trailblazing guide signing for MTGs, but also indispensable in modern Route Guidance System (RGS) and Advanced Traveler Information System (ATIS), which are important components of the Intelligent Transportation System (ITS).

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CHAPTER 1

INTRODUCTION

Dynamic Traffic Assignment (DTA) models have evolved rapidly during the past three decades, since the work done by Merchant and Nemhauser [1] [2]. Numerous formulations and models have been introduced to consider different traffic assignment procedures under various systems and behavior assumptions. With the development and progress of in-vehicle Route Guidance System (RGS), Vehicle Management System (VMS), and Dynamic Message Sign (DMS), more and more traffic assignment models incorporate information on roadway systems that affect drivers' route choice behaviors [3-15].

Drivers' information on roadway systems normally comes from either their daily driving experiences of the network as commuters, or the dynamic message signs and/or en-route guide signs including trailblazing guide signs.

The trailblazing guide sign is a town sign that directs the traveling public to the central core area of the town, or to specific destinations or sites within or nearby the town center. This is accomplished by installing trailblazer assemblies at strategic locations in the network to indicate the direction to the nearest or most convenient point of access [16].

The placement of guide signs and the display of dynamic message signs greatly affect drivers' understanding of the network and therefore their route choices. Past experiments have shown that drivers' familiarity with the network layout is an essential component in route choices [6-7]. Compared with the impact analysis of dynamic massage signs, less attention is placed on the implication of guide signing, especially trailblazing guide signing to traffic assignments.

Most of the existing DTA models can hardly be directly used in the process of the evaluation of the impacts of trailblazing guide signs on a network. There are basically two reasons for the unseemliness of current models.

The first reason is related to the assumption of network users. Traditional DTA models assume that all users have sufficient information of the network travel time and should choose a route that minimizes either their own travel time or other generalized cost [17]. Other DTA models realize that network users may not have perfect information on travel time, and therefore focus on the modeling of the probability distribution of such perception errors [3-5]. These models are also based on the assumption that travelers may have enough knowledge of network layouts.

The second reason is related to the sign performance. The popular research trend on Advanced Traveler Information Systems (ATIS) has resulted in a bunch of models [8-12] considering the effects and performance of different types of information provided to travelers. According to the work by Muizelaar and van Arem [9], the actual content of the information that is converted through ATIS can be classified into the following levels:

- Descriptive congestion information (length, location, cause of congestion, etc.).
- Enriched congestion information (delay time, travel time, time of arrival, etc.).
- Descriptive network information (indicating one or more route alternatives).

Much of the above information is actually dynamic, which is different from the information provided by guide signs. Some models do incorporate the possible effects of guide sign information to the travelers' route choices, but most of them are either descriptive or simply treating sign information as a factor of one function with no explicit format [15, 17-18]. Thus, there is a need to develop a kind of model incorporating the effects of guide signing on traffic assignments.

In this research, a new DTA model is developed with the consideration of drivers' unfamiliarity of network layouts, which can be used not only on sign performance evaluations, but also in ATIS and Intelligent Transportation System (ITS).

In the following sections, the route choice model is formulated, and the methodology adopted in this paper is explained with the incorporation of drivers' unfamiliarity with the network. The basic assumptions and procedures of the designed experiments and control experiments are then illustrated and compared. Finally, the conclusions and recommendations of the proposed model are presented.

CHAPTER 2

MODEL FORMULATION

2.1 Definition of Recognition Level

As mentioned above, different drivers may have different familiarities of the network layout and different perceptions of route travel time. For example, if the drivers' destination is a Major Traffic Generator (MTG), i.e. a major regional attraction such as an event or facility that attracts persons or groups from beyond a local community, city, or metropolitan area, [16] then those who have previously visited this MTG should have more knowledge of the network topology and the possible traffic conditions than those who have never visited, In order to capture these diverse characteristics, such drivers can be divided into several categories based on their recognition levels of the network layout. The representative recognition levels are listed below:

- Level 1: Drivers are complete strangers to the studied network without any information about the network layout and traffic conditions.
- Level l : Drivers are fully familiar with both the network layout and traffic conditions. They will switch their route dynamically according to the performance of all alternative routes.
- Levels between 1 and l : Drivers have some extent of knowledge of the network layout and traffic conditions.

The quantitative description of different recognition levels is represented as the recognition parameters ε_i in the utility functions explained in the next section.

2.2 Utility Function for a Simple Network

Considering a network G = (N, A), where N is the node set and A is the link set. Let W be the origin-destination (O-D) pair set. The utility function of link *a* for recognition level *i* (*i*=1, 2 … l) can be expressed as:

$$u_a^i = -\varepsilon_i \cdot T_a - (1-\varepsilon_i) \cdot T_a^{ff} \tag{1}$$

where ε_i is the recognition parameter; Ta and T_a^{ff} are real travel time and free flow travel time of link *a*, respectively.

The combination of real travel time and free flow travel time in the utility function is based on the fact that unfamiliar drivers will either search the information of candidate route(s) online before departure or follow the instruction of in-vehicle guidance systems such as GPS. Though advanced GPS devices providing the real time traffic information integrated with cell phone service have been developed, many existing in-vehicle guidance systems only provide static map information.

