Florida Activity Mobility Simulator

Overview and Preliminary Validation Results

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The development of modeling systems for activity-based travel demand ushers in a new era in transportation demand forecasting and planning. A comprehensive multimodal activity-based system for forecasting travel demand was developed for implementation in Florida and resulted in the Florida Activity Mobility Simulator (FAMOS). Two main modules compose the FAMOS microsimulation model system for modeling activity–travel patterns of individuals: the Household Attributes Generation System and the Prism-Constrained Activity–Travel Simulator. FAMOS was developed and estimated with household activity and travel data collected in southeast Florida in 2000. Results of the model development effort are promising and demonstrate the applicability of activity-based model systems in travel demand forecasting. An overview of the model system, a description of its features and capabilities, and preliminary validation results are provided.

Over the past few decades, great strides have been made in understanding the derived nature of travel demand (*1, 2*). Travel demand is derived from the human need to participate in activities that are distributed in time and space. Recently, activity-based models of travel demand have gained attention because of their strong behavioral foundation and intuitive theoretical appeal (*3–7*). Many urban areas and regional agencies around the world are transitioning or contemplating a transition to new activity-based travel demand models (*8*).

In recognition of the growing interest in and importance of emerging activity-based models for travel demand forecasting, the Florida Department of Transportation sponsored a research project called the Phased Implementation of a Multimodal Activity Based Travel Demand Modeling System for Florida. This multiyear research project resulted in the development of a state-of-the-art activity-based model system called the Florida Activity Mobility Simulator (FAMOS).

FAMOS simulates activity–travel patterns at the level of the individual decision maker. Thus, it is a microsimulation model system that is capable of modeling travel demand in a region along a continuous time axis (*9*). The output of FAMOS is essentially a series of activity–travel records for all people in the simulation. These activity–travel records can be aggregated spatially and temporally to obtain zone-level origin–destination (O-D) matrices by trip purpose, mode, and time of day. These O-D matrices may then be fed into any static or dynamic traffic assignment routines for obtaining link volumes by time of day.

There are several different approaches for implementing activity-based concepts in a travel demand modeling context (*3*). One of the key aspects to activity-based modeling of travel demand is to recognize that people pursue their activities and trips within a constrained environment (*10, 11*). People are constrained in time and space with respect to the locations they can visit at any given time. Household, institutional (work and school), modal, financial, and situational constraints limit the activity–travel choices of an individual. The explicit recognition of constraints is necessary to ensure that activity-based models are responsive to socioeconomic, transportation system, and policy changes (*12*). FAMOS has been developed to explicitly account for such constraints and thus provides a robust platform for analyzing the impacts of alternative transportation policies on travel demand (*13*).

This paper describes the basic structure, framework, capabilities, and performance of FAMOS. It does not provide a detailed explanation of the model formulations, specifications, and methods; several references cited in this paper contain the technical details of the model specifications and methods. First, the structure and the data requirements, respectively, are described for FAMOS. Then, the two components of FAMOS are described. Finally, preliminary validation results for FAMOS in the southeast Florida application context and concluding thoughts are provided.

STRUCTURE OF FAMOS

Figure 1 provides a broad schematic of the structure and logic of FAMOS. FAMOS includes two primary components: the Household Attributes Generation System (HAGS) and the Prism-Constrained Activity–Travel Simulator (PCATS).

HAGS is primarily a population synthesizer. Using zonal socioeconomic data and household travel survey data, HAGS generates (synthesizes) households and people within households. In addition to generating household and person attributes, HAGS also generates the agenda of mandatory or fixed activities that must be accomplished by each individual. For example, workers engage in work activities that generally tend to be fixed in time and space. Thus, this step generates a basic skeleton around which the complete activity–travel agenda of a person will be formed. HAGS also includes work and school location choice models to identify the spatial locations of the fixed activities.

PCATS (Figure 2) models activity and travel patterns for each person synthesized by HAGS. The simulator uses the notion of Hägerstrand's time–space prisms to recognize the spatiotemporal

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Transportation Research Record: Journal of the Transportation Research Board, No. 1921, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 123–130.

