Evolution of Network Flows Under Real-Time Information: Day-to-Day Dynamic Simulation Assignment Framework

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A day-to-day dynamic framework, in which the DYNASMART simulation assignment model was applied to evaluate the performance of traffic networks, was developed to study network dynamics under different information systems. Two levels of tripmaker decision-making processes are identified: (*a*) day-to-day dynamics and (*b*) real-time dynamics. Day-to-day dynamics consider the choices of departure time and route according to indifference bands of tolerable "schedule delay" defined as the difference between the user's actual and preferred arrival times. Real-time dynamics consider en route switching decisions. Numerical experiments were conducted to investigate the day-to-day evolution of network flows under real-time information and assess the effectiveness of such information in a proper dynamic perspective.

Advanced traveler information systems (ATIS) and advanced traffic management systems provide a variety of capabilities to alleviate traffic congestion in urban networks by strengthening the connection between traffic control and available information (*1*). The evaluation of such information-based systems has been concerned primarily with the potential of this information to redistribute flows spatially over the network during the peak period on a given day (*2–4*). However, real-time information can also induce changes in time of departure, leading to temporal redistribution of the flows. Such effects tend to take place over several days. In other words, although the ability of real-time information to affect en route switching is well recognized, its potential effect on the day-to-day decisions of departure time and route remains to be investigated systematically. A key question is how tripmakers make decisions on the basis of experienced or received information, or both. Although the importance of learning processes in such systems has been recognized (*5–8*), consideration of such processes needs to be incorporated into the effectiveness of analysis and evaluation of information systems.

This paper describes a day-to-day dynamic simulation assignment framework to study the interaction among individual decisions, traffic control strategies, and network flow patterns under real-time information systems. The framework integrates two previous lines of investigation, namely (*a*) day-to-day forecasting methods for commuter systems, previously considered only in a corridor context and without en route real-time information (*9*), and (*b*) time-dependent assignment-simulation modeling for networks with general topology under real-time ATIS in the form of DYNASMART (*10*). The resulting methodology is applicable to general networks with detailed representation of traffic processes, including traffic control actions, and provides a tool for forecasting the day-to-day evolution of the system under various information policies, network supply actions or control strategies. System users are represented individually in the model, and their daily decisions of route and departure time (and possibly mode) provide the principal mechanism governing day-to-day evolution. Similarly, user decisions in response to information, both en route and pretrip, are also represented individually. As such, this framework provides an illustration of an operational dynamic demand forecasting tool on the basis of microsimulation of individual tripmaking decisions (although traffic interactions are modeled using macroscopic relations).

The next section presents the day-to-day dynamic simulation assignment model framework and DYNASMART. The algorithmic procedure and experimental design and numerical results are discussed, and concluding comments follow.

DAY-TO-DAY DYNAMIC SIMULATION ASSIGNMENT FRAMEWORK

Given the focus on peak-period network flows, the framework considers primarily the variation in route and departure time in the context of commuting trips to work, for which tripmaker behavior rules for day-to-day decisions have been calibrated in previous work. Extensions to consider noncommuters and nonwork trips are conceptually straightforward in terms of overall framework, although appropriate individual decision rules for these situations remain to be developed.

Consider a network $G(N,A)$ consisting of a set of nodes N connected by the set of directed arcs A. Suppose user i intends to go from origin r to destination s and arrives at his or her preferred arrival time (PAT_i), $\forall i \in D$, the set of all drivers. PAT_i reflects inherent preferences and risk attitudes of commuter i, as well as the characteristics of the work place. In this paper, PAT_i is assumed fixed for a given tripmaker; however, it could be generalized and varied through appropriate behavior models to reflect flexible work schedules. The selected departure time $j_{i,t+1}$ and route $k_{i,t+1}$ for driver i on Day $t + 1$ are the outcomes of its decision-making process, described as

$$k_{i,t+1} = f_r(X_i, Z_{i,t}, Y_{i,t} \mid \theta_r) \tag{1}$$

$$j_{i,t+1} = f_{dt}(X_i, Z_{i,t}, Y_{i,t} \mid \theta_{dt}) \tag{2}$$

where

$k_{i,t+1}$ = selected route for driver i on day $t + 1$
$j_{i,t+1}$ = selected departure time for driver i on day $t + 1$,
$f_r(.)$ = route choice decision-making process function,

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$f_{dt}(.)$ = decision-making process function for departure time,
X_i = vector of driver characteristics,
$Z_{i,t}$ = vector of endogenous information characteristics for driver i up to day t,
$Y_{i,t}$ = vector of exogenous information characteristics for driver i up to day t, and
θ_r, θ_{dt} = parameter vectors to be calibrated.

The choices of departure time and route of tripmaker i on day $t + 1$ depend on individual tripmaker characteristics, endogenous information from personal experience, and exogenous information from traffic control centers.

The aggregated departure time decisions of all users determine a three-dimensional time-dependent origin-destination (OD) matrix; the route choices determine the spatial distribution of flows over the peak period. The time-dependent OD matrix and the initial route assignment form the major input for DYNASMART, in which individual en route decisions are represented. Within the simulation period, tripmaker i equipped to receive in-vehicle information makes en route decisions according to his or her own behavioral characteristics and information received about prevailing traffic conditions in the network. Let $\delta_{i,n,1}$ denote a binary indicator that is 1 when driver i switches to a new path 1 at node n from the current path and 0 otherwise; $\delta_{i,n,1}$ can be determined by the user's characteristics, knowledge of the paths at node n, $Z_{i,t}(n)$ and new information about path from node n to his or her destination and is expressed as

$$\delta_{i,n,1} = f_s[X_i, Z_{i,t}(n), Y_{i,t}(n)|\theta_s] \quad (3)$$

where

$Z_{i,t}(n)$ = endogenous knowledge of driver i at node n on day t,
$Y_{i,t}(n)$ = exogenous information for driver i at node n on day t,
f_s (.) = en route path-switching function, and
θ_s = parameter vector, to be calibrated.

