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

Availability of Information and Dynamics of Departure Time Choice: Experimental Investigation

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The effect of information availability on the dynamics of user behavior in urban commuting systems is investigated through an experimental procedure that involves real commuters interacting in a simulated traffic system under two distinct informational situations: in one only the decision maker's own performance on the previous day is available, and in the other complete information about the system's performance on the previous day is available. The results are examined from the perspective of a theoretical framework articulated previously in conjunction with the results of the first, limited-information, experiment. The focus of this paper is on the results of the complete-information experiment relative to those obtained in the first one. It is found that additional information raises users' aspiration levels and generally improves their predictive capability, but results in greater day-to-day departure time switching and longer convergence periods to a steady state, which is superior, in terms of user costs, to that attained under limited information.

The dynamics of individual choice behavior in transportation systems remain one of the least understood aspects of travel demand analysis. Of particular interest are the dynamics of trip-timing decisions, which determine the time-varying flow patterns in commuting systems and are important elements in the design and evaluation of peak-period congestion relief strategies. A major source of complexity in addressing these phenomena is the dynamic interaction between user decisions and the system's performance, which greatly diminishes the ability of conventional survey methods to generate observational data at a meaningful level of richness within practical resource constraints.

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Recently, a promising experimental approach was proposed by Mahmassani et al. *(1)*, whereby real commuters were involved during a period of 24 days in a simulated traffic system. The consequences of individual departure time decisions on a given day were evaluated by simulating traffic patterns in the system resulting from the aggregated time-varying departure functions. Given feedback from the simulation, participants would select their departure time for the next day. This approach provides a useful alternative to prohibitive large-scale, real-world experiments for studying the commuting system's overall behavior and dynamic properties as well as the behavioral mechanisms that govern the day-to-day choices of individual trip makers. In particular, it can effectively support theoretical development and model building, which could be subsequently validated, if only in part, in the field.

One of the attractive features of this approach is that it affords the analyst a high degree of control over the information available to participants, thereby allowing the investigation of the effect of availability of information on the system's dynamic properties. In the first such experiment conducted *(1, 2)*, the informational situation considered was one in which users had only their own experience to rely on. Everyday, participants were provided with their performance on the previous day, in the form of an arrival time at the work destination.

A theoretical framework for the day-to-day departure time decision-making dynamics of individual commuters was presented by Mahmassani and Chang *(2)*, along with the results of that first experiment. The principal behavioral hypothesis were subsequently verified through the calibration of individual choice models *(3, 4)*. In particular, user behavior under limited information in the commuting system was viewed as a dynamic boundedly rational search for an acceptable departure time. The acceptability of a given departure time ($DT_{i,t}$) for user i on day t and the resulting arrival time ($AT_{i,t}$) are determined relative to some "aspiration level," according to Simon's well-known "satisficing" decision rule *(5)*. Specifically, the notion of an "indifference band" of tolerable schedule delay [defined as the difference between user i's preferred arrival time (PAT_i) and actual arrival time ($AT_{i,t}$)] was introduced as the principal acceptability mechanism. The dynamic variation of this indifference band and its generally increasing response to unsuccessful experience with the facility's performance was established, reflecting a downward revision of aspiration level *(2, 3)*.

The role of information and the nature and degree of its availability in this framework are essential in determining user behavior and therefore in influencing the dynamics of the entire traffic commuting system. Information operates on two key behavioral processes: (*a*) perception and learning about the facility's performance, which ultimately determine user actions, in the form of departure time adjustments, and (*b*) aspiration level revision, as previously mentioned. Information can come from two principal sources in this context: the decision maker's own experience with the facility; or exogenous sources, such as media traffic reports, word of mouth, and so on, which are of particular concern to information-related congestion control policies; or a combination of the two sources. In the first experiment, only the first source was available to participants. This prevented the assessment of the effect of information, because only one level of this experimental factor was employed.

A second experiment was therefore conducted, under the same conditions as the previous one except for the informational situation, in which participants were provided with a complete profile of the system's performance on the previous day. The details are given in the next section.

In this paper is presented a comparative analysis of the two experiments, focusing on the effect of information on (*a*) the system's overall behavior, particularly convergence to an equilibrium and the patterns of this evolution, and (*b*) the processes governing the choice dynamics of individuals. The analysis parallels that presented previously for the first experiment *(2)* and is therefore essentially exploratory in nature. It is aimed at developing the principal insights and hypotheses that would be subsequently addressed through more formal and elaborate econometric analysis.

EXPERIMENTS

None of the participants in the second experiment had taken part in the first one, thereby controlling for initial bias and learning effects. This is also part of the reason for which two experiments were required instead of a single one during the course of which the informational situation would be changed. Such alternative experimental designs include changing availability of information for all or only some participants (*a*) after convergence is achieved under one level, (*b*) at prespecified intervals during the experiment, or (*c*) at random. However, such designs would unduly confuse participants, diminish their goodwill, and generally reduce the realism of the situation, in addition to increasing the difficulty of analyzing and interpreting the experimental results.

The details of the first experiment are described elsewhere *(1, 2)*. The second one followed essentially the same procedure, including the commuting context, which consisted of a single highway facility (two lanes in each direction, access limited to a finite number of entry points) and adjoining residential sectors. All commuters must use the facility to travel to their common destination, such as a city's central business district (CBD) or a major suburban industrial park. The commuting corridor is subdivided into nine 1-mi sectors, with the common destination located at the end of the last sector (number 9, because sectors are numbered from 1 to 9 in decreasing order of distance from the destination). Only the first five sectors were designated as residential, and there was no traffic generation from the remaining sectors.

One hundred participants, all working staff at the University of Texas at Austin, were carefully selected and assigned equally to the five residential sectors. The selection process made it extremely improbable for direct communication to take place among participants, thereby precluding cooperative behavior and controlling for availability of information. Participants were given a description of the commuting situation and instructed that they needed to be at work by 8:00 a.m., with the stipulation that no late arrival at the workplace was tolerated, which is not very different from their own working conditions. The identical work start time and no lateness conditions were imposed in order to eliminate nonessential complication in the interpretation of the results and to keep the number of participants at a manageable level while allowing a meaningful level of interaction to develop in the traffic system.

The procedure can be summarized as follows:

1. Supply each participant i, $i = 1, \ldots, 100$, with initial information and instructions.
2. On day t, all participants supply their departure time decisions ($DT_{i,t}$); these are aggregated by sector into time-dependent departure functions [$N_{k,t}(T)$] where T is the time of day, $k = 1, \ldots, 5$.
3. The departure functions are input to a special-purpose macroparticle traffic simulation model [or MPSM, described in detail elsewhere *(6)*], which yields the respective arrival times ($AT_{i,t}$), travel times ($TT_{i,t}$), and other pertinent traffic performance measures. Note that each participant was treated as 20 trip makers making identical decisions for traffic simulation purposes.
4. If steady state is established, or a maximum experiment duration is reached, stop; otherwise, set $t = t + 1$, supply each participant with information on actual performance on the preceding day, and go to Step 2 for updated departure time decisions from the participants.

It is in this last step that the two experiments are different. As mentioned earlier, only $AT_{i,t-1}$ was provided to participant i on day t in the first experiment. However, in the second experiment, each participant was supplied with the arrival times corresponding to an array of possible departure times between 7:00 a.m. and 7:50 a.m., in 5-min increments, from that participant's origin sector. Note that the 5-min increments were chosen on the basis of the earlier observation that participants appeared to naturally select departure times in this manner *(1, 2)*. The information was presented in the form of "if you had left at 7:15, you would have arrived at 7:40." Therefore, trip makers essentially had complete information about the travel time performance of the facility for departures from their origin sector on the preceding day. Naturally, in an evolving system, there was no guarantee that this pattern would be maintained on the next day.

EXPERIMENTAL RESULTS

The following questions are addressed in this presentation of the experimental results: (*a*) initial preferences, (*b*) convergence and system performance, and (*c*) behavioral processes.

Initial Preferences

It has been shown in previous work that the state to which a given commuting system converges, if at all, as well as the evolutionary path toward such a state, depend on the initial conditions of the system *(7)*. Similar conclusions were reached by Horowitz in the somewhat different context of stochastic route choice in a two-link network *(8)*. In the present experiments, all initial elements except the actual participants were identical, including the initial information supplied to participants. As discussed earlier, it is neither practical nor desirable to use the same participants in the two informational situations nor to employ more complicated experimental designs.

Initial preference was found to be a key factor in explaining differences in the dynamics of user behavior in the first experiment. It is captured in these experiments by the preferred arrival time (PAT_i) supplied by each participant at the beginning of the experiment. This quantity is generally different from the actual work start time (note that $PAT_i \leq WS$) and reflects inherent differences of individual tastes and preferences, as well as an indication of a user's attitude toward risk. As before, it serves as a basis for segmenting the participants into three groups: (*a*) Group 1, which includes all users *i* such that 7:30 a.m. $\leq PAT_i <$ 7:40 a.m.; (*b*) Group 2, for whom 7:40 a.m. $\leq PAT_i <$ 7:50 a.m.; and (*c*) Group 3, for whom 7:50 a.m. $\leq PAT_i <$ 8:00 a.m.

Comparisons of the distribution of participants in these groups across sectors (within the same experiment) and between the two experiments were performed using chi-square tests. No systematic variation across sectors could be detected in either case. More significant, the hypothesis that this distribution is the same for the two different sets of participants could not be rejected at the 10 percent significance level. This is indeed a remarkable result that provides a stronger basis for comparing the results of the two experiments. Because the initial conditions can be considered to be essentially the same in both cases, differences in the dynamics of the system can be more clearly attributed to the effect of the availability of information.

