Behavior-consistent real-time traffic routing under information provision

Alexander Paz[a], Srinivas Peeta[b,*]

[a] *Howard R. Hughes College of Engineering, Civil and Environmental Engineering, University of Nevada, 4505 Maryland Parkway,PO Box 454015, Las Vegas, NV 89154-4015, USA.*
[b] *School of Civil Engineering, Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907-2051, USA.*

Abstract

The problem addressed here involves a controller seeking to enhance traffic network performance via real-time routing information provision to drivers while explicitly accounting for drivers' likely reactions towards the information. A fuzzy control modeling approach is used to determine the associated behavior-consistent information-based network control strategies. Experiments are performed to compare the effectiveness of the behavior-consistent approach with traditional dynamic traffic assignment based approaches for deployment. The results show the importance of incorporating driver behavior realistically in the determination of the information strategies. Significant differences in terms of system travel time savings and compliance to the information strategies can be obtained when the behavior-consistent approach is compared to the traditional approaches. The behavior-consistent approach can provide more robust performance compared to the standard user or system optimal information strategies. Subject to a meaningful estimation of driver behavior, it can ensure system performance improvement. By contrast, approaches that do not seek to simultaneously achieve the objectives of the drivers and the controller can potentially deteriorate system performance because the controller may over-recommend or under-recommend some routes, or recommend routes that are not considered by the drivers.

---

[*]Corresponding author. Tel.:+1 765 494 2209; fax:+1 765 496 7996.
E-mail address: peeta@purdue.edu. (S. Peeta).

1. Introduction

The state-of-the-art uses Dynamic Traffic Assignment (DTA) models to enhance in real-time the performance of vehicular traffic systems. These models predict the time-dependent network states and determine the corresponding information-based network control strategies. However, the current DTA literature does not factor driver behavior realistically or adequately in the determination of these strategies. Thereby, existing models can achieve system-wide objectives for assumed, though not necessarily realistic, scenarios that require the pre-specification of driver response behavior to the information strategies (Peeta and Yu, 2006). This implies a single level decision-making structure where the system controller determines: (i) in a prescriptive context, the vehicular route that each driver must take with the assumption that the driver follows this route, (ii) in a descriptive context, the estimated choice of the driver, or (iii) in a formal but inadequate consideration of the effect of behavior, the set of routing alternatives from which the driver chooses a route.

Most existing literature addresses the determination of deployable information-based network control strategies by focusing on generating consistent anticipatory route guidance and/or employing online consistency checking techniques. Here, "consistent" implies that traffic conditions used to generate the guidance must be similar to the realized conditions once the guidance is deployed. Doan et al. (1999) and Peeta and Bulusu (1999) identify various sources that can cause inconsistencies between the predicted and realized conditions. Peeta and Bulusu (1999) propose a generalized singular value decomposition approach to enable consistency between the predicted and realized network states in terms of link traffic counts and the number of users on various paths. Ben-Akiva et al. (2001) suggest that consistent guidance entails the formulation and solving of a fixed point problem. Bottom (2000) proposes a conceptual framework for the analysis of the consistent route guidance problem. It identifies the principal elements of the problem and their key relationships, and proposes some solution methods to the problem. It explicitly recognizes the need to estimate how drivers will react to the information provided to them. The solution methods are based on the idea of solving a fixed point problem formed by three alternative composite maps: (i) route assignment fractions to network states, (ii) network states to guidance messages, and (iii) guidance messages to route assignment fractions. He indicates that the solution to this fixed point problem leads to consistency. However, the problem is computationally intensive for real-world networks and this may preclude the deployment of the information in a timely manner. In addition, the framework focuses on the algorithmic and computational aspects of the problem while driver behavior is still represented using a traditional DTA approach. To alleviate the computational intensity of Bottom's framework (2000), Crittin and Bierlaire (2001) propose a heuristic method based on an approximated objective function. Zhou and Mahmassani (2005) address origin-destination demand consistency checking in conjunction with addressing network state consistency.

While the online consistency problem recognizes the need for an estimation of driver behavior, existing formulations and solution frameworks do not explicitly and/or realistically estimate and represent driver behavior while determining the information strategies. In reality, information provision and content can be used as control mechanisms

to only influence driver behavior but cannot imply perfect or pre-specified partial compliance rates, as is predominantly assumed in the DTA arena. This is because drivers make route choice decisions based on several factors related to behavior, information, and traffic conditions, and the information provided by the controller is only one aspect. It implies the need for a bi-level framework that captures the interactions between the controller objectives and driver decisions. Thereby, there is the need for the controller to factor the drivers' likely response to information-based control strategies while determining these strategies, suggesting a fixed-point problem structure. That is, deployable information strategies need to be more carefully constructed and are not as straightforward as suggested by the standard DTA deployment approaches. Also, even after such strategies, labeled behavior-consistent in this study, are determined and disseminated by the controller, there is no guarantee that the recommended route will be taken. However, as will be illustrated in Section 3.1.2, the likelihood of compliance increases as only routes that belong to the set of preferred routes of the individual drivers are recommended. Hence, this paper focuses on behavior-consistent strategies which are more acceptable to drivers and simultaneously are more likely to meet controller objectives.

The various limitations of DTA models to realistically represent driver route choices under information provision have motivated the development of new paradigms aimed at bridging functional gaps between driver behavior models and DTA models in terms of predicting the time-dependent network traffic flow patterns. In this context, Peeta and Yu (2006) develop a behavior-based consistency-seeking (BBCS) modeling approach. The approach uses a hybrid probabilistic-possibilistic behavior model to consistently address day-to-day learning and within-day dynamics of driver behavior in a single framework. It avoids assumptions of *a priori* knowledge of driver behavior class fractions as it is able to determine them in real-time based on link volumes. The BBCS models can be used to develop alternatives to DTA models to deploy information-based control strategies that are more realistic.

While the BBCS approach has modeling richness in the context of driver response behavior to information, the role of the controller is limited to the consistency-seeking process whereby the parameters of the driver behavior model are updated across multiple timescales based on the day-to-day and within-day experiences of the drivers. The logical next step is to involve the controller to develop behavior-consistent information-based network control strategies. It addresses the question: what information-based network control strategies should the controller adopt so that the drivers behaving the way they do also enable the controller to achieve its system-wide objectives? In other work (Paz and Peeta, 2009a), and as a first step to addressing this question, the authors develop a fuzzy logic control based approach to determine information-based strategies that are consistent with the controller-estimated response behavior of drivers to the information provided. It entails solving a fixed-point problem where these strategies depend on the controller-estimated driver response behavior and vice versa. In this paper, we close the loop by extending the framework to enable real-time deployment, and analyze the effectiveness of behavior-consistent information-based control strategies at the network level using a rolling horizon stage based approach where the actual driver behavior model is independent of the controller-estimated behavior model (Paz and Peeta, 2009b). The study also illustrates the limitations of standard DTA-based strategies.

The explicit consideration of driver behavior leads to a new dimension of complexity in predicting traffic states which is further complicated by the need to adequately capture the traffic flow dynamics that represent the network-level spatio-temporal interactions of driver route choice decisions. Typical DTA objectives (such as user equilibrium (UE) and/or system optimum (SO)), inherited from static traffic assignment concepts, have a single-level optimization structure which is at the controller level. However, in an operational context, using UE as a behavioral paradigm, or UE and SO as the information-based network control strategies with partial or perfect compliance rates, is an inherently restrictive approach from behavioral and information-related standpoints. Peeta and Yu (2004, 2006) illustrate the limitations of these strategies and the need to capture information-related driver learning processes and consider situational factors. Further, from an information standpoint, these strategies make strong assumptions on drivers' real-time knowledge about dynamic network conditions and their abilities to process the information provided by the controller in real-time, both of which can significantly influence driver route choice decisions.

This paper addresses the bi-level interactive decision-making process where the controller determines behavior-consistent information-based network control strategies and the drivers' route choice decisions are influenced by several factors. Fig. 1 illustrates conceptually the difference between the traditional DTA-based and the proposed behavior-consistent approaches. The traditional approach (part a) uses the DTA solutions directly as the information strategies to provide to drivers, while the behavior-consistent approach (part b) uses a fuzzy control based search procedure (Paz and Peeta, 2009a) to determine these strategies using the standard DTA solution and a controller-estimated driver behavior model.

This paper integrates several components in a rolling horizon framework to analyze the bi-level interactive decision-making process: a DTA model (Peeta, 1994), an iterative search based optimization procedure involving a fuzzy control model and a controller-estimated driver behavior model (Paz and Peeta, 2009a), a traffic flow simulator DYNASMART (Mahmassani, 2001) as a proxy for field conditions, and a path-size multinomial logit model to represent actual driver behavior. The latter two models will not be required in the real-world deployment context as field data is available. The DTA model computes the ideal proportion of drivers who should choose specific routes for the objective considered; for example, the SO solution. The optimization procedure is used to determine behavior-consistent strategies that direct the traffic system as close as possible to the DTA objective. The traffic flow simulator is used to capture the dynamic network level interactions and evaluate the system performance.

Given the tradeoffs that exist between the computational needs for real-time operations and the need to incorporate various problem dimensions adequately (for example, traffic flow and behavior modeling), the proposed solution framework does not explicitly solve the fixed point problem proposed by Bottom (2000) involving the three alternative composite maps. Instead, it takes advantage of an explicit estimation of driver behavior, and leverages the beneficial characteristics of the rolling horizon procedure and the projected SO solution, to determine the information strategies. The approach adopted here is to direct the system, through behavior-consistent information strategies, as close as possible to the projected SO DTA solution within a rolling horizon framework. It has four

synergistic characteristics. First, and the primary contribution of this paper, is that behavior consistency is explicitly incorporated. Second, the determination of the SO DTA solution for a specific roll period using projected traffic conditions provides a desirable goal for the controller to achieve through information provision. Third, the incorporation of evolving field traffic conditions through the rolling horizon framework from one roll period to the next significantly limits potential error propagation that can result from the non-projection of traffic conditions after the behavior-consistent strategies to be provided to drivers are determined. Finally, and consequent to the second and third characteristics, the determination of computationally very expensive iterative real-time DTA solutions to estimate projected traffic conditions is avoided. This enables the determination, in a timely manner, of effective and behaviorally more realistic information strategies that can lead to an enhancement in system performance.

The remainder of this paper is organized as follows. Section 2 describes the problem and Section 3 formulates it. Section 4 presents the solution concept. Section 5 discusses experiments and analyzes their results. Section 6 presents some concluding comments.

2. Problem description

The problem being addressed here is the behavior-consistent control of a vehicular traffic network for the period of interest, typically a peak traffic period. It is labeled behavior-consistent real-time traffic routing under information provision (BCRTRIP), and can be described as follows. A controller seeks to continuously optimize network performance by providing real-time traffic routing information to drivers where the drivers' likely response behavior is factored in determining the information. Hence, the problem being addressed here requires the determination of information-based network control strategies that are, to the extent possible, simultaneously consistent with the controller-estimated driver behavior and the objectives of the controller. After the information strategies are generated, they are disseminated to the drivers to influence their route choice decisions, and consequently system performance. We assume that every node (with alternative routing options) on the current route of a driver is a potential decision point, implying that en-route re-routing is possible. The performance of the system under the information strategies is continuously measured in real-time and new information strategies are computed based on the field data measurements.

Fig. 2 shows the conceptual flowchart for the BCRTRIP problem. The problem is represented using a rolling horizon stage based framework (Peeta, 1994) due to its deployment characteristic and the uncertainty associated with future time-dependent demand and network conditions. The planning horizon of interest, taken here as the peak traffic period, is divided into stages. Each stage is divided into a roll period and a tail period. Using the traffic network conditions in the roll period of the current stage σ, and the projected time-dependent O-D demand for the next stage $\sigma+1$, the behavior-consistent information-based network control strategies for the next roll period are determined at some point during the current roll period. At the end of the current roll period, the stage counter is incremented by one. In the next stage, the controller uses these information strategies to provide route recommendations to drivers. Each driver uses his/her behavioral logic (based on inherent behavioral tendencies, ambient traffic conditions, and the information provided

by the controller) to select a route from his/her preferred set of alternatives. The aggregation of all individual driver route choice decisions determines the network performance. The rolling horizon framework terminates if the end of the planning horizon is reached. If not, the controller tracks the system state (Paz and Peeta, 2009b) using sensor data (link traffic counts), and repeats the rolling horizon deployment process.

It should be noted here that the route selected by a driver can coincide with that recommended by the controller or differ from it partially or fully. Since the information provided by the controller factors the drivers' likely reactions to the information, the likelihood that a driver chooses the route recommended by the controller increases. Another point to note is that departure time choice is exogenous in our problem; that is, the possible impacts of pre-trip route guidance on departure time choice are not considered here.

Details on the implementation of the rolling horizon approach are shown in Fig. 3. Each stage consists of h discrete time intervals of length Δ time units. τ denotes the departure time interval. Further, as discussed in Section 4, for computational efficiency, a stage is also divided into discrete assignment intervals w. Each assignment interval consists of l time units. The first assignment interval is also the roll period of the stage. Thus, the stage length is a multiple of the roll period length. This facilitates, without loss of generality, the formulation description and solution implementation. The next section discusses the formulation.

