

Modeling Driver Behavior in a Road Network with Route Choice Based on Real Time Traffic Information

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Abstract

Intelligent Transportation Systems (ITS) applications require a thorough understanding of drivers' route choice behavior in a complex network under real-time information. The purpose of this paper is to describe and model driver route choice behavior in a road network based on real time traffic information at the disaggregate individual level and from a psychological decision-making process perspective. The framework of routing choice and driver dynamic route choice behavior model that uses concepts from Decision Field Theory (DFT) and Bayesian belief network (BBN) is proposed. A real-time planning algorithm for route choice processes is discussed in great detail. Using this algorithm, a driver develops his route dynamically until he reaches his destination. The simulation results show that the combination of DFT and BBN can effectively describe the driver's travel dynamics behavior.

Keywords: dynamic route choice behavior, decision field theory, preference, road network, real-time traffic information

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1. Introduction

The effect of ITS ultimately depends on drivers' response on real-time traffic information. Understanding drivers' response to this information is therefore critical to the design and implementation of ITS. It is evident that the Microeconomic Theory approach to route choice modeling is dominant in the literature [1]. Although several modeling attempts have departed from the formal utility-maximization paradigm and adopted more behaviorally realistic frameworks [2-3], there remains a lack of an explanatory mechanism of the decision process itself. Modeling of drivers' choices is mainly perceived from a structural-oriented perspective wherein a relationship is formulated between a set of inputs and outputs without a realistic understanding of the underlying psychological process. The deliberation time dimension seems to have been completely ignored.

The complexity of drivers' route choice decisions stems from two main contributing factors. On one hand, drivers' route choice decisions are the outcome of complex deliberation processes involving uncertainty. Uncertainty is a typical characteristic of any traffic network, even under real-time congestion information. There is uncertainty on the demand side as well as the supply side of the network [4]. Moreover, there is another dimension of uncertainty within traffic information sources. The reliability of disseminated information is never guaranteed. On the other hand, choice decisions are not instantaneous but rather time-consuming. The direct influence of the length of a deliberation process on choice decisions cannot be ignored. Drivers are commonly faced with divergence decisions while driving. The length of the deliberation process is restricted to a time frame prior to tentative bifurcation or divergence points. Available time frames might vary according to many factors, such as driver familiarity with the network geometry, daily traffic conditions, and the timing and location of information dissemination. Limited deliberation time frames pressure drivers to make choices possibly before their preferences mature to a satisfactory level.

As such, we realize the need for a scientifically sound behavioral decision theory that attempts to abstract the deliberation process rather than focusing on formulating a relationship between inputs and outputs. This need motivates crossing the engineering borders to the behavioral science seeking an appropriate ground for modeling drivers' route selection processes. DFT [5], recently developed in psychology, is used to study drivers' multi-attribute

cognition and decision process under real-time traffic information and construct the model of dynamic route choice behaviors. Bayesian belief network is chosen to describe drivers' prediction, judgment, and dynamic updating of travel time and weights on each attribute for routes. Thereby, the model of driver route choice behavior in a road network under real-time traffic information is obtained and a real-time planning algorithm for route choice behavior and processes is discussed in great detail. Using this algorithm, a driver develops his route dynamically until he reaches his destination.

2. Dynamic Route Choice Model Frameworks

Drivers' route choices are outcomes of complex interactions of several psychological processes. On one hand, drivers make their choices through a mental deliberation process that includes a trade-off between the perceived attributes of available alternatives. Drivers form perceptions about these attributes based on previous experiences, day-specific experiences, and, in many cases, traffic information sources. Driver characteristics influence the operation of the underlying psychological processes and the resulting choices. On the other hand, drivers' route choices are performed within a unique choice environment. The complexity of the choice environment stems from several contributing factors, the most prominent of which are uncertainty and time pressure. In addition, situational conditions (such as road works), and environmental conditions (such as weather-related obstructions) further impact drivers' perceptions of the decision attributes. The highly intertwined aspects of the overall route choice behavior mandate the abstraction of the main underlying processes/factors for understanding and modeling purposes. Figure 1 illustrates an abstract representation of the main contributing processes/factors and their interrelations.

For the route choice problem, our alternatives are naturally a number of available routes between a given Origin Destination (OD) pair. During the deliberation process, drivers compare and trade off alternatives based on the expected payoffs of some attributes. During the past decade, extensive research was focused on the analysis of factors influencing drivers' route choice decisions. While considered attributes could differ from driver to another, specification of a set of measurable attributes is obviously essential. For the proposed model, two main trade off aspects or attributes are represented; Travel Time (T) and Distance (D). Specification of these two aspects is based on extensive review of relevant literature as well as informal discussions with a large number of drivers.

