Behavior-based Consistency-Seeking Models as Deployment Alternatives to Dynamic Traffic Assignment Models

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Abstract: This paper proposes a behavior-based consistency-seeking (BBCS) model as an alternative to the dynamic traffic assignment paradigm for the real-time control of traffic systems under information provision. The BBCS framework uses a hybrid probabilistic-possibilistic model to capture the day-to-day evolution and the within-day dynamics of individual driver behavior. It considers heterogeneous driver classes based on the broad behavioral characteristics of drivers elicited from surveys and past studies on driver behavior. Fuzzy logic and *if-then* rules are used to model the various driver behavior classes. The approach enables the modeling of information characteristics and driver response to be more consistent with the real-world. The day-to-day evolution of driver behavior characteristics is reflected by updating the appropriate model parameters based on the current day's experience. The within-day behavioral dynamics are reactive and capture drivers' actions vis-à-vis the ambient driving conditions by updating the weights associated with the relevant *if-then* rules. The BBCS model is deployed by updating the ambient driver behavior class fractions so as to ensure consistency with the real-time traffic sensor measurements. Simulation experiments are conducted to investigate the real-time applicability of the proposed framework to a real-world network. The results suggest that the approach can reasonably capture the within-day variations in driver behavior model parameters and class fractions in the traffic stream. Also, they indicate that deployment-capable information strategies can be used to influence system performance. From a computational standpoint, the approach is real-time deployable.

Key words: Real-time deployment, consistency-seeking, hybrid route choice model, real-time information.

1. Introduction

The real-time deployment of a dynamic traffic assignment (DTA) system is a critical operational problem in the context of Advanced Traveler Information Systems (ATIS). The primary functional capabilities of a DTA system for ATIS operations are to predict the network state over time and to provide routing information to drivers consistent with some individual and/or system-wide objectives. However, while conceptually elegant, there are significant barriers to the deployment of a DTA model for real-time operations. Driver behavior is a fundamental determinant of the traffic network states unfolding over time. The current DTA literature does not model driver behavior realistically. This is partly because most DTA models assume rigid behavioral tendencies *a priori*, and commonly categorize drivers into classes such as user equilibrium (UE), system optimal (SO), boundedly-rational (BR), stochastic user equilibrium (SUE), pre-specified/fixed route, deluded equilibrium, and combinations thereof (for example, Peeta and Mahmassani, 1995; Lo et al., 1996; Nakayama et al., 1999). These classes are also assumed to reflect the amount of information availability to drivers and/or the information supply strategy of system controllers or information service providers. The models then analyze the time-dependent interactions of the various driver behavior classes assuming that instantaneous or anticipatory travel costs are the primary basis for route choice.

From a deployment perspective, DTA models can be classified into iterative, reactive and hybrid types. Iterative DTA models solve for the optimal routes based on some pre-specified system-wide and/or individual driver behavior class objectives using an iterative search process that projects future traffic conditions (for a detailed review, see Peeta and Ziliaskopoulos, 2001). Reactive DTA models use instantaneous and/or local traffic information to predict the routes by focusing more on the real-time computational tractability (Hawas and Mahmassani, 1997; Pavlis and Papageorgiou, 1999; Peeta and Yang, 2003). Hybrid DTA models (Peeta and Zhou, 2002) exploit both historical and current traffic information by combining off-line and real-time computational components so that the real-time solution update strategies are computationally efficient. However, only a few DTA models consider heterogeneous driver behavior. Even these models are behaviorally restrictive, and assume that the driver behavior classes are pre-specified, where a driver behavior class is defined as a group of drivers who are behaviorally homogeneous. Further, they assume that the driver behavior class fractions in the ambient traffic stream are known deterministically *a priori*. This is a strong assumption in reality based on the current progress of technology. In the real-world, the natural mechanism for driver route choice, even under information provision, is based on the driver's innate behavioral tendencies, past experience, situational factors (such as time-of-day, weather conditions, and trip purpose), and the ambient traffic conditions encountered. This is true irrespective of whether drivers receive personalized, generic, or no information. While information provision and content can be used as control variables to influence system performance (Peeta and Gedela, 2001), they cannot imply perfect compliance by the drivers to the supplied information, as is predominantly done in the DTA arena. Even studies that view compliance as a variable are restrictive because they still assume rigid behavioral classes. Further, they mostly model compliance through compliance rates by assuming that these rates represent the fraction of drivers that fully comply or do not comply with the provided route. This approach has limitations from a real-world perspective. First, not all drivers with access to information receive personalized routes. Second, even when personalized routes are recommended, compliance is not an "all-or-nothing" variable in terms of how the information is used. People may use the information to partly modify the existing route based on their behavioral tendencies and past experience. An all-or-nothing perspective assumes that either the driver complies fully with the recommended route or completely ignores it.

While realistic driver behavior modeling is critical to the effectiveness of DTA models in the operational context, their behavioral weaknesses have origins in the historical developmental perspective that DTA models are conceptual extensions of static traffic assignment (STA) models to the time-dependent case. The added dimension identified as being critical to DTA models was the need to realistically represent traffic flow dynamics, leading to the general consensus on the acceptability of simulation-based DTA models for deployment (Peeta and Ziliaskopoulos, 2001). Thereby, realistic behavioral representation has not been sufficiently emphasized in the methodological and algorithmic constructs for DTA models. The common DTA objectives, inherited from STA concepts, are UE and SO. Assumptions of UE and its underlying behavioral basis can partly be justified in a long-term planning context, both for STA and DTA. Similarly, a SO solution can serve as a benchmark for planning and operational strategies under STA and DTA. However, in the DTA operational context, using UE as a behavioral paradigm, or UE and SO as information supply strategies with partial or perfect compliance, are inherently restrictive from a behavioral standpoint. This is because they exclude from *explicit* consideration situational factors and driver learning (which is based on past experience, personal characteristics, and latent tendencies towards information provision), both of which can significantly affect driver route choice decisions on a specific day. This also implies the need for seamless and consistent modeling of day-to-day and within-day behavior.

Traditional route choice models focus primarily on the socio-economic characteristics of drivers. Route choice models under information provision additionally consider some information-related characteristics of drivers. They typically do not incorporate the network-level interactions resulting from traffic flow dynamics due to the decisions by individual drivers in terms of route choice, into the future route choice decision-making. En-route driver behavior models seek to address this aspect by modeling the en-route route switching decisions. Mahmassani and Jayakrishnan (1991) assume boundedly-rational driver behavior based on instantaneous route travel times and capture the network-level traffic flow interactions by simulating the driver en-route switching decisions. Abdel-Aty (1998) uses a nested logit model to predict en-route routing decisions for incident-related congestion under real-time information provision. Srinivasan and Mahmassani (2000) develop a multinomial probit framework and introduce two en-route behavioral factors under real-time information: inertia and compliance. The former represents a driver's propensity to continue on the current path he/she is taking, while the latter represents the willingness to take the route recommended by the traveler information system. The study results show that driver en-route choices are affected by traffic congestion levels and drivers' past experience with information.

The day-to-day (or pre-trip, for a specific day) and en-route behavior models are mostly addressed in separate frameworks. There are very few studies that consistently address both within a common framework. Hu and Mahmassani (1997) use a simulation-assignment approach to investigate pre-trip and en-route routing decisions under real-time information provision. The selection of the route and departure time at the pre-trip stage each day are based on the driver's scheduled delays experienced on the previous day. En-route switching is assumed to be based on boundedly-rational behavior under information provision. Mahmassani and Liu (1999) extend this work using a multinomial probit framework to model driver departure time and route choices. An interactive dynamic traveler simulator is used to generate route choice data through laboratory experiments. The study concludes that driver en-route routing decisions are based on their expected travel time savings to their destinations.

Lam and Yin (2001) propose an activity-based DTA model in which the activity choice behaviors of individuals are modeled using a multinomial logit formulation, and the driver route choices are assumed to satisfy a dynamic user equilibrium assumption. The combined activity/route choice variational inequality formulation is solved using a heuristic approach. However, the problem framework is still DTA-based with a specific objective (UE). Also, the notion of predicting the activities of drivers implies the microscopic modeling of the causes of driver trip-making. While this perspective may be justifiable for pre-trip route prediction, it is unrealistic for modeling en-route route choice in the dynamic setting of real-time operations, especially under information provision. Also, in general, existing models do not consider the dynamically changing route characteristics represented by the situational factors.

We propose a behavior-based consistency-seeking (BBCS) modeling approach to bridge the functional gaps between route choice models and dynamic traffic assignment models vis-à-vis predicting the time-dependent network traffic flow patterns. The approach consistently addresses day-to-day learning and within-day dynamics using a single hybrid probabilistic-possibilistic behavioral model (Peeta and Yu, 2004, 2005) through intuitive *if-then* rules that are based on the findings of past studies in the literature. The traffic flow dynamics and network-level interactions of driver route choice decisions are captured using a traffic flow simulator. The approach avoids rigid assumptions on driver behavioral tendencies and *a priori* knowledge of driver behavior class fractions. It enables the classification of information characteristics and the modeling of information effects more consistently with the real-world. From a deployment perspective, it uses the data available currently, both in terms of the time-scale and technology. It circumvents the need for a search procedure to predict the dynamically evolving traffic flow pattern. Thereby, it is a computationally tractable approach for real-time deployment. In the rest of the paper, we propose to show that a BBCS model can be viewed as an alternative to the behaviorally-restrictive DTA models to predict dynamic traffic flow patterns and to develop information-based system management strategies.

2. Approach

In this section, we define the BBCS problem, discuss the BBCS modeling framework, introduce a hybrid route choice behavior model, describe the modeling of information characteristics and effects, and then briefly compare the proposed BBCS problem with the consistency-seeking problem that arises in the DTA deployment context (for example, Peeta and Bulusu, 1999). The BBCS framework incorporates the hybrid model and a consistency-seeking model to update driver behavior class fractions.

2.1. The behavior-based consistency-seeking problem

The BBCS problem can be defined in descriptive and prescriptive contexts. The descriptive BBCS problem is defined as follows: given the time-dependent origin-destination (O-D) trip demand on a specific day, determine the time-dependent traffic flow pattern consistent with the traffic flow measurements and driver behavior. Under information provision, this problem implies the prediction of driver routes by accounting additionally for the influence of the supplied information. Hence, in the absence of an explicit control mechanism, the BBCS problem seeks to describe the traffic flow pattern. Information can also be used as a control variable to enhance system performance. Hence, the BBCS problem can be used in a prescriptive context to improve system performance through information provision strategies that are realistic in a deployment context. Section 2.4 discusses the modeling of information availability and information provision strategies consistent with the current technological progress.

The BBCS problem is tailored for route prediction using realistically available data in a deployment context. The real-time data that is reasonably available based on current technology consists of the sensor-based traffic flow measurements (such as volume, occupancy, speed, and vehicle classification). In addition, the trends of the socio-economic characteristics of drivers in the region can be determined through census data and questionnaire surveys. Also, more detailed behavioral characteristics, especially under information provision, can be inferred through driver diaries, surveys, and driving simulators.

2.2. Behavior-based consistency-seeking framework

The proposed behavior-based consistency-seeking framework, illustrated in Figure 1, combines the hybrid route choice model (Peeta and Yu, 2004, 2005) for network loading and a consistency-seeking model that updates driver behavior class fractions. The planning horizon of interest for the current day is divided into discrete time intervals, denoted by τ. The BBCS procedure starts at $\tau = \tau_0$. The hybrid route choice model uses two types of data as inputs: (i) static, and (ii) dynamic. The static inputs are assumed known *a priori* for the entire planning horizon. They include the network structure and the driver behavior classes. The dynamic inputs are not known *a priori* and are obtained in real-time. They consist of the time-dependent O-D demand, driver behavior class fractions, real-time information, and ambient driving conditions. The initial routes for the new O-D desires originating in interval τ are their pre-trip route choices determined using the day-to-day component of the hybrid route choice model and the real-time information provided. The within-day component of the hybrid model for interval τ updates the current routes of existing drivers at decision nodes based on the ambient driving conditions, the driver behavior class characteristics, and the real-time information provided. The routes of all drivers are used to predict the traffic network states for interval τ using a traffic flow simulator. The actual traffic flow measurements, in terms of link vehicular counts for interval τ, are obtained from the real-time network monitoring systems. The aggregate percentage difference between the actual and predicted link counts as a ratio of the corresponding actual counts is computed across all links for which measurements are available for interval τ, as shown in Equation (5) of Section 4.2. If this value exceeds a pre-specified threshold amount, a consistency-seeking model is executed to adjust the driver behavior class fractions so as to minimize the time-dependent prediction errors. Then, τ is incremented by one and the procedure is repeated until the end of the time horizon of interest is reached.

