SMASH (simulation model of activity scheduling heuristics) : some simulations

Citation for published version (APA):

Ettema, D. F., Borgers, A. W. J., & Timmermans, H. J. P. (1996). SMASH (simulation model of activity scheduling heuristics) : some simulations. *Transportation Research Record*, 1551, 88-94.
<https://doi.org/10.3141/1551-12>

DOI:

[10.3141/1551-12](https://doi.org/10.3141/1551-12)

Document status and date:

Published: 01/01/1996

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

www.tue.nl/taverne

Take down policy

If you believe that this document breaches copyright please contact us at:

openaccess@tue.nl

providing details and we will investigate your claim.

SMASH (Simulation Model of Activity Scheduling Heuristics): Some Simulations

DICK ETTEMA, ALOYS BORGERS, AND HARRY TIMMERMANS

Travel decision making is increasingly regarded as a highly complex process in which individuals not only decide about frequency of trips, travel modes, and routes, but also about activity participation and sequencing and timing and duration of activities and trips. This raises the question of whether or not traditional discrete-choice models still provide the best starting point for realistically modeling such a process. Some scholars consider computational process models (CPMs) a promising approach because they allow for heuristic search and suboptimal reasoning processes, which are typical for complex decision making. A model of activity scheduling, SMASH (Simulation Model of Activity Scheduling Heuristics), which incorporates aspects of discrete-choice modeling and CPMs, has been proposed. The model describes the pretrip planning phase, in which individuals decide which activities to perform, at what locations, at what times, in which sequence, and how to travel to the various activity sites. The calibration of this model, using data collected with the interactive computerized procedure MAGIC, has been described in the literature. The results indicated that when scheduling their activities, subjects seem to trade off attributes of activities (time constraints, duration), attributes of the schedule (time spent on activities, overall travel time, realism) and characteristics of the scheduling process (amount of effort already involved in the scheduling process) to obtain feasible schedules. More extensive tests, using simulation experiments, of the model's internal, predictive, and face validity are described. SMASH was used to predict subjects' activity schedules based on their activity agenda and information about their spatio-temporal circumstances. The predicted schedules were then compared with the activity schedules conceived by the subjects themselves under different circumstances, to assess the model's validity. The tests indicated that the model provided satisfactory results with respect to the reproduction of the observed activity schedules. The results of the validity test warrant the use of the model for assessing the effects of various policy measures such as time policies, land use policies, and travel demand management.

During the last 2 years, transportation researchers' conceptualizations of travel behavior have changed considerably. Travel is increasingly regarded as a demand that is derived from activities people pursue (1). Consequently, travel behavior is strongly influenced by the way in which activities are organized in time and space as the outcome of a scheduling process. This new conceptualization also implies that many interdependencies exist between the different activities and trips in the activity pattern. The activity-based approach to travel behavior research is representative of changes in society that have invoked changes in behavior. For example, smaller household sizes and larger combinations of household tasks undertaken by individuals have led to more complex activity and travel patterns. The activity-based approach offers a suitable framework for analyzing these patterns in their full complexity. Moreover, the activity-based approach reflects increased concern for the external effects and social implications of transportation and infrastructure planning. This development raises the question of what type of model offers the best opportunities for assessing policies and predicting future travel behavior.

Since the early 1970s, discrete-choice models have constituted the core of modeling practice in travel-behavior research (2). These models, which typically rely on utility-maximization theory, have been applied to describe and predict a variety of travel-related decisions, such as mode choice, destination choice, route choice, and departure-time choice. Originally, discrete-choice models were developed as econometric models, which are calibrated on the basis of revealed-preference data. However, since the mid 1980s, the theoretical foundations have been developed to apply discrete-choice theory to conjoint measurement methods, as well (3,4). Conjoint-choice or stated-choice models are derived from choices made under hypothetical circumstances. The great advantage of stated-choice models is that choice sets are constructed according to the principles of experimental design, implying that the researcher has control over the covariance structure of the data. Typically, orthogonal designs are constructed to allow the unbiased estimation of the utility parameters. Currently, revealed-preference and stated-choice models are widely applied in transportation planning practice for policy evaluation and traffic forecasting (5,6).

