

Adaptability of a Hybrid Route Choice Model to Incorporating Driver Behavior Dynamics under Information Provision

Srinivas Peeta and Jeong W. Yu

Abstract—This paper proposes a seamless framework to incorporate the day-to-day and within-day dynamics of driver route choice decisions under real-time information provision by adapting a hybrid probabilistic-possibilistic model previously developed by the authors. The day-to-day dynamics are captured through the update of driver perception and route choice rules based on the current day's experience. The within-day dynamics are captured through the en-route adjustment of the weights of the driver route choice rules in response to situational factors. Experiments are conducted to analyze the model's ability to capture driver behavior dynamics, and the associated prediction accuracy. The results suggest that the framework can reflect the evolution of driver route choice behavior over time, and adapt to the within-day variability in ambient driving conditions. This is illustrated by its ability to capture phenomena such as inertia, compliance, delusion, freezing, and perception update under information provision, in addition to the effects of familiarity and route complexity. In the within-day context, the results highlight the sensitivity to the situational factors unfolding in real-time. The results also illustrate the better prediction power of the hybrid model compared to that of a traditional multinomial probit model; however, this gap reduces with increasing heterogeneity in driver behavioral class fractions. Elsewhere, the authors show that the proposed framework can be used to predict the ambient driver class fractions, thereby addressing a key deployment limitation of existing dynamic network models for real-time traffic control through route guidance.

Index Terms—Hybrid route choice model, probabilistic and possibilistic approaches, driver behavior dynamics.

Manuscript received September 20, 2002. This material is based upon work supported by the National Science Foundation under Grant No. 9702612.

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I. INTRODUCTION

FLOW patterns in a traffic network are primarily governed by driver pre-trip and en-route route choice behavior. For the successful deployment of Advanced Traveler Information Systems (ATIS), this implies capabilities to predict driver routing decisions under information provision and calibrate the associated model parameters. Driver route choice decisions under information provision are significantly affected by their past experience, perception, subjective interpretation of the traffic information provided, situational factors (such as time-of-day, weather conditions, and trip purpose), and the ambient traffic conditions. The presence of several qualitative factors in driver routing decisions makes it difficult to accurately capture their latent preferences towards alternative routes. In addition, most existing models are limited in their ability to incorporate the qualitative judgements that arise due to the linguistic nature, subjectivity, uncertainty, and/or vagueness associated with the input data for situational factors and information provision. Also, they typically cannot simultaneously capture driver route choice dynamics in the within-day and day-to-day contexts. This would entail a capability to adjust model parameters via consistency-checking procedures that compare the actual traffic conditions with the model predictions.

The aforementioned time-scale dimension is important vis-à-vis the modeling approach for route choice behavior. Some characteristics are dynamic and evolve over time, and are behaviorally more meaningful in a day-to-day modeling context. These include phenomena such as inertia, compliance, delusion, freezing, and perception update under information provision, and attributes such as familiarity. By contrast, situational factors and ambient traffic conditions unfold in real-time, and influence the real-time or within-day route choice decisions. Therefore, the within-day modeling should capture the sensitivity of the model parameters to the ambient driving conditions. This implies that a single consistent route choice model that reflects both day-to-day and within-day behavior dynamics should consist of parameters that are updated using different time-scales. The proposed probabilistic-possibilistic approach provides a convenient and modular framework to develop such a model.

The day-to-day modeling of driver route choice behavior entails capabilities to incorporate the perception of information provided, and the impact of any perception change on route choice. Jha et al. [1] propose a Bayesian perception updating model in which drivers' travel choices are based on their day-to-day variations in the perception of travel times in the network. It updates their day-to-day travel time perceptions based on the information provided on the current day and past experience. Driver travel time perception is modeled using a probability distribution, and

the perception update is enabled by updating the mean and variance. While the study provides a systematic approach to update driver perceptions, it focuses only on addressing the confidence in the traveler information system. Mahmassani and Jou [2] analyze the day-to-day variation in commuter trip-chaining behavior through field surveys and laboratory experiments. They show that route and departure time switching decisions are interrelated, and view the day-to-day dynamics of commuter behavior as a boundedly rational search for a departure time and route. Fujii and Kitamura [3] propose two hypotheses to analyze the effects of information acquisition and driving experience using survey data collected over a two-day period. Under the information dominance hypothesis, information effects are larger for drivers who acquire more information. By contrast, under the experience dominance hypothesis the influence of generic information weakens as the driver gains more driving experience. Nakayama and Kitamura [4] investigate drivers' day-to-day inductive learning. They model driver learning by updating a set of *if-then* rules through a genetic algorithm. The study demonstrates the concepts of delusion and freezing under traffic information provision. Delusion is a driver's biased perception of a route on which he/she has only limited information. Freezing is a driver's habitual behavior that is formed by continued delusion. For example, the exclusion of a route from consideration.

Other research efforts focus on the day-to-day dynamics of driver route choice behavior under information provision, while addressing some aspects of within-day dynamics. Hu and Mahmassani [5] use a simulation-assignment approach to investigate real-time dynamics in terms of en-route switching decisions and day-to-day evolution of the traffic system 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 [6] extend this work by using an interactive dynamic traveler simulator to generate data through laboratory experiments. They develop a multinomial probit framework to model driver departure time and route choices. The study suggests that commuters' en-route path switching decisions are based on their expected travel time savings to their destinations. Srinivasan and Mahmassani [7] explore two en-route behavioral factors, inertia and compliance, under real-time information using a multinomial probit framework. Inertia represents a driver's propensity to continue on the current path he/she is taking, while compliance represents the willingness to take the route recommended by the traveler information system. The simulation-based study indicates that within-day behavior

dynamics are affected by traffic congestion levels and drivers' past experience with information.

Most existing route choice models that analyze driver behavior dynamics are probabilistic discrete choice models [8]. Abdel-Aty et al. [9] use a logit framework to model the effect of traffic information on commuter route choices using stated preference data. Khattak and de Palma [10] propose ordered probit models to capture the effect of weather on commuter travel patterns. Peeta et al. [11] develop logit models to predict drivers' en-route route diversion decisions under traffic information provision through variable message signs.

Driver behavior models based on probabilistic frameworks entail well-defined probability distributions to treat the randomness and uncertainty embedded in driver behavior. Hence, they may be restrictive in modeling qualitative phenomena and linguistic variables that arise in the context of information provision to drivers. This is because such variables are subjectively interpreted, and lack clearly identifiable boundaries as implied in probabilistic discrete choice models when variables are continuous.

Other modeling approaches have been suggested to address driver route choice behavior under information provision. In particular, fuzzy rule-based systems, based on possibilistic concepts, provide a convenient modeling approach to treat linguistically-expressed traffic information and the subjective knowledge of drivers. Several fuzzy logic based models have been proposed for driver route choice under information provision. Lotan and Koutsopoulos [12] develop rule-based fuzzy models to analyze the interactions between a driver's existing perception and the real-time traffic information. They test various compatibility measures to combine existing knowledge and new information. Lotan [13, 14] extends this model to incorporate a mechanism for perception update and the effect of driver familiarity under real-time information provision. Pang et al. [15] use a rule-based fuzzy system to model driver route choice behavior and calibrate the associated membership function parameters using a neural network.

The aforementioned fuzzy models provide two generic arguments in favor of the fuzzy logic approach for route choice behavior modeling: (i) that rule-based frameworks are more transparent than probabilistic approaches in this context since drivers are likely to process simple *if-then* rules in their decision-making process, and (ii) that fuzzy logic is more amenable to modeling linguistic variables. However, they do not articulate the specific modeling limitations of discrete choice models in the context of information provision. Peeta and Yu [16] illustrate some associated modeling limitations and propose a hybrid probabilistic-possibilistic framework to circumvent them. These limitations are articulated in the context of behavior dynamics in Section III of this paper. The hybrid

framework combines quantitative and qualitative variables in a single framework for en-route driver routing decisions under real-time information provision. In addition, unlike the earlier models, Peeta and Yu [17] suggest an improved theoretical basis to determine S-shaped fuzzy membership functions rather than using analytically convenient shapes that are not necessarily consistent with the problem data.

This paper investigates the adaptability of the hybrid model [16] to addressing the day-to-day and within-day dynamics of driver route choice behavior under information provision. It contains parameters that are updated in a day-to-day context, and others that are adjusted in a within-day context. Through these parameter updates, phenomena such as inertia, compliance, delusion, freezing, and perception update under information provision are captured, in addition to the effects of familiarity and route complexity. Also, the sensitivity of the model to the situational factors unfolding in real-time is illustrated.

II. ROUTE CHOICE UNDER INFORMATION PROVISION

A. Hybrid Probabilistic-Possibilistic Route Choice Model

Peeta and Yu [16] provide a comprehensive description of the hybrid route choice model. It is a probabilistic discrete choice model in which the quantitative variables are directly incorporated and the qualitative variables are converted to fuzzy variables. In this framework, a variable that is naturally amenable to quantitative measurements is treated as a quantitative variable. A variable that is linguistically expressed and/or susceptible to subjective interpretation is characterized as a qualitative variable.

Fig. 1 illustrates the flowchart of the hybrid modeling approach. A detailed description of the model is provided in [16]. The attractiveness of a route is viewed as the utility of that route, and utility maximization is used to determine the driver route choice. The utility of a route is determined using the original values of some quantitative variables, the adjusted values of other quantitative variables, and the transformed continuous values of the qualitative variables. The utility contributions of the quantitative variables are directly obtained using their original measurements in the absence of interactions. The fuzzy model quantifies the latent attractiveness of alternative routes with regard to the qualitative variables using *if-then* rules to generate fuzzy values. The rules used in this study are discussed in Section IV. Peeta and Yu [17] provide a detailed description of the three steps to quantify the qualitative data. When

interactions among quantitative variables can imply a qualitative phenomenon, those interactions are captured using a fuzzy combination scheme [16] to determine adjusted values for those variables. The hybrid probabilistic discrete choice model is then used to determine the driver route choice.

B. Model Structure

The hybrid probabilistic discrete choice model has the following form:

$$U_{in} = V_{in} + \varepsilon_{in} = \sum_l \beta^l X_{in}^l + \sum_m \gamma^m \Omega_m(Y_{in}^m) + \varepsilon_{in} \quad (1)$$

where,

U_{in} = utility of route i for driver n

V_{in} = systematic utility of route i for driver n

β^l, γ^m = coefficients of variables

X_{in}^l = value of quantitative or adjusted quantitative variable l on route i for driver n

Y_{in}^m = value of qualitative variable m on route i for driver n

$\Omega_m(\cdot)$ = transformation function to determine the fuzzy value of qualitative variable m

ε_{in} = disturbance term for route i for driver n

The first set of variables on the RHS represents the quantitative variables and the second set denotes the transformed fuzzy values for the qualitative variables. The disturbance term can be interpreted as incorporating the traditional sources of randomness for the quantitative variables, and additionally potential errors introduced by the fuzzy modeling component. However, it should be noted that the fuzzy component may mitigate error contributions by more robustly representing qualitative variables.

III. DRIVER BEHAVIOR DYNAMICS

A. Framework for Driver Behavior Dynamics

Driver behavior dynamics can be 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 perception

update mechanism consists of the day-to-day updating based on the current day's travel experience. In addition, the *if-then* rules can be updated at an aggregate level in the day-to-day context. Learning at an individual level in a within-day context can be represented by updating the relative weights among the *if-then* rules.

The widely-used probabilistic framework employs probability distribution functions to model the driver perceptions of travel time and traffic information provided. The variance of the probability distribution is typically used to indicate a driver's confidence in that source of information. However, probability theory may not be sufficient to fully explain driver perception updating and its dynamics in the context of driver route choice behavior modeling as it consists of linguistically-oriented and/or qualitative attributes. These attributes are treated in most probabilistic models as categorical variables, which are discrete and have the limitations discussed earlier. Fuzzy logic provides capabilities to address these issues. First, it enables the continuous modeling of subjectively interpreted traffic information using membership functions. This precludes rigid boundaries to demarcate driver perception of that information and allows for overlaps between adjacent attribute values to account for subjective interpretation. Thereby, it provides a robust modeling capability to capture the uncertainties in the driver perception of the traffic information provided. Second, the membership functions can be different for different drivers, implying heterogeneity in driver behavior. Third, the parameters of the membership functions can be updated over time to reflect the day-to-day evolution of driver perceptions. Finally, a driver's *if-then* rules can be modified to be consistent with the day-to-day evolution of his/her route choice behavior. In the context of the within-day adjustment, the situational factors determine the *if-then* rules used in en-route decision-making, and the weights of those rules can be adjusted based on the en-route decisions made up to the current time on a specific day.

Fig. 2 illustrates the framework for driver behavior dynamics. There are two stages in the framework: day-to-day dynamics and within-day dynamics. 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 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 time. Instead, driver en-route decisions are more sensitive to situational factors that unfold on the current day. Hence 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.

B. Day-to-Day Dynamics

1) *Perception Update*: The perception update mechanism is used to analyze the influence of driver perception of the traffic information and past experience on system performance. A driver's perception of a variable is represented by the membership function of that variable. Thereby, the day-to-day perception updating component is the mechanism by which the associated membership parameters are adjusted. Since, both quantitative and qualitative variables can exist in the driver route choice problem, the update mechanism of the membership functions depends on the variable type.

a) *Quantitative Variable*: If a variable is quantitative, a probability distribution can be generated for it. Then, the transformation from the probability distribution to the possibility distribution can be used to generate the membership functions. The parameters of these membership functions are updated through transformation on a day-to-day basis based on the cumulative data up to the current day. The parameters of the S-shaped membership function of a variable are updated such that the function best represents the observed probabilities. Hence, the changes in the membership function for a variable are directly related to the mean and variance of the probability distribution of that variable. For example, in the context of the travel time experienced by a driver, if the variance of the experienced travel time is large, the corresponding membership function is wider. By contrast, a lower variance implies a tighter membership function.

b) *Qualitative Variable*: If a variable is qualitative, a probability distribution cannot typically be derived for it. Hence, the membership function of that variable cannot be derived through the transformation procedure. Instead, other approaches are used to generate the parameters of the membership function. For example, as shown in Fig. 3, driver confidence in traffic information can be characterized through membership functions that depend on his/her experience with the information provided. Driver A who has a lower confidence has a wider membership function than driver B.

The membership function for driver A's perception of travel time x in response to traffic information, $\mu_A(x)$, is defined using four parameters as follows:

$$\mu_A(x) = \begin{cases} 0, & \text{for } x \leq a_1 \\ 2\left(\frac{x-a_1}{a_2-a_1}\right)^2, & \text{for } a_1 \leq x \leq \frac{a_1+a_2}{2} \\ 1-2\left(\frac{x-a_2}{a_2-a_1}\right)^2, & \text{for } \frac{a_1+a_2}{2} \leq x \leq a_2 \\ 1, & \text{for } a_2 \leq x \leq a_3 \\ 1-2\left(\frac{x-a_3}{a_4-a_3}\right)^2, & \text{for } a_3 \leq x \leq \frac{a_3+a_4}{2} \\ 2\left(\frac{x-a_4}{a_4-a_3}\right)^2, & \text{for } \frac{a_3+a_4}{2} \leq x \leq a_4 \\ 0, & \text{for } x \geq a_4 \end{cases} \quad (2)$$

The tail regions of a membership function of a variable contribute little behaviorally to its explanatory power vis-à-vis the driver routing decisions. Hence, the estimation of a_1 and a_4 is not as critical to the membership function updating. Here, a_1 and a_4 are defined as the minimum and maximum travel time that the driver experiences, respectively, when the traveler information system describes the traffic condition as “Normal”. By contrast, the region between a_2 and a_3 has the highest explanatory power in a driver’s perception of traffic information. Hence, an accurate estimation of a_2 and a_3 is critical to the prediction of routing decisions. The values of a_2 and a_3 are adjusted by applying the following recursive relationship:

$$a_2^{r+1} = \begin{cases} t_r, & \text{for } t_r \leq a_2^r \\ \lambda \cdot a_2^r + (1-\lambda) \cdot t_r, & \text{for } a_2^r \leq t_r \leq a_3^r \\ a_2^r, & \text{for } t_r \geq a_3^r \end{cases} \quad (3)$$

$$a_3^{r+1} = \begin{cases} a_3^r, & \text{for } t_r \leq a_2^r \\ \lambda \cdot a_3^r + (1-\lambda) \cdot t_r, & \text{for } a_2^r \leq t_r \leq a_3^r \\ t_r, & \text{for } t_r \geq a_3^r \end{cases} \quad (4)$$

where,

$a_m^r = a_m$ value on the r^{th} day, $m = 2, 3$

t_r = travel time the driver experiences on the r^{th} day

λ = adjustment parameter, $0 \leq \lambda \leq 1$

If the travel time experienced by a driver today is within the confidence region between a_2 and a_3 , the driver’s

confidence in the traffic information increases and the confidence region becomes narrower. However, if the experienced travel time is outside this region, the driver's confidence decreases and the confidence region becomes wider. The parameter λ represents the adjustment step size and reflects the driver's adaptation attitude based on his/her experienced travel time on the current day. Thus, λ can be used to classify drivers in terms their willingness to change travel time perceptions associated with the supplied traffic information. A higher λ implies that the driver perception is more sensitive to the current day's experience. For the simulation experiments conducted in this study, discussed in Section IV, λ is assumed to be 0.5 for all drivers. However, in these experiments there are several factors more dominant than λ in influencing driver route choice using the hybrid model. Hence, the results of the initial sensitivity analysis performed for λ show that the predicted route choices are not significantly sensitive to λ . If the travel times change by substantial magnitudes across days, λ can have a significant effect on the route choice prediction. Hence, λ can be a significant and/or time-dependent parameter in the real-world deployment of the hybrid model. Also, it is important to note that a detailed sensitivity analysis for λ should be conducted to infer its value for each driver class in a specific network as λ is not directly observable in the real-world.

c) Interacting Quantitative Variables: When interactions exist among variables, a fuzzy combination scheme is used for the perception update to reflect those interactions. For example, a driver's estimated travel time based on his/her past experience and the quantitative travel time information provided may be inconsistent with each other. A linear combination scheme is used for this purpose. It uses weights for the estimated travel time and the supplied travel time information:

$$\mu_P(x) = (1 - \omega) \cdot \mu_E(x) + \omega \cdot \mu_I(x) \quad (5)$$

where,

$\mu_P(x)$, $\mu_E(x)$, $\mu_I(x)$ = fuzzy sets for a driver's perceived travel time, estimated travel time, and supplied travel time information, respectively

ω = weight parameter, $0 \leq \omega \leq 1$

Since the distribution of the estimated travel time and the driver's confidence in traffic information potentially change after each trip, the weights ω used in the combination scheme can be updated as well. The determination of ω values for the experiments in this study is discussed in Section V-A.

2) *If-then Rules Update*: The fuzzy *if-then* rules used for a driver's route choice decisions may be updated based on his/her actual experience. The hybrid model estimated identifies unimportant or problematic variables, and aids in the adjustment of erroneous *if-then* rules used in the fuzzy rule-based model. If the estimated coefficient of a variable in the hybrid model appears unreasonable and/or is statistically insignificant, the associated *if-then* rules are reconsidered.

C. Within-Day Dynamics

The within-day dynamics addresses the real-time en-route routing decisions. It is reasonable to assume that compliance and inertia are influenced en-route by situational factors. Hence, the inconsistency between the en-route route choice prediction obtained using the hybrid model and the actual decision in real-time may be partly due to the lack of accounting for the influence of situational factors on compliance and inertia. The other potential factor contributing to the inconsistency is data measurement errors. To focus on updating the incorrect model parameters vis-à-vis within-day dynamics, we assume that the data measurements are accurate here.

Compliance and inertia are modeled as functions of the situational variables in the hybrid model: $\Omega_C(\cdot)$ and $\Omega_I(\cdot)$. These functions are represented using fuzzy rule-based models. In the context of en-route driver behavior under real-time information provision, drivers are not likely to use sophisticated mechanisms in making their route switching decisions, due to the limited capability for processing information and the time pressure for decision-making. This is consistent with the *if-then* rules proposed in the hybrid model. The transformation functions for compliance and inertia are modular, implying that *if-then* rules corresponding to situational factors can be added or removed easily. This is important in the context of the within-day dynamics, where situational factors change with time.

