Dynamic Aspects of Departure-Time Choice Behavior in a Commuting System: Theoretical Framework and Experimental Analysis

HANI S. MAHMASSANI and GANG-LEN CHANG

ABSTRACT

The day-to-day dynamics of departure-time decisions of urban commuters and the underlying behavioral mechanisms determining user responses to dynamically varying time-dependent congestion patterns are addressed. A conceptual model is presented incorporating the boundedly-rational notion of an indifference band of tolerable schedule delay. The results of an experiment involving real commuters interacting daily within a simulated traffic corridor are examined, with particular emphasis on the dynamics of user behavior.

The departure-time decision of urban commuters is of fundamental importance to the study of peak-period traffic congestion and to the analysis of traffic control as well as to broader, demandside congestion relief measures, such as pricing, ridesharing incentives, flex time, and others (1). Previous work on the departure-time problem has followed one of two principal lines: (a) econometric models of individuals' departure-time choices under fixed and known transportation level-of-service attributes (2-5) and (b) dynamic user equilibrium formulations in idealized traffic systems consisting of a single origin-destination pair connected by either a single route (6-13) or multiple routes (14,15), with congestion modeled either by using deterministic queues (6,14) or traffic-flow relationships (15). More elaborate reviews of these studies may be found elsewhere (15-17).

There is, however, an important dimension of the dynamics of this problem that has received very little attention, namely, the processes governing commuters' day-to-day responses to the system's performance, including the effect of prior experience and perceptions on current decisions. These processes are undoubtedly complex because they involve behavioral aspects of individual decision making, learning, and judgment in the context of a complex interactive system. However, the understanding of these processes and the ability to represent them analytically are of considerable importance to the design and evaluation of congestion relief measures, particularly with regard to time lags that may be associated with users' responses to these measures and information dissemination programs that could influence these responses. Furthermore, these dynamic aspects have significant implications for the stability of the system, as demonstrated by Horowitz in the context of route choice in a simplified transportation network (18). It is these dynamic processes underlying users' departure-time decisions in an urban commuting corridor that form the focus of this paper.

An effort in this direction was recently presented by Mahmassani and Chang (16), who addressed the day-to-day evolution of the time-dependent demand pattern resulting from the interaction between system congestion and user decisions. In addition, that study differed from the previous lines of research in its use of a process model of individual behavior consisting of a combination of relatively simple decision rules and heuristics, including explicit mechanisms for learning over time, and incorporating the notion of an "indifference band" of tolerable schedule delay. The latter reflects boundedly-rational, or satisficing (19), behavior of users in their daily commuting choices in an effort to explore behaviorally realistic decision rules as an alternative to the more restrictive but convenient utility maximization rule adopted in all previous studies. Another different feature in that study was the use of a special-purpose traffic simulation model for the performance side, thus allowing for greater flexibility and realism in system representation.

Understanding of these processes can of course best be furthered when coupled with observations of actual behavior. However, the acquisition of the necessary data at the desired level of richness in the real world presents formidable difficulties, including (a) the need to monitor in great detail both user decisions and the facility's time-varying congestion levels over a period of at least a few weeks and (b) the high degree of experimental control required. An alternative approach has recently been used by Mahmassani et al. (20) whereby the behavior of actual commuters is observed under controlled conditions. Participants, facing a hypothetical though realistic commuting situation, supply daily departure-time choices in response to congestion conditions, which are in turn obtained by using a special-purpose traffic simulation model, given the time-varying demand pattern (resulting from the aggregation of the individual participants' decisions).

In this paper the results of the first such experiment, involving 100 participants over 24 days, are examined from the perspective of the processes governing the dynamics of the users' behavior. Other aspects, such as traffic conditions or convergence properties of the system, are discussed elsewhere (20). The related conceptual background is presented in the next section, followed by a brief description of the experiment. The principal results are then examined and compared with the simulation results obtained earlier (16), and concluding comments are presented.

CONCEPTUAL BACKGROUND

Because the principal concern here is with the departure-time decision for home-to-work trips, it will be assumed that it is the only short-term decision available to trip makers. This would be the case in a commuting corridor consisting of a single highway facility with residences and workplaces distributed along this facility. As such, other choice dimensions normally available to trip makers, such as the choice of mode or route, do not unduly divert the discussion from its central focus. Extension to the more general case would be possible, though it would require considerably more complexity in the presentation and notation.

Given a work starting time WS_i, a trip maker i will select, on day t, a departure time $DT_{i,t}$. The outcome of this decision will be an arrival time $AT_{i,t}$, which follows the identity

$$AT_{i,t} \equiv DT_{i,t} + TT_{i,t} \tag{1}$$

where $TT_{i,t}$ is the trip time experienced on day t (including travel time on the facility and all other components). The trip time naturally depends on the user's departure-time decision as well as that of all other users of the facility, that is,

$$TT_{i,t} = f(DT_{i,t}, \text{all } i) \tag{2}$$

As mentioned in the previous section, prior studies have assumed that users select their respective $DT_{i,t}$ so as to maximize their utility, which is usually formulated as a weighted sum of the attributes of the departure-time opportunities. Although theoretically appealing, the maximization paradigm has a number of limitations from a behavioral standpoint, especially in the context of a descriptive model of day-to-day choice dynamics. For instance, it requires users to possess information on all the decision alternatives, that is, that they know a priori or can predict the time-dependent congestion pattern on any given day. This is clearly a difficult task in view of the often substantial and well-documented variability of travel time during the peak period (9,21). In addition, it is not clear that the parameters of one's utility function would remain constant from day to day, but rather that users may update their relative trade-offs as they learn about the system's performance. Another assumption that is difficult to support in this context is that of the individual ability to evaluate the optimal solutions of rather complicated objective functions (22).

An alternative behavioral notion that suggests itself here is that of satisficing, proposed by Simon (19) as a model of so-called boundedly-rational decision makers in search of an acceptable solution as opposed to a necessarily optimal one. Acceptability is usually defined relative to some aspiration level. In addition, it is well established in behavioral science that decision rules employed by individuals are greatly influenced by the nature of the task and the decision environment (22,23). In everyday decisions, the predominance of mental heuristics in individual judgment, learning, and decision making is generally well accepted (23, 24). Preference is usually for simpler, less demanding (in terms of cognitive strain on the decision maker) rules, which subsequently may become more demanding in response to a more complex decision environment.

A useful analogy here is between commuting behavior and consumers' repurchase decisions, to the extent that the latter are repeated daily or frequently and involve nonmajor items. As such, the marketing research literature can provide some useful insights and possible guidance. Satisficing models have received increased attention and acceptance in marketing research because of their ability to capture consumer choice behavior (25-27). The role of satisfaction in the consumer decision process has been documented in a number of studies (28,29), including that of Oliver (30), who identified the adaption-level theory (31) as an appropriate one for explaining how past experience and current satisfaction interact in affecting repeat purchase behavior [see also the paper by Labarbera (32)]. Worthy of note is the recognition that the very basis for satisfaction and acceptability of a given outcome itself dynamically varies in response to prior outcomes as well as recent experience (28).

The application of some of these concepts to the dynamics of the departure-time choice problem is presented next. Trip makers can be viewed as searching for a departure time that yields a satisfactory outcome or arrival time. When user i is satisfied with $AT_{i,t}$, he is expected to maintain the same departure time on the following day; thus $DT_{i,t+1} = DT_{i,t}$. The acceptability of a particular outcome is evaluated with respect to the trip maker's own desired arrival time. Note here that the latter quantity is generally different from the work start time WS_i, as shown empirically by Hendrickson and Plank (5). Users typically possess a preferred arrival time PAT_i, which would prevail in the absence of congestion (yet still be within the constraints of the workplace). It generally incorporates a safety margin to protect against lateness at work and allow some time for preparation at the onset of the working day. One can thus expect a distribution of preferred arrival times across the population, reflecting both workplace conditions as well as inherent individual preferences and risk attitudes. Further support for this notion is presented later in this paper based on analysis of the experiment.

A plausible satisficing mechanism used in earlier simulations (16) is based on the notion of an "indifference interval" or band of acceptable schedule delay. On a given day t, user i's schedule delay is $SD_{i,t} \equiv PAT_i - AT_{i,t}$. Letting $\delta_{i,t}$ be a binary variable that takes the value 1 if the actual arrival time on day t is acceptable to user i, and 0 otherwise, the decision rule can be stated as

$$\delta_{i,t} = \begin{cases} 1 \text{ if } 0 \le SD_{i,t} < IB^e_{i,t} \text{ or } IB^\ell_{i,t} < SD_{i,t} \le 0 \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

where $IB^e_{i,t}$ and $IB^\ell_{i,t}$ are two nonnegative threshold values reflecting what user i considers tolerable earliness and tolerable lateness, respectively. The time interval within which an arrival time $AT_{i,t}$ will be considered acceptable then becomes $(PAT_i - IB^e_{i,t}, PAT_i + IB^\ell_{i,t}]$.