Both methods, searching from web-based drive directions and using the guidance system(s), are based on shortest route selections. This means unfamiliar drivers may incline to follow the shortest route since they have no further knowledge on the network. Therefore, the link length should be one of the important factors in the link utility function (1). Besides, travel time is probably a major consideration for the drivers who are familiar with the network. A combination of travel time and link length should be better than only considering one of these two factors. To keep the coherence of these two factors, free flow travel time is used in (1) instead of the link length directly.

According to the formulation above, the utility U_r^i of route r for recognition level i can be calculated as:

$$U_r^i = \sum_{a \in A} u_a^i \cdot \delta_r^a \tag{2}$$

where,

$$\delta_r^a = \begin{cases} 1, & \text{if } r \text{ uses link } a \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

<u>*2.3 C-Utility Function for a Large Network*</u>

In real networks, there are normally overlaps among all possible routes between origin and destination. In this case, the utility function in (2) should be modified considering the impact of such overlap. Inspired by the C-logit model [19], which is a variation of general logit model, the C-utility function is defined in (4):

$$U_r^i = \sum_{a \in A} u_a^i \cdot \delta_r^a - CF_r \tag{4}$$

In (4), CF_r is the overlap factor for route r, which is proportional to the overlapping degree of route r with other alternative routes; δ_r^a is also defined in (3). Highly overlapped routes have larger CF factor and therefore a smaller utility value. CF_r is calculated as:

$$CF_r = \beta \cdot \ln \sum_{l \in O_r} \left(\frac{L_{lr}}{L_l^{1/2} \cdot L_r^{1/2}} \right)^k \tag{5}$$

In (5), Or is the set of routes that have overlap links with route r; L_{lr} is the length of links shared for route l and route r; and L_l, L_r are lengths of route l and route r, respectively. Parameters β and k determine the weight of overlap factor. Larger values of β mean that the overlap factor is significant to the value of utility. Usually taken in the range of [0, 2]. is k, a positive parameter.

2.4 Route Choice Behavior

In order to depict the dynamics of route choice behavior, here, a concept of decision node is introduced. Decision node refers to a node from where there is more than one path heading to the destination. The utility $U_{d,w}^i$ of sub-route from decision node d to the destination for O-D pair w and recognition level i can be calculated using (4).

Let ss be the sub-route with the maximum utility from decision node d to the destination, then:

$$U_{ss}^i = \max U_{d,w}^i \tag{6}$$

Therefore, the next link employed with recognition level i is assumed to be the first link of sub-route ss.

2.5 Flow Chart of the Proposed Model

Fig. 1 is the flow chart of the proposed model as is described in Equations (1) to (6) in previous sections. It begins with loading basic information such as the network layout, time-dependent O-D matrix, initial link utilities and flow. A training procedure is applied to pre-assign the basic traffic demand to the network for initial system equilibrium with no consideration of demand to MTG.

After that, vehicle movements are simulated one by one and the time steps could vary according to the designed time-dependent O-D matrix. At each time step, vehicles arriving at the decision node should make a decision either to keep the previous route, or to switch to another route. Utilities of the sub-routes are the criteria of this en-route switching behavior. Travel time and link flows are updated at each time step.