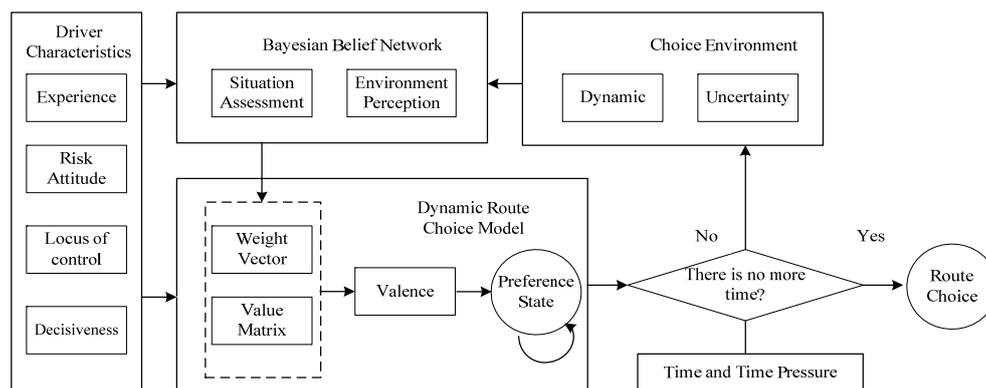


Figure 1. Route Choice Behavior Abstraction

2.1. BBN Inferring Travel Time and Weights on Each Attribute for Routes

BBN is a cause and effect network that captures the probabilistic relationship, as well as historical information. BBN contains prior and conditional probabilities that can be used to infer the posterior probability through the Baye's theorem [6]. The major advantage of BBN is its ability and flexibility to handle uncertain and dynamic environments.

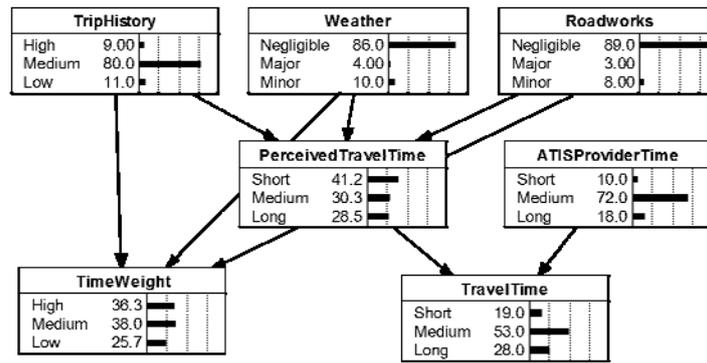


Figure 2. BBN Inferring Travel Time and Time Weight for a Route

Figure 2 depicts a BBN used to infer the belief of a driver under the route choice processes. The beliefs inferred by BBN given environmental information (e.g. road works, weather and ATIS time) include 1) evaluation of values for attribute (travel time) for the considered option (a route from an intersection) and 2) weights on each attribute. The weights on each attribute at time t , $W(t) = \begin{pmatrix} w_T(t) \\ w_D(t) \end{pmatrix}$, is obtained from 'Time Weight' node of BBN in Figure 2 by defining $w_T(t) = \text{'Time Weight'}$ and $w_D(t) = \text{'Distance Weight'} = 1 - \text{'Time Weight'}$.

Similarly, the evaluations of available options on Travel Time attribute, $M = \begin{pmatrix} m_T^1 & m_D^1 \\ m_T^2 & m_D^2 \\ \vdots & \vdots \end{pmatrix}$, can

be obtained from 'Travel Time' nodes of BBN by assigning $m_T^i = \text{'Travel Time'}$ and from $m_D^i = \text{'Distance'}$ for route i . The inferred belief from BBN is intended to be similar to that of real human. In this research, this similarity can be obtained by constructing BBN based on the data from human-in-the-loop experiments.