The threshold values $IB^e_{i,t}$ and $IB^\ell_{i,t}$ can be expected to vary across individuals, reflecting differing preferential attitudes as well as workplace conditions. To the extent that the preferred arrival time PAT_i reflects some of these same sources of variation, it can be expected to be correlated with those threshold values. For this reason, in the empirical analysis section, various user groups will be considered on the basis of their preferred arrival times.

An individual's indifference band, reflecting his aspiration level on a given day, is not necessarily constant over time, particularly if the system is not in a steady state, such as after the implementation of a major new control or policy. This band is instead dynamically changing in response to the user's personal experience with the facility as well as information that he may have actively or passively acquired from other sources. Insight into this phenomenon was obtained in earlier simulations (16). In particular, more distant users (relative to a common work destination) would tend to adjust their aspirations more frequently than closer users in order to accommodate greater day-to-day variability and fluctuation in their longer commutes. Similarly, more distant users appear to require wider indifference bands. These aspects of user behavior are explored in the section on analysis of experimental results.

Information acquired through repeated usage of the facility, as well as from other possible sources, influences trip makers' short-term departure-time choice behavior in two major ways: (a) the previously mentioned effort on the aspiration level, defining the acceptability of particular outcomes, and (b) learning about the facility's performance, which provides the basis for the user's travel time estimate and the subsequent departure-time adjustment in the event that the latest outcome was not acceptable. This adjustment is determined by both the current indifference band and the user's perception of the system's travel time characteristics; it can thus be viewed as the following function:

$$DT_{i,t+1} - DT_{i,t} = g(TT_{i,s}, SD_{i,s}; s = 1,\ldots,t) \quad (4)$$

In this expression, the relative importance of terms corresponding to different values of s (days) is not expected to be uniform. Clearly, recent experience is likely to contribute more heavily than that of more distant days. At one end of the spectrum, user behavior could be purely myopic and affected by the latest day only. At the other extreme, all days from 1 to t could contribute with equal intensity to the user's decision on day (t+1). However, because of memory capacity limitations, the retrieval of prior information is not likely to go beyond a relatively small number of recent days.

In summary, user behavior in this commuting system can be viewed as a boundedly-rational search for a satisfactory departure time. Conceptually, it consists of two principal components: (a) the acceptance or rejection of a given day's decision outcome, which determines, respectively, whether the user will or will not maintain the same departure time on the following day and (b) the amount by which departure time should be adjusted, if that is needed. The first component can be viewed as the stopping criterion in the user's search process, whereas the second is analogous to the "step size." The former is based on the key notion of an indifference band of tolerable schedule delay. Prior experience with the facility, as the principal mechanism of information acquisition, enters the first component through its effect on the indifference band, and the second component through its contribution to the user's learning about the facility's performance.

It should be noted here that the use of schedule delay as the principal criterion for acceptability of a given decision outcome should not be taken to imply that other attributes, particularly travel time, will under no circumstances be explicitly evaluated by trip makers. Implicit is the assumption that the range of travel times encountered by individuals in this urban commuting system is such that users are effectively indifferent among the travel time outcomes of their departure decisions. Naturally, for excessively long travel times, this assumption is not likely to hold. In an intercity context, where travel times are much more substantial, explicit trade-offs between schedule delay and travel time should be expected, as in airline flight selection. However, in an urban commuting context, particularly for short-range, day-to-day decisions, schedule delay is clearly significantly more highly valued (negatively) than travel time, as evidenced by the findings of Hendrickson and Plank (5). Users are likely to control for their travel times through longer-run choices such as that of residence or workplace location. In a dynamically changing context, where users possess only limited information on the system's performance, boundedly-rational behavior predicated on the most-important attribute appears to be plausible descriptivity.

In the remainder of this paper, the results of an experiment for additional insight into the foregoing aspects of user behavior and the extent to which they appear consistent with the conceptual model presented in this section are analyzed. However, no formal functional specification and estimation will be conducted herein, because the analysis is exploratory in nature and is intended at this stage primarily as an indication of the usefulness of this general approach to studying the complex day-to-day dynamics of commuter behavior. The experiment itself is described in the next section.

DESCRIPTION OF EXPERIMENT

Given the previously mentioned difficulties of obtaining adequate data for the study of the day-to-day dynamics of commuter behavior, the approach recently described by Mahmassani et al. (20) consists of observing the decisions of real commuters placed in controlled and carefully designed hypothetical commuting situations. A number of important features characterize this type of experiment, including the following:

1. All the departure-time decisions that collectively determine the system's service levels can be observed,
2. The analyst has a high degree of control over the information available to participants, and
3. The interactions in the traffic system, which determine the user's decisions, are realistically captured by a special-purpose traffic simulation model.

The commuting context considered in this experiment consists of an urban corridor composed of a four-lane highway (two lanes in each direction) used by residents who live adjacent to it for their daily home-to-work trips to a single work destination, such as a central business district (CBD) or a major industrial park. Concern here is with the inbound, or home-to-work, direction. The corridor is subdivided into nine identical 1-mi sectors, with the common destination located at the end of the last sector. Sectors are numbered from 1 to 9 in order of decreasing distance from the destination; Sector 1 is the farthest outbound. Commuter residences are located in Sectors 1 through 5 only, each of which is treated as distinct trip origin, whereas Sectors 6 through 9 are treated as a nonresidential fringe area in which no trips are generated.

The time-dependent departure pattern from each residential sector on any given day results from departure-time decisions made by the participants.

Each participant is assigned to only one sector and is assumed to represent a group of 20 trip makers who make identical decisions. A total of 400 trip makers was assumed in each of the residential sectors (or 200 trip makers per lane per sector), resulting in 20 participants for each of the five sectors in this experiment.

The following information was initially provided to each participant: (a) a general description of the foregoing commuting context, (b) the participant's residential sector, (c) the highway facility's characteristics (number of lanes, free-flow speed), and (d) the work start time.

With regard to the third item, note that similar facilities in the Austin area were indicated to the participants for anchoring purposes. With regard to the fourth item, all participants were placed in the familiar situation of having to start work at 8:00 a.m. Although it would have been more representative of the real world to have had a distribution of work start times, still strongly peaked at 8:00 a.m. (5), it would have required considerably more participants to attain a meaningful level of interaction in the system. The specification of a single work start time in this first experiment captures all the key phenomena of interest and avoids undue complexity.

At the onset of the experiment, each participant was asked to state his or her preferred arrival time at work (PAT_i for participant i), in the absence of traffic congestion, given the official work start time WS. Naturally, $PAT_i \leq WS$ for all i.

Every simulation day, each participant supplied a departure time and an anticipated arrival time, denoted hereafter by $DT_{i,t}$ and $AAT_{i,t}$, respectively, for user i on day t. The departure-time decisions of all individuals in a given sector were aggregated into a time-dependent departure pattern for that sector. These patterns formed the input to the highway traffic flow simulation model, briefly described later in this section. The outcome of each participant's decision (the actual arrival time $AT_{i,t}$) and the corresponding travel time $TT_{i,t}$ were determined by the simulation and supplied to each participant individually on the following day before that day's choice. This iterative interactive process covered 24 simulation days, by the end of which the system had evolved to a stable state, with all participants maintaining the same choices from one day to the next. In order to relate the experiment to the participants' daily commute, it was administered daily, 5 days per week, during the entire period.

The importance of information acquired through one's own commuting experience and from other possible sources was discussed in the previous section. In this experiment, the informational scenario under which users have only their own actual experience to rely on is considered. Furthermore, to the extent that commuters do not usually maintain a written log of their departure and arrival times over a number of days, only the latest day's decision outcome was displayed to each participant. Other informational scenarios involving additional sources, such as mass media reports or word of mouth, were outside the scope of this particular experiment and may be addressed in future work.

In order to achieve the desired quality of the results, participants were selected very carefully, especially because their involvement was required for a period of several weeks. All 100 participants were affiliated with the University of Texas at Austin, and most were staff members or graduate students with formal work experience. In addition, these participants were scattered over various parts of the campus, thus controlling for information exchange among participants during the survey period.

Before this experiment was conducted, a pretest was administered to a smaller and different group of individuals. Responses and suggestions from this pretest group led to helpful improvements in the procedure as well as initial insights into the behavior of the system.

A special-purpose, fixed-step macroscopic highway traffic simulation model was developed in conjunction with this experiment. The highway facility is segmented into a number of sections, in which traffic flow is modeled by using well-established fundamental traffic flow relationships; of particular interest is the speed-density model, which has the following form:

$$v = (V_f - V_0)(1 - K/K_0)^c + V_0 \quad (5)$$

where

- V and K = speed and density prevailing on a given highway section, respectively;
- V_f and V_0 = free-flow speed and the minimum allowable speed on the facility, respectively;
- K_0 = maximum or "jam" density; and
- c = parameter reflecting the sensitivity of travel speed to density variations.

In this experiment, the following parameter values were used: V_f = 40 mph, V_0 = 6 mph, K_0 = 180 vehicles/lane-mile, and c = 1.0. Further details of the simulation model are outside the scope of the present paper and can be found elsewhere (20,33).

ANALYSIS OF EXPERIMENTAL RESULTS

The presentation of the principal results of interest to the behavioral processes underlying user decision dynamics is organized around four types of quantities:

1. Actions, meaning the actual departure-time decisions of users over the survey period (i.e., $DT_{i,t}$) for i = 1,...,100 and t = 1,...,24;
2. Outcomes, which result from the foregoing actions, namely, the actual arrival time $AT_{i,t}$ and associated travel time and schedule delay ($TT_{i,t}$ and $SD_{i,t}$, respectively);
3. Perceptions, by users, of the foregoing outcomes, translating into anticipated travel times and schedule delays ($ATT_{i,t}$ and $ASD_{i,t}$, respectively); and
4. Intentions, or preferences, which, when combined with the foregoing anticipated quantities, result in actual decisions; of concern here are the preferred arrival times PAT_i for all i and the anticipated arrival times $AAT_{i,t}$ stated by all users along with their departure decisions on any given day.

In addition to the description of the evolution of the foregoing quantities and their variation by geographic sector (as a function of distance from the destination) and other factors, their interrelation, as discussed in the previous section, is explored. However, first the overall evolution of the system's behavior is summarized.

Summary of System Evolution

The system equilibrates when all users are essentially satisfied with the outcome of their departure-time choices, thus maintaining the same daily departure pattern. In this experiment, no user changed his or her departure time as of day 21; however, the steady-state values were first attained on day 18 but were perturbed by a few participants who tried, unsuccessfully, to improve their outcome and subsequently returned to their steady-state choices. A clear geographic pattern in the evolution to the steady-state choices was apparent, with sectors closer to the destination generally reaching their steady-state earlier than more distant sectors. For instance, the steady-state departure patterns were reached (and maintained) in Sectors 1 through 5 as of days 20, 17, 16, 16, and 5, respectively. Furthermore, only a small fraction of the users in Sector 4 kept searching for a satisfactory outcome beyond day 7, as revealed by Figure 1, which shows the day-to-day evolution of the departure-time distribution (i.e., the fraction of users departing before time t on a given day) in Sector 4. The "ease" with which users in different sectors are able to attain a satisfactory outcome is further documented later in this section by looking at the frequency of departure time as well as anticipated arrival-time changes.

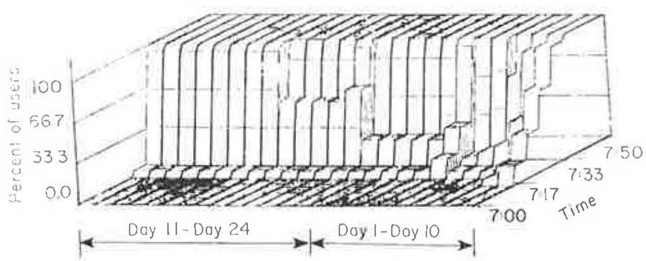

FIGURE 1 Cumulative departure pattern evolution for Sector 4.

Of course, the overall system cannot be considered in equilibrium so long as some sector has not yet reached its steady state, because changes in any sector will affect the outcomes of user decisions in other sectors through the traffic interactions. Actually, the fact that many users maintained their departure-time choice despite the continued variation of travel times and schedule delays suggests the existence of the tolerable range associated with the boundedly-rational behavior described earlier. For instance, the day-to-day variation of the average of the absolute value of schedule delay, per sector, is shown in Figure 2, which reveals that

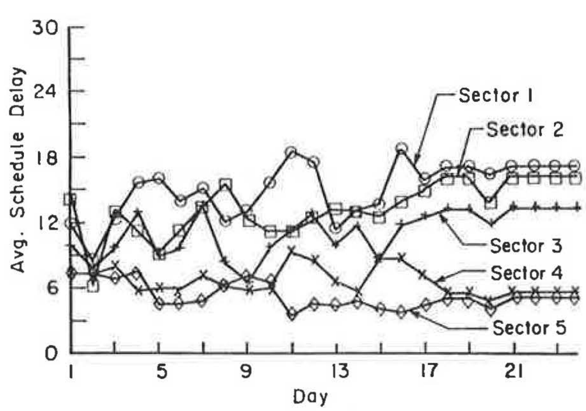

FIGURE 2 Evolution of average schedule delay in absolute values per sector.

this quantity still varied for Sector 5 for many days after users in that sector had stopped adjusting their departure times.

Although it is clear that convergence was attained, it is not possible to ascertain, on the basis of this single experiment, the uniqueness of this pattern nor to derive conditions for its existence. Further discussion of the convergence properties of this experimental system may be found elsewhere (20).

Preferred Arrival Time

As mentioned earlier, commuters have different preferred work arrival times. In this experiment, although the same common work start time (8:00 a.m.) was specified for all participants, the stated preferred arrival time followed the distribution shown in Figure 3, which reveals that over 40 percent prefer to reach their workplace at least 15 min before the official work start time. This distribution is primarily a reflection of inherent differences in individual preferences and does not exhibit any systematic variation across sectors. To the extent that

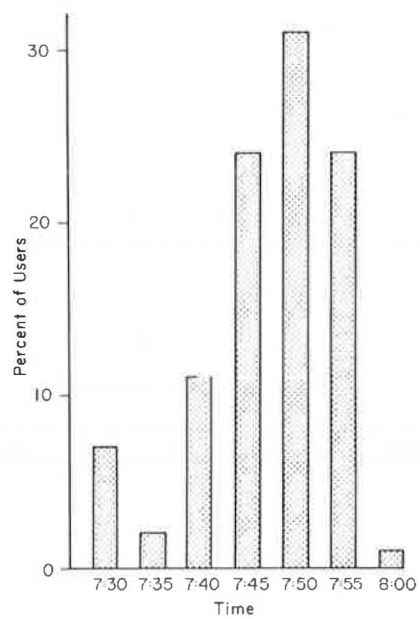

FIGURE 3 Preferred arrival time distribution.

the excess time preferred by users can be interpreted as a safety margin for avoiding lateness, the preferred arrival time provides a useful indication of a user's risk attitudes. Therefore, it has been used as a basis for segmenting the participants, and indeed significant differences in behavior across the three groups that were defined were found:

- Group 1, including all users i such that 7:30 $\leq$ PAT_i < 7:40 a.m.,
- Group 2, where 7:40 $\leq$ PAT_i < 7:50 a.m., and
- Group 3, where 7:50 $\leq$ PAT_i $\leq$ 8:00 a.m.

The relative frequency distribution of users into each of the foregoing three categories is given in Table 1 per sector, as well as overall.

The preferred arrival times represent the initial intentions of users before their experience with and

TABLE 1 Relative Frequency Distribution of Users into Preferred Arrival-Time Groups per Sector

	Percentage of Users by Sector					
Group	1	2	3	4	5	All
1 (7:30-7:39 a.m.)	10	15	5	5	10	9
2 (7:40-7:49 a.m.)	40	30	30	40	35	35
3 (7:50-8:00 a.m.)	50	55	65	55	55	56

subsequent learning about the system's performance. However, as learning develops through usage, these intentions evolve, as seen later in this analysis of the daily anticipated arrival times.

Actions: Departure-Time Decisions

Patterns exhibited by the frequency of departure-time changes and the time interval between successive changes across sectors and across user groups are examined first. Also the effect of the previous day's outcome on the decision to adjust one's departure time, particularly with regard to the existence of an indifference band of schedule delay, is highlighted. In addition, the magnitude of this adjustment is examined relative to the previous day's schedule delay.

Table 2 shows the respective proportion of participants in each sector who changed their daily departure time at least n times, where n = 1, ..., 15 (15 was the highest number of changes observed out of a maximum of 23 possible changes in 24 days). The overwhelming pattern is that the frequency of these changes increases with distance from the destination, thus confirming the observation that more distant sectors experience greater difficulty in converging to a steady state.

TABLE 2 Proportion of Users in Each Sector with at Least n Departure-Time Changes

	Percentage of Users by Sector				
No. of Changes[a]	1	2	3	4	5
1	100	100	100	100	75
2	100	100	95	65	25
3	100	100	90	60	
4	100	95	85	15	
5	90	90	70	5	
6	90	80	40		
7	90	75	30		
8	80	60	10		
9	65	50			
10	50	30			
11	35	15			
12	25				
13	20				
14	10				
15	5				

[a]Minimum number.