The theoretical justification and capability of predicting complex behavioral responses to policy measures of discrete-choice models have recently been criticized. A serious concern is that discrete-choice theory offers a simplified representation of human decision making (7,8). In particular, the assumption that choices are the outcome of a rational process in which an individual processes all available information has been criticized. Instead, it has been argued that human decision making is based on suboptimal strategies and decision rules that do not take into account all information. Tversky and Kahneman (9) and Payne et al. (10) argue that individuals use a variety of decision rules, including weighted-additive decision rules, elimination by aspects, sufficing rules, and lexicographic rules. The rules differ in the amount of information that is processed, their efficiency in finding acceptable solutions, and the quality of their outcomes. Which specific decision rule is applied depends on the specific context of the choice task. The findings by Tversky and Kahneman and Payne et al. raise the question of whether or not utility-maximization theory provides a good basis for developing models of travel behavior, given a requirement that these models describe the mechanisms underlying actual travel decision making.

Another criticism of discrete-choice models stems from the complexity of travel decision making. Activity-based approaches in travel behavior research, as described, for example, by Jones et al. (11), designate travel decisions as the outcome of an activity-scheduling process, which entails the planning and coordination of activities to be pursued during a 1-day period subject to capability, coupling, and authority constraints (12). Consequently, travel decision making is part of a decision process in which many different decisions are considered, including which activities to perform and locations to visit, what the timing and sequence of activities should be, and how to travel between locations. Therefore, decisions made

for different trips are highly interdependent, being part of the same activity pattern and subject to the same constraints.

Traditionally, discrete-choice models have been applied to describe travel decisions separately, thereby disregarding the interdependency among various travel and activity decisions. Attempts to integrate multiple choices within one modeling framework have resulted in great computational difficulties, which makes application of the models problematic [e.g., Kitamura (13)]. Alternatively, ad hoc assumptions are made concerning the relationships between different decisions, which are modeled separately [e.g., Ben-Akiva and Bowman (14)]. Consequently, there is an increasing interest in new modeling techniques that can at least potentially describe activity scheduling in its full complexity and interdependency by using suboptimal decision strategies that may be more representative of human decision making (15).

Computational process models (CPMs) have been proposed as an alternative approach to modeling complex travel behavior in the context of activity scheduling. CPMs are basically rule-based models, which describe how individuals process and store data to solve complex planning problems. A distinction is made between the long-term memory in which long-term information about the solution space is stored, and the short-term memory (STM), which contains information about the specific solution path. CPMs are particularly suitable for modeling heuristic search procedures, which are typical for human decision making (7). The crucial elements of CPMs are rules of IF <condition> THEN <action>, which process the contents of STM in case the information stored there matches the condition side. Furthermore, a control mechanism is defined to determine which rule is fired in case multiple conditions are met.

CPMs offer more flexibility than discrete-choice models because many alternative decision rules can be represented. Furthermore, the data bases and rules can be defined such that CPM can integrate many interrelated decisions at different levels [e.g., Hayes-Roth and Hayes-Roth (16)]. A serious drawback of the models, however, is that they lack a statistical error theory, which makes it more difficult to generalize their outcomes and apply them to policy evaluation. It can be concluded that both discrete-choice models and CPMs have some attractive properties, but also suffer from limitations that should be noted. Consequently, neither of them can be considered superior in the prediction of travel behavior.

Recently, a model of complex travel decision making, SMASH, which integrates the attractive features of discrete-choice theory and CPM modeling, has been developed (17). Specifically, SMASH models the pretrip activity-scheduling process, in which it is determined which activities will be performed at which locations, and in which sequence. Therefore, the output consists of a sequence of activity/location pairs that automatically implies the trips needed to execute the schedule. The decision process assumed in the model is one of stepwise adaptation and extension of the activity schedule. Each step involves the adaptation of the schedule according to a decision rule that identifies the best adaptation. This process is consistent with the structure of CPM models. However, the decision rule applied at each step is based on utility-maximization theory. That is, the choice of the best adaptation depends on a utility function that contains a stochastic term. This assumption allows derivation of the parameters that describe the trade offs that guide the scheduling process from observed behavior, according to a statistical error theory. By applying principles of both CPM modeling and discrete-choice modeling, a model is obtained that combines the flexibility and comprehensiveness of CPMs with the possibility of calibration according to a statistical error theory. SMASH has been

calibrated based on activity-scheduling data (18) to determine the model parameters. The estimation results suggested that the model structure is realistic and that the variables included in the model significantly contribute to the explanation of the variation in observed scheduling behavior. However, if the model is to be applied for policy evaluation, it should be tested more thoroughly. Additional tests of the model's internal validity and face validity are described. The internal validity of the model was tested by investigating the extent to which the model reproduces the schedules observed in the sample. Furthermore, the effects of different policies were simulated to determine whether the simulation results correspond with common sense and findings described in the literature.