Convergence and System Performance

Four questions are of concern here:

1. Does the system converge to a steady state?
2. How long does it take to do so?
3 What temporal and spatial patterns can be distinguished in the system's evolution under each informational situation?
4. Does it converge to the same state in both experiments? How do the two equilibria differ (in terms of user costs)?

Convergence in these experiments has been defined in terms of the departure patterns from each sector. When all users stop adjusting their departure times, steady state is reached. Because the traffic simulation is deterministic, all system performance measures associated with a given set of steady-state departure functions also converge. Steady state was reached as of day 20 (for the overall system) in the first, limited information, case, and maintained for 5 days before the experiment was stopped. Steady state was reached as of day 29 in the second case. Note that although only one final day with no switching was observed in the second experiment, the system was considered essentially at steady state because only an insignificant amount of switching had been taking place during the preceding 5 days. The total duration of the second experiment was therefore 6 weeks (5 days per week).

The first striking result is that the system takes longer to converge under complete information than when users are provided with only their own preceding day performance. This is true in all sectors, as indicated by the data in Table 1, which gives the time until convergence in each sector under both informational situations. Because this time could be unduly affected by a small number of persisting participants, it is useful to examine the day-to-day evolution of the fraction of users who change departure time, shown in Figure 1 for Sectors 1–5, respectively, for each experiment. Table 2 gives a further summary of this information by listing the number of days of each experiment on which at least 25, 50, and 60 percent, respectively, of users in each sector change their departure time. This provides a more meaningful comparison across sectors and between experiments because it captures the intensity of switching activity in each sector. The conclusion that it takes longer for each sector to converge under the complete-information situation than under the limited-information one is clearly borne out by the results.

TABLE 1 TIME, IN DAYS, UNTIL CONVERGENCE IN EACH EXPERIMENT, BY SECTOR

	Sector				
Experiment	1	2	3	4	5
1	21	18	17	17	5
2	27	27	29	22	18

Particularly noteworthy is the substantially greater difficulty of convergence exhibited by Sectors 2–5 in the second experiment relative to the first, as revealed by the switching frequency data. It can also be noted that Sectors 2 and 3 exhibit even greater difficulty than Sector 1 in the second experiment, unlike the situation in the first experiment, in which sectors closer to the destination converged sooner than more distant ones *(1)*. This apparent difference in the spatial pattern of the system's evolution is a manifestation of a more fundamental result that holds in both cases. Namely, sectors in which residents encounter greater day-to-day fluctuations in system performance require a longer time to converge (and will experience more intense switching activity in the process). In the first experiment, more distant sectors exhibited greater day-to-day fluctuations than closer ones. In the second, Sector 3 had by far the most drastic fluctuations, as shown in Figures 2 and 3 that depict the day-to-day evolution of the average (of the absolute value of) schedule delay and travel time, respectively, experienced by users in each sector [these can be contrasted with similar figures for the first experiment given elsewhere *(2)*].

The fluctuation pattern in a given sector is a result of the complex interaction of decisions made by users in all sectors and

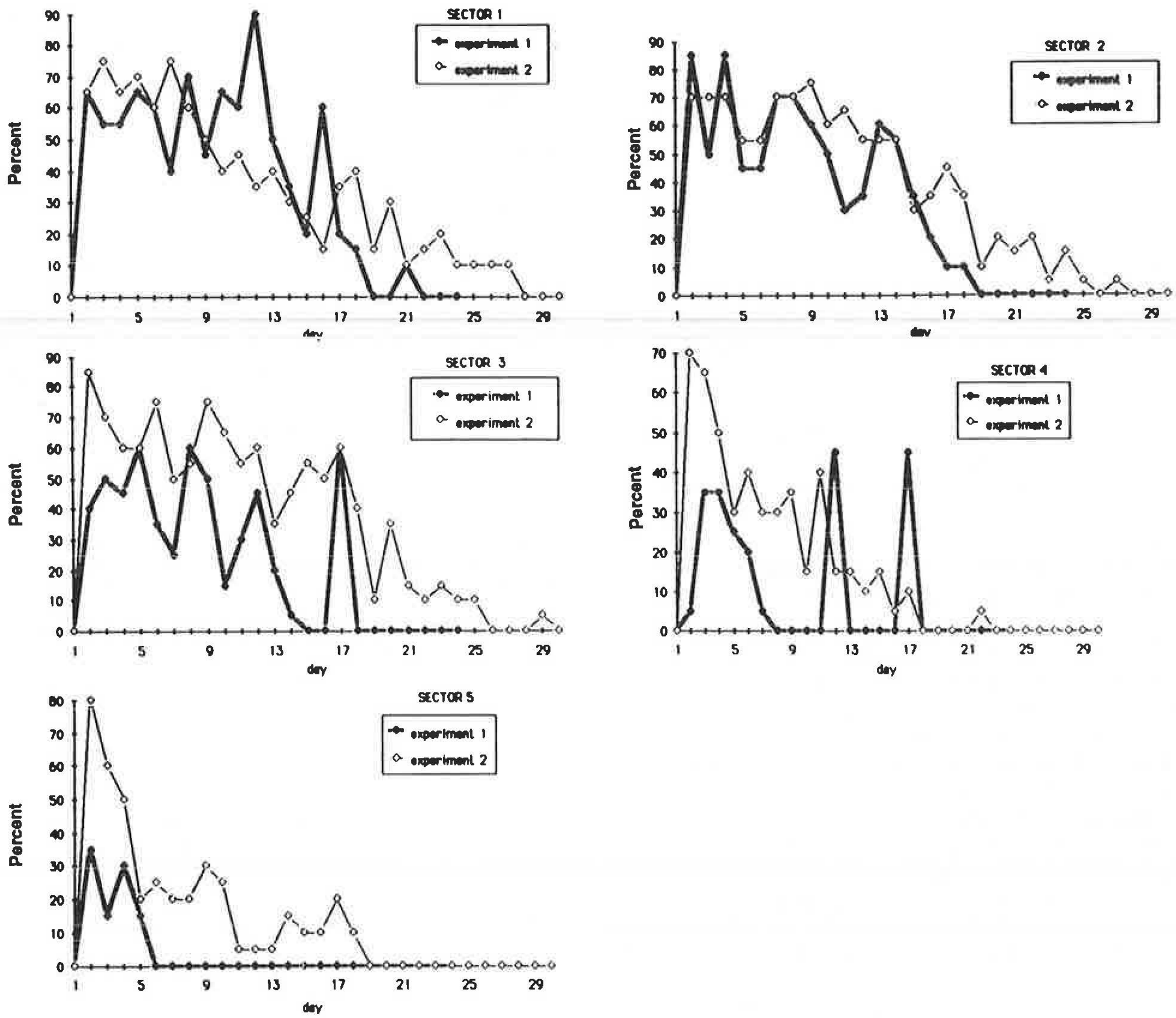

FIGURE 1 Day-to-day evolution of the fraction of users who change departure time in each experiment, by sector.

TABLE 2 NUMBER OF DAYS OF EACH EXPERIMENT WITH AT LEAST 25, 50, AND 60 PERCENT OF USERS CHANGING DEPARTURE TIME, BY SECTOR

Fraction Changing (%)	Experiment	Sector 1	2	3	4	5
≥25	1	14	14	11	5	2
	2	17	17	18	9	6
≥50	1	11	9	5	0	0
	2	8	13	14	3	3
≥60	1	7	6	2	0	0
	2	7	8	9	2	2

cannot be predicted. Evidently, there is a higher degree of interaction when users are provided with more information, which is reflected in the longer convergence times for each sector. At this stage, a possible explanation is that users have greater expectations when provided with more information and may therefore have a greater willingness to experiment. However, a traffic commuting system such as the one in question is a highly nonlinear interactive system in which the travel time profile on day $t - 1$ may be a misleading predictor for travel time on day t. In other words, it is not clear that users, no matter how sophisticated they might be, can process and integrate the provided information to accurately predict system performance. These questions will be addressed to a greater extent later in this paper in conjunction with the discussion of users' behavioral mechanisms.

It can further be noted in Figures 2 and 3 that, despite the continuing fluctuation of schedule delay and travel time, users in sectors already in steady state (particularly Sectors 4 and 5) maintained their departure decisions. This was observed in both experiments and is consistent with what can be expected under boundedly rational behavior and the associated "indifference band" notion described in the first section *(2, 3)*.

The steady-state schedule delay and travel time shown in Figures 2 and 3 are contrasted in Figure 4 with those obtained under the limited-information situation. This figure consists of a scatter plot in the schedule delay-travel time space of the steady-state performance of each sector under the two experiments, thereby making it possible to compare and assess the states to which the system converged under the two informational situations. It is clear from the steady-state departure distributions and all other

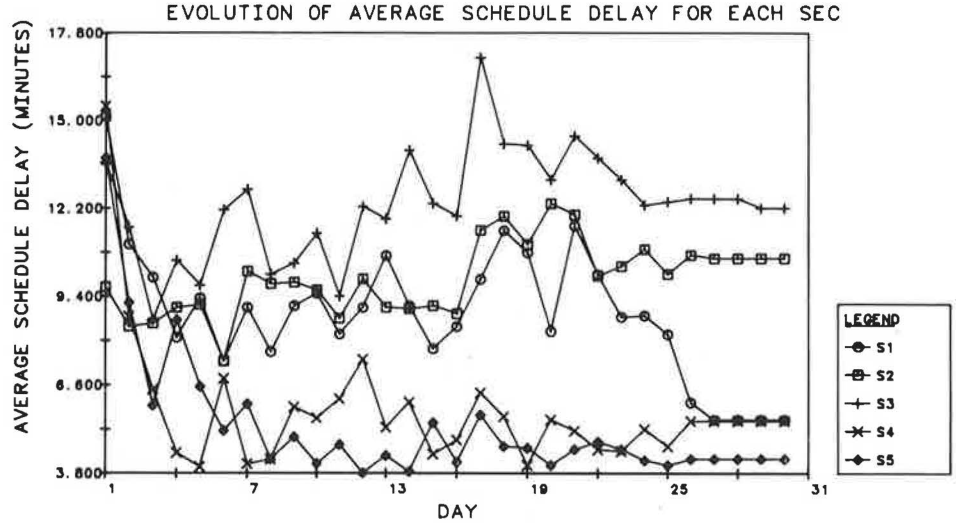

FIGURE 2 Day-to-day evolution of the average absolute schedule delay for each sector, Experiment 2.

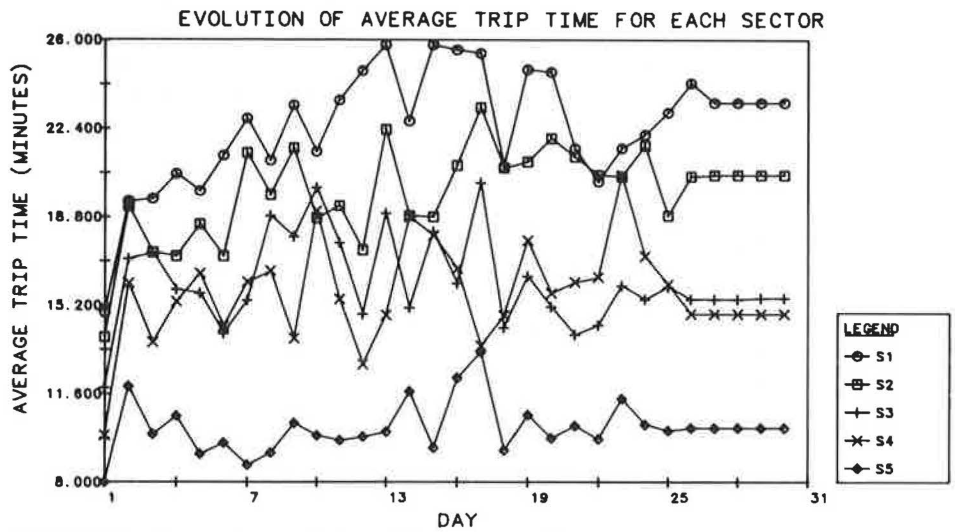

FIGURE 3 Day-to-day evolution of the average trip time for each sector, Experiment 2.

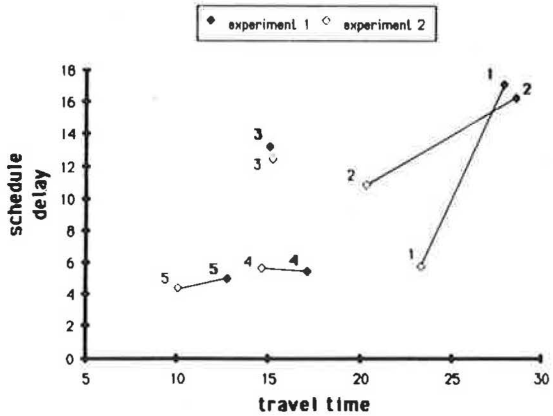

FIGURE 4 Comparative steady-state performance of each sector under the two informational situations.

associated performance measures that the two states are quite distinct. Therefore, despite identical system elements and similar initial preferences of participants, two different equilibria were reached. This nonuniqueness is consistent with the results, derived by Mahmassani and Chang for an idealized situation *(9)*, regarding the properties of boundedly rational user equilibrium (BRUE). The latter is attained in a system when all users have accepted their current outcome and no longer desire to change decisions. Similar results were also obtained in a number of computer simulations with endogenously specified commuter decision rules *(7)*.

Figure 4 also permits the assessment of how the two equilibria compare in terms of user costs (or components thereof). The conclusion is once again striking: overall, users are better off under the second informational situation. This is particularly true for Sectors 1 and 2, where quite significant reductions of about 67 and 33 percent, respectively, in average schedule delay, and 16 and 29 percent, in average trip time, were observed. Sector 3, which took the longest to converge in the second experiment, experienced virtually no improvement, with a slight decrease in schedule delay and about the same average trip time. Sector 4 exhibited a decrease in average trip time of about 15 percent and a slight increase in schedule delay.

The overall picture that emerges from the comparisons is that providing uses with more complete information about the system's performance has induced higher aspiration levels and allowed users to ultimately attain a better equilibrium state. However, given the difficulty of learning and prediction in a system with the kind of nonlinear interactions present here, users switched with greater frequency, which resulted in longer times until convergence. User behavior is further explored hereafter.

User Behavior

Following the presentation *(2)* of the results of the first experiment in which users were supplied with their own previous performance only, user actions, intentions, and perceptions and learning are examined in turn.

Actions

The evolution of the fraction of users who change departure time in each sector was seen earlier. This is examined further through the distribution of the number of departure time changes across users in the various sectors. In the first experiment, this frequency increased with distance from the destination and exhibited a marked dependence on users' initial preference group; users with earlier initial preferred arrival time (e.g., Group 1) have to change actions less frequently than do those with a later *PAT*.

Table 3 gives the same information for the second experiment, showing the fraction of users in each sector who changed their departure time at least n times, where $n = 1 \ldots, 23$ (highest number of changes observed). Figure 5 shows that information on a *PAT* group basis within each sector. Overall, all sectors experience greater switching frequency under the complete-information situation, which is consistent with the results of the previous section. The same general trends as before are still present; first, sectors that experience greater fluctuations of system performance have higher switching frequencies, in particular Sectors 2 and 3. This same principle resulted in the apparent dependence on distance in the first experiment. Regarding the *PAT* group effect, it can be noted that Group 1, consisting of users with the earliest preferred arrival times, exhibits in all sectors the same trend as in the first experiment, with a considerably smaller number of changes than are made by users in the other groups. Groups 2 and 3 are not so well differentiated in terms of switching frequency; this distinction was not particularly strong in the first experiment either.

As was mentioned previously, the mechanism that triggers a departure time change was found under the limited-information experiment to consist of an indifference band of tolerable schedule delay, which increased over time (in the first experiment) as users interacted with the traffic system in their search for an acceptable departure alternative *(2–4)*. Figure 6 shows scatter plots of the magnitude of the departure time adjustment on day t (i.e., $DT_{i,t} - DT_{i,t-1}$) versus $SD_{i,t-1}$, the schedule delay on day $t-1$, for all users in the system, for t = 2, 6, 11, 16, 21, 26, and 30 in Experiment 2. Focusing on the evolution of the points corresponding to a zero departure time adjustment, these plots provide a rather effective illustration that (*a*) there indeed exists a range of schedule delay that users are willing to tolerate and (*b*) this range appears to increase over time, reflecting users' acceptance of progressively greater schedule delay. Both conclusions were also evident in similar plots for the first experiment *(2)*.

There are notable differences, however, between the two informational situations. Under complete information, the scatter in the plots of Figure 6 is greater than in the first experiment, particularly

TABLE 3 PERCENTAGE OF USERS, IN EACH SECTOR, WITH AT LEAST *n* DEPARTURE TIME CHANGES

No. of	Sector 1		Sector 2		Sector 3		Sector 4		Sector 5		All Sectors	
Changes	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2
1	100	95	100	100	100	100	100	85	75	90	95	94
2	100	90	100	100	95	100	65	75	25	70	77	87
3	100	90	100	100	90	90	60	70		55	70	81
4	100	90	95	95	85	90	15	55		40	59	74
5	90	90	90	90	70	90	5	45		40	51	71
6	90	80	80	80	40	90		40		30	42	64
7	90	65	75	75	30	75		35		30	39	56
8	80	60	60	70	10	75		30		20	30	51
9	65	45	50	65		65		20		20	23	43
10	50	45	30	50		60		15		5	16	35
11	35	40	15	45		55		5		5	10	30
12	25	35		40		55		5		5	5	28
13	20	35		35		45					4	23
14	10	25		35		40					2	20
15	5	25		20		35					1	16
16		20		20		20						12
17		15		15		5						7
18		10		5		5						4
19				5		5						2
20				5		5						2
21				5								1
22				5								1
23				5								1

Note: Exp. = experiment.

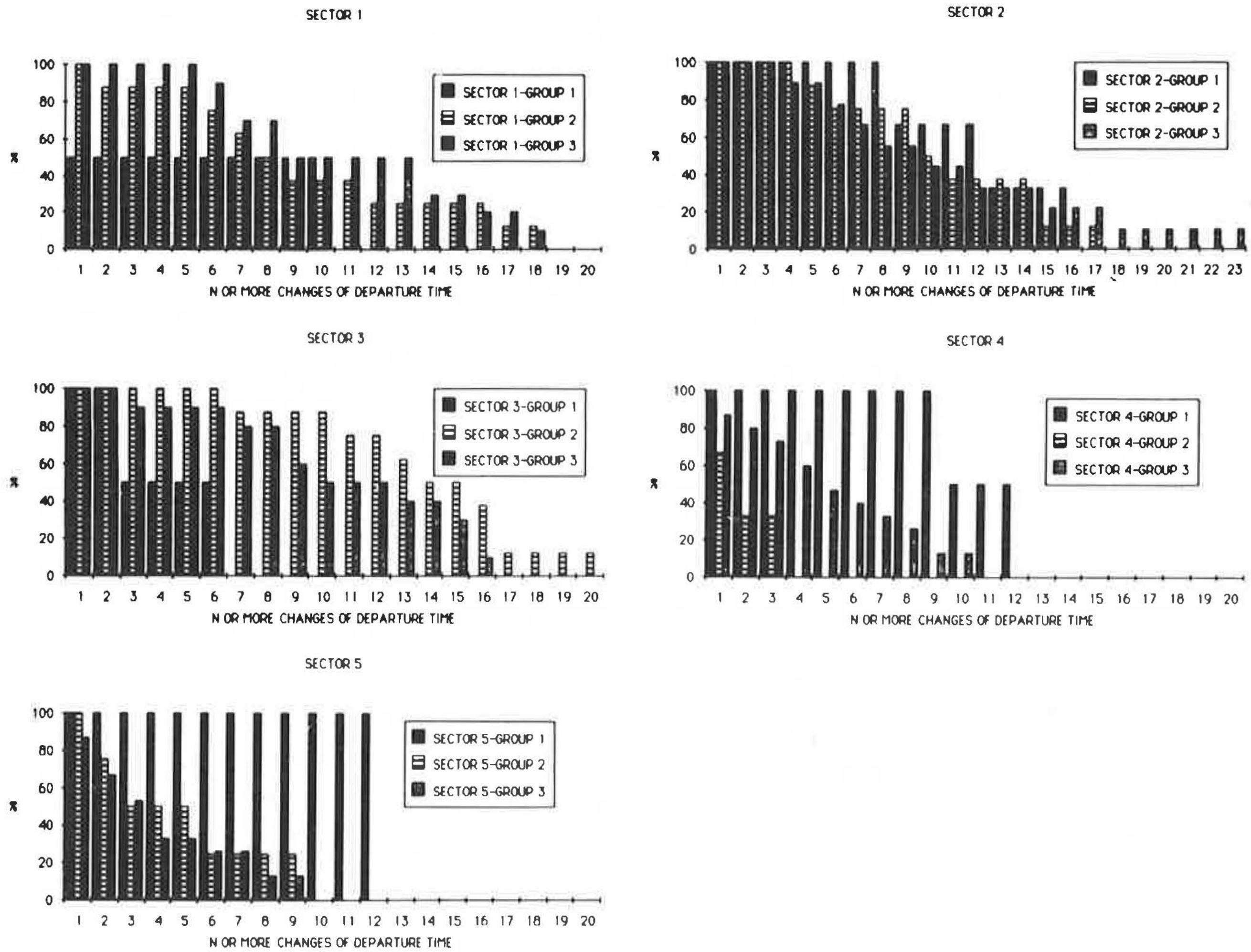

FIGURE 5 Fraction of users in each group with at least *n* departure time changes, by sector, Experiment 2.

during the early stages. This is due to a somewhat less "myopic" adjustment behavior than that observed when users had information about their own performance only. Namely, it was noted then that early arrival (relative to the individual's *PAT*) on day $t - 1$ almost always implied later (or same) departure on day t, whereas late arrival implied earlier (or same) departure the next day. This no longer appears to hold when users were provided with more information, as seen in the first two parts of Figure 6. However, as the system evolved, this adjustment pattern became the dominant one, as seen in Figure 6 for day 11 through day 30. A plausible explanation is found in the effect of information on the departure time selection process itself. Under limited information, departure time choice from one day to the next is viewed as an adjustment process anchored in the current decision, whereby a quantity is added to or subtracted from the present departure time, based on the individual's latest experience. When information is provided on all possible alternatives, many users become aware of these other alternatives and may be willing to select the one that has yielded (or that they predict will yield) what they consider to be the best outcome, independently of their current or previous decisions. Therefore, providing information on all alternatives appears to have induced some users to behave in what can be interpreted as a more optimizing manner. However, as noted earlier, the effective use of this information to predict the system's performance on any given day is difficult if the system has not yet approached steady state, and seemingly paradoxical or otherwise confusing situations may be encountered by users. This would explain the tendency to revert to the "anchoring" adjustment strategy after a number of unsuccessful trials or after the user has identified an acceptable departure time that serves as an anchor for subsequent adjustment. Along the same line, it can be hypothesized that there is a clearer compensatory feature in (at least some) users' behavior, whereby the trade-off between travel time and schedule delay is explicitly considered, as this trade-off becomes more apparent and salient to users when they are supplied complete information. This hypothesis will be further explored in subsequent modeling work.

An essential difference between the plots in Figure 6 and those obtained in the first experiment concerns the evolution of the indifference band of tolerable schedule delay. It was claimed earlier, in explaining the overall dynamic performance of the system under the two informational situations, that providing users with more information generally raised their aspiration levels. The net result was a lower average schedule delay in each sector at steady state and a longer time period to reach this state. Figure 6 generally indicates a slower rate of increase of the indifference band, with more users rejecting any given schedule delay, than under limited information. This is further substantiated by examining the response, in each sector, to different levels of schedule delay (in 5-min increments), as explained hereafter.

The percentage of those users experiencing a given schedule delay on day $t-1$ who have changed their departure time on day t has been calculated for each sector on a weekly basis (each including 5 days; this aggregation is necessary in order to have a meaningful number of observations in each schedule delay category). Table 4 gives the principal trends by presenting a week-by-week comparison of these percentages for selected sectors and schedule delay values that typify the underlying patterns. In particular, in any given week and sector, when users are provided with more information, a higher fraction of those exposed to the same schedule delay choose to reject it and switch departure times on the next day, often for 2 or more weeks after all corresponding switching has subsided under limited information. This indicates that the indifference band is increasing at a slower rate, which reflects users' higher aspiration levels. Furthermore, it is noted that, during the system's evolution, users in the second experiment were exposed to schedule delays of the same magnitude as those encountered in the first. Therefore the higher switching frequencies and longer time to converge in the second case are not due to users experiencing higher schedule delays than in the first experiment but to users rejecting comparable outcomes, evidently in the hope of achieving ultimately better outcomes.

Intentions

User intentions are captured by the anticipated arrival time ($AAT_{i,t}$) provided by each participant i on day t, $i = 1, \ldots, 100$, $t = 1, \ldots, 30$, along with the departure time ($DT_{i,t}$). In the first experiment, it was found that users were much more willing to change actions ($DT_{i,t}$) before changing intentions, and that the time period between consecutive *AAT* changes decreased somewhat as the system evolved. In the second experiment, supplying users with complete information about the facility's performance led to a markedly greater willingness to change anticipated arrival time

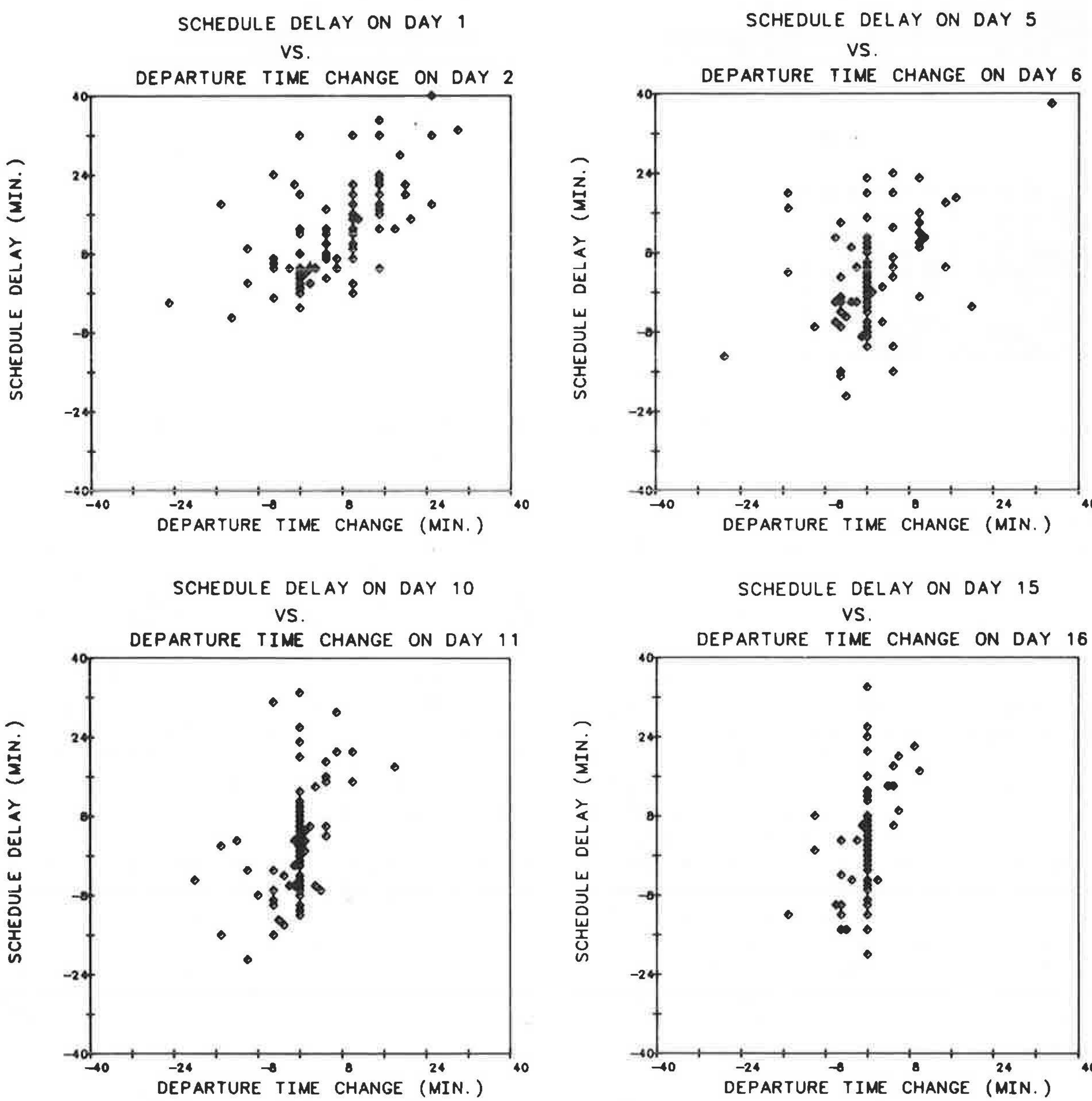

FIGURE 6 Scatter plots of departure time adjustment ($DT_{i,t} - DT_{i,t-1}$) versus schedule delay on previous day ($SD_{i,t-1}$) for selected days (t = 2, 6, 11, 16, 21, 26, and 30), Experiment 2.