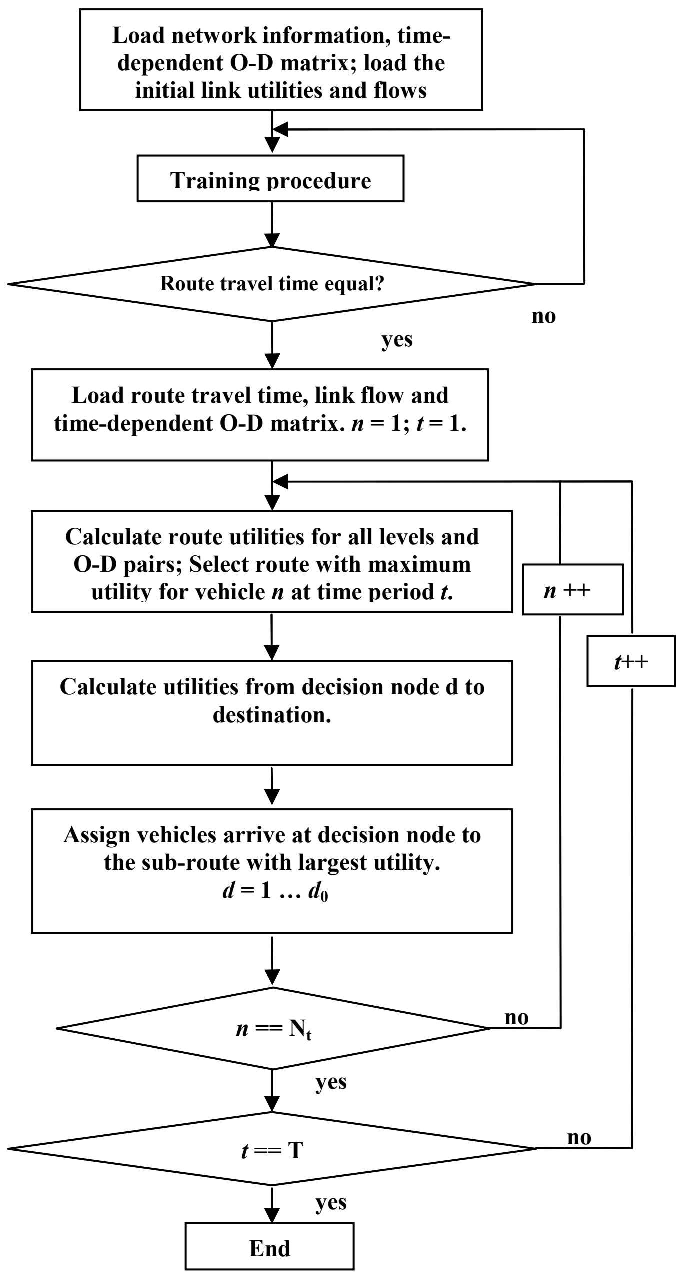


Figure 1 Flowchart of the Solution Algorithm

CHAPTER 3

EXPERIMENT OF A TWO RING NETWORK

Two exemplary networks are designed to illustrate the proposed model. The first network is a virtual one (the two ring network) for the feasibility test, where all parameters are assumed. The second network is a real network in the south part of the central Houston area. The network and traffic information and values of parameters are based on a field survey and on-line traffic information from Houston TranStar.

3.1 Defining the Two Ring Network

The two ring network is illustrated in Fig. 2, which contains four links, two decision nodes (origin node 1 and intermediate node 2) and one destination node (node 3). All links are with one-direction only. Link lengths and free flow travel time are also noted in the same figure. There are in total four possible routes from origin (node 1) to destination (node 3). They are: (1) Route 1 (Link 1 and 2); (2) Route 2 (Link 3 and 4); (3) Route 3 (Link 3 and 2); and (4) Route 4 (Link 1 and 4).

The total demand from origin node to destination node is set as 2,600 vehicle/hours. The simulation time span is one hour, which is divided into six periods with ten minutes each. The travel demand pattern of these six periods follows a distribution as is shown in Fig. 3.

In this case study, four recognition levels are designed. For simplification, it is assumed that the total travel demand is evenly assigned to each recognition level at each time period.

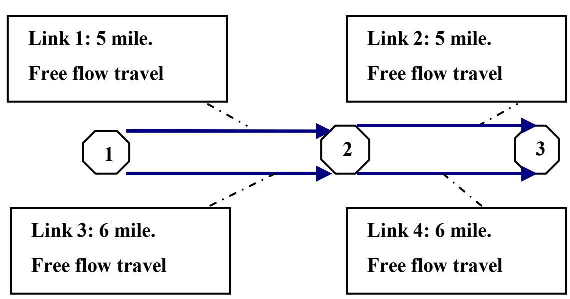


Figure 2 Illustration of the Designed Two Ring Network

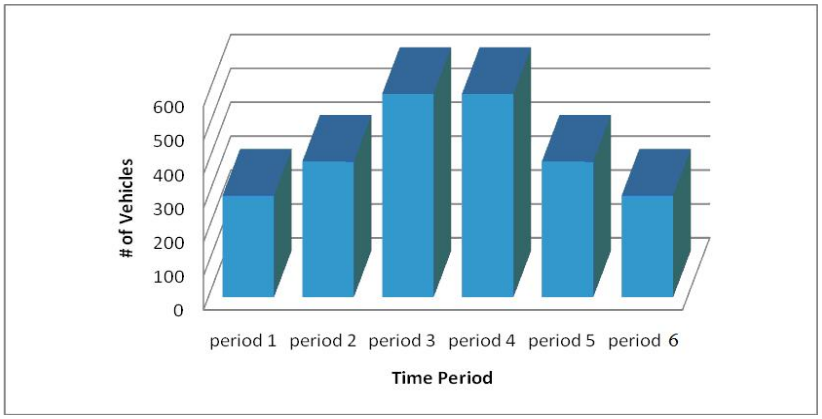


Figure 3 Travel Demand Pattern for the Two Ring Network

The recognition parameters are set to be 0, 1/3, 2/3, and 1, respectively. Following (1), the link utility functions are defined as:

$$u_a^1 = -T_a^{ff} \tag{7}$$

$$u_a^2 = -\frac{1}{3} * T_a - \frac{2}{3} * T_a^{ff} \tag{8}$$

$$u_a^3 = -\frac{2}{3} * T_a - \frac{1}{3} * T_a^{ff} \tag{9}$$

$$u_a^4 = -T_a \tag{10}$$

The calculation of free flow travel time is based on the assumption that free flow speeds for all links are 50 miles/hour.