The remainder of this paper is organized as follows: the SMASH model is discussed, some theoretical notions underlying the model are briefly summarized, and the model structure is outlined; the procedure used to reproduce observed schedules and simulate the effect of policies is addressed and attention is paid to the input data and the stochastic procedure underlying the simulations; the internal validity of the model, which was tested by comparing observed and reproduced schedules in the current situation, is addressed; results of a test of the predictive validity that compared simulations under changed circumstances with the schedules conceived by subjects under these circumstances are described; the simulation of the effects of flexible work hours are described and because the predictions could not be compared to observed activity schedules, the results give an indication of the face validity of the model, and some conclusions are drawn on the internal validity of the SMASH model and possibilities for applying the model to policy evaluation.

THEORY AND MODEL STRUCTURE

SMASH is a model of pretrip activity scheduling. It describes the process by which individuals decide which activities to perform, at which locations, in what sequence, and how to travel to the various activity sites. It should be noted that the execution of the schedule may differ from the original plan as a result of unexpected events or information acquired during the execution (14,19). For example, on the basis of information about congestion levels on different routes a traveler may decide to change destinations. SMASH only describes the decision-making process preceding travel, and consequently uses an outlook different from that of models that describe the execution of activity patterns, such as STARCHILD (20,21).

One of the basic assumptions underlying SMASH is that activity scheduling should be considered a sufficing instead of an optimizing process, in the sense that the overall outcome of the process does not necessarily create optimal distance minimization or time allocation. This assumption is consistent with the more general conclusion drawn by Simon (7) that human decision making and problem solving are by nature only rational within limits, as a result of human computational limitations. The amount of information that has to be processed and stored to reach optimal solutions to everyday planning problems such as activity scheduling is simply too much to be handled by the human mind. Typically, heuristic search methods are then applied to find a satisfactory solution in the state space of the problem. Heuristics can be considered rules of thumb and chart the most promising direction for search in the state space. Because heuristics cover only a limited part of the total solution space, they are not guaranteed to find the best possible solution. However, they usually lead to satisfactory solutions with acceptable effort. The concept of heuristic search matches quite well the structure of

CPMs, which are particularly suitable for representing sufficing decision-making strategies.

The use of heuristic search in the context of activity scheduling has been elaborated by Gärling et al. (22). Specifically, the SCHEDULER framework assumes that activity scheduling is a stepwise heuristic search process. As a starting point, it is assumed that an individual selects a set of activities to be performed from the so-called long-term calendar (LTC). This selection is based on the priorities of various activities and a first estimation of how many activities can be performed. Information is also sought about when and where activities can be performed. On the basis of temporal constraints, the activities are first partially sequenced. The sequence is then optimized using a nearest-neighbor heuristic. Next, starting with the first activity, the schedule is mentally executed. This means that a more detailed schedule is formed in which mode choice, activity durations, travel times, and waiting times are determined. In this stage of mental execution the first sequence formed may be altered if conflicts between activities (e.g., overlapping starting and finishing times) occur. Other possibilities are the replacement of an activity with an activity of lower priority or the adding of activities from LTC when open time slots are present in the schedule. Basically, the schedule is worked out in a cyclic process of evaluation and adaptation until it is satisfactory.

SMASH and SCHEDULER similarly regard activity scheduling as a process of stepwise adaptation of the activity schedule. However, in SMASH the process is conceptualized in a more structured way that enables the calibration of the model based on observed behavior using statistical estimation techniques. The input data of the model consists of an agenda containing the 31 predefined activities listed in Table 1. For each activity the information assumed to be available is (a) its possible locations; (b) the number of times per day it can be performed; (c) the available time slots within which it can be performed at each location; (d) how often it is performed; (e) its duration; (f) a measure of its priority; and (g) the last time it was performed. Furthermore, it is assumed that travel times between

each possible activity site are known. On the basis of these data the set of all feasible schedules can be defined. A schedule in this context is defined as a sequence of activities that are performed at specified locations. The feasibility of a schedule requires adherence to the following criteria.