Table 3 presents the same information as Table 2, but for each of the previously defined user groups within each sector. As expected, users in Group 1, who were initially willing to accept a wide safety margin, were able to conclude their search for an acceptable departure time significantly sooner than the other groups. (It should be noted here that comparisons of Group 1 users across sectors is not meaningful given the small number of participants in this group in any one sector.) The same general trend is present for Groups 2 and 3, especially in Sector 1, in which residents encounter greater travel time fluctuation than in closer sectors, thus making it particularly difficult to successfully maintain a departure time that results in arrival within less than 10 min from the work start time. In addition, the preferential differences captured by the user groups may correspond to varying degrees of individual persistence, whereby users in Group 3 are less willing to adjust their indifference band to accommodate otherwise unacceptable outcomes. This particular aspect is more specifically explored in the context of the discussion of intentions.

Table 4 shows, per user group within each sector, the mean number of days since the previous change for the nth change (n = 1,...,15) as well as its standard deviation. Naturally, these numbers must be interpreted with caution because many of these averages, particularly for higher values of n, are taken over a small number of participants. Although no strong patterns are present in a uniform manner, the time until the first change appears to be of the same order of magnitude across the categories considered, with the notable exception of Sector 4, in which a large fraction of users did not have to change their initial selection for a long time, which resulted in the large means and standard deviations seen in Table 4. It is also apparent that the variability of the interval between changes is greater for the closer sectors (though not for Sector 5, where very few changes took place). More accurately, this variability is more evident for user groups in sectors where the decision to change was not clear-cut. For instance, users in Groups 2 and 3 in Sectors 1 and 2 experienced outcomes that were clearly unacceptable to most, resulting in the low observed standard deviations in Table 4. This was less the case in Sectors 3 and 4, where the time between consecutive changes varied considerably across users. These results will be contrasted later in this section with the time interval between changes in anticipated or intended arrival times reported by users.

To ascertain the effect of the previous day's outcome on the decision to change departure time, the response, in each sector, to different levels of schedule delay (in 5-min increments) has been examined. Thus for each sector, the fraction of those users experiencing a given schedule delay on day t - 1 that have changed their departure time on day t has been calculated. In order to detect the postulated evolution (see section on conceptual background) of the users' indifference bands as the search progresses and still have enough observations to yield meaningful fractions, the data were aggregated on a weekly basis (each including 5 days). Although not all schedule delay levels are sufficiently represented, two rather clear trends are suggested by these data.

First, as expected, the fraction of users who find a particular schedule delay unacceptable and thus change departure time on the next day increases with the magnitude of the delay. This is exemplified in Table 5, which shows these fractions for Sector 1 during the third week of the survey. Interestingly, no user experiencing lateness of up to 5 min or earliness of up to 10 min (relative to his or her respective preferred arrival time) decided to adjust departure time on the following day.

The second trend concerns the evolution of the indifference band, whereby the fraction of users rejecting a given outcome appears to decrease as the search progresses, shown as follows for selected

TABLE 3 Proportion of Users in Each User Group Within Sectors 1, 2, and 3 with at Least n Departure-Time Changes

	Percentage of Users by Sector								
	1			2			3		
No. of Changes[a]	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
1	100	100	100	100	100	100	100	100	100
2	100	100	100	100	100	100		100	100
3	100	100	100	100	100	100		83.4	100
4	100	100	100	66.7	100	100		83.4	92.8
5		100	100	33.3	100	100		83.4	69.7
6		100	100	33.3	66.7	100		66.7	31.2
7		100	100	33.3	66.7	90.9		50.0	23.4
8		71.5	100		50.0	81.8		16.7	7.8
9		28.6	100		50.0	63.6			
10		14.3	81.9		33.2	36.3			
11			63.7			27.3			
12			45.5						
13			36.4						
14			18.2						
15			9.1						

[a]Minimum number.

TABLE 4 Mean and Standard Deviation of Number of Days Between Consecutive Departure-Time Changes per User Group Within Each Sector

	Sector and Group														
Change Sequence No.	1,1	1,2	1,3	2,1	2,2	2,3	3,1	3,2	3,3	4,1	4,2	4,3	5,1	5,2	5,3
1															
Mean	1.50	1.71	1.50	1.0	1.25	1.50	1.0	2.83	1.84	1.0	5.3	5.58	–	1.50	2.50
SD	0.70	1.25	0.53	0.0	0.50	0.85	–[a]	2.31	0.89	0.0	6.0	4.28	–	1.00	0.68
2															
Mean	2.50	2.14	1.27	1.0	1.40	1.70		2.85	1.76		1.5	3.67		1.0	1.0
SD	1.00	0.78	0.47	0.0	0.55	0.48		3.10	1.64		1.0	4.30		0.0	0.0
3															
Mean	2.50	1.28	1.09	5.67	1.20	1.60		2.80	2.92		4.75	7.57			
SD	1.00	0.49	0.30	2.89	0.45	1.07		1.64	1.78		4.30	5.50			
4															
Mean	7.50	2.28	1.20	3.50	1.80	1.60		1.0	3.83		4.50	4.0			
SD	0.70	1.25	0.63	1.85	0.83	1.58		0.0	3.00		4.90	–[a]			
5															
Mean		1.29	2.00	4.0	1.60	1.40		1.75	4.0		4.0				
SD		0.76	1.61	–[a]	0.89	0.52		0.95	3.24		–[a]				
6															
Mean		1.71	1.36	2.0	1.40	1.90		2.25	3.0						
SD		1.25	0.92	–[a]	0.55	1.28		0.78	2.3						
7															
Mean		1.85	1.36	5.0	6.00	1.44		5.0	3.67						
SD		1.46	0.94	–[a]	4.12	1.33		4.20	1.15						
8															
Mean		1.50	1.40		1.0	1.87		4.0	1.0						
SD		1.00	0.96		0.0	1.64		–[a]	–[a]						
9															
Mean		2.00	1.33		1.0	2.83									
SD		0.85	1.00		0.0	1.94									
10															
Mean			1.50		1.0	1.0									
SD			1.24		–[a]	0.0									
11															
Mean			1.40			3.30									
SD			0.55			0.58									
12															
Mean			1.25												
SD			0.50												
13															
Mean			1.0												
SD			0.0												
14															
Mean			1.0												
SD			–[a]												
15															
Mean			2.0												
SD			–[a]												

Note: SD = standard deviation in days.

[a]Only one participant accounted for this change.

TABLE 5 User Response to Previous Day's Schedule Delay, Sector 1, Week 3

Schedule Delay on Day t − 1 (min)[a]	Proportion of Users Experiencing Delay Who Change Departure Time on Day t (%)
<−15	100.0
−15 to −11	84.6
−10 to −6	56.3
−5 to −1	0.0
0-5	0.0
6-10	0.0
11-15	11.1
16-20	33.3
21-25	37.5
>25	100.0

[a]Note that schedule delay on day t for a given user is defined as the difference between that user's preferred arrival time and his or her actual arrival time on day t. As such, negative values of schedule delay correspond to late arrivals, whereas positive values correspond to early arrivals (relative to the preferred arrival time).

schedule delays (the first column for lateness and the second for earliness) for Sector 1:

Week	Proportion of Users (%) by Schedule Delay (min) -10 to -6	16-20
1	81.8	100.0
2	45.5	78.6
3	56.3	33.3
4	40.0	0.0

A comparison of the responses between the first and the final weeks reveals this decrease in all cases where sufficient data exist. However, the path during the intervening weeks is not necessarily monotonic, particularly for the negative schedule delays as shown in the second column of the foregoing tabulation. Naturally, there are other factors affecting this response, such as the user preferential group, in addition to daily effects (aggregated in the weekly data) and random variation across users and days, which is of particular concern when the number of participants is relatively small.

Further support for the above two trends can be obtained by examining the magnitude of the departure time adjustment on day t (i.e., $DT_{i,t} - DT_{i,t-1}$) as a function of $SD_{i,t-1}$. Figures 4-8 show this adjustment versus $SD_{i,t-1}$, for all users in the system for t = 2, 6, 11, 16, and 24. In Figures 4-8, an asterisk corresponds to a single observation, a plotted number (2 to 9) refers to the number of participants with identical coordinates, whereas a plus sign represents at least 10 participants. When the focus is on the evolution of the points corresponding to a zero adjustment, these plots suggest that (a) as expected, there is a range of schedule delay that users are willing to tolerate and for which they do not adjust their departure time and (b) this range increases over time, indicating that users progressively accept greater schedule delay. In addition, examining the relative magnitudes of the two plotted variables reveals that (a) earliness on a given day implies a later (or same) departure on the next day, whereas lateness implies an earlier (or same) departure, and (b) the magnitude of the adjustment on day t is in most cases less than the corresponding magnitude of the earliness or lateness on day t - 1, which is consistent with a hypothesized rule in earlier simulations (16).