2.2. DFT for Dynamic Route Choice

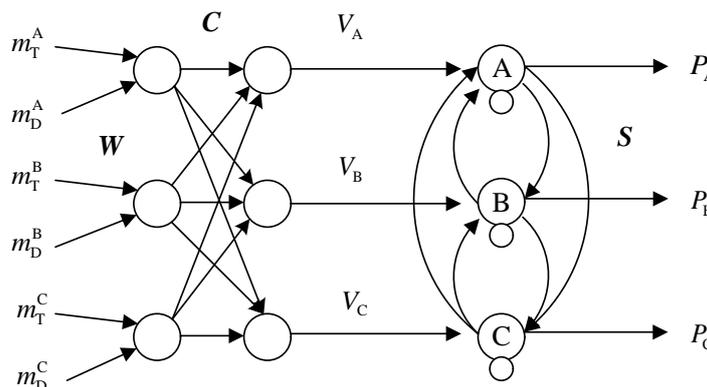


Figure 3. Connectionist Network Model of DFT

DFT was developed based on psychological principles drawn from two different lines of psychology, approach-avoidance theories of motivation and information processing theories of choice time. As a behavioral decision theory oriented about decision-making process, it dynamically approaches the cognition of human's decision-making process based on

psychological rather than economic principles. DFT differs from most mathematical approaches to decision making in that it is stochastic and dynamic rather than deterministic and static. "Dynamic" here denotes that DFT considers "time" as a factor affecting the decision. In contrast, "dynamic" in this paper means that multiple and interdependent decisions are made in an autonomously changing environment. DFT was initially applied to the study of decision making under uncertainty, and then to the research of decision-making behaviors such as multi-attribute decisions, multi-alternative choices, and multiple measures of preference [7]. Figure 3 provides an interpretation of the Decision Field Theory as a connectionist network that has three layers [8]. The first layer computes the weighted utility according to the attributes of different options and attention weights as formulated in (1).

$$U_i(t) = \sum_j w_j(t) \cdot m_i^j \quad (1)$$

Where, $U_i(t)$ is the weighted utility for option i at time t, m_i^j is the evaluations for attribute j of option i. $w_j(t)$ is the momentary attention weights linked to attribute j. The average value of the attention weights corresponds to the weight in deterministic utility theory.

The outputs of the second layer are valences which represent the advantage or disadvantage being considered for each option at a particular time point. These valences change stochastically over time as the decision maker's attention shifts unpredictably from one attribute to another.

$$v_i(t) = U_i(t) - U_g(t) \quad (2)$$

$$U_g(t) = \sum_{k \neq i} U_k(t) / (n-1) \quad (3)$$

Where, $v_i(t)$ is the valence for option i. $v_i(t) > 0$ indicates that the option i has an advantage under the current focus of attention while $v_i(t) < 0$ indicates that the option i has a disadvantage under the current focus of attention. $U_g(t)$ is the average utility of the other (n-1) options and n is the number of options.

The third layer is a competitive recursive network. The outputs of this layer are the evolving accumulative preferences for the options at a particular time point. The accumulative preference is formed by the integration of the preference at previous time points and the temporal input valences. The preference state for option i is computed according to the linear dynamic system.

$$P(t+h) = S \cdot P(t) + V(t+h) \quad (4)$$

$P(t+h)$ (n-elements vector) represents a preference state for all options at time t+h, $V(t+h)$ is the valence vector for all options at time t+h, and h is a time step. The feedback matrix S of (4) represents the effect of the preference from the previous state (the memory effect) in the diagonal elements and the effect of the interactions among the options in the off-diagonal elements. For the stability of this linear system, the eigenvalues λ_i of S are assumed to be less than one in magnitude ($|\lambda_i| < 1$). Equation (4) can be further expanded as:

$$P_i(t+h) = s_{ii} \cdot P_i(t) + \sum_{k \neq i} s_{ik} \cdot P_k(t) + v_i(t+h) \quad (5)$$

Where $P_i(t+h)$ is the preference state for option i at time $t+h$. Equation (4) can be used for the model of dynamic route choice behavior [9]. As described above, m_i^j and $w_j(t)$ can be inferred from BBN in our research. For example, if we have three options in our route choice processes, the corresponding DFT formula, by definition of Equation (4), is following:

$$\begin{pmatrix} p_1(t+h) \\ p_2(t+h) \\ p_3(t+h) \end{pmatrix} = \begin{pmatrix} s_{11} & s_{12} & s_{13} \\ s_{21} & s_{22} & s_{23} \\ s_{31} & s_{32} & s_{33} \end{pmatrix} \begin{pmatrix} p_1(t) \\ p_2(t) \\ p_3(t) \end{pmatrix} + \begin{pmatrix} 1 & -0.5 & -0.5 \\ -0.5 & 1 & -0.5 \\ -0.5 & -0.5 & 1 \end{pmatrix} \begin{pmatrix} m_T^A & m_D^A \\ m_T^B & m_D^B \\ m_T^C & m_D^C \end{pmatrix} \begin{pmatrix} w_T(t+h) \\ w_D(t+h) \end{pmatrix} \quad (6)$$

In model (6), $s_{ii} = 0.98$ and $s_{ij} = -0.03$ for $i \neq j$.