3. Problem formulation

3.1. Notation and terms

3.1.1. Notation

Variable	Description
N	Set of nodes in the network
A	Set of links in the network
n	Index for a node in the network, $n \in N$
a	Subscript for a link in the network, $a \in A$
I	Set of origins in the network
J	Set of destinations in the network
i	Subscript for an origin node, $i \in I$
j	Subscript for a destination node, $j \in J$
κ	Superscript denoting a departure time interval up to the end of the current roll period, $\kappa = 1,\dots, \sigma \cdot l$
τ	Superscript for a departure time interval for the next stage, $\tau = \sigma \cdot l+1,\dots,\sigma \cdot l+h$
t	Superscript for the current time interval
$\rho(\sigma)$	Roll period indicator for stage σ; corresponds to $\kappa = (\sigma-1) \cdot l+1,\dots,\sigma \cdot l$
i^*	Subscript for the origin node of a driver who departed up to time interval $\sigma \cdot l$ and does not reach his/her destination in the current roll period, $i^* \in I$
φ	Number of time intervals of length Δ required to determine the information strategies for $\rho(\sigma+1)$

υ	Superscript for the time interval in which the computation of the information strategies for the next roll period begins, $\upsilon = \sigma\cdot l - \varphi$
K_{ij}	Set of routes connecting origin-destination (O-D) pair ij
k	Subscript for a route in the network, $k \in K_{ij}$
U	Set of driver classes in terms of information availability, $U \equiv \{1, 2\}$
u	Superscript for driver information class, $u \in U$; $u = 1$ if driver can receive information, and $u = 2$ if driver cannot receive information
$R_{ij}^{u\tau}$	Actual new O-D demand for the next stage, expressed as set of drivers of class u who wish to depart from i to j in time interval τ, $\tau = \sigma\cdot l+1,\dots, \sigma\cdot l+h$
$\hat{R}_{ij}^{u\tau}$	Forecasted new O-D demand for the next stage, expressed as the set of drivers of class u who wish to depart from i to j in time interval τ, $\tau = \sigma\cdot l+1,\dots,\sigma\cdot l+h$
$Q_{i*j}^{\kappa ua}$	Set of drivers of class u that departed origin i^* to destination j in time interval $\kappa = 1,\dots,\sigma\cdot l$ who have not reached their destinations at the end of the current roll period, and are on link a in time interval $\sigma\cdot l$
$\hat{S}_{i*ij}^{\kappa u\tau}$	Set of drivers of class u that departed origin i^* in time interval $\kappa = 1,\dots,\sigma\cdot l$ who have not reached their destinations at the end of the current roll period, and are forecasted to depart from the first intermediate node i to destination j in time interval τ in the next stage, $\tau = \sigma\cdot l+1,\dots,\sigma\cdot l+h$
$S_{i*ij}^{\kappa u\tau}$	Set of drivers of class u that departed origin i^* in time interval $\kappa = 1,\dots,\sigma\cdot l$ who have not reached their destinations at the end of the current roll period, and depart from the first intermediate node i to destination j in time interval τ in the next stage, $\tau = \sigma\cdot l+1,\dots,\sigma\cdot l+l$
$S_{ij}^{u\tau}$	Intermediate O-D demand for the next roll period due to previously generated vehicles, expressed as the set of drivers of class u who depart from i to j in time interval τ, $\tau = \sigma\cdot l+1,\dots,\sigma\cdot l+l$
$\hat{S}_{ij}^{u\tau}$	Forecasted intermediate O-D demand for the next stage due to previously generated vehicles, expressed as the set of drivers of class u who are forecasted to depart from i to j in time interval τ, $\tau = \sigma\cdot l+1,\dots,\sigma\cdot l+h$
r	Superscript for an individual driver in the network
$P\hat{K}_{ij}^{r}$	Controller-estimated set of preferred routes connecting O-D pair ij for driver r, $P\hat{K}_{ij}^{r} \subseteq K_{ij}$
PK_{ij}^{r}	Set of preferred routes connecting O-D pair ij for driver r, $PK_{ij}^{r} \subseteq K_{ij}$
$P\hat{K}_{ij}$	Controller-estimated set of driver-preferred routes connecting O-D pair ij, $P\hat{K}_{ij} = \left\{\bigcup_{r} P\hat{K}_{ij}^{r}\right\} \subseteq K_{ij}$
PK_{ij}	Set of driver-preferred routes connecting O-D pair ij, $PK_{ij} = \left\{\bigcup_{r} PK_{ij}^{r}\right\} \subseteq K_{ij}$
$DK_{ij}^{\rho(\sigma)}$	Set of controller-desired routes connecting O-D pair ij in roll period $\rho(\sigma)$ of stage σ, $DK_{ij}^{\rho(\sigma)} \subseteq K_{ij}$
$CK_{ij}^{\rho(\sigma)}$	Set of controllable routes connecting O-D pair ij in roll period $\rho(\sigma)$ of stage σ,

	$CK_{ij}^{\rho(\sigma)} \equiv \{ DK_{ij}^{\rho(\sigma)} \cap P\hat{K}_{ij} \}$
Ω^{ur}	Driver's information class relationship; 1 if driver r belongs to class u, and 0 otherwise
$\delta_{ijk}^{r\tau}$	Route choice dummy; 1 if driver r leaves from i to j in time interval τ and chooses route k, and 0 otherwise, $k \in PK_{ij}^r$
$\hat{\delta}_{ijk}^{r\tau}$	Controller-estimated route choice dummy; 1 if driver r is leaving from i to j in time interval τ and is estimated to take route k, and 0 otherwise, $k \in P\hat{K}_{ij}^r$
δ_{ijk}^{rv}	Dummy variable for current route of driver; 1 if driver r is traveling on route k from i to j in time interval v, and 0 otherwise, $k \in P\hat{K}_{ij}^r$
$\theta_{ijk}^{\rho(\sigma)}$	Prescriptive information defined as the proportion of drivers that must be recommended to take route k in roll period $\rho(\sigma)$ of stage σ, $k \in CK_{ij}^{\rho(\sigma)}$
$Y_{ijk}^{r\tau}$	Dummy variable for route recommendation for driver r leaving from i to j in future time interval τ; 1 if route k is recommended, and 0 otherwise, $k \in P\hat{K}_{ij}^r$
Y_{ijk}^{rv}	Dummy variable for the past route recommended to driver r as of time interval v; 1 if route k was recommended, and 0 otherwise, $k \in P\hat{K}_{ij}^r$
$X_{ijk}^{r\tau}$	Vector of attributes for route k, excluding information, that influence the route choice decision of driver r in time interval τ, $k \in PK_{ij}^r$
$\hat{X}_{ijk}^{r\tau}$	Controller-estimated vector of attributes for route k, excluding information, that influence the route choice decision of driver r in time interval τ, $k \in P\hat{K}_{ij}^r$
$T_{ijk}^{r\tau}$	Travel time experienced during the next roll period by driver r leaving node i at some point during that roll period for node j on route k in time interval τ, $k \in PK_{ij}^r$
$\varsigma_{ijk}^{tar\tau}$	Time-dependent driver spatio-temporal variable; 1 if driver r choosing route k (connecting O-D pair ij) in time interval τ is on link a in time interval t, and 0 otherwise
$d_{ijk}^{tau\tau}$	Number of drivers of class u traveling from i to j on route k in time interval τ who enter arc a in time interval t
$m_{ijk}^{tau\tau}$	Number of drivers of class u traveling from i to j on route k in time interval τ who exit link a in time interval t
x^{ta}	Number of drivers on link a at the beginning of time interval t
L_n^t	Number of drivers representing the demand at node n in time interval t
O_n^t	Number of drivers exiting the network through node n in time interval t
d^{at}	Number of drivers who enter link a in time interval t
m^{at}	Number of drivers who exit link a in time interval t
$B(n)$	Set of links incident from node n
$C(n)$	Set of links incident to node n
$\hat{F}$	Function to denote the controller-estimated driver behavior model used to estimate the route choices of the individual drivers

F	Function to denote the driver behavior model used to represent the actual route choices of the individual drivers
$\|\cdot\|$	Set cardinality denoting the number of elements in set $(\cdot)$

3.1.2. Definition of terms

Controller-Desired Routes (*DK*): These are routes that the controller would like the drivers to choose. These time-dependent routes can be determined, for example, by solving a SO DTA problem for a stage.

Driver-Preferred Routes (*PK*): These routes are preferred by the drivers and are likely to be accepted by them. These routes can be generated (Bekhor, et al., 2006) using historical data, travel surveys and/or technologies such as two-way communication systems and global positioning systems.

Controllable Routes (*CK*): These routes belong to both controller-desired and driver-preferred route sets. Recommending a route from this set to drivers increases the probability that it will be accepted by them, thereby enabling the controller to better influence system performance.

Behavior-Consistency Gap: The behavior-consistency gap for controllable route k connecting O-D pair ij is defined as the difference between the controller-desired proportion of drivers that should choose route k and the proportion of drivers $\theta_{ijk}^{\rho(\sigma)}$ that must be recommended route k in order to achieve the controller-desired proportion. Hence, depending on the system dynamics and driver behavior, greater/lesser proportions of drivers may have to be recommended controllable routes to achieve the controller-desired proportions.

3.2. Problem definition

Consider a directed graph $G(N,A)$ representing a traffic network with N nodes, A directed arcs, origins $i \in I$, and destinations $j \in J$. An origin, a destination and/or just a junction of physical links can be represented by a node. We are given the time-dependent O-D demand forecasts for the next stage, the number of previously assigned drivers who are present in the network at the beginning of the next stage and their current routes, the associated forecasts for the intermediate demand, the controller-estimated set of driver-preferred routes and their attributes, the information class of each driver, and the controller-estimated driver behavior model. The controller determines towards the end of the current roll period the behavior-consistent information-based network control strategies $\theta_{ijk}^{\rho(\sigma+1)}$ for the next roll period to provide to the O-D demand route recommendations so as to minimize the system travel time for the next roll period.

3.3. Formulation

Given:
(i) $G(N,A)$

(ii) $\hat{R}_{ij}^{u\tau}$; $\qquad \forall\, i, j, u,\ \tau = \sigma\cdot l+1,...,\sigma\cdot l+h$

(iii) $Q_{i*j}^{\kappa ua}$; $\qquad \forall\, i^*, j, u, a, \kappa = 1,...,\sigma\cdot l$

(iv) $\hat{S}_{i*ij}^{\kappa u\tau}$; $\qquad \forall\, i^*, i, j, \kappa = 1,...,\sigma\cdot l, u, \tau = \sigma\cdot l+1,...,\sigma\cdot l+h$

(v) $P\hat{K}_{ij}^{r}$; $\qquad \forall\, i, j, r\in\{\hat{R}_{ij}^{u\tau}\cup\hat{S}_{i*ij}^{\kappa u\tau}\}$

(vi) $\hat{X}_{ijk}^{r\tau}$; $\qquad \forall\, i, j, k\in P\hat{K}_{ij}^{r}, r\in\{\hat{R}_{ij}^{u\tau}\cup\hat{S}_{i*ij}^{\kappa u\tau}\}, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l$

(vii) $Y_{ijk}^{r\upsilon}$; $\qquad \forall\, i, j, k\in P\hat{K}_{ij}^{r}, r\in\hat{S}_{i*ij}^{\kappa u\tau}$

(viii) $\delta_{ijk}^{r\upsilon}$; $\qquad \forall\, i, j, k\in P\hat{K}_{ij}^{r}, r\in\hat{S}_{i*ij}^{\kappa u\tau}$

(ix) Ω^{ur} $\qquad \forall\, u, r\in\{\hat{R}_{ij}^{u\tau}\cup\hat{S}_{i*ij}^{\kappa u\tau}\}$

(x) $\hat{F}$

Objective function (controller objective):

$$\text{Min.}\{\sum_j\sum_u\sum_{t=\sigma\cdot l+1}^{\sigma\cdot l+l}[(\sum_{i*}\sum_{\kappa=1}^{\sigma\cdot l}\sum_a |Q_{i*j}^{\kappa ua}| - \sum_i\sum_{\tau=\sigma\cdot l+1}^{t}\sum_{r\in S_{ij}^{u\tau}}\sum_{k\in PK_{ij}^r}\delta_{ijk}^{r\tau}\cdot)\cdot\Delta] +$$

$$\sum_i\sum_j\sum_u\sum_{\tau=\sigma\cdot l+1}^{\sigma\cdot l+l}\sum_{r\in S_{ij}^{u\tau}}\sum_{k\in PK_{ij}^r}[T_{ijk}^{r\tau}\cdot\delta_{ijk}^{r\tau}(\theta_{ijk}^{\rho(\sigma+1)})] + \sum_i\sum_j\sum_u\sum_{\tau=\sigma\cdot l+1}^{\sigma\cdot l+l}\sum_{r=R_{ij}^{u\tau}}\sum_{k\in PK_{ij}^r}[T_{ijk}^{r\tau}\cdot\delta_{ijk}^{r\tau}(\theta_{ijk}^{\rho(\sigma+1)})]\} \qquad (1)$$

Subject to:

Controller-estimated driver behavior

$$\hat{\delta}_{ijk}^{r\tau} = \hat{F}[(\hat{X}_{ijk}^{r\tau}, Y_{ijk}^{r\tau}), \ \forall k\in P\hat{K}_{ij}^r]; \quad \forall\, i, j, k\in P\hat{K}_{ij}^r, r\in\{\hat{R}_{ij}^{u\tau}\cup\hat{S}_{ij}^{u\tau}\}, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (2)$$