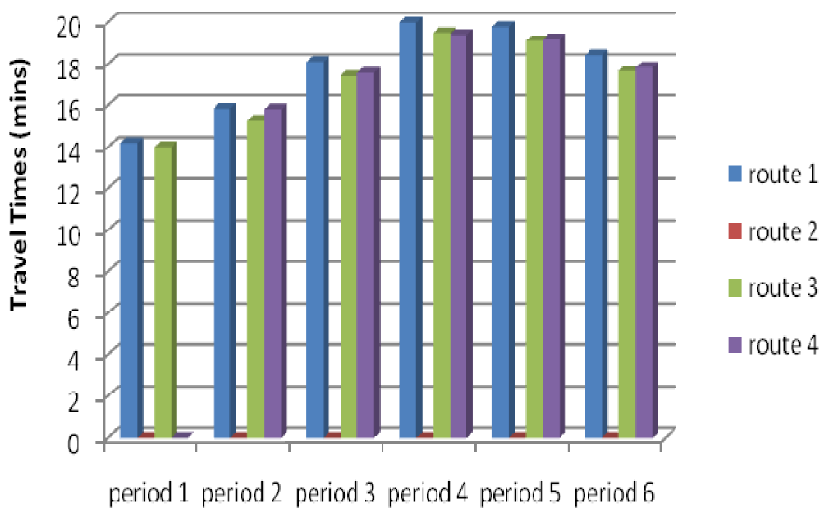
3.2 Results of a Two Ring Network

To demonstrate the accuracy and feasibility of the proposed model in the two ring network, a control experiment is conducted with the same parameter settings as the designed experiment except for drivers' familiarities with the network.

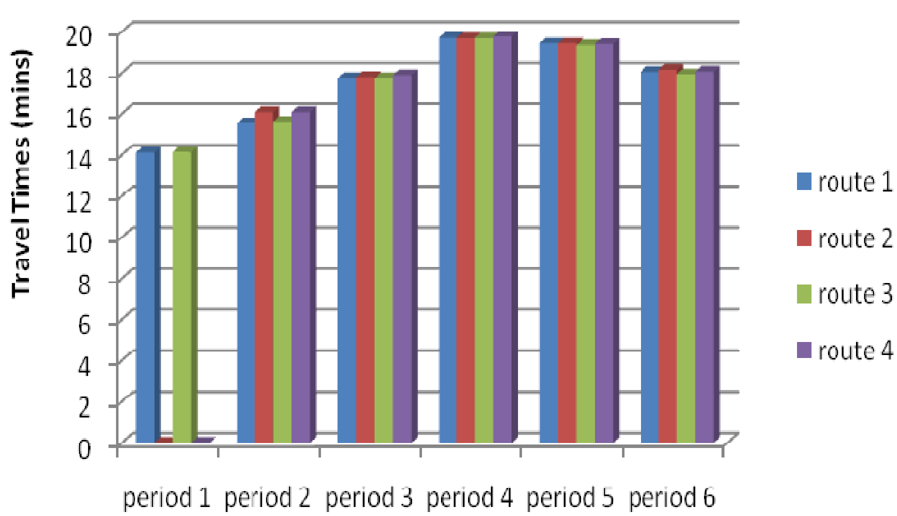
Drivers on the control experiment are assumed to be all familiar with the network layout and traffic condition, while drivers on the designed experiment have four levels of recognition to the network and thus have four types of utility functions (7)-(10).

For the simulation purpose, a computer program in MATLAB following the proposed algorithm in Fig. 1 is developed, which is suitable for not only the two ring network, but also the real network in the next section.

Through simulation, the average values of travel time at all selected routes are obtained as are illustrated in Fig. 4. Since Route 2 (along Link 3 and Link 4 with the longest free flow travel time 7.2 min + 7.2 min = 14.4 min) is never selected by drivers in the designed experiment (listed in Fig. 4), the actual values of travel time at all six periods for Route 2 are zero. For the same reason, travel time on Route 4 in the first period of both the designed and control experiments are zero. Values of travel time for Route 1 (Link 1 and Link 2 with the shortest free flow travel time 6 min + 6 min = 12 min) are longer than other selected routes in the designed experiment (results for designed experiment in Fig. 4).



(a) Designed experiment



(b) Control experiment

Figure 4 Route travel time for the two ring network

The explanation is that since unfamiliar drivers have little knowledge of alternative routes and traffic conditions on alternative routes, they may prefer to select the shortest route (Route 1), which causes higher demand on Route 1 and results in longer travel time.

Compared with the designed experiment, travel time values among all routes at each time period are nearly equal in the control experiment (results for control experiment in Fig. 4), implying that the dynamic user equilibrium is approximately achieved. This can be explained by Wardrop's user equilibrium principle: when drivers are familiar with all alternative routes and associated traffic conditions, they will select the "shortest" routes dynamically based on the real travel time. Under such condition, travel time on all selected routes will be equal and (or) less than travel times on unselected routes [20].

CHAPTER 4

EXPERIMENT OF A REAL NETWORK

4.1 Description of the Network

In order to further validate the proposed model, a real network is selected in the southern part of the central Houston area. The Robertson Stadium on the University of Houston campus is within this network, which is home to the Houston Dynamo Soccer Team, the champion of back-to-back Major League Soccer (MLS) with the capacity of 32,000 seats. The test in this network demonstrates the entire procedure of modeling and simulation, including demand acquisition, drivers split into different recognition levels and traffic simulation. For simplification, all on and off ramp demands are not considered in this simulation.

