

Modelling Framework and Implementation of Activity- and Agent-Based Simulation: An Application to the Greater Boston Area

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1 **ABSTRACT**

2 This paper presents a utility-maximizing approach to agent-based modeling with an application to the
3 Greater Boston Area (GBA). It leverages day activity schedules (DAS) to create a framework for
4 representing travel demand in an individual's day. DAS are composed of a sequence of stops that make up
5 home-based tours with activity purposes, intermediate stops, and subtrips. The framework introduced in
6 this paper includes three levels: (1) the Day Pattern Level, which determines if an individual will travel
7 and, if so, what types of primary activities and intermediate stops they will do; (2) the Tour Level, which
8 models the mode, destination, and time-of-day of the different primary activities; and (3) the Intermediate
9 Stop Level, which generates intermediate stops. The models are estimated for the GBA using the 2010
10 Massachusetts Travel Survey (MTS). They are then implemented in SimMobility, the agent-based, activity-
11 based, multimodal simulator. It runs in a microsimulation using a Synthetic Population. Produced results are
12 consistent with the MTS. Compared to similar activity-based approaches, the proposed framework allows
13 for more flexibility in modeling a wide range of activity and travel patterns.

1. INTRODUCTION

Transportation modeling has played a key role in how planners and politicians make decisions for transport networks and cities. With the increase in available data, the complexity of the designed interventions is growing. To complement and inform these decisions, transportation models must develop to reflect the multidimensional scope of the impact of such interventions and the individualized responses to them. Activity-based models, such as the one presented in this paper, model travelers' behaviors as a sequence of trips originating and ending at home, known as a tour. In addition, many agent-based modeling (ABM) approaches leverage personalized daily schedules for each individual to represent their behavior throughout a day. The generated day activity schedules (DAS) are composed of a sequence of activities, classified as primary activities, intermediate stops, and subtrips. In turn, they are used to extract aggregate demand metrics and to simulate travel behavior. By using a variation of the DAS (1) approach—a sequence of discrete choice models following utility maximization—we implement a framework that models different travel patterns and can model impacts of behavioral interventions.

In the applications of activity-based travel demand models, Rasouli and Timmermans (2) identified three different approaches: (1) constraints-based models, (2) utility-maximizing models, and more recently, (3) computational process models. These three approaches mainly differ in the way individual and household activity travel patterns are modeled.

Constraints-based models are the earliest type of activity-based models. They are only designed to check whether any given activity programme is feasible given spatial and temporal constraints rather than to predict travel patterns. The constraints in these models originate from Hägerstrand's (3) formulation of "time geography," which classifies these constraints into three categories: capability constraints, coupling constraints, and authority constraints. Besides not being able to predict activity travel patterns, these models suffer from major limitations, including the unrealistic assumption of isotropic conditions (4), and more importantly, their inability to deal with uncertainty as well as spatial and temporal variability.

On the other hand, utility-maximizing models utilize econometric models—mainly discrete choice models—in order to model household and individual's travel. In the earlier applications of these models, Adler and Ben-Akiva (5) and Recker and McNally (6,7) proposed a multinomial logit (MNL) model to represent an individual's choice of the optimal travel pattern, defined in terms of the tours traveled on a given day and the number of stops made within each tour.

This approach was further developed by Ben-Akiva and Bowman (1,8,9,10,11,12) who proposed the daily activity schedule model. It utilizes nested logit (NL) models to represent different travel choices as a multidimensional choice with shared unobserved elements. The topmost choice within this approach is an activity pattern choice, in which the primary activity, the primary tour type, and the number and purpose of secondary tours are modeled. The number of secondary tours is restricted between zero, one, or two or more tours. Lower levels—which are conditional on the activity pattern choice—include time-of-day choice for the primary tour, mode and destination choice for the primary tour, time-of-day choice for the secondary tours, and mode and destination choice for the secondary tours. This approach also has a coarse representation of tour time-of-day decisions, which is limited to sixteen alternatives representing different combinations of four time periods: AM peak, midday, PM peak, and other. DaySim, the extension to this model implemented in Sacramento, allows for greater variability by estimating tour types and numbers separately (13).