1. The schedule should meet space-time constraints. That is, taking into account activity durations, travel times, and available time slots for activities, it must be possible to perform the activities in the specified sequence;
2. Activities should not be scheduled in unlikely sequences, such as going to a pub before breakfast. To put this criterion into operation all sequences of two activities that were observed in the sample used to calibrate the model (see the following section) are regarded as feasible sequences. If a sequence was not observed, it is considered unrealistic and the schedule is thus rejected; and
3. If a schedule contains an activity that is performed twice or more at the same location, the instances of this activity should not be scheduled without a different intervening activity or trip.

The solution space therefore depends on the contents of the activity agenda, wherein time constraints are defined, and on the spatial setting from which travel times are derived. The activity scheduling process is subsequently depicted as follows: the initial state is defined as that in which no activities are included in the schedule. From the initial state an individual can stepwise adapt the schedule adding activities from the agenda. Any single activity can be inserted at any position in the existing sequence. Furthermore, the location at which an activity takes place is specified. Alternatively, an individual may decide that no more activities should be added and the scheduling process is ended. This implies that the current state contains the final schedule.

The choice to stop the scheduling process or of which activity to add in each step is modeled according to discrete-choice theory. That is, it is assumed that the operation from which an individual

TABLE 1 Activities Used in the Experiment

in-home task	in-home leisure	out-of-home task	shopping	out-of-home personal
<ul style="list-style-type: none"> • study • breakfast • prepare food • lunch • ironing • dishwashing • dinner 	<ul style="list-style-type: none"> • hobbies • reading • watching TV • having visitors 	<ul style="list-style-type: none"> • education • work/voluntary job 	<ul style="list-style-type: none"> • buying groceries • buying clothes/shoes • getting food (snackbar) • specialty shop 	<ul style="list-style-type: none"> • post office/bank • sports • watch sports match • sightseeing trip • visiting someone • club activity • library • museum/exhibition • theater/concert/movies • deliver a parcel • bring/get someone • cafe/bar/restaurant • doctor/dentist • strolling/biking

derives the highest utility is chosen. The utility in this context is a function of characteristics of the schedule resulting from the operation. Furthermore, the utility function contains a stochastic error term. On the basis of the assumptions made about the distribution of the error term, a choice model can be derived to describe the adaptation made at each step. In particular, it is assumed that the process can be modeled as a series of sequential choices in which each choice involves two decisions: whether or not to stop the scheduling process and accept the current state as a satisfactory solution, and (if the schedule is not yet satisfactory) what specific *ADD operation* to apply (i.e., what activity is added, at which location, and at which position in the schedule).

Because it cannot be assumed right away that both choices are of the same order, a nested logit model is used to represent this two-level choice. Specifically, the choice to continue or stop scheduling is modeled on the higher level, and the choice of which option to add is modeled on the lower level. It was assumed that the choice to continue or stop scheduling is affected by characteristics of the current schedule, whereas the choice of an ADD operation is supposedly influenced by the effect the operation has on time expenditures associated with different activities and travel. The model has the following formulation:

$$V_{\text{ADD}} = \alpha_{\text{ADD}} + \theta I$$

$$V_{\text{STOP}} = \beta \text{TIMEUSED}_{\text{STOP}}$$

$$I = \ln \sum_i \exp V_{\text{add},i}$$

$$V_{\text{add},i} = \sum_j (\gamma_j \text{TIMEUSED}_{\text{act},j}) + \lambda \text{TRAVTIME} \quad (1)$$

where

V_{ADD} = utility of adding another activity on the higher level;

V_{STOP} = utility of stopping the scheduling process;

I = inclusive value, representing the expected maximum utility derived from any ADD operation;

θ = parameter representing the proportion of the scales of the disturbance terms on the higher and lower level;

$V_{\text{add},i}$ = utility of a specific ADD operation;

$\text{TIMEUSED}_{\text{act},j}$ = time spent on all activities of type j after adjusting the schedule;

$\text{TIMEUSED}_{\text{STOP}}$ = time spent on all activities of type j according to the current schedule; and

TRAVTIME = total travel time by all modes implied by the schedule.