2.3. Decision Making Rules of Route Choice

There are two DFT decision-making rules [5]:

(1) The stopping of decision-making process is controlled by stopping time: Set T_D as the stopping time. The decision process begins at $t=0$ and stops at $t=T_D$. If $p_m(T_D) = \max(p_i(T_D), i=1, \dots, n)$ at that moment, alternative $p_m(T_D)$, with the maximum preference state at T_D , is chosen.

(2) The stopping of decision process is controlled by threshold θ : Set a threshold θ . If $p_m(t) \geq \theta$, $p_j(t) < \theta$, $j \neq m$, alternative $p_m(t)$, the first one to reach the threshold, is chosen. It worth mentioning that a decision-maker threshold bound is not fixed but rather varies according to the choice situation and time constraints.

3. Real-time Planning Algorithms for Route Choice

This section discusses the planning algorithm implemented within Matlab and Netica in a greater detail. Using this algorithm, a driver develops his route dynamically until he reaches his destination. The preferences of routes which are directly accessible from the current position are obtained via BBN and DFT.

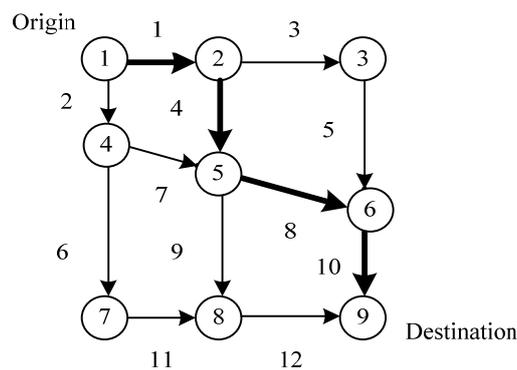


Figure 4. The Example Road Network

To illustrate the algorithm for various situations, we apply them to an exemplary road network as shown in figure 4, consisting of 9 nodes, 12 links, and 1 OD pairs. The OD pair is served by a total of 6 routes: links 1,3, 5 and 10 for route A; links 1, 4, 9 and 12 for route B; links 1, 4, 8 and 10 for route C; links 2, 7, 8 and 10 for route D; links 2, 7, 9 and 12 for route E; links

2, 6, 11 and 12 for route F. The travel times and the distance for each link on the road network are shown in Table 1. In this example, it is supposed that a driver in node 1 is searching for a route to the destination node 9. A series of selection process (of a route) can be described as following:

Table 1. Link Characteristics

Link	Travel Time(min)			Distance (km)
	short	medium	long	
1	14	20	36	15
2	9	14	24	10
3	20	29	53	22
4	16	23	41	17
5	27	40	72	30
6	32	47	84	35
7	15	21	38	16
8	25	36	65	27
9	26	37	67	28
10	14	20	36	15
11	14	20	36	15
12	20	29	53	22

Step 1: At node 1, the driver evaluates each route (A, B, C, E, F, G) in terms of weather, road works, ATIS time and distance to the destination.

Step 2: Based on his observation, the driver infers evaluation matrix M ,

$$M = \begin{pmatrix} m_T^A & m_D^A \\ m_T^B & m_D^B \\ \vdots & \vdots \end{pmatrix}, \text{ and weight vector } W(t) = \begin{pmatrix} w_T(t) \\ w_D(t) \end{pmatrix}, \text{ via BBN (see Fig. 2), where } m_T^A$$

represents the evaluation of route A on the Travel Time (T) attribute, and $w_T(t)$ is the weight on the Travel Time (T) attribute at time t .

Step 3: M and $W(t)$ obtained in Step 2 is provided to Equation (1), which generate the choice preference $P_A, P_B, P_C, P_D, P_E, P_F, P_G$ for each route.

Step 4: Now, the route with maximum choice preference is selected. Suppose route A has been selected. Then, the same process (see Steps 1, 2, 3, and 4) is used to pick a route before the driver approaching node 2 (intersection 2).

Step 5: Before approaching node 2 (intersection 2), the driver repeats Step 1 to evaluate each route (links 3, 5 and 10 for route A; links 4, 9 and 12 for route B; links 4, 8 and 10 for route C.). However, this evaluation is for the updated travel time to the destination (travel time to node 9 from nodes 2). Then, the driver repeats Step 2 to infer evaluation matrix M and weight vector $W(t)$ via BBN, where BBN uses the updated travel time to the destination. Then,

the driver repeats Step 3 to obtain the choice preference P_A, P_B, P_C . Then, the driver repeats Step 4, selecting route C.

Step 6: Before approaching node 5 (intersection 5), the driver repeats Steps 1, 2, 3, 4. However, as shown in Figure 4, the available routes are route B (links 9 and 12) and route C (links 8 and 10). Then, the driver selects a route based on the choice preference P_B and P_C . This way, route C is selected again.

4. Simulation and Analysis of Route Choice Behaviors

The preference model shown in Equation (6) has been simulated. Figure 5 presents the evolution of a driver preference with time before approaching node 2. At the beginning of the deliberation, process, the driver's preference oscillates back and forth among the three options before it matures in the direction favoring route C over route A and B. Terminating the deliberation process is either performed by specifying an upper threshold bound, or by externally imposing stopping time.

The threshold (θ) is the level of preference that terminates the deliberation process when reached for any of the available alternatives, i.e. if the driver preference to a given alternative peaks beyond this threshold, the corresponding route is taken, regardless of the length of deliberation time. This bound is expected to be individual dependent as it may vary according to the driver's characteristics, such as age, gender, and personal profile. Researchers have discovered that cautious drivers often use higher thresholds but impetuous ones tend to use lower values. In addition, it is also expected to be situational dependent as decision-makers could alter their level of acceptance according to the prevailing conditions: weather conditions, road works, trip purpose, and most importantly, time pressure constrains. Threshold is an important parameter to reach a trade-off between the decision-making speed and quality. This is because the driver cannot search and evaluate all consequences at the beginning of route choice, resulting in an often slow and time-consuming decision-making process (unless the intuition or other initial tendency is rather intense or the time stress is too high). The driver often recalls, evaluates, and consolidates various results (including the examination of conflicts) step by step and the entire decision-making process will last until the choice tendency (preference state) exceeds the threshold at a certain time instant. If the threshold is set so low that there are too little cycles of repeated calculations on model (6), the deliberation time will be short, resulting in insufficiently profound processing of information. Two values of θ , a high value ($\theta=5$) and a low value ($\theta=3$), are to be tested in our worked example to illustrate the threshold's effect.

In many route choice situations, an externally imposed stopping time terminates the deliberation process even before it matures. An example could be approaching a bifurcation point on a freeway, where a decision must be made regardless of the level of maturity of the deliberation process. The direct influence of time pressure constraints can be clearly depicted in figure 5 where low threshold bound and short time frames may result in an immature decision. On the other hand, relaxing the time pressure constraint is expected to result in a better, well-informed choice decision.

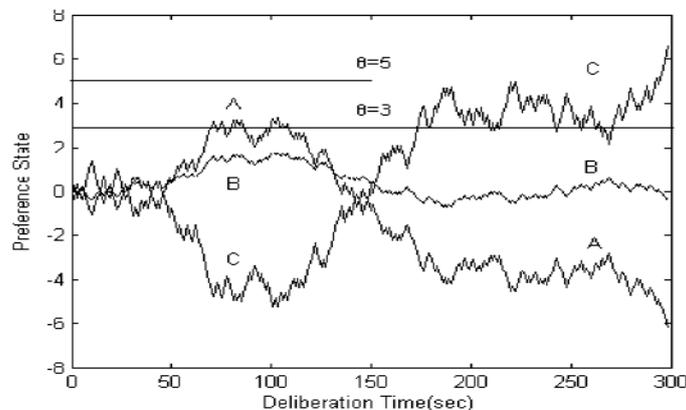


Figure 5. Preference State Evolution Before Approaching Node 2

5. Conclusion

The dynamic nature of drivers' choice behavior together with the uncertainty of the choice environment and the high variability of human preferences motivated the adoption of DFT as a theoretical foundation of our framework of the routing choice. DFT offers a sound theoretical ground for modeling the psychological process underlying drivers' choice decisions. In this paper, we create a drivers' dynamic route choice model through DFT research and build a model of drivers' prediction, judgment and dynamic updating of travel time and weights on each attribute for routes via BBN. The simulation results show that the combination of DFT and BBN can effectively explain the driver's travel dynamics behavior in a road network based on real time traffic information. The approach provides a new thought for describing and studying the effect, as well as the mechanism of action, of real-time traffic information on driver route

choice behavior. It can be used not only to analyze the effect of real-time traffic information on drivers' route choice behaviors, but also to describe more complex cognitive behaviors of drivers.

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