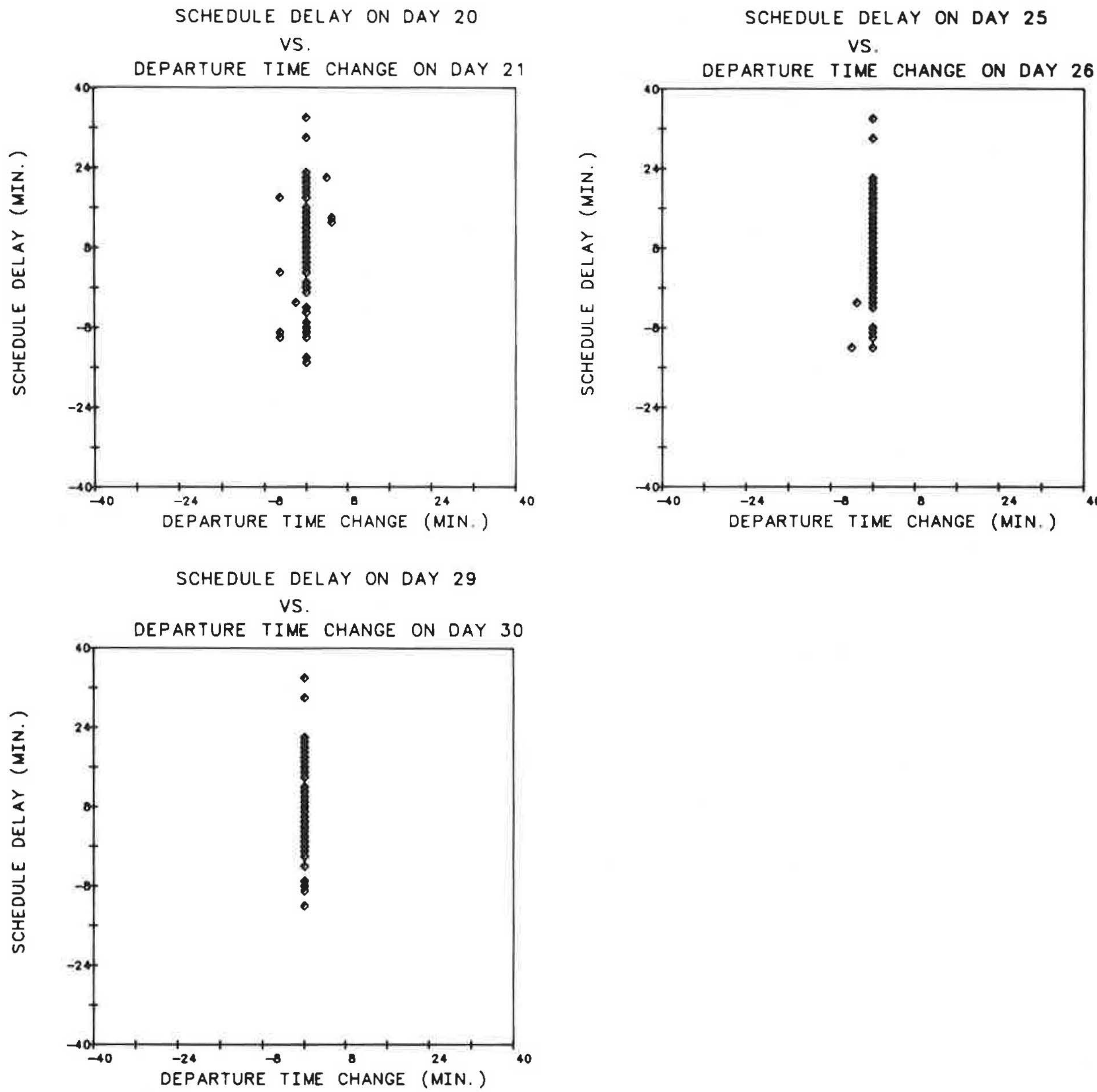

FIGURE 6 ***continued***

among users, without the initial resistance to changing intentions present in the first experiment. This is illustrated by the data in Table 5, which is a list of the percentage of users in each sector with at least *n* departure time changes, $n = 1, \ldots, 21$, for both experiments.

This greater propensity to revise anticipated arrival time is a plausible result of the availability of complete information on system performance. Under limited information, users perceived a greater level of uncertainty and were often not sure how to revise their *AAT*, especially at the beginning. However, as they progressively learned about the facility's performance, they were more willing to perform such a revision. In the first experiment, a clear decreasing pattern in the average time between consecutive *AAT* changes was present *(2)*. No such pattern is present in the second experiment.

The effect of *PAT* group on the frequency of *AAT* changes is essentially similar to its effect on departure time switching frequency. Group 1 users, with the earliest *PAT*, generally tend to experience less switching frequency than those in later *PAT* groups. Group 3 users still appear to exhibit the highest switching frequencies overall, though they are closely matched or surpassed by Group 2 users in some sectors. The significance of differences across these two groups cannot be ascertained on the basis of this exploratory analysis and will be addressed in formal statistical work, similar to that discussed elsewhere *(3–4)* for the first experiment.

Perceptions and Learning

Two principal aspects are addressed here: (*a*) how commuters use the information with which they are supplied in predicting their travel time and (*b*) the accuracy of their predictions as the system evolves. In the first experiment, travel time prediction models were calibrated at the individual level, which revealed that travel time on the previous day ($t - 1$) was the overwhelmingly dominant

TABLE 4 COMPARISON OF USER RESPONSE TO PREVIOUS DAY'S SCHEDULE DELAY: PERCENTAGE OF USERS EXPERIENCING GIVEN SCHEDULE DELAY WHO SWITCH DEPARTURE TIME ON FOLLOWING DAY, BY WEEK, UNDER BOTH EXPERIMENTS, FOR SELECTED SECTORS AND SCHEDULE DELAY VALUES

		Week					
Sector	Experiment	1	2	3	4	5	6
Schedule Delay of 11 to 15 min (early arrival)							
1	1	90.0	60.0	11.1	0		
	2	90.9	66.7	12.5	10.0	13.3	0
2	1	73.7	66.7	0	0		
	2	62.5	64.7	20.0	38.5	0	0
3	1	100.0	31.25	0	0		
	2	71.4	66.7	40.0	20.0	20.0	0
5	1	58.3	0	0	0		
	2	77.8	33.3	0	0	0	0
Schedule Delay of 6 to 10 min (early arrival)							
2	1	69.2	0	0	0		
	2	60.0	70.0	26.7	23.1	5.3	0
4	1	0	0	0	0		
	2	41.2	43.8	25.0	0	0	0
Schedule Delay of –1 to –5 min (late arrival)							
2	1	11.1	22.2	17.7	11.1		
	2	81.8	75.0	71.4	27.3	5.3	0
Schedule Delay of –6 to –10 min (late arrival)							
5	1	80.0	0	0	0		
	2	75.0	60.0	20.0	0	0	0

TABLE 5 FRACTION OF USERS IN EACH SECTOR WITH AT LEAST *n* ANTICIPATED ARRIVAL TIME CHANGES

No. of	Sector 1		Sector 2		Sector 3		Sector 4		Sector 5		All Sectors	
Changes	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2
1	75	90	75	90	80	100	30	90	35	90	59	92
2	50	85	60	90	25	100	5	90		85	28	90
3	20	85	30	90	10	90		65		70	12	80
4	15	75	10	85		90		65		65	5	76
5	15	70	5	80		85		60		50	4	69
6	10	65		75		85		55		45	2	65
7		55		75		85		45		35		59
8		55		75		80		30		35		55
9		50		65		75		30		35		51
10		50		65		60		15		25		43
11		50		45		55		15		15		36
12		45		45		40		10		15		31
13		30		45		40		10		10		27
14		25		35		35		5		5		21
15		15		15		25		5		5		13
16		5		15		25		5				10
17		5		10		20		5				8
18		5		5		15		5				6
19		5		5		15		5				6
20		5				10		5				4
21		5										1

Note: Exp. = experiment.

explanatory variable (anticipated travel time, defined later, is the dependent variable), with actual experienced travel time on day $t-2$ also being a significant variable statistically for some user groups, though its coefficient was an order of magnitude less than that of $TT_{i,t-1}$ (3). No elements in the time series were significant beyond $t-2$. However, that analysis also revealed a rather thorny empirical problem in the definition of predicted travel time. The use of anticipated travel time $ATT_{i,t} = AAT_{i,t} - DT_{i,t}$ as a proxy suffers from its reliance on two decision variables (AAT and DT) selected by the participant, often without explicit concern that their difference corresponds to travel time. Furthermore, some participants may not have been careful with their specified AAT because they knew that its value would have no bearing on the actual outcome. Therefore, the anticipated travel time cannot always be interpreted, strictly, as a predicted travel time. Nevertheless, it provides useful insight into a process that is probably one of the least understood and least researched in travel behavior.

Unlike the first experiment, providing users with complete information offers greatly expanded opportunities for learning and introduces yet another level of complexity in the process. Because users are exposed to more information on any given day, their ability to retain much of this information beyond the immediately preceding day (which is displayed to them when they select their departure time) is greatly diminished. Essentially, one of two principal quantities, or possibly both, can be expected to play a dominant role in determining $ATT_{i,t}$, namely (*a*) the actual travel time experienced on the previous day ($TT_{i,t-1}$) and (*b*) the supplied travel time, also on day $t-1$, corresponding to the departure time selected on day t. Naturally, if departure times on day t is not changed, the two quantities are identical.

Figure 7 shows the day-to-day evolution of the mean absolute value of the difference between the anticipated travel time ($ATT_{i,t}$) and these two quantities, respectively, for each sector. As expected, the two curves tend to coincide toward the end of the experimental

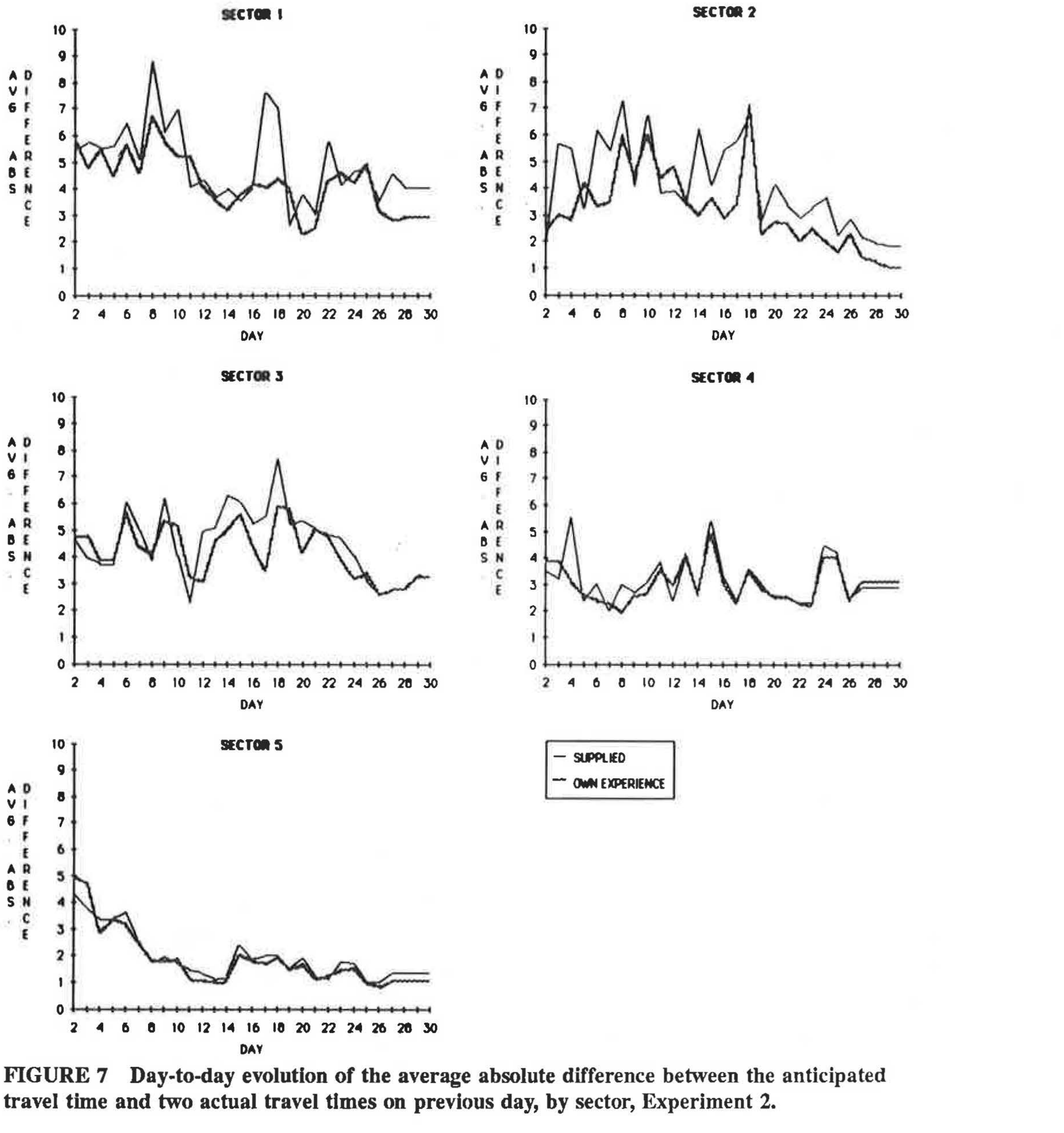

FIGURE 7 Day-to-day evolution of the average absolute difference between the anticipated travel time and two actual travel times on previous day, by sector, Experiment 2.

period, as steady state is approached and fewer people change departure time. This holds over most of the experiment in the closest sectors (4 and 5, as shown in Figure 7). Overall, it appears that the average difference is generally smaller relative to the actual experienced travel time than to the supplied travel time corresponding to the selected departure time, as defined previously. It is also clear that users are not simply taking one or the other quantity as the anticipated value for the current day but are subjecting this information to some level of processing. Furthermore, it can be expected that different strategies will be employed by different trip makers, with varying degrees of reliance on the supplied information. Further exploration of these questions will be pursued in more formal mathematical model development.

Finally, the quality of the users' predictions is examined. Figure 8 shows the evolution of the average (absolute value of the) difference between the anticipated and actual travel times on each given day (i.e., $| TT_{i,t} - ATT_{i,t} |$) for the second experiment. Note that this difference is also identical to $| SD_{i,t} - ASD_{i,t} |$, where $ASD_{i,t}$ is the anticipated schedule delay by user i on day t. In all cases, there is a noticeable decreasing pattern in the first few days of the experiment. A steady increasing pattern then appears in Sector 3 (Figure 5), which indicates that users' predictions were getting worse from one day to the next and thereby explains the intense departure time switching activity exhibited by this sector. Considerable fluctuation is seen in this sector, as well as in Sector 2 (Figure 5), even though the dynamic pattern for the latter differs by the occurrence of unexpected (by the users) peaks (e.g., days 7 and 17) that are followed by periods during which the difference generally decreases at a fairly steady rate. This pattern is also found in Sector 1 but with less extreme peaks. The closer sectors, 4 and 5, exhibit generally less extreme fluctuations, as expected, even though the distinct worsening and turbulence seen in the more distant sectors during the period ranging from day 15 to 18 are also reflected, though to a lesser extent, in these closer sectors.

Comparing the plots of Figure 8 with similar ones for the limited-information experiment, shown elsewhere *(2)*, is quite

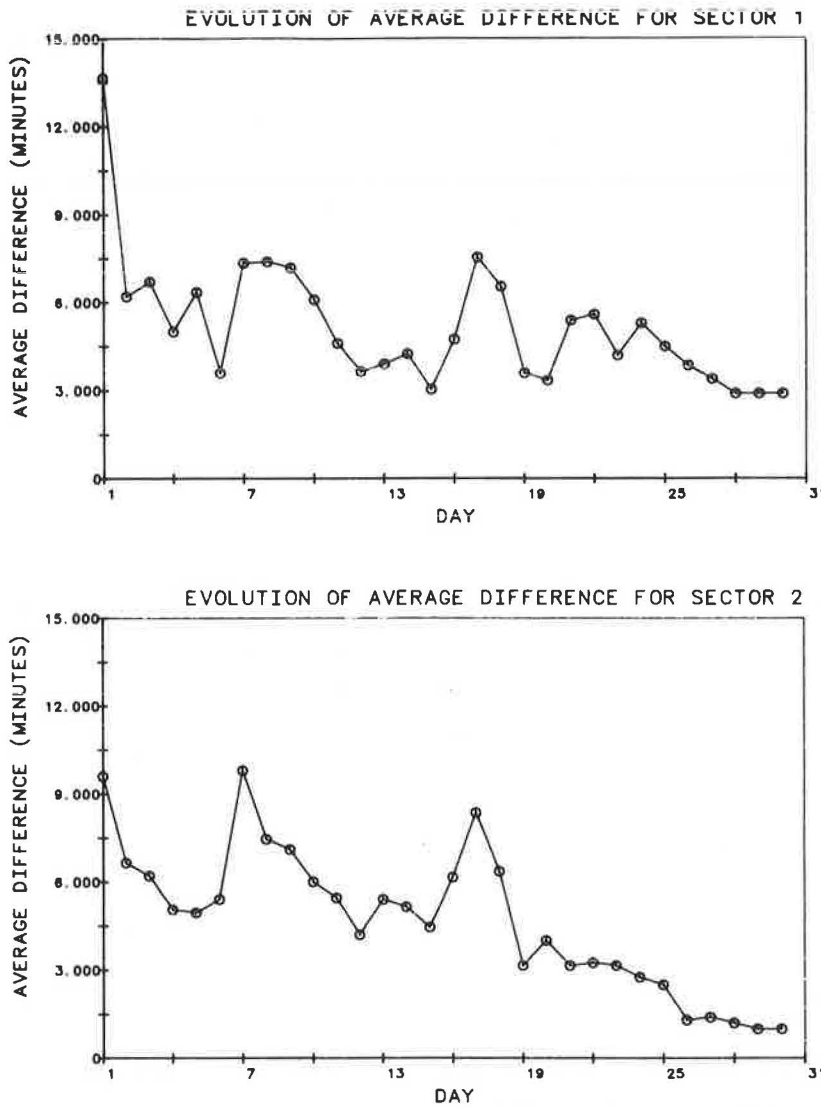

FIGURE 8 Day-by-day evolution of the average absolute difference between actual and anticipated travel time, Experiment 2.