As a consequence, the flow pattern in the network on day t, F_t, resulting from a time-dependent OD, initial path selections for day t, and en route path-switching decisions can be expressed as

$$F_t = \text{flow}_t\ (k_{i,t}, j_{i,t}, \delta_{i,n,1}, \forall_i \in D \text{ and } n \in N) \quad (4)$$

Endogenous and exogenous information $Z_{i,t}$ and $Y_{i,t}$ can be written as

$$Z_{i,t} = f_n\ (X_i, F_t) \quad (5)$$

$$Y_{i,t} = f_x\ (C_{r,t+1}, C_{s,t+1}, F_t) \quad (6)$$

where

f_n (.) = endogenous information acquisition function,
f_x (.) = exogenous information provision function, and
$C_{r,t+1}$ and $C_{s,t+1}$ = route control and signal control on day $t + 1$.

$Z_{i,t}$ and $Y_{i,t}$ are then used in Equations 1 and 2 to determine the departure time and initial route on day $t + 1$. Note that the control actions $C_{r,t+1}$ and $C_{s,t+1}$ on day $(t + 1)$ are generated with knowledge by the controller on traffic conditions associated with flow pattern F_t on day t. The whole process takes place in a recursive form. Naturally, the complexity of the interactions depicted earlier precludes analytic solution of system performance descriptors.

Information Systems

Information types and flow for different types of user classes within this framework are defined to illustrate the possible interaction between them. Vehicles (i.e., users) are differentiated into equipped and nonequipped classes on the basis of their ability to communicate in real time with a central controller. Nonequipped vehicles do not receive real-time information and are assumed to follow the initial path selected before their departure. Although users in this class do not make decisions on the basis of in-vehicle real-time information, they can still respond to exogenous information supplied through variable message signs. Equipped vehicles communicate with the controller, and their drivers can therefore make decisions on path selection en route.

Information strategies can be categorized into two general types: descriptive and normative. Descriptive information, currently the most common type used or proposed, provides tripmakers with current traffic conditions through different communication channels. Tripmakers can use this information to make their own travel decisions, independently of other users' decisions. On the other hand, normative information delivers instructions aimed at achieving some systemwide objectives. Information can be experienced by travelers or collected by control centers by probes, detectors, or equipped vehicles, or all of these.

A fundamental problem is what actions drivers might make on the basis of different information types. In the day-to-day dynamics context, studies that have explicitly dealt with this aspect have relied on a convenient Markovian assumption, whereby the anticipated travel time on a given day is assumed to be equal to its actual value on the preceding day only (*11–13*.) Horowitz (*14*) proposed to model the predicted trip time on day t as a weighted sum of all previous days' trip times. Empirical investigation of this issue is limited. Mahmassani and Chang (*15*) and Tong et al. (*16*) have calibrated departure time adjustment rules in which the predicted travel time is based on the driver's own previous experience as well as exogenous information. The calibrated models show that the influence of travel time on the immediately preceding day, $TR_{i,t-1}$, is much greater than that of $TR_{i,t-2}$ (experienced 2 days previously). Functional forms of how information is processed can thus be generalized as the weighted sum of all previous days' information and different assumptions on tripmaker behavior can be reflected by varying the relative weights.

Day-to-Day Dynamic Choice Behavior

The behavior component within the day-to-day framework addresses the selection of route and departure time in accordance with individual attributes and received information. The theoretical underpinnings of the model are grounded in Simon's well-known notion of bounded rationality, applied to commuter day-to-day decisions of departure time and route in work by Mahmassani and Chang (*17,18*). Essentially, the model is founded on the simple notion that if tripmakers are not satisfied with their previous selections, they will seek to select a new route or adjust their departure time, or both. Satisfaction is implemented on the basis of "indifference bands" of tolerable schedule delay (relative to one's preferred arrival time).

This decision process consists of two levels, as indicated in Figure 1. The first level is concerned with acceptability of the conse-

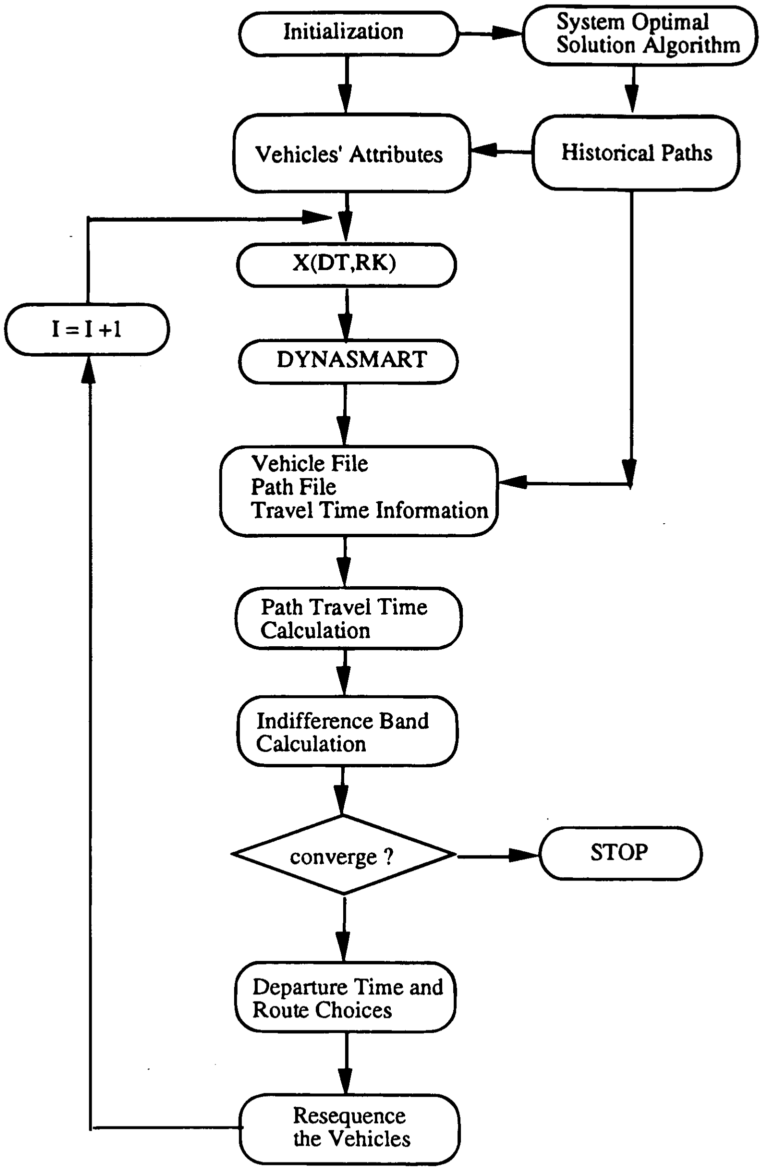

FIGURE 1 Day-to-day dynamic analysis procedure.