Demand conservation constraints

$$\hat{S}_{ij}^{u\tau} = \bigcup_{\kappa=1}^{\sigma\cdot l}\bigcup_{i*}\hat{S}_{i*ij}^{\kappa u\tau}; \qquad \forall\, i, j, u, \tau = \sigma\cdot l+1,...,\sigma\cdot l+h \qquad (3)$$

$$S_{ij}^{u\tau} = \bigcup_{\kappa=1}^{\sigma\cdot l}\bigcup_{i*}S_{i*ij}^{\kappa u\tau}; \qquad \forall\, i, j, u, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (4)$$

$$\sum_{r\in S_{ij}^{u\tau}}\sum_{k\in PK_{ij}^r}[\delta_{ijk}^{r\tau}\cdot\Omega^{ur}]=|S_{ij}^{u\tau}|; \qquad \forall\, i, j, u, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (5)$$

$$\sum_{r\in R_{ij}^{u\tau}}\sum_{k\in PK_{ij}^r}[\delta_{ijk}^{r\tau}\cdot\Omega^{ur}]=|R_{ij}^{u\tau}|; \qquad \forall\, i, j, u, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (6)$$

Information-based network control constraints

$$\theta_{ijk}^{\rho(\sigma+1)} = g_\theta[(G(N,A), \hat{R}_{ij}^{u\tau}, \hat{S}_{ij}^{u\tau}, PK_{ij}^r, \hat{X}_{ijk}^{r\tau}, Y_{ijk}^{r\upsilon}, \delta_{ijk}^{r\upsilon}, \Omega^{ur}, \hat{\delta}_{ijk}^{r\tau}(\hat{F})), \forall\, i, j, k\in P\hat{K}_{ij}^r, u,$$
$$r, \tau = \sigma\cdot l+1,...,\sigma\cdot l+h]; \forall\, i, j, k\in CK_{ij}^{\rho(\sigma+1)} \qquad (7)$$

$$Y_{ijk}^{r\tau} = g_Y(\theta_{ijk}^{\rho(\sigma+1)}, Y_{ijk}^{r\upsilon}, \delta_{ijk}^{r\upsilon}, \Omega^{ur}); \ \forall\, i, j, k\in PK_{ij}^r, r\in\{R_{ij}^{u\tau}\cup S_{ij}^{u\tau}\}, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (8)$$

Flow modeling constraints

$$\delta_{ijk}^{r\tau} = F[(X_{ijk}^{r\tau}, Y_{ijk}^{r\tau}), \ \forall k\in PK_{ij}^r]; \quad \forall\, i, j, k\in PK_{ij}^r, r\in\{R_{ij}^{u\tau}\cup S_{ij}^{u\tau}\}, \tau = \sigma\cdot l+1,...,\sigma\cdot l+l \qquad (9)$$

$$\xi_{ijk}^{ta\,r\tau} = g_\xi[(R_{ij}^{u\tau}, Q_{i*j}^{\kappa ua}, \delta_{ijk}^{r\tau}),\ \forall\ i, i*, j, k \in PK_{ij}^r,\ \kappa = 1,...,\sigma \cdot l,\ u, a, r \in \{R_{ij}^{u\tau} \cup Q_{i*j}^{\kappa ua}\},$$

$$\tau = \sigma \cdot l+1,...,\sigma \cdot l+l];\ \forall\ i, j, k \in PK_{ij}^r,\ t, a, r \in \{R_{ij}^{u\tau} \cup Q_{i*j}^{\kappa ua}\},\ \tau = \sigma \cdot l+1,...,\sigma \cdot l+l \tag{10}$$

$$x^{ta} = \sum_i \sum_j \sum_k \sum_r \sum_\tau \xi_{ijk}^{t-1,ar\tau};\qquad \forall\ t, a \in A \tag{11}$$

$$T_{ijk}^{r\tau} = \sum_{t=\sigma \cdot l+1}^{\sigma \cdot l+l} \sum_a (\xi_{ijk}^{ta\,r\tau} \cdot \Delta);\qquad \forall\ i, j, k \in PK_{ij}^r,\ r \in \{R_{ij}^{u\tau} \cup S_{ij}^{u\tau}\},\ \tau = \sigma \cdot l+1,...,\sigma \cdot l+l \tag{12}$$

$$x^{\sigma \cdot l+1,a} = \sum_{\kappa=1i*}^{\sigma \cdot l} \sum_j \sum_u | Q_{i*j}^{\kappa ua} |;\qquad \forall\ a \in A \tag{13}$$

Flow conservation constraints at nodes and links

$$\sum_b d^{tb} = \sum_c m^{tc} + L_n^t - O_n^t;\qquad \forall\ t, n \in I,\ b \in B(n),\ c \in C(n) \tag{14}$$

$$x^{ta} = x^{t-1,a} + d^{t-1,a} - m^{t-1,a};\qquad \forall\ t, a \in A \tag{15}$$

Definitional constraints

$$d^{ta} = \sum_i \sum_j \sum_k \sum_u \sum_\tau d_{ijk}^{tau\tau};\qquad \forall\ t, a \in A \tag{16}$$

$$m^{ta} = \sum_i \sum_j \sum_k \sum_u \sum_\tau m_{ijk}^{tau\tau};\qquad \forall\ t, a \in A \tag{17}$$

$$L_n^t = \sum_j \sum_u | R_{nj}^{ut} | + \sum_j \sum_u | S_{nj}^{ut} |;\qquad \forall\ t, n \in I \tag{18}$$

$$O_n^t = \sum_i \sum_k \sum_c \sum_u \sum_\tau m_{ink}^{tcu\tau};\qquad \forall\ t, n \in J \tag{19}$$

0-1 *variable constraints*

$$\xi_{ijk}^{ta\,r\tau} = 0\ \text{or}\ 1;\qquad \forall\ i, j, k \in PK_{ij}^r,\ t, a \in A,\ r \in \{R_{ij}^{u\tau} \cup S_{ij}^{u\tau}\},\ \tau = \sigma \cdot l+1,...,\sigma \cdot l+l \tag{20}$$

$$\hat{\delta}_{ijk}^{r\tau} = 0\ \text{or}\ 1;\qquad \forall\ i, j, k \in P\hat{K}_{ij}^r,\ r \in \{\hat{R}_{ij}^{u\tau} \cup \hat{S}_{ij}^{u\tau}\},\ \tau = \sigma \cdot l+1,...,\sigma \cdot l+l \tag{21}$$

$$\delta_{ijk}^{r\upsilon} = 0\ \text{or}\ 1;\qquad \forall\ i, j, k \in PK_{ij}^r,\ r \in Q_{i*j}^{\kappa ua} \tag{22}$$

$$\Omega^{ur} = 0\ \text{or}\ 1;\qquad \forall\ u, r \in \{R_{ij}^{u\tau} \cup Q_{i*j}^{\kappa ua}\} \tag{23}$$

$$Y_{ijk}^{r\tau} = 0\ \text{or}\ 1;\qquad \forall\ i, j, k \in PK_{ij}^r,\ r \in \{R_{ij}^{u\tau} \cup S_{ij}^{u\tau}\},\ \tau = \sigma \cdot l+1,...,\sigma \cdot l+l \tag{24}$$

$$Y_{ijk}^{r\upsilon} = 0\ \text{or}\ 1;\qquad \forall\ i, j, k \in PK_{ij}^r,\ r \in Q_{i*j}^{\kappa ua} \tag{25}$$

Temporal correctness constraint

$$\tau \le t \tag{26}$$

Non-negativity constraints

all variables ≥ 0 $\tag{27}$

This formulation is a non-linear mixed integer model with some stochastic variables ($\hat{\delta}_{ijk}^{r\tau}, \delta_{ijk}^{r\tau}$). It integrates in a stage-based rolling horizon framework several components

that are required to adequately model and address the BCRTRIP problem. A primary contribution to the literature is that it explicitly considers network dynamics and driver behavior. That is, the system states and the information strategies depend on both driver behavior and traffic flow dynamics resulting from individual driver route choice decisions. Another key contribution is that the controller does not pre-specify driver behavior but rather estimates their likely behavior under information provision. Hence, the formulation includes two driver behavior models; one ($\hat{F}$) is used to explicitly estimate driver behavior while the other (F) is used to represent actual driver behavior. It is important to note that in a real-world deployment context the controller does not know the actual driver behavior *a priori*. Consequently, the information strategies are determined using only the estimation of the driver behavior. The information strategies are used to provide routing information to the drivers who make route choice decisions based on their behavioral tendencies and the controller-provided information. This denotes the bi-level interactive decision-making structure discussed in Section 1. The formulation also uses the concept of route classification based on the relevance of routes to the drivers and the controller, as defined in Section 3.1.2. This concept is developed by Paz and Peeta (2009a) and is used here to provide a realistic deployment mechanism to enhance driver compliance in a behavior-consistent manner. Further, the approach determines whom to provide information to, based on the identification of priorities (Paz and Peeta, 2009a). These contributions together enable the development of the behavior-consistent approach.

The decision variables are the set of information-based network control strategies $\theta_{ijk}^{\rho(\sigma+1)}$, $\forall\ i, j, k \in CK_{ij}^{\rho(\sigma+1)}$. The set of controller-desired routes $DK_{ij}^{\rho(\sigma+1)}$ is explicitly differentiated from the controller-estimated set of driver-preferred routes PK_{ij} leading to the concept of controllable routes $CK_{ij}^{\rho(\sigma+1)}$, $\forall\ i, j$. There are different time scales associated with: (i) the projection of network conditions to determine the information strategies, and (ii) the evaluation of system performance under these strategies. Depending on the case, the superscript τ is defined to take values corresponding to the length of a stage or the length of a roll period.

3.3.1. Objective function

Equation (1) represents the controller's objective, the minimization of the system travel time for the next roll period. This travel time is equal to the summation of all the realized individual driver travel times during this period, and can be computed using three components. The first component is the travel time that drivers who have not reached their destinations before the end of the current roll period ($r \in Q_{i*j}^{\kappa u a}$) spend traveling in the next roll period before reaching their first intermediate node. It is possible that a driver may not reach such a node in the next roll period. This component is divided in two sub-components. The first sub-component is a constant term equal to the number of drivers in the set $Q_{i*j}^{\kappa u a}$ times the number of time intervals in the next roll period, multiplied by Δ, resulting in the travel time that those drivers would spend during the next roll period if they

did not reach their first intermediate node. The second sub-component computes the cumulative number of drivers in $Q_{i*j}^{\kappa u a}$ that reach their first intermediate node in each successive time interval of the next roll period, and multiplies them with Δ, to determine the travel time that those drivers would spend traveling during the next roll period after reaching their first intermediate node. Hence, the difference between these two sub-components gives the travel time that drivers in $Q_{i*j}^{\kappa u a}$ spend traveling in the next roll period before reaching their first intermediate node. The second component is the travel time of the intermediate demand ($r \in S_{ij}^{u\tau}$) drivers from their first intermediate node in the next roll period. Similarly, the third component computes the travel time of the new demand ($r \in R_{ij}^{u\tau}$) drivers from their origin in the next roll period.

3.3.2. Controller-estimated driver behavior

Constraint (2) denotes the controller-estimated route choice for driver *r* (represented through $\hat{\delta}_{ijk}^{r\tau}$) as a function ($\hat{F}$) of the estimated route attributes $\hat{X}_{ijk}^{r\tau}$, and the route recommendation 0-1 dummy $Y_{ijk}^{r\tau}$. A hybrid fuzzy multinomial logit model is used to represent the controller-estimated driver behavior model. It is a fuzzy model because its systematic component is determined using simple *if-then* rules processed through fuzzy logic (Tsoukalas and Uhrig, 1997), while its error terms are i.i.d extreme value distributed (Lotan and Koutsopoulos, 1993, 1999; Peeta and Yu, 2004, 2006). $\hat{X}_{ijk}^{r\tau}$ consists of the controller-estimated expected route travel times *TT* and the number of nodes *NN* for each route. Table 1 shows the set of *if-then* rules used in this study. Details on function $\hat{F}$ are provided in Paz and Peeta (2009b).

3.3.3. Demand conservation constraints

Constraints (3) and (4) represent intermediate demand conservation constraints. Constraint (3) states that the intermediate O-D demand for the next stage forecasted towards the end of the current roll period is equal to the aggregation of all previously forecasted drivers that have not yet reached their destination ($\hat{S}_{i*ij}^{\kappa u\tau}$). This forecasted demand is used along with the forecasted new demand to generate information strategies for the next roll period towards the end of the current stage. Constraint (4) indicates that the actual intermediate O-D demand for the next roll period is equal to the aggregation of all drivers that departed their initial origin before the end of the current roll period and have not reached their destination before the beginning of the next roll period ($S_{i*ij}^{\kappa u\tau}$).

Constraints (5) and (6) denote actual intermediate and new demand conservation constraints, respectively. They are used to ensure that all drivers in $S_{ij}^{u\tau}$ and $R_{ij}^{u\tau}$ have chosen a route to their corresponding destinations. Here, the product $\delta_{ijk}^{r\tau} \cdot \Omega^{ur}$ takes value 1 if driver *r* of class *u* chooses route *k* in time interval τ, and 0 otherwise.

3.3.4. Information-based network control constraints

Constraints (7) and (8) represent the information-based network control constraints. Constraint (7) states that the behavior-consistent information-based network control strategies are a function of the time-dependent O-D demand forecasts for the next roll period, the number of previously assigned drivers who are present in the network at the beginning of the next stage and their current routes, the controller-estimated set of driver-preferred routes and their attributes, the information class of each driver, and the controller-estimated driver behavior model. Here, g_θ denotes a procedure used to determine the information strategies for the next roll period; in this study we use the iterative search based optimization procedure described in Paz and Peeta (2009a) as part of the solution algorithm described in Section 4. The iterative search based optimization procedure is a sub-problem of the broader problem discussed in this paper. It only solves for the information strategies but does not address the broader problem depicted in Fig. 2 and described in Section 2.

Constraint (8) denotes the discretization of the information strategies to determine the specific routes to recommend to a subset of drivers selected according to the behavior-consistent strategy. It uses a priority scheme where drivers considered to receive route recommendations are categorized in priority subgroups based on their existing routes, prior route recommendations, and their responses to these recommendations. Constraints (2), (7) and (8) together indicate that $\hat{\delta}_{ijk}^{r\tau}$ is a function of $\theta_{ijk}^{\rho(\sigma+1)}$ and vice versa, implying the fixed-point structure of (7). Details of the priority scheme are provided in Paz and Peeta (2009a).

3.3.5. Flow modeling constraints

Constraints (9)-(13) represent the flow modeling constraints. Constraint (9) states that the route choice for driver r (represented through dummy $\delta_{ijk}^{r\tau}$) is a function (F) of the route attributes $X_{ijk}^{r\tau}$ (such as past experience, inertia, and route complexity) and the route recommendation (information) dummy $Y_{ijk}^{r\tau}$. Function F symbolically represents individual driver behavior and is not an explicit model/procedure. In reality, the actual driver behavior mechanism is unknown to the controller and manifests itself through the realized network conditions. In the study experiments, in the absence of field data, a specific model (discussed in Section 5.1.4) is used to represent F.

Constraints (10)-(12) incorporate time-dependent driver spatio-temporal variables $\zeta_{ijk}^{tar\tau}$ to represent traffic flow evolution as a function of the driver route choices ($\delta_{ijk}^{r\tau}$). Constraint (10) uses the time-dependent driver spatio-temporal variable $\zeta_{ijk}^{tar\tau}$ to track the driver; it indicates if driver r leaving from i to j choosing route k in time interval τ is on link a in time interval t. Function g_ζ symbolically represents the traffic flow evolution in the network and captures the complex nonlinear spatio-temporal interactions among vehicles. It is typically modeled using a traffic flow simulator. However, in the real-world deployment

context, $\zeta_{ijk}^{tar\tau}$ represents the realized network conditions. Existing DTA models do not incorporate the driver spatio-temporal variables which involve driver decision-making as an integral element of these variables. Instead, they use time-dependent link-path incidence variables to determine the presence of a vehicle on a given link across time intervals. These incidence variables are typically the outcome of an assignment process undertaken by a system controller where full or partial compliance to the information provided is assumed. Hence, the incidence variables do not adequately represent driver behavior and the resulting models are behaviorally restrictive and limited in their ability to model driver response to information provision. By contrast, the time-dependent driver spatio-temporal variables seamlessly incorporate driver behavior and the network-level interactions. That is, the $\zeta_{ijk}^{tar\tau}$ variables enable the actual network dynamics to be the result of the actual driver route choices.

Constraint (11) computes the number of drivers on link a at the beginning of time interval t using the driver spatio-temporal variable values from interval t-1. Constraint (12) states that the individual route travel times are the summation of the number of time intervals in which a 0-1 driver spatio-temporal variable (for a given i, j, k and τ) takes a value 1, multiplied by Δ. It implies the number of discrete time intervals that the corresponding driver r spends in the system. Constraint (13) is a boundary conservation constraint that ensures that all drivers who have not reached their destinations before the end of the current roll period are present at the beginning of the next roll period where they are located at the end of the current roll period.

3.3.6. Flow conservation constraints at nodes and links

Constraints (14) and (15), respectively, represent the conservation of vehicles at nodes and links. Constraint (14) states that at time t on node n, the number of vehicles entering all links incident from the node should equal the sum of the number of vehicles exiting from all links incident to that node and the net demand. Constraint (15) states that at the beginning of time interval t, the number of vehicles on link a is the sum of the number of vehicles on the link at the beginning of the previous time interval (t-1) and vehicles entering the link in the previous time interval, minus the vehicles exiting the link in the previous time interval.

3.3.7. Definitional constraints

Constraints (16)-(19) are definitional constraints. Constraints (16) and (17) are, respectively, the definitional constraints for the number of vehicles entering and exiting links. Constraint (18) states that the number of vehicles representing the demand at node n in time interval t is the sum of the corresponding new and intermediate demand. Constraint (19) is the definitional constraint for the number of vehicles exiting the network at node n in the time interval t.

3.3.8. 0-1, temporal correctness, and non-negativity constraints

Constraints (20)-(25) restrict specific variables to take a value 0 or 1. Constraints (26) are the temporal correctness constraints that restrict the departure time interval τ to be at most the current time interval t. Constraints (27) indicate the non-negativity requirement for all variables.

4. Solution concept

A key difference of the behavior-consistent approach compared to most traditional DTA approaches is that the controller only recommends routes to a subset of drivers, and does not assume compliance, whether complete or based on an artificial rate. The system states are determined by the driver decisions, but these decisions can be influenced by the information provided by the controller. Thus, the controller only has limited "control" on the system through information provision. Therefore, the controller objective is to "guide" the system, to the extent possible, towards a desired state in each stage (for example, the SO solution) by adjusting its information provision strategies. The route chosen by a driver is decided by his/her (actual) behavior.

Fig. 4 shows the solution framework for the BCRTRIP problem. The controller uses a rolling horizon stage-based deployment framework and seeks to direct the system towards the time-dependent SO DTA state. It should be noted here that the UE DTA state or any other controller objective could also be used in this framework without loss of generality. Given the traffic network conditions in the current roll period $\rho(\sigma)$ and the projected time-dependent O-D demand for the next stage $\sigma+1$, the corresponding SO DTA solution for the next stage is generated. For computational efficiency, the SO route assignment proportions are assumed constant within each assignment interval of the stage, though they vary across these intervals. The controller then uses the SO proportions and an iterative search procedure to determine the behavior-consistent information-based network control strategies to provide route guidance to the drivers, so that the actual driver decisions in the next roll period result in close to SO route proportions. The iterative search optimization procedure (Paz and Peeta, 2009a), represented by the non-shaded box located in the middle of the flowchart in Fig. 4, involves a controller-estimated driver behavior model and a fuzzy control model. The fuzzy control model represents the search mechanism (direction and step size). The iterative search optimization procedure determines the behavior-consistent route proportions for the next roll period that should be recommended to the drivers. At the end of the current roll period, the stage counter is incremented by one. In the next roll period, the controller uses the behavior-consistent route proportions to provide route recommendations to a prioritized subset of drivers (Paz and Peeta, 2009a). The system states for that roll period are a function of the driver routes, which include decisions by the subset of drivers that receive information. If the end of the current roll period does not represent the end of the planning horizon, the controller measures the system state using sensor data, and repeats the process for the next roll period. Otherwise, the rolling horizon framework is terminated.

In this framework, the routes that are recommended to the drivers are only those that are simultaneously driver-preferred and move the system closer to the SO state. That is, the SO routes which are not considered by the drivers (do not belong to their preferred choice set) are not recommended to them. Some O-D pairs may not have routes that are simultaneously

SO and driver-preferred, in which case no search is done for them. In other work, the authors have developed alternative paradigms where the controller uses routes that match SO routes to a significant degree (Paz and Peeta, 2009c). This introduces deployment flexibility by enabling the practical implementation of the behavior-consistent strategies.

The solution approach computes the SO proportions for each assignment interval of the next stage by solving the SO DTA problem for the length of that stage. However, the information strategies are determined only for the next roll period using the corresponding SO proportions. The effects of the projected O-D demand and the network level interactions on the information strategies for the next roll period are captured to some extent through the computation of the SO DTA for the length of the stage. This is because the SO proportions in each assignment interval are interdependent with the projected conditions and/or assignments for the rest of the stage.

4.2. Algorithmic solution framework

The algorithmic steps of the solution framework are briefly described hereafter. It uses off-line and on-line components. The off-line component, which is represented by Step 0, determines the driver-preferred route sets and the corresponding controller-estimated expected travel times for drivers. The on-line components, represented by Steps 1-6, are used to determine and deploy the information-based network control strategies.

Step 0: estimation of preferred routes and expected travel times for the current day

Estimate the driver-preferred route sets and their corresponding time-dependent controller-estimated expected travel times for the current day. These can be done through a combination of historical data, travel surveys, and/or technologies such as two-way communication systems and global positioning systems. In this paper, a heuristic approach is used to generate the route sets and the expected travel times for the experiments, as discussed in the experimental setup.

Step 1: initialization

To initialize the stage-based solution framework for the current day, set $\sigma = 1$ and $\theta_{ijk}^{\rho(\sigma+1)} = 0, \forall i, j, k$.

Step 2: determination of the SO states

Given the network conditions for the roll period $\rho(\sigma)$ and the projected time-dependent O-D demand for the next stage $\sigma+1$, the time-dependent SO DTA solution is computed for the various assignment intervals of the next stage. The SO DTA solution provides the controller-desired route sets $DK_{ij}^{\rho(\sigma+1)}$ and the corresponding SO proportions $SO_{ijk}^{\rho(\sigma+1)}$ of drivers assigned to these routes during the next roll period, $\forall i, j, k \in DK_{ij}^{\rho(\sigma+1)}$.

Step 3: *iterative search based optimization procedure*

This step consists of sub-steps 3.1-3.3 that represent an iterative search procedure. The iteration counter is set to 1.

Step 3.1*: controller's estimation of driver behavior*

The controller-estimated driver behavior model $\hat{F}$ is used to compute the controller-estimated proportions of drivers, $E_{ijk}^{\rho(\sigma+1)}$, taking routes for the next roll period based on the corresponding information-based network control strategies $\theta_{ijk}^{\rho(\sigma+1)}$, $\forall$ *i, j, k*$\in CK_{ij}^{\rho(\sigma+1)}$.

Step 3.2*: update of the information strategies*

The fuzzy control model is used to adjust the information-based network control strategies $\theta_{ijk}^{\rho(\sigma+1)}$ based on the difference between the SO proportions $SO_{ijk}^{\rho(\sigma+1)}$ and the controller-estimated route choice proportions $E_{ijk}^{\rho(\sigma+1)}$, $\forall$ *i, j, k*$\in CK_{ij}^{\rho(\sigma+1)}$.

Step 3.3*: convergence check*

Check for convergence. Convergence is achieved when the controller-estimated proportions $E_{ijk}^{\rho(\sigma+1)}$ do not change from one iteration to the next by more than a pre-specified threshold value, $\forall$ *i, j, k*$\in CK_{ij}^{\rho(\sigma+1)}$. If convergence is achieved, the set of behavior-consistent information-based network control strategies $\theta_{ijk}^{\rho(\sigma+1)}$ for the next roll period are available; go to Step 4. If convergence is not achieved, the iteration counter is updated by 1; go to Step 3.1.

Step 4*: stage update and dissemination of information*

At the end of the roll period, the projection horizon is rolled forward by *l* time units to obtain the next stage ($\sigma = \sigma +1$). Route recommendations $Y_{ijk}^{r\tau}$ are provided to the drivers during the roll period $\rho(\sigma)$ using the behavior-consistent information-based network control strategies $\theta_{ijk}^{\rho(\sigma)}$.

Step 5*: evaluation of system performance*

The system performance and the field conditions for the roll period are determined by the driver route choice decisions (based on behavioral tendencies, the routes

characteristics $X_{ijk}^{r\tau}$, and the information provided by the controller $Y_{ijk}^{r\tau}$.

Step 6: check for termination

The solution framework terminates if the end of the planning horizon for the day is reached. If not, go to Step 2 of the algorithm.

5. Experiments

Simulation experiments are conducted for the BCRTRIP problem to address two primary objectives: (i) to provide insights in terms of the ability of the iterative search based optimization procedure to determine, at the network-level and in real-time, robust behavior-consistent information-based network control strategies, and (ii) to compare the performance of the behavior-consistent strategies with that of the traditional DTA-based strategies. Here, robustness implies the explicit assurance of behavior consistency. That is, it reduces the possibility that the controller may over-recommend or under-recommend routes, or recommend routes that are not considered by the drivers. The results show that the behavior-consistent approach is capable of determining information strategies that improve system performance under different levels of responsiveness. Elsewhere (Paz and Peeta, 2009c), the authors show that the proposed approach can provide effective information strategies when the controller seeks to direct the system towards different objectives (e.g., SO, UE) and/or recommends routes that do not perfectly match SO routes.

5.1. Experimental setup

5.1.1. Network characteristics

Fig. 5 illustrates the Borman expressway corridor network. Experiments are conducted using this network and synthetic data. The network is located in northwest Indiana and consists of a sixteen-mile section of I-80/94 (known as the Borman expressway), I-90 toll freeway, I-65, and the surrounding arterials and streets. It has 197 nodes, 460 links, and 43 zones (with centroids that represent origins/destinations). The Borman expressway is a highly congested facility with substantial truck traffic. An advanced traffic management system has been installed on the network to provide drivers with real-time traffic information, especially during incidents. A potential alternative to divert traffic is the Indiana toll road I-90, which operates parallel to the Borman expressway. Depending on the destination, other potential major alternative routes also exist.

5.1.2. Behavior characteristics

As illustrated in Table 1, two types of drivers are considered based on their level of responsiveness to information. The first type of drivers, categorized as "less responsive" to information strategies, are drivers that are slightly influenced by the information provided. To make route choice decisions, these drivers rely more on past experience and behavioral

tendencies than on information. The second type of drivers, labeled as "more responsive" to information strategies, are more influenced by information compared to the "less responsive" drivers. Experiments are conducted to evaluate the performance of the proposed approach under these two levels of responsiveness. It is assumed that drivers are either 100 % less responsive or 100 % more responsive. This is designed to isolate the effects of the information strategies due to different behavioral tendencies from those of other issues such as market penetration.

5.1.3. Driver-preferred routes and their controller-estimated expected travel times

The driver-preferred route sets and their corresponding time-dependent controller-estimated expected travel times are estimated using a two-step off-line approach. In the first step, a UE DTA problem is solved for the entire planning horizon using an average time-dependent demand matrix. It provides an initial set of UE routes based only on travel time as input for the next step. In the second step, several simulation runs are conducted using the controller-estimated driver behavior model to determine up to five routes that represent the routes of most drivers for an O-D pair. These routes and their corresponding time-dependent travel times represent, respectively, the driver-preferred route sets and the time-dependent controller-estimated expected travel times.

The two-step approach is designed to represent the learning process that most drivers experience over time in the context of the determination of their preferred route choice set and their corresponding expected travel times. This is based on the premise that a driver considers only a subset of possible O-D routes based on past experience and imperfect/incomplete current knowledge of the traffic network.

5.1.4. Actual driver behavior

This study uses a random coefficients path-size multinomial logit model to represent the actual behavior of the drivers (function F in Section 3.3). Equation (28) shows the model specification. The path-size component (Equation (29)) corresponds to the general specification proposed by Ben-Akiva and Bierlaire (1999) and extended by Ramming (2002). It accounts for links being common to different routes. That is, the path-size component is an approximated measure of the amount of overlap of a route with all other routes in the choice set. Ignoring the effects of link overlaps across the choice set can result in unrealistic volumes over the set of common links.

It is assumed in this study that the distributions of the coefficients (β) are identical across all drivers. However, as indicated in Equation (28), the values of these coefficients vary across individual drivers to represent random taste variations across drivers. This study assumes a 10% uniform random variation with respect to the mean ($\pm 5\%$) of the coefficients.

$$U_{ijk}^{rt} = \beta_{ET}^r \cdot ET_{ijk}^{rt} + \beta_C^r \cdot C_{ijk} + \beta_Y^r \cdot Y_{ijk}^{rt} + \beta_{PS}^r \cdot \ln(PS_{ijk}^r) + \beta_{SW}^r \cdot SW_{ijk}^{rt} + \varepsilon_{ijk}^{rt}; \quad \forall\ i,j,k \in PK_{ij}^r, r, t \quad (28)$$

where,

$$PS_{ijk}^{r} = \sum_{a \in \Gamma_{ijk}} \left(\frac{l_a}{L_{ijk}} \right) \frac{1}{\sum\limits_{m \in PK_{ij}^{r}} \left(\frac{L_{ijk}^{\lambda}}{L_{ijm}^{\lambda}} \cdot \Theta_{aijm} \right)}; \qquad \forall\, i, j,\, k \in PK_{ij}^{r},\, r \qquad (29)$$

$$SW_{ijk}^{rt} = 1 \Leftrightarrow \left[\frac{\sum\limits_{n \in \Pi_{ijk}} n}{\sum\limits_{n \in \Pi_{ij\widetilde{m}}} n} = 1 \right],\, 0 \text{ otherwise;} \qquad \forall\, i, j,\, k \in PK_{ij}^{r},\, r, t \qquad (30)$$

U_{ijk}^{rt} is the utility of route k for driver r leaving node i for node j in period t, $k \in PK_{ij}^{r}$

β_x^r is the coefficient of variable/function x for driver r

ET_{ijk}^{rt} is the driver-expected travel time on route k for driver r leaving node i for node j in period t, $k \in PK_{ij}^{r}$

C_{ijk} is the number of nodes on route k connecting ij, $k \in PK_{ij}^{r}$

PS_{ijk}^{r} is the path-size component for driver r and route k connecting ij, $k \in PK_{ij}^{r}$

Γ_{ijk} is the set of links on route k connecting ij, $k \in PK_{ij}^{r}$

l_a is the length of link a, $a \in A$

L_{ijk} is the length of route k connecting ij, $k \in PK_{ij}^{r}$

Θ_{aijm} is the link-route incidence dummy; 1 if route m connecting ij uses link a, and 0 otherwise

λ is a path-size model parameter

Π_{ijk} is the set of nodes on route k connecting ij, $k \in PK_{ij}^{r}$

SW_{ijk}^{rt} is a route switching dummy; 1 if by choosing route k connecting ij in period t, driver r is not making a route switching from his/her current route $\widetilde{m}$, and 0 otherwise, $k \in PK_{ij}^{r}$

ε_{ijk}^{rt} is an i.i.d. extreme value disturbance or random component for driver r in time period t for route k connecting ij, $k \in PK_{ij}^{r}$

The mean values of the coefficients were selected based on previous studies and problem characteristics. For example, a slightly higher value for β_Y is used to represent more responsive behavior in comparison to the less responsive behavior.

In the study experiments, it is assumed that the approach adopted in Section 5.1.3 provides reasonable estimates for the controller-estimated expected travel times, which are then multiplied by a uniform random number (between 0.95 and 1.05) to determine the driver-expected travel times (ET). This is to represent the notion that the controller may not have perfect knowledge of the driver-expected travel times.

In addition, it is important to reiterate here that the model used to represent driver behavior is completely different from the model used to estimate it. In the real world

deployment context, the actual driver behavior replaces the model (Equation (28)) used to determine it and the controller-estimated driver behavior model is calibrated using the observed data.

The route choice probabilities obtained from this model are converted to $\delta_{ijk}^{r\tau}$ using the following approach. First, the probability range for a driver is demarcated into smaller ranges according to the choice probabilities. For example, if there are three routes with estimated choice probabilities 0.2, 0.3, and 0.5, the ranges associated with them are 0.0-0.2, 0.2-0.5, and 0.5-1.0, respectively. Second, a uniform random number generator is used to generate a value between 0 and 1. Third, if the generated random number falls in the range associated with a specific route, that route is assigned to the driver. The same approach is used to determine $\hat{\delta}_{ijk}^{r\tau}$ from the values obtained through $\hat{F}$.

5.1.5. Traffic flow simulation-assignment model

A traffic simulation-assignment model, DYNASMART, is used here to achieve two objectives: (i) to determine in each stage the time-dependent SO solution (Step 2 of the solution framework) using the DTA module of DYNASMART, and (ii) to evaluate the system performance in each roll period under the time-dependent demand and driver route choice decisions (Step 5 of the solution framework) using the traffic flow simulator module of DYNASMART.

An overview of the capabilities of DYNASMART is provided by Chiu (2002). Pre-trip routing and en-route re-routing capabilities are enabled by embedding in DYNASMART the model used to represent the actual driver behavior (Equation (28)). As illustrated in Equation (31), the actual compliance is a function g_ψ of the route recommendation provided to individual drivers and the driver route choice behavior. The compliance variables ψ_{ijk}^{rt} take value 1 if route k is recommended to driver r in time interval t and he/she chooses this route; and 0 otherwise.

$$\psi_{ijk}^{rt} = g_\psi(\delta_{ijk}^{rt}, Y_{ijk}^{rt}); \qquad\qquad \forall\ i, j,\ k \in PK_{ij}^{r}, r,\ t = \sigma \cdot l + 1, ..., \sigma \cdot l + l \qquad (31)$$

δ_{ijk}^{rt} is the route choice dummy that takes value 1 if driver r chooses route k connecting O-D pair ij in time interval t; and 0 otherwise.

5.1.6. Scenarios

Six scenarios are evaluated in the experiments to investigate system performance under different information-based network control strategies. These scenarios are as follows.

Scenario I (no information): No information is provided to the drivers (NO-info). It is the do-nothing strategy and represents the base-case. Here, drivers make route choice decisions based only on past experience.

Scenario II (SO DTA): In this scenario, all drivers are assumed to fully comply with the recommended SO routes (SO). By definition, it represents the best possible system

performance.

Scenario III (SO-based information): Here, route guidance is provided using the SO solution route proportions (SO-info). SO routes (*DK*) are recommended to the drivers based on the proportion of drivers that are required to take each SO route. The SO route recommended to a driver may or may not belong to his/her driver-preferred route set. If the recommended route is not in the driver-preferred set, the driver completely ignores the information provided by the controller in the route choice decision-making process. If the recommended route is a driver-preferred route (*PK*), the driver uses the information in his/her decision-making process. If so, the likelihood of choosing the recommended route is increased.

Scenario IV (SO-based information only about controllable routes): In this scenario, only controllable (*CK*) routes based on their proportions in the SO solution are recommended (SO-CK-info). Hence, if no driver-preferred route exists in the SO solution, the controller does not recommend a route to that driver. This approach increases the likelihood that drivers comply with the controller recommendation.

Scenario V (UE-based information): Here, route guidance is provided using the UE solution route proportions (UE-info). This is conceptually similar to Scenario III; UE routes (*DK*) are recommended by the controller to the drivers based on the proportion of drivers that are required to take each UE route. The UE route recommended to a driver may or may not belong to his/her driver-preferred route set. If the recommended route is not in the driver-preferred set, the driver completely ignores the information provided by the controller in the route choice decision-making process.

Scenario VI (behavior-consistent information): In this scenario, routes are recommended based on the behavior-consistent information-based network control strategy (BC-SO-info). Akin to Scenario IV, only controllable routes are recommended to the drivers. However, these recommendations are based on the proportion of drivers that must be recommended to take these routes so as to approach as close as possible to the time-dependent SO solution proportions. This can imply the controller recommending routes in higher or lower proportions than the corresponding SO solution proportions so that the actual proportions achieved *after* the driver decision-making process come close to the SO solution proportions.

5.1.7. Assumptions

Without loss of generality, the study experiments assume that: (i) the controller-forecasted demand is the same as the actual demand, (ii) all drivers with the same O-D pair have the same set of driver-preferred routes, (iii) except for the no-information case, all drivers have capabilities to receive personalized information, and (iv) the controller-estimated set of driver-preferred routes is the same as the actual set of driver-preferred routes. These assumptions ensure that the focus of the experiments is on analyzing the effectiveness of the behavior-consistent strategy relative to existing DTA strategies.

5.1.8. Computational aspects

In all scenarios, 120,000 drivers are loaded during the first 60 minutes of analysis and

the simulation is executed until all vehicles reach their destinations. Further, each stage has a length of 20 minutes and a roll period (assignment interval) of 5 minutes. The behavior-consistent information strategies are computed for all node-destination pairs, implying 8471 (197 x 43) O-D pairs. This represents a significant computational load but enables the provision of information at any point in time and space. The experiments were conducted with a single Pentium 4 Extreme Edition processor running at 4.0 GHz. To the extent that the focus of this paper is on developing a behavior-consistent paradigm, the computational aspects are not analyzed here. However, the proposed solution framework lends itself to a significant amount of parallelization at the O-D pair level. Further, Paz and Peeta (2008) develop an off-line H-infinity filtering approach that optimizes the parameters of the fuzzy control model resulting in significant additional computation savings. Hence, the parallelization in conjunction with the optimization of parameters can be used to enhance computation efficiency.

5.2. Results and analysis: less responsive behavior

Fig. 6 shows the percentage cumulative system travel time savings (over the horizon of interest) under the five information-based network control strategies for the less responsive behavior case relative to the base-case (NO-info) where no information is provided. By definition, Scenario II (SO DTA) has the highest cumulative system travel time savings. Hence, it represents the benchmark for comparing the performance under the other strategies.

The results show that all information strategies result in significant improvements to the system performance compared to the NO-info case. However, the behavior-consistent information-based network control strategy (BC-SO-info) outperforms both the SO-based information strategies (SO-info, SO-CK-info) and the UE-based information strategy (UE-info). By estimating drivers' likely reactions and only recommending routes that are behavior-consistent, the controller is able to move the system closer (to the extent possible given driver behavior) to the ideal SO state. In addition, there is a region of negative travel time savings in the early stages of the planning horizon. The negative values indicate that the base-case results in better system performance for the relevant duration. This implies that for some levels of demand and network dynamics, the SO-based and UE-based information strategies can potentially deteriorate system performance. Hence, the common practice of assigning the DTA solutions directly to the O-D demand may overestimate the system performance.

The significance of ensuring behavioral consistency in the controller-recommended routes is also reflected in Fig. 7, where higher compliance rates are obtained for the BC-SO-info strategy compared to the other strategies. Fig. 7 also illustrates that the compliance rates are perceptible even for the SO- and UE-based strategies (between 45% to 56 %), though not as much as for the behavior-consistent strategy (around 65%). In all of the information-based network control strategies, the route recommended by the controller is considered by the drivers only if the recommended route is a driver-preferred route. In addition, the values for compliance rates indicate that there are many preferred routes (*PK*) that fully overlap with desired routes (*DK*). This may overestimate the performance of the SO- and UE-based strategies because they do not consider the likely response behavior to

the route recommendations. Figs. 7 and 9 illustrate the compliance rates for stages 15 to 30 only so as to obviate startup and end effects when few drivers are present in the network. In Figs. 6 and 8, the focus is on illustrating cumulative system savings from the start to the end.

5.3. Results and analysis: more responsive behavior

Fig. 8 shows the percentage cumulative total travel time savings (over the horizon of interest) under the five information-based network control strategies for the more responsive behavior case relative to the base-case (NO-info). The results show that both the SO- and UE-based information strategies perform worse than even the NO-info strategy. This is consistent with the trends identified in previous studies involving system performance under large market penetration levels of personalized information provision.

In these experiments, the travel times are significantly increased because the controller is over-recommending routes to highly responsive drivers. There are some controllable-routes with large numbers of drivers choosing them even when no information is given about them. This is because drivers are familiar with these routes, and favor them based on past experience. When the controller recommends these routes, they become even more attractive. If the proportions of drivers choosing these routes are higher than the SO proportions for these routes, they become congested leading to higher total travel times. This situation is circumvented under the behavior-consistent information-based network control strategy (BC-SO-info) because it takes into account the drivers' likely reactions to the information strategies and hence does not over-recommend those routes. Hence, as seen in Fig. 8, the behavior-consistent information-based network control strategy not only outperforms the SO- and UE-based strategies, but also significantly improves overall system performance. By estimating drivers' likely reactions and only recommending routes that are behavior-consistent, the controller is able to move the system (to the extent possible under driver behavioral tendencies) in the SO direction. Hence, the BC-SO-info strategy improves performance and increases compliance rates (as seen in Fig. 9).

The results illustrated in Figs. 6 and 8 are conservative as they include end effects due to the head and tail periods of the planning horizon when few vehicles are present in the system (the experiments are conducted starting with an empty network, and statistics are collected until the last vehicle leaves the network). Hence, the contribution of the head/tail periods is not significant and they are provided here for completeness. That is, the benefits of the proposed strategies are higher when end effects are excluded.

In general, it should be noted that some drivers are likely to experience travel times that are longer than anticipated if they comply with the recommendations of strategies that are not behaviorally consistent (such as SO-info or UE-info strategies). This makes it less likely that they will comply with the controller recommendation in the long-term (Peeta and Yu, 2006).

6. Concluding comments

From the controller's perspective, ideally all drivers are equipped to receive personalized information, and follow the SO routes provided to them. However, such

behavioral simplicity is not realistic. Different drivers may have different preferences in terms of route choice, and may have different responses to the same information. Further, drivers may have different levels of capabilities to receive information. This study is the first to develop a behavior-consistent approach for information-based network-level control. It explicitly factors the drivers' likely response behavior while determining the information that directs the system as close as possible to the SO solution. Thereby, the resulting information strategies address the controller and driver objectives simultaneously, and are more likely to be accepted by drivers.

The study experiments illustrate the benefits of the behavior-consistent information-based network control strategies. In all cases, the system travel time savings are significantly higher for the behavior-consistent approach compared to those of the no-information, the SO-based and UE-based information strategies. In addition, compliance rates are higher for the behavior-consistent strategy compared to those for the SO- and UE-based strategies. These insights suggest that factoring driver behavior while determining the controller route recommendations can further enhance performance as well as driver compliance. A detailed analysis of the results suggests that most of the preferred routes of the drivers tend to have large behavior-consistency gaps because large numbers of drivers take these routes independent of information provision. That is, to achieve the ideal route assignment percentages (whether UE or SO, obtained through the standard DTA approaches), the controller may have to recommend more or less users to take those routes depending on the network dynamics and driver behavior tendencies.

Under the proposed framework, only routes that are simultaneously desired by the controller and preferred by the drivers are recommended. Elsewhere (Paz and Peeta, 2009c), the authors extend this framework by considering routes that overlap mostly, but not fully, with the controller-desired routes. It enhances deployment realism by providing additional routing options for the controller to recommend to drivers. Further, the authors analyze behavior-consistent routes determined using the UE DTA solution as UE routes are more likely to overlap with driver-preferred routes.

The controller-estimated driver behavior model is based on aggregate simple *if-then* rules developed using findings from past studies and field observations. Hence, it does not require individual driver behavior data, implying reduced data sensitivity for the behavior-consistent approach. This feature enhances the ability to deploy the behavior-consistent approach as data needs typically represent key practical barriers in the route guidance context.

The controller-estimated driver behavior model is calibrated off-line using the actual driver behavior model. In other work (Paz and Peeta, 2009b), the authors propose an on-line consistency-seeking procedure that fits within the framework proposed in this study to calibrate the parameters of the controller-estimated model. It enables the simultaneous on-line determination of behavior-consistent information strategies and the calibration of the controller-estimated model parameters.

References

Bekhor, S., Ben-Akiva, M.E., Ramming, M.S., 2006. Evaluation of choice set generation algorithms for route choice models. Analysis of Operations Research 154(1), 245-257.

Ben-Akiva, M.E., Bierlaire, M., 1999. Discrete choice methods and their applications to short-term travel decisions, In: Hall R. W. (ed.) Handbook of Transportation Science, Kluwer Academic Publishers, Boston, MA.

Ben-Akiva, M.E., Bottom, J.A., Ramming, M.S., 2001. Route guidance and information systems. Journal of Systems and Control Engineering 215(4), 317-324.

Bottom, J.A., 2000. Consistent anticipatory route guidance, PhD thesis. Department of Civil and Environmental Engineering, MIT.

Chiu, Y-C., 2002. Generalized real-time route guidance strategies in urban networks, PhD thesis. Department of Civil and Environmental Engineering, University of Texas at Austin.

Crittin, F., Bierlaire, M., 2001. New algorithmic approaches for the anticipatory route guidance generation problem. 1st Swiss Transport Research Conference, Monte Veritá/Ascona.

Doan, D., Ziliaskopoulos, A.K., Mahmassani, H.S., 1999. An on-line monitoring system for real-time traffic management applications. Transportation Research Record 1678, 142-150.

Lotan, T., Koutsopoulos, H. N., 1993. Models for route choice behavior in the presence of information using concepts from fuzzy set theory and approximate reasoning. Transportation 20, 129-155.

Lotan, T., Koutsopoulos, H. N., 1999. Modeling default behavior in the presence of information and its application to the route choice problem. International Journal of Intelligent Systems 14, 501-533.

Mahmassani, H.S., 2001. Dynamic network traffic assignment and simulation methodology for advanced system management applications. Networks and Spatial Economics 1(3/4), 267-292.

Paz A, Peeta S., 2009a. Information-based traffic control strategies consistent with estimated driver behavior. Transportation Research, Part B 43(1), 73-96.

Paz A, Peeta S., 2009b. On-line calibration of behavior parameters for behavior-consistent route guidance. Transportation Research, Part B 43(4), 403-421.

Paz A, Peeta S., 2009c. Paradigms to deploy a behavior-consistent approach for information-based real-time traffic routing. Networks and Spatial Economics. In press, http://dx.doi.org/10.1007/s11067-008-9077-4.

Paz A, Peeta S., 2008. Fuzzy control model optimization for behavior-consistent traffic routing under information provision. IEEE Transactions on Intelligent Transportation Systems, 9(1), 27-37.

Peeta, S., 1994. System optimal dynamic traffic assignment in congested network with advanced information systems, PhD thesis. Department of Civil and Environmental Engineering, University of Texas at Austin.

Peeta, S., Bulusu, S., 1999. A generalized singular value decomposition approach for consistent online dynamic traffic assignment. Transportation Research Record 1667, 77-87.

Peeta, S., Yu, J.W., 2004. Adaptability of a hybrid route choice model to incorporating driver behavior dynamics under information provision. IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans 34, 243-256.

Peeta, S., Yu, J.W., 2006. Behavior-based consistency-seeking models as deployment

alternatives to dynamic traffic assignment models. Transportation Research, Part C 14(2), 114-138.

Ramming, M.S., 2002. Network knowledge and route choice, PhD thesis. Department of Civil and Environmental Engineering, MIT.

Tsoukalas, L., Uhrig, R., 1997. Fuzzy and Neural Approaches in Engineering. John Wiley and Sons, Inc., New York, NY.

Zhou, X., Mahmassani, H.S., 2005. Recursive approaches for online consistency checking and OD demand updating for real-time dynamic traffic assignment operation. Transportation Research Record 1923, 218-226.