4.2 Network Geometry

The map of this network is illustrated in Fig. 5. The origin (node A) is set at the intersection of US-59N and I-610S, and the destination (Node B) is set at the exit off I-45S towards the Robertson Stadium. Three freeways (US-59, I-610 and I-45) are within the range of the network. Their topologic information is illustrated in Fig. 5 as well.

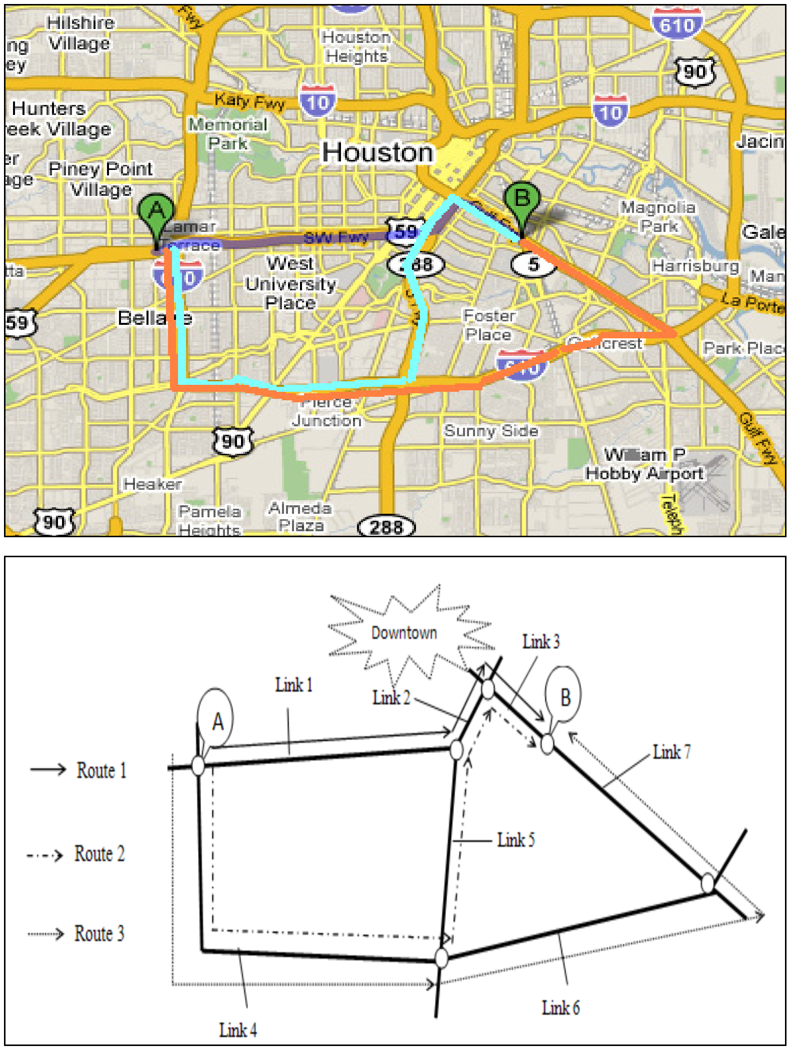


Figure 5 Geometric Information of the Studied Real Network

In reality, vehicles may prefer to exit a little earlier than the designed off ramp and continue heading to the destination on local or frontage routes. Such kinds of behavior are not included in this simulation.

Other geometric information of these three routes, such as length and free flow travel time, are obtained from Houston TranStar online traffic map (www.houstontranstar.org).

The route starting from US-59N is the shortest one, with a length of 8.5 miles and free flow travel time 9 minutes. Lengths of the other two routes are 14.6 miles and 17 miles, respectively. Their free flow travel times are 16 minutes and 21 minutes respectively.

4.3 Survey Information

A questionnaire survey to event visitors in Robertson Stadium was conducted on June 26th, 2008. Information collected includes the zip codes of the visitors' origins and the number of times they have ever been to this site (Robertson Stadium). Based on what kind of information they find for this destination and other basic information such as age and years of driving experiences, 148 visitors were interviewed and the effective survey results were analyzed afterwards.

4.4 Demand Prediction

To predict the total demand from the designed origin, all collected zip code information was clustered into ten catalogs. Each catalog was labeled with one freeway, which connects the central and external Houston. The 10 freeways were: I-45N, US-59E, I-10E, SH225, I-45, SH288, US-59S, Westpark Tollway, I-10W, and US290. The external part of Houston was divided into ten zones according to the catalogs of these freeways. Each recorded zip code represents one vehicle generated from the zone labeled with its nearest freeway.

Table 1 Survey results clusters and prediction of demand

Cluster label	**I-15**	**US-59E**	**I-10E**	**SH225**	**I-45**
# of vehicles	22	2	9	3	16
Demand Prediction	975	89	399	133	709
Cluster label	**SH288**	**US-59S**	**Westpark**	**I-10E**	**US-290**
# of vehicles	15	16	2	25	7
Demand Prediction	665	709	89	1,108	310

OUT of the 148 survey responses, 130 provided valid zip codes. However, 13 valid zones were located too close to the destination, and were therefore eliminated from the sample pool. In total, 117 zip codes were recorded to relocate the vehicles to their original zones. The cluster results are shown in the row named "# of vehicles" in Table I.