quences of the latest choices, vis-à-vis the indifference bands; the second level is used to select an alternative conditional on the decision to switch taken at the first level. Previous studies have shown that arrival time is of major concern to commuters and have suggested that an indifference band of tolerable "schedule delay," defined as the difference between the actual arrival time (AT) and the preferred arrival time (PAT) for a given tripmaker, is the primary mechanism governing the day-to-day responses of commuters to congestion. In their daily commute, tripmakers are assumed to maintain the choice as long as they can tolerate the associated earliness or lateness relative to PAT.

$$\gamma_{i,t} = \begin{cases} 0 & \text{if } 0 \leq \text{ESD}_{it} \leq \text{EBD}_{it} \text{ or } -\text{LBD}_{it} \leq \text{LSD}_{it} \leq 0 \\ 1 & \text{otherwise} \end{cases} \quad (7)$$

$$\lambda_{i,t} = \begin{cases} 0 & \text{if } 0 \leq \text{ESD}_{it} \leq \text{EBR}_{it} \text{ or } -\text{LBR}_{it} \leq \text{LSD}_{it} \leq 0 \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

where

$\gamma_{i,t}$ = departure-time switching binary indicator, equal to 1 if switch, 0 otherwise;
$\lambda_{i,t}$ = route choice indicator, equal to 1 if switch, 0 otherwise;
$\text{ESD}_{i,t}$ = early schedule delay, equal to $\text{Max}(\text{PAT}_{i,t-1} - \text{AT}_{i,t-1}, 0)$; and
$\text{LSD}_{i,t}$ = late schedule delay, equal to $\text{Max}(\text{AT}_{i,t-1} - \text{PAT}_{i,t-1}, 0)$.

There are four possible combinations of departure time and route-choice switching decisions, corresponding to the combinations of values for the pair $(\gamma_{i,t}, \lambda_{i,t})$. Note that EBD and LBD are the respective departure time indifference bands of tolerable schedule delay corresponding to early and late arrivals for day *t*, and EBR and LBR denote the early and late indifference bands governing route switching. Because the indifference bands are latent terms, internal to each individual, and therefore can be neither observed nor measured directly, the indifference bands are treated as random variables, distributed over days and across commuters with systematically varying mean values (*9*).

The second level in Figure 2 is the selection of an alternative, which could be a new departure time, a new route, or both, conditional on the decision to switch. Several rules, based on different behavioral assumptions, can be applied in the individual selection process. In this study, alternative selection is based on a simple utility maximization process. Two particular models, proposed by Small (*19*) and Hendrickson and Plank (*20*), respectively, are used in the numerical experiments.

DYNASMART Simulation Assignment Model

DYNASMART is a descriptive analysis tool for the evaluation of information supply strategies, traffic control measures, and route assignment rules at the network level (*2,4,21,22*) The model is designed around a flexible structure that provides sensitivity to a wide range of traffic control measures for both intersections and freeways, capability to model traffic disruptions as a result of incidents and other occurrences, and representation of several user classes corresponding to different vehicle performance characteristics (e.g., cars verses trucks), access to physical facilities (e.g., high occupancy vehicle lanes), different information availability status, and different behavioral rules.

The framework of DYNASMART is shown in Figure 2. The approach integrates traffic flow models, path processing methodologies, behavioral rules, and information supply strategies into a single simulation assignment framework. The input data include a time-dependent OD matrix (or a schedule of individual departures) and network data. Given the network representation, the simulation component will take a time-dependent loading pattern and process the movement of vehicles on links and the transfers between links according to specified control parameters. These transfers, which are determined by path processing and path selection rules, require instructions that direct vehicles approaching the downstream node of a link to the desired outgoing link. The user behavior component is the source of these instructions.

DYNASMART uses established macroscopic traffic flow models and relationships to model the flow of vehicles through a network. Whereas macroscopic simulation models do not keep track of individual vehicles, DYNASMART moves vehicles individually or in packets, thereby keeping a record of the locations and itineraries of the individual particles. This level of representation also has been referred to as "mesoscopic." Multiple user classes of different vehicle performance characteristics are modeled as packets, consisting of one or more passenger car units; for instance, a bus is represented by a packet with two (or other user-specified values) passenger car units. The traffic simulation consists of two principal modules: link movement and node transfer, as described previously (*4,22*).

One of the principal features of DYNASMART that allows it to interface with activity-based behavioral models is its explicit representation of individual tripmaking decisions, particularly for path selection decisions, both at the trip origin and en route. Behavioral rules governing route choice decisions are incorporated, including the special case in which drivers are assumed (required) to follow specific route guidance instructions. Experimental evidence presented by Mahmassani and Stephan (*23*) suggested that commuter route choice behavior exhibits a boundedly rational character. This means that drivers look for gains only outside a threshold, within which the results are satisfying and sufficing for them. This can be translated to the following route switching model (*2*):

$$\delta_{i,n,1} = \begin{cases} 1 & \text{if } TTC_i(n) - TTB_i(n) > \max[\eta_i \cdot TTC_i(n), \tau_i] \\ 0 & \text{otherwise} \end{cases} \qquad (9)$$

where

$\delta_{i,n,1}$ = binary indicator variable of 1 when user i switches from current path to best alternate 1 and 0 if current path is maintained;
$TTC_i(n)$, $TTB_i(n)$ = trip times along current path and along best path from node k to destination on current path, respectively;
η_i = relative indifference threshold; and
τ_i = absolute minimum travel time improvement needed for a switch.

The threshold level may reflect perceptual factors, preferential indifference, or persistence and aversion to switching. The quantity η_i governs users' responses to the supplied information and their propensity to switch. The minimum improvement τ_i is currently taken to be identical across users. Efforts are under way to calibrate these parameters from the results of laboratory experiments.