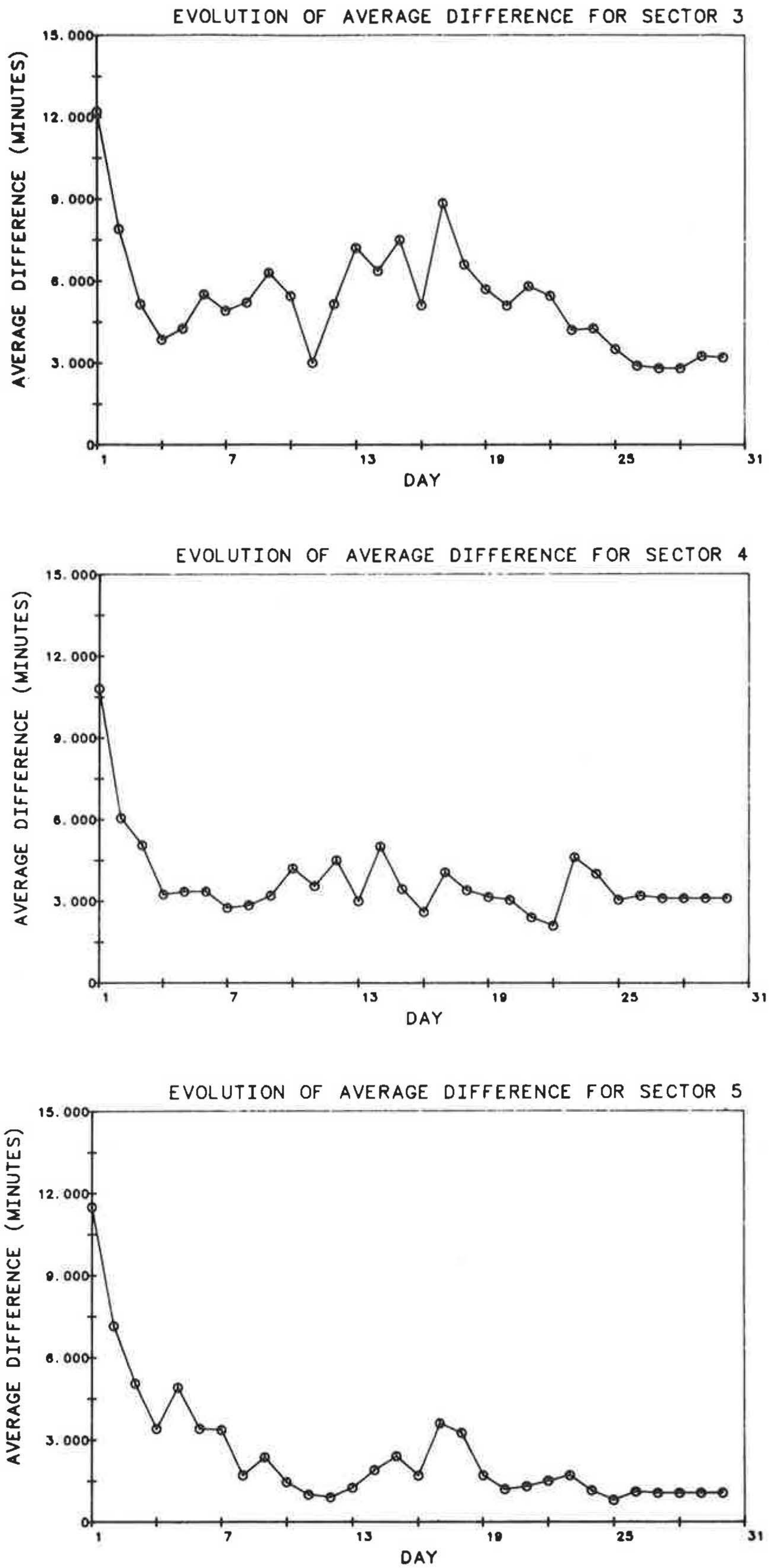

FIGURE 8 ***continued***

revealing and is consistent with the earlier interpretation of the effect of information on user behavior and the resulting performance of the system. In particular, providing users with more information did indeed improve their prediction of the system's performance, which is reflected by the consistently lower average differences observed for virtually all sectors in the second experiment. Furthermore, the dynamic pattern exhibits fewer erratic fluctuations under the complete-information situation. For instance, in the first experiment, a high value was typically followed by a low one, and vice versa, throughout most of the first 3 weeks, especially in the more distant sectors, and no detectable decreasing pattern emerged until the system closely approached steady state. This is not the case in the second experiment, in which clear decreasing patterns could be detected in all sectors over significant portions of the experiment (or, in Sector 3, increasing patterns resulting in user frustration, confusion, and switching). However, as mentioned earlier, the interactions taking place in this dynamic commuting system are quite complex, which results in the predictable jumps. Therefore, although providing users with more information has generally improved their ability to predict the system's performance, it has also raised their expectations, which, coupled with the inherent complexity of the system and the associated unpredictable shocks, has resulted in the increased frequency of switching and longer convergence time relative to the limited-information situation.

CONCLUSIONS

Comparison of the results of two experiments involving real commuters interacting in a simulated traffic system, under two distinct informational situations, has confirmed that the provision of additional information influences user behavior and the resulting overall performance of the system. The results were examined from the perspective of a behavioral framework proposed in previous work, in which users are viewed as boundedly rational seekers of an acceptable departure time, who behave as if they had a dynamically varying indifference band of tolerable schedule delay. Although the present paper is primarily exploratory in nature, important insights into the nature of the effect of availability of information on the dynamics of departure time decisions have been presented. These insights constitute the principal hypotheses that guide subsequent formal model specification, estimation, and testing.

Providing users with complete information on the previous day's performance of the system has apparently raised the aspiration levels of most of these users, as reflected in the slower increase of their indifference band. Although the additional information proved generally helpful in improving their performance prediction capability, the complex interactions in the traffic system preclude complete predictability. The juxtaposition of effects resulted in higher departure time (and anticipated arrival time) switching frequency levels and a longer convergence time to steady state than under limited information. However, the steady state ultimately reached proved superior, in terms of user costs, to the one attained under limited information.

Although quite insightful into important phenomena that have to date benefited from virtually no significant research, due, to a large extent, to the difficulties and the scale of obtaining appropriate observational data, the experimental procedure followed here involves obvious restrictions due to the simulated nature of the commuting corridor. This paper, however, further illustrates its usefulness in exploring the dynamics of user behavior in complex traffic systems and as a tool to support theory and model development that could ultimately be subjected to field verification.

Regarding the comparability of the test situations considered in the two experiments to real-world commuting systems, it can be noted that both are probably extreme. Commuters usually do not routinely have access to nor do they explicitly rely on information that is as comprehensive as that supplied in the second experiment. On the other hand, users might have access to more than just their own performance through word-of-mouth or media reports that they only passively receive. Therefore, real-world situations, although naturally exhibiting a certain degree of variation, tend to be somewhere between the two informational situations considered in the experiments. This aspect would undoubtedly benefit from further probing, as fine tuning generally follows extreme cases intended to provide useful bounds on the range of system behavior that can be expected. The results of these experiments also suggest potentially promising avenues for the control of commuting systems, as they begin to illustrate the potential role of information in improving overall system performance (reflected here through lower user costs at steady state). On the other hand, the evolution toward this improved state may be turbulent, as suggested by the longer convergence periods observed in the second experiment. In addition to the costs incurred in the transition, the length of this period could be excessive, and instabilities might prevail, possibly precluding the attainment of steady state. It would be desirable to understand how the convergence process can be controlled through provision of information. Experiments such as those described here provide a good starting point for developing this understanding.

ACKNOWLEDGMENTS

The authors are indebted to Robert Herman for many fruitful discussions on various aspects of the research effort involving the dynamics of user behavior in traffic systems. The authors are also grateful to Gang-Len Chang for his collaboration and tremendous help in conducting this second experiment, as well as his intellectual contribution to the evolving paradigm. Funding for the work presented in this paper and for continuing efforts in this area was provided by a National Science Foundation grant.

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DISCUSSION

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In this and an earlier paper *(1)*, Mahmassani et al. have described two experiments in which the consequences of departure time choices of real commuters are evaluated using a special purpose simulation model. The results of their experiments provide valuable insight into a field of research that, until now, has not been extensively studied. This discussion of their work is intended as an addition to their studies not as a critique.

A central position in their model is given to the notion of an "indifference band" of tolerable schedule delay, where schedule delay is defined as the difference between preferred arrival time and actual arrival time. It is assumed that a user considers a particular departure time acceptable (and, as a consequence, will not change departure time the following day) if the resulting schedule delay is within that user's indifference band. The indifference band is expected to be dependent on each individual's preference, observable characteristics, and related environmental factors. Furthermore, the indifference band can vary dynamically with each commuter's perceived system performance variability. This latter proposition will be discussed later in more detail.

MEASUREMENT OF INDIFFERENCE BAND

The authors partition the indifference band into two components, an early side and a late side *(1)*. The early side of the indifference band is defined as the tolerated arrival times before the preferred arrival time, and the late side as the tolerated arrival times after this preferred arrival time. They propose to build a formal mathematical model to estimate these two components, apparently assuming that these cannot be observed or measured directly. That is true insofar as measurement with a yardstick or stopwatch is concerned; however, there exist psychometric methods to measure such an indifference band. One of these has been used in our own study on preferences for departure times *(2, 3)*. The method can be used to measure arrival times as well. In short, the method is as follows:

1. In addition to being asked for preferred arrival time (which Mahmassani et al. did ask), subjects are requested to estimate the times before and after this preferred arrival time that they consider to be (almost) as acceptable as their preferred time. The period between these two times is considered to constitute the indifference band.

2. Furthermore, subjects are asked to give estimates of the earliest and latest time at which they are willing to arrive.

On the basis of these four estimates a trapezoidal distribution can be fitted (Figure 9) with the additional assumption of either an equal total area for each subject or an equal height at the most preferred times. The choice of restriction would depend on the problem under consideration.