Further insight into the relation between this adjustment and schedule delay on the previous day is obtained by examining $(DT_{i,t} - DT_{i,t-1})/SD_{i,t-1}$. For each user group in each sector, the average of this ratio was calculated for the nth change given that the user was respectively late and early on day t - 1, with n = 1,...,8, and that the adjustment was nonzero. Table 6 shows these averages for Sector 1, which is representative of the other sectors. The variation of this ratio across user groups takes place in opposite directions depending on whether the adjustment is in response to an early or late arrival on the previous day. A plausible explanation

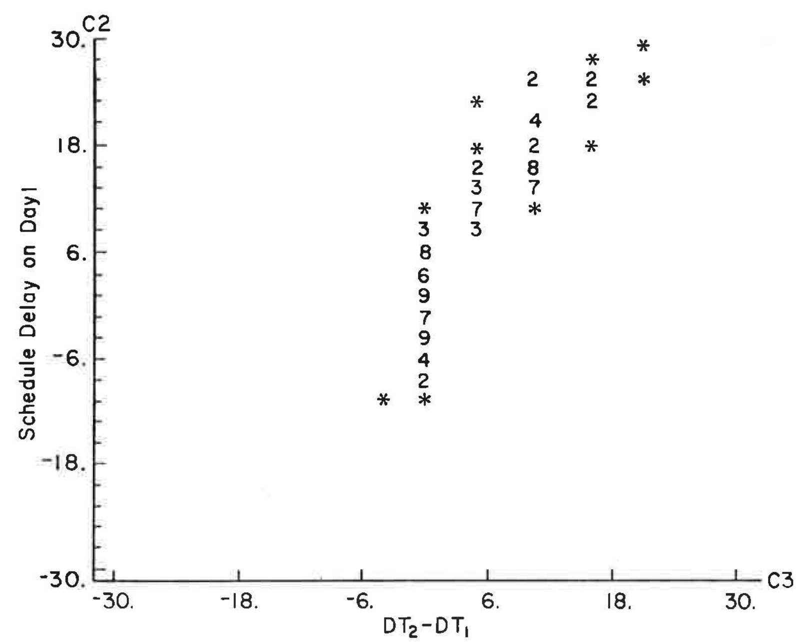

FIGURE 4 Departure time adjustment versus deviation from preferred arrival time on previous day: Day 2.

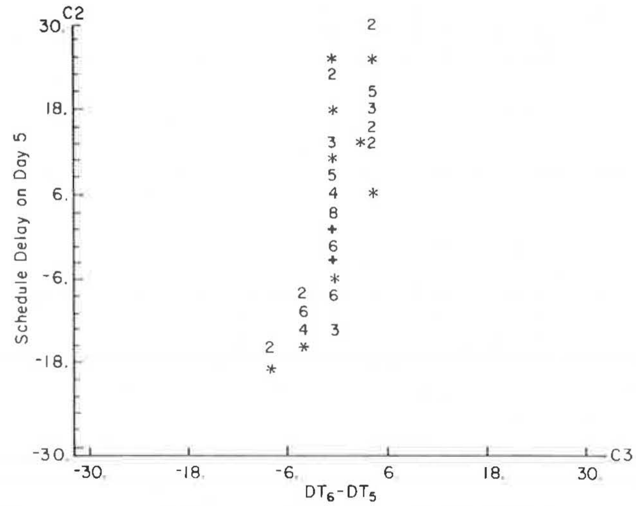

FIGURE 5 Departure time adjustment versus deviation from preferred arrival time on previous day: Day 6.

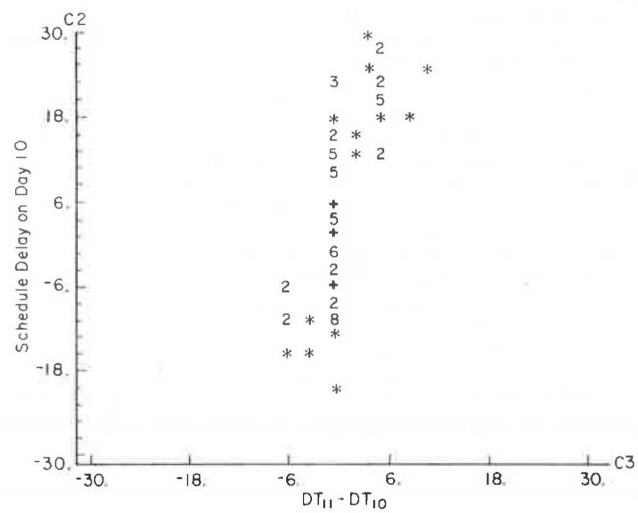

FIGURE 6 Departure time adjustment versus deviation from preferred arrival time on previous day: Day 11.

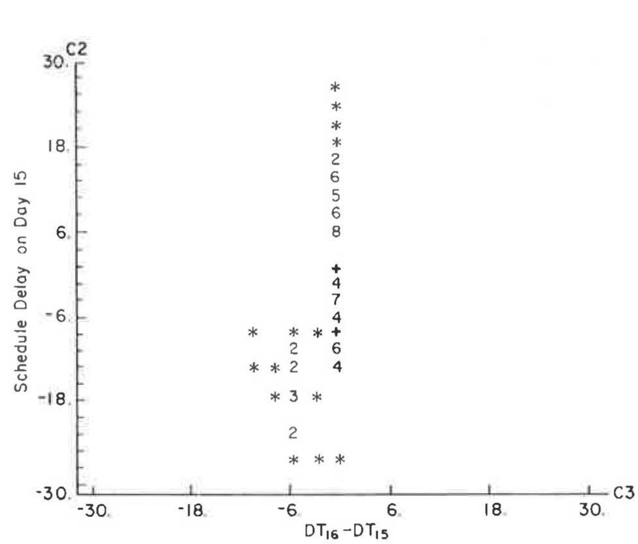

FIGURE 7 Departure time adjustment versus deviation from preferred arrival time on previous day: Day 16.

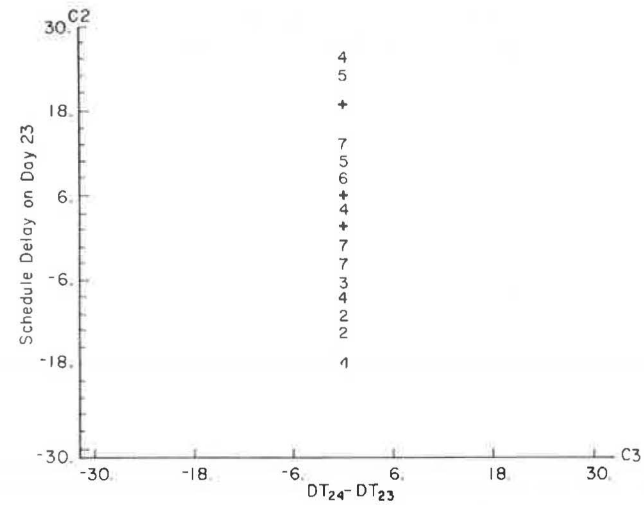

FIGURE 8 Departure time adjustment versus deviation from preferred arrival time on previous day: steady state.

TABLE 6 Average Ratio of Departure-Time Adjustment to Previous Day's Schedule Delay, Sector 1

Change Sequence No.	Average Ratio by User Group 1 E	1 L	2 E	2 L	3 E	3 L
1	0.67	0.29	0.56	0.38	0.50	0.52
2	0.55	0.22	0.24	0.40	0.26	0.46
3	0.38		0.23	0.24	0.19	0.46
4			0.20	0.21	0.17	0.46
5			0.11	0.25	0.12	0.51
6					0.11	0.63
7						0.90
8						0.36

Note: E and L refer to departure-time changes in response to earliness and lateness, respectively, on the previous day.

is that lateness relative to a preferred arrival time that is closer to the official work start time is more likely to result in actual lateness for work; the adjustment in this case is larger (relative to $SD_{i,t-1}$) than that when the lateness is entirely within the excess time between PAT_i and WS. On the other hand, adjustments in response to earliness are larger for users with earlier preferred arrival times, to avoid otherwise excessive earliness relative to the work start time. Table 6 also reveals the general trend of a decreasing adjustment ratio across successive changes, particularly in response to earliness. The trend is not as clear for responses to lateness. It should also be noted as one interprets Table 6 that the averages for the later changes are based on very few participants.

Outcomes: Schedule Delay and Travel Time

It was seen earlier that the average schedule delay ultimately accepted by users in each sector increases with distance from the destination (Figure 2), which suggests that more distant users ultimately accept larger schedule delays and as such possess wider indifference bands of tolerable schedule delay. This is supported by the more detailed analysis of the proportion of users accepting (at equilibrium) various levels of schedule delay, in 5-min increments, presented in Table 7.