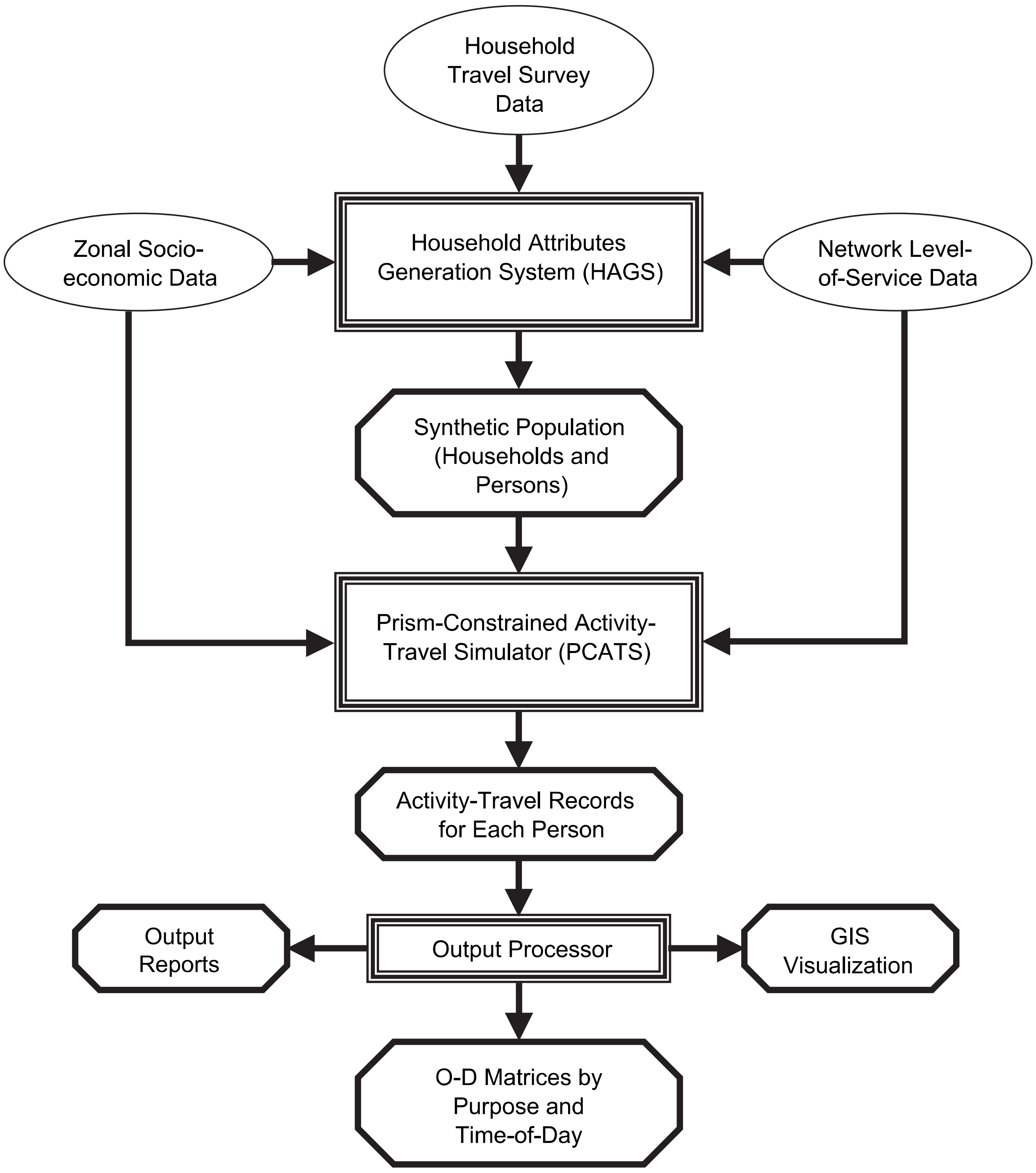

FIGURE 1 Structure and logic of FAMOS (GIS = geographical information system).

constraints under which individuals must undertake their activities and trips. For each individual, PCATS determines the time–space prism constraints and then simulates activity–travel records by using a series of submodels that predict activity type choice, activity duration, and destination and mode choices.

The activity–travel records simulated by PCATS can be fed directly into any dynamic traffic assignment algorithm to simulate traffic flow on a network. The full benefits of an activity-based travel demand model are realized only by interfacing it with a dynamic traffic micro-simulator. However, as travel demand models in practice are still largely based on static traffic assignment routines, FAMOS includes a basic output processor in which activity–travel records simulated by PCATS may be aggregated into user-specified O-D matrices by purpose, mode, and time of day.