Table 1
If-then rules for the controller-estimated driver behavior model

| Category	LHS	RHS
Controller-estimated driver-expected travel time (*TT*)	If *TT* is Very Low (VL)	Driver will choose the alternative (O)
	If *TT* is Low (L)	Driver will probably choose the alternative (PO)
	If *TT* is Medium (M)	Driver is indifferent to the alternative (I)
	If *TT* is High (H)	Driver probably will not choose the alternative (PN)
	If *TT* is Very High (VH)	Driver will not choose the alternative (N)
Route complexity (*NN*)	If *NN* is Very Low (VL)	Driver will choose the alternative (O)
	If *NN* is Low (L)	Driver will probably choose the alternative (PO)
	If *NN* is Medium (M)	Driver is indifferent to the alternative (I)
	If *NN* is High (H)	Driver probably will not choose the alternative (PN)
	If *NN* is Very High (VH)	Driver will not choose the alternative (N)
Prescriptive information (*Y*) for more responsive drivers	If *Y* is Route is Recommended (RR)	Driver will choose the alternative (O)
	If *Y* is Route Was Recommended (RWR)	Driver will probably choose the alternative (PO)
	If *Y* is Route is Not Recommended (RNR)	Driver will not choose the alternative (N)
Prescriptive information (*Y*) for less responsive drivers	If *Y* is Route is Recommended (RR)	Driver will probably choose the alternative (PO)
	If *Y* is Route Was Recommended (RWR)	Driver is indifferent to the alternative (I)
	If *Y* is Route is Not Recommended (RNR)	Driver probably will not choose the alternative (PN)
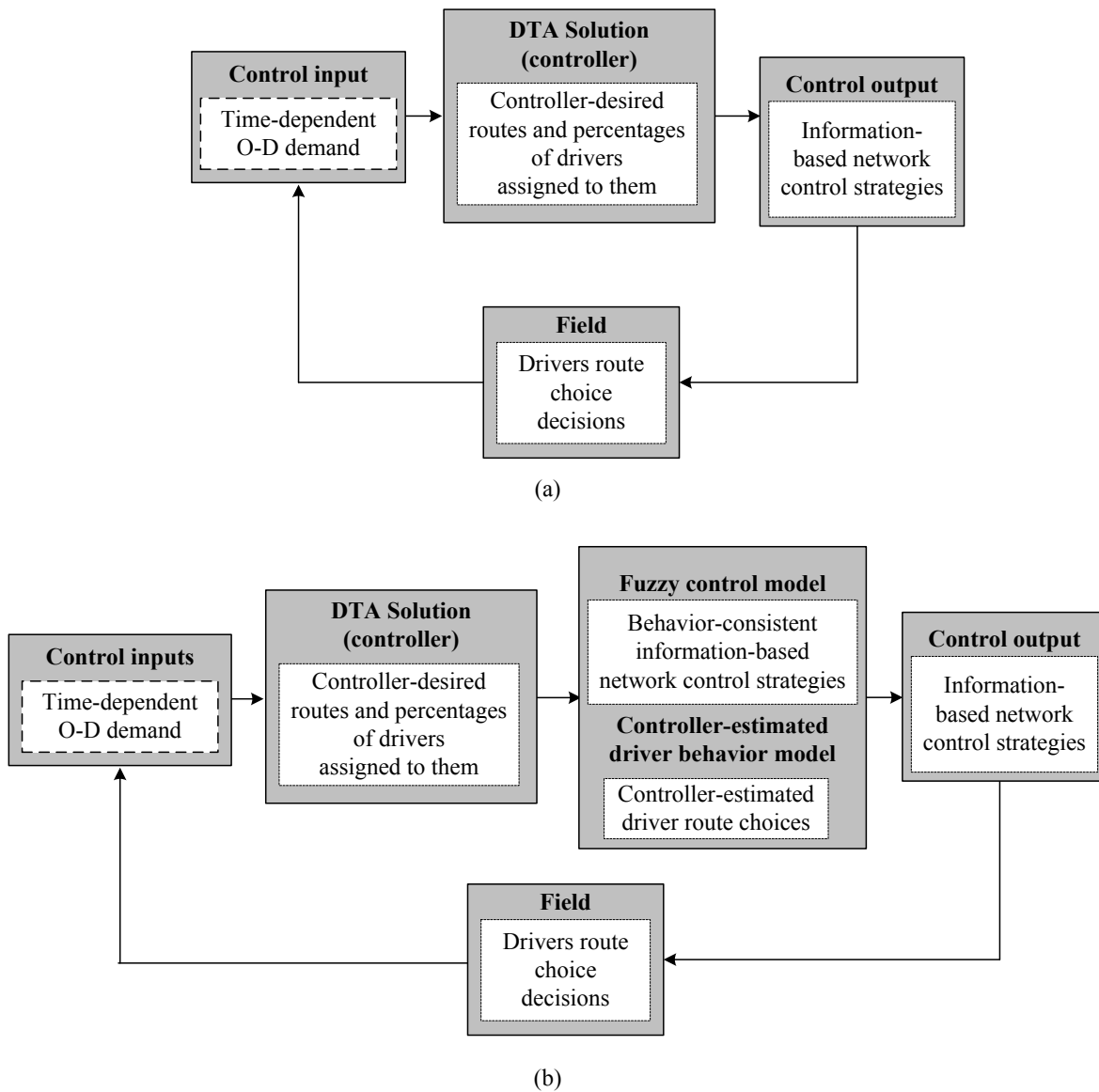
Fig. 1. Information-based network control framework: (a) traditional DTA-based approach, (b) proposed behavior-consistent approach.
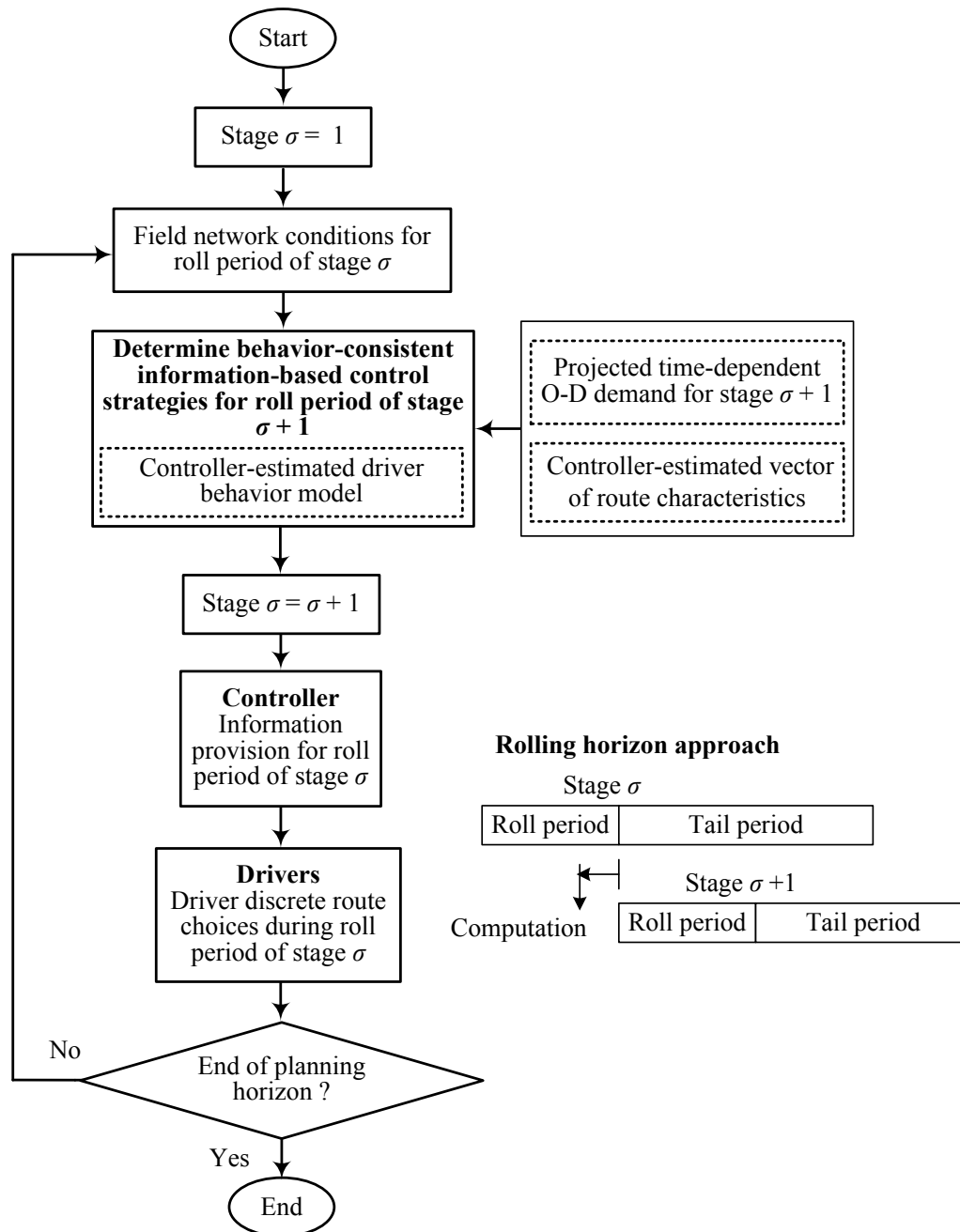
Fig. 2. Conceptual framework for the behavior-consistent traffic routing problem under information provision.
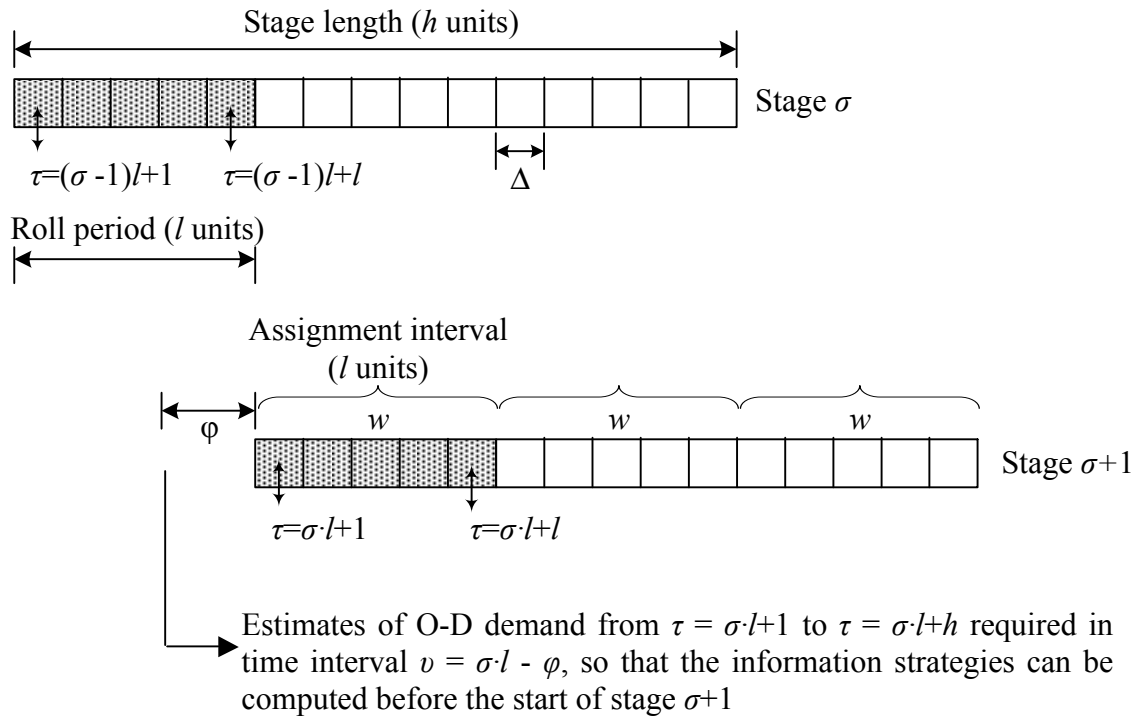
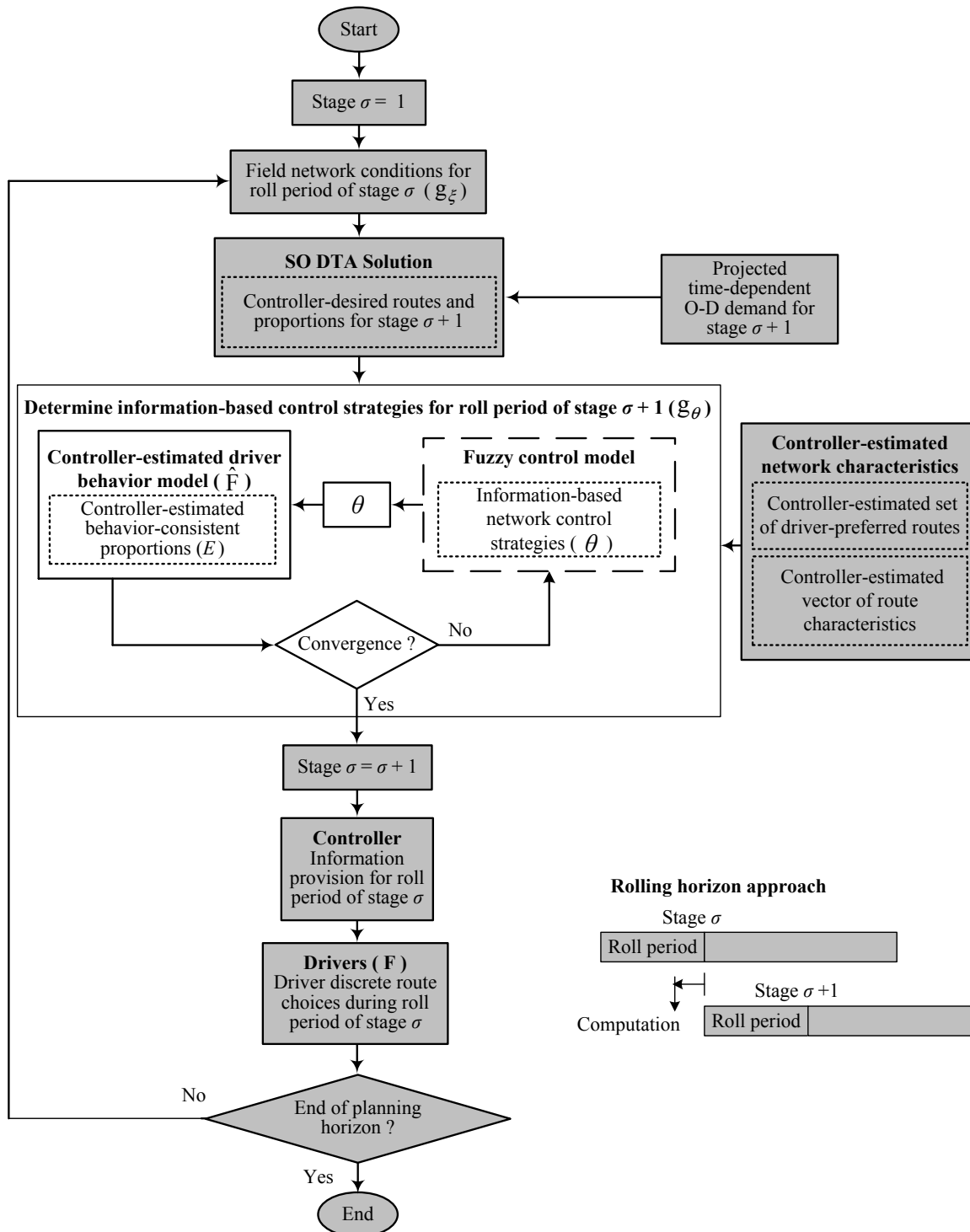Fig. 3. Rolling horizon framework.

Fig. 4. Solution framework for the behavior-consistent traffic routing problem under information provision.
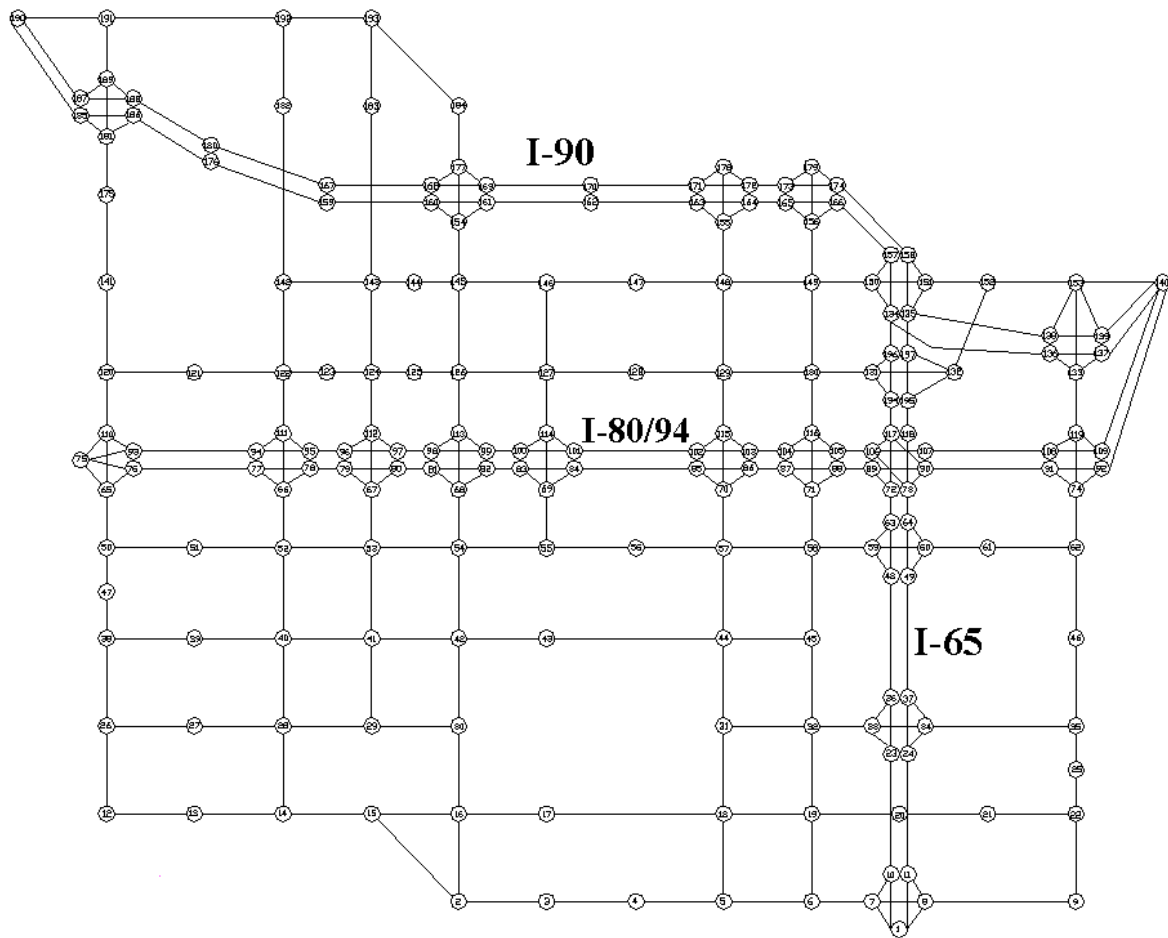
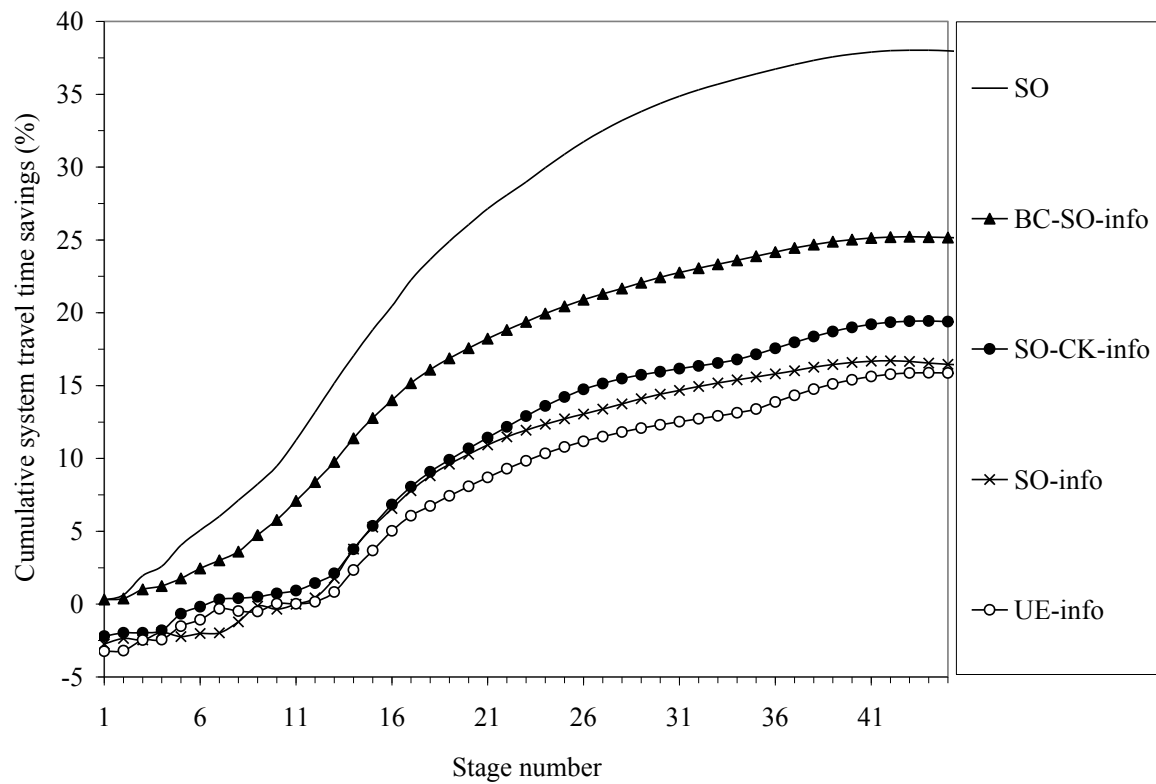Fig. 5. Borman expressway corridor network.

Fig. 6. Cumulative system travel time savings under the less responsive behavior benchmarked against the no-information case (base-case).
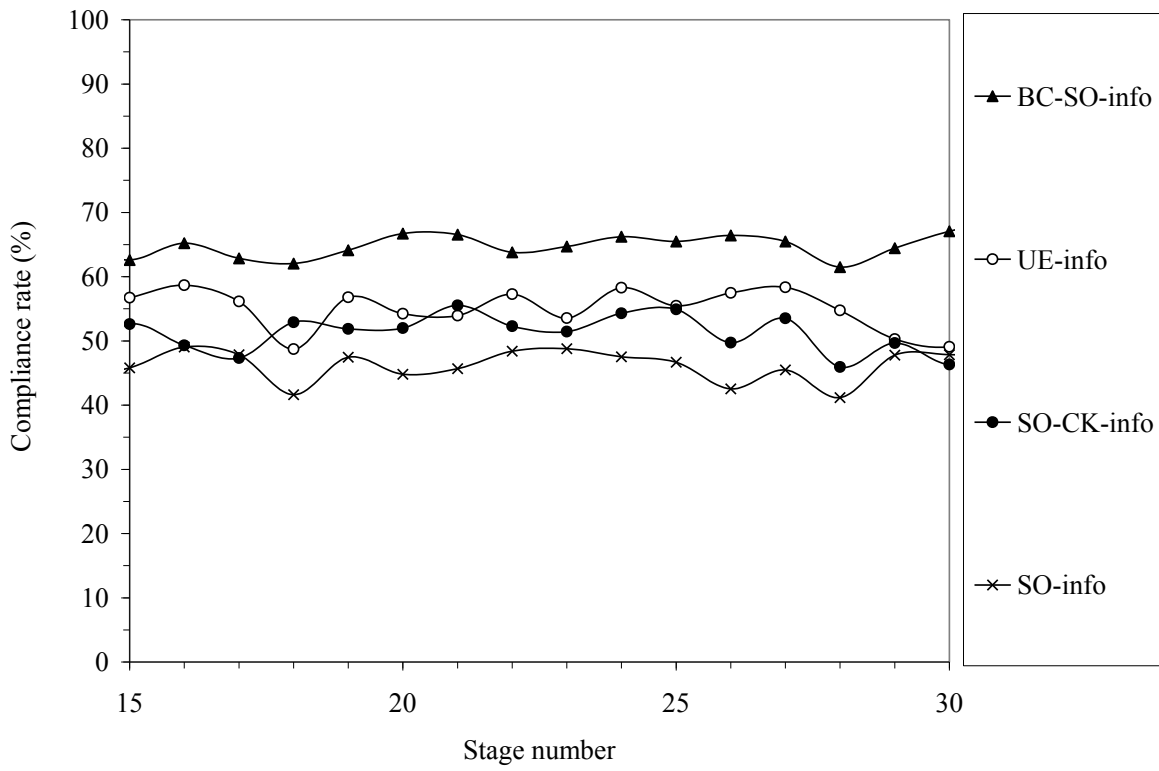
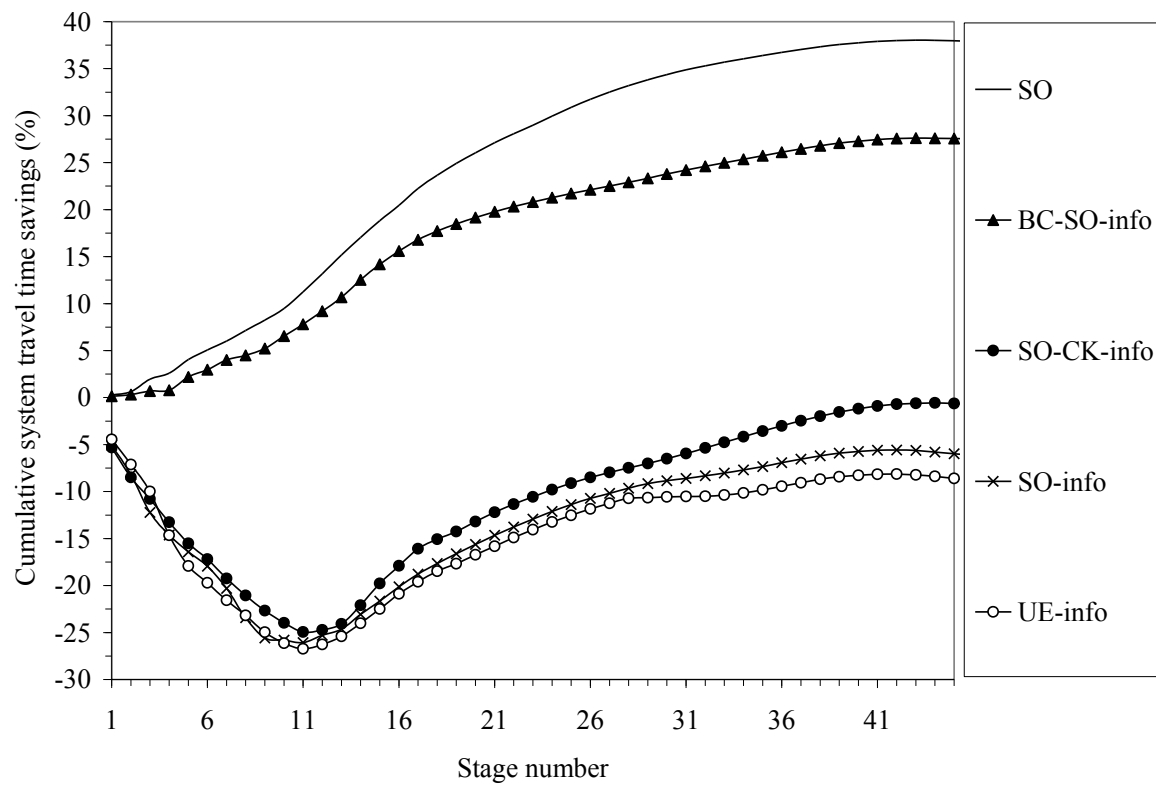Fig. 7. Compliance rates under less responsive behavior.

Fig. 8. Cumulative system travel time savings under the more responsive behavior benchmarked against the no-information case (base-case).
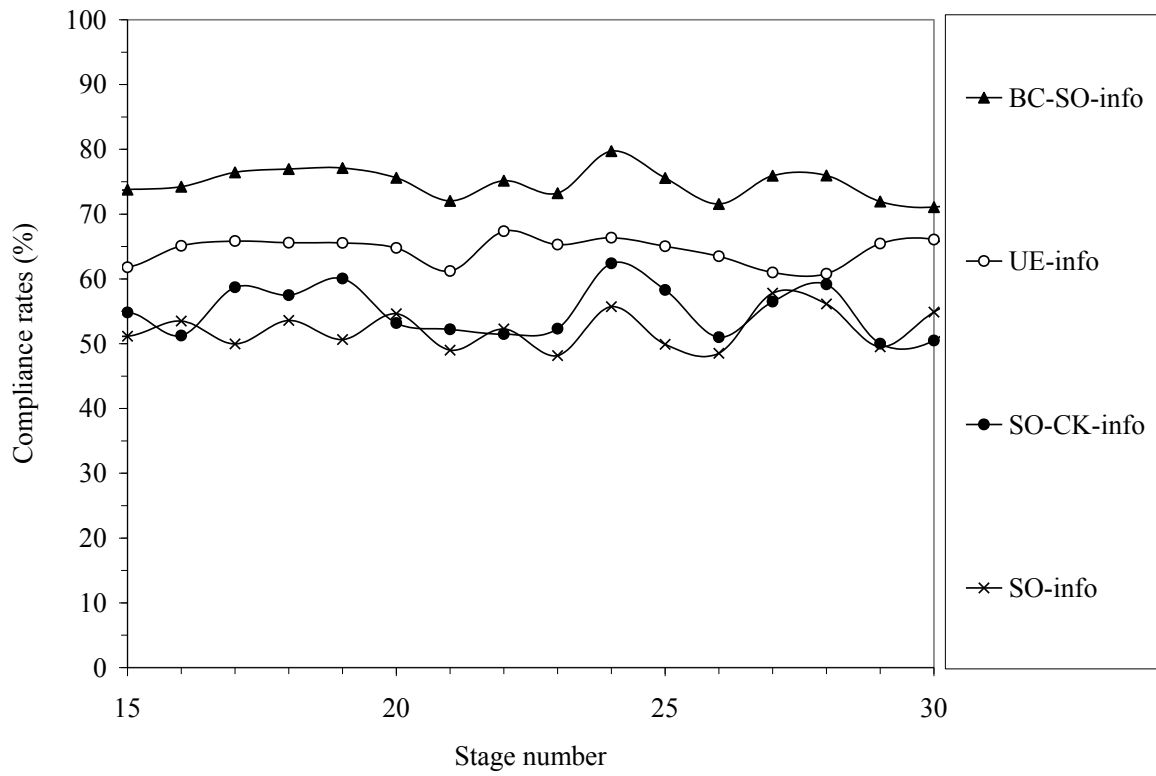
Fig. 9. Compliance rates under more responsive behavior.