ALGORITHMIC STEPS OF DAY-TO-DAY DYNAMIC MODEL

Day-to-Day Dynamic Algorithm

The conceptual framework of day-to-day dynamics was discussed in the previous section. The procedure, as shown in Figure 3, can be summarized as follows:

- Step 0: *Initialization.* Generate vehicles' attributes and historical paths. Obtain a set of paths from origin r to destination s for each discrete departure time interval, denoted as $P^t_{r,s}$. Also, each driver i will be assigned a set of simulation attributes, S_i, and a set of behavior attributes, B_i. Set iteration counter $I = 1$.
- Step 1: *Network loading.* For each driver i, assign a path p from r to s, $p_i \in P^t_{r,s}$, an initial departure time, and a loading location, i.e., a generation link. For each day, the number of vehicles for each time interval DT and for each path RK, denoted $X(DT,RK)$, is generated to form a three-dimensional matrix over both space and time.
- Step 2: *Traffic simulation.* Simulate network performance during peak period under given demand pattern using DYNASMART. Obtain an updated vehicle file, additional path files (if any diversion rule is applied), and time-dependent travel time information for links and movements.
- Step 3: *Information update.* Update the historical path information in terms of travel time, add new paths, or delete obsolete paths from the historical path file.
- Step 4: *Day-to-day behavior: indifference bands.* Calculate the departure time and route choice indifference bands for the driver i according to B_i. Determine values of the switching indexes $\gamma_{i,t}$ and $\lambda_{i,t}$ $\forall_i$ for all given t.
- Step 5: *Convergence test.* If convergence criterion is satisfied (the current flow pattern is stable), stop. Otherwise, continue.
- Step 6: *Selection of departure time and route.* If the outcomes of $\gamma_{i,t}$ and $\lambda_{i,t}$ are (1,0), (0,1), or (1,1), update departure time and route choice according to B_i.

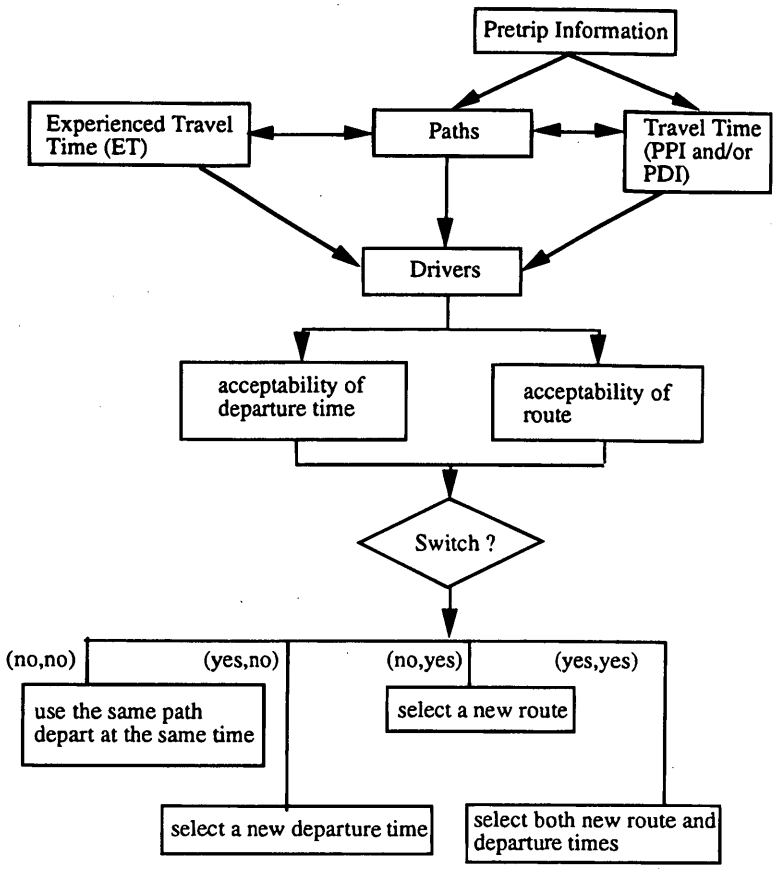

FIGURE 2 Pretrip decision-making process.

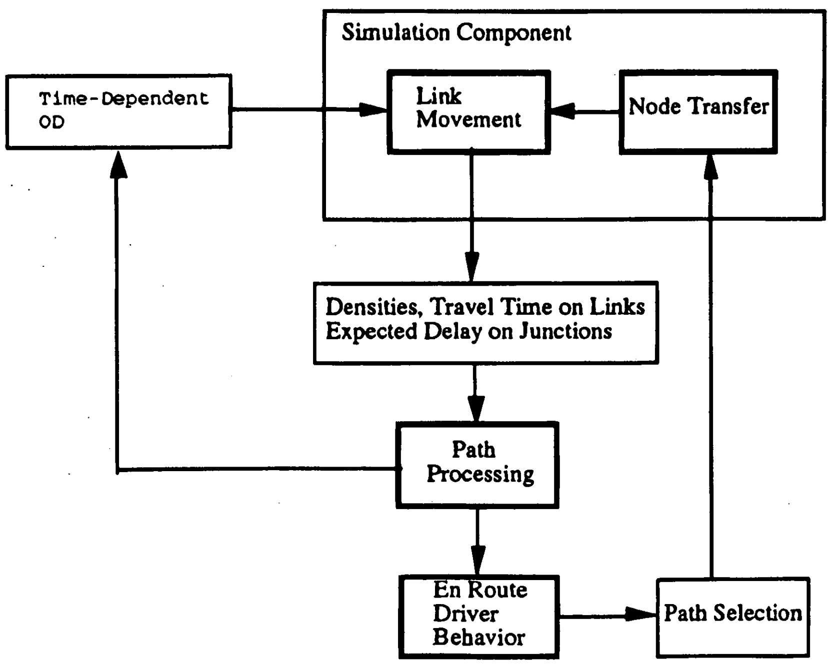

FIGURE 3 Framework of simulation assignment model with real-time information.

• Step 7: *Resequence and feedback.* Resequence vehicles according to their departure time. Obtain a time-dependent OD matrix. Set $I = I + 1$ and go to Step 1.