2.3. Hybrid route choice model for network loading

This section briefly summarizes the network loading mechanism for interval τ using the hybrid route choice model, as illustrated in Figure 2. A detailed description of the hybrid probabilistic-possibilistic model is provided in Peeta and Yu (2005). Its use in a consistent framework to integrate day-to-day driver behavior evolution and real-time behavioral dynamics is discussed in Peeta and Yu (2004).

The interval τ is divided into discrete sub-intervals, denoted by σ. Each sub-interval has a time duration Δ. The start time of sub-interval σ is denoted by t_σ. Then, t_1 represents the start time of interval τ. During sub-interval σ, the new O-D desires for the sub-interval σ+1 are considered for predicting the network state in σ+1. The set of initial route alternatives for each new driver is determined based on the *k*-dominant paths obtained through several test simulation runs (or in practice, using driver surveys and the historical traffic data collected). This is based on the assumption that a driver considers only a subset of possible O-D routes based on past experience and knowledge of the traffic network. Here, "dominant" routes imply the set of routes for an O-D pair that represent the routes of most drivers. The initial routes for the new drivers in sub-interval σ+1 are determined using the day-to-day component of the hybrid route choice model based on the driver personal attributes for interval τ as well as dynamic inputs at t_σ in terms of information provision, ambient driving conditions, and the current route characteristics. The within-day component of the hybrid route choice model determines driver en-route route choices for sub-interval σ+1 at decision nodes using the dynamic inputs at t_σ and the driver personal attributes for interval τ. Driver en-route route switching is considered for sub-interval σ+1 if unfinished trips exist in the network at time t_σ. For $\sigma = 1$, en-route switching is considered if unfinished trips exist at the end of interval τ-1. Since the hybrid model has a probabilistic discrete choice model structure, its outputs are the choice probabilities for the alternative routes for each driver. These probabilities need to be converted into the discrete route choice for each driver. Monte Carlo simulation is used to generate these discrete choices from the predicted driver route choice probabilities (Peeta and Yu, 2005). The predicted driver routes are simulated using a traffic simulator, DYNASMART (Jayakrishnan et al., 1994), to generate the predicted time-dependent traffic flow conditions for the sub-interval σ+1. If $t_{\sigma+1}$ represents the end of the interval τ, the network loading for τ is terminated. If not, the procedure is repeated until $t_{\sigma+1}$ reaches the end of interval τ. This implies that the predicted network states for the first sub-interval of the interval τ+1 are obtained at the end of interval τ.

The key feature of the hybrid model is its ability to capture the qualitative attributes considered in driver route choice behavior such as the subjective interpretation of route characteristics, linguistically expressed traffic information, and situational factors. Figure 3 illustrates the hybrid model logic which treats qualitative and quantitative variables in a single framework. It first categorizes variables into quantitative and qualitative variables based on their nature. Qualitative variables are expressed as linguistic labels and/or require subjective interpretation, while quantitative variables are naturally amenable to quantitative measurements. A rule-based fuzzy model is used to quantify qualitative variables. If interactions exist among quantitative variables, an adjustment procedure is used to capture them. For example, a fuzzy combination scheme can be used to capture the perceived travel time from the estimated travel time and the quantitative traffic information provided. For each route alternative, the original values of quantitative variables and the transformed continuous values of the qualitative and adjusted interaction variables are used to determine its utility. The hybrid model has a probabilistic discrete choice model structure and generates the route choice probabilities using the utilities. The utility function used in this study is as follows (Peeta and Yu, 2004), except that no alternative-specific constant is specified for one of the alternatives:

$$V_{in} = \alpha_i + \beta_1 D_i + \beta_2 L_i + \beta_3 \Psi(T_{in}, K_{in}) + \beta_4 \Omega_Q(Q_{in}) + \beta_5 \Omega_F(F_{in}) + \beta_6 \Omega_P(P_i) + \beta_7 \delta_{in} \Omega_C(W_n, G_n, S_n) + \beta_8 \kappa_{in} \Omega_I(W_n, G_n, S_n) \quad (1)$$

where,

α_i = alternative specific constant for route i
β_j = coefficient of variable/function j
D_i = travel distance on route i
L_i = toll on route i
$\Psi(\cdot)$ = adjustment function to capture the perceived travel time
T_{in} = travel time estimated by driver n for route i
K_{in} = quantitative traffic information on route i for driver n
$\Omega_Q(\cdot)$ = transformation function to determine the fuzzy value of descriptive qualitative traffic information
Q_{in} = descriptive qualitative traffic information on route i for driver n
$\Omega_F(\cdot)$ = transformation function to determine the fuzzy value of familiarity
F_{in} = number of times driver n took route i in the past
$\Omega_P(\cdot)$ = transformation function to determine the fuzzy value of route complexity
P_i = number of nodes in route i
δ_{in} = 1 if route i is the recommended route for driver n; 0 otherwise
$\Omega_C(\cdot)$ = transformation function to determine the fuzzy value of compliance vis-à-vis recommended route i
W_n = weather conditions for driver n
G_n = time-of-day for driver n
S_n = trip purpose of driver n
κ_{in} = 1 if route i is the current route for driver n; 0 otherwise
$\Gamma_I(\cdot)$ = transformation function to determine the numerical value of inertia for current route i

The hybrid route choice model is amenable to incorporating the day-to-day evolution of driver behavior and the within-day behavior dynamics consistently in a single framework, as shown in Figure 4. The driver behavior dynamics are captured by modeling the perception update of routes by the individual driver, and the update of the *if-then* rules at the individual and/or aggregate levels, using the hybrid model. The day-to-day dynamics are captured through perception and *if-then* rule updates based on the current day's experience, which are reflected in the pre-trip decisions for the next day. Thereby, a driver's membership functions (Peeta and Yu, 2002) that represent his/her perception, and *if-then* rules, are updated on a daily basis. The within-day dynamics are captured through the en-route update. Behaviorally, drivers are not likely to change their *if-then* rules and perceptions en-route as they characterize phenomena that evolve over a longer timescale. Instead, driver en-route decisions are more sensitive to situational factors that unfold on the current day. These situational factors determine the *if-then* rules used in en-route decision-making. The en-route update is reflected by the within-day adjustment of the weights associated with the *if-then* rules in response to the situational factors.

In the context of driver behavior classes, all drivers in a class use the same utility function and *if-then* rules. Also, the weights of the *if-then* rules are identical for all drivers in that behavioral class. Each individual driver in a behavioral class has specific membership functions that are updated on a day-to-day basis based on his/her experience on the current day. However, the *if-then* rules are updated for the entire behavioral class based on the current day's experience for all drivers in that class. Similarly, the within-day updates of the weights of the *if-then* rules are also based on the real-time traffic flow measurements for all drivers in that class. In summary, the hybrid model affords the behavioral consistency of the BBCS framework in a transparent manner by updating the membership functions and the *if-then* rules.

2.4. Modeling information characteristics

In the context of information provision to drivers, existing DTA models typically combine information characteristics with behavior characteristics to define driver behavior classes. A common mechanism combines information availability to drivers, information supply strategy, and driver behavior to categorize drivers. The information supply strategy is usually modeled by providing: (i) instantaneous or projected travel time information under the descriptive strategy, and (ii) UE or SO paths based on the instantaneous or projected travel times under the prescriptive strategy. Driver behavior is viewed in terms of UE, SUE or BR type behavior under descriptive information provision, and in terms of compliance characteristics for prescriptive information provision. As discussed in Section 1, this modeling approach is restrictive in depicting both information characteristics and driver response behavior realistically.

In this study, information availability is classified into personalized, generic, and no information categories. It is consistent with the current state of information dissemination technologies. This is because personalized information (through sources such as cellular phone, pager, and wireless in-vehicle devices) is path-independent, while generic information for the en-route context (through sources such as variable message signs (VMS) or highway advisory radio (HAR)) is path-dependent and that for pre-trip context (through mass-media sources such as television, radio, and Internet) is path-independent. That is, the en-route generic information is targeted at a subset of drivers in the network while the pre-trip generic information typically describes the network conditions and is independent of the O-D pair. The proposed taxonomy does not exclude the possibility that a driver has access to both personalized and generic information.

Information provision strategies in the BBCS model are classified into: (i) instantaneous, and (ii) projected. Instantaneous strategies use current traffic conditions for information provision, while the projected strategies use the projected future traffic conditions. A key difference from existing DTA models is in terms of the realism of the information content provided. DTA models typically provide link/path travel times from a descriptive perspective or the recommended path in a prescriptive context. In the BBCS context, the information provided can be qualitative or quantitative, which is consistent with current information dissemination technologies. That is, the hybrid model component of the BBCS model enables the interpretation of linguistic messages such as “congestion ahead” or “30 minute delays”. Also, information can be provided for: (i) part of a path, (ii) the entire path, or (iii) for a local area around the current location of the driver. This is more realistic than the assumption of complete network-level information provision used in the commonly computed UE-based DTA solutions, which implies that the driver can process link travel time information on all links in real-time to determine a UE path. Also, in the BBCS framework information content can be used as a control variable; that is, different messages may lead to different driver response behaviors. The framework can also use the commonly modeled information provision strategies such as UE or SO. However, from a deployment context, this implies trade-offs between the computation time required for the iterative search procedures for SO/UE-type strategies and the operational tractability of simpler strategies based on *k*-dominant path computations.

As discussed in Section 1, the modeling of driver response behavior to supplied SO/UE type information using a compliance variable is rather restrictive from a real-world perspective.

Additionally, information is not the only factor for driver route choice and is not necessarily the dominant factor either. In the BBCS approach, the hybrid model treats information as only one of the factors drivers consider for route choice. Its contribution to a driver's route choice depends on his/her interpretation of that information, past experience, personal preferences, and ambient driving conditions. In the prescriptive context, the approach does not presume driver characteristics with regard to information. It does not pre-specify driver compliance, and captures the effects of situational factors on compliance (Peeta and Yu, 2005). Of considerable significance, it can consistently capture the evolution of information-related driver behavior phenomena such as compliance, inertia, delusion and freezing over time (Peeta and Yu, 2004). The flexibility in modeling information availability, information content, information provision strategy, and driver response behavior facilitate the use of information as a control variable to seek optimal routing patterns vis-à-vis network performance.

2.5. Analogy between the BBCS problem and the consistency-seeking DTA problem

The BBCS model is functionally analogous to consistency-seeking DTA models in that both address the consistency between the predicted network states and the actual conditions unfolding in real-time to determine driver routes for the deployment problem. Both models view incorrect O-D demand, traffic incidents, incorrect traffic flow modeling, incorrect prediction of driver route choices, and detector errors as the primary sources of inconsistency. Also, both evaluate consistency typically in terms of time-dependent travel times and link traffic counts. However, while there are key similarities, subtle differences exist in the context of the BBCS model addressed in this paper. While the BBCS model is an alternative to the deployable DTA model, the consistency-seeking problem is only one component of the deployable DTA model.

In the DTA consistency-seeking framework, a DTA model is used to estimate driver routes for the current prediction period based on time-dependent O-D demand forecasts available towards the end of the previous prediction period. Then, the predicted traffic flow measurements are compared to the actual measurements at discrete time points in the current prediction period. The differences between the two measurements at the various time points serve as inputs to the consistency-seeking model, which adjusts the associated DTA model parameters for the next prediction period. By contrast, the BBCS framework uses the actual measurements to determine the driver behavior class fractions, and then predicts the traffic patterns based on driver route choices.

3. The Consistency-Seeking Problem

3.1. Background on the DTA consistency-seeking problem

A key issue for the operational deployment of a DTA system is to ensure consistency between the model predictions and the actual traffic network states over time. This is critical to the effectiveness of control strategies implemented to enhance the traffic system performance. Several factors potentially contribute to the inconsistency between the predicted states and the actual conditions unfolding in real-time. They include (Peeta and Bulusu, 1999): (i) incorrect prediction of time-dependent O-D demands, (ii) traffic incidents, (iii) incorrect traffic flow modeling, (iv) incorrect driver behavior modeling, (v) incorrect driver behavior class fractions, (vi) incorrect assumptions on system-related parameters, (vii) noise/sparsity in measurements, and (viii) failure of ATIS components. Among these, the effects of incidents can be modeled seamlessly in existing DTA frameworks. Also, the system-related parameter errors and/or ATIS component failures are typically observable and can be accounted for in a direct manner.

However, despite the importance of the consistency issue to successful on-line DTA deployment, the literature in this area is rather sparse and recent. These deployment models lack a seamless mechanism to incorporate adjustments to behavioral parameters. Past research primarily compares the predicted and measured traffic flow parameters (such as link counts and/or travel times) to infer on inconsistency in an aggregate sense, rather than explicitly modeling the contributions of specific factors. Most studies focus on the inconsistency in terms of O-D demand predictions by drawing on the abundant literature in O-D demand estimation. Others view inconsistency in terms of traffic flow model parameters and O-D demands (Doan et al., 1999), or detector measurement errors (Peeta and Anastassopoulos, 2002). Yet others view inconsistency as the aggregate effect of several factors and manifesting in terms of errors in path assignment proportions (Peeta and Bulusu, 1999). None explicitly address incorrect driver behavior modeling and/or incorrect driver behavior class fractions.

Peeta and Bulusu (1999) develop a theoretical framework for the operational consistency of real-time DTA in traffic networks with ATIS. They view inconsistency as arising from incorrect O-D demand, traffic incidents, incorrect prediction of paths of unequipped drivers, and incorrect prediction of compliance characteristics of equipped drivers, and measure their aggregate effect using link traffic counts. The consistency approach seeks to correct the time-dependent path assignment proportions within a rolling horizon scheme. The model first solves a rolling horizon based deterministic DTA problem to predict the traffic network state for the near-future, and then seeks consistency between the predicted network states and actual conditions unfolding in real-time. The consistency problem is formulated as a constrained least squares model and is solved using the generalized singular value decomposition technique. The model performance is evaluated in terms of the time-dependent travel times and link/path traffic counts.

Mahmassani et al. (1998) categorize the error sources in terms of on-line and off-line components. The on-line error sources identified are in terms of on-line data observation, traffic flow propagation, and path estimation, while off-line errors are in terms of O-D demand estimation and internal traffic model structure. Based on this classification, Doan et al. (1999) propose a consistency-seeking framework that consists of on-line and off-line adjustments. The on-line adjustment is performed for the paths and traffic simulator parameters, while the off-line adjustment is for the day-to-day O-D demand. The approach uses a feedback control procedure for the on-line adjustments and a linear programming formulation for the off-line adjustment. Sawaya et al. (2000) use a similar feedback control procedure to correct the inconsistency between predicted and actual travel times under freeway incidents. On-line measurements are used to adjust some traffic flow simulator parameters to address these inconsistencies.

He and Ran (2000) propose a consistency-seeking framework under incomplete real-time link traffic counts and absence of data due to detector malfunctions. They use the maximum likelihood estimation method to update the time-dependent route choices based on the joint probability distribution function of the corresponding link flows. He et al. (2002) extend this method to estimate the updated time-dependent route choices and O-D demand simultaneously using real-time and historical traffic flow data.

While different combinations of the aforementioned factors can cause inconsistency, this study focuses on inconsistency due to the incorrect values of driver behavior class fractions. The study assumes that the traffic flow modeling, the O-D demand predictions, and the data used are accurate. This is primarily to derive insights on the driver behavior modeling aspects by isolating its effects. The BBCS approach can address consistency issues related to O-D demand predictions and data used, in the current framework. However, some extensions are necessary to incorporate traffic flow modeling related inconsistencies. To address the driver behavior modeling related inconsistencies, the approach should be able to reflect the evolution of driver route choice behavior over time, because route choice is significantly influenced by past experience, intuition, and subjective interpretation/perception of the traffic information provided. This entails a capability to calibrate the appropriate behavior model parameters in real-time, implying an efficient consistency-seeking algorithm to update driver behavior class fractions. The notion of considering driver behavior class fractions is reasonable in this context because the behavior classes can be naturally identified using drivers' socioeconomic and information-related characteristics.

The BBCS model uses a combination of the hybrid route choice model and a consistency-seeking model to update driver behavior class fractions in real-time. The consistency-seeking model captures the driver behavior class fractions using link traffic counts observed from the traffic flows unfolding in real-time. In Section 4, simulation experiments are conducted to obtain insights on the BBCS framework in terms of: (i) its ability to incorporate the real-time dynamics of driver en-route route choice behavior, (ii) its ability to capture driver behavior class fractions, and (iii) the real-time tractability of the consistency-seeking algorithm.

3.2. Update of driver behavior class fractions

The consistency-seeking model seeks to update driver behavior class fractions at discrete time points so as to minimize the difference between the observed and predicted link counts. In general networks, the number of time-dependent paths is substantially larger than the number of links. Hence, multiple path-based solutions can exist to minimize the objective function. More importantly, the computation can be highly intensive, precluding the real-time operational tractability of the consistency-seeking model. Here, an efficient mechanism for computing the driver behavior class fractions is developed to seek consistency between the predicted and observed link counts. The formulation for the consistency-seeking model in interval τ is represented by:

$$\text{minimize: } [\mathbf{Y}^\tau - \mathbf{X}^\tau]^2 \tag{2}$$

$$\text{subject to: } \mathbf{Y}^\tau = \mathbf{Z}^\tau + \boldsymbol{\Sigma}_\sigma (\mathbf{M}^\tau \times \mathbf{C}^\sigma \times \mathbf{R}^\sigma) \tag{3}$$

$$\mathbf{R}^\sigma = \mathbf{F}^\tau \times \mathbf{D}^\sigma \times \mathbf{P}^\sigma \tag{4}$$

where,

$\mathbf{Y}^\tau$ = the vector of the predicted link traffic counts for interval τ

$\mathbf{X}^\tau$ = the vector of the observed link traffic counts for interval τ

$\mathbf{Z}^\tau$ = the vector of the predicted link traffic counts for interval τ representing drivers that do not reach their destinations during interval τ–1

$\mathbf{M}^\tau$ = link-path incidence matrix for the *k*-dominant paths for interval τ

$\mathbf{C}^\sigma$ = link-path incidence adjustment matrix for sub-interval σ

$\mathbf{R}^\sigma$ = the vector of the number of drivers taking each route for sub-interval σ

$\mathbf{F}^\tau$ = the vector of driver behavior class fractions for interval τ

$\mathbf{D}^\sigma$ = the vector of O-D desires for sub-interval σ

$\mathbf{P}^\sigma$ = the vector of route choice probabilities for sub-interval σ

$\mathbf{P}^{\sigma}$ is the vector of time-dependent route choice probabilities obtained from the hybrid model. $\mathbf{M}^{\tau}\times\mathbf{C}^{\sigma}\times\mathbf{R}^{\sigma}$ represents the vector of the predicted link count contributions from the new O-D desires entering the network in sub-interval σ. The link-path incidence matrix $\mathbf{M}^{\tau}$ is time-dependent, but known *a priori* since the initial routes for each τ are chosen from the time-dependent *k*-dominant paths identified from historical data. Unlike the use of the time-dependent link-path incidence matrix in DTA to track vehicle trajectories, $\mathbf{M}^{\tau}$ is used here only to generate initial routes for interval τ. The drivers can change these routes en-route at decision nodes based on the ambient driving conditions. $\mathbf{C}^{\sigma}$ denotes the adjustment to $\mathbf{M}^{\tau}$ to ensure consistency between the observed link travel times for each sub-interval σ and the vehicle trajectories of the new O-D desires entering the network in sub-interval σ. Note that the consistency-seeking is done at the end of interval τ, at which time the observed link travel times for all sub-intervals in τ are available.

From Equations (2) – (4), the only unknown variables are the driver behavior class fractions. Link traffic counts for interval τ serve as the data points to estimate these fractions using the least squares method. Typically, the number of data points is greater than the number of driver behavior classes. In the rare instance that the number of behavior classes is greater than the number of data points, the length of interval τ needs to be increased to obtain more observations. However, this may degenerate the quality of the predictions because new O-D desires generated in the earlier part of interval τ may switch routes en-route during the later part of that interval, leading to errors due to the assumption of constant $\mathbf{M}^{\tau}$ in Equation (3). This introduces trade-offs for the length of τ.

The proposed consistency-seeking approach is synergistic with the real-time deployment of the BBCS model as driver behavior class fractions change dynamically over time even at the same location. Also, the current model structure can be extended seamlessly to the case where driver behavior class fractions vary across O-D pairs.

4. Application of the BBCS Model

This section analyzes the effectiveness of the BBCS model in enhancing network performance under information provision, and performs sensitivity analyses of the associated parameters. In addition, it analyzes the ability of the consistency-seeking model in capturing the dynamically varying driver class fractions.

4.1. Experimental setup

Figure 5 illustrates the Borman corridor network in northwest Indiana (USA) which consists of a 26 km section of I-80/94 (called the Borman expressway), I-90 toll freeway, I-65, and the surrounding arterials. It has 197 nodes and 458 links, and is divided into 14 zones. The Borman expressway is a highly congested freeway that has a large percentage of semi-trailer truck traffic. To manage traffic under incidents and peak-period congestion, an advanced traffic management system has been installed on the Borman network to provide drivers real-time traffic information. The Indiana toll road, I-90, which operates parallel to the Borman expressway is a potential alternative to it. Depending on the destination, other potential major alternative routes are US-20, US-30, Ridge road, and 73rd avenue. In all study experiments other than the incident-related ones, the network is congested only at the low to medium level as travel speeds on most links range between 40%-70% of the corresponding free flow speeds.

Two types of driver route choice decisions are analyzed in the experiments: pre-trip and en-route. At the beginning of their trips on the current day, drivers are assumed to choose their routes to their respective destinations based on their individual pre-trip route choice models. The en-route route choice models are used to determine the potential route switches of drivers at decision nodes in response to situational factors and/or real-time information. In the pre-trip context, four quantitative variables (travel distance, toll, estimated travel time, and quantitative traffic information) and five qualitative variables (qualitative traffic information, familiarity, route complexity, compliance, and inertia) are assumed to influence driver route choice decisions. For the en-route decisions, three situational factors (weather conditions, time-of-day, and trip purpose) are considered in addition to the pre-trip factors.

As discussed in Section 2.1, the BBCS framework is based on realistically available data. Since observed field data is currently not available for the Borman corridor network, route attribute data is generated for analyzing the BBCS model. The procedure to generate the values of variables is discussed in detail in Peeta and Yu (2004, 2005). The values of path travel distances and tolls are obtained by summing up the associated link quantities for the Borman corridor network. The values for the estimated travel time and quantitative traffic information are generated using a traffic simulator. The numerical values of qualitative attributes are generated using pre-specified functions (Peeta and Yu, 2004). For example, the descriptive qualitative traffic information consists of five linguistic labels. Its values are generated using a simple discrete function which assigns a meaningful value to each linguistic label. By contrast, a non-linear function of the number of nodes is used to generate the numerical values associated with route complexity, as the perceived complexity is assumed to increase more rapidly with the number of nodes. The specification of the route choice set is an important step in predicting the route choices. In this study, the route choice sets for drivers' pre-trip and en-route routing decisions at every decision node consist of up to 5 dominant paths revealed from ten test simulation runs. Each simulation run assumes different traffic conditions in terms of travel demand, and considers all likely routes for that O-D pair. The ten simulations runs are used to identify a subset of these routes which are labeled the dominant routes.

In the experiments, the personalized information drivers receive for their pre-trip decision-making are the recommended route to their destination and/or descriptive information for requested links. The generic information drivers acquire is descriptive information on some links via mass-media such as television, radio, or Internet. For en-route decision-making, the personalized information consists of the recommended route from the current location to the destination and descriptive information on links of interest, through cellular phone, pager, or wireless in-vehicle devices. The generic information in this context is descriptive information disseminated through VMS based on the path of the driver. Other generic sources such as radio or HAR are not modeled because drivers are less likely to use these media while driving, unlike VMS messages that are conveniently located. The information conveyed through VMS is either descriptive information on downstream traffic conditions or prescriptive information on detour routes.

Since field data is unavailable currently, driver routing decisions are assumed to be based on the combination of two rules: (i) lexicographic, and (ii) utility maximization subject to a threshold indifference band. The associated logic, illustrated in Table 1, is also used to define driver behavior classes using the attribute ranks and the functions specified in the table. It is important to note here that the BBCS model is unaware of this driver route choice decision process, and has access only to the associated observable data in practice (the route choice of the driver and associated route attributes). The driver attitudes to information content are based on a stated preference survey conducted in the Borman corridor network (Peeta et al., 2000). The attributes are assumed to be rank-ordered by importance. At each rank-level, utility functions are used to determine the utilities of alternatives. The driver eliminates inferior alternatives by excluding those alternatives whose utility values are less than a certain threshold percentage of the maximum utility value for that rank. The driver is indifferent to all alternatives that satisfy this threshold. The attributes belonging to the first rank are considered first to eliminate alternatives. If the route choice is not determined according to these attributes, the driver evaluates the second-ranked attributes. If a single alternative is not obtained even with the last-ranked attributes, utility maximization is used to determine the route choice at that point.

4.2. Update of driver behavior class fractions

The socioeconomic characteristics considered here to determine driver behavior classes are age, gender, income, and information type. The associated categories are: age (young and old), gender (male and female), income (high and low), and information type (personalized and non-personalized). The non-personalized category implies that generic information is potentially available to all drivers who travel past VMS locations, and no information is available to the remaining drivers in that category. Four cases are considered by varying the number of driver behavior classes as follows: (i) 2 (information type) driver behavior classes = 2, (ii) 2 (information type) × 2 (age) = 4, (iii) 2 (information type) × 2 (age) × 2 (income) = 8, and (iv) 2 (information type) × 2 (age) × 2 (income) × 2 (gender) = 16.