The compliance *if-then* rules are applied to evaluate the utility of the route recommended by prescriptive traffic information, while the inertia *if-then* rules are applied to evaluate the utility of a driver's current route. Let us assume that there are J and K *if-then* rules for compliance and inertia, respectively. Then, the fuzzy rule-based model to capture the compliance yields J defuzzified values by evaluating the corresponding *if-then* rules, while the fuzzy model for the inertia yields K values. Each defuzzified value indicates driver willingness to choose a route based on the corresponding rule. The driver's willingness to comply with the prescriptive information is then determined by combining these J defuzzified values, and his/her willingness to continue on the current route by combining the K defuzzified values. A weighted sum method is used for the combining step:

$$u^C = \sum_{j=1}^J w_j^C \cdot u_j^C \quad (6)$$

$$u^I = \sum_{k=1}^K w_k^I \cdot u_k^I \quad (7)$$

where

u^C = willingness to follow the recommended route

w_j^C = the weight of compliance rule j

u_j^C = willingness to follow the recommended route based on the compliance rule j

u^I = willingness to continue on the current route

w_k^I = the weight of inertia rule k

u_k^I = willingness to continue on the current route based on the inertia rule k

The use of weights is convenient because the contributions of each situational factor to compliance and inertia differ across drivers. For instance, weather conditions may be more important than time-of-day for some drivers. In addition, for the same driver, the relative weights among relevant *if-then* rules may vary en-route within a day because situational factors vary with time. Hence, the following calibration method is employed in this study to obtain the relative weights among the *if-then* rules. Suppose we have N observations of en-route choices, and prescriptive traffic information is provided in M out of those N observations. Then:

$$w_j^C = \frac{\sum_{m=1}^M \chi_j^m \eta_C^m - \sum_{m=1}^M \chi_j^m (1 - \eta_C^m)}{\sum_{m=1}^M \chi_j^m}, \text{ for } j = 1, \dots, J \quad (8)$$

$$w_k^I = \frac{\sum_{n=1}^N \chi_k^n \eta_I^n - \sum_{n=1}^N \chi_k^n (1 - \eta_I^n)}{\sum_{n=1}^N \chi_k^n}, \text{ for } k = 1, \dots, K \quad (9)$$

where

$\chi_j^m = 1$ if the compliance rule j is used for the m^{th} case; 0 otherwise

$\eta_C^m = 1$ if the model prediction is correct for the m^{th} case; 0 otherwise

$\chi_k^n = 1$ if the inertia rule k is used for the n^{th} observation; 0 otherwise

$\eta_I^n = 1$ if the model prediction is correct for the n^{th} case; 0 otherwise

The initial weights of the *if-then* rules on a specific day are the weights used at the end of the previous day. These weights are adjusted based on the actual en-route choices on the current day.

IV. APPLICATION OF THE HYBRID MODEL

A. Study Network

Simulation experiments are conducted using the Borman expressway corridor network in northwest Indiana to illustrate the adaptability of the hybrid model to incorporating driver behavior dynamics under information provision. The Borman network consists of a sixteen-mile section of I-80/94 (called the Borman expressway), I-90 toll freeway, I-65, and the surrounding arterials and streets, as shown in Fig. 4. It has 197 nodes and 458 links, and is divided into 14 zones. The Borman expressway is a highly congested freeway with a large fraction 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 with 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.

B. Decision Variables

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 as shown in Fig. 2. The en-route route choice models are used to determine the potential route switches of drivers at every decision node in response to situational factors and/or real-time information.

The three main categories of criteria for driver route choice decisions under information provision are: (i) driver attributes: socio-economic characteristics, network familiarity, confidence in information, sensitivity to delay, and personal preferences; (ii) route characteristics: travel time, travel distance, toll, facility type, route complexity, and location type; and (iii) situational factors: weather conditions, time-of-day, and trip purpose. 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. The qualitative traffic information consists of descriptive and prescriptive information. The latter is related to driver compliance. 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.

The travel distance and toll on each route are obtained by summing up their corresponding link-level values. The estimated travel time for the current day on each route for a driver is obtained based on the day-to-day update of the experienced travel times from previous days. The quantitative traffic information is the route travel time value predicted by the traveler information system. Driver familiarity with a route is determined as the average of the driver familiarity over all links of that route. The familiarity of a link is inferred from the number of times a driver has traveled on it. The number of nodes in a route is assumed to be a proxy for the route complexity. It should be noted that in general the number of nodes does not necessarily represent the route complexity as routes with identical number of nodes may have different levels of complexity depending on several route characteristics. A more robust measure to infer route complexity is one that factors in characteristics such as the number of turns and stops that a driver has to make on a route. However, the assumed proxy is a reasonable indicator of route complexity in the study experiments where the set of route alternatives for a driver consists of the five most dominant paths. These paths are obtained through several test simulation runs as the driver considers only a subset of possible origin-destination (O-D) routes based on his/her past experience and knowledge of the traffic network. Among these the simplest routes generally consist of the least number of nodes indicating the minimum number of turns and stops. The descriptive qualitative traffic information provided to drivers consists of five linguistic labels: “Long delay expected”, “Incident ahead”, “Slow traffic”, “Normal”, and “Free flow”. The prescriptive qualitative traffic information is the route recommended by the traveler information system, and compliance is addressed only in this context. Inertia is addressed in the context of a driver’s current route. The weather conditions consist of two categories: (i) good and (ii) bad. The time-of-day consists of two categories: (i) daytime and (ii) nighttime. The trip purpose consists of two categories: (i) business and (ii) leisure.

C. Route Choice Decision Process: Data Generation

In the absence of field data, data is generated on driver routing decisions for the study experiments based on an assumed behavioral mechanism. It is very important to note here that the hybrid model is unaware of this mechanism

and uses the model structure in equation (1) to predict the driver decisions. In the study experiments, the 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. All attributes are assumed to be rank-ordered by importance, and several attributes may be considered equally important by a driver. At each rank-level, utility functions are used to determine the utilities of alternatives. Within each rank, the driver eliminates the inferior alternative(s) 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 the first-ranked attributes, a driver evaluates the second-ranked attributes. This process is continued until a single route remains. If a single alternative is not obtained when the last-ranked attributes are reached, utility maximization is used to determine the route choice at that point.

Table I shows the route choice decision process used for the data generation. Travel distance, toll, estimated travel time, quantitative traffic information, and descriptive qualitative traffic information are assumed to have the first rank. After computing all U_{in}^1 values, we eliminate the alternative(s) whose utilities are less than $\phi_1\%$ of U_*^1 . If more than one alternative remains, the second-ranked attributes are considered. They include familiarity and route complexity. The inferior alternative(s) is(are) eliminated using the threshold value, $\phi_2\%$ of U_*^2 . If the route is not chosen yet, the third-ranked attributes are considered, and utility maximization is used to determine the chosen route. This process is used for the en-route decision-making. For the pre-trip decision-making, only the first- and second-ranked attributes are considered as discussed earlier.

In the table, $\Gamma(\cdot)$ refer to the functions that are assumed in the experiments to generate the numerical values of the corresponding qualitative attributes. This is purely to generate data to determine the driver route choice decisions for the study experiments to analyze the hybrid model. In a real-world situation, fuzzy transformation functions in the hybrid model are used to capture the mechanisms of the drivers to interpret these qualitative variables based on the observed data. For data generation purposes, the variable Q_{in} consists of five linguistic labels. Thus, $\Gamma_Q(Q_{in})$ can be defined as a simple discrete function which assigns a meaningful value to each linguistic label:

$$\Gamma_Q(Q_{in}) = \begin{cases} q_1, & \text{if } Q_{in} = \text{"Long delay expected"} \\ q_2, & \text{if } Q_{in} = \text{"Incident ahead"} \\ q_3, & \text{if } Q_{in} = \text{"Slow traffic"} \\ q_4, & \text{if } Q_{in} = \text{"Normal"} \\ q_5, & \text{if } Q_{in} = \text{"Free flow"} \end{cases} \quad (10)$$

On the other hand, $\Gamma_P(P_i)$ can be viewed as a non-linear function, with the perceived complexity increasing more rapidly with the number of nodes. Hence, $\Gamma_P(P_i)$ can be defined in a piecewise manner:

$$\Gamma_P(P_i) = \begin{cases} P_i, & \text{if } P_i \leq X_n^1 \\ P_i^2, & \text{if } X_n^1 < P_i \leq X_n^2 \\ e^{P_i}, & \text{otherwise} \end{cases} \quad (11)$$

where X_n^1 and X_n^2 are thresholds in terms of the number of nodes, and depend on the individual n . This implies that the perceived complexity varies across individuals.

By varying the ranks, the threshold values for the attributes, the utility functions, and the functions for the qualitative variables, various sets of driver route choice data can be generated to represent various driver classes and the evolution of driver route choice behavior. A vehicular network traffic simulator, DYNASMART [18, 19, 20], is used to generate the time-dependent traffic flow conditions resulting from driver route choice decisions. DYNASMART (Dynamic Network Assignment-Simulation Model for Advanced Road Telematics) is a fixed time step mesoscopic simulation model. It uses macroscopic traffic flow relationships to move vehicles while tracking vehicles individually. It is designed to model traffic flow patterns and evaluate the overall network performance under real-time information systems for a given network configuration, time-dependent O-D demand, and other system inputs. The modeling approach integrates a traffic flow simulator, a network path processing component, user behavior rules and information supply strategies. In the context of the current study, only the traffic flow simulator of DYNASMART is used to generate data based on driver routing decisions. Thereby, driver routing behavior is determined using the mechanism described in Section IV-C. This leads to: (i) en-route route changes being simulated using DYNASMART, and (ii) the origin, destination, departure time, and initial route being specified to DYNASMART in the day-to-day context.

In summary, DYNASMART is used in the within-day context to: (i) generate the time-dependent traffic flow conditions in real-time based on the predefined O-D demand for the Borman corridor and the pre-trip routing

decisions of drivers, and (ii) simulate driver en-route routing decisions based on the route choice decision process specified in Table I. In the day-to-day context, the route characteristics obtained for the current day from DYNASMART are used to update the driver's: (i) estimated travel times for various routes, (ii) route familiarity, and (iii) confidence in the traveler information system.

The time-dependent O-D demand matrix for the Borman corridor network is assumed to be known for a 90-minute planning horizon. A total of 14,060 drivers (trips) are generated over the 90-minute duration for the first day. Each generated driver is assigned a unique identification number to track his/her route choices on a day-to-day basis. To identify the set of route alternatives for each O-D pair, ten different simulations are performed by assuming different traffic conditions. The day-to-day evolution of driver route choice behavior is observed by running the simulator for a 30-day period; the driver behavior characteristics are updated after each day's experience before simulating the traffic pattern for the next day. The perception update of routes by the individual drivers, and the update of the route choice rules (specified in Table I) at the individual driver and/or driver class levels are simulated to analyze the day-to-day evolution of driver behavior. This is done by updating driver attributes and perception using the current day's observations. Thereby, the route choices made by a driver can be different from one day to the next, implying that his/her perception and route choice rules are updated on a daily basis. The within-day dynamics using the driver behavior mechanism described in this section are simulated in DYNASMART through the en-route update of the weights of the route choice rules based on the ambient traffic conditions and situational factors. In order to model various situational factors, the 90-minute simulation differs across experiments in terms of the time-of-day and weather conditions.

As discussed in Section III-A, from a driver behavior perspective, drivers are not likely to change their route choice rules and perceptions en-route. In the context of driver behavior classes, all drivers in a class are assumed to use the same route choice rules while the individual drivers have different attributes and perceptions. Each individual driver in a driver behavior class has specific attribute values that are updated on a day-to-day basis based on his/her experience on the current day. However, the route choice rules are updated for the entire driver class based on the current day's experience for all drivers in that class.

The discussion heretofore in this section describes the data generation process. It should be emphasized again that the hybrid model is unaware of the route choice rules in Table I and the driver day-to-day and within-day behavior

dynamics used to generate data. The hybrid model uses the probabilistic-possibilistic framework to infer on the observed driver routing decisions, by using the *if-then* rules in Table II and membership functions consistent with the observed (generated) data.

D. Model Formulation

The hybrid model is used to predict the driver day-to-day and within-day route choice decisions that are observed in the generated data. The route choice set of each driver at every decision node depends on his/her origin and destination. The systematic utilities are represented as follows, except that no alternative-specific constant is specified for one alternative:

$$V_{in} = \alpha_i + \beta_1 D_i + \beta_2 L_i + \beta_3 \Psi(T_{in}, K_{in}) + \beta_4 \Omega_Q(Q_{in}) + \beta_5 \Omega_F(F_{in}) + \beta_6 \Omega_P(P_i) + \beta_7 \delta_{in} \Omega_C(W_n, G_n, S_n) + \beta_8 \kappa_{in} \Omega_I(W_n, G_n, S_n) \quad (12)$$

where,

α_i = alternative specific constant for route i

β_j = coefficient of variable/function j

$\Psi(\cdot)$ = adjustment function to capture the perceived travel time

$\Omega_Q(\cdot)$ = transformation functions to determine the fuzzy value of descriptive qualitative traffic information

$\Omega_F(\cdot)$ = transformation functions to determine the fuzzy value of familiarity

$\Omega_P(\cdot)$ = transformation functions to determine the fuzzy value of route complexity

$\Omega_C(\cdot)$ = transformation functions to determine the fuzzy value of compliance for recommended route i

$\Omega_I(\cdot)$ = transformation functions to determine the fuzzy value of inertia for current route i

The hybrid model does not require a specific discrete model structure, which implies that any structure used for probabilistic discrete choice models can be used for it. Hence, if a specific model structure is desirable from a discrete choice theory perspective, the same structure can be used for the hybrid model. Here, we consider the traditional multinomial logit (MNL) and multinomial probit (MNP) structures [8] for the hybrid model. The MNP form is computationally more intensive whereas the MNL form assumes that the error terms are not correlated across alternatives. Hence, MNP is not suitable for an en-route route choice model where time matters, and MNL is restrictive when routes share several common links. The pre-trip route choices are determined off-line before the start

of the current day. Hence, the MNP structure can be used to determine them since the computational time is not a primary concern off-line. The MNL structure is used for the en-route route choice model as computational time is a fundamental issue for real-time operations. Also, unlike in the pre-trip context, the link overlaps across alternative en-route routes reduce as a driver gets closer to the destination.

The values of the quantitative variables without interaction such as travel distance and toll are directly used in the above utility function. However, as discussed earlier, the values for the quantitative variables with interaction (estimated travel time and quantitative traffic information) and qualitative variables (descriptive qualitative information, familiarity, route complexity, compliance and inertia) are determined through the adjustment and transformation functions, respectively. Each transformation function $\Omega(\cdot)$ is generated using the corresponding *if-then* rules illustrated in Table II.

V. ANALYSIS OF RESULTS

A. Day-to-Day Dynamics

1) *Perception Update*: The day-to-day route choice dynamics are revealed through the update of a driver's perception based on his/her past experience and confidence in the traveler information system. This is done by updating the membership functions for that driver's estimated travel time and quantitative traffic information daily based on his/her experience on the current day, and then using equation (5) to determine the perceived travel time. The weight parameter ω for a driver on the $(r+1)^{\text{th}}$ day is obtained by comparing his/her actual travel time on day r , and the estimated travel time and quantitative information provided before the trip on day r . Hence, the weight can vary from one day to the next.

To analyze the perception update characteristics, a trip from node 1 to node 190 is observed for a driver over a 30-day period. In the pre-trip decision-making for this trip, three prominent routes exist: (i) route 1: I-65 \rightarrow I-80/94 \rightarrow US 41, (ii) route 2: I-65 \rightarrow I-90, and (iii) route 3: US 30 \rightarrow US 41. The driver's pre-trip route choice decisions are observed over the 30-day period to capture the day-to-day update of his/her estimated travel time, confidence in the quantitative traffic information, and the weight parameter ω .

Fig. 5 illustrates the update of the membership function for that driver's perceived travel time for route 1. On day

1, the membership function for the estimated travel time is obtained from the actual travel time distribution for that route on day 0 (base day), while the membership function for the quantitative traffic information is an arbitrary function. Here, on each day, the quantitative traffic information provided to a driver is assumed to be “Expected travel time: 45 minutes”. As illustrated in the figure, based on this driver’s specific experience, tighter membership functions are observed on day 30 compared to those on day 1. This is because the actual travel times do not fluctuate much from day 1 to day 30 and the quantitative traffic information provided is close to the actual travel time. Also, the weight parameter ω is assumed to be 0.5 for day 1, and is observed to be 0.72 for day 30 due to the greater confidence in the traveler information system.

The weight parameter ω is an important indicator of the interactions between a driver’s past experience and the traffic information provided. It reflects his/her confidence in the traveler information system. To investigate these interactions, pre-trip route choices by 200 drivers going from node 1 to node 190 are observed. Of these, 100 drivers are provided incorrect travel time information on route 1 along the I-80/94 segment, while the other 100 drivers are provided correct travel information. Here, correct information on day $r+1$ implies that the travel time provided by the traveler information system on day $r+1$ is within $\pm 5\%$ of the actual travel time on the r^{th} day. The corresponding range for the incorrect information is either $+20\%$ to $+40\%$ or -20% to -40% of the actual travel time. The average weight parameters for these two groups are obtained from day 1 to day 30. Fig. 6 shows the day-to-day variation of the weight parameter ω . On day 1, all 200 drivers are assumed to weigh their experience and traffic information equally. Over time, drivers provided with correct information gain more confidence in the traffic information as illustrated by the increase in the parameter value in the figure. By contrast, those provided with incorrect information progressively lose their confidence in the traveler information system. Hence, the hybrid model structure can capture the day-to-day perception updates of drivers.

2) *Delusion and Freezing*: If incorrect traffic information is provided to drivers, it induces qualitative phenomena called delusion and freezing. On a day-to-day basis, a driver’s confidence in the traffic information system is affected by his/her actual travel experience compared to the traffic information provided. Over time, this leads the driver to update his/her perception of a route. Hence, a driver who has experienced limited or incorrect information on a route may have a lesser propensity to consider that route as a valid alternative in the short-term. This short-term phenomenon is called delusion as the driver forms a biased perception of that route. If a driver’s delusion with a

route continues over time, he/she will believe his/her biased perception of that route to be true. In the long-term, the driver will make route choices based on the biased perception of that route or potentially exclude it from the set of route alternatives. This phenomenon is called freezing as the driver's biased route decisions become habitual. Here, the ability of the hybrid model to capture these phenomena is analyzed. The pre-trip route choices by 500 drivers are observed under the following scenario: (i) 100 drivers are provided incorrect travel time information on route 1 along the I-80/94 segment, (ii) 200 drivers are provided correct information on route 2 along the I-90 segment, and (iii) no information is provided to the remaining 200 drivers. Since drivers update their perceptions of route travel time and the traveler information system on a daily basis, the number of drivers choosing each route is affected by their updated perceptions. Fig. 7 shows the percentage of drivers choosing each of the three routes over a 30-day period. As illustrated by the figure, incorrect information provided on route 1 induces drivers to switch to routes 2 and 3, while the correct information on route 2 attracts drivers to route 2. This implies that incorrect information on a route reduces the driver's propensity to consider that route as an alternative in the short-term, as reflected by the rapid reduction in the percentage choosing route 1. Also, by about day 20, the number of drivers choosing route 1 goes below 20%, implying that this route is potentially excluded from the alternatives under consideration in the long-term. These two phenomena are delusion and freezing, respectively. This implies that the hybrid model structure can capture day-to-day phenomena observed under information provision. From the figure, it can be observed that during the first few days the hybrid model is not sufficiently sensitive to the route choice data to adequately update the model parameters. This is an artificial limitation due to the experimental set-up which starts on day 1, leading to limited past experience on the part of the drivers for the first few days. A better feel for the ability of the hybrid model to capture the day-to-day phenomena is reflected by the more rapid switching from route 1 from about day 7 when a reasonable amount of past history is built up. For the same reason, in general, the gap between the actual and predicted percentages reduces over time.

B. Within-Day Dynamics

The hybrid model reflects the effects of situational factors on en-route route switching decisions. The en-route route switching decisions used to analyze the within-day dynamics are simulated on nine intersections of I-65 and I-80/94 in response to the real-time traffic information provided when traveling from node 1 to node 75. While inertia and compliance evolve on a day-to-day basis, their influence is in a within-day context. Hence, en-route decision-

making is analyzed by exploring the effects of inertia and compliance. $\Omega_C(\cdot)$ and $\Omega_I(\cdot)$ are the transformation functions to capture the effects of weather conditions, time-of-day, and trip purpose on compliance and inertia, respectively. Each $\Omega_C(\cdot)$ and $\Omega_I(\cdot)$ consists of six *if-then* rules as shown in Table II. They yield six fuzzy values by evaluating the corresponding *if-then* rules. The utility contributions of compliance and inertia are determined using equations (6) and (7), respectively. The relative weights of the *if-then* rules determine the contributions of situational factors to en-route route switching decisions.

Fig. 8(a) and (b) show the within-day variations in the weights of compliance and inertia *if-then* rules, respectively, based on the calibration scheme represented by equations (8) and (9). Here, rule calibration is done after every 100 observations of driver route switching decisions under information provision. After the first calibration, the rule weights are quite different from the initial weights which are based on the previous day, due to changes in situational factors. However, after a few calibrations, the weights become stable because they are better adapted to the situational factors on the current day. This suggests that the hybrid model can capture the within-day dynamics in driver en-route behavior through a calibration mechanism.

Fig. 9 shows the prediction rates of the hybrid model with and without the en-route calibration of the weights over the 30-day period. It suggests that the calibration has value always, and contributes significantly to the prediction accuracy during the initial days. Also, it can be noted that the prediction accuracy without calibration itself becomes stable around day 15 since the weights used for *if-then* rules associated with situational factors become quite stable by then.

C. Prediction Tests

The hybrid model is compared with the standard MNP model in terms of the pre-trip prediction capability. The standard MNP model uses ordinal values for a driver's subjective interpretation of the qualitative variables. Also, a driver's estimated travel time based on his/her past experience, and the quantitative traffic information provided, are treated as separate variables. Thus, the MNP model does not explicitly incorporate the associated interactions between them. Compliance, inertia, and situational factors are also treated as separate dummy variables. The MNP specification used is as follows:

$$V_{in} = \alpha_i + \beta_1 D_i + \beta_2 L_i + \beta_3 T_{in} + \beta_4 K_{in} + \beta_5 Q_{in} + \beta_6 P_i + \beta_7 F_{in} + \beta_8 C_{in} + \beta_9 I_{in} + \beta_{10} W_n$$

$$+ \beta_{11}G_n + \beta_{12}S_n \quad (13)$$

where,

β_j = coefficient of variable j

C_{in} = compliance for prescriptive information on route i for driver n ; 1 if route i is the recommended route; 0 otherwise

I_{in} = inertia effect on route i for driver n ; 1 if route i is the current route; 0 otherwise

W_n = weather condition for driver n ; 1 if good; 0 otherwise

G_n = time-of-day for driver n ; 1 if daytime; 0 otherwise

S_n = trip purpose of driver n ; 1 if business trip; 0 otherwise

The percentage of correct predictions is used here as a consistent measure to compare the hybrid and standard MNP models. The hybrid and MNP model probabilities are transformed into discrete route choices through Monte Carlo simulation [17]. First, a uniform random number generator is used to generate values between 0 and 1. In addition, the probability range between 0 and 1 is demarcated into smaller ranges according to the probabilities of choosing various routes by a driver. For example, if there are three routes with choice probabilities 0.3, 0.2, and 0.5, the ranges associated with each route are 0.0-0.3, 0.3-0.5, and 0.5-1.0, respectively. If the random number generated falls in the range of choosing a specific route, the driver is assumed to choose that route. This process is repeated for all drivers, and the prediction rate is determined by comparing the actual and predicted choices across all drivers. The entire procedure is repeated 10 times to generate a set of potential route choice scenarios consistent with the probabilities predicted by a model, and an average prediction rate is computed. This average prediction rate is used to compare the two models.

In the real-world, traffic streams consist of many heterogeneous driver classes in terms of behavioral rules and characteristics. In the current context, this can be enabled by uniquely defining driver classes using attribute rank, utility function, and/or functions used in the route choice decision process as illustrated in Table I. Here, two driver classes are constructed by just switching the first- and second-ranked attributes to obtain the second driver class. The following three driver class fraction ratios are considered for the two driver classes for the analysis: (i) 90%:10%, (ii) 70%:30%, and (iii) 50%:50%. The 90%:10% ratio implies a more homogeneous driver grouping while the 50%:50% ratio implies a more heterogeneous grouping.

Fig. 10 shows the aggregate prediction rates of the hybrid and standard MNP models over a 30-day period as a function of the driver class fractions. It suggests that the hybrid models have better prediction power than the MNP models. However, the relative difference in the prediction capability reduces with increasing heterogeneity. This provides key insights into the differences in the mechanisms of the hybrid and standard discrete choice models vis-à-vis day-to-day update. In this experiment, to be consistent with the real-world data availability, the hybrid models update membership function parameters, interaction effects among variables, and *if-then* rules in a day-to-day context assuming that they have no knowledge of the driver class fractions. This also enables a fair comparison with the MNP model. Hence, seemingly inconsistent choices across drivers reduce the robustness of model parameters during the update process. This loss of robustness is higher when heterogeneity increases. The MNP model mechanism to update the underlying behavioral tendencies on a day-to-day basis is different. It simply estimates the coefficients of attributes that best represent the current data set (which increases from each day to the next). Thereby, it is able to improve the prediction capability because of the increased data set size in a day-to-day context. However, for both the hybrid and MNP models, the effects of heterogeneity dominate the benefits due to increased data size, as reflected by the almost unchanged prediction rates beyond day 20.

In actual applications, aggregate behavior is analyzed through market segmentation by defining behavioral classes. Hence, the hybrid model, or for that matter any discrete choice model, can be used for a homogeneous driver group after predicting driver class fractions in traffic streams through socioeconomic surveys in the region. Then, the higher prediction accuracy of the hybrid model provides real value. However, the fundamentally new implications of the hybrid modeling approach are in the context of real-time operations, where a knowledge of the driver class fractions in the ambient traffic stream is essential for ensuring consistency between the actual and predicted traffic conditions. This implies that not only the driver behavioral characteristics but also the driver class fractions need to be accurately captured to correctly predict the actions of real traffic streams consisting of heterogeneous driver behavioral classes. This lack of a capability to estimate the ambient driver class fractions has been a key barrier to the prediction accuracy in real-time traffic operations vis-à-vis the use of dynamic traffic assignment under advanced information systems. The proposed hybrid modeling approach bridges this gap by providing a mechanism that can seamlessly capture driver behavior dynamics and driver class fractions through parameter and/or rule updates.

Beyond the benefits of the hybrid model for aggregate behavior prediction and real-time operations, it provides: (i)

a seamless single framework to capture day-to-day and within-day dynamics, (ii) the ability to explain qualitative phenomena through consistently-interpreted parameters, and (iii) capabilities to better elucidate driver behavior dynamics through the transparent structure of *if-then* rules.

VI. CONCLUDING COMMENTS

This study models the day-to-day and the within-day dynamics of driver route choice decisions under advanced information systems using a seamless framework by adapting a hybrid route choice model [16]. It enables the day-to-date update of driver behavioral characteristics in a transparent manner by updating the membership functions and *if-then* rules. In a within-day context, it is sensitive to situational factors whose effects are captured through the within-day adjustments of the weights of the *if-then* rules. This affords the consistency of a single seamless framework to model both short-term and long-term behavioral characteristics in the context of driver route choice under information provision.

Peeta and Yu [16] describe the hybrid model and show that it can incorporate the subjectivity in qualitative variables more robustly compared to standard discrete choice models. They also highlight the influence of the level of heterogeneity in driver behavioral classes on the route choice prediction capability. Here, the hybrid model is used as part of a framework to capture: (i) the evolution of phenomena such as route perception update, inertia, compliance, delusion, and freezing, and (ii) the sensitivity to situational factors. Further, the study experiments highlight the better prediction accuracy of the hybrid model compared to a multinomial probit model, especially for homogeneous driver groupings. The ability to robustly incorporate both day-to-day and within-day dynamics of driver decisions, in conjunction with the transparent mechanism to represent different driver classes, has fundamental deployment implications for real-time traffic operations under advanced information systems.

Existing dynamic traffic assignment models, which are the methodological tools for real-time traffic control through driver information provision, assume that the driver behavioral class fractions in the ambient traffic stream are known. This is an unrealistic assumption based on the current technological capabilities. Peeta and Yu [21] use the hybrid model's ability to capture the driver route choice behavior dynamics to propose a behavior-based consistency-seeking model as a deployment alternative to dynamic traffic assignment models. It predicts the driver class fractions in the ambient traffic stream using the real-time measurable data, and then determines the routing

information to be provided to drivers. This addresses an important practical barrier in the deployment of dynamic traffic assignment and control procedures, since these fractions cannot be measured in real-time. Detailed insights in this regard for real-time consistency-checking and calibration are provided in Peeta and Yu [21].

From an operational standpoint, since the hybrid model based framework uses a rule-based system, it circumvents the artificial construction of rigid behavioral rules such as user equilibrium for real-time operations. This leads to a more generalized model that is sensitive to situational factors in real-time. Hence, when its modeling flexibility in terms of adding or deleting rules associated with situational factors (based on the current driving conditions) is factored in, the proposed framework can represent a robust mechanism to model en-route driver behavior under real-time information. In addition, the effects of traffic incidents that a driver may face en-route can also be incorporated by updating the weights associated with the compliance and inertia rules.

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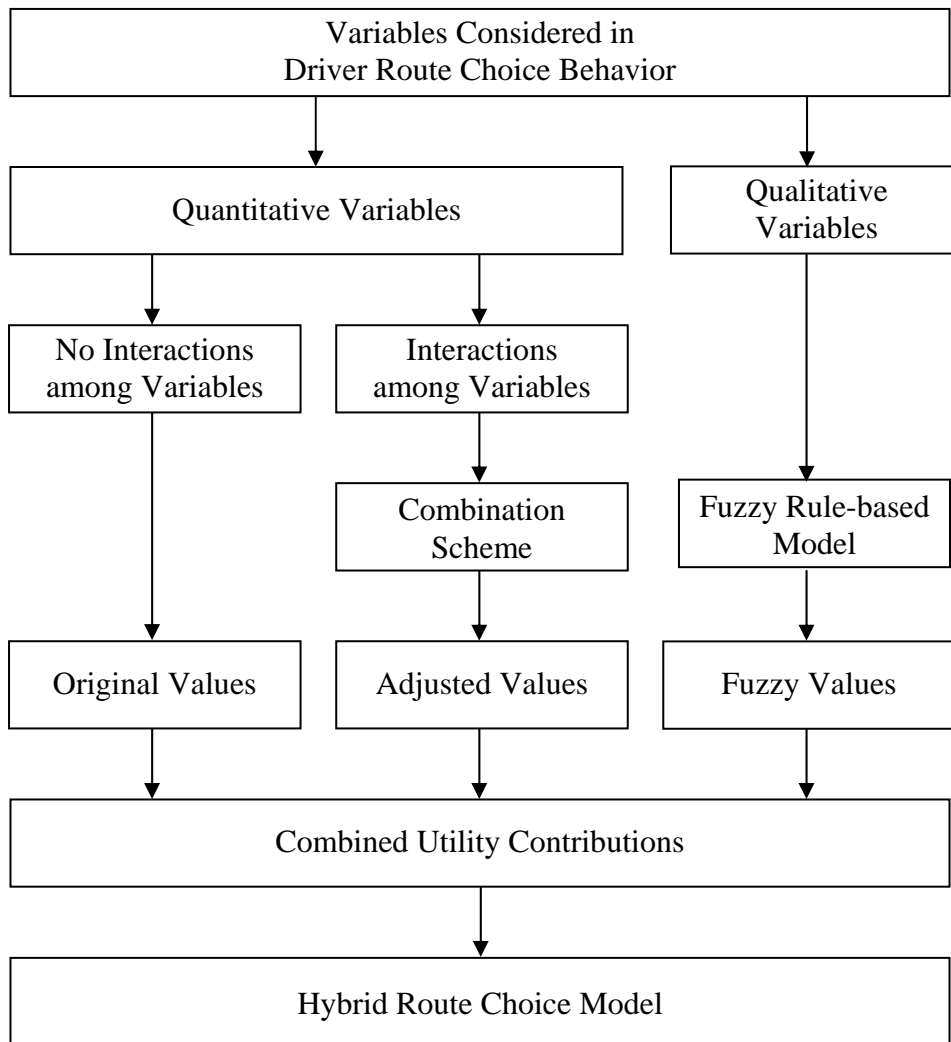


Fig. 1. Hybrid modeling approach.