TABLE 7 Relative Frequency per Sector of Difference Between Preferred Arrival Time and Actual Steady-State Arrival Time

Δ^a (min)	Frequency by Sector 1	2	3	4	5	All
Early						
21–25	20	15	10	0	0	9
16–20	30	25	25	0	0	16
11–15	0	10	40	10	5	13
6–10	10	10	15	35	25	19
1–5	0	5	5	30	45	17
0	0	0	0	0	0	0
Late						
(−1) − (−5)	20	0	5	10	15	10
(−6) − (−10)	20	20	0	15	5	12
(−11) − (−15)	0	15	0	0	5	4

[a]Δ = preferred arrival time minus actual arrival time at steady state.

The evolution of average travel time per sector is shown in Figure 9, which reveals the greater day-to-day fluctuation encountered by commuters originating in more distant sectors and the ensuing difficulty in converging to a steady state. Further details on the facility's traffic flow performance and the travel time characteristics of the system may be found elsewhere (20,23).

Perceptions and Learning

Direct information on user perception of travel time and schedule delay was not available from this experiment. However, of related interest are the anticipated travel time and schedule delay derived from the anticipated arrival time reported daily by users along with their departure-time choice.

In order to examine how actual experience on a given day influences perception on the following day, the ratio of the actual travel time on day t − 1 to the anticipated travel time on day t is considered (i.e., $TT_{i,t-1}/ATT_{i,t}$). The average of this ratio is taken separately over users experiencing lateness and earliness (relative to PAT_i), respectively, on day t − 1 for each sector. Table 8 shows these averages for days 1 through 6 along with the corresponding standard deviations. If the ratio is greater than 1, travel time is anticipated to be lower than on the previous day. It can thus be seen that users arriving late on day t − 1 appear, on average, to anticipate travel time on day t to be lower than on the previous day, whereas those arriving early on day t − 1 anticipate higher travel time on the next day. This somewhat counterintuitive finding can be attributed to the allowance by early users of a safety margin over their latest experienced travel time when they reset their departure time. On the other hand, late users are somehow hoping to compensate for the latest experienced travel time by an earlier departure that would face less congestion.

In order to compare the anticipated travel time on a given day with the actual travel time on that day, Figure 10(a-e) shows the day-to-day evolution of the average difference $TT_{i,t} - ATT_{i,t}$ for Sectors 1 through 5. Figure 10 reveals considerable daily fluctuation, with no clear decreasing pattern appearing until day 16. Overall (with the exception of Sector 5), there seems to be no particular tendency of overestimation as opposed to underestimation. The key conclusion suggested here is that users can be good travel time predictors only when the system has essentially stabilized. There is therefore no support for the contention that users are systematically learning about the facility's time-dependent performance, as is usually implied in a perfectly rational decision framework. Instead, local and somewhat myopic rules seem to be governing users' perception of the facility's performance.

The day-to-day evolution of the average absolute value of the difference between actual and anticipated schedule delay on a given day is shown in Figure 11. The same conclusions apply here as previously because it can be established algebraically that $SD_{i,t} - ASD_{i,t} \equiv ATT_{i,t} - TT_{i,t}$.

Intentions: Anticipated Arrival Time

This analysis parallels that of the departure-time choices, particularly because the concern is primar-

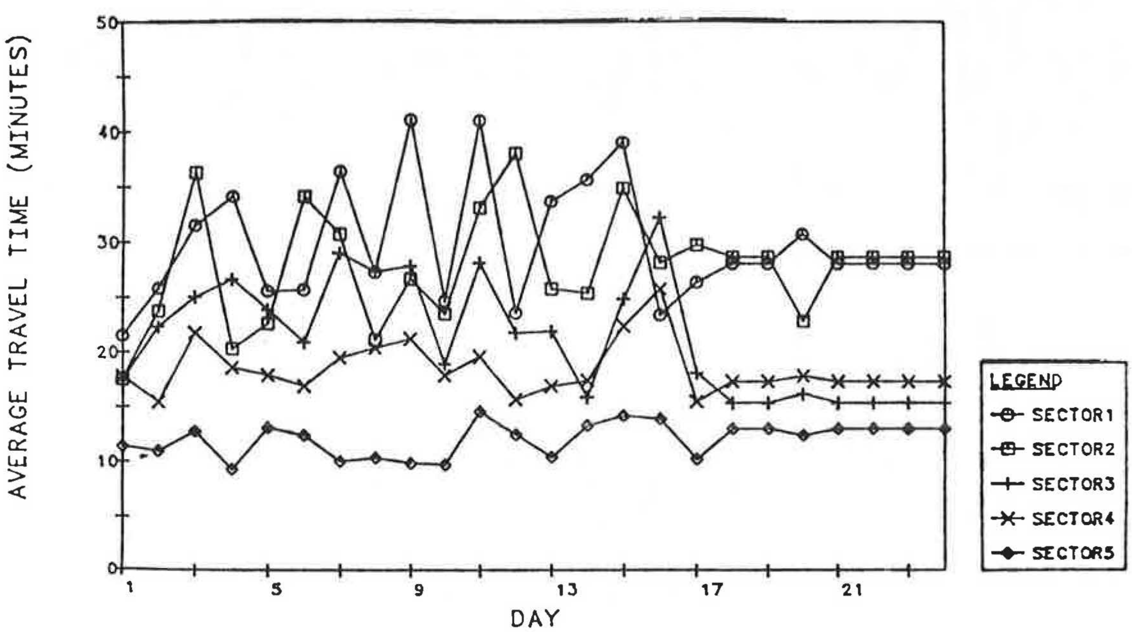

FIGURE 9 Evolution of average travel time for each sector.

TABLE 8 Average Ratio of Actual Travel Time on Day t – 1 to Anticipated Travel Time on Day t for Early Versus Late Users by Sector

	Day t									
	2		3		4		5		6	
Sector	Ratio	SD	Ratio	SD	Ratio	SD	Ratio	SD	Ratio	SD
1										
E	0.75	0.07	0.78	0.05	0.74	0.13	0.47	0.06	0.48	0.08
L	1.19	0.15	1.14	0.09	1.36	0.12	1.23	0.13	1.36	0.30
2										
E	0.65	0.22	0.76	0.09	0.64	0.21	0.66	0.11	0.69	0.16
L	1.04	0.03	1.15	0.30	1.26	0.24	1.35	0.27	1.15	0.09
3										
E	0.72	0.16	0.71	0.17	0.75	0.06	0.44	0.08	0.62	0.23
L	1.31	0.29	1.30	0.29	1.21	0.17	1.38	0.22	1.33	0.23
4										
E	0.76	0.14	0.76	0.13	0.75	0.13	0.85	0.11	0.88	0.08
L	1.26	0.11	1.29	0.14	1.33	0.31	1.17	0.13	1.29	0.19
5										
E	0.70	0.11	0.67	0.13	0.64	0.16	0.50	0.12	0.73	0.11
L	1.10	0.14	1.23	0.23	1.22	0.18	–	–	1.10	0.0

Note: E = group of users with early arrival on day t – 1. L = group of users with late arrival on day t – 1.

ily with the changes in intentions in response to experience with the facility. Table 9 shows the fraction of users in each sector who modified their anticipated arrival time at least n times, where n = 1,...,6. Comparing these data with Table 2 indicates that users are more prone to change actions before shifting intentions, as evidenced by the significantly fewer anticipated arrival-time changes. The same information is presented in Table 10 for each user group within Sectors 1, 2, and 3, respectively, thus confirming the general trend, discussed in conjunction with Table 3, that users with earlier preferred arrival times have to compromise less as the search progresses.

TABLE 9 Proportion of Users in Each Sector with at Least n Anticipated Arrival-Time Changes

No. of Changes[a]	Percentage of Users by Sector					
	1	2	3	4	5	All
1	75	75	80	30	35	59
2	50	60	25	5		28
3	20	30	10			12
4	15	10				5
5	15	5				4
6	10					2

[a]Minimum number.

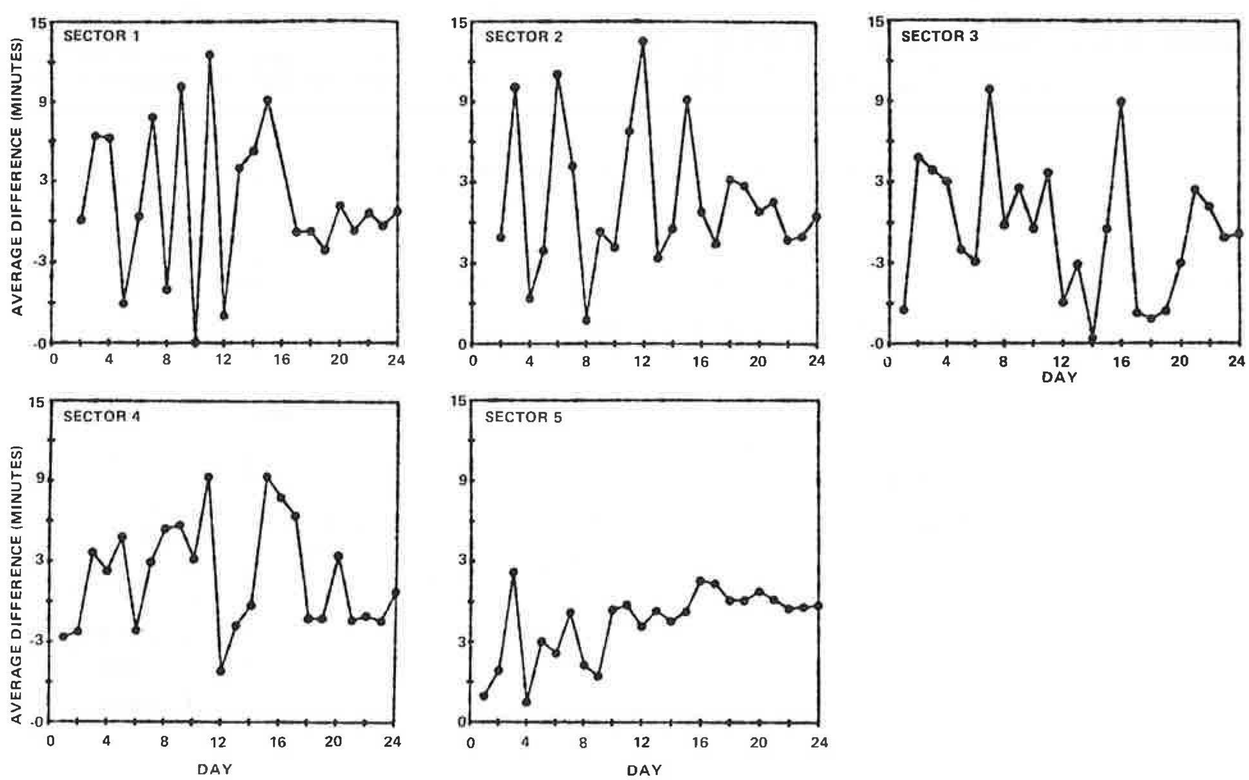

FIGURE 10 Day-to-day evolution of average difference between actual and anticipated travel time for each sector.

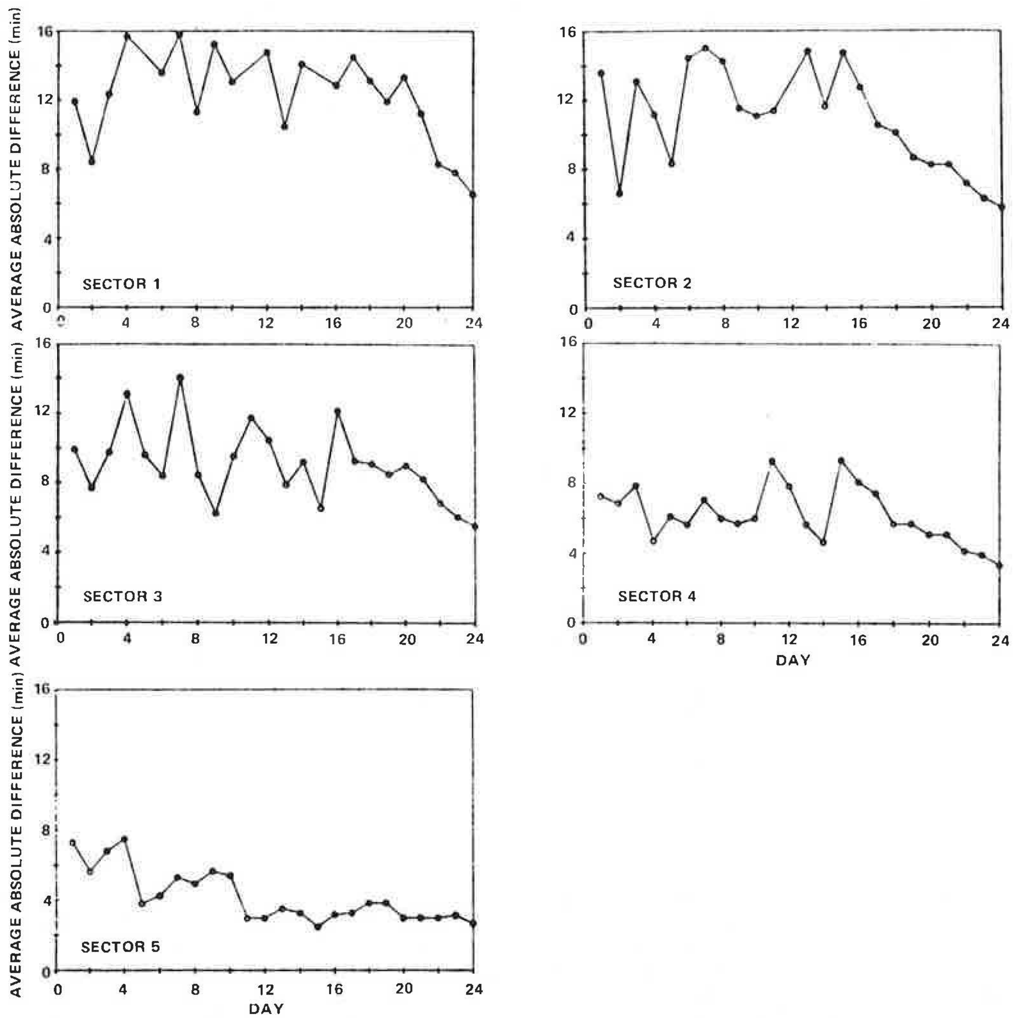

FIGURE 11 Day-to-day evolution of average absolute difference between actual and anticipated schedule delay for each sector.

Table 11 gives for each sector the mean number of days (and the standard deviation) since the previous revision for each of the n anticipated arrival-time changes, n = 1,...,6. Unlike Table 4, a clear decreasing trend is evident here, whereby users revise intentions at gradually smaller time intervals. As a matter of fact, the mean time until the first change is quite large, which indicates user persistence in initial intentions. However, as users progressively realize the inability to achieve their initial preference, and as they develop a better feel for the system's performance, they appear more willing to revise their anticipated arrival time. Increasingly, a number of participants updated their anticipated arrival time only after the system had reached steady state.

Table 12 presents the average number of departure-time changes (and the standard deviation) that took place since the previous revision for each of the six anticipated arrival-time revisions. The number of departure-time changes is an indication of the number of intervening unacceptable outcomes, and

TABLE 10 Proportion of Users in Each User Group Within Sectors 1, 2, and 3 with at Least n Anticipated Arrival-Time Changes

	Percentage of Users by Sector								
	1			2			3		
No. of Changes[a]	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
1	0	62.5	100	33.3	50.0	100	0	66.6	100
2		37.5	90.0		16.7	100		33.3	61.5
3		25.0	70.0		16.7	63.6		16.7	23.1
4		12.5	40.0			18.2		16.7	
5			30.0			9.1			
6			20.0			9.1			

[a]Minimum number.

TABLE 11 Mean and Standard Deviation of the Number of Days Between Consecutive Anticipated Arrival-Time Changes per Sector

Change Sequence No.	Sector 1		2		3		4		5		All Users	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	7.62	4.12	6.53	4.42	9.63	5.32	14.52	6.98	9.14	3.92	8.77	5.21
2	4.54	2.99	5.08	3.68	6.89	5.13	6.00	–[a]			5.43	3.81
3	3.63	1.60	3.80	2.90	2.00	2.00					3.44	2.28
4	1.67	1.15	4.06	4.24							2.33	2.42
5	1.00	0.00	4.00	–[a]							1.75	1.55
6	1.50	0.72									1.50	0.72

[a]Only one participant was involved in this change.

TABLE 12 Mean and Standard Deviation of the Number of Departure-Time Changes Between the Consecutive Anticipated Arrival-Time Changes per Sector

Change Sequence No.	Sector 1		2		3		4		5	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
No change	6.00	1.80	6.00	2.60	3.50	2.30	2.50	1.22	1.30	0.63
1	4.50	2.58	3.70	1.87	3.00	1.93	1.33	1.50	0.57	0.53
2	2.61	2.14	2.74	1.72	1.56	2.06	1.00	–[a]		
3	1.00	1.32	1.20	1.20	1.00	0.00				
4	0.80	0.83	1.50	0.70						
5	0.75	0.52	1.00	–[a]						
6	1.00	0.00								

[a]Only one participant was involved in this change.

is as such a measure of the number of failures until the next revision. As expected from the foregoing discussion, this number decreases as the search progresses, reflecting the initial resistance (to revising intentions), which appears to weaken progressively. Table 12 also reveals that users in closer sectors encounter fewer "failures," on average, than those in more distant sectors.