As was previously noted, SMASH combines principles of CPM modeling with discrete-choice theory. The stepwise adaptation of the schedule, based on the outcome of alternative ADD operations, opens the possibility of integrating a number of interrelated travel and activity decisions, such as destination choice, departure time choice, time expenditures, and trip chaining. At the same time it creates the option of modeling activity scheduling as a suboptimal heuristic search process. The use of a nested logit model to describe each consecutive step makes it possible to derive the parameters of the model based on observed activity-scheduling behavior. The aim of this combined approach is to overcome the shortcomings of both model types.

TEST AND SIMULATION PROCEDURES

To test the internal validity of the model and to simulate the effect of different policies, principally the same procedure is applied. The procedure generates individual activity schedules, based on individual travel and activity environments. This is accomplished by applying a probabilistic simulation procedure, which generates the subsequent scheduling steps. This section describes the probabilistic simulation procedure and the input data that were used to perform the validity test and the simulations.

Monte Carlo Simulations

Individual activity schedules are produced by sequentially applying a two-stage Monte Carlo simulation. That is, based on the current schedule, the next ADD operation is randomly selected subject to the probabilities given by the nested logit model described by Equation 1. First the decision whether or not to go on scheduling was determined by Monte Carlo simulation based on the following probabilities:

$$p_{\text{ADD}} = \frac{\exp(V_{\text{ADD}})}{\exp(V_{\text{ADD}}) + \exp(V_{\text{STOP}})}$$

$$p_{\text{STOP}} = \frac{\exp(V_{\text{STOP}})}{\exp(V_{\text{ADD}}) + \exp(V_{\text{STOP}})}$$

If the outcome of the simulation is to continue, the next move is simulated by a Monte Carlo simulation based on the following probabilities:

$$p_{\text{add},i} = \frac{\exp(V_{\text{add},i})}{\sum_j \exp(V_{\text{add},j})}$$

Starting from scratch, activities are added to the schedule by applying the above procedure until the STOP option is selected. The schedule at that stage is the outcome of the simulation procedure.

Input Data

To produce an individual schedule, SMASH requires two types of input data—an activity agenda and the travel times between all pairs of locations—to determine the set of feasible schedules and calculate the utility functions of the different ADD and STOP options.

An activity agenda consists of the following information for each activity: the time it takes to perform the activity (minimum, average, and maximum time) and the locations at which the activity can be performed. In addition, for each location at which an activity can take place, the name of the location, the hours at which the subject can perform the activity at this location, the attractiveness of the location on a 0–10 scale, and the address of the location are required.

Both types of input data were collected using the interactive computer procedure MAGIC (23). Data was collected for a sample of 145 individuals living in the city of Veldhoven (population 39,949), located in the southeastern part of the Netherlands. Individuals sampled had home addresses distributed equally across different districts. The individuals were also screened for age and gender to obtain a valid representation of the population. MAGIC also recorded the activity schedules conceived by the subjects themselves for the day

TABLE 2 Parameters Used in the Simulation Procedure

variable	description	parameter value	t-value
TRAVTIME	total travel time implied by the schedule	-0.948	-2.824
TIMEUSED _{in-home leisure}	time spent on in-home leisure activities	-1.684	-10.84
TIMEUSED _{in-home task}	time spent on in-home task activities	-2.172	-8.209
TIMEUSED _{out-of-home task}	time spent on out-of-home task activities	0.099	1.349
TIMEUSED _{out-of-home shopping}	time spent on shopping	-3.938	-5.254
TIMEUSED _{out-of-home personal}	time spent on out-of-home personal activities	0.646	3.300
α_{add}		4.300	4.300
TIMEUSED _{stop}	total time spent on activities	0.162	3.386
θ		0.086	0.086

after the interview. These were used to test the internal validity of SMASH by investigating to what extent the model could reproduce the original schedules. In addition to being asked to provide an activity schedule for the day after the interview, subjects were also asked to create a schedule given shopping hours extended until 10:00 p.m. MAGIC recorded all subsequent ADD operations that were applied by the subjects while constructing schedules.

SMASH also requires parameter values to calculate the utilities of specific ADD options. The parameters used in the test and simulation procedures were taken from a model calibration described by Ettema et al. (18). Specifically, to estimate the model parameters the same data as described for the second type above were used. The model given by Equation 1 was estimated based on the observed search path and the data on the activity agenda and travel distances. This results in the parameters displayed in Table 2.

INTERNAL VALIDITY TEST

To test the internal validity of the model the procedure described in the preceding section was applied to reproduce the activity schedules of 33 individuals. These 33 constituted a subset of the sample used to estimate the model, so that input data of the model is available for each individual. Specifically, for each individual five schedules were created. As a first indication of the model predictions, the characteristics of the simulated schedules were compared with those of the schedules conceived by the subjects themselves. Table 3 gives the means of the characteristics aggregated across all individuals and simulation runs. The results indicate that for aggregated data, the model's predictions of the mobility and activity indices of the sample are quite good. In particular, the number of activities and the number of trips are predicted quite accurately. The number of locations visited and the total time spent on travel are in the same order of magnitude as in the original schedules. However, the total time spent on activities is seriously underpredicted. The figures of the time expenditures of separate activity classes suggest that the time spent on in-home task activities, especially, is underpredicted. Nevertheless, the results for the prediction of trip generation and kilometers are encouraging.

To test whether the figures of the original and the predicted schedules differed in a statistically significant way, the means of the characteristics of the simulations run for each individual were calculated. A *T*-test was performed on these figures to investigate whether the

differences between observed and simulated schedules were statistically significant. As the results displayed in Table 3 indicate, a significant difference is observed in the overall time expenditures. However, if separate categories are considered, a significant difference is only observed for in-home task activities. An almost significant difference was found for shopping. For travel characteristics, a significant difference only occurred in the number of locations visited.

The results of the test procedure suggest that the internal validity of the model is sufficient, especially as far as the reproduction of trip making and mobility is concerned.

PREDICTIVE VALIDITY TEST

To test the predictive validity of the model, schedules were simulated given a change in the opening hours of shops. Specifically, the input data of the same 33 subjects was adapted such that the avail-

TABLE 3 Characteristics of Reproduced and Original Schedules

	original schedule	reproduced schedules (average)	T-test (t-value)
total time spent on all activities (minutes)	882.15	656.59	3.17
time spent on in-home leisure	267.73	190.45	1.93
time spent on in-home task	223.52	106.27	2.96
time spent on out-of-home task	266.36	267.45	-1.64
time spent on shopping	25.15	16.68	1.91
time spent on out-of-home personal activities	95.45	66.09	0.78
nr. of activities	11.58	13.16	-1.50
travel time	115.03	89.33	1.44
nr. of locations	3.15	2.47	3.91
nr. of trips	4.79	4.59	-0.10

able time slot for all shopping activities ended at 10:00 p.m. on weekdays and Saturdays. Dutch shops are open until 7:00 p.m. at least on weekdays and until 5:00 p.m. at least on Saturdays. The results were compared to the schedules produced by SMASH in the base situation and with schedules conceived by the 33 subjects under the extended shopping hours scenario.

The results displayed in Table 4 indicate that SMASH modeled the response to the new circumstances correctly for most of the characteristics. SMASH predicted a decrease in the total time spent on activities, whereas in reality this figure increases. However, for separate categories, most changes have the correct sign. Only the change in time spent on out-of-home personal activities has the wrong sign, but the change in this figure is only minor. The decrease in the overall time is primarily due to differences in the magnitudes of the changes. For mobility figures, the changes in travel time and the number of locations visited is predicted correctly. The increase in the number of activities and trips is not predicted correctly, although the overall changes in these figures are relatively small.

FACE VALIDITY TEST

To test the model's face validity, schedules for the 33 subjects were simulated under a scenario representing a change in work hours. To simulate the effects of more flexible work hours, the input data was changed such that the available time slot for work activities started 1 hr earlier and ended 1 hr later. Because no schedules were available to which the simulation results can be compared, the results are used to get an impression of the face validity of the model. The results displayed in Table 5 indicate that as the available time slot for work increases, more time is spent on out-of-home task activities, as could be expected. Apparently, more and longer work episodes are scheduled. Logically, this comes at the cost of a decrease in time spent on other activities, such as in-home task and leisure activities and shopping. However, the time spent on out-of-

home personal activities also increases. This is possibly due to the overlap in the time slots for work and personal activities in this scenario, making possible their easy combination in one trip chain. The total time spent on activities also increases in this scenario. Travel time increases considerably when work hours become more flexible. The same holds for the number of trips made. Given that the average number of locations visited does not change, this might indicate that more remote locations are visited or that the share of single-purpose trips increases.

CONCLUSION AND DISCUSSION

A series of simulation studies is described, the aim of of which was to test both the internal validity and the face validity of predictions of the simulation model SMASH, which combines principles of discrete-choice modeling and CPM models to describe activity scheduling as a heuristic search process.

The internal validity of the model was tested by investigating whether the model could reproduce the original schedules observed for the sample. Furthermore, simulations were carried out to predict the activity schedules of the individuals under different scenarios that reflected extended opening hours of shops and flexible work hours respectively.

The results of the internal validity test suggest that SMASH is capable of reproducing the mobility and activity indices of the sample. In particular, the number of trips made, the number of activities, and the number of locations visited were accurately predicted. Furthermore, the time spent traveling was reasonably well predicted. In addition, time expenditures for various activity classes were predicted well, with the exception of in-home task activities, which was seriously underpredicted. Nevertheless, the internal validity of the model appears to be sufficient in the prediction of travel.

To test the predictive validity of the model, simulations were run under the scenario of an extension of shopping hours. The results were compared with schedules created by subjects under this scenario and

TABLE 4 Original and Simulated Schedules in the Base Situation and Under the Scenario of Extended Shopping Hours

	original schedules		simulated schedules		
	base situation	extended shopping hours	base situation	extended shopping hours	correct response ?
total time spent on all activities (minutes)	882.15	890.33	649.39	627.20	no
time spent on in-home leisure	267.73	265.00	197.73	180.68	yes
time spent on in-home task	223.52	237.76	100.68	110.45	yes
time spent on out-of-home task	266.36	252.12	259.55	244.09	yes
time spent on shopping	25.15	32.42	16.82	21.97	yes
time spent on out-of-home personal	95.45	96.36	63.86	63.18	no
nr. of activities	11.58	11.73	13.15	13.02	no
travel time	115.03	116.26	78.86	81.58	yes
nr. of locations	3.15	3.26	2.50	2.59	yes
nr. of trips	4.79	4.89	4.52	4.47	no

TABLE 5 Simulated Schedules in the Base Situation and Under the Scenario of Flexible Work Hours

	base situation	flexible work hours
total time spent on all activities (minutes)	649.39	664.17
time spent on in-home leisure	197.73	174.09
time spent on in-home task	100.68	96.06
time spent on out-of-home task	259.55	300.91
time spent on shopping	16.82	14.62
time spent on out-of-home personal	63.86	70.91
nr. of activities	13.15	12.94
travel time	78.86	100.95
nr. of locations	2.50	2.50
nr. of trips	4.52	4.83

indicated that the response to the new condition was predicted well for most indices. It can be concluded generally that an extension of shopping hours leads to an increase in the total time spent on activities, in-home task activities, and shopping. The time spent on out-of-home task activities decreases. For mobility measures, an increase in the number of activities performed, total travel time, number of locations visited, and the number of trips is observed.

Simulations under the scenario in which work hours can be chosen more freely suggest an increase in out-of-home task and personal activities and a decrease in the time spent on other activities. The total travel time and the number of trips also increase, although the number of locations visited does not change.

An important conclusion of the simulation studies is that the model is capable of modeling complex behavioral responses and indirect side effects. For example, an extension of shopping hours not only leads to a change in shopping behavior, but also affects the time spent on other activities. Similarly, the propensity to include out-of-home locations of various types in trip chains may change, which has an effect on trip generation and total travel time. In this respect SMASH can be considered an important improvement compared with models that only describe direct responses to policy measures. Therefore, it can be concluded that the simulations described warrant the use of SMASH for policy evaluation.

Finally, it has been demonstrated that combining quantitative discrete-choice models and more qualitative CPM models offers a promising direction for developing models that can predict the effect of policies for larger populations. In particular, side effects and external and social implications of models can be handled very well by models of the type described.