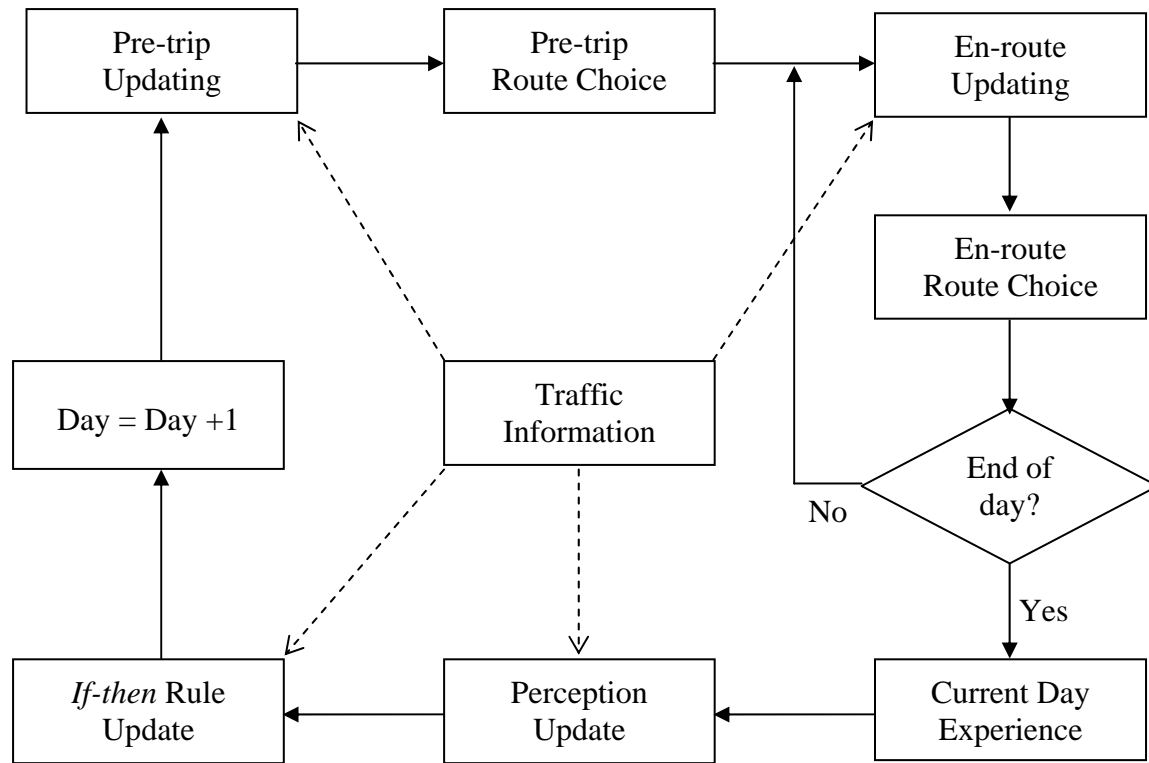


Fig. 2. Framework for driver behavior dynamics.

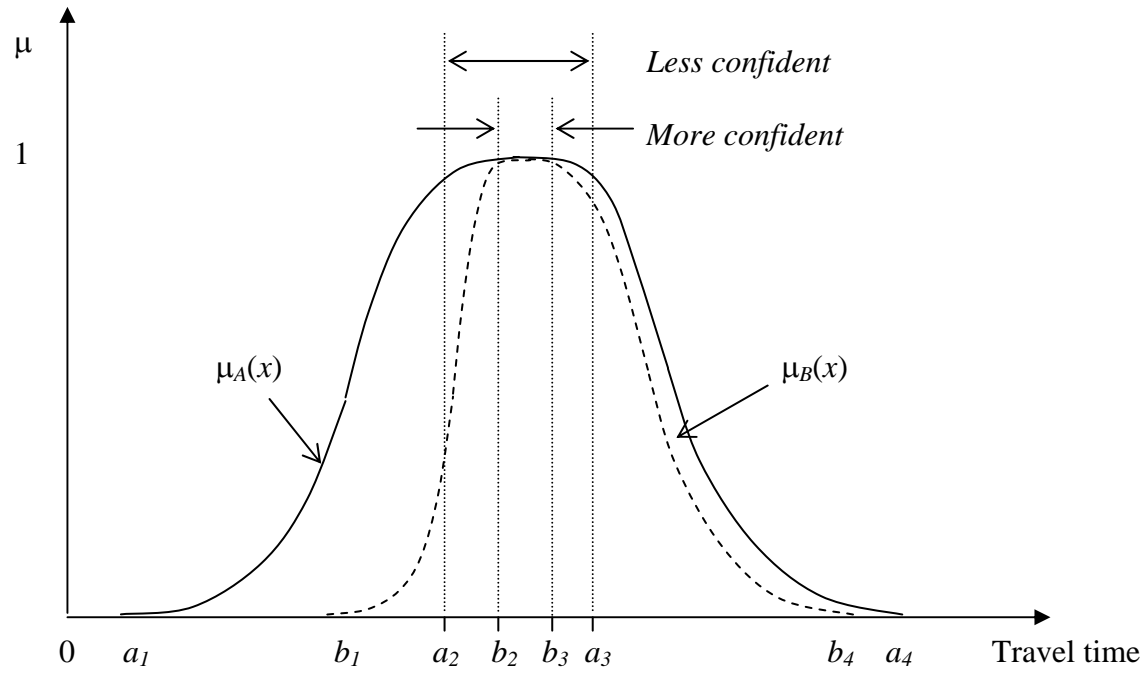


Fig. 3. Driver's perception of traffic information message, "Normal".

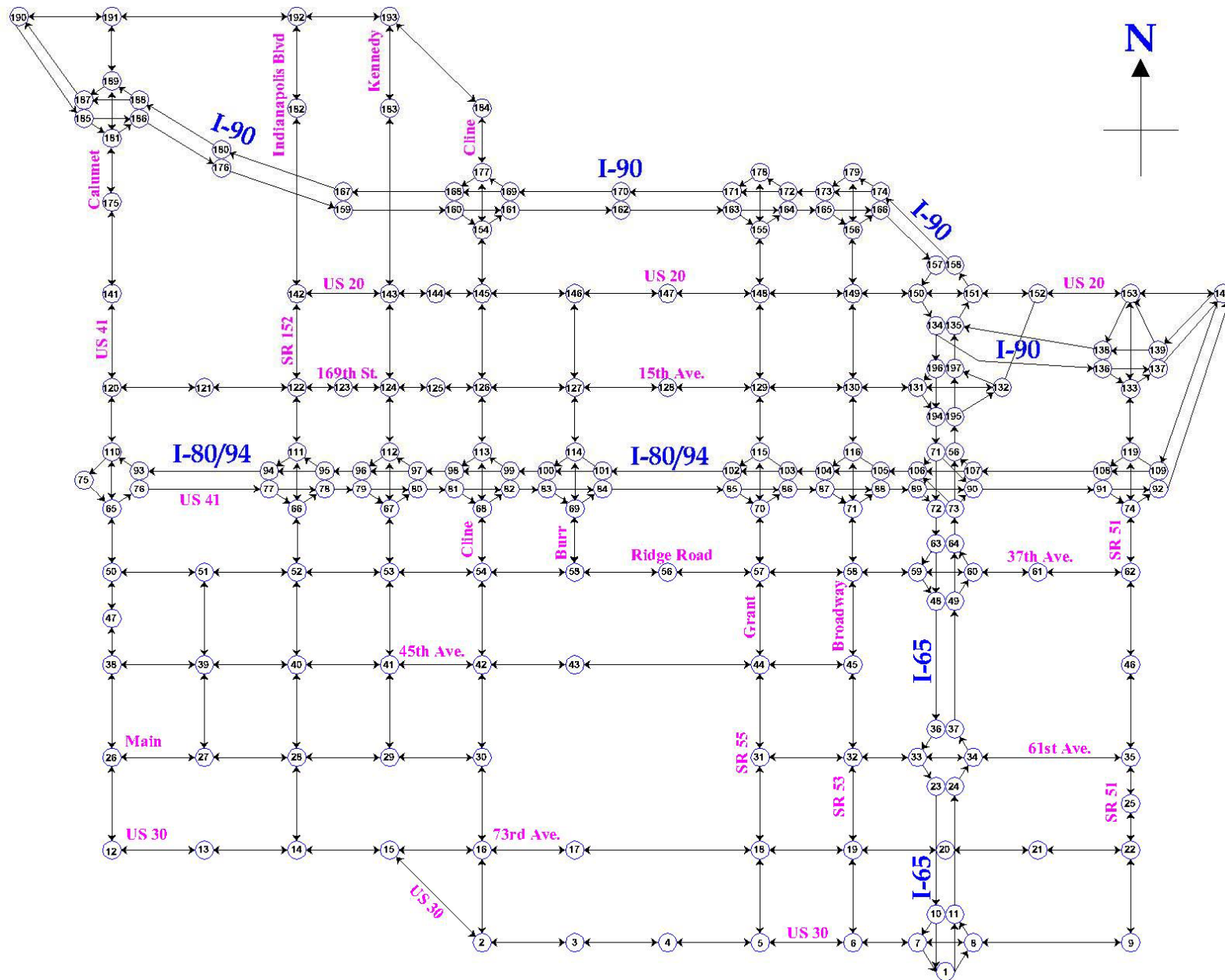


Fig. 4. Borman expressway corridor network.