The results of our study support some of the assumptions and findings of Mahmassani et al. For example, the indifference band

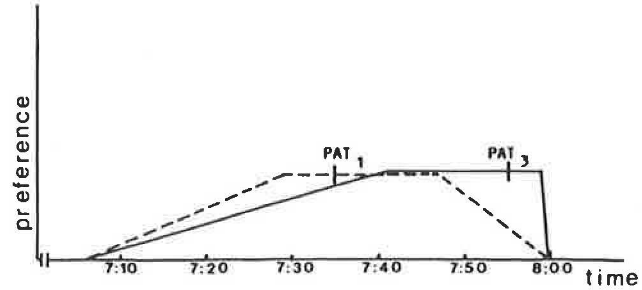

FIGURE 9 Time preference distributions for members of Group 1 and Group 3 (PAT_1 = preferred arrival time of a Group 1 subject and PAT_3 = preferred arrival time of a Group 3 subject).

correlated significantly with age *(5)*, and a significant interaction was found among journey motive, gender of the subject, and direction of the journey (from home or return home). For the journey to work an average was found of 54 min for the total acceptable period and of 18 min for the indifference band. Mahmassani and Chang *(1)* reported that no user experiencing lateness of up to 5 min or earliness of up to 10 min (relative to his respective preferred arrival time) decided to adjust departure time on the following day, which indicates that these deviations fell within the indifference band. The width of the indifference band would, then, be at least 15 min, a value remarkably close to the 18 min found in our study.

Mahmassani et al. divided the commuters in their experiments into three groups, according to their preferred arrival times: Group 1 preferred to arrive between 7:30 a.m. and 7:40 a.m., Group 2 between 7:40 a.m. and 7:50 a.m., and Group 3 between 7:50 a.m. and 8:00 a.m. To illustrate the method two hypothetical arrival time preference distributions are depicted in Figure 9, one for a Group 1 member and the other for a Group 3 member. As the preferred arrival times (*PAT*), the midpoints of Mahmassani's group intervals, are chosen, the widths of the indifference bands and total acceptable periods are set to the average values found in our study. Furthermore, earliest and latest times are assumed to be equal (in the experiment work starting time was stressed to be 8:00 a.m., sharp).

The advantage of this psychometric measurement method is that it takes account of arrival times that are preferred less than those within the indifference band but that are still acceptable to people. Moreover, the method enables the researcher to quantify time preferences as a more continuous variable (namely, as the height of the preference distribution at a specific arrival time) instead of a binary one (as Mahmassani et al. essentially do).

UNDERLYING BEHAVIORAL PROCESSES

As Mahmassani and Tong have already stated, in the experiments at least two behavioral processes take place. First, subjects have to learn the travel times in the particular system, a rather difficult task because travel times will vary as long as steady state is not reached. The second process, according to Mahmassani and Tong, is the revision of the aspiration level (i.e., the indifference band). In our opinion, it is not the indifference band that is revised. The seemingly dynamic nature of the indifference band is a consequence of the definition Mahmassani and Tong use: that the indifference band is the tolerated schedule delay (i.e., the tolerated difference between preferred arrival time and actual arrival time). We would suggest that the second task of the subject is minimizing travel time while maximizing preference for an arrival time (defined as the height of the time preference distribution at that particular time), in essence a two-dimensional task. Individual differences can exist in the weighing of dimensions and the width of the time preference distributions. This two-dimensional decision process can very well result in an accepted arrival time outside the indifference band but within the total acceptable interval, as long as this arrival time occurs together with a preferred travel time. An indication that travel times are important indeed, is the finding reported by Mahmassani and Tong that in the second experiment travel times for most sectors were much lower than in the first experiment. The decision process is further complicated because the travel times are not known by the subject and are, furthermore, varying until steady state is reached. This results in a difficult task not only for the subject but also for the researcher. To get more insight about the decision process it would be interesting to carry out an experiment in which the subjects received bogus feedback on their travel times. In this way the experimenters could manipulate the length of the travel times and schedule delays. The experiment would, admittedly, lose some generalizability; the increased potential for insight, however, could very well compensate for this.

A second, less strong reason for our doubts about a dynamic indifference band is that in our study the test-retest correlations for the indifference band (with half a year between tests) appeared to be reasonable to rather high: .52 for the width of the indifference band and .98 for the two times that form the bounds of the indifference band.

PEAK-HOUR TRAFFIC: A SOCIAL DILEMMA

Peak-hour traffic can be described as a specific type of social dilemma, namely a chicken dilemma *(5)*. In a chicken dilemma, a person can choose one of two strategies: either cooperate (C) or defect (D). Unlike the situation in a prisoner's dilemma game, there is no dominating strategy in the chicken dilemma (i.e., there is no particular behavior that enhances personal gains in all circumstances). A choice for defecting only yields the highest payoff if more than a specific number of other persons choose to cooperate. To illustrate the applicability of the chicken dilemma paradigm, we will use a very simplified version of the problem at hand.

Consider the choice of persons, all living in the same sector, between two specific departure times. If everyone chooses the late departure time, the result will be congestion. If some persons decide to leave early they will benefit (by shorter travel times), and the others will suffer less (by some reduction of the congestion). However, if all persons decide to leave early the result is again congestion. Whether the choice of a particular subject for a specific departure time (early or late) should be considered as cooperative or defective depends on the behavior of the other participants and on the payoff structure. When most subjects prefer to leave late, leaving early cannot be regarded as purely cooperative: the subject leaving early also profits from this choice (by having a shorter travel time). Conversely, if all people leave early, a choice for a late departure time cannot be considered strictly defective: although the person leaving late profits from this choice, other subjects also benefit (by a reduction of congestion). We will, therefore, refer to leaving early as Strategy A and to leaving late as Strategy B. Furthermore, because in the present case the choice of a particular departure time cannot be consistently denoted as cooperative or defective, we must relax one of the assumptions of the chicken dilemma, namely that the payoff given that all persons cooperate is higher than the payoff given that all persons defect.

The payoff structure of this particular chicken dilemma is rather complicated because it is clear that several factors interact. For example, if no one chooses to leave early, the costs could be longer travel times and the chance of being late, but [if leaving early is indeed preferred less, as the findings reported *(1)* suggest] all would benefit by not having to leave early. On the other hand, if all participants choose to leave early, all encounter the costs of leaving early and of longer travel times, but the chance of being late would be much less. An example of such a payoff structure is shown in Figure 10 with the costs of travel time, leaving early, and the chance of being late rather arbitrarily set at a ratio of 3:2:1.

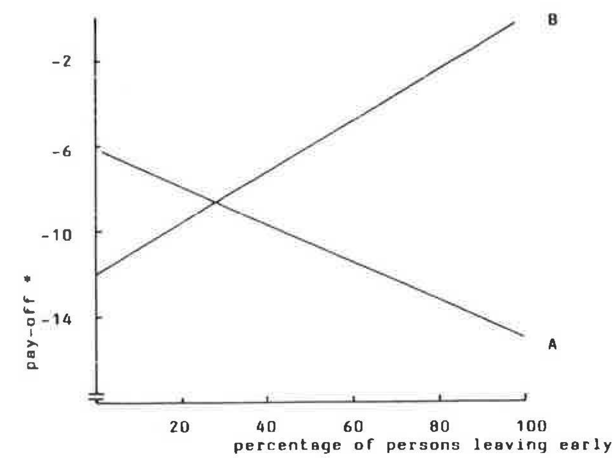

FIGURE 10 Payoff structure of Strategies A and B, expressed in arbitrary units.

If the payoff structure is correctly specified, the point where the lines representing the two strategies intersect would be expected to give the percentage of persons leaving early in steady state.

As was mentioned previously, this is a very simplified version of the problem Mahmassani et al. tackle. In the experiment (as in reality) people could choose between more than two departure times. Existing models for the chicken dilemma should, therefore, be extended to more than two choices.

It might be useful to apply social dilemma models to the analysis of Mahmassani's task. One of the things that become clear is that more insight is needed about the payoff structure: What is perceived as benefit or cost? Are there individual differences in these perceptions, and how are the factors that determine the payoff weighed?

From the social dilemma literature several factors are known to affect choice behavior *(5)*. One factor of particular interest for the present case is the expectation a subject has about other people's behavior. Expectations are important because the question whether

Strategy A or B is advantageous depends, in the chicken dilemma's payoff structure, on other people's choices. Information concerning collective choice behavior may influence participants' expectations of others' choice behavior and, in turn, these expectations may influence their actual behavior. Thus, in terms of the present problem, if people are informed that numerous others are leaving early, the best strategy is to leave late. On the other hand, if people are informed that very few are leaving early, the best strategy is to leave early (see the payoff structure in Figure 10).

In Mahmassani's second experiment, subjects were provided with information about the performance of the system on the previous day, specifically with arrival times corresponding to an array of posible departure times. This information would enable a subject to select the departure time that would result, hypothetically, in the shortest travel time and the most preferred arrival time (i.e., within the indifference band). The results of the second experiment provide some evidence for this point of view: for most sectors travel times were shorter in the second experiment, as were schedule delays for Sectors 1 and 2. It could be argued that the feedback provided to the subjects may also have had some confusing effects. Subjects may have been tempted to choose a departure time associated with the shortest travel time on the previous day, underestimating the effect of other participants using the same strategy. At least in the initial stages of the experiment, this may have resulted in delays. It probably took subjects some time to resist these seemingly advantageous choices, as a result of which a longer convergence time was obtained. One of the possible ways to investigate this process is to examine the relationship between choice of departure time and travel times on the previous day that were presented as information (i.e., not just own travel time on the previous day as Mahmassani et al. analyzed), in combination with preferred arrival time.

Mahmassani et al. express concern over the longer period it took to reach steady state. It could be that information directed at a better assessment of other people's behavior (enabling subjects to have more realistic expectations of other people's behavior) would shorten the convergence period. Supplying information on the number of travelers at particular times (adjusted for distance differences between sectors) could be considered.

We would like to conclude with the observation that Mahmassani et al. have presented a very interesting research method, which is undoubtedly a valuable contribution to this field of study. In our view, further research in this area might benefit from the development of appropriate extensions of the chicken dilemma and from the use of psychometric methods for the assessment of individual departure and arrival time preferences.

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