FAMOS may be used in conjunction with an existing four-step travel demand model. FAMOS is able to use zonal socioeconomic data and network level-of-service (LOS) data (peak and off-peak modal LOS attributes) associated with a typical four-step model. Similarly, on the output end, the FAMOS is capable of providing O-D matrices by mode, purpose, and time of day that may be fed directly into any static network assignment. Thus, the current version of FAMOS is capable of replacing the trip generation, trip distribution, and mode choice steps of the traditional four-step modeling process. Ongoing efforts include incorporating a dynamic event-based network simulator into FAMOS (*14*).

DATA REQUIREMENTS

FAMOS has been designed to make maximum use of existing four-step travel demand model databases. The basic data requirements for FAMOS include

• Zonal socioeconomic data, which include population, household, and employment (by place of work) data for all TAZs in the model region. Most four-step travel demand models use zonal socioeconomic data for estimating trip productions and attractions. These data sets are adequate for FAMOS.

• Zonal network LOS data, which include the intra- and interzonal network skims that are associated with four-step travel demand models. Most four-step travel demand models are able to generate both free-flow and congested skims for various modal LOS variables. They may include modal cost, travel time, and distance information by time of day.

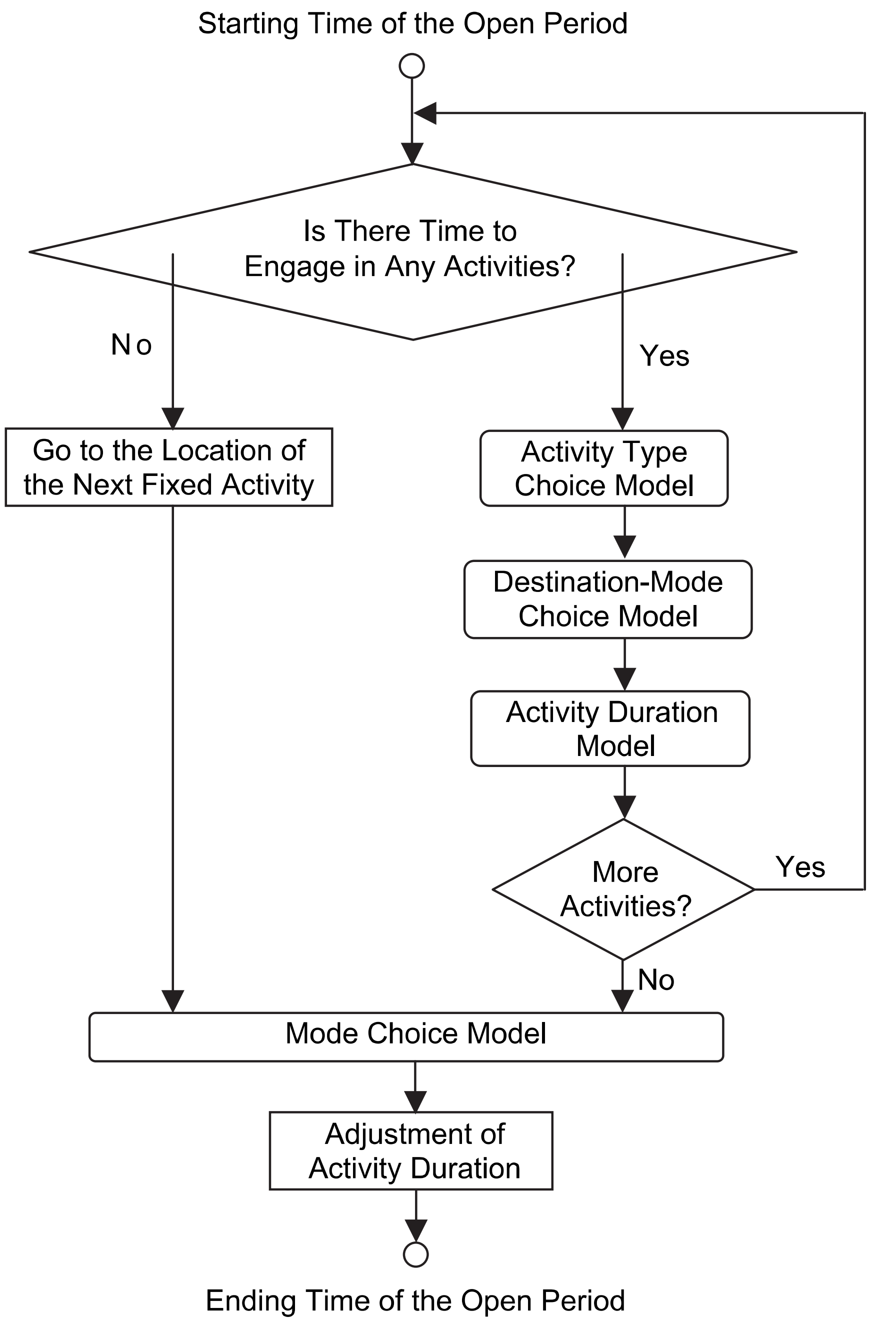

FIGURE 2 Structure of PCATS.