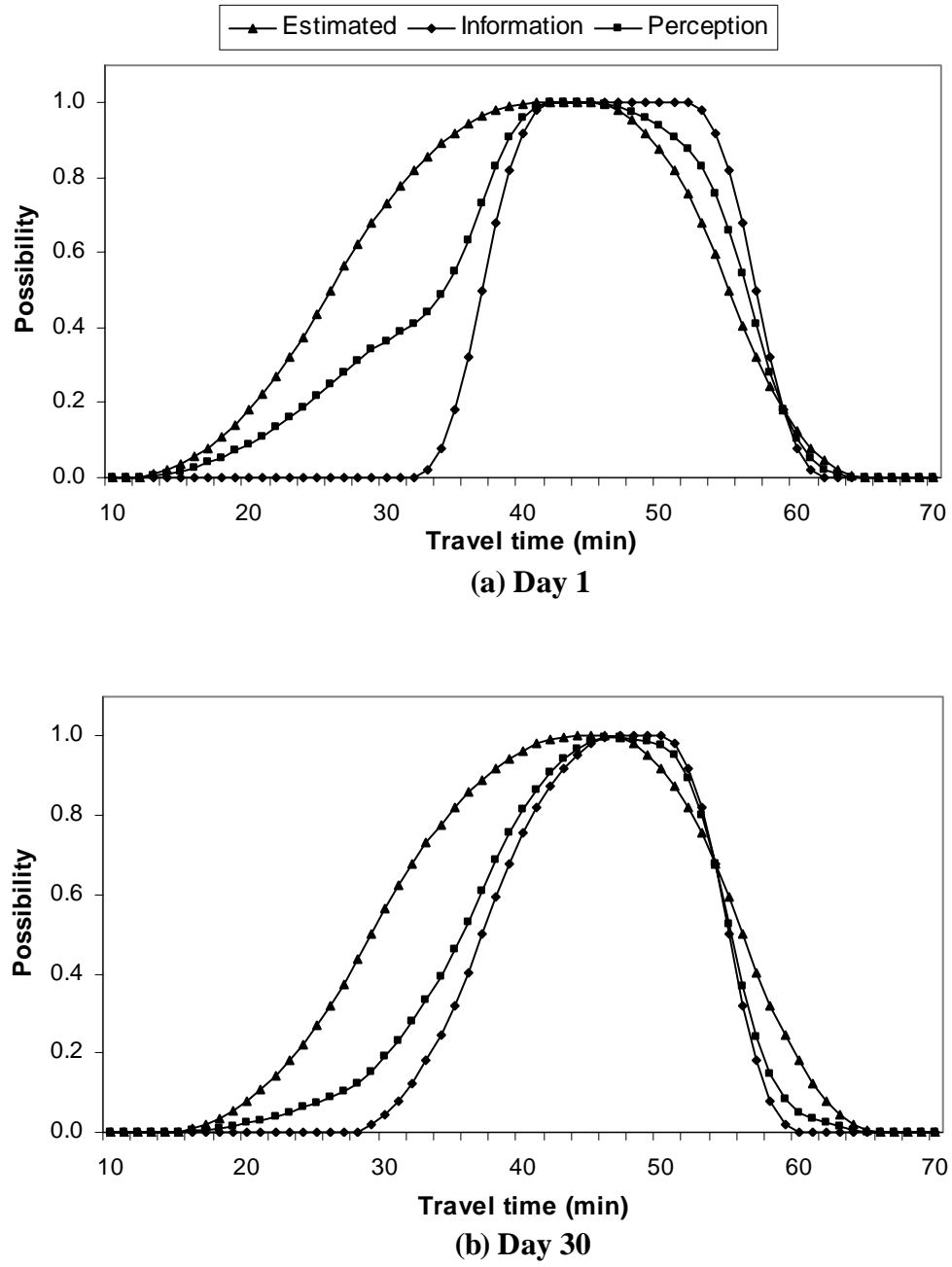


Fig. 5. Membership function update.

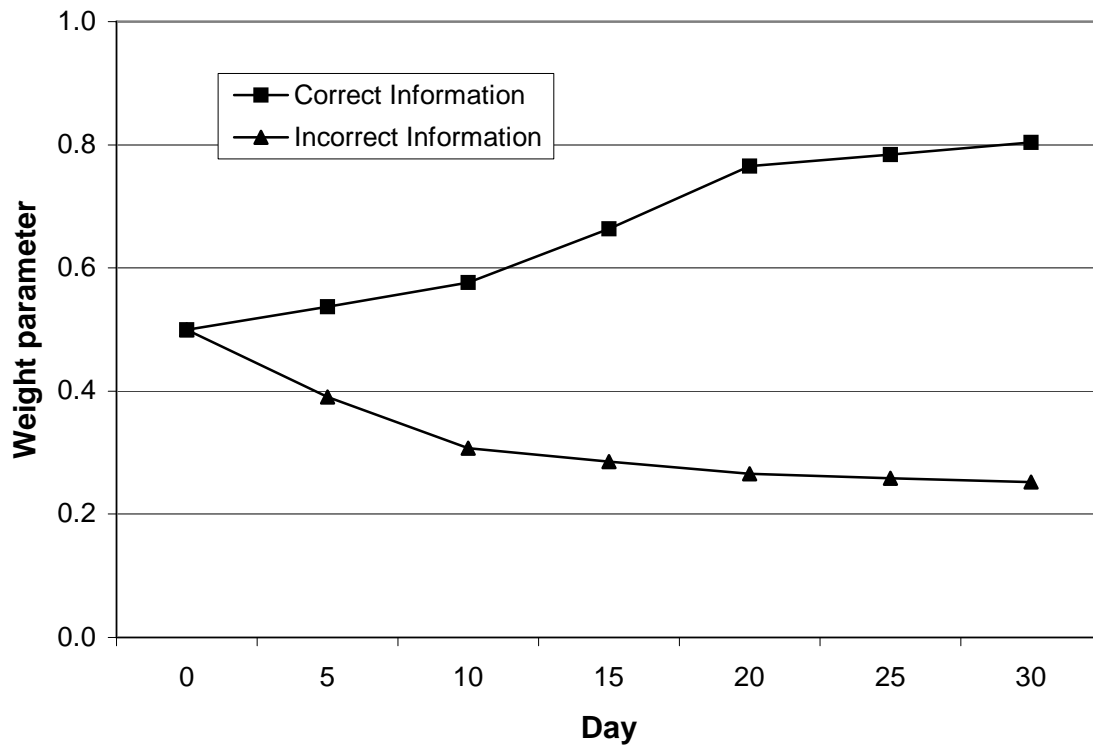


Fig. 6. Day-to-day variation of the weight parameter ω .

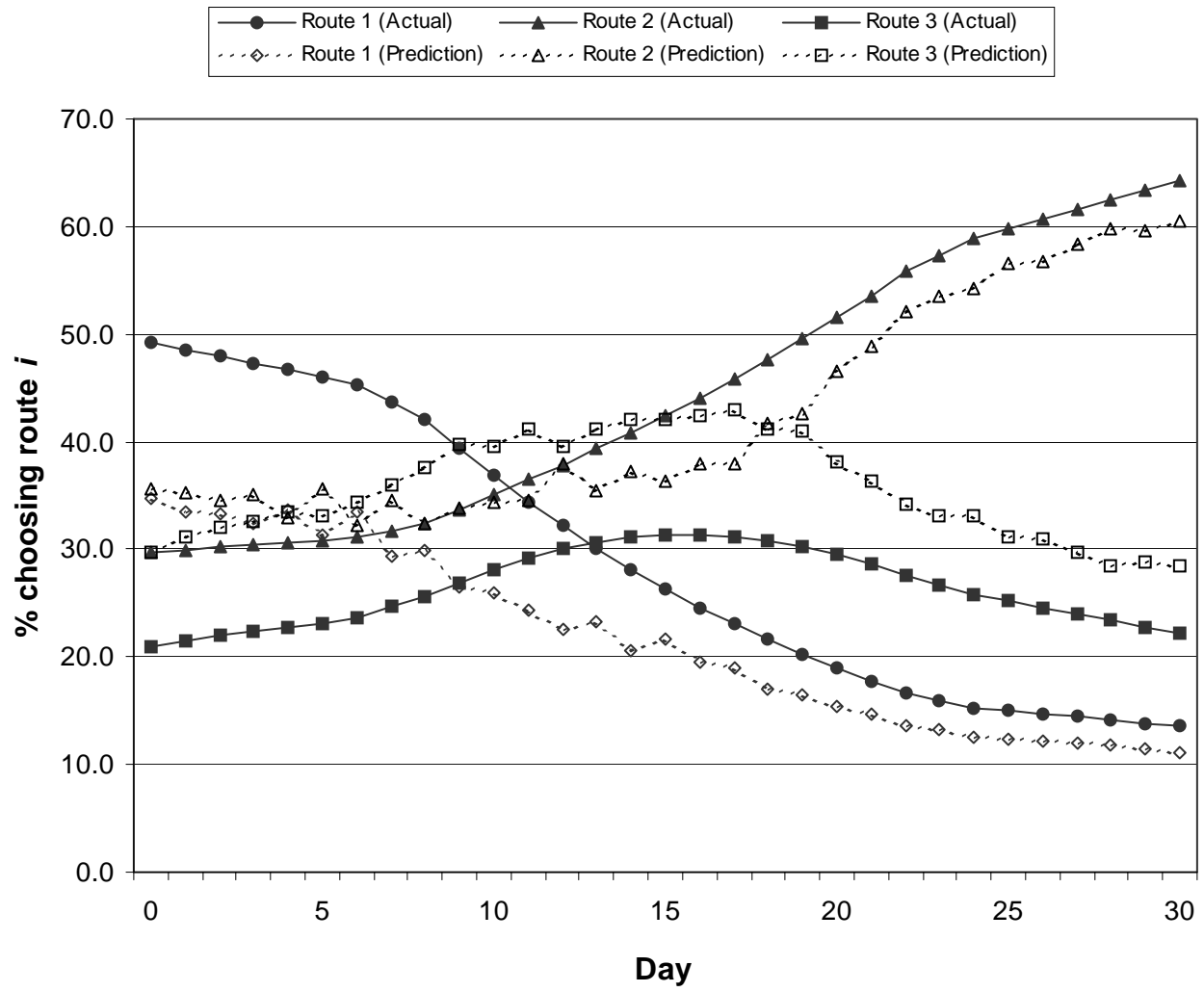


Fig. 7. Delusion and freezing phenomena.