Finally, the direction of these readjustments is examined. Are users shifting their anticipated arrival to an earlier or a later time? And are they doing so consistently in one or the other direction? As suggested in the second section, users would tend to accept increasing earliness relative to their preferred arrival time in order to accommodate the fluctuations in system performance. This is indeed the case in this experiment, with 72 percent of all users who adjusted anticipated arrival time at least once consistently shifting to an earlier time. Only 7 percent consistently shifted to a later time (actually only two participants, both in Sector 4), with the remaining 21 percent moving at least once in each direction.

CONCLUSION

This paper has presented the principal elements of a theoretical framework to describe the processes governing commuters' daily departure-time decisions in response to experienced congestion patterns. Commuter behavior is viewed as a boundedly-rational search for an acceptable departure time. A key notion is that of an indifference band of tolerable schedule delay that determines the acceptability of a particular decision outcome on any given day. This indifference band, which varies across individuals, also shifts in response to users' experience with the facility.

Although not intended as a formal validation of the foregoing model, an experiment involving real commuters interacting daily with a hypothetical simulated traffic corridor was conducted over a period of 24 days, yielding valuable insights into the dynamics of the departure-time decision and its interaction with system performance. The results pertaining to the underlying behavioral processes were analyzed in this paper from the perspective of the key notions articulated in the conceptual framework.

Of course, this is only one such experiment, which involves obvious restrictions because of the hypothetical nature of the commuting corridor. Nevertheless, it has been quite insightful, particularly given the difficulty and the scale of corresponding real-world observations at the desired level of detail. As such, it offers a useful complementary approach to support the development of a comprehensive descriptive theory that would be subsequently validated, if only in part, in the field. Other experiments under different informational situations (e.g., where information about system congestion is available by word of mouth or through media reports) are also contemplated. In addition, formal mathematical model building and parameter estimation will be conducted.

ACKNOWLEDGMENTS

The contribution of Robert Herman to the overall research effort on which this paper is based is gratefully acknowledged, as are the many profitable discussions with him on various aspects of this problem.

Initial support for this work was provided by a grant from the Bureau of Engineering Research at the University of Texas at Austin. Computer support was provided, in part, by the Department of Civil Engineering. Further support for this work and its continuation is provided by a grant from the National Science Foundation.

REFERENCES

1. S. Rosenbloom. Peak-Period Traffic Congestion: A State-of-the-Art Analysis and Evaluation of Effective Solutions. Transportation, Vol. 7, 1978, pp. 167-191.
2. S. Cosslett. The Trip Timing Decision for Travel to Work by Automobile. In Demand Model Estimation and Validation, Urban Travel Demand Forecasting Project, Phase 1 Final Report, Vol. 5, Institute for Transportation Studies, University of California, Berkeley, 1977.
3. M. Abkowitz. Understanding the Effect of Transit Service Reliability on Work Travel Behavior. In Transportation Research Record 794, TRB, National Research Council, Washington, D.C., 1981, pp. 33-41.
4. K. Small. The Scheduling of Consumer Activities: Work Trips. American Economic Review, Vol. 72, 1982, pp. 467-479.
5. C. Hendrickson and E. Plank. The Flexibility of Departure Times for Work Trips. Transportation Research A, Vol. 18A, No. 1, 1984.
6. W.S. Vickrey. Congestion Theory and Transportation Investment. American Economic Review, Vol. 59, 1969, pp. 251-261.
7. J.V. Henderson. The Economics of Staggered Work Hours. Journal of Urban Economics, Vol. 9, 1981, pp. 349-364.
8. C. Hendrickson and G. Kocur. Schedule Delay and Departure Time Decisions in a Deterministic Model. Transportation Science, Vol. 15, No. 1, 1981, pp. 62-77.
9. C. Hendrickson, D. Nagin, and E. Plank. Characteristics of Travel Time and Dynamic User Equilibrium for Travel-to-Work. In Proceedings of the Eighth International Symposium on Transportation and Traffic Theory, (V.F. Hurdle, E. Hauer, and G.N. Steuart, eds.), University of Toronto Press, 1983, pp. 321-347.
10. M.J. Smith. The Existence of a Time-Dependent Equilibrium Distribution of Arrivals at a Single Bottleneck. Presented at the International Symposium on Transportation Equilibrium and Supply Models, Montreal, Canada, 1981.
11. P.H. Fargier. Effects of the Choice of Departure Time on Road Traffic Congestion: Theoretical Approach. Proceedings of the Eighth International Symposium on Transportation and Traffic Theory, (V.F. Hurdle, E. Hauer, and G.N. Steuart, eds.), University of Toronto Press, 1983, pp. 223-263.
12. A. De Palma, M. Ben-Akiva, C. Lefevre, and N. Litinas. Stochastic Equilibrium Model of Peak Period Traffic Congestion. Transportation Science, Vol. 17, No. 4, 1983.
13. M. Ben-Akiva, M. Cyna, and A. De Palma. Dynamic Model of Peak Period Congestion. Transportation Research B, Vol. 18B, No. 45, 1984, pp. 339-356.
14. M. Ben-Akiva, A. De Palma, and P. Kanaroglou. Analysis of Peak-Period Traffic Congestion with Elastic Demand. Presented at the Tenth Transportation Planning Research Colloquium, Netherlands, 1983.
15. H.S. Mahmassani and R. Herman. Dynamic User Equilibrium Departure Time and Route Choice on Idealized Traffic Arterials. Transportation Science, Vol. 18, No. 4, 1984.
16. H.S. Mahmassani and G.-L. Chang. Experiments with Departure Time Choice Dynamics of Urban Commuters. Transportation Research Board (1986, in press).
17. A.S. Alfa. Modelling the Temporal Distribution of Peak Traffic Demand: State of the Art and Directions. Presented at the Spring Joint Annual Meeting of ORSA/TIMS, San Francisco, Calif., 1984.
18. J.L. Horowitz. The Stability of Stochastic Equilibrium in a Two-Link Transportation Network. Transportation Research B, Vol. 18B, No. 1, 1984.
19. H. Simon. A Behavioral Model of Rational Choice. Quarterly Journal of Economics, Vol. 69, 1955, pp. 99-118.
20. H.S. Mahmassani, G.-L. Chang, and R. Herman. Collective Effects and Individual Decisions in a Traffic System. Submitted to Transportation Science, 1984.
21. R. Herman and T. Lam. Trip Time Characteristics of Journeys to and from Work. In Proceedings of the Sixth International Symposium on Transportation and Traffic Flow, Sydney, Australia, 1974, pp. 57-85.
22. J.W. Payne. Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis. Organization Behavior and Human Performance, Vol. 16, 1967, pp. 366-387.
23. H.J. Einhorn and R.M. Hogarth. Behavioral Decision Theory: Processes of Judgment and Choice. Annual Review of Psychology, Vol. 32, 1981, pp. 53-88.
24. P. Slovic, B. Fischoff, and S. Lichtenstein. Behavioral Decision Theory. Annual Review of Psychology, Vol. 31, 1977, pp. 1-39.
25. R. Cardozo. An Experimental Study of Consumer Effort, Expectations and Satisfaction. Journal of Marketing Research, Vol. 2, 1965, pp. 240-249.
26. R.C. Oliver. Effect of Expectation and Disconfirmation on Post-Exposure Product Evaluations: An Alternative Interpretation. Journal of Applied Psychology, Vol. 62, 1977, pp. 480-486.
27. J.C. Olson and P.A. Dover. Disconfirmation of Consumer Expectation Through Product Trial. Journal of Applied Psychology, Vol. 64, 1979, pp. 179-189.
28. J.W. Thibout and H.H. Kelley. The Social Psychology of Groups. John Wiley and Sons, Inc., New York, 1959.
29. S. Latour and N. Peat. Conceptual and Methodological Issues in Satisfaction Research. Advances in Consumer Research, Vol. 6, 1979, pp. 431-437.
30. R.C. Oliver. A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. Journal of Marketing Research, Vol. 17, 1980, pp. 460-469.
31. H. Helson. Adaption Level Theory: An Experimental and Systematic Approach to Behavior. Harper and Row, New York, 1964.
32. P.A. Labarbera and D. Mazursky. A Longitudinal Assessment of Consumer Satisfaction/Dissatisfaction: The Dynamic Aspect of the Cognitive Process. Journal of Marketing Research, Vol. 20, 1983, pp. 393-404.
33. G.-L. Chang, H.S. Mahmassani, and R. Herman. A Macroparticle Traffic Simulation Model to Investigate Peak-Period Commuter Decision Dynamics. In Transportation Research Record 1005, 1985, pp. 107-121.

The authors are solely responsible for the content of this paper.

Publication of this paper sponsored by Committee on Traveler Behavior and Values.