To overcome the problem of an arbitrary starting point, the initial set of paths is system optimal in terms of minimizing total trip time and is obtained using an algorithm recently developed by Mahmassani and Peeta (*24*), for the given time-dependent demand pattern. The vehicle file and the historical path file are used and updated through the whole simulation period. Currently, for each discrete departure time for each OD pair, up to 10 paths are stored and dynamically updated in terms of travel time for each path. All the path travel times are updated by combining recent travel time information with "historical" information, as follows:

$$\mathrm{PT}(T,r,s,j,k) = \sum_{t=1}^{T-1} w(t) \cdot \mathrm{PT}(t,r,s,j,k) \qquad (10)$$

where $\mathrm{PT}(t,r,s,j,k)$ is the path travel time for day t on route j at departure time k, and $\Sigma w(t)$ is 1 and can be used to express the relative importance of historical travel time. Currently, the particular values used for $w(T - 1) = 1$, and $w(T - 2) = 0$.

Convergence Concept: BRUE

The boundedly rational user equilibrium (BRUE) concept proposed by Mahmassani and Chang (*15*) was applied in this study as the convergence concept. A BRUE arises in a system when no user is compelled to change his or her current selection, which he or she considers satisfactory in a boundedly rational sense. In this context, this corresponded to all users' arrival times falling within their respective departure time and route indifference bands. The particular operational definition adopted in the simulation experiments required at least a certain fraction, say 90 percent, of tripmakers to be satisfied with their current decisions.

EXPERIMENTAL DESIGN

Numerical experiments were performed to illustrate the day-to-day dynamic framework and to explore the evolution of a traffic system in response to different information supply strategies under different assumptions. The primary concerns of these experiments were (*a*) the dynamic evolution of the system, (*b*) congestion formation and dissipation, and (*c*) effectiveness of real-time information.

Traffic Characteristics

The network structure indicated in Figure 4 was used in these experiments. It consists of 50 nodes and 168 links and includes 10 demand zones with 32 origins and 10 destinations. Each link is 0.25 mi (0.4 km) long. The freeway links have a free-flow speed of 55 mph and all other links have a 30-mph (48-kph) mean free speed. The maximum bumper-to-bumper and jam densities are assumed to be 260 and 160 vehicles per mile (approximately 152 and 100 vehicles per kilometer), respectively, for all links of the network. With regard to intersection signal control, 26 nodes have pretimed signalization, 8 have actuated signal control, and the rest have no signal control. The pretimed signals have a 60-sec cycle length with two phases, each with 26 sec of green time and 4 sec of amber time. The actuated signals have 10 sec of minimum green time and 26 sec of maximum green time for each phase. In these experiments, signal control parameters are assumed fixed. The OD matrix D has a total number of 9,634 vehicles for a period of 25 min (8:05 to 8:30 a.m.) in the first day from 32 origins to 10 destinations. Time of departure is discretized into 40 intervals of 1 min between 8:00 and 8:40 a.m.

Models of Departure Time and Route Switching

The particular models applied in this dynamic analysis were calibrated by Jou et al. (*25*) using survey data from the Dallas, Texas, area. Tripmakers in that survey had an average travel time of 23.5 min. Because the average trip time in the simulation experiments is much smaller, the indifference bands given by the models are adjusted by the average travel time in the simulation experiments. The indifference band for departure time selection is as follows:

$$\begin{aligned} \mathrm{IBDT}it = {} & \beta_1 && \text{[initial bands]} \\ & + \beta_2\mathrm{AGE}_i + \beta_3\mathrm{GENDER}_i && \text{[socioeconomic component]} \\ & + \beta_4\mathrm{NFAIL}_{it}^{\beta_5} && \text{[dynamic component]} \\ & + \beta_6\delta_{i,t}\left(\frac{\Delta\mathrm{TR}_{it}}{\Delta\mathrm{DT}_{it}}\right) && \text{[myopic component]} \\ & + \epsilon_{it} && \text{[unobserved component]} \end{aligned} \qquad (11)$$

where

$\beta_1, \ldots, \beta_6$ = estimated parameters;
AGE, GENDER = individual's characteristics;
NFAIL_{it} = number of unacceptable early and late arrivals until day t;
$\Delta\mathrm{TR}_{it}$ = difference between travel times of commuter i on day t and $t - 1$;
$\Delta\mathrm{DT}_{it}$ = departure time that commuter i has adjusted between day t and $t - 1$;
δ_{it} = binary indicator variable equal to 0 if $DT_{it} = DT_{it-1}$; otherwise 1; and
ϵ_{it} = error term for commuter i on day t.

The values of the estimated parameters are indicated as follows:

	Early	*Late*
β_1	23.26	17.82
β_2	7.61	4.51
β_3	−5.59	−6.57
β_4	5.49	4.36
β_5	1.16	0.78
β_6	4.17	2.98

The calibrated indifference band for route choice is as follows:

$$\begin{aligned} \mathrm{IBRC}_{it} = {} & \beta_1 && \text{[initial bands]} \\ & + \beta_2\mathrm{STDTR}_{it} && \text{[dynamic component]} \\ & + \beta_3\mathrm{NFAIL}_{it} && \text{[myopic component]} \\ & + \tau_{it} && \text{[unobserved component]} \end{aligned} \qquad (12)$$

where

$\beta_1, \ldots, \beta_3$ = estimated parameters,
STDTR_{it} = standard deviation of travel time up to day t, and
τ_{it} = error term for commuter i on day t.

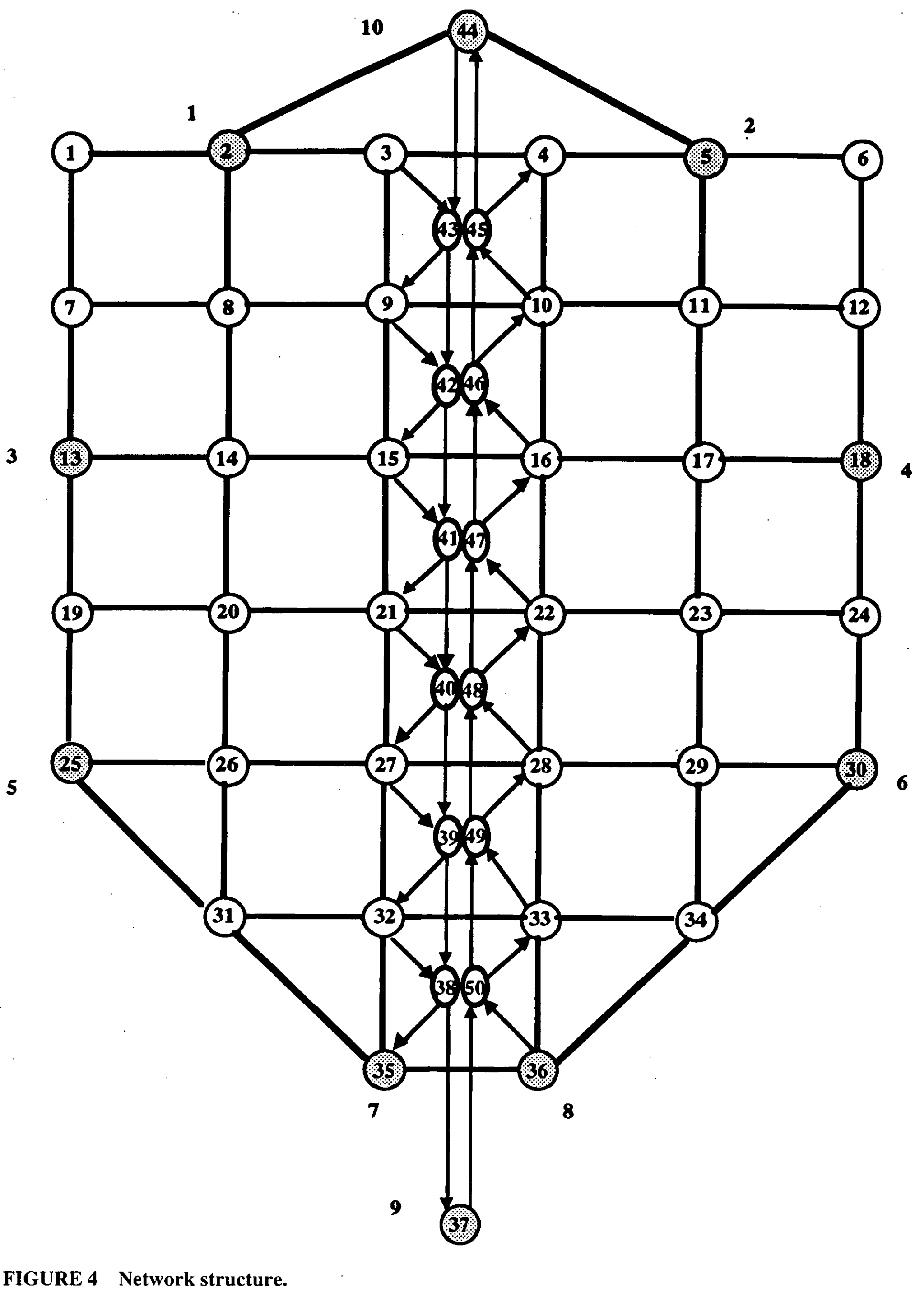

FIGURE 4 Network structure.

The values of the estimated parameters are indicated as follows:

	Early	*Late*
β_1	27.22	18.76
β_2	8.87	4.37
β_3	8.95	9.13

Models of Departure Time and Route Selection

Two particular models, proposed by Small (*19*) and Hendrickson and Plank (*20*), are used. The specification of the functional form proposed by Small can be summarized in the following equation:

$$U_{ij} = -0.106\text{TR}_{ij} - 0.065\text{SDE}_{ij} - 0.254\ \text{SDL}_{ij} - 0.58D1L_{ij} + \epsilon_{ij} \quad (13)$$

where

U_{ij} = measure of utility or "attractiveness" of trip characteristics for individual i and alternative j;
SDE = max {− SD,0}, early schedule delay for individual i under alternative j;
SDL = max {SD,0}, late schedule delay,
$D1$L = late dummy variable of 1 if SD ≥ 0, and 0 otherwise;

SD = schedule delay, arrival time minus official work start time (min); and

TR = travel time (min).

The originally calibrated utility function was based on 363 observations from four suburban areas and included constant terms for mode, such as drive alone, shared ride, and transit automobile. Some terms in the function are not applicable in this study; therefore, a modified utility function without those terms is used, as follows:

$$U_{ij} = -0.021\text{TR}_{ij} - 0.00042\text{SDE}_{ij} - 0.148\ \text{SDL}_{ij} + 0.0014\ \text{SDL}^2 + \epsilon_{ij} \quad (14)$$

All the variables are the same as those listed earlier. In this particular expression, late arrival incurs a high penalty.

NUMERICAL RESULTS

The numerical results are discussed in three parts. The first part describes the evolution of daily flows in the base case. The results of two random utility maximization models are discussed in the second part. The last part discusses the impact of real-time information in the day-to-day dynamic flow patterns, followed by a brief discussion of computational results.

Base Case

In the base case, all vehicles are assumed to be nonequipped (to receive real-time information), but to have access to path information from the preceding day's experience. Starting with a uniform loading pattern, the day-to-day dynamic flow patterns of Days 1,2, and 14 are indicated in Figure 5. The temporal loading pattern on the first day begins with a uniform profile, starting from 8:05 to 8:30 a.m. (Note: time 0 in the figure corresponds to 8:00 a.m.; the work start time is 8:30 a.m. or Time 30). However, a peak develops from day to day. On Day 14 (final state), fewer than 10 percent of vehicles are still not satisfied with their current selection; the associated pattern indicates that most drivers want to arrive at their preferred arrival time instead of being uniformly distributed along the whole time span. The fact that the dynamic flow pattern shifts dramatically from Day 1 to Day 2 indicates the unreasonableness of the initial uniform load spreading assumption. As expected, peak-period congestion forms because most tripmakers do not wish to arrive too early or too late in relation to their scheduled work time. Although the dynamic flow pattern tends to shift to a higher peak in this case from Day 2 to Day 14, this does not mean that all vehicles will select the same departure time in the final steady state. In the base case, the number of vehicles departing at the peak 5-min interval is about 700 vehicles for Day 2 and 1,010 vehicles for Day 14, an increase of about 50 percent.

The peaks shift from Time 28 of Day 2 to Time 22 of Day 14. Experiencing congestion, most of the drivers choose to leave earlier, although a few of them choose to leave later to avoid the congestion. In the process of adjusting to satisfy the schedule delay constraint, drivers collectively generate more serious congestion, as implied by the higher peak. Although demand managers and traffic control centers seek to spread the demand in a smoother pattern, drivers have a tendency to collectively create a peak-period flow pattern. If this is representative of what happens in actual systems, in-vehicle information systems probably can only shift or raise the peak instead of eliminating it altogether.