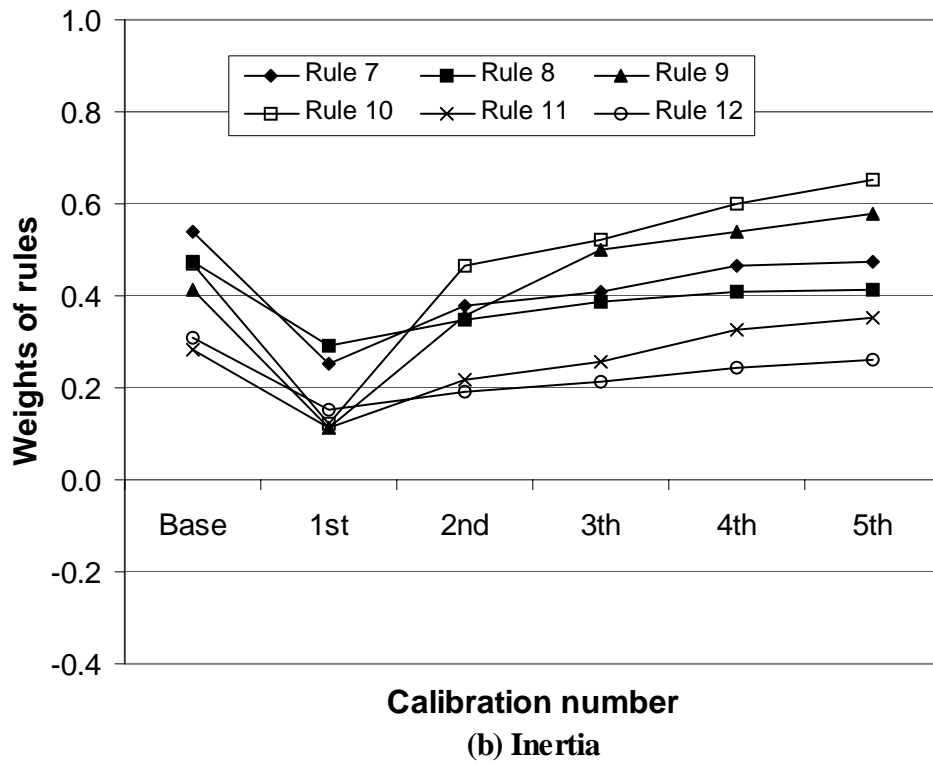
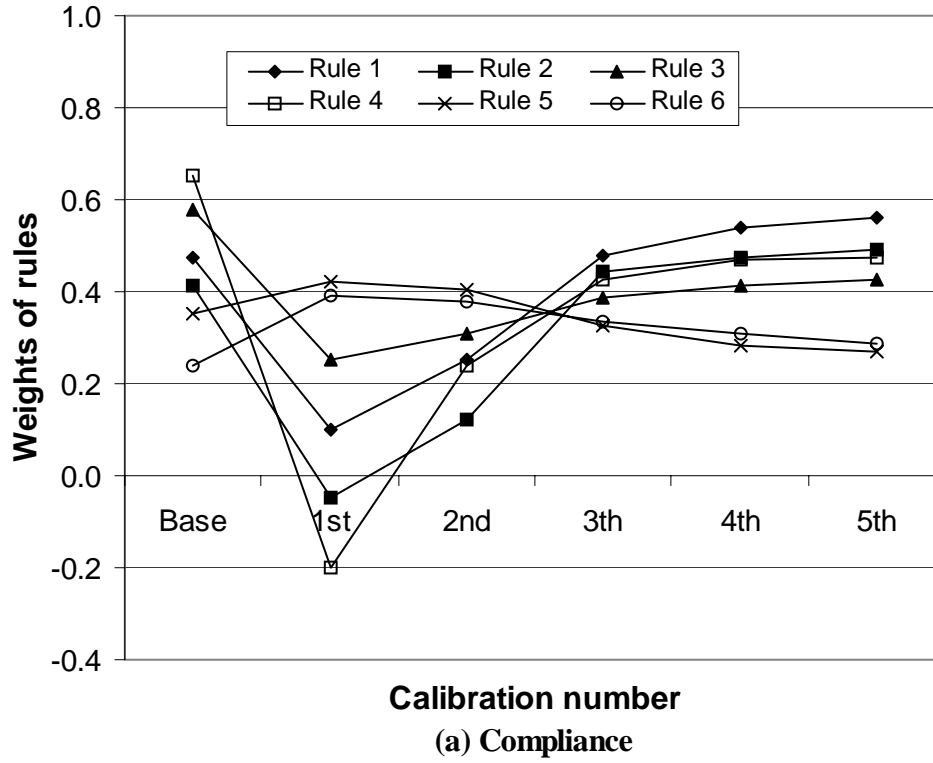


Fig. 8. Within-day variations in the weights of compliance and inertia rules.

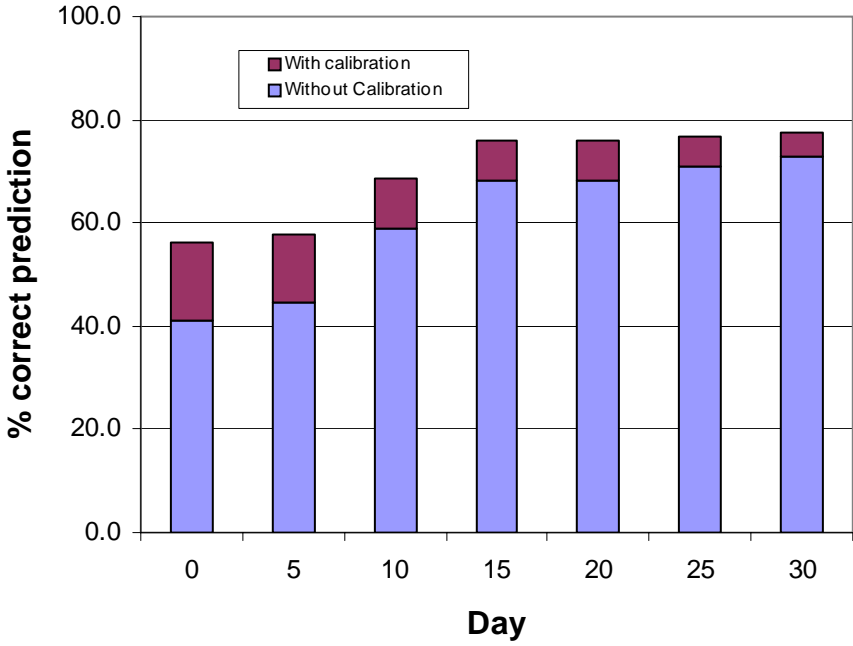


Fig. 9. Prediction improvement through rule calibration.

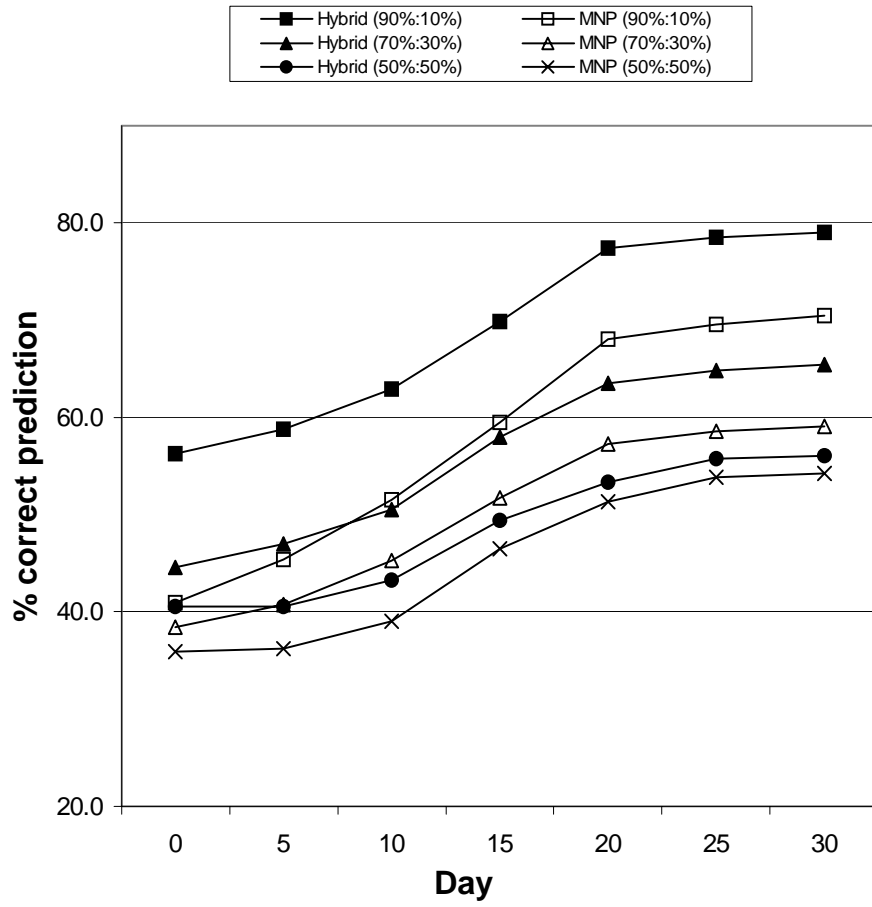


Fig. 10. Effect of the heterogeneity in driver behavior.

TABLE I
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	$U_{in}^1 = a_1 D_i + a_2 L_i + a_3 T_{in} + a_4 K_{in} + a_5 \Gamma_Q(Q_{in})$	$\phi_1\%$ of U_*^1
2	Familiarity Route Complexity	$U_{in}^2 = U_{in}^1 + a_6 \Gamma_F(F_{in}) + a_7 \Gamma_P(P_i)$	$\phi_2\%$ 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,

D_i = travel distance on route i

L_i = toll on route i

T_{in} = travel time estimated by driver n for route i

K_{in} = quantitative traffic information on route i for driver n

$\Gamma_Q(\cdot)$ = function to determine the numerical value of descriptive qualitative traffic information

Q_{in} = descriptive qualitative traffic information on route i for driver n

$\Gamma_F(\cdot)$ = function to determine the numerical value of familiarity

F_{in} = the number of times driver n took route i in the past

$\Gamma_P(\cdot)$ = function to determine the numerical value of route complexity

P_i = the number of nodes in route i

$\delta_{in} = 1$ if route i is the recommended route for driver n ; 0 otherwise

$\Gamma_C(\cdot)$ = function to determine the numerical value of compliance for 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

$\kappa_{in} = 1$ if route i is the current route for driver n ; 0 otherwise

$\Gamma_I(\cdot)$ = function to determine the numerical value of inertia for current route i

U_*^1, U_*^2 = the maximum utility values among U_{in}^1 and U_{in}^2 , respectively, over all n

TABLE II
FUZZY IF-THEN RULES

Attribute		LHS	RHS
Qualitative traffic information		If traffic condition is good If traffic condition is normal If traffic condition is poor	He/she will probably take the route He/she will be neutral He/she will probably not take the route
Familiarity		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	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
Complexity		If a route is simple If a route is normal If a route is complex	He/she will probably take the route He/she will be neutral He/she will probably not take the route
Compliance	Weather conditions	<i>Rule</i> ¹ : If weather is good <i>Rule</i> ² : If weather is bad	He/she will probably follow the recommended route He/she will probably not follow the recommended route
	Time-of-day	<i>Rule</i> ³ : If time-of-day is daytime <i>Rule</i> ⁴ : If time-of-day is nighttime	He/she will probably follow the recommended route He/she will probably not follow the recommended route
	Trip purpose	<i>Rule</i> ⁵ : If driver is on a business trip <i>Rule</i> ⁶ : If driver is on a leisure trip	He/she will probably follow the recommended route He/she will probably not follow the recommended route
Inertia	Weather conditions	<i>Rule</i> ⁷ : If weather is good <i>Rule</i> ⁸ : If weather is bad	He/she will probably switch from the current route He/she will probably not switch from the current route
	Time-of-day	<i>Rule</i> ⁹ : If time-of-day is daytime <i>Rule</i> ¹⁰ : If time-of-day is nighttime	He/she will probably switch from the current route He/she will probably not switch from the current route
	Trip purpose	<i>Rule</i> ¹¹ : If driver is on a business trip <i>Rule</i> ¹² : If driver is on a leisure trip	He/she will probably switch from the current route He/she will probably not switch from the current route