REFERENCES

1. Jones, P., F. Koppelman, and J. P. Orfeuil. Activity Analysis: State-of-the-Art and Future Directions. In *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, (P. Jones, ed.). Avebury, Aldershot, England, 1990, pp. 34–55.
2. Ben-Akiva, M., and S. R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, Mass., 1985.
3. Louviere, J. J., and G. Woodworth. Design and Analysis of Simulated Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, Vol. 20, 1983, pp. 350–367.
4. Louviere, J., and H. Timmermans. A Review of Recent Advances in Decompositional Preference and Choice Models. *TESG*, Vol. 81, 1990, pp. 214–224.
5. Hensher, D. A. Stated Preference Analysis of Travel Choices: The State of Practice. *Transportation*, Vol. 21, 1994, pp. 107–134.
6. Timmermans, H., T. Arentze, A. Borgers, B. Dellaert, D. Ettema, and H. Oppewal. *Modellen voor Keuzeprocessen en Activiteitspatronen: Enkele Recente Ontwikkelingen (Models of Choice Processes and Activity Patterns: Some Recent Developments)*. European Institute of Retailing and Services Studies, Eindhoven, The Netherlands, 1995.
7. Simon, H. A. Invariants of Human Behaviour. *Annual Review of Psychology*, Vol. 41, 1990, pp. 1–19.
8. Gärling, T. Behavioral Assumptions Overlooked in Travel Choice Modeling. Presented at Seventh International Conference on Travel Behaviour, Valle Nevado, Santiago, Chile, 1994.
9. Tversky, A., and D. Kahneman. The Framing of Decisions and the Psychology of Choice. *Science*, Vol. 211, 1981, pp. 453–458.
10. Payne, J. W., J. R. Bettman, E. Coupey, and E. J. Johnson. A Constructive Process View of Decision Making: Multiple Strategies in Judgment and Choice. *Acta Psychologica*, Vol. 80, 1992, pp. 107–141.
11. Jones, P. M., M. C. Dix, M. I. Clarke, and I. G. Hoggie. *Understanding Travel Behavior*. Gower, Aldershot, England, 1983.
12. Hägerstrand, T. What about People in Regional Science? *Papers of the Regional Science Association*, Vol. 23, 1970, pp. 7–21.
13. Kitamura, R. Incorporating Trip Chaining into the Analysis of Destination Choice. *Transportation Research*, Vol. 18B, 1984, pp. 67–81.
14. Ben-Akiva, M., and J. Bowman. An Activity Based Disaggregate Travel Demand Model System with Daily Activity Schedules. Presented at the Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, The Netherlands, 1995.
15. Golledge, R. G., M.-P. Kwan, and T. Gärling. Computational Process Modelling of Travel Decisions. *Papers in Regional Science*, Vol. 73, 1994, pp. 99–117.
16. Hayes-Roth, B., and F. Hayes-Roth. A Cognitive Model of Planning. *Cognitive Science*, Vol. 3, 1979, pp. 275–310.
17. Ettema, D., A. Borgers, and H. Timmermans. Simulation Model of Activity Scheduling Behavior. In *Transportation Research Record 1413*, TRB, National Research Council, Washington, D.C., 1993, pp. 1–11.
18. Ettema, D., A. Borgers, and H. Timmermans. SMASH (Simulation Model of Activity Scheduling Heuristics): Empirical Tests (in preparation).
19. Ettema, D., K. Axhausen, and J. Polak. Activities and Travel Behaviour: Modelling and Data Issues. Presented at ESF/EC Euroconference on European Transport and Communication Networks: Policies on European Networks, Espinho, Portugal, 1995.
20. Recker, W. W., M. G. McNally, and G. S. Root. A Model of Complex Travel Behavior: Part 1: Theoretical Development. *Transportation Research*, Vol. 20A, 1986, pp. 307–318.
21. Recker, W. W., M. G. McNally, and G. S. Root. A Model of Complex Travel Behavior: Part 2: An Operational Model. *Transportation Research*, Vol. 20A, 1986, pp. 319–330.
22. Gärling, T., K. Brännäs, J. Garvill, R. G. Golledge, S. Gopal, E. Holm, and E. Lindberg. Household Activity Scheduling. Presented at Fifth World Conference on Transport Research, Yokohama, Japan, 1989.
23. Ettema, D., A. Borgers, and H. Timmermans. Using Interactive Computer Experiments for Investigating Activity Scheduling Behaviour. *Proc., PTRC 21st Summer Annual Meeting, University of Manchester*, Vol. P366, 1993, pp. 267–282.