- Household travel survey data, which serve several purposes in an activity-based microsimulation model system. First, it is the basis for all of the model specifications included in the system. Although FAMOS offers a set of default submodels that comprise the activity-based microsimulation system, the user may choose to estimate a new set of models that are applicable to the particular context in which FAMOS will be applied. The household travel survey data allow the estimation of the various submodels that comprise FAMOS. In addition, the household travel survey data set (if sufficiently large and weighted) can provide information about the joint distribution of demographic characteristics in the population. These joint distributions are then used to generate a synthetic population of households and people in HAGS. In addition, any population census database (e.g., the Public Use Microdata Sample database) may be consulted for information about joint distributions of characteristics in the population.

SYSTEM FOR GENERATING HOUSEHOLD ATTRIBUTES

HAGS is a model system developed to generate synthetic households. It populates each geographical zone with synthetic households while observing marginal distributions of pertinent variables in census or zonal data. A typical output from HAGS consists of a simulated population of households, people, and fixed activity schedules. The current version of HAGS consists of two components: the household distributor and the fixed activity generator.

The household distributor component determines the distribution of attributes of households in the respective zones based on data from the census, travel surveys, and other sources. An iterative proportional fitting (IPF) method (*15*) is applied to base-year marginal distributions of pertinent household and person attributes in each zone and their areawide joint distribution to yield a frequency distribution of households by their attributes for each zone. The base-year marginal distributions are obtained from the census and other data, while their areawide joint distribution is obtained from base-year travel survey data. Each zone is then populated by cloning households from the travel survey data according to the distribution obtained for the zone.

As mentioned earlier, FAMOS explicitly recognizes the notion of Hägerstrand's time–space prism constraints in simulating individual activity–travel patterns (*16*). The fixed activity generator component determines the starting vertex of the morning prism, the ending vertex of the evening prism, and the start and end times of fixed activities for each household member generated by the household distributor component. Nonworkers without any fixed activities have only one prism for the entire day, with the starting and ending vertices for this prism determined by the fixed activity generator component. The locations of prism vertices are estimated using the stochastic frontier modeling methodology (*10, 11, 17*). As explanatory variables, these models incorporate attributes of people, households, land use, and commute trips. Because only work (including work-related business) and school activities are considered fixed activities, start and end times of work or school are generated probabilistically for each worker or student on the basis of distributions observed in the base-year travel survey data. Work or school zones are determined for workers or students using multinomial logit models of work or school location choice. These models may be viewed as a version of production-constrained gravity models. Their explanatory variables include land use characteristics, measures of separation between zones, and some of the variables used in the stochastic frontier models. Thus, HAGS provides a means by which synthetic households can be generated and located, people in each synthesized household can be simulated, and work or school locations and schedules can be probabilistically determined.

HAGS is implemented by initially developing a joint distribution of selected population segment variables for each zone. In the current implementation of FAMOS, vehicle ownership and household type are used as the segmentation variables. Using marginal distributions available for these variables at the regional and zonal level, the joint distribution of these segmentation variables is developed with the use of the IPF method. (However, if a joint distribution is already available at the zonal level, then the IPF method does not need to be applied.) The IPF method adopted in HAGS closely follows that proposed by Beckman et al. (*15*). After the joint distribution of the market segmentation variables is ascertained for each zone, the synthetic households and personal attributes can be simulated in a four-step process.

1. Households are drawn from the sample (sample data) with replacements to match the target population by segment for each zone (population data). The residential location of the sample draw is ignored and changed to match the target population at each draw.
2. The person records corresponding to the identical household identification number drawn in Step 1 are extracted from the survey sample data, and the residential location is changed to that of the zone determined in Step 1.
3. For workers or students, the work or school location is determined by using a multinomial logit model of work or school location

choice. Because the number of alternatives is large, the Markov chain Monte Carlo algorithm (*18*) is used to simulate choice sets for each individual with explicit consideration of time–space prism constraints (thus zones that are very far away are not drawn).

4. Start and end times of work or school are preserved from the original sample data to be consistent with the observed distribution of work or school start and end times. However, a small value of ±5 min is randomly added to reported start and end times to avoid round-off problems that might lead to many trips starting at exactly the same instant.

PRISM-CONSTRAINED ACTIVITY–TRAVEL SIMULATOR

PCATS is a system of behavioral models that together simulate individuals' activity and travel in urban space. All model components are statistically estimated and adjusted with the use of household travel survey data. The PCATS within FAMOS is based on the 2000 Southeast Florida Household Travel Survey of the tricounty region of Miami, Broward, and Palm Beach. This traditional travel diary survey resulted in a respondent sample of approximately 33,000 trips made by 9,500 people in 5,000 households.

Although PCATS submodels ideally would be developed specific to a geographic area with the use of locally available survey data, it may be possible to use the PCATS default activity-based submodels as a starting point when implementing FAMOS in a different area. In general, activity characteristics show lower variance across geographic areas, indicating a greater possibility of transferability of activity-based models between areas (*19*). Activity-based models are considered to be more behavioral in nature and therefore fundamentally more transferable than traditional trip-based four-step models.

PCATS simulates the behaviors of sample households in time and space over a 1-day period. Results of the simulation may be visualized as a set of trip records for each household member, with information about trip purpose, start and end times, origin and destination zones, and travel mode. These data are accompanied by information about person and household attributes that are typically contained in travel survey data.

Sample households may contain synthetic households, generated from census data and travel survey results and distributed over the study area to represent its current or future population. The number of sample households can be adjusted to achieve the desired levels of precision and spatiotemporal resolution in the simulation results. In general, more precise results can be obtained by increasing the number of sample households by generating additional synthetic households. At this time, FAMOS simulates the entire population and thus provides a high level of spatiotemporal resolution and accuracy. However, recognizing that full population simulation is computationally intensive and time consuming, FAMOS incorporates the ability to undertake sample-based simulation in which the user can specify the sampling fraction desired for the simulation run and then weight and expand the results to obtain regional travel estimates. The computational efficiency associated with sample-based simulation is gained at the expense of accuracy and precision.

The development of PCATS was motivated by the recognition that various constraints imposed on individuals' activity and travel are not well represented in conventional models of travel behavior (*11*). Therefore, PCATS emphasizes the constraints imposed on the individual's movement in geographical space over time. Because the speed of travel is finite whereas the time available for travel and activity is limited, the individual's trajectory in time and space is necessarily confined within Hägerstrand's prism (*16*).

Before simulating activity–travel behavior, PCATS identifies the set of prisms that govern an individual's behavior, then generates activities and trips within each prism while observing constraints involving private travel modes and operating hours of public transit. Prisms are defined over a system of traffic analysis zones (TAZs) that comprise the area. PCATS first determines for each individual the periods in which the individual is committed to engage in a certain activity or bundle of activities at a predetermined location; these periods are called "blocked periods" (e.g., a worker's hours at work may constitute blocked periods).

The complement of a set of blocked periods for each individual is a set of open periods (e.g., a worker's lunch break is an open period). A Hägerstrand's prism is established for each open period available to an individual by the following procedure. Given the mode of travel being used, determined for each zone is whether the zone can be visited within the open period and, if so, the amount of time that can be spent in the zone before starting to move toward the next committed activity. This determination is repeated for all zones to identify the earliest possible arrival time at and the latest possible departure time from each zone. These arrival times and departure times comprise a prism for the open period.

Blocked periods for workers are typically determined by work schedules (e.g., between 8:00 a.m. and noon and between 1:00 p.m. and 5:00 p.m.). Then, a worker's day may be assumed to include three prisms: one before work, one during the lunch break, and one after work. The start time of the first prism before work and the end point of the last prism after work are not well defined. In FAMOS, stochastic frontier models were developed to estimate such unobserved prism vertices or end points.

The gradient of the lines or edges defining the prism represents the speed of travel. Thus, the time–space prism based approach to activity–travel pattern simulation offers a powerful framework for modeling the impact of system changes on activity–travel patterns. If congestion were to increase, speeds would drop and the prisms would shrink. Conversely, if added capacity improved travel speeds, then constraints would loosen and prisms would grow. The prism-based framework can be used to address the issue of induced or suppressed travel and model impacts of travel demand management strategies on activity–travel patterns.