When divided the number of vehicles with 130, the total number of valid origins, the percentages of vehicles generated from these ten zones were calculated. The actual total number of tickets sold that day was 16,932. According to the spot check, average vehicle occupant rates were 2.94 persons per vehicle. Therefore, the total number of vehicles attended in this event is 5,760. The demand of each zone is then estimated. The total demand for the selected origin which is located in the US 59 is 709 vehicles from Table I.

4.5 Recognition Level Classification

The classification of recognition levels in this experiment was generated according to the cluster results of surveyed participants' visit times to the subject destination. With the same proportion, the number of vehicles that belong to each recognition level can be calculated. Table II lists the number of vehicles of each visit time for the cluster of US-59S. Under the conditions, with surveillance information, the classification of recognition levels could be based on data from the sensors and other sources.

Table 2 Number of Participants of Each Visit Time Cluster for Southwest Freeway

Survey Results Analysis	Visit Times	1	2--5	>5	Sum
	# of Participants	37	26	85	148
	Percentages	25%	18%	57%	100%
Prediction	# of Vehicles	177	124	408	709

4.6 Deducted Utility for Link Spill-Back Congestion

A utility deduction method is applied to deal with the problem of link spill-back congestion. If a vehicle is going to take the congested link where demand exceeds the capacity, and the starting node is not a decision node, this vehicle will add to the queue at the end of the previous link. The extra waiting time for this vehicle is equal to the waiting queue length multiplied by the average vehicle waiting time. The queue will affect the previous link travel time by decreasing its capacity.

However, if the starting node of the totally congested link is a decision node, the utility of this link should be deducted associated with the waiting time of the arrived vehicle.

By assuming that a0 is a congested link, the deducted utility can be expressed in (11) and (12).

$$\tilde{u}^i_{a_0} = u^i_{a_0} - \varepsilon_i \cdot P(\text{queue length}) \tag{11}$$

$$\tilde{u}^i_{a_0} = -\varepsilon_i \cdot T_{a_0} - (1-\varepsilon_i) \cdot T^{ff}_{a_0} - \varepsilon_i \cdot P(\text{queue length}) \tag{12}$$

Here, $u^i_{a_0}$ is the original utility for link a0 and $\tilde{u}^i_{a_0}$ is the deducted utility, P (queue length) is a function to calculated waiting time caused by the corresponding queue length.

Based on the deducted utilities, the driver could make a decision on whether to join the queue for the congested link or to switch to another link.

4.7 Simulation Design

The simulation on the studied real network was conducted for a 30-minute span (from 6:15-6:45), which was divided into three 10-minute periods. The travel patterns are 25%, 50% and 25% of the total demand in periods one, two and three, respectively. The proportion of vehicles belonging to each recognition level was similar to the results shown in Table II. After the 30-minute simulation, a tail program was conducted to assign vehicles generated in the last period or generated in other periods but did not arrive at the destination. In calculating link travel time, the standard volume-travel time relationship from the United States Bureau of Public Roads (BPR) Traffic Assignment Manual (or called BPR function, [18]) was employed.

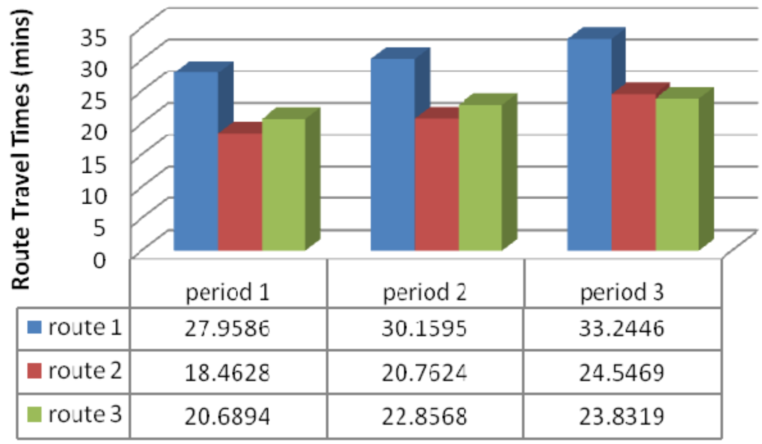
4.8 Comparison with a Control Experiment

With the two rings network, a control experiment was conducted to examine the effectiveness of the proposed model.

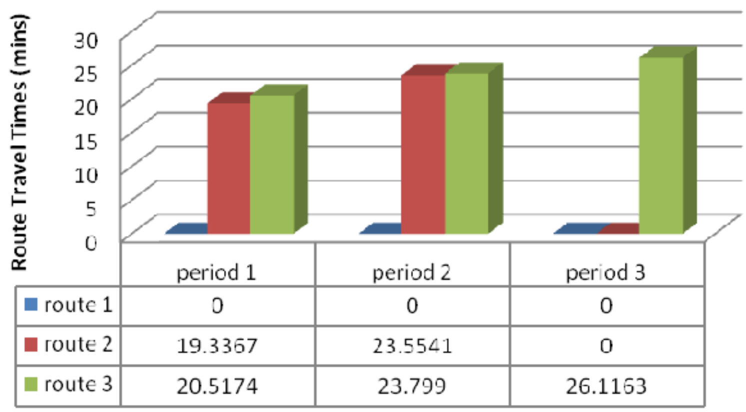
The average values of route travel time on the designed and control experiment are shown in Fig. 6. Since only values of travel time of selected routes are presented, travel time on Route 1 at all three periods and on Route 2 at period three are equal to zero.