The Prism-Constrained Activity-Travel Simulator (PCATS) (14) is another utility-based model which utilizes Hägerstrand's time-space prisms. It divides the day into blocked periods in which individuals are engaged in fixed activities at specific times and locations. A two-tier nested logit model is used for open periods, whereby individuals first choose between an "in-home activity," an "activity at or near the location of the next fixed activity," and a "general out-of-home activity." Similarly, mode and destination choice models and activity duration models are used to develop the full patterns.

A similar approach is adopted by Bhat, et al. (15) in the Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (CEMDAP), which divides the population into workers and

non-workers. The activity patterns of workers are divided into five periods with regards to work while the patterns for non-workers consists of a sequence of home-based tours. The simulator uses a generation-allocation model to determine activity participation which includes (1) work and school activities, (2) children's travel needs, and (3) independent activities for personal and household needs. Afterwards, a scheduling model is applied to determine the sequencing of the activities produced by the generation-allocation model.

The Comprehensive Utility-based System of Travel Options Modelling (CUSTOM) (16) has recently been developed as an approach that considers time budgets for activity scheduling. In the prototype application, trips purpose, mode, location, and time allocation decisions are made sequentially for workers. After each activity, an individual decides to either go home permanently, go home temporarily, or perform another activity.

A number of activity-based approaches have also been implemented in different regions of North America. Coordinated Travel-Regional Activity Modeling Platform (CT-RAMP) (17), differentiates between non-mandatory and mandatory activities, such as work and education. It determines the frequency of mandatory tours and schedules those, and then uses the remaining time to schedule additional tours. TASHA (18), active in the Greater Toronto-Hamilton Area, generates individual projects for each individual including a start time and duration. It schedules household member's days by adjusting the predetermined start times.

More recently, computational process models have been utilized in developing heuristics that represent activity and travel patterns. Some examples of these applications are SCHEDULER (19), AMOS (20,21), and ALBATROSS (22,23,24). On the other hand, MATSIM (25) draws agents' activity chains conditional on their socio-demographics from the observed distribution in the population. ActivitySim, the open-source agent-based simulator developed by Los Alamos National Laboratory, uses optimization to choose the best schedule at any point based on utilities, priority functions, and location functions (26). Other models assume a planning horizon and scheduled and unscheduled trips to be generated, such as ADAPTS (27). However, most of these models lack behavioral interpretability compared to utility-maximizing models. For a detailed description of these three approaches, we refer the reader to Rasouli and Timmermans (2).

Even though utility-based approaches—particularly the DAS approach—allow for high flexibility in modeling travel patterns, their applications were sometimes restrictive. For example, the approach in Ben-Akiva and Bowman (1) did not account for all possible activity patterns; only a finite set of predefined patterns was considered, such as home-work-home (hwh), home-other-home (hoh), etc. Later applications of the model in DaySim utilize a similar approach to this paper. CEMDAP (15), on the other hand, divides worker's time periods in (1) before work, (2) the to-work commute, (3) during work, (4) from work, and the (5) after work, imposing scheduling behavioral assumptions in how an individual's pattern is built. In addition, these approaches suffered from a tradeoff between the computational complexity of the model and its ability to model a wider range of activity patterns.

The remainder of this paper is structured as follows: Section 2 presents the modeling framework used and explains its different components. An application of this framework to the Greater Boston Area (GBA) and the illustration of how this framework was implemented in the activity-based simulator: SimMobility (28) is presented in Section 3. Section 4 presents the estimated significant variables for key models and model groups and simulation results. Finally, Section 5 presents the limitations and future extensions and concludes the paper.

2. MODEL FRAMEWORK

2.1 Model Overview

The activity-based modeling framework presented was proposed by Siyu (29) for Singapore. The framework leverages utility-maximization to create a complex variety of DAS. It is built with a

1 sequence of discrete choice models, which are functions of different personal characteristics and
2 network parameters.

3 The framework for each individual's day schedule is divided into three sections: (1) the
4 Day Pattern Level, (2) the Tour Level, and (3) the Intermediate Stop Level. Each of these levels is
5 conditional on the ones above and they are modeled as a sequence of discrete choice models, linked
6 via inclusive values.

7 The **Day Pattern Level** determines if the individual will make tours, what activity purposes
8 those tours will have, and what types of intermediate stops those tours may contain. Furthermore,
9 it determines how many tours of each chosen tour purpose an individual will execute.

10 The **Tour Level** is then performed for each chosen tour. It determines the mode, the
11 destination, and the start and end time of each activity. For work tours, a work-based subtour—
12 originating and ending at work during the allocated duration of the work activity—may be
13 modeled. The mode, destination, and time-of-day of those subtours are modeled as well.

14 Finally, the **Intermediate Stop Level** generates stops for trips to and from the primary
15 activity. Each intermediate stop has a purpose, a mode, a destination, and a time-of-day.

16 Inclusive values from lower models are included in higher models to represent the nested
17 nature of the decision-making process, in which higher level decisions are affected by the expected
18 utilities of lower level ones. The general framework presented above is summarized in Figure 1.
19 All models are further discussed and can be estimated using travel diaries with individual and
20 household characteristics.

21 The output of the sequence of models is a DAS, which includes a sequence of stops that
22 make up tours. Each tour has a primary activity and every stop has an arrival time, departure time,
23 purpose, and mode taken to it.
24

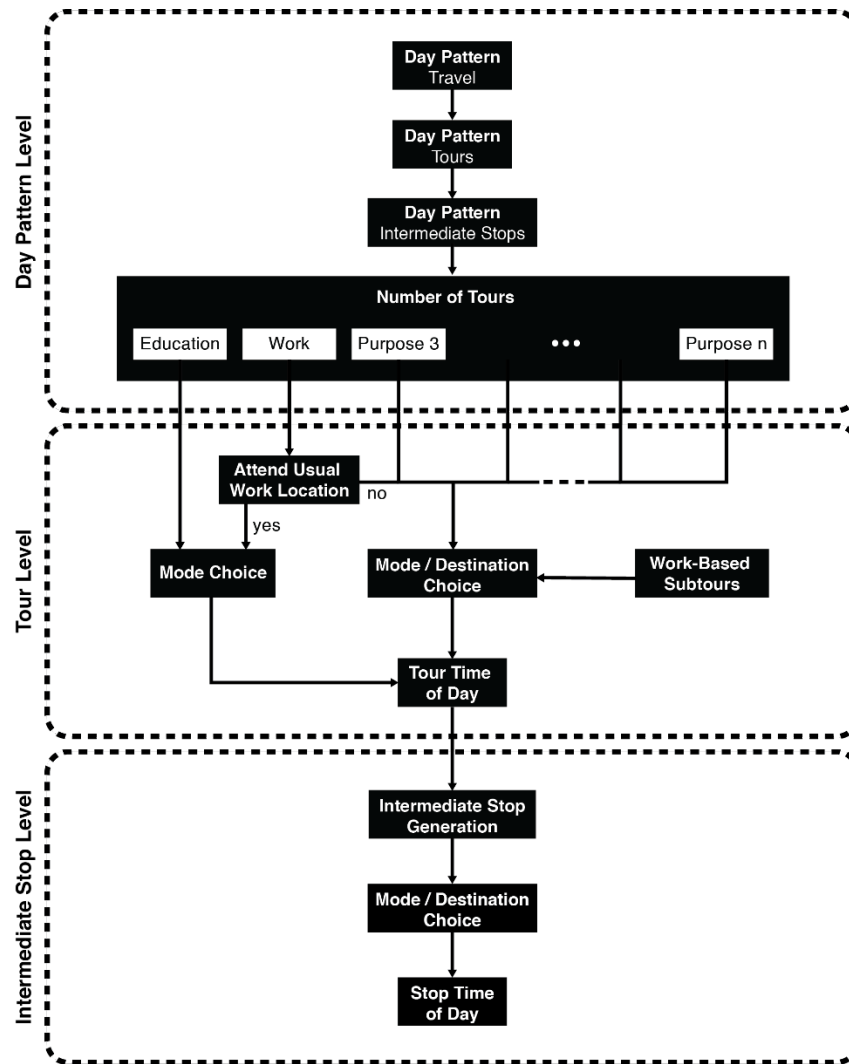


FIGURE 1 Model framework schematic.

2.2 Model Components

This section explains each of the models presented in Figure 1 in detail: their structure, inputs, and outputs.

2.2.1 Day Pattern Level

Day Pattern Travel

The Day Pattern Travel model determines if the individual makes any tours in a given day. The model takes the form of a binary logit (BL), where the choices are either to travel and to stay at home. It takes personal characteristics of the individual and the inclusive value of the Day Pattern Tours model, explained next, as inputs. A decision to travel will lead to Day Pattern Tours model.

Day Pattern Tours

The Day Pattern Tours model determines which activity purpose(s) the individual will pursue as their primary purpose(s) of the tour(s) they make. The model is a MNL where the choice set includes a combination of each the available activity purposes. The limit on the number of activity purposes in the combinations is empirically determined. Each choice's utility includes pattern-specific parameters, such as purpose-specific constants; individual-specific parameters, such as socio-demographics; and inclusive values from the tour-level models of each activity type. Furthermore, the formulation includes purpose-interaction parameters, which capture the added utility of performing two or more purposes in combination. Work tours are only available for individuals who are employed and education tours are only available for individuals who are enrolled in an educational institution.

Day Pattern Stops

Similar to the Day Pattern Tours model, the Day Patten Stops models the choice between the allowed combination of purposes, yet for for stops performed before or after the primary activity of the tour. It includes the same variables as the Day Pattern Tours model, excluding the inclusive values. The availabilities are also determined in the same manner. The output of the Day Pattern Stops model is used to determine the availability of stops in the Intermediate Stop Generation Model, explained in Section 2.2.3.

Number of Tours

Using the output of the Day Pattern Tours model, the Number of Tours is then determined for each of the selected tour purposes. The models are either BL—if the choice is in between one or two tours—or MNL if the choice includes more tours. The number of tours in the choice set for each purpose is determined from the data. Variables in the model include individual characteristics and inclusive values from tour-level models.

2.2.2 Tour Level

Each of the tours, determined after the Number of Tours model, is processed through the Tour Level and then the Intermediate Stop Level.

Usual Work

The Usual Work model is performed for work tours only. It determines whether or not the individual is going to their usual work location. The decision is thus modeled as a BL. The model includes individual characteristics as well as the inclusive value of either the Mode model or the Mode and Destination model for work. If the usual location is chosen, then the Mode is modeled; otherwise, the Mode and Destination model is used.

Tour Mode

The Tour Mode models determine the mode for work tours with a usual location and any other tours which have fixed locations, such as education. The mode choice is modeled as a MNL (or NL) with the choice between the available mode alternatives. This structure allows for the

inclusion of new modes, such as on-demand mobility. The models include individual parameters as well as travel time and cost. Alternative availabilities are determined based on distance thresholds for walking and biking, transit availability between different origin-destination pairs, and household characteristics, such as owning a car or bicycle. The usual location of the tour is determined in the synthetic population, such as a worker's work location or a student's school location.

Tour Mode and Destination

Mode and destination are modeled jointly for any tour that has a non-fixed destination. The final choice set includes all combinations of modes and destinations. Destinations are usually the traffic analysis zones (TAZ) in the modeled region. