Paradigms to Deploy a Behavior-consistent Approach for Information-based Real-time Traffic Routing

Alexander Paz

Civil and Environmental Engineering Department, University of Nevada, Las Vegas,
4505 Maryland Parkway, PO Box 454015, Las Vegas, NV 89154-4015, USA
email: apaz@unlv.edu

Srinivas Peeta*

School of Civil Engineering, Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907-2051, USA.
email: peeta@purdue.edu

Published online:

Springer Science + Business Media, LLC 2008

Abstract A behavior-consistent information-based network control approach determines real-time traffic routing strategies by explicitly accounting for drivers' likely response to the controller-recommended routes while generating these strategies. This paper proposes paradigms to deploy a behavior-consistent approach developed by the authors (Paz and Peeta, 2007). These paradigms seek to enhance deployment effectiveness by analyzing the effects of alternative controller objectives and driver-preferred route sets used to recommend routes. Experiments are conducted using a test network. They analyze: (i) the performance of the behavior-consistent approach under commonly-used controller objectives, (ii) the deployment flexibility enabled by increasing the number of driver-preferred routes considered by the controller for routing, and (iii) the effects of augmenting the driver-preferred route choice set through various paradigms. The results suggest that the behavior-consistent approach can perform better than standard dynamic traffic assignment models while directing the system towards the desired state. They also illustrate the effectiveness of considering more driver-preferred routes in developing the information strategies. Further, they suggest that driver-preferred route choice set augmentation and the associated route types can have differential impacts on performance. Also, performance is influenced by trade-offs between the number of driver-preferred routes considered by the controller for routing and the quality of routes relative to the controller objective. The results suggest that higher compliance rates may not translate to better performance and question the justification of user equilibrium solutions for route guidance on the ground that a system optimal strategy is not behaviorally sustainable.

Keywords Traffic routing · Behavior-consistent strategies· Degree of overlap · Driver route choice · Deployment paradigms

1 Introduction

The benefits of real-time traffic network control through information provision using Advanced Traveler Information Systems (ATIS) hinge on the controller's ability to identify effective routing strategies that entail high levels of acceptability by drivers. Current efforts to deploy information provision strategies are primarily concentrated under the umbrella of Dynamic Traffic Assignment (DTA). However, the behavioral foundations of most DTA models are idealistic and insufficient to address real-world driver behavior (Peeta and Ziliaskopoulos, 2001). This is primarily because existing DTA models are not behavior-consistent; they do not realistically factor the drivers' likely response towards information while generating these strategies. They mostly pre-specify driver behavior. Some assume artificial compliance rates to predict traffic conditions or generate control strategies. Others use the DTA solution route assignment proportions "as is" for route guidance, and use a feedback loop or a consistency-checking procedure to correct for prediction errors. Thereby, most approaches do not have interactive linkages between route recommendations and driver response. Peeta and Yu (2006) propose a consistency-seeking procedure that updates behavior model parameters in an operational context based on unfolding field conditions. However, it is also reactive and does not entail a behavior-consistent paradigm. In summary, DTA models do not simultaneously consider network flow interactions and behavior realism to develop meaningful information-based network control strategies.

To address the behavior realism gap of traditional DTA models vis-à-vis determining the time-dependent traffic flow patterns, Paz and Peeta (2007, 2008a) propose a behavior-consistent approach to determine and deploy real-time information-based network control strategies. It determines the information strategies by explicitly accounting for the drivers' likely response to these strategies while determining them. That is, "behavior-consistent" implies that the information provided to the drivers is determined in such a way that the drivers are likely to follow the route recommendations because the information is based on an explicit estimation of the drivers' likely route choices under the provided information. This implies solving a fixed-point problem that arises because the information strategies depend on driver behavior and vice versa. The proposed approach enhances system performance while being consistent with driver behavior. It also has reduced sensitivity to data needs as it is based on aggregate *if-then* rules that preclude the need for information at the individual driver level. These rules relate the route choice decisions to the routes characteristics, the driver attributes in terms of information availability, and level of responsiveness to the information strategies. As drivers are likely to use simple rules and/or a few factors (Nakayama and Kitamura, 2000; Peeta and Yu, 2005) to make on-line routing decisions due to the associated time constraints, the aggregate if-then rules consist of simple and straightforward one-dimensional left- and right- hand side components (Paz and Peeta, 2008b).

The behavior-consistent approach proposed by Paz and Peeta (2007, 2008a) implements a control mechanism that continuously directs the traffic system towards a desired system state through information provision. That is, the controller directs the system towards a particular objective such as the time-dependent system optimal (SO) state. Thereby, the controller may need to recommend routes for an origin-destination (O-D) pair to more or less drivers than suggested by the SO DTA solution so as to achieve close to SO route proportions. This is done using a controller-estimated *if-then* rules based driver behavior model. Further, the approach uses the concept of controllable routes to enhance behavior consistency whereby the route recommended to a driver belongs to the controller's SO (desired) route set and the preferred route set for that driver. This increases the likelihood of the recommended route being accepted by the driver. It also circumvents a key practical concern that potentially arises for ATIS-based information provision. That is, while some researchers have advocated that drivers could be persuaded to use SO routes, others (such as Hall, 1996) stress the value of "honest" information, and that in the long run drivers will resist SO routes that are not user optimal.

While the notion of controllable routes enhances behavior consistency, it may entail practical limitations. For example, it is possible that an O-D pair may not have a controllable route as no controller-determined SO route coincides with a driver-preferred route. This motivates the consideration of alternative definitions for controllable routes to enable the deployment effectiveness of the behavior-consistent approach. In this paper, alternative controllable route paradigms are proposed that entail significant overlap of the controller-determined SO routes with the driver-preferred routes, but do not require perfect match. This enables the controller to recommend driver-preferred routes that are not necessarily SO routes, as well as target drivers who do not consider SO routes. At a more basic level, such a study can shed light on the interplay between route quality relative to controller objectives and driver real-time route choice decisions.

By definition, the SO solution entails some long routes which may imply fewer common routes with the driver-preferred set. While the alternative overlap paradigms represent one mechanism to increase the controllable route set, another strategy is to use the user equilibrium (UE) solution as the controller's objective. This is because UE routes have a more defensible behavioral rationale, possibly having a greater degree of commonality with the driver-preferred route set. In this study, we compare the performance of the behavior-consistent approach under the UE and SO objectives. It should be noted here that the commonly cited advantages of the UE paradigm over the SO benchmark for standard DTA models do not necessarily apply for the behavior-consistent approach. Since the behavior-consistent approach provides a trajectory to approach the desired system state in a manner consistent with individual driver routing decisions, the limitations arising from the behavioral underpinnings of the standard SO strategy relative to the UE strategy are obviated. That is, the compliance rates under the behavior-consistent approach are perceptibly higher than under the standard DTA paradigms (Paz and Peeta, 2007). Further, the relative gap in compliance rates between UE and SO under the behavior-consistent approach tends to be smaller than under the standard DTA approach. It suggests that focusing on the SO paradigm can represent a legitimate deployment alternative with better behavior-consistent performance, rather than the UE centric focus of the current literature based on the behavior rationale. This aspect is analyzed in depth in this paper.

A long-term phenomenon vis-à-vis driver behavior under information-based traffic routing is the influence of learning effects on driver response. Peeta and Yu (2005) show that several information-related phenomena can manifest over time based on past driving experience and the experience with the provided information. These include familiarity, trust in information, inertia, delusion, freezing, etc. Vaughn et al. (1993) and Bonsall and Joint (1991) present evidence that drivers may not comply with information perceived to be inaccurate. Over time, these effects and experiences can lead to changes in the set of routes preferred by a driver. Nakayama and Kitamura (2000) show that drivers may ignore routes associated with poor travel experience and remove them from their preferred route sets. By contrast, it is also possible that a driver may add new alternatives to his/her preferred route set based on positive experiences with a controller-recommended or a newly-explored route. Hence, the driver-preferred route set can potentially change over time. The number of routes in the driver-preferred route set is significantly influenced by the driver's network familiarity. Familiar drivers are likely to have larger preferred route sets compared to unfamiliar drivers. While this paper does not consider a day-to-day learning framework, we explore the effect of increasing the driver-preferred route set with alternative route type paradigms, and compare the performance of these paradigms from a deployment perspective.

The remainder of this paper is organized as follows. Section 2 summarizes the solution framework for the behavior-consistent approach and defines relevant terms. Section 3 describes the alternative controllable route paradigms proposed in this study. Section 4 discusses experiments and analyzes their results. Section 5 presents some concluding comments.

2 Behavior-consistent approach

2.1 Solution framework

Fig. 1 depicts the proposed solution framework for the real-world deployment of the behavior-consistent approach used to influence system performance through information provision. A comprehensive description of this framework is provided in Paz and Peeta (2007). It illustrates the case where the controller seeks to direct the system towards the time-dependent SO DTA state. However, it applies to the UE DTA state or any other controller objective without loss of generality. It uses a rolling horizon stage-based procedure for a pre-determined planning horizon. The planning horizon is divided into stages, and a stage is divided into a roll period and a tail period. In each stage σ, the traffic network field conditions for the current roll period and the projected time-dependent O-D demand for the next stage (σ+1) are used to generate the SO DTA solution for the next stage. This SO DTA solution and an iterative search optimization procedure are then used to determine the behavior-consistent information-based network control strategies to provide route guidance to drivers, so that the actual driver decisions in the next roll period result in close to SO route proportions for the controllable routes. The non-shaded box located in the middle of the flowchart in Fig. 1 represents the iterative search optimization procedure (Paz and Peeta, 2008a). It consists of a controller-estimated driver behavior model and a fuzzy control model. The controller-estimated driver behavior model provides the estimated proportion of drivers taking routes under the information strategies. It is a fuzzy multinomial logit model with the systematic component obtained using aggregate *if-then* rules. The fuzzy control model represents the search mechanism which includes the determination of the step size and move direction. At convergence, the iterative search optimization procedure generates the behavior-consistent proportions of drivers that should be recommended to take specific routes in the next roll period so as to achieve close to SO proportions. Convergence is achieved when the estimated proportions of drivers choosing routes do not vary beyond a threshold value across successive iterations for all controllable routes (Paz and Peeta, 2008a). The stage counter is incremented by one at the end of the current roll period. In the next roll period, routing information is provided to a subset of drivers based on the behavior-consistent route proportions. The network performance for the roll period is obtained using a traffic simulator. If the end of the planning horizon is not reached at the end of the current roll period, the controller measures the field network conditions and repeats the entire procedure for the next roll period. Otherwise, the rolling horizon framework is terminated.