The same as in the two ring network, values of travel times within each period on selected routes (Routes 1, 2, and 3) were much closer to each other in the control experiment (Fig. 6). In the designed experiment, values of travel time on selected routes were much different with those in the control experiment. This difference could be even larger when the proportion of drivers' unfamiliarity increases. The drivers with less knowledge of the network would not prefer to switch between routes, since they were not familiar with the available alternative routes. Some of them would keep on the shortest route in distance among all available routes, even if this route was already congested.

Fig. 6 shows that there was no vehicle selecting Route 1 in the control experiment although Route 1 is the shortest one among all three available routes. Remember in the control experiment, all drivers were assumed to have perfect knowledge of the network, and so they should have known Route 1 was already congested during the afternoon peak hour (v/c ratio = 1.53 actually).



(a) Designed experiment

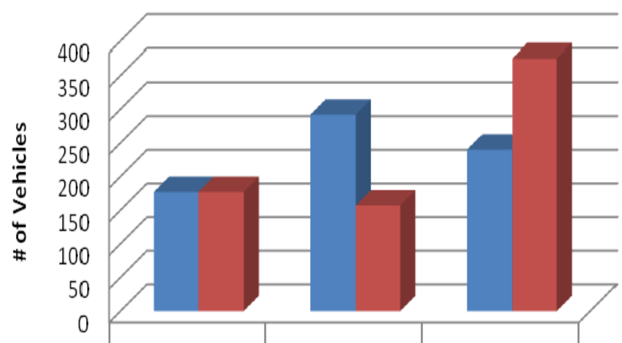


(b) Control experiment

Figure 6 Comparison of Route Travel Times at each Time Period between Designed and Control Experiment.

While there were portions of vehicles choosing Route 1 in the designed experiment (Fig. 6), they were those who were not familiar with the network, and thus always experienced the longest travel time (in the left of Fig. 6 for all time periods).

The numbers of vehicles choosing each route are illustrated in Fig. 7, demonstrating the route switching behavior.



	route 1	route 2	route 3
at starting	177	292	240
final	177	157	375

Figure 7 Comparison of Number of Vehicles on Selecting each Route.

According to the results, vehicles choosing Route 1 at the beginning of their journeys would prefer to continue on this route while part of the vehicles choosing Route 2 switched to Route 3 at the second decision node. This is why the number of vehicles choosing Route 2 decreases, and the number of vehicles choosing Route 3 increases in Fig. 7. Combined with findings in Fig. 6 and Fig. 7, it is concluded that drivers who were not familiar with the road network preferred to keep on their original routes and were less flexible in their diversion behavior en-route. This complies with the experiment results of Hamed and Abdul-Hussain [6], and Lotan [7].

Fig. 8 compares the simulated traffic map and the published -. The link speeds in the three plots in the left column in Fig. 8 were calculated from the simulation for each time period, and the three plots in the right column were from Houston TranStar Real Time Traffic Map at 6:20 p.m., 6:30 p.m., and 6:40 p.m. of June 26, 2008, which were the center points of the three designed time periods in modeling.

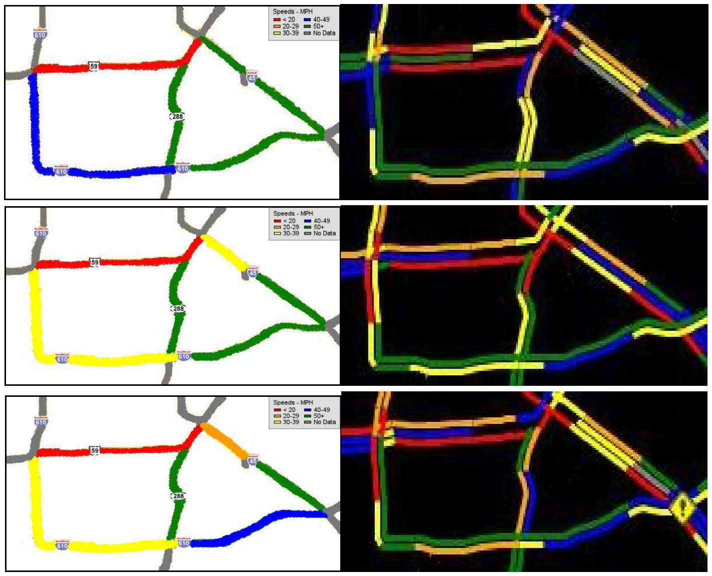


Figure 8 Comparison of Simulated and Real-Time Traffic Map.

In the left plots of Fig. 8, only values of travel time from those links heading toward the destination are illustrated. Since the link partition in simulation network (left) and in the real-time traffic map (right) are different, to compare the experiment results and real traffic condition numerically, speed intervals at the real traffic map were aggregated using (13).

$$n_a = Round\left(\frac{n_{a,1} \cdot L_{a,1} + n_{a,2} \cdot L_{a,2} + \cdots + n_{a,t} \cdot L_{a,t}}{L_a}\right) \tag{13}$$

In (13), n_a is the numerical representative of the speed interval of link a, $L_{a,i}$ is the length of segment *i* on link *a*; *La* is the length of link *a*; $n_{a,i}$ is the numerical representative of the speed interval of segment *i* on link a; and $Round(\cdot)$ is a mathematical function converting a real number to its nearest integer. Each speed interval was converted to a numerical representative following the rules as: (1) if the speed interval is < 20 mile/hour, then its numerical representative is 1; (2) if the speed interval is 20mile/hour~29mile/hour, its numerical representative is 2; …; and (3) if the speed interval is > 50mile/hour, its numerical representative is 5.

The results from this aggregation process and the simulated link speed are tabulated in Table III. In Table III, the simulated speeds for the designed experiment (S_d) fit the real speed from traffic map (S_r) very well in most cases. Among the 21 sets of speed (seven links and three periods) from the simulation, eleven of them are exactly located in the real-time speed interval based on the aggregation process in (13); and two of them are very close to the real speed interval. The other eight values that have larger differences between the simulated ones and the real ones are located on Link 3 (Periods 1 and 2), Link 4 (Period 1), Link 5 (Periods 1, 2 and 3), Link 6 (Period 1) and Link 7 (Period 3).

Table 3 Comparison of Simulated Link Speed and Real Link Speed

Link #	Period 1 (6:15-6:25)			Period 2 (6:25-6:35)			Period 3 (6:35-6:45)		
	S_d	S_c	S_r	S_d	S_c	S_r	S_d	S_c	S_r
1	15.5	**24.1**	<20	15.5	**24.1**	<20	15.5	**24.1**	<20
2	15.5	**26.7**	<20	15.9	**26.4**	<20	15.5	**27.8**	<20
3	**53.9**	55.5	30~39	**39.9**	**41**	20~29	26.9	31	20~29
4	**46**	**44.5**	30~39	34.9	37.8	30~39	31.2	36.3	30~39
5	**56.6**	**51.1**	20~29	**52.2**	**50.6**	30~39	**55.3**	**46.3**	30~39
6	**53.1**	49.6	40~49	52.2	49.6	40~49	43.5	47.6	40~49
7	53.9	50.3	>50	54.8	50.3	>50	**64.3**	**52.3**	40~49

Checking the freeway operation record, an incident happened at the end of Link 6 during Period 1 and Link 7 during Period 3. This incident affected the real driving speed, however, it is not simulated in the modeling process. The differences on Link 3 and Link 5 may be caused by complicated on-ramp and off-ramp demands from the Houston downtown area since the ramps collecting speeds on the local streets of the Houston downtown area and freeways in southern Houston are mainly located on Link 3 and Link 5.

In all, differences between the simulated speeds (S_d) and real speeds (S_r) in Table III are possibly caused by accidents, congestions at the off-ramp, delays due to switching freeways, etc. All of these factors will be taken into consideration, along with the evolution of the proposed model in the future.

In Table III, the simulated speeds in the control experiment (S_c) are also listed for comparison purposes. In this case, only five sets of speeds are exactly located in the real-time speed interval (S_r); and five of them are very close to the real speed interval. The other eleven values that have larger differences are located on Link 1 (Periods 1, 2, and 3), Link 2 (Periods 1, 2 and 3), Link 3 (Periods 1 and 2), and Link 5 (Periods 1, 2 and 3).

In Table III, the largest differences between Sc and Sr are on Link 3 and Link 5 in the control experiment. This phenomenon is the same as in the design experiment (*i.e.* large difference between S_d and S_r), which could be caused by factors such as disturbances of on- and-off flow from Downtown Houston other than familiarity levels to the network.

From the comparison of the two sets of results for the designed and control experiment, it is obvious that the designed experiment, which assumes that drivers have different knowledge on the network layout, fits the real condition better than the control experiment.

CHAPTER 5

CONCLUSIONS

In this paper, a novel DTA model considering drivers' unfamiliarity with network layout is proposed. Drivers' unfamiliarity with network layout and route choice possibility is defined in a parameter named, which is further incorporated into a modified utility function (C-utility function) that is associated with travel time and link length as well. Considering that drivers may not always keep on their initially selected route, an en-route switching behavior scheme is integrated into the modeling process. A computer program in MATLAB is compiled to simulate drivers' route choices and path switching behaviors.

In order to validate the necessity of the proposed model, a simple two ring test network and a real network in the central Houston area were employed to exam the feasibility and accuracy of the proposed model.

Control experiments on both test and real networks were carried out with all the same settings as the designed experiment except the unfamiliarity levels of the network. Test results show that considering drivers' knowledge of network layout will better fit the real traffic operation. To obtain more accurate results from this model, a better method should be developed to determine the distribution of recognition parameters.

Turning penalty, occurrence of incidents, and on- and - off ramp demand modeling could be considered in the next step of research. The utility function, including how to calibrate the parameters in the utility functions, the en-route route choice formulation, and the entire modeling process, can then be further improved accordingly.

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