The effectiveness of the BBCS model is analyzed by predicting traffic flows. The performance measure used here is the average percentage difference between the actual and predicted states in terms of link traffic counts:

$$\left[\sum_{l=1}^{L}\frac{\left|X_l^\tau - Y_l^\tau\right|}{X_l^\tau}\right]\times\frac{100}{L} \tag{5}$$

where,

X_l^τ = observed counts on link l at time τ

Y_l^τ = predicted counts on link l at time τ

L = number of links for which real-time measurements are obtained

The performance measure is also used to determine whether the consistency-seeking model needs to be implemented at the end of each interval τ, as shown in Figure 1. In the study experiments, the consistency-seeking model is activated if a threshold value of 5% is exceeded for this performance measure.

Figure 6 illustrates the performance measure value under the four cases in terms of the number of driver behavior classes. Since the driver class fractions are not known *a priori*, this experiment arbitrarily assumes that initially all drivers belong to the first driver behavior class. Hence, the initial error between the actual and predicted network states ranges from about 35% and 55%. The BBCS model updates the driver behavior class fractions to minimize the error between the actual and predicted network states. In cases 1 and 2, the average percentage errors towards the latter part of the planning horizon range from 5%-10%, while in cases 3 and 4 they are between the 35%-42%. The results suggest that the consistency-seeking component of the BBCS model can capture the driver behavior class fractions by reducing the prediction errors. But, as illustrated by cases 3 and 4, if many distinct driver behavior classes co-exist in traffic stream, it is difficult to estimate the driver behavior class fractions robustly due to the limited data. However, these results are rather conservative because over time historical trends can suggest more robust initial values for the driver class fractions than the single class considered here. Also, to the extent that en-route route choices are significantly influenced by situational factors and other ambient driving conditions, it is unlikely that several distinct behavioral classes will exist en-route. Hence, the results are promising for the real-time deployment of the BBCS model.

To test the effect of different initial values for the driver behavior class fractions on the performance of the consistency-seeking procedure, Figure 7 analyzes the case of the four driver behavior classes. It is assumed here that the actual driver class fractions are 25%:25%:25%:25%. Three different sets of initial values are tested: (i) 100%:0%:0%:0%, (ii) 50%:50%:0%:0%, and (iii) 30%:30%:20%:20%. The results show that there are significant differences in the model performance initially, but they dissipate with time. Initially, the third set of initial values has the lowest percentage difference since it is closest to the actual set of driver class fractions.

Figure 8 illustrates the update of driver behavior class fractions under different class fraction values when four driver behavior classes exist. Three scenarios are tested by varying the actual fractions as follows: (a) 70%:10%:10%:10%, (b) 40%:30%:20%:10%, and (c) 25%:25%:25%:25%. The model predicts the fractions of the larger groups better than those of smaller groups because the route choices associated with a large driver behavior class contribute more to determining the unfolding traffic flow patterns. When the actual fractions are close to each other (Figure 8 (c)), the model prediction is robust.

4.3. Sensitivity tests

Since driver route choices differ behaviorally across classes, the associated fractions differ by location. The four locations considered and the associated actual average driver class fractions are: (i) I-80/94 (25%:25%:25%:25%), (ii) I-90 (30%:20%:30%:20%), (iii) US-20 and 15th avenue (25%:25%:30%:20%), and (iv) Ridge road and 45th avenue (30%:20%:25%:25%). Figure 9 illustrates the average percentage difference between the actual and predicted link traffic counts at various locations for the four driver behavior classes case. The classes considered vary by information type and driver age: (i) young drivers with personalized information, (ii) young drivers without personalized information, (iii) old drivers with personalized information, and (iv) old drivers without personalized information. The model has no information on the driver behavior class fractions at any location. Hence, the initial values at all locations are set as 100%:0%:0%:0%. The model prediction for the freeway traffic streams is better than that for the street/arterial traffic streams. This is because more route choices are generally available at street/arterial decision nodes irrespective of driver behavior classes.

In the real-time context, driver behavior class fractions may vary with time. Figure 10 illustrates the ability of the BBCS model to estimate the corresponding class fractions. In this experiment, driver behavior class fractions are assumed to vary every 60 minutes, and the initial fractions are obtained from the historical data. Figure 10(a) indicates that the model estimates these fractions adequately due to the robust initial values used. Also, as illustrated in Figure

10(b), the prediction improves with time for the period in which the driver class fraction values are constant, due to the increasing amount of data available for those values.

Experiments are conducted to analyze the effectiveness of the BBCS model under incidents. A traffic incident can be viewed as a situational factor that affects compliance and inertia. The severity and duration of incidents affect both compliance and inertia. Hence, the effect of a traffic incident on the driver routing decisions is incorporated by updating the weights associated with the compliance and inertia rules. The *if-then* rules for traffic incidents for the hybrid route choice model are shown in Table 3. The modified utility function in the hybrid model that incorporates the severity and duration of the incident is as follows:

$$V_{in} = \alpha_i + \beta_1 D_i + \beta_2 L_i + \beta_3 \Psi(T_{in}, K_{in}) + \beta_4 \Omega_Q(Q_{in}) + \beta_5 \Omega_F(F_{in}) + \beta_6 \Omega_P(P_i) + \beta_7 \delta_{in} \Omega_C(W_n, G_n, S_n, A_n, B_n) + \beta_8 \kappa_{in} \Omega_I(W_n, G_n, S_n, A_n, B_n) + \beta_9 \zeta_i \Omega_D(A_i, B_n) \quad (6)$$

where the additional variables used are:

$\Omega_D(\cdot)$ = transformation function to determine the fuzzy value of incident effects

A_i = severity of the incident occurring on route i

B_i = duration of the incident occurring on route i

ζ_i = 1 if incident occurs on route i; 0 otherwise

Figure 11 illustrates the performance of the BBCS model under various incident scenarios in terms of severity and duration. Incidents are generated on one link each on I-80/94 and I-90. For the first set of experiments, various incident severities are assumed for a 10-minute duration. For the second set of experiments, various durations of incidents are considered with a 40% reduction in capacity. Both sets of experiments suggest that the BBCS model significantly enhances the link counts prediction capability under incidents, as illustrated in Figures 11(a) and 11(b).

4.4. Information strategies consistent with deployment: alternative to DTA

As discussed in Section 2.4, the modeling of information characteristics and the associated driver response behavior in the BBCS model is more consistent with a real-world deployment capability compared to that of existing DTA models. Information provision, personalized and/or generic, is based on instantaneous or near-future projected travel times. The projected travel times are obtained using a traffic simulator that uses the pre-trip (initial) routes of the near-future O-D desires. These strategies are deployable because they can be computed in less than real-time, irrespective of whether they provide descriptive or prescriptive information. In addition, UE or SO type strategies can be solved off-line using DTA by assuming an idealized demand scenario to generate additional strategies for real-time information provision. Note that unlike in a DTA model, the BBCS model interprets the UE/SO type routes consistent with the drivers' behavioral tendencies (such as familiarity, route complexity, compliance, and inertia) represented through the hybrid model. This also holds for the prescriptive routes provided using instantaneous or projected travel times.

Figure 12 illustrates the network performance under the following information provision strategies: (i) instantaneous, (ii) 5-minute projection into future, (iii) 15-minute projection into future, and (iv) UE information based on projection for the entire planning horizon. Two driver behavior classes are used to test these strategies: with and without personalized information. Under the instantaneous information strategy, the current travel times are provided to drivers, while the 5-minutes and 15-minutes projected strategies use the corresponding projected travel times. When routes are prescribed, they are based on solving for the *k*-dominant paths using the corresponding travel times. The UE information projected strategy (UE-Info) provides each driver who can receive personalized information a projected UE route obtained by solving the idealized DTA problem off-line. However, the information provision strategies based on the prediction of future network states entail the prediction of future O-D desires, leading to trade-offs in terms of the O-D demand prediction accuracy and more informed decision-making by the drivers. In addition, trade-offs also exist in terms of the computational requirements and the future projection duration. In the current experiments, future O-D desires are assumed to be known accurately, leading to optimistic system performance results for the projected strategies.

Figure 12(a) compares the average system travel times under the various information provision strategies for different percentages of drivers with personalized information. The results suggest that information provision strategies can be used to influence system performance. They also illustrate that the marginal benefits associated with market penetration in terms of personalized information provision taper off in the 40%-80% range. Also, in some cases performance worsens with higher market penetration beyond the 60% value. This is consistent with the trends identified in previous studies involving system performance under personalized information provision. However, the worsening is not as marked as suggested by some of the prior literature. This is partly because some drivers have access to generic information through VMS which enables them to make more informed decisions though they may not receive personalized information.

In terms of the information provision strategies, Figure 12(a) suggests that there is value to projecting the future traffic conditions. While the 15-minute projected strategy does better than the 5-minute one, there are trade-offs involved in terms of the computational time and the accuracy of the predicted future O-D desires. Hence, in some situations, the 5-minute projected strategy may be more attractive from a deployment perspective. The UE-Info strategy performs the best among the strategies considered. However, it assumes that the actual O-D desires for the current day are known *a priori* off-line for the entire planning horizon, which is unrealistic. This implies that the use of an idealized O-D demand matrix (such as the time-dependent mean O-D demand matrix) to generate the UE routes may degrade the UE-Info strategy performance for the current day, leading to substantially lesser benefits than those suggested in Figure 12(a). Hence, the UE-Info may not be an effective deployment strategy. When the computational requirements to obtain the UE routes in real-time (that is, using the current day O-D demand forecasts) are factored in, it may not even be a realistic deployment strategy.

Figure 12(b) illustrates the percentage savings under the various information provision strategies compared to the case where no driver has access to personalized information. In this experiment, drivers with and without personalized information each constitute 50% of the traffic stream, except for the UE-DTA case where all drivers are assumed to follow the personalized UE routes specified to them. The results mostly mirror the conclusions based on Figure 12(a). In addition, they suggest that the UE-Info strategy does not perform significantly better than the 15-minute projected strategy though it assumes that O-D demand forecasts are known *a priori* for the entire planning horizon. The UE-DTA solution is specified purely for benchmarking purposes, and unlike the other strategies assumes that 100% drivers have access to personalized UE routes. Hence, just solving for the UE solution using DTA may lead to overly optimistic performance predictions, especially when heterogeneous driver classes exist.

In Figure 12, the results associated with the various information strategies are obtained using the simulation executed on the 10th day based on day-to-day evolution. While the UE-DTA solution does not consider day-to-day evolution, the BBCS model consistently incorporates this feature. Figure 13 compares the solutions of UE information provision based on DTA and the BBCS model that factors in day-to-day evolution. It assumes that 100% drivers have access to personalized UE routes. The UE-DTA solution is compared with the BBCS solutions for the 10th, 20th, and 30th days to capture the effect of UE information provision. In this experiment, situational factors are not considered in the BBCS model. It is important to note that existing DTA models do not consider situational factors and day-to-day behavior dynamics, and predominantly focus on travel costs. The results show that some differences exist among the various solutions, but they are not emphatic because all drivers receive UE routes and most follow them based on their past experience. This is also partly because situational factors are ignored in the BBCS model for this experiment. However, the results highlight the effects of other route characteristics on the day-to-day evolution leading to different benefits levels for the 30th day compared to the 10th day. These differences become more emphasized when situational factors and heterogeneity in driver classes and information characteristics are considered.

5. Concluding comments

This paper proposes the BBCS framework as an alternative to DTA for the deployment of information provision strategies for real-time control in vehicular traffic systems with heterogeneous driver behavior classes. It is real-time deployable, and combines a hybrid probabilistic-possibilistic driver route choice model and a constrained least squares consistency-seeking model to update driver behavior class fractions in real-time based on field traffic flow measurements. The hybrid model captures the day-to-day evolution and within-day dynamics of driver behavior seamlessly within a single framework using observable data. There is a key philosophical distinction between existing DTA models to predict driver routes and the proposed consistency-seeking route choice determination using the hybrid model. The BBCS approach simultaneously considers real-time network-level traffic flow interactions and the causal factors of driver route choice behavior. Here, information is only one of the variables influencing driver route choice. Also, it enables a more realistic modeling of information characteristics and the associated driver response behavior. Further, it uses intuitive *if-then* rules based on historical data and/or past studies to model driver behavior.

The experiments indicate the effectiveness of the BBCS model in predicting driver routes and the response to the supplied information. They also illustrate its ability to capture driver learning over time in the information context and the reactive aspects of decision-making based on the ambient driving conditions. The experiments also suggest that information strategies that are realistic in a deployment context can be used to influence the system performance. The BBCS model can also be used to effectively manage the traffic system under incidents by better predicting the traffic conditions. Also, it can capture the driver behavior class fractions robustly using the real-time traffic measurements. In the real-world, the traffic stream consists of behaviorally heterogeneous drivers and the driver class fractions can be time-varying. To our knowledge, this is the first study that considers the driver behavior class fractions as variables.