2.2 Definition of terms

While the behavior-consistent approach addresses a real-time problem using a stage-based procedure, the time dimension is ignored hereafter without loss of generality to simplify the notation.

Controller-Desired Routes (*DK*): These are routes that the controller would like the drivers to choose. Depending on the controller objective, they are the time-dependent SO or UE DTA routes, which are obtained using current network conditions and projected demand by solving a deterministic DTA problem for the appropriate time duration (represented by the stage length in this paper).

Driver-Preferred Routes (*PK*): These routes are preferred by the drivers and are likely to be accepted by them. The estimation of the driver-preferred route set is a key step for any route choice model. From a technological standpoint, these route sets can be obtained in a straightforward manner for drivers with personalized information/communication devices through two-way communication. More generally, they are estimated (Bekhor et al., 2006) based on historical data collected through travel surveys and/or technologies such as two-way communication systems and global position systems.

Controllable Routes (*CK*): These routes belong to both controller-desired and driver-preferred route sets. In the behavior-consistent approach, they represent the set of routes used by the controller to influence system performance.

Degree of Overlap (*DOV*): The degree of overlap DOV_{ijk} for a driver-preferred route k ($k \in PK_{ij}$) from origin i to destination j, is a fraction defined by the maximum amount of common link length between that route and any controller-desired route m ($m \in DK_{ij}$) divided by the length of the driver-preferred route (k):

$$DOV_{ijk} = \frac{1}{L_{ijk}} \left[\max_{m \in DK_{ij}} \sum_{a \in \Gamma_{ijk}} l_a \cdot \Theta_{aijm} \right]; \;\; \forall\, i, j, k \in PK_{ij} \tag{1}$$

where

Γ_{ijk}	set of links on route k connecting O-D pair ij, $k \in PK_{ij}$
l_a	length of link a
L_{ijk}	length of route k, $k \in PK_{ij}$
Θ_{aijm}	link-route incidence dummy; 1 if route m connecting O-D pair ij includes link a, and 0 otherwise

Threshold degree of overlap (λ): Minimum degree of overlap at which a driver-preferred route ($k \in PK$) is accepted as a controllable route ($k \in CK$).

3 Control and controllable route paradigms

As stated in Section 1, this study focuses on identifying mechanisms to increase the controllable route set to enhance deployment effectiveness of the behavior-consistent approach. Another positive outcome of increasing the controllable route set is that it diffuses the effects of errors in estimating the driver-preferred route sets. This is because the controller has more options to recommend and the likelihood of recommending a route that does not belong to the actual driver-preferred set decreases. The paradigms discussed hereafter seek to increase the controllable route sets relative to the SO-based behavior-consistent approach.

3.1 SO and UE control paradigms

Under the SO paradigm developed in previous work (Paz and Peeta, 2007, 2008a), the controller seeks to direct the system towards the SO DTA state. Hence, for O-D pair *ij*, the controller-desired route set is its time-dependent SO route set SOK_{ij}, and the controllable route set is the subset of driver-preferred routes for that O-D pair across all drivers that perfectly match routes in SOK_{ij}. This paradigm, labeled as BC-SO-info, is expressed as follows:

$$k \in CK_{ij} \Leftrightarrow k \in \{SOK_{ij} \cap PK_{ij}\} \tag{2}$$

Paz and Peeta (2007) show that the behavior-consistent approach using the SO control paradigm results in better performance than traditional DTA-based approaches while being behaviorally realistic.

Under the UE control paradigm, the controller seeks to direct the system towards the UE DTA state. In this case, for O-D pair *ij*, the controller-desired route set is its time-dependent UE route set UEK_{ij}. The controllable route set is the subset of driver-preferred routes for that O-D pair across all drivers that perfectly coincide with routes in UEK_{ij}. This paradigm, labeled as BC-UE-info, is expressed as follows:

$$k \in CK_{ij} \Leftrightarrow k \in \{UEK_{ij} \cap PK_{ij}\} \tag{3}$$

As stated in Section 1, the behavioral underpinnings of UE routes typically make them more likely to overlap with driver-preferred routes, leading to a potential increase in the controllable route set compared to the SO control paradigm. However, as illustrated in Section 4, this does not necessarily translate into better system performance. Hence, the controllable route paradigms proposed in Section 3.2 are based on the SO control paradigm.

3.2 Controllable route paradigms

3.2.1 Degree of overlap paradigms

These paradigms use the *DOV* to define the controllable route sets.

3.2.1.1 1st *DOV paradigm*

The 1st *DOV* paradigm is called the "full overlap paradigm". This is an all-or-nothing approach where only driver-preferred routes that fully overlap (match) with controller-desired routes are classified as controllable routes. That is, only driver-preferred routes with a degree of overlap equal to 1 are classified as controllable. This paradigm is expressed as follows:

$$k \in CK_{ij} \Leftrightarrow DOV_{ijk} = 1 \tag{4}$$

As discussed in Section 1, Paz and Peeta (2007, 2008a) use this paradigm to analyze the performance of the behavior-consistent approach. However, the strict match requirement can preclude the consideration of "good" route alternatives in the driver-preferred route sets that significantly overlap with the controller-desired routes, potentially limiting deployment effectiveness. This represents the motivation for the 2nd and 3rd *DOV* paradigms. Under these paradigms, the controller uses threshold *DOV* related rules to treat appropriate driver-preferred routes as controller-desired routes, and consequently as controllable routes.

3.2.1.2 2nd *DOV paradigm*

The 2nd *DOV* paradigm is labeled the "threshold degree of overlap paradigm". Here, a threshold *DOV* value is pre-specified and only driver-preferred routes with *DOV* values greater than or equal to this threshold are classified as controllable. This paradigm can be represented as follows:

$$k \in CK_{ij} \Leftrightarrow DOV_{ijk} \geq \lambda \tag{5}$$

where λ is an external parameter specified by the user to evaluate the effect of increasing or decreasing the *DOV* required for a route to become controllable. This paradigm potentially provides more deployment options to the controller when compared to the 1st *DOV* paradigm. However, it precludes the consideration of the effects of alternative combinations of controllable routes beyond the combination that satisfies the pre-specified threshold. Presumably, other combinations could result in a more favorable performance. This motivates the next *DOV* paradigm.

3.2.1.3 3rd *DOV paradigm*

The 3rd *DOV* paradigm is called the "combination degree of overlap paradigm". It uses various threshold *DOV* values and an error function to identify the set of controllable routes. The error function computes the total error TE_{ij} for O-D pair *ij*, defined as the summation over the set of controllable routes CK_{ij} of the absolute difference between the controller-desired proportion of drivers SO_{ijk} ($k \in CK_{ij}$) taking those routes and the corresponding controller-estimated proportion of drivers choosing those routes E_{ijk} ($k \in CK_{ij}$) obtained at the convergence of the iterative search procedure. In the iterative search procedure described in Section 2.1, the controller-estimated driver behavior model is used to compute E_{ijk} for each iteration. Hence, E_{ijk} is the result of estimating individual route choices over the set of driver-preferred routes. TE_{ij} can be expressed as:

$$TE_{ij} = \sum_{k \in CK_{ij}} | SO_{ijk} - E_{ijk} | \tag{6}$$

Under this paradigm, two threshold *DOV* values, λ_L and λ_U are pre-defined. λ_L is a lower threshold value and λ_U is an upper threshold value. These threshold values and the total error are used as part of a systematic three-step procedure to identify the controllable route set:

Step 1: Driver-preferred routes that perfectly match (*DOV*=1) controller-desired routes are classified as controllable, and represent the initial set of controllable routes CK_{ij}^1 for O-D pair *ij*. This is equivalent to the 1st *DOV* paradigm:

$$k \in CK_{ij}^1 \Leftrightarrow DOV_{ijk} = 1 \tag{7}$$

Step 2: In this step, at most one additional driver-preferred route is identified as controllable using the heuristic rules of Eq. (8). That is, CK_{ij}^2, an updated set of controllable routes has at most one route more than CK_{ij}^1. This additional route, if it exists, is the one with the lowest TE_{ij} among all driver-preferred routes not in CK_{ij}^1 which also has a *DOV* value greater than or equal to λ_U. In Eq. (8), CK_{ij}^1' denotes the complement of the set CK_{ij}^1.

$$\begin{gathered} k \in CK_{ij}^2 \Leftrightarrow (k \in CK_{ij}^1) \cup \{\, k \mid (DOV_{ijk} \geq \lambda_U) \cap [TE_{ij}(CK_{ij}^1 \cup k) \leq TE_{ij}(CK_{ij}^1 \cup m) \\ \forall\, k, m \in (PK_{ij} \cap CK_{ij}^{1}{}')]\} \end{gathered} \tag{8}$$

Step 3: As in Step 2, at most one additional driver-preferred route is identified as controllable using the heuristic rules of Eq. (9). That is, CK_{ij}, the final set of controllable routes identified using the 3rd *DOV* paradigm has at most one route more than CK_{ij}^2. This additional route, if it exists, is the one with the lowest TE_{ij} among all driver-preferred routes not in CK_{ij}^2 which also has a *DOV* value greater than or equal to λ_L.

$$k \in CK_{ij} \Leftrightarrow (k \in CK_{ij}^2) \cup \{\, k \mid (DOV_{ijk} \geq \lambda_L) \cap [TE_{ij}(CK_{ij}^2 \cup k) \leq TE_{ij}(CK_{ij}^2 \cup m) \tag{9}$$

$$\forall\ k,\ m \in (PK_{ij} \cap CK_{ij}^{2}\text{'})]\}$$

The last two steps of this paradigm partly include implementing the 2nd *DOV* paradigm for two different threshold values. Since, in each of these steps, the route possibly added to the controllable route set has the smallest total error among all routes that could be considered, this paradigm is more sensitive to the impact on the total error of adding a route.

3.2.2 Route type paradigms

These paradigms increase the controllable route set by adding a route according to a specific route type rule.