Average travel time (ATT) and average stopped time (AST) from day to day are indicated in Figure 6. While starting from a system-optimal solution point, drivers experience longer travel time and greater stopped time from day to day to arrive at their preferred arrival time. The overall average travel time doubles, from about 2.5 to 5.0 min. However, the travel time after Day 11 tends to reach a maximum limit.

Variation of daily time-dependent concentration is indicated in Figure 7. The figure provides a clear picture of system convergence. Although about 10 percent of vehicles are still seeking better alternatives, the system does not change because of those slight varia-

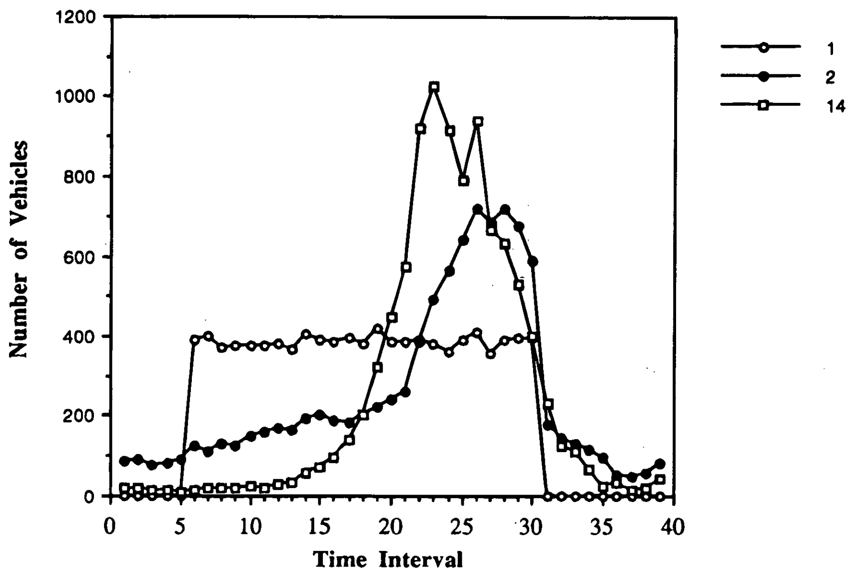

FIGURE 5 Variation of day-to-day dynamic flow patterns (Days 1, 2, and 14) for base case.

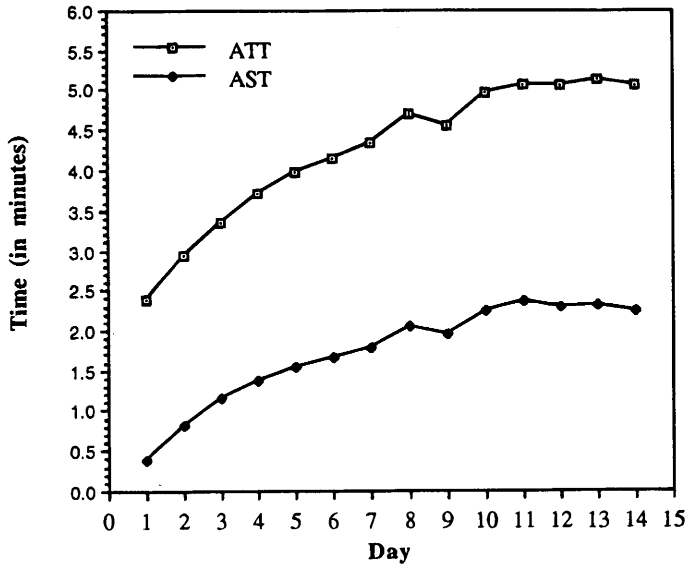

FIGURE 6 Comparison of ATT and AST of day-to-day dynamic flows for base case.

tions. It is evident that a traffic system with a fixed traffic control strategy can always absorb slight variations of demand pattern without this causing additional congestion.

Random Utility Maximization Models

The previous results were based on experiments performed with Hendrickson and Plank's modified model described earlier. Similar experiments were conducted using Small's model. The results indicated in Figure 8 depict similar patterns in terms of the evolution of dynamic flow, switching percentage, and system-wide average travel time. The results suggest that different random utility models might have a similar effect as long as they can capture the relative magnitudes of the travel time and schedule delay. In other words, the day-to-day evolution patterns appear robust vis à vis the underlying choice models.

Effectiveness of Real-Time Information

The effectiveness of real-time information is evaluated from day to day for different market penetrations of equipped vehicles (Table 1). Nonequipped vehicles must continue along their assigned initial path set. However, if equipped vehicles are satisfied with their new paths, they are assumed to use the paths as their initial paths. In this set of experiments, three levels of market penetrations, 10, 25, and 50 percent, and two real-time behavior assumptions,

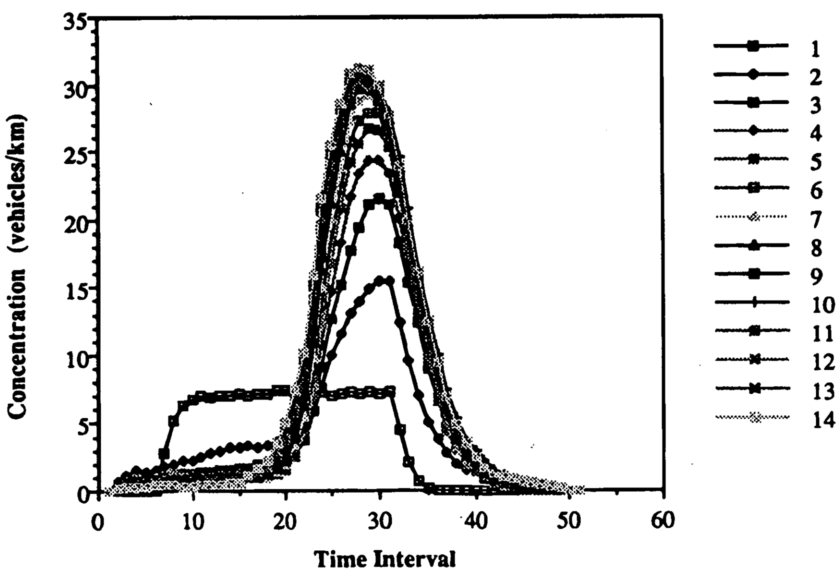

FIGURE 7 Variation of time-dependent network concentration from day to day for base case (1 km = 0.6 mi).