The authors view this study as only the starting point of a different methodological perspective to address the complex deployment problem associated with the real-time control of traffic systems using information provision strategies. Several aspects merit further attention. While several sources of inconsistency can exist, this study assumes that only the driver behavior class fractions explain the gaps between the predicted and actual states. Hence, the study needs to be extended to additionally consider other sources such as the traffic-flow modeling related inconsistencies. Also, the study assumes that the departure times of drivers are fixed. The proposed approach can be seamlessly extended to simultaneously consider departure times and route choices. In addition, while this study is one of the few efforts to consider heterogeneous driver behavior classes, akin to the rest it assumes that these behavior classes are known *a priori*. This may be reasonable if historical data is available and regular socio-economic surveys exist. Currently, a two-stage approach is being developed to simultaneously identify the driver behavior classes and their fractions in the traffic stream.

A note of caution in interpreting the study results is that they are based on the particular assumptions of actual driver behavior described in Table 1 and the BBCS model being unaware of it. In reality, driver behavior may be different from the one assumed here. Hence, the benefits under information strategies may be more or less than the ones shown in Figures 12 and 13. However, they clearly illustrate that a UE-DTA solution may overestimate the benefits achievable under information provision. This implies that an adequate consideration of the behavior-side is essential to the meaningful practical deployment of these strategies.

Due to the current sparsity in observable field data sets, route attribute data and driver route choices are generated using computer simulations for analyzing the BBCS model here. However, simulation data is limited in its ability to represent the randomness in driver behavior associated with causes that are not clearly understood. Currently, observable data is being collected from a real network to further analyze the BBCS approach. Hence, in general, models based on observable data and behavioral consistency are essential for deployment. The BBCS approach also fosters the design of targeted information provision strategies that are consistent with the socioeconomic characteristics of a specific region.

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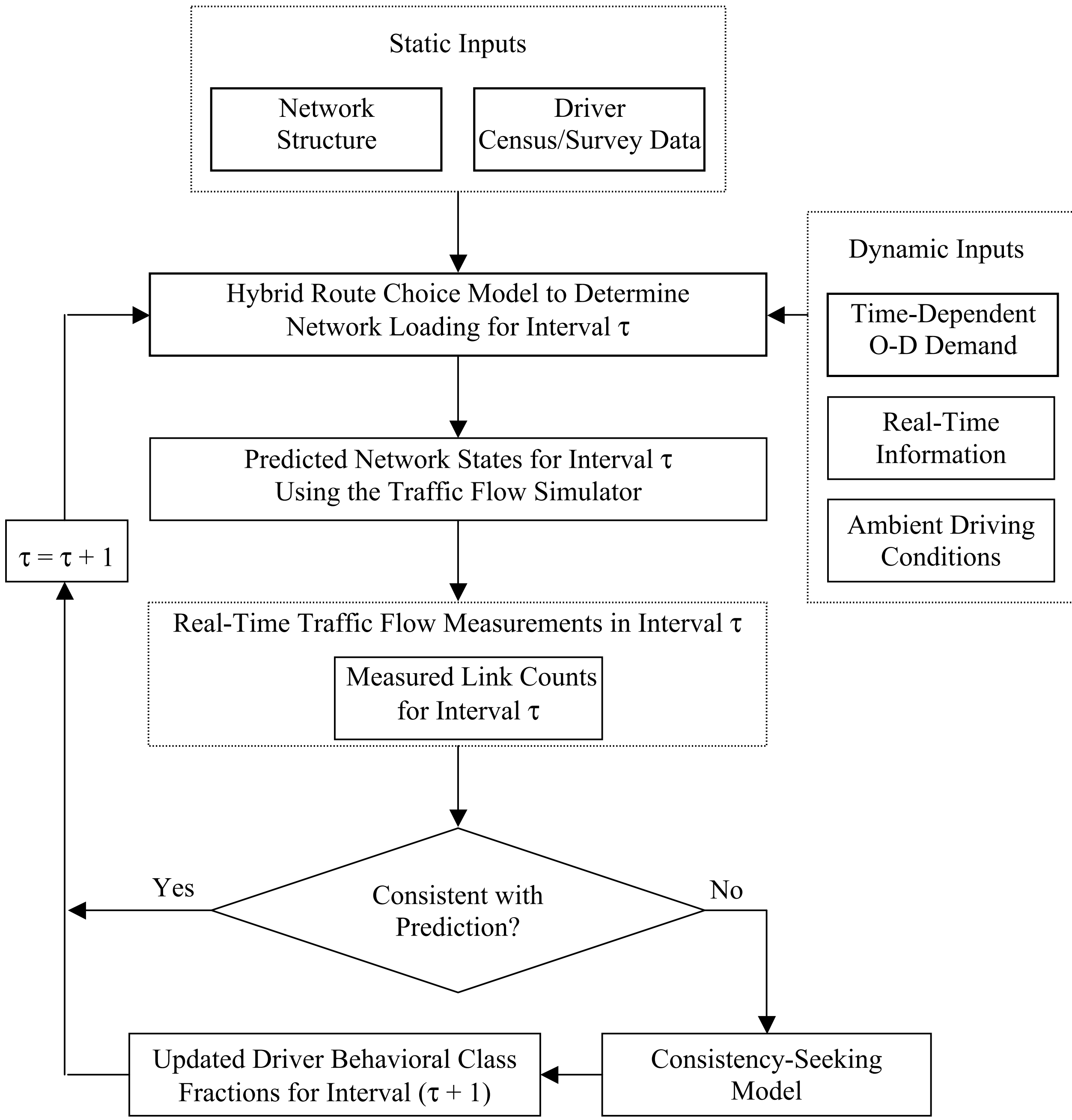


Fig. 1. Behavior-based consistency-seeking framework.

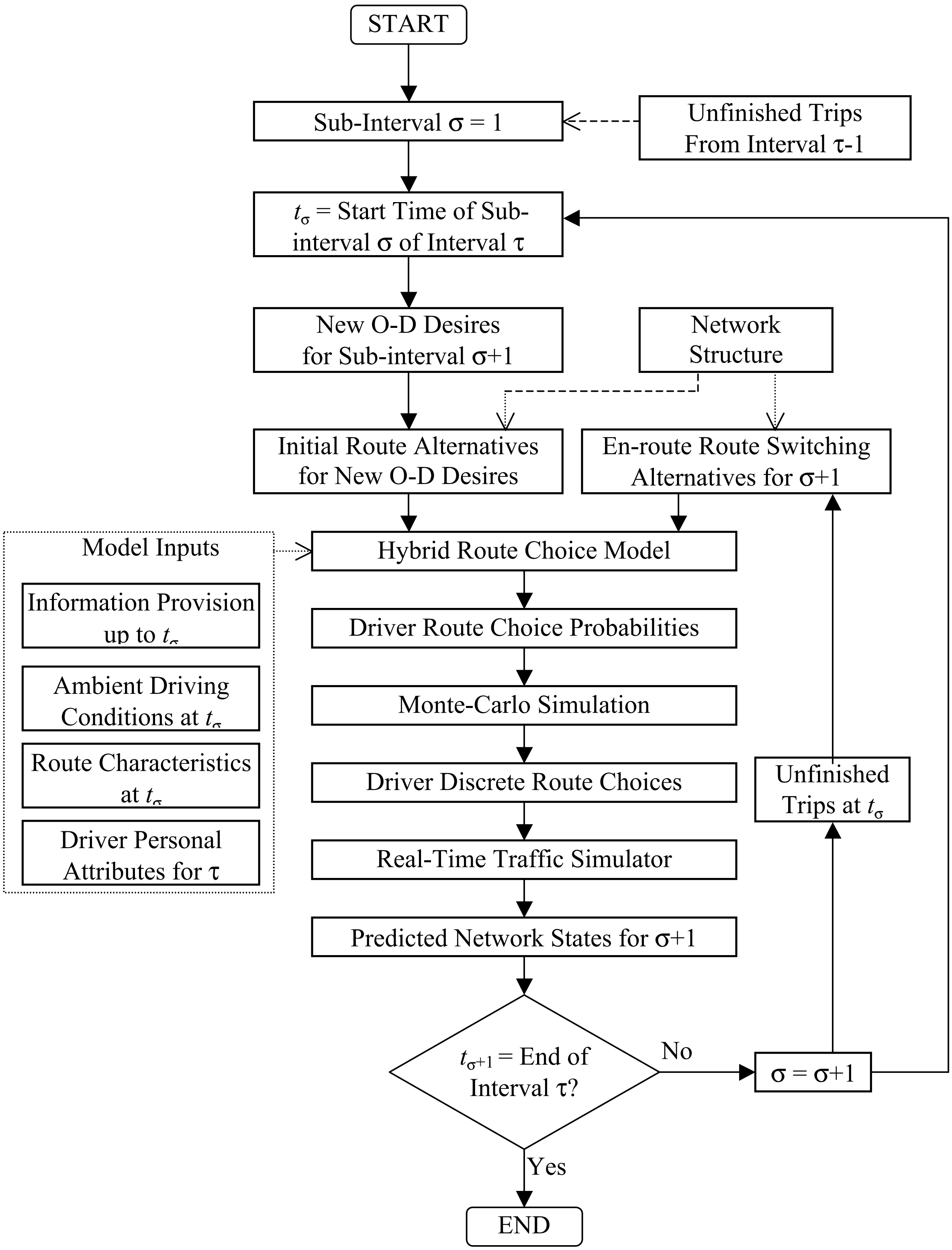


Fig. 2. Network loading for interval τ using the hybrid route choice model.

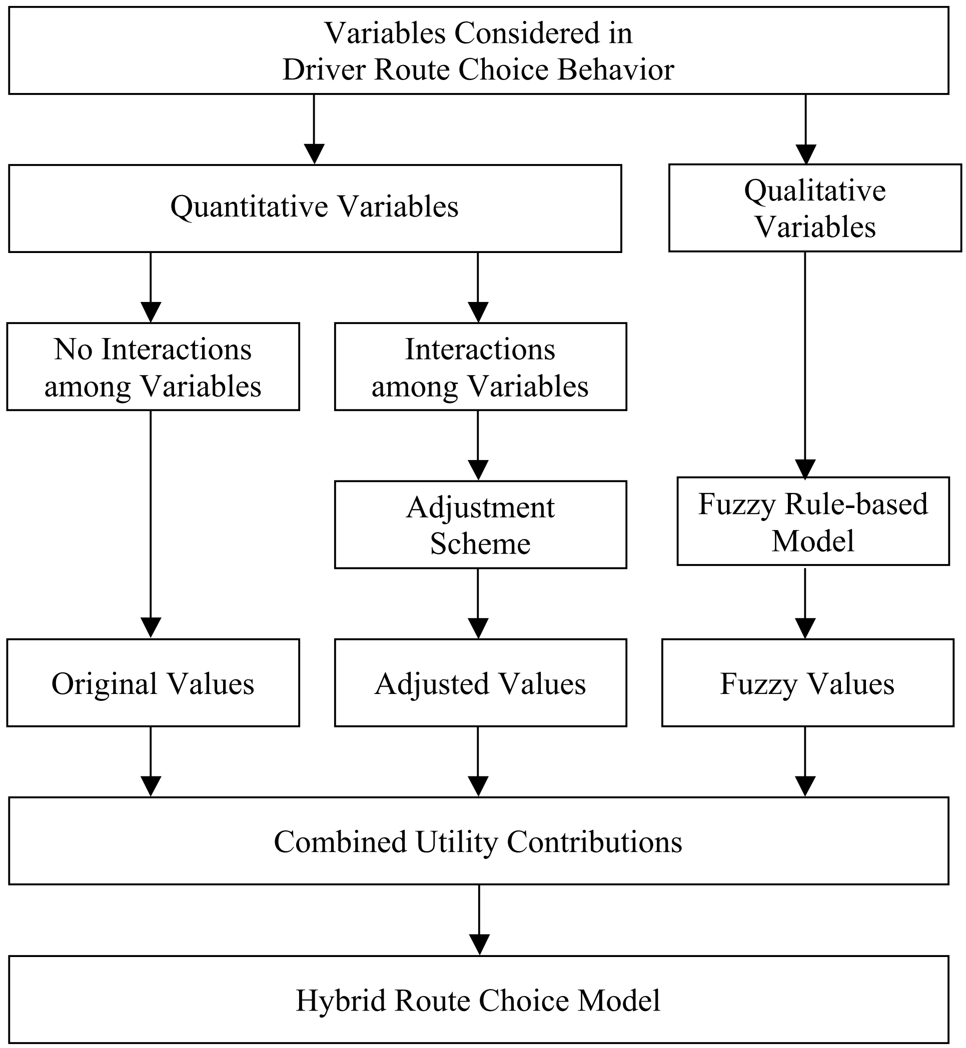


Fig. 3. Hybrid route choice model logic.

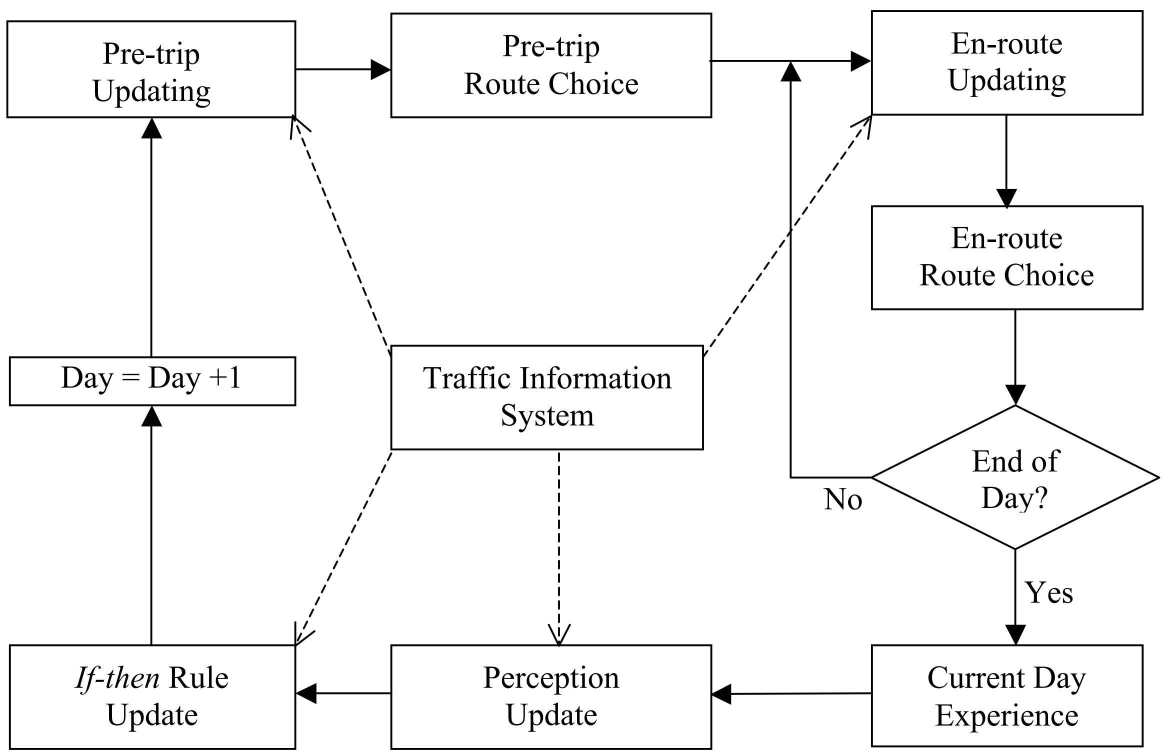


Fig. 4. Framework for driver behavior dynamics.

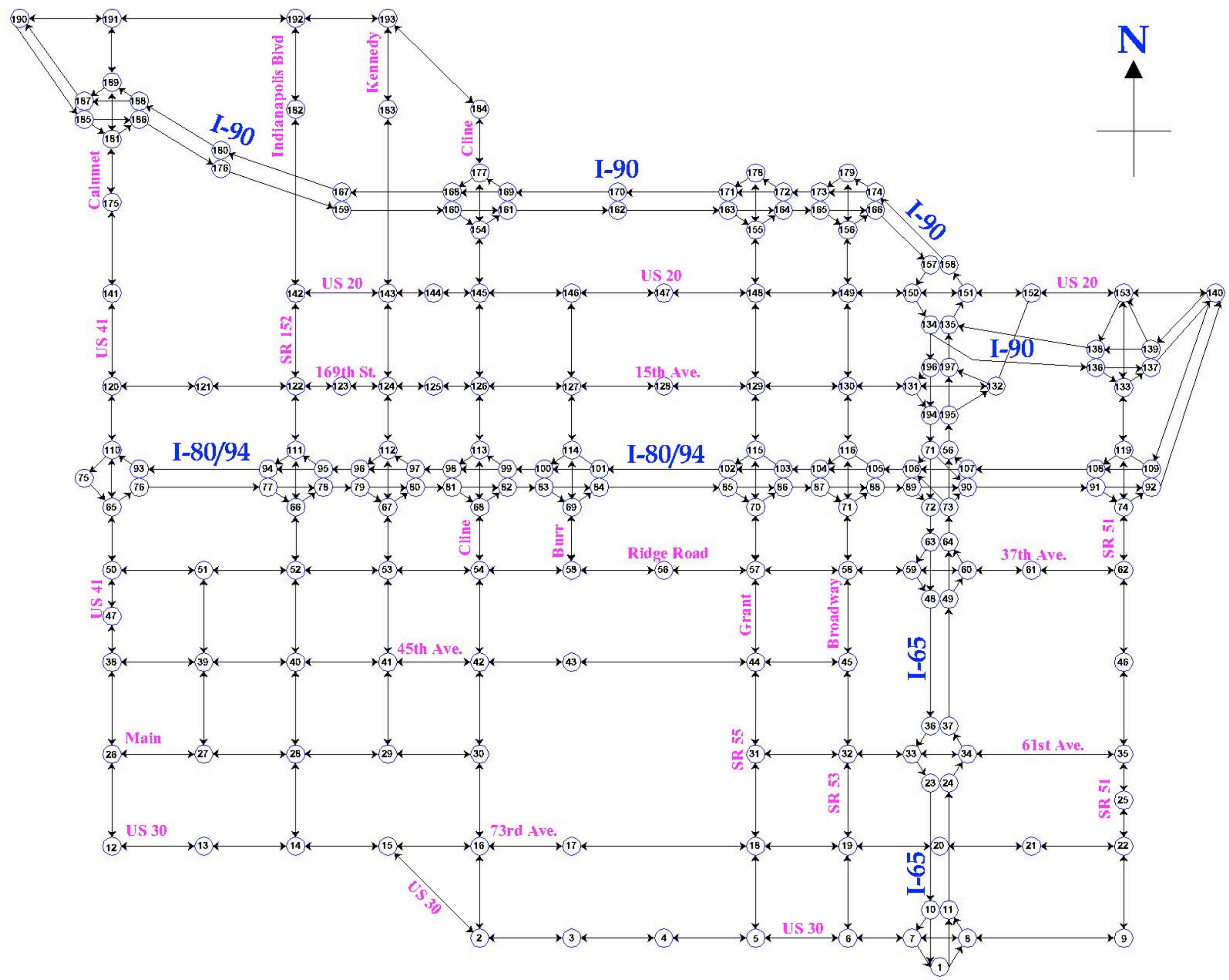


Fig. 5. Test network.

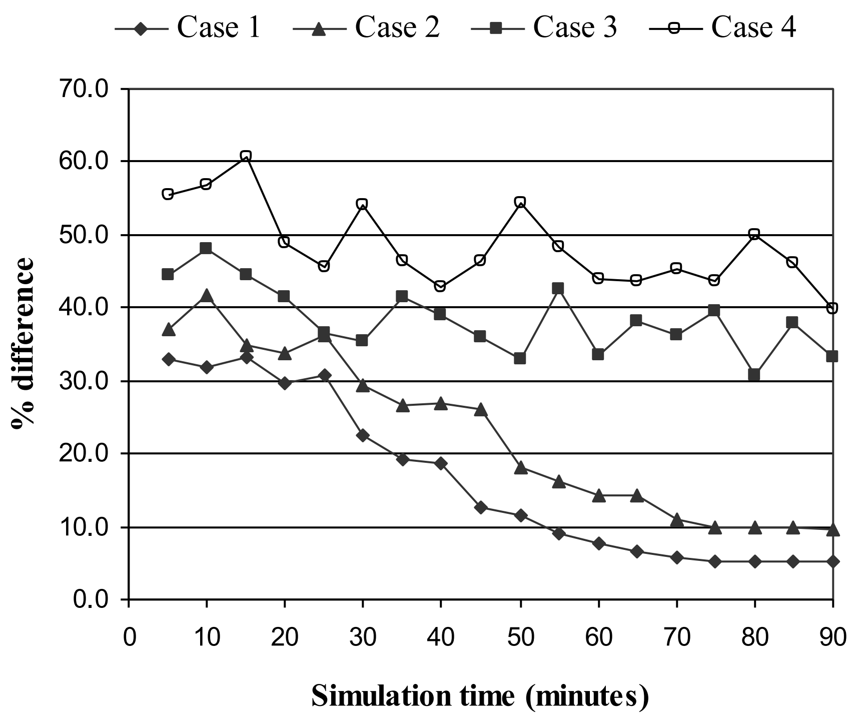


Fig. 6. Effectiveness of the consistency-seeking model.

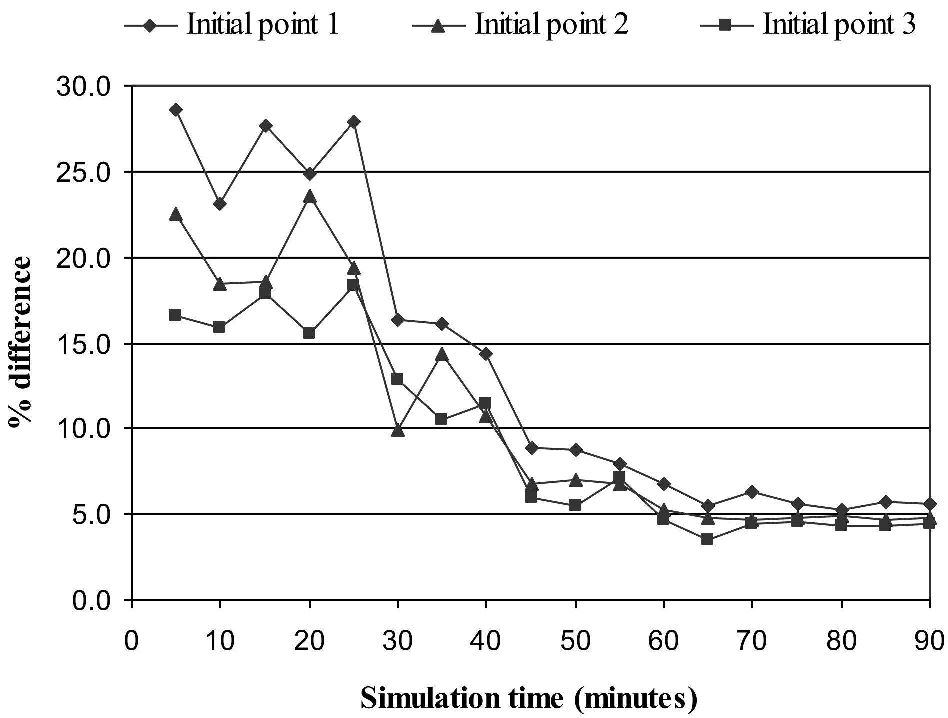
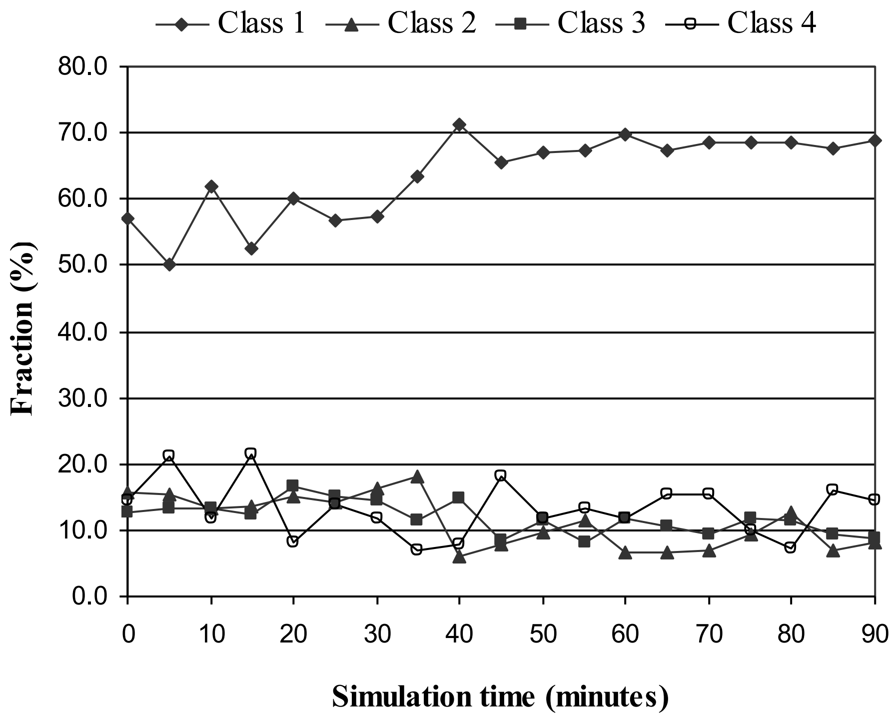
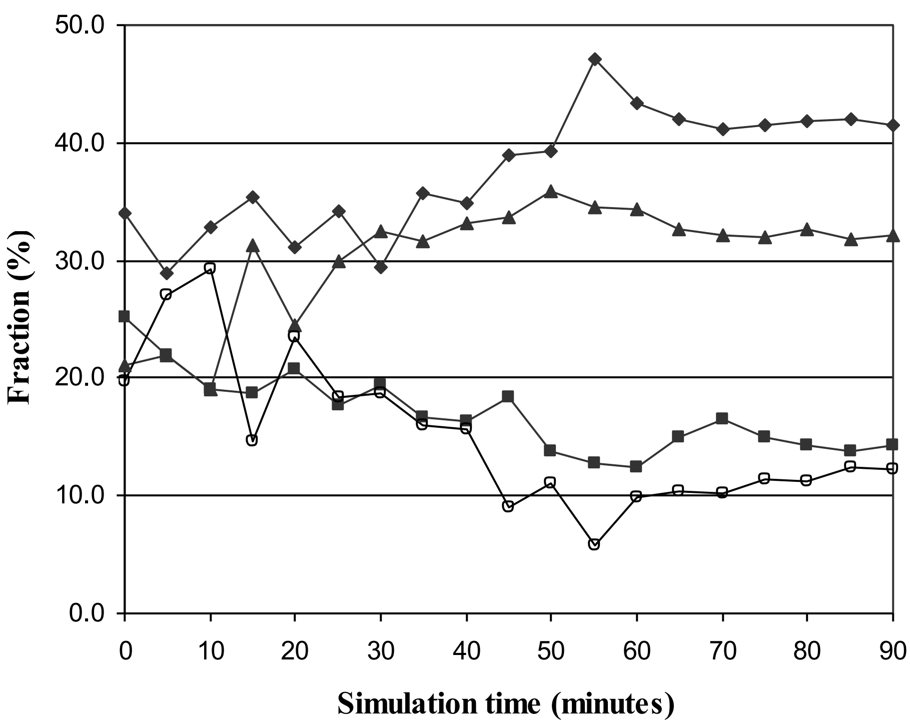


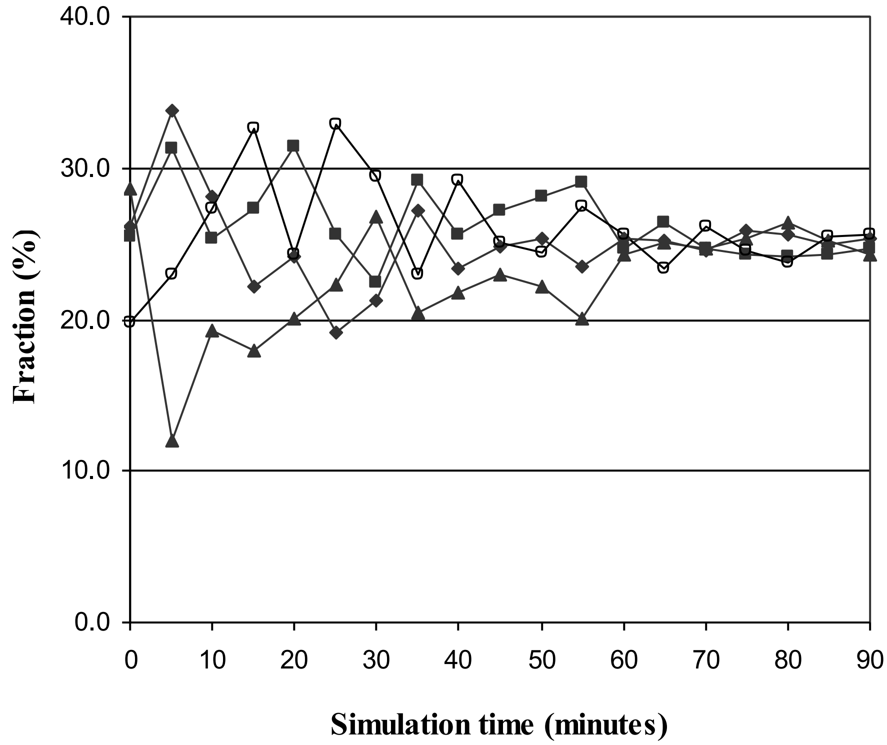
Fig. 7. Effect of different initial values for the driver behavior class fractions.



(a) 70%:10%10%:10%



(b) 40%:30%20%:10%



(c) 25%:25%25%:25%

Fig. 8. Prediction of driver behavior class fractions.

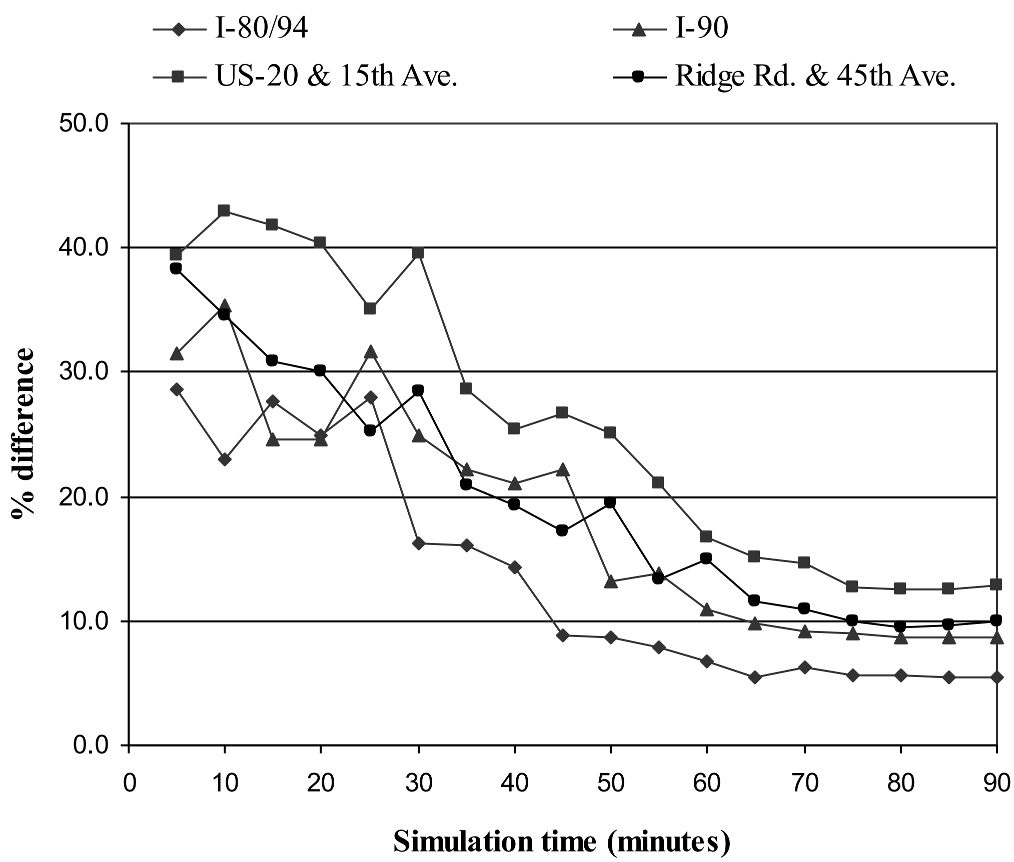
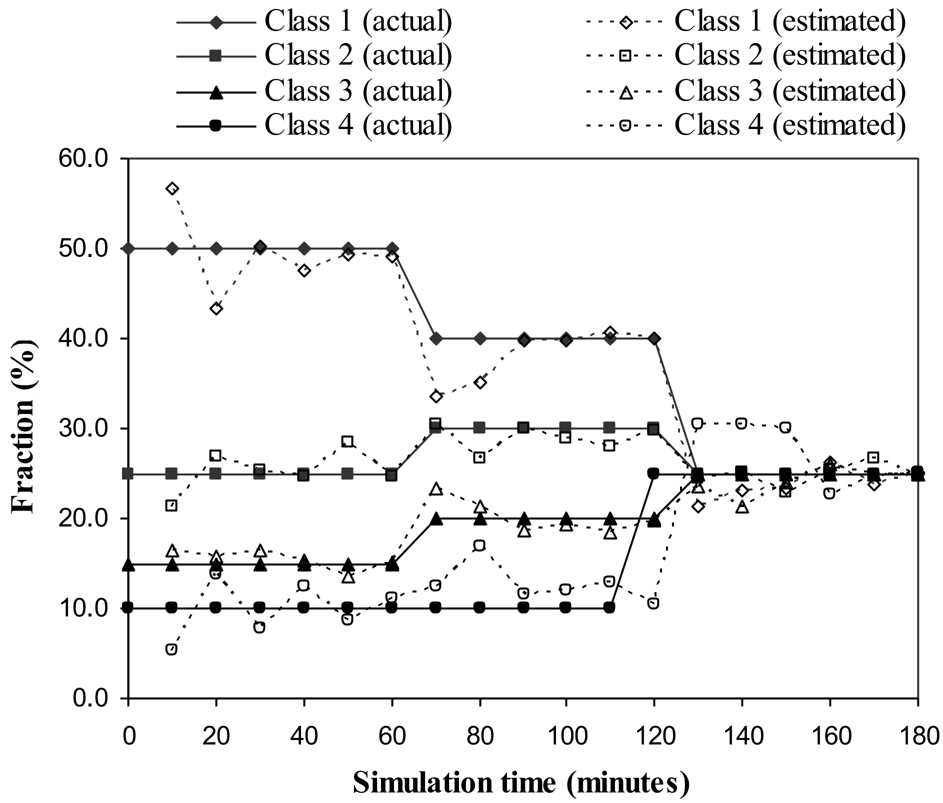
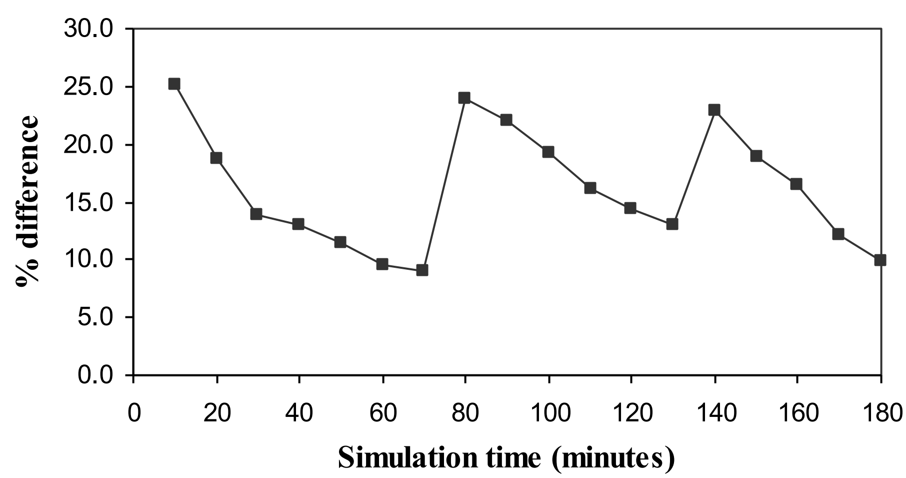


Fig. 9. Effect of different locations on the prediction of driver behavior class fractions.

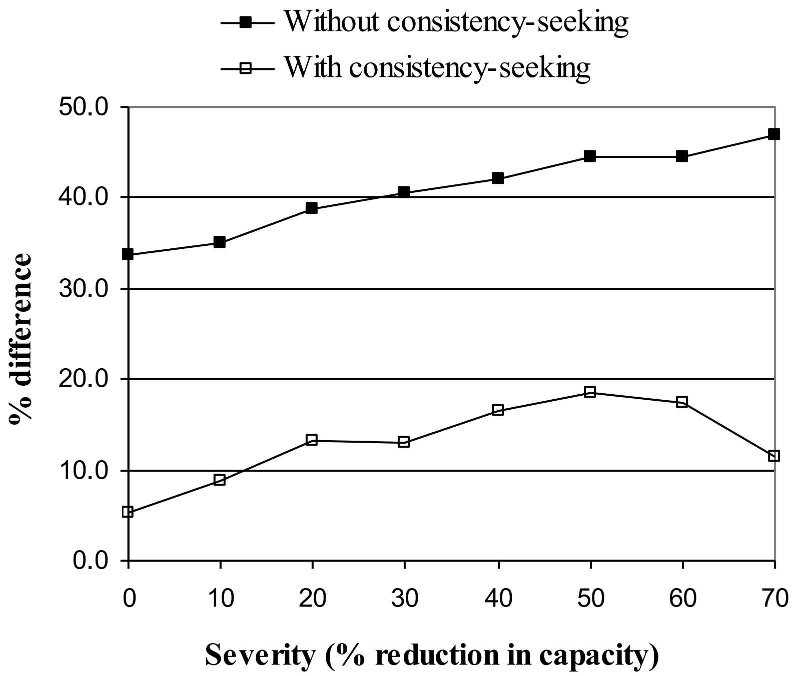


(a) Estimated driver class fractions

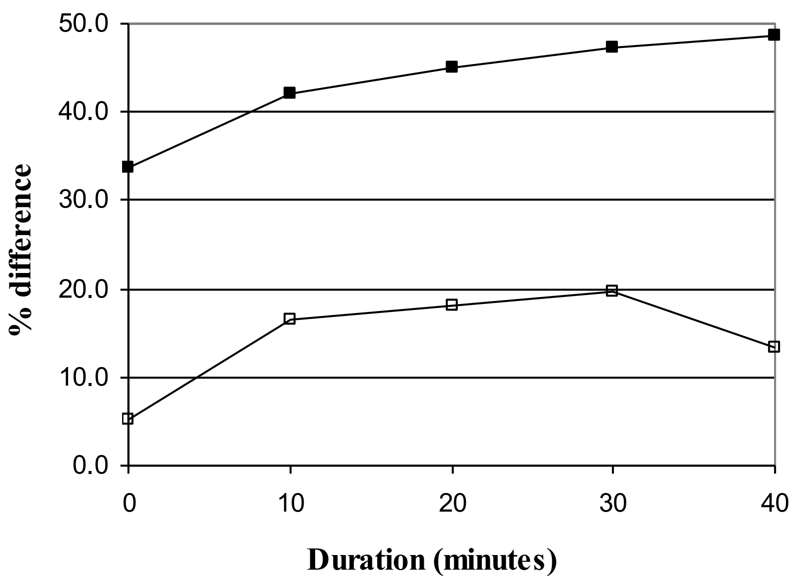


(b) Performance measure

Fig. 10. Within-day variation of driver behavior class fractions.

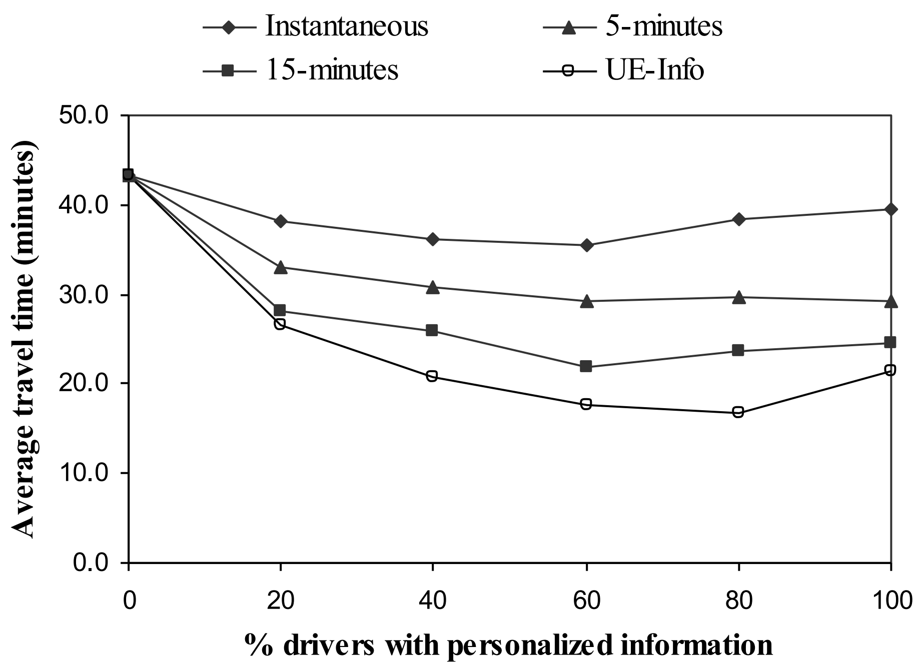


(a) Severity of a traffic incident

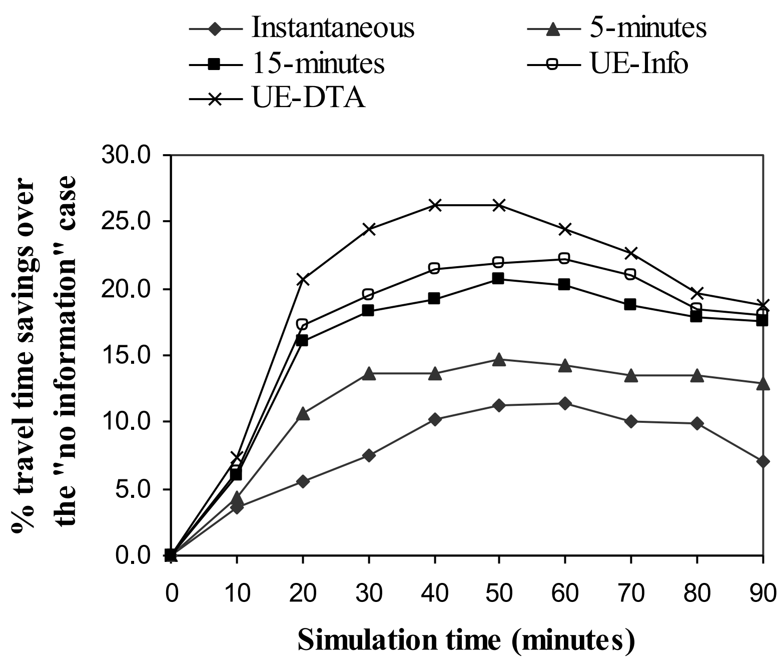


(b) Duration of a traffic incident

Fig. 11. Effect of traffic incidents.



(a) Average travel times



(b) Total travel times

Fig. 12. System performance under various information provision strategies.

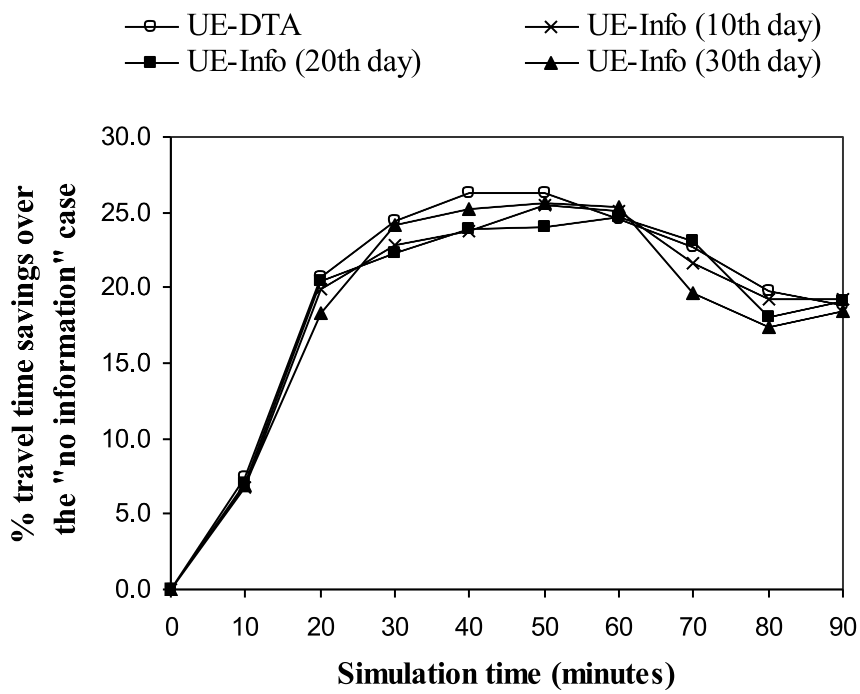


Fig. 13. Comparison between UE information strategies when 100% drivers receive UE routes.

Table 1. Route Choice Decision Process Used for Data Generation

Rank	Attribute	Utility Function	Threshold
1	Travel distance Toll Estimated travel time Quantitative traffic information Qualitative (descriptive) information	$U_{in}^1 = a_1 D_i + a_2 L_i + a_3 T_{in} + a_4 K_{in} + a_5 \Gamma_Q (Q_{in})$	ϕ_1% of U_*^1
2	Familiarity Route complexity	$U_{in}^2 = U_{in}^1 + a_6 \Gamma_F (F_{in}) + a_7 \Gamma_P (P_i)$	ϕ_2% of U_*^2
3	Compliance Inertia	$U_{in}^3 = U_{in}^1 + U_{in}^2 + a_8 \delta_{in} \Gamma_C (W_n, G_n, S_n) + a_9 \kappa_{in} \Gamma_I (W_n, G_n, S_n)$	

where,

$\Gamma_Q(\cdot)$ = function to determine the numerical value of descriptive qualitative traffic information
$\Gamma_F(\cdot)$ = function to determine the numerical value of familiarity
$\Gamma_P(\cdot)$ = function to determine the numerical value of route complexity
$\Gamma_C(\cdot)$ = function to determine the numerical value of compliance vis-à-vis recommended route i
$\Gamma_I(\cdot)$ = function to determine the numerical value of inertia vis-à-vis current route i
U_*^1, U_*^2 = maximum utility values among U_{in}^1 and U_{in}^2, respectively

Table 2. Fuzzy *If-then* Rules

<table>
<tr><th colspan="2">Attribute</th><th>LHS</th><th>RHS</th></tr>
<tr><td colspan="2">Qualitative traffic information</td><td>If traffic condition is good
If traffic condition is normal
If traffic condition is poor</td><td>He/she will probably take the route
He/she will be neutral
He/she will probably not take the route</td></tr>
<tr><td colspan="2">Familiarity</td><td>If a driver is very familiar with a route
If a driver is familiar with a route
If a driver's familiarity is undecided
If a driver is unfamiliar with a route
If a driver is very unfamiliar with a route</td><td>He/she will take the route
He/she will probably take the route
He/she will be neutral
He/she will probably not take the route
He/she will not take the route</td></tr>
<tr><td colspan="2">Complexity</td><td>If a route is simple
If a route is normal
If a route is complex</td><td>He/she will probably take the route
He/she will be neutral
He/she will probably not take the route</td></tr>
<tr><td rowspan="3">Compliance</td><td>Weather conditions</td><td>If weather is good
If weather is bad</td><td>He/she will probably follow the recommended route
He/she will probably not follow the recommended route</td></tr>
<tr><td>Time-of-day</td><td>If time-of-day is daytime
If time-of-day is nighttime</td><td>He/she will probably follow the recommended route
He/she will probably not follow the recommended route</td></tr>
<tr><td>Trip purpose</td><td>If driver is on a business trip
If driver is on a leisure trip</td><td>He/she will probably follow the recommended route
He/she will probably not follow the recommended route</td></tr>
<tr><td rowspan="3">Inertia</td><td>Weather conditions</td><td>If weather is good
If weather is bad</td><td>He/she will probably switch from the current route
He/she will probably not switch from the current route</td></tr>
<tr><td>Time-of-day</td><td>If time-of-day is daytime
If time-of-day is nighttime</td><td>He/she will probably switch from the current route
He/she will probably not switch from the current route</td></tr>
<tr><td>Trip purpose</td><td>If driver is on a business trip
If driver is on a leisure trip</td><td>He/she will probably switch from the current route
He/she will probably not switch from the current route</td></tr>
</table>

Table 3. Fuzzy *If-then* Rules for Traffic Incidents

Attribute	LHS	RHS
Incident effects	If incident is very severe	He/she will definitely not take the route on which incident occurs
	If incident is severe	He/she will not take the route on which incident occurs
	If incident is not severe	He/she will probably not take the route on which incident occurs
	If incident duration is long	He/she will definitely not take the route on which incident occurs
	If incident duration is medium	He/she will not take the route on which incident occurs
	If incident duration is short	He/she will probably not take the route on which incident occurs
Compliance	If incident is very severe	He/she will definitely follow the recommended route
	If incident is severe	He/she will follow the recommended route
	If incident is not severe	He/she will probably follow the recommended route
	If incident duration is long	He/she will definitely follow the recommended route
	If incident duration is medium	He/she will follow the recommended route
	If incident duration is short	He/she will probably follow the recommended route
Inertia	If incident is very severe	He/she will definitely switch from the route on which incident occurs
	If incident is severe	He/she will switch from the route on which incident occurs
	If incident is not severe	He/she will probably switch from the route on which incident occurs
	If incident duration is long	He/she will definitely switch from the route on which incident occurs
	If incident duration is medium	He/she will switch from the route on which incident occurs
	If incident duration is short	He/she will probably switch from the route on which incident occurs