3.2.2.1 1st *route type paradigm*

This paradigm is labeled the "maximum SO route type paradigm". The controller-desired route to be added to the driver-preferred route set is that route, if it exists, with the highest SO proportion that does not belong to the initial driver-preferred route set PK_{ij}^{r0}. The driver-preferred route set according to this paradigm is denoted by PK_{ij}^{r}. It is expressed as follows:

$$k \in PK_{ij}^{r} \Leftrightarrow \{(k \in PK_{ij}^{r0}) \cup [\ k \mid (SO_{ijk} \geq SO_{ijm}\ \forall\ m \in DK_{ij},\ m \notin PK_{ij}^{r0}) \cap (k \notin PK_{ij}^{r0})]\} \tag{10}$$

The motivation for this paradigm is that by adding a SO route with high routing proportion to the driver-preferred set, the system performance can potentially be enhanced. However, due to the nature of the SO solution, there is a possibility that the added route may be significantly longer than those in PK_{ij}^{r0}, and drivers may ignore it. This is the motivation for the next paradigm.

3.2.2.2 2nd *route type paradigm*

This paradigm is called the "maximum degree of overlap route type paradigm". It is conceptually similar to the second route type paradigm, but adds the controller-desired (SO) route that does not belong to PK_{ij}^{r0} and has the highest associated *DOV* with a driver-preferred route. It can be expressed as follows:

$$k \in PK_{ij}^{r} \Leftrightarrow \{(k \in PK_{ij}^{r0}) \cup [\, k \mid (DOV_{ijk} \geq DOV_{ijm} \quad \forall\ k, m \in DK_{ij}) \cap (k \notin PK_{ij}^{r0})]\} \tag{11}$$

Akin to the first two *DOV* paradigms, this paradigm does not use driver behavior to determine the enhanced controllable route sets. This represents the motivation for the next paradigm.

3.2.2.3 3rd *route type paradigm*

This paradigm is labeled the "combination route type paradigm". Similar to the 3rd *DOV* paradigm, this paradigm adds the controller-desired route that does not belong to PK_{ij}^{r0} and results in the lowest TE_{ij}. This paradigm is expressed as follows:

$$k \in PK_{ij}^{r} \Leftrightarrow \{(k \in PK_{ij}^{r0}) \cup [\, k \mid TE_{ij}(PK_{ij}^{0} \cup k) \leq TE_{ij}(PK_{ij}^{0} \cup m) \quad \forall\ k, m \in DK_{ij}] \cap (k \notin PK_{ij}^{r0})\} \tag{12}$$

This paradigm is likely to perform at least as well as the previous two paradigms because it considers the expected driver response in the determination of the driver-preferred route set while seeking to minimize the total error.

4 Experiments

Simulation experiments are conducted using the solution framework for the behavior-consistent approach (Fig. 1) to address three primary objectives: (i) evaluate the sensitivity of the approach under alternative definitions for the set of controllable routes, (ii) analyze mechanisms to enhance the performance of the approach, and (iii) enhance deployment effectiveness. These objectives are assessed based on the system travel time savings that result from each deployment paradigm.

4.1 Experimental setup

This section describes the experimental setup used to address the above objectives. Several aspects of the experimental setup in terms of network and behavior characteristics are described hereafter.

4.1.1 Network characteristics

Experiments are conducted using the network illustrated in Fig. 2. It corresponds to the Borman expressway corridor network which is located in northwest Indiana and consists of a sixteen-mile section of I-80/94 (Borman expressway), I-90 toll freeway, I-65, and the surrounding arterials and streets. The network has 197 nodes, 460 links, and 43 zones (with centroids that represent origins/destinations). The Borman expressway serves a large amount of semi-trailer truck traffic and experiences high congestion levels. To manage traffic, especially under incidents, an ATIS was installed on the Borman network to provide drivers with real-time traffic information. Depending on the destination, several alternative routes can be used to divert traffic.

4.1.2 Actual driver behavior model

A model with a completely different structure compared to the rule-based controller-estimated driver behavior model is used to represent the actual behavior of the drivers. This is to ensure that the analysis is conservative in terms of the performance of the behavior-consistent approach. The model used here corresponds to a random coefficients multinomial path-size logit model. It uses travel time, number of nodes, a path-size component (Ben-Akiva and Bierlaire, 1999, Ramming, 2002) to capture the overlap between routes, and the route recommendation provided by the controller to represent actual driver behavior. The model is described in detail in Paz and Peeta (2007).

4.1.3 Level of responsiveness

Two levels of driver responsiveness to the information strategies are used to analyze the performance of the behavior-consistent approach. The first level of responsiveness defines the “less responsive” drivers. These are drivers that are slightly influenced by the information provided. They rely more on their past experience and behavioral tendencies to make route choice decisions than on the traffic information. The second level of responsiveness defines the “more responsive” drivers. These drivers are more influenced by the information than the first type of drivers. They are more likely to accept the route recommended by the controller. The details of these driver types for the controller-estimated and actual behavior models are provided in Paz and Peeta (2007).

4.1.4 Traffic flow simulation and assignment model

A traffic simulation-assignment model, DYNASMART, is used to model the network dynamics and determine the SO solution. The DTA module of DYNASMART is used in each stage to determine the SO solution that is required by the behavior-consistent approach. The traffic flow simulator module of DYNASMART is used to replicate traffic flow so as to evaluate the performance of the system under the time-dependent demand and driver route choice decisions. The model used to represent the actual driver behavior (discussed in Section 4.1.2) is embedded in DYNASMART to provide pre-trip and en-route routing capabilities. A comprehensive exposition of DYNASMART and a discussion of its capabilities are provided in Mahmassani (2001) and Chiu (2002), respectively.

4.1.5 Estimation of the driver-preferred route sets

The initial driver-preferred route sets are estimated using a two-step approach. First, a UE DTA problem is solved for the entire planning horizon using an average time-dependent demand matrix. These UE routes represent the initial set of routes used as input in the second step. Second, the initial route set and the controller-estimated driver behavior model are used to determine the route choice proportions. Then, several simulation runs are conducted in a sequential manner as follows. A random-number generator is used to allocate a route to a driver in each run consistent with the route choice proportions. The actual route taken by the driver is based on the allocated route information, the controller-estimated driver behavior model, and the controller-estimated expected travel time for each driver. Hence, each run can generate several new routes for each O-D pair. The output from a run, in terms of the actual route chosen by the driver and the updated expected link travel times for the UE routes (which update the UE route choice proportions for random allocation in the next run), are used sequentially for the next run. This process is repeated several times. Then, the top five routes (or as many as available, if the number of routes is less than five) taken by the set of drivers for an O-D pair are assumed to represent the driver-preferred route set. This approach is designed to represent the learning process that most drivers experience over time to determine their preferred route choice set. It is based on the premise that drivers consider only a subset of the routes connecting O-D pairs based on past experience and imperfect/incomplete knowledge of the current field network conditions.

4.1.6 Other details for experiments

Different scenarios are used to evaluate the performance of the behavior-consistent approach under each of the proposed paradigms. All drivers are assumed to have capabilities to receive personalized information in all scenarios except for the no-information case. This is designed to isolate effects and enable equitable comparison of the effects of the different control paradigms.

In all scenarios, other than the SO and UE DTA cases, the same model is used to represent the actual driver behavior (as discussed in Section 4.1.2). This is done so as to ensure that the insights are focused on the relative performance of the behavior-consistent approach. Similarly, all drivers with the same O-D pair are assumed to have the same set of driver-preferred routes. A total of 120,000 vehicles are loaded during the first 60 minutes of analysis. Each stage of the rolling horizon has a length of 20 minutes and a roll period of 5 minutes.

4.1.7 Benchmark scenarios for experiments

Three scenarios are used to benchmark the performance of other scenarios.

Scenario I (base-case): No information is provided to the drivers. 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): This is the SO DTA solution. By definition, it represents the theoretical best possible system performance.

Scenario III (BC-ideal): Under this scenario, the driver-preferred route set is assumed to be identical to the controller-desired (SO DTA) route set. So, the controller recommends routes from the SO DTA route set under the behavior-consistent approach, and the drivers choose routes from the SO DTA route set as well as it represents their preferred-route set. Thereby, though practically unrealistic, this scenario represents the benchmark for the best possible performance for the behavior-consistent approach because the controller can use its “ideal” route set (SO routes) to recommend routes. Hence, it is more meaningful to compare the performance of other behavior-consistent paradigms with this benchmark rather than the SO DTA solution. However, the system performance under this scenario cannot exceed the SO DTA performance because routes are chosen by the drivers based on their behavioral tendencies though they are recommended the SO routes.

4.2 Results and analysis

The following simulation scenarios are designed to evaluate each paradigm described in Section 3. Scenarios IV to VIII are described in Section 4.2.1. Scenarios IV to VI are used as additional benchmarks for the control paradigms while Scenarios VII and VIII are used to evaluate the control paradigms. Scenarios IX to XII are described in Section 4.2.2 and are used to evaluate the *DOV* paradigms. Scenarios XIII to XV are described in Section 4.2.3 and are used to evaluate the route type paradigms.

4.2.1 Control paradigms

Three other benchmark scenarios are evaluated here: one for the UE DTA, and one each for the routing using SO and UE DTA solution routing proportions. Two scenarios related to the control paradigms are analyzed: one each for the behavior-consistent approach directing the traffic system towards the SO or UE states. Figs. 3 and 4 show the percentage cumulative system travel time savings relative to the base-case (where no information is provided) for each of these scenarios under the less and more responsive behavior cases, respectively.

Scenario IV (UE DTA): This is the UE DTA solution. As is well-known in the literature, Figs. 3 and 4 indicate significant travel time savings with respect to the base-case scenario (Scenario I) but not as much as under Scenarios II and III.

Scenario V (SO-info): SO routes and their corresponding proportions are used to provide route guidance. These SO routes may or may not match driver-preferred routes. A driver completely ignores information provided about routes that do not belong to his/her preferred route choice set. This scenario is used to illustrate the effects of directly using the SO DTA solution to provide information. As shown in Fig. 3, while this scenario results in travel time savings relative to the base-case for the less responsive behavior case, there is a substantial performance gap compared to the SO and UE DTA solutions. Paz and Peeta (2007) illustrate that the SO-info scenario can perform worse than the base-case under more responsive behavior. This illustrates trade-offs between level of compliance and overreaction, implying that lack of behavior consistency can result in poor information-based control strategies.