Another set of constraints incorporated into PCATS concerns the availability of travel modes. As noted earlier, the availability of public transit is determined by its operating hours. Outside the operating hours, public transit is eliminated from the choice set of the destination–mode choice models. PCATS also tracks the location of private travel modes such as the automobile and bicycle. For example, if a private automobile is not located at the origin of a trip, then it will be eliminated from the choice set of the destination–mode choice models.

Generation of Activities

In PCATS, the probability that a particular daily activity–travel pattern will be made is decomposed into a series of conditional probabilities, each associated with one activity bundle and the trip to reach the location where it is pursued. The conditional probability of an activity bundle is further decomposed to yield three sets of model components: activity type choice models, destination and mode choice models, and activity duration models. These models are applied repeatedly to simulate activities and trips undertaken within each open period while explicitly recognizing the history dependency in daily activity–travel patterns.

The PCATS models are estimated separately for different market segments to recognize the inherent differences among market groups such as workers, students, and others. For each market segment, separate sets of models are estimated for different trip purposes such as work, shopping, social recreation, personal business, and other nonwork.

Activity Type Choice Models

The activity type choice models are two-tier nested logit models (*20*). The top tier includes two categories of activity bundles: in-home activities and out-of-home activities (e.g., social, recreational, or shopping). They are defined by the trip purposes in the travel diary data used for model specification and estimation.

The type of the first activity bundle in an open period is determined with the use of an activity type choice model. In the models, the probability that a given activity type will be selected decreases as the time available in the prism shortens relative to the distribution of activity durations for that type of activity. In other words, the models reflect the fact that activities tend not to be pursued if there is not enough time for them. The time of day is another important factor that affects the choice of activity type. The explanatory variables used in the activity type choice models include age, sex, household auto ownership, household size, and time of day.

Given the activity type, a destination–mode pair is next determined by using a destination and mode choice model. Following this, the duration of the activity at the destination is determined. At this point, the time of day when and the location where the next activity ends can be determined. The activity type choice model is applied again to simulate activity engagement during the remainder of the open period, using the updated amount of time available. This process is repeated until all available time in the open period is exhausted.

Destination and Mode Choice Models

The destination and mode choice models also are nested logit models. Alternative destinations are the top-level alternatives, and available travel modes are nested under each destination alternative. Any unit of spatial geography may be used to represent location. As noted earlier, the geographical extent of the prism is evaluated for each travel mode, and destination–mode pairs are excluded from the choice set if they do not fall in the prism. The amount of time available at the destination is one of the determinants of the choice probability, along with the attributes of destination zone and trip to the destination by respective travel modes. Travel modes are classified as auto/drive alone, auto/multioccupant vehicle (driver and nondriver), public transit, and walk and bicycle.

Given a travel mode, PCATS evaluates travel time to the destination zone with the use of network skim data that is provided as an input. If the automobile or public transit is used, then a zone-to-zone travel time is obtained from the modal LOS database depending on the time of day (peak or off-peak). Travel times by bicycle or walking are computed from an assumed mean speed of travel (12.0 mph for bicycle and 4.0 mph for walking) and the zone-to-zone distance. The computed travel time is used to determine the starting time of the activity at the destination.

Activity Duration Models

The duration of the activity at the destination is determined next using the activity duration model corresponding to the activity type. The activity duration models in PCATS are hazard-based, split population survival models (*21*) that recognize history dependency in activity engagement (*22*). In these models, the maximum possible activity duration is determined first on the basis of prism size, which is a function of speed of travel, location of the trip origin, location of the current activity, and location of the next fixed activity. Then, an individual is assumed to decide whether to allocate all the time available in the current open period to a single activity or to two or more activities. Binary logit models are developed to represent this binary choice.

If a person chooses a single activity, then the activity duration is the maximum possible activity duration in the current open period. If the person chooses two or more activities, then the duration of the next activity is determined with the use of a hazard-based duration model. A set of hazard-based duration models is deployed in PCATS. A model is developed for each activity type, and the parameters of the distribution (the mean and a shape parameter) are formulated as functions of personal attributes and other explanatory variables. Weibull distributions are used exclusively in the current version of PCATS. Some explanatory variables used in the duration models are person and household attributes, time of day, time availability, and a location type indicator. The distribution as given by the duration model for the activity type is right-truncated (i.e., a probability mass equal to the probability that the activity duration will exceed the maximum available time is placed at the maximum). The resulting mix distribution is used to generate activity durations in the simulation. The two submodels—the binary logit model and hazard-based duration model—are estimated simultaneously for each activity type.

As noted earlier, after all the attributes of an activity bundle are determined, the procedure is repeated for the next activity bundle in the same prism. Activity and travel in each open period is thus simulated by recursively applying these model components while considering the history of past activity engagement. Activity start and end times are determined on the basis of simulated activity durations and travel times (from the modal LOS tables). The procedure is repeated until each open period is filled with activities and associated trips.

Running PCATS and Saving Results

To estimate the PCATS components and simulate an individual's activity–travel pattern in the target area, the following data are required:

- Household person attributes (e.g., age, sex, license, household size, and car ownership), usually obtained from running HAGS;
- Attributes of blocked periods (e.g., start time, end time, and type and location of each fixed activity within each blocked period), usually obtained from running HAGS;
- LOS data by mode for each zone pair in the study area (e.g., travel time, travel cost, and number of transfers), usually available with a four-step travel demand model; and
- Zone characteristics (e.g., area, population, population density, number of employees, and number of commercial establishments), usually associated with current four-step models.

The output from PCATS can be visualized as a set of individual activity–travel records that may be fed directly into a dynamic traffic assignment algorithm. Alternatively, O-D matrices suitable for traditional static traffic assignment in a standard four-step travel model may be obtained by aggregating individual activity–travel records according to selected criteria.

A key feature of FAMOS is its simulation of activity–travel patterns along the continuous time axis. Thus, it offers explicit time-of-day modeling capability that has been missing in traditional trip-based travel demand models. Coupled with a robust activity-based simulation model system that is behavioral in nature, the time-of-day modeling capability makes FAMOS a useful policy analysis tool for addressing such issues as induced demand, trip rescheduling, trip chaining, and changes in destination choice.

SOFTWARE AND VALIDATION RESULTS

FAMOS is a computationally intensive software package and should be run on a high-end personal computer with, at a minimum, a 2-GHz Pentium 4 processor, 512 MB of RAM, and 4 GB of free hard disk space. The software has been applied to and several runs have been made in the southeast Florida application. This region consists of about 3,000 TAZs and has a population of about 3 million. In the current implementation of FAMOS, HAGS generates a synthetic population and fixed activity agenda for the entire region in about 3 h. A full PCATS simulation requires 4 to 8 h to run.

Selected summary validation results are furnished here to illustrate the ability of FAMOS to replicate observed travel behavior data. These results were obtained with no adjustments, special calibration procedures, or adjustment factors from a complete run of FAMOS. They are based on comparisons between travel measures provided by FAMOS and those found in a random validation sample of the Southeast Florida Travel Survey data. Average daily travel characteristics are compared in Table 1, and mode splits for different market segments are compared in Table 2.

With respect to daily trip rates and activity rates, FAMOS predicts samplewide rates quite well, but flexible activity engagement appears to be systematically underestimated. This underestimation may reflect the rather rigid constraints-based algorithm implemented in PCATS; a more heuristic algorithm that allows for exceptions to the constraints may remedy this situation (*23*). The comparison also shows that FAMOS captures the temporal aspects of travel behavior quite well while recognizing the spatiotemporal constraints governing these aspects of behavior. In Table 1, time is represented in continuous clock minutes, with 12:00 midnight being zero and 12:00 midnight at the end of the day being 1,440 min. Thus, 6:00 a.m. would be 360, 6:00 p.m. would be 1,080, and so on.

The data in Table 2 indicate that the model system is a reasonably good match with observed mode split patterns. In a few situations, predictions differ more substantially. FAMOS overpredicts transit use and underpredicts high-occupancy vehicle use for students in flexible activities. Also, the model system overpredicts the use of walk and bicycle modes (Other modes) for the Other market segment in flexible activities but underpredicts the use of Other modes for this market segment in fixed activities. These findings are consistent with expectations given the wide variety of individuals that comprise the Other market segment.

TABLE 1 Comparison of Observed and Predicted Travel Characteristics

Characteristic	Market Segment	Observed	FAMOS
Daily trip rates	Worker	3.9	4.3
	Student	3.0	3.3
	Other	4.2	3.8
Fixed activities	Worker	1.2	1.2
	Student	1.0	1.0
	Other	0	0
Flexible activities	Worker	2.4	2.2
	Student	2.0	1.8
	Other	2.7	2.2
First home departure time (min)	Worker	470	440
	Student	472	496
	Other	627	498
Final home arrival time (min)	Worker	1075	1192
	Student	986	1055
	Other	962	967

TABLE 2 Mode Split Validation Results by Market Segment, by Percentage

		To Fixed Activities		To Flexible Activities	
Market Segment	Mode	Observed	FAMOS	Observed	FAMOS
Workers	SOV	79.3	76.9	63.1	69.1
	HOV driver	12.0	14.0	26.6	19.9
	HOV passenger	5.4	6.5	7.2	7.1
	Transit	1.4	1.1	0.7	1.1
	Other	1.9	1.5	2.4	2.9
Students	SOV	13.6	17.2	18.2	18.4
	HOV driver	6.4	10.0	14.1	11.0
	HOV passenger	54.6	47.0	60.5	57.1
	Transit	17.6	13.7	1.3	8.3
	Other	7.9	12.2	5.9	5.2
Others	SOV	39.1	50.0	42.2	42.0
	HOV driver	26.1	25.3	28.9	31.8
	HOV passenger	28.0	21.1	23.4	16.7
	Transit	1.7	2.6	1.4	1.1
	Other	5.1	1.1	4.1	8.4

Given that no special calibration procedures were used to fit FAMOS output to observed travel survey data, the validation results indicate that comprehensive activity-based models such as FAMOS can replicate observed travel behavior quite well. Additional validation studies and forecast or sensitivity tests within specific market segments, modes, and geographical areas are needed to fully understand the feasibility of applying activity-based model systems.

CONCLUSIONS

This paper describes the structure, framework, and paradigm underlying FAMOS, a comprehensive activity–travel simulator developed for implementation in Florida. The model is composed of two major components: HAGS, which generates synthetic households and people and simulates a fixed activity agenda around which more discretionary activities and trips can be scheduled, and PCATS, which simulates detailed activity–travel records for each person in the simulation.

FAMOS simulates activity–travel patterns along the continuous time axis while accounting for the interdependency among trips as a result of trip chaining. Recent travel surveys have found that trip chaining (linking trips) is common practice among travelers and that trip chains are becoming increasingly complex over time. By accounting for trip chaining and recognizing the interdependency among trips that trip chaining entails, FAMOS can realistically simulate modes, destinations, and trips or activities while recognizing the spatiotemporal and modal constraints that exist in daily activity–travel patterns. The other major benefit of using FAMOS is its inherent time-of-day modeling capability. As activity–travel patterns are simulated along the continuous time axis, FAMOS can provide time of day–based O-D matrices by mode and purpose suitable for time of day–based traffic assignment and policy analysis.

FAMOS has been designed to work with readily available databases. To get started with FAMOS, zonal socioeconomic data (commonly available with all traditional four-step models), zonal-level network LOS data (commonly available with all traditional four-step models), and household travel survey data are needed.

Although FAMOS is quite comprehensive in its treatment of activity–travel patterns, it does not currently model freight and goods travel, taxi travel, external trips, or visitor and tourist travel. Information about these trips should be obtained from a traditional four-step model to augment the output from FAMOS. The current version of FAMOS was estimated and calibrated with the 2000 Southeast Florida Household Travel Survey data set. Initial validation results are very encouraging and demonstrate the feasibility of developing and applying an activity-based microsimulation model system for forecasting regional travel demand.

Ongoing work has focused on further enhancing FAMOS to reflect behavioral relationships among several activity–travel characteristics of individuals. Recent work into unraveling the relationships among activity–travel variables has shed light on how the various submodels should be applied and sequenced when simulating activity–travel patterns (*24–26*). Similarly, FAMOS is being enhanced to account for intrahousehold interactions and to capture task-allocation behavior among household members (*27, 28*). In addition, a Dynamic Event Based Network Simulator (DEBNetS) is being integrated into FAMOS to provide a dynamic assignment capability to the model system (*14*). Such a capability will maximize the benefits that accrue from simulating individual activity–travel records along the continuous time axis.

ACKNOWLEDGMENTS

The authors thank the Florida Department of Transportation for providing much of the funding that resulted in the development of the Florida Activity Mobility Simulator (FAMOS); Ike Ubaka of the Florida Department of Transportation Public Transit Office, who was project manager of the FAMOS development effort; and anonymous reviewers, for helpful comments.

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The authors are responsible for all errors and omissions.

The Moving Activity–Based Approaches to Practice Task Force sponsored publication of this paper.