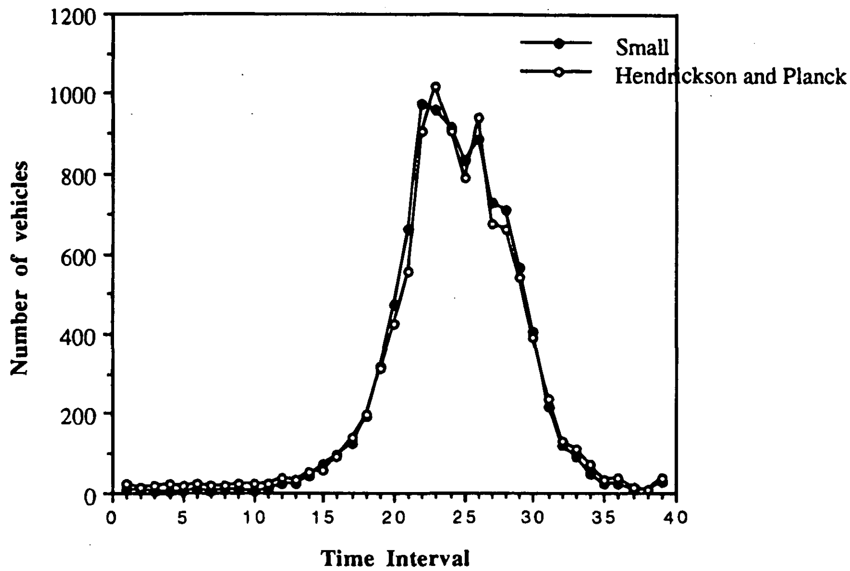

FIGURE 8 Comparison of day-to-day flow patterns with different utility models.

namely, myopic and boundedly rational behavior with a threshold of 0.2 and a minimum bound of 0.5 min, are considered. These tests are termed info-10, info-25, info-50, info-10-b, info-25-b, and info-50-b. Real-time information provides path information for equipped vehicles switching en route; in the meantime, the new experienced paths are collected and added into the path file for all vehicles to use for the next day. In brief, this case is termed "info-50-np," which means new path information is collected through equipped vehicles and distributed to all the tripmakers.

General Flow Dynamics

The evolution of day-to-day dynamic flow patterns is similar to that of the previous cases. Therefore, the results are summarized in Table 1 instead of in the figures. The results show that similar patterns are reached in the final steady state, although with different peak heights, in spite of different assumptions. The peak-period flow pattern indicates that most drivers wish to depart closer to their work schedule times in spite of the congestion. It is surprising to note that real-time information has an insignificant effect on improving the formation of the peak pattern; on the contrary, such information apparently can lead to raising the peak, reducing the travel time, and shifting the peak toward the work start time.

With real-time information, the peaks of all the info cases shift toward the work schedule time. The gap between the base case and info-10 is about 3 min, more than 50 percent of the travel time in these experiments. The info-50 case not only shifts the peak by 3 min but also raises the peak to about 1,100 vehicles. Although the increase of the peak is not quite significant, it offers insight into how drivers respond to real-time information through their day-to-day dynamic choices. These shifts imply that real-time information improves drivers' understanding of the traffic system, so tripmakers select late departure times without delaying their arrival time. In other words, the information system may lead to a reduction in travel time, but the traffic system compensates by attracting more tripmakers to use the facility and maintain the same level of service. Such phenomena are not quite clear in traffic systems and need some validation from field tests.

Real-Time Information Paths

The comparison is made for the info-50 case and the info-50-np case. The loading patterns of the final state (Day 12 for info-50 and Day

TABLE 1 Summary Statistics of Effectiveness of Real-Time Information Experiments

	Time of Peak	Height of Peak (number of vehicles)	ATT (in minutes)	AST (in minutes)	ATD (in km[1])	ATS (in km/hr)	Days for Convergence
BASE	23	1010	5.1	2.2	1.95	22.94	14
info-10	26	994	4.2	1.8	1.78	25.43	11
info-25	26	1065	4.1	1.7	1.78	26.05	11
info-50	26	1085	4.2	1.7	1.76	25.14	12
info-10-b	26	994	4.5	1.9	1.79	23.87	11
info-25-b	26	1062	4.4	1.9	1.81	24.68	11
info-50-b	25	1095	4.3	1.8	1.81	25.26	12
info-50-np	23	1061	5.4	2.3	2.08	23.11	19

[1] 1km = 0.6 mi.

19 for info-50-np) in both cases have a similar shape, but the peak in the info-50-np case is earlier than that of the info-50 case. This early peak implies that vehicles have an earlier departure time to satisfy their indifference bands in the evolution of the info-50-np case. To maintain the same level of convergence, more days are required for info-50-np, probably because of the higher level of congestion.

The execution time of the model on a CRAY YMP for the test network (50 nodes and 168 links) takes about 110 sec/day, including the input/output time from module to module.

CONCLUDING COMMENTS

The analysis of information-based traffic systems needs to consider tripmaker behavior, flow patterns, and traffic control systems. In this paper, two levels of tripmaker decision-making processes are identified: (*a*) day-to-day and (*b*) real-time dynamics. Day-to-day dynamics considers drivers' choices of departure time and route according to indifference bands of tolerable "schedule delay." Real-time dynamics is incorporated within DYNASMART to simulate driver's real-time en-route switching behavior. Flow patterns are obtained by simulating vehicle movement in the network, whereas traffic control systems update flow information or control strategies.

The day-to-day dynamic simulation-assignment framework presented in this paper provides a practical tool for the evaluation of network flows and associated performance measures in information-based traffic systems. The methodology allows investigation of a wide variety of alternatives and provides fundamental insights into the performance of traffic networks under a variety of assumptions on information availability and user behavior.

Naturally, the numerical results presented here should be interpreted with caution, given the limited set of experiments and the nature of the test network and associated conditions. Nonetheless, the results provide useful insights into actual traffic systems. It is also notable that the impact of the real-time information is manifested in several ways: reduces travel time, raises the peak, and pushes the peak toward the work schedule time.

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