Scenario VI (UE-info): This scenario is conceptually similar to Scenario V. However, instead of using SO routes, it uses UE routes and their corresponding proportions to provide route guidance. This scenario is used to illustrate the implications of directly using the UE DTA solution to provide information. Fig. 3 shows that while the UE-info scenario has savings over the base-case, its performance is worse than that of the SO-info scenario, indicating the inherent value of the SO objective. However, this difference is small, suggesting the existence of trade-offs between the number of controllable routes and the quality of routes relative to the controller objective. Fig. 5 illustrates that the UE-info scenario has higher compliance rates compared to the SO-info scenario. As discussed in Section 1, this is because more UE routes match driver-preferred routes compared to SO routes. However, higher compliance rates may not translate to better performance. It questions the justification of the focus on UE for route guidance based on the notion that the SO strategy is not behaviorally sustainable. This point is further illustrated in the next two scenarios where behavior-consistent strategies are used.

Scenario VII (BC-SO-info or 1st *DOV* paradigm BC-SO-info): Here, the controller uses the behavior-consistent approach to direct the system towards the SO DTA state. This scenario corresponds to basic behavior-consistent approach where information is provided for only the driver-preferred routes that fully match with controller-desired routes. As shown in Figs. 3 and 4, the system performance under this paradigm results in significant travel time savings relative to the SO-info and UE-info scenarios. It highlights the value of developing behavior-consistent strategies, which leads to significantly higher compliance rates (Fig. 5). However, the BC-SO-info scenario results in fewer savings compared to the idealized SO or UE DTA scenarios which unrealistically assume 100% compliance with the corresponding routing strategies. In reality, the controller has only limited control over the system as drivers make route choice decisions using several factors.

Scenario VIII (BC-UE-info with λ = 1): Here, the controller uses the behavior-consistent approach to direct the system towards the UE DTA state. Akin to the previous scenario, the controller recommends routes using only driver-preferred routes that fully match with controller-desired routes. The BC-UE-info scenario performs better than the SO-info and UE-info scenarios because of the behavior-consistent approach. It implies that the controller can significantly enhance system performance by directing the system towards either the SO or the UE DTA states in a behavior-consistent manner. However, for the reasons discussed under Scenario VI, it does not perform as well as the BC-SO-info scenario.

Figs. 3 and 4 indicate that the gap between SO DTA and BC-SO-info is larger than the gap between UE DTA and BC-UE-info. As discussed in Section 3.1, this is because there are more controllable routes under BC-UE-info that under BC-SO-info. Hence, the controller has more options to approach to its objective when it seeks the UE state. For the reasons discussed in Scenarios VI and VIII, the BC-SO-info scenario performs better than the BC-UE-info scenario. This is in contrast to most of the current literature that advocates UE-based information strategies over SO-based ones. While many route guidance models (e.g., Mahmassani et al., 1994, Ben-Akiva et al., 1997) include both SO and UE as driver classes, there is a marked bias to considering the UE solution as the preferred approach for route guidance, while the SO solution is typically relegated to being an upper bound or justified only for special cases such as incident management. Stier-Moses (2004) and Jahn et al., (2005) discuss the inefficiency of UE-based information strategies. They propose the use of SO-based constrained routing approaches, where a static SO problem is solved while precluding relatively long routes from being included in the solution to generate a better routing approach compared to UE.

Fig. 6 illustrates that there are more controllable routes when the behavior-consistent approach seeks to direct the system towards the UE state rather than towards the SO state. This is consistent with the earlier discussion on UE strategies entailing higher compliance rates compared to SO ones. In general, more controllable routes imply higher compliance rates under the behavior-consistent approach. Fig. 7 shows the compliance rates for the BC-UE-info and BC-SO-info scenarios under the two levels of responsiveness. As expected, the compliance rates are higher for the "more responsive" case under both the UE and SO strategies.

4.2.2 Degree of overlap paradigms

The 1st *DOV* paradigm corresponds to Scenario VII. Two scenarios each are evaluated for the 2nd and 3rd *DOV* paradigms. Figs. 8 and 9 plot the percentage cumulative system travel time savings relative to the base-case scenario for these scenarios for less and more responsive drivers, respectively.

Scenario IX (2nd *DOV* paradigm BC-SO-info λ = 0.90): This scenario implements the threshold *DOV* paradigm with λ equal to 0.90. The results indicate that scenario enhances system performance relative to the 1st *DOV* paradigm. It implies that additional "good quality" controllable routes are available for traffic routing as λ is relatively high. Thereby, there are some driver-preferred routes that are almost identical to some controller-desired routes. This is a case where the number of routes added to the controllable set and their quality are significant enough to positively affect performance.

Scenario X (2nd *DOV* paradigm BC-SO-info λ = 0.80): When λ equal to 0.80 is used, the trade-offs between the number of routes and route quality become apparent. Hence, while this scenario performs better than the base-case, it does worse than the 1st *DOV* paradigm. The trade-offs are nicely illustrated in Fig. 10 which shows the system travel time savings relative to the base-case for various λ values under the less responsive behavior. As the λ value decreases from 1, more routes are identified as controllable though their quality degrades relative to the controller objective. Initially, the presence of more controllable routes improves performance beyond the 1st *DOV* paradigm, but as λ is decreased further, the negative effect of route quality kicks in. In the context of route guidance, this implies that simply increasing the number of routing options does not necessarily imply better performance, and the effectiveness of a route vis-à-vis the controller objective is as important.

Scenario XI (3rd *DOV* paradigm BC-SO-info λ_U = 0.90 & λ_L = 0.80): This scenario represents the 3rd *DOV* paradigm with λ_U equal to 0.90 and λ_L equal to 0.80. Fig. 8 shows that this scenario performs worse than Scenario IX and about the same as the 1st *DOV* paradigm. For the more responsive case (Fig. 9), it performs similar to Scenario IX. This suggests that there may not be a need for the complex approach represented by the 3rd *DOV* paradigm, and the 2nd *DOV* paradigm is sufficient to achieve comparative results. The performance of the 3rd *DOV* paradigm is not superior because at most it adds one route each in the last two steps of its approach, while Scenario IX can add several good quality routes as part of its paradigm.

Scenario XII (3rd *DOV* paradigm BC-SO-info $\lambda_U = 0.85$ & $\lambda_L = 0.75$): The savings under this scenario are lower than under Scenario XI. This is expected based on the 2nd *DOV* paradigm insights relative to the value of λ (Fig. 10); the quality of the additional controllable routes is not significant enough to positively affect performance.

Figs. 8 and 9 also illustrate that the BC-UE-info strategy does not perform as well as Scenarios IX and XI, both of which perform at least as well or better than the BC-SO-info strategy with λ equal to 1. This further corroborates the insights discussed in Section 4.2.1 on the relative value of SO-based strategies.

In summary, the 2nd *DOV* paradigm with a high λ value provides the best approach to enhance system performance beyond that under the 1st *DOV* paradigm.

4.2.3 Route type paradigms

Each BC-SO-info route type paradigm described in Section 3.2.2 is associated with one scenario. Figs. 11 and 12 depict the percentage cumulative system travel time savings relative to the base-case for less and more responsive drivers, respectively. It should be noted here that the three scenarios discussed hereafter, Scenarios XIII-XV, have a larger driver-preferred route set (one more route) compared to Scenarios IV-XII, and hence, may have an *a priori* advantage over them. This is confirmed in Figs. 11 and 12, where the performance of Scenarios XIII-XV is at least as good as or better than the various *DOV* paradigm based scenarios.

Scenario XIII (1st route type BC-SO-info): This scenario performs better than the 1st *DOV* paradigm. This is because for each O-D pair one additional controller-desired route is likely to become a driver-preferred route, providing more options to the controller.

Scenario XIV (2nd route type BC-SO-info): The results under this scenario are very similar to the ones under the previous scenario. This implies that adding the SO route that overlaps the most with a driver-preferred route is as effective, in terms of system performance, as adding the route with the highest SO proportion. From the behavior-consistent approach perspective, this suggests that the 2nd route type paradigm may suffice compared to exploring the 1st route type paradigm as its focus is on the degree of overlap.

Scenario XV (3rd route type BC-SO-info): This scenario performs better than Scenarios XIII and XIV. This is because it uses the estimation of driver behavior to select the controller-desired route to add to the driver-preferred route set that minimizes the total error. It corroborates the importance of behavior-consistent approaches for the development of information-based network control strategies.

The travel time savings illustrated in Figs. 8, 9, 11 and 12 indicate how various paradigms perform relative to the BC-ideal and full overlap paradigms. The objective of the analysis is to obtain insights on the tradeoffs offered by the various paradigms and specific trends (Fig. 10) that can aid deployment strategies. As noted before, the BC-ideal case is an idealized strategy and the full overlap paradigm may have deployment limitations. Hence, the experiments seek to explore potential alternative paradigms in terms of their deployment effectiveness.

5 Concluding comments

This paper proposes alternative paradigms to enhance the performance and the deployment effectiveness of a behavior-consistent information-based network control approach (Paz and Peeta, 2007). It compares the performance and compliance aspects associated with directing the system towards the UE or SO states. It evaluates the sensitivity of the behavior-consistent approach under various definitions for the sets of controllable and driver-preferred routes so as to improve performance and analyze practical aspects to enhance deployment effectiveness.

The study captures the interdependencies between network interactions and driver response to information by explicitly focusing on the acceptability of routes to drivers, the quality of those routes relative to the controller objective, and ensuring behavior consistency in route recommendations. Existing approaches, addressed primarily under the DTA label, tend to mostly focus on adequately capturing the network flow interactions and dynamics, while making strong assumptions on driver behavior under information provision.

Broadly, the study results confirm the primary finding of the behavior-consistent approach proposed previously by the authors (Paz and Peeta, 2007; 2008a); the simultaneous consideration of controller objectives and driver behavior is essential to identifying realistic and superior information-based control strategies. Here, "realistic" implies that the expectation of the controller in terms of the likely response of drivers to the route recommendations is a reasonable representation of the evolving network conditions. The superior performance is due to the explicit assurance of behavior consistency, thereby preventing the possibility that the controller may over-recommend or under-recommend routes, or recommend routes that are not considered by the drivers.

A key insight from this study is that there are trade-offs between the number of driver-preferred routes considered by the controller for routing and the quality of routes relative to the controller objective. They manifest during the investigation of alternative control (SO and UE) and *DOV* paradigms. In the control paradigm context, the results suggest that while a larger percentage of UE routes match driver-preferred routes, the inherent quality of the SO solution has intrinsic value. That is, even when routing is performed in a behavior-consistent manner, higher compliance rates need not necessarily translate to better system performance. This questions the justification of UE DTA solutions for route guidance on the ground that a SO strategy is not behaviorally sustainable or implies unfair routing recommendations. A fundamental corollary is that focusing primarily on robustly addressing either driver behavior (enhancing compliance) or controller objective (quality of routes) while representing the other aspect in a rudimentary manner is not adequate to ensure effective performance in the real-world. That is, approaches driven primarily by either network traffic flow modeling or behavior modeling do not suffice, implying the need for models with explicit supply-demand integration.

The trade-offs between the number and quality of routes are further illustrated by the *DOV* paradigm experiments (as shown in Fig. 10). In these paradigms, higher threshold *DOV* values are associated with better quality of routes, but may lead to fewer controllable routes. Hence, the trade-offs lead to an "optimal" threshold *DOV* value at which the system performs the best. The system performance deteriorates dramatically as the threshold *DOV* value decreases from the "optimal" value, and at some point this paradigm may not generate savings over even the base-case.

Over time, the learning processes of drivers vis-à-vis route guidance can alter their preferred-route choice set. The controller can potentially influence this process by providing "new" routes based on its objectives and by factoring driver preferences. For example, these can be controller-desired routes that highly overlap driver-preferred routes. Hence, they are likely to be accepted as new preferred-route alternatives by the drivers, increasing the controller's ability to enhance system performance.

The use of the controller-estimated driver behavior model in the behavior-consistent approach to determine the routes to be recommended to drivers and to identify new driver-preferred routes is a key element of the behavior-consistent approach. There are numerous route choice models in the literature that can potentially be used to meaningfully estimate driver route choice decisions and calibrate the associated model parameters. For example, Peeta and Yu (2006) propose a consistency-seeking mechanism for a hybrid route choice model (Peeta and Yu, 2005) that updates the model parameters on-line. In on-going work, the authors develop an on-line consistency-seeking model that calibrates the parameters of the proposed rule-based controller-estimated driver behavior model using field data to minimize the difference between the actual and the estimated network states in terms of link volumes. It closes the loop for the deployment of the behavior-consistent approach by enabling the simultaneous on-line determination of the behavior-consistent information strategies and the calibration of the controller-estimated model parameters.

References

Bekhor S, Ben-Akiva ME, Ramming MS (2006) Evaluation of choice set generation algorithms for route choice models. Analysis of Operations Res 154(1):245-257

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

Ben-Akiva ME, Bierlaire M, Bottom J, Koutsopoulos HN, Mishalani RG (1997) Development of a route guidance generation system for real-time application. Papageorgiou M, Pouliezos A, (ed) Proc of the 8th IFAC Sympos on Transpo Sys. Elsevier Science, Oxford, UK

Bonsall PW, Joint M (1991) Evidence on drivers' reaction to in-vehicle route guidance advice. Proc of the 24th Int. Sym. on Automotive Technology and Automation, Florence, Italy

Chiu Y-C (2002) Generalized real-time route guidance strategies in urban networks. Ph.D. Thesis, Department of Civil and Environmental Engineering, University of Texas, Austin

Hall RW (1996) Route choice and advanced traveler information systems on a capacitated and dynamic network. Transpo Res, Part C 4(5):289-306

Mahmassani HS, Hu T-Y, Peeta S, Ziliaskopoulos A (1994) Development and testing of dynamic traffic assignment and simulation procedures for ATIS/ATMS applications. Technical report DTFH61-90-R-0074-FG, Center for Transportation Research, University of Texas, Austin

Mahmassani HS (2001) Dynamic network traffic assignment and simulation methodology for advanced system management applications. Netw and Spat Econ 1(3/4):267-292

Nakayama S, Kitamura R (2000) Route choice model with inductive learning. Transp Res Rec 1725, TRB, National Research Council, Washington, D.C:63-70

Jahn O, Möhring RH, Schulz AS, Stier-Moses NE (2005) System-optimal routing of traffic flows with user constraints in network with congestion. Operations Res 53(4):600-616

Paz A, Peeta S (2007) Network-level evaluation of real-time behavior-consistent traffic routing strategies. In: Proc of the 86th Annual Meeting of the Transp Res Board, Washington, DC.

Paz A, Peeta S (2008a) Information-based network control strategies consistent with estimated driver behavior. Transportation Research Part B, http://dx.doi.org/10.1016/j.trb.2008.06.007

Paz A, Peeta S (2008b) On-line calibration of behavior parameters for behavior-consistent route guidance. Transportation Research Part B, http://dx.doi.org/10.1016/j.trb.2008.07.007

Peeta S, Yu JW (2005) A hybrid model for driver route choices incorporating en-route attributes and real-time information effects. Netw and Spat Econ 5(1):21-40

Peeta S, Yu JW (2006) Behavior-based consistency-seeking models as deployment alternatives to dynamic traffic assignment models. Transp Res, Part C 14(2):114-138

Peeta S, Ziliaskopoulos A (2001) Foundations of dynamic traffic assignment: The past, the present and the future. Netw and Spat Econ 1(3/4):233-266

Ramming MS (2002) Network knowledge and route choice. Ph.D. Thesis, Department of Civil and Environmental Engineering, MIT, Boston

Stier-Moses NE (2004) Selfish versus coordinated routing in network games. Ph.D. Thesis, Sloan School of Management, MIT, Boston

Vaughn KM, Abdel-Aty MA, Kitamura R, Jovanis PP, Yang H (1993) Experimenting analysis and modeling of sequential route choice under ATIS in a simple traffic network. PATH Research Report 93-12

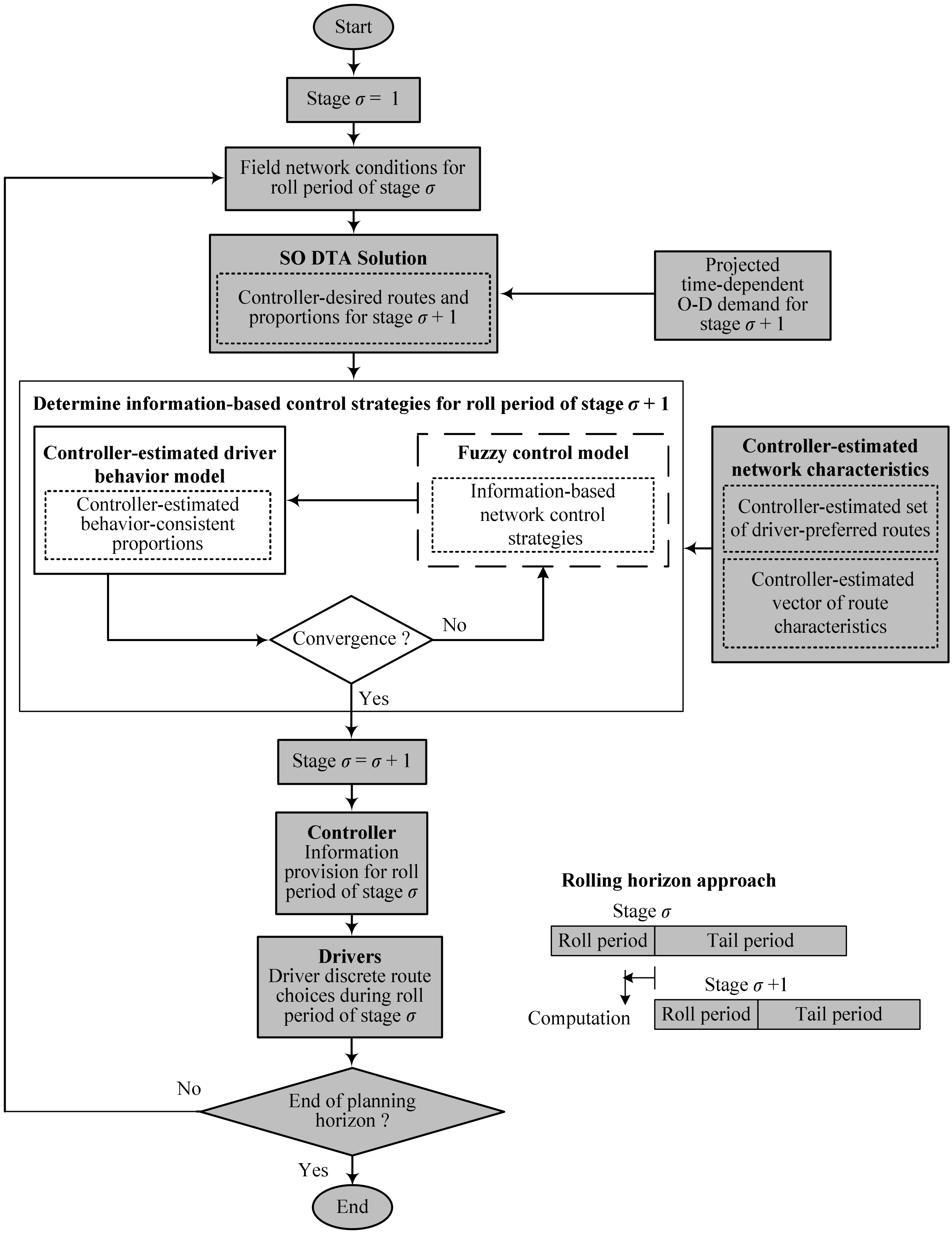

Fig. 1 Solution framework for the behavior-consistent traffic routing problem under information provision

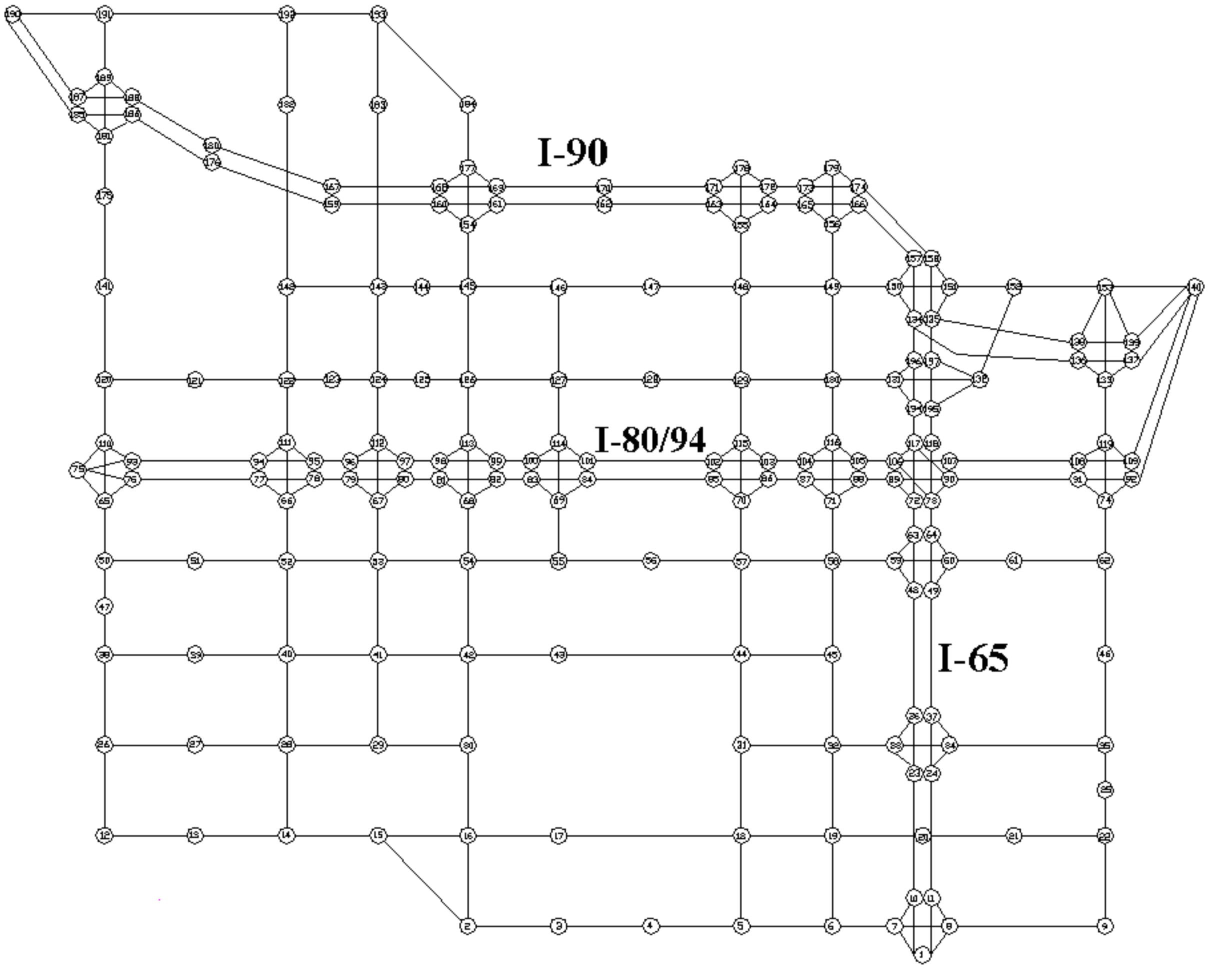

Fig. 2 Borman network

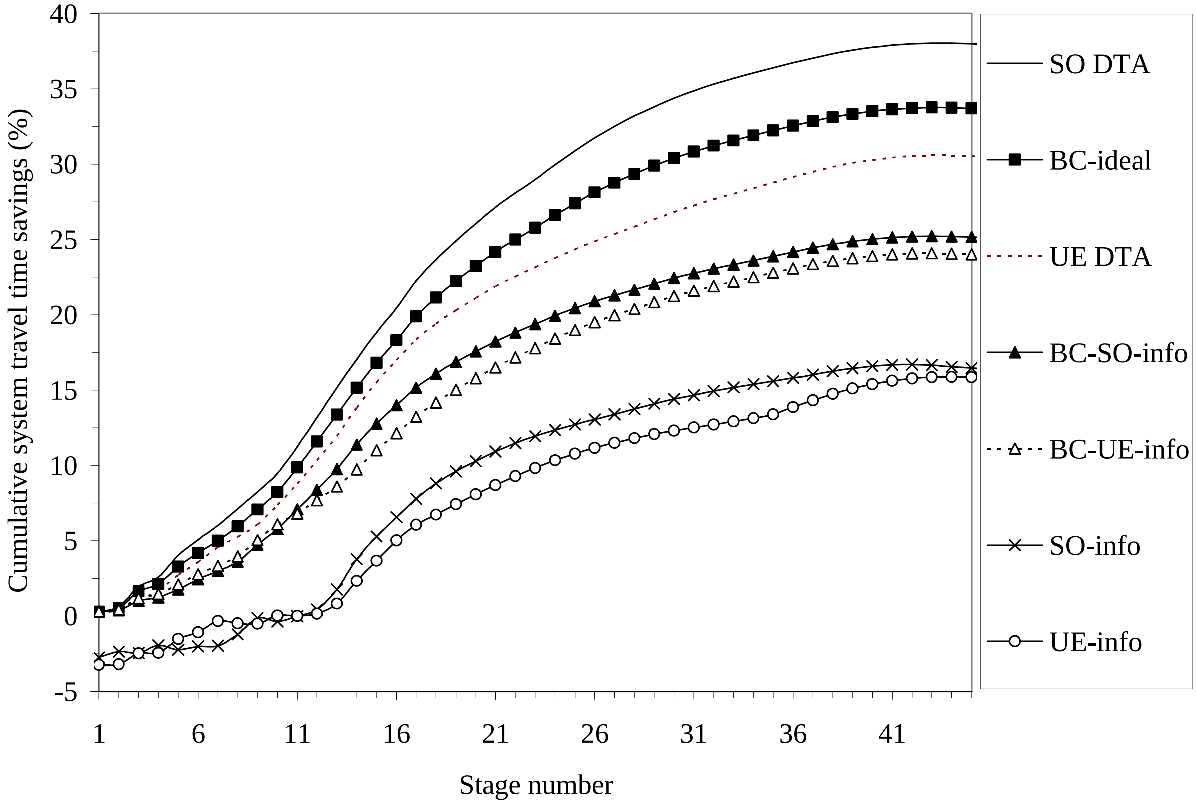

Fig. 3 Cumulative system travel time savings under the less responsive behavior benchmarked against the no-information case (base-case)

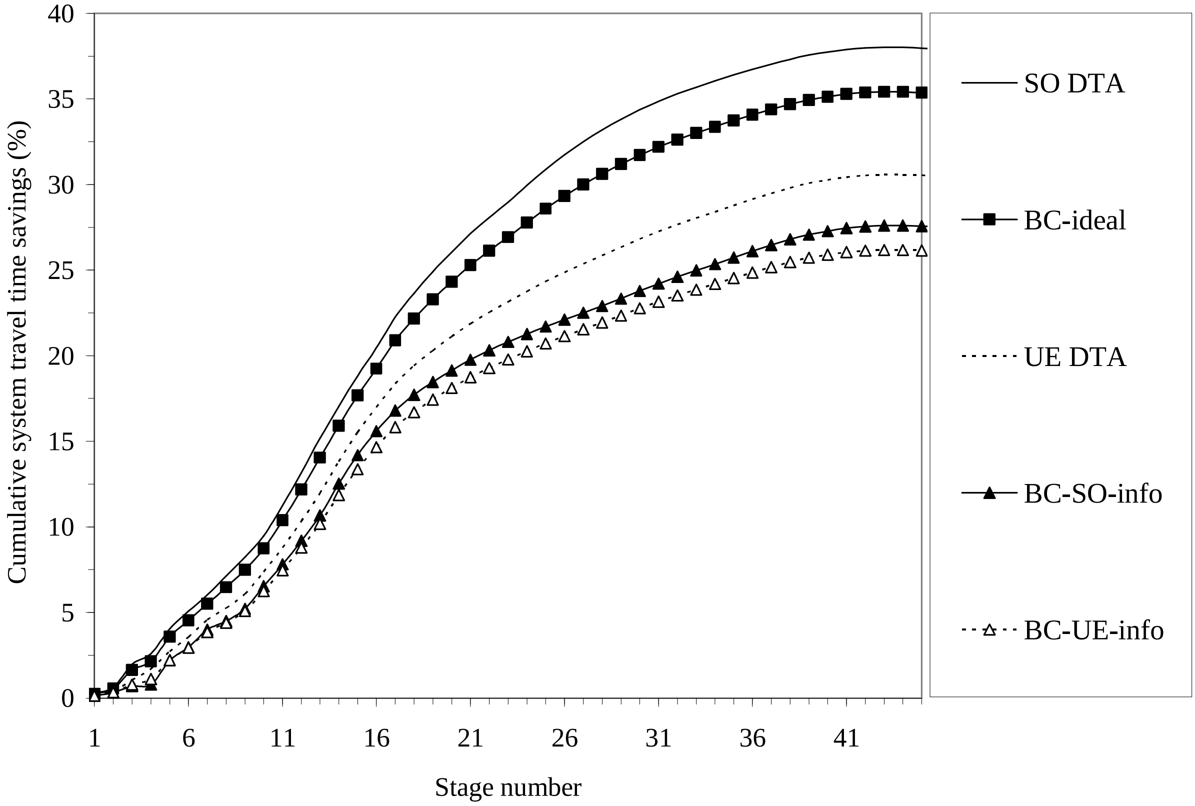

Fig. 4 Cumulative system travel time savings under the more responsive behavior benchmarked against the no-information case (base-case)

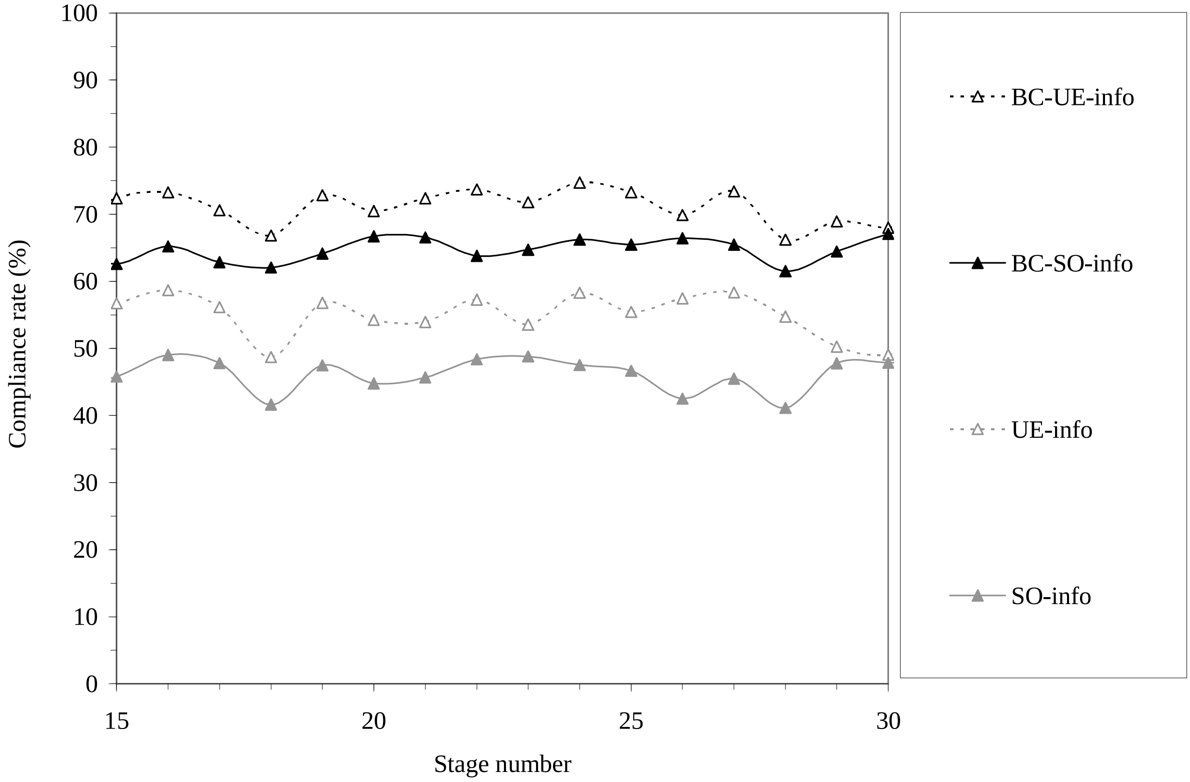

Fig. 5 Compliance rates for the less responsive behavior case under the standard DTA and behavior-consistent approaches

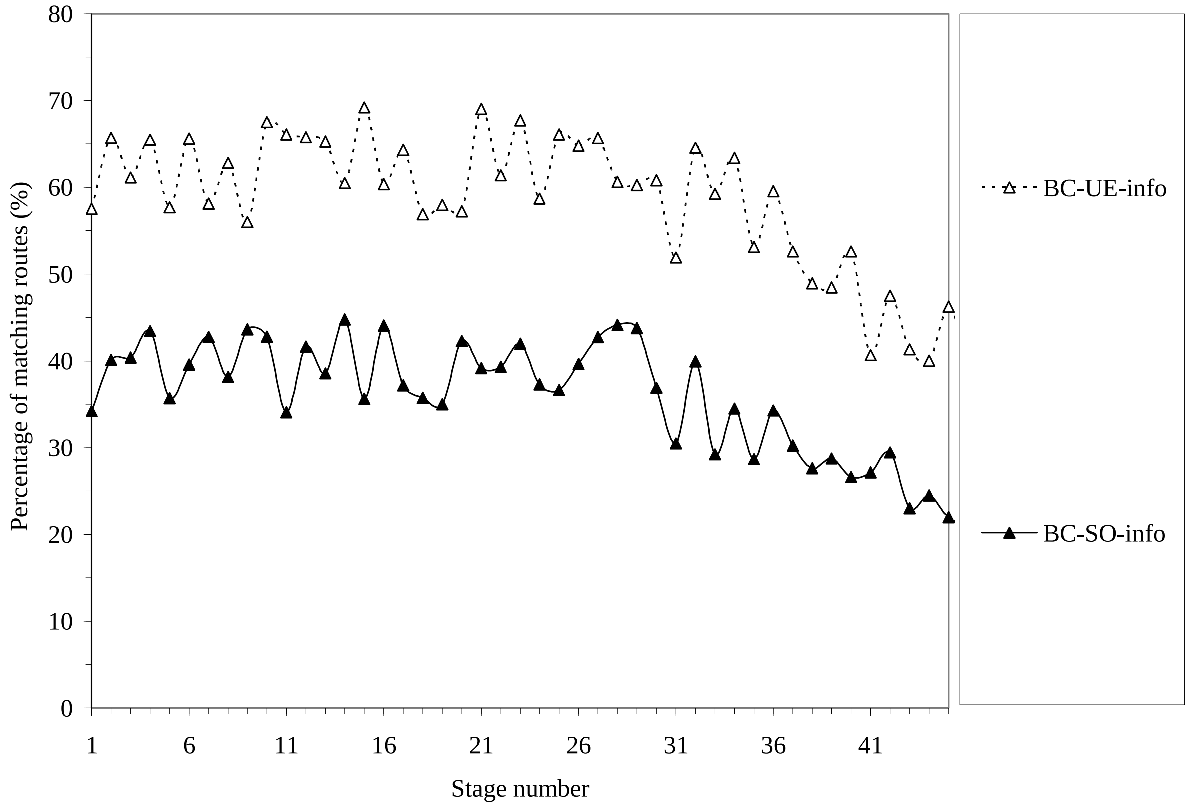

Fig. 6 Percentage of driver-preferred routes matching UE and SO routes

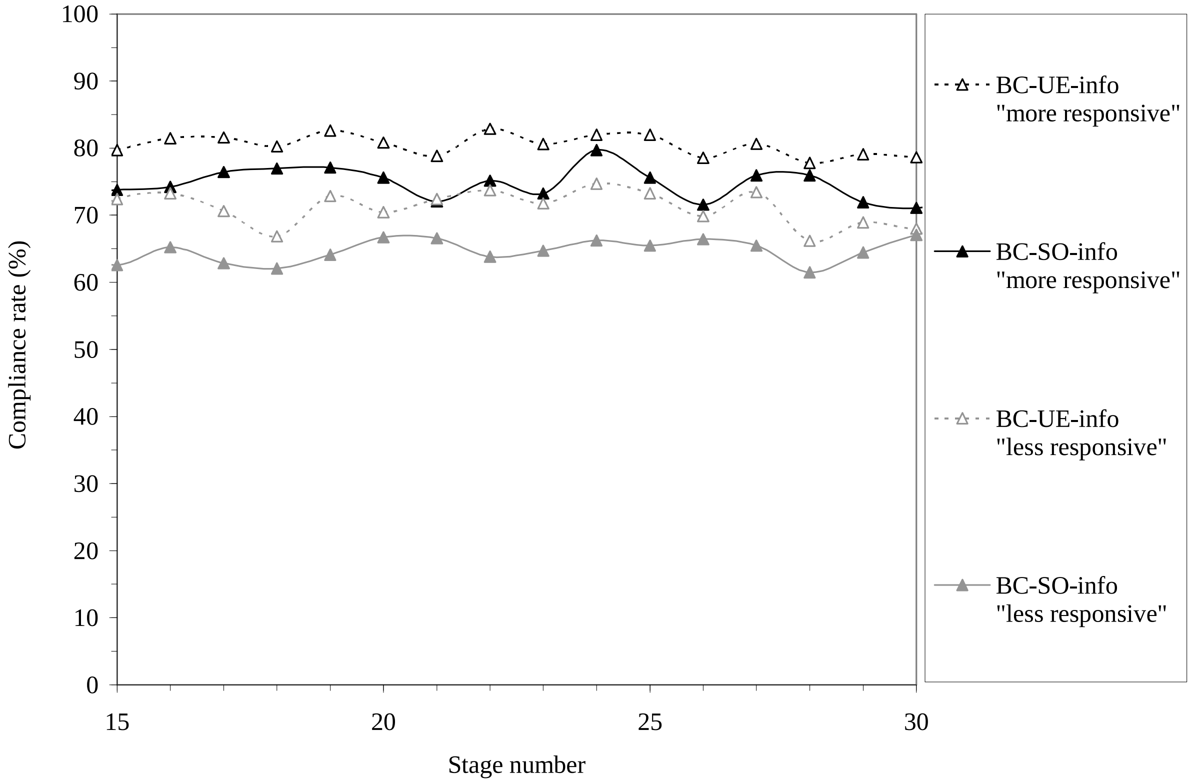

Fig. 7 Compliance rates for more and less responsive behaviors

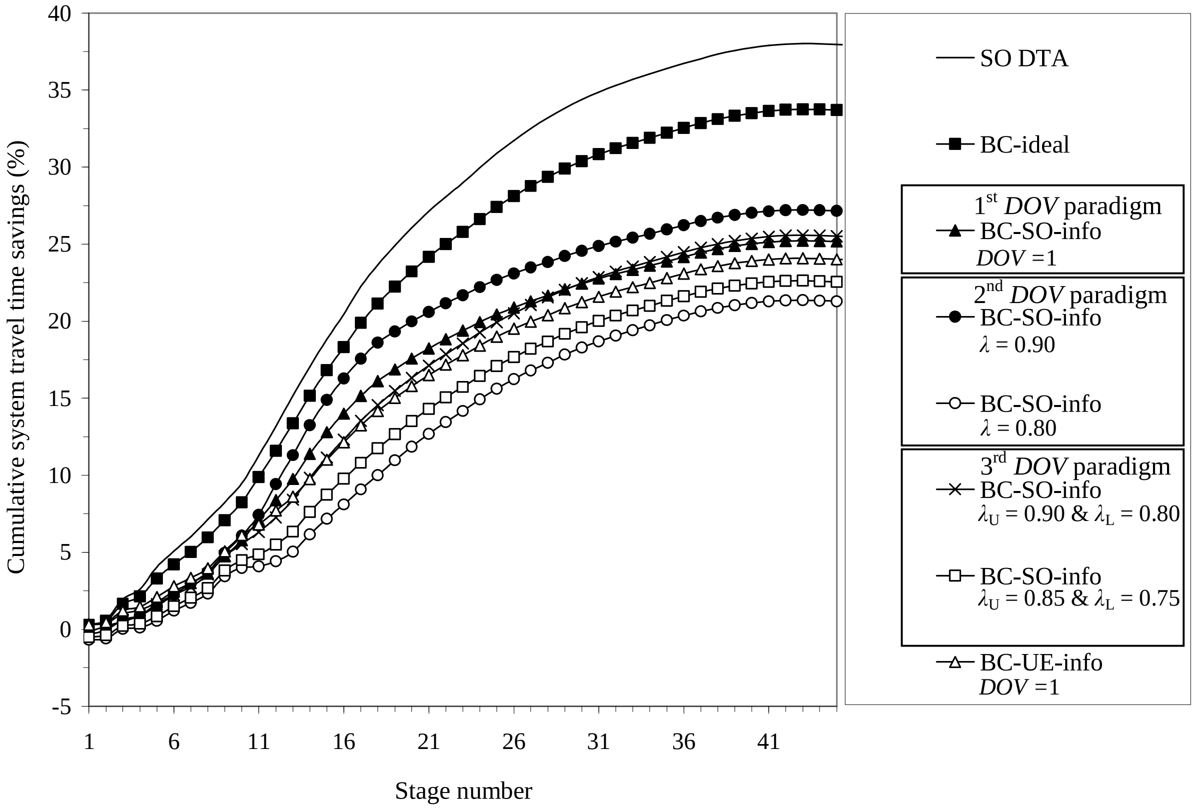

Fig. 8 Cumulative system travel time savings under the less responsive behavior relative to the base-case for the *DOV* paradigms

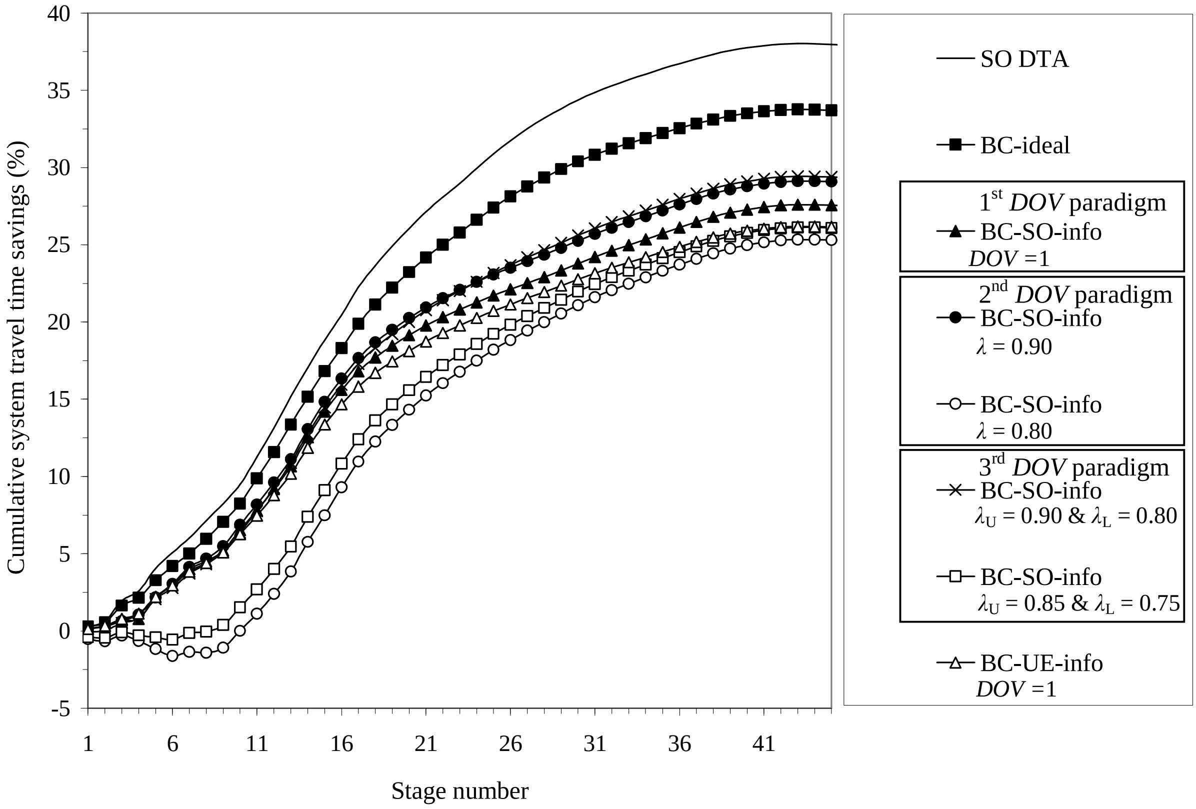

Fig. 9 Cumulative system travel time savings under the more responsive behavior relative to the base-case for the *DOV* paradigms

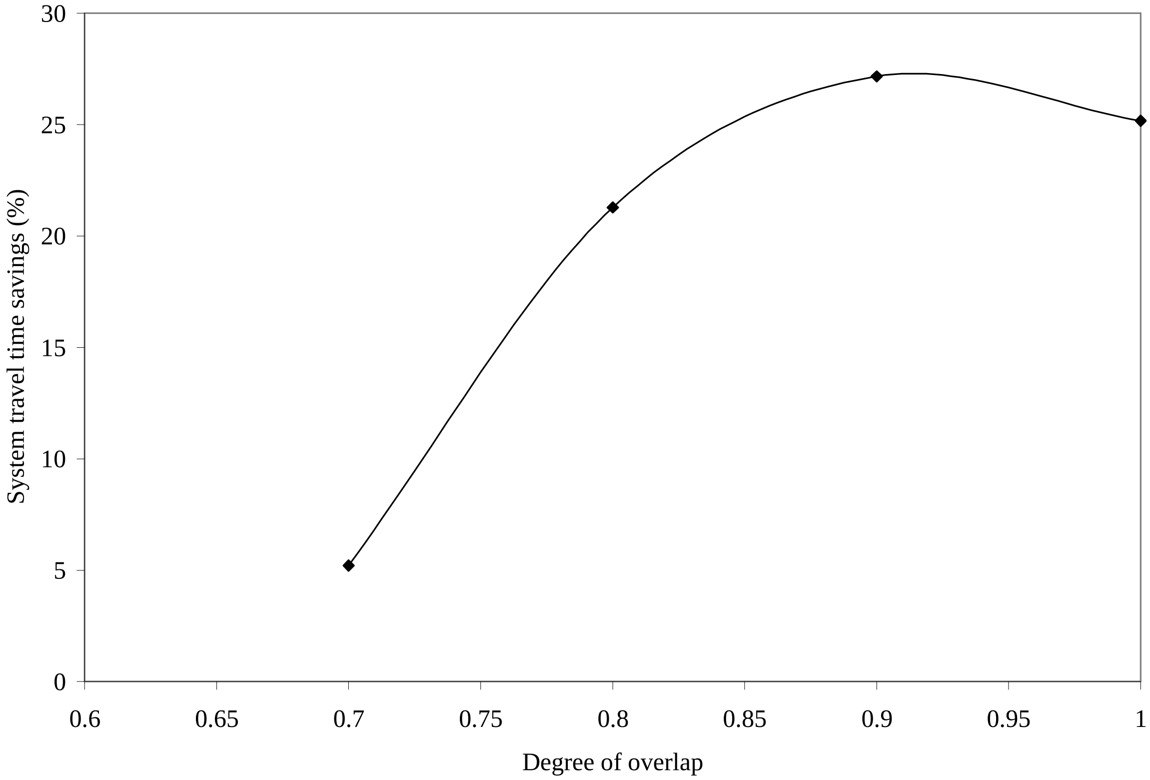

Fig. 10 System travel time savings under the less responsive behavior relative to the base-case versus the *DOV*

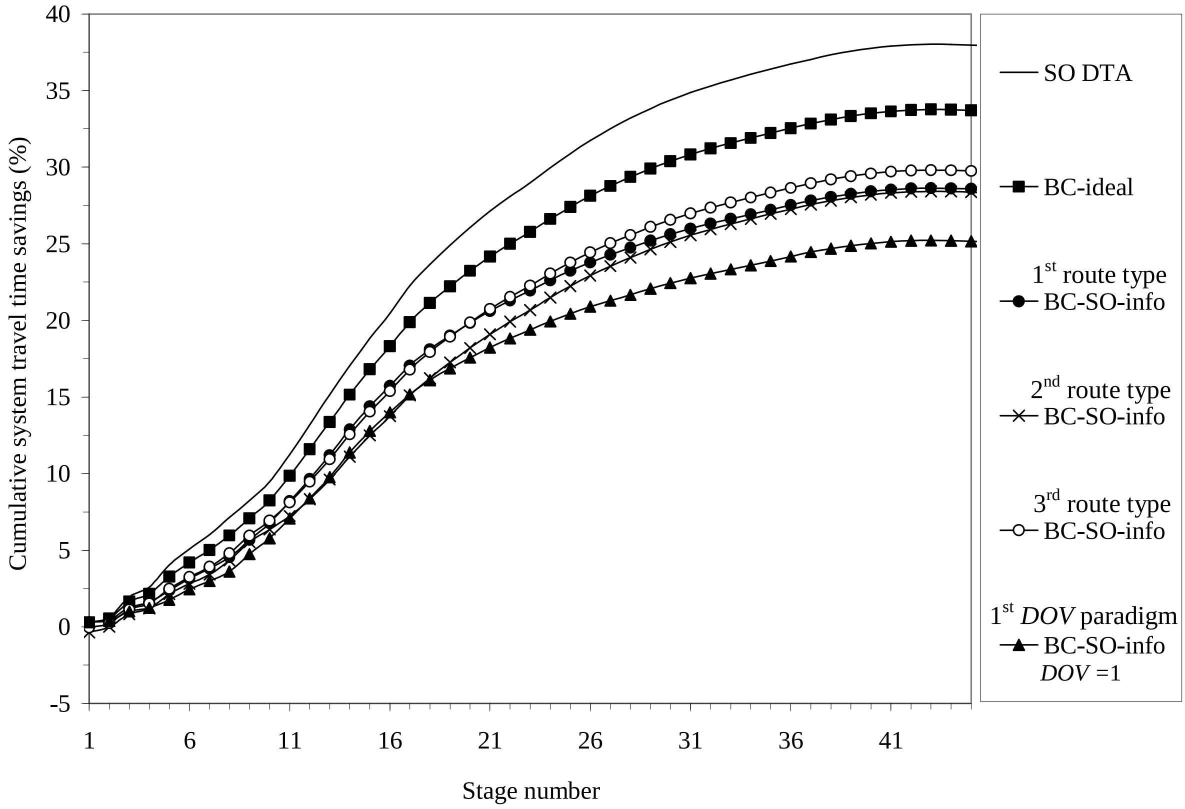

Fig. 11 Cumulative system travel time savings under the less responsive behavior relative to the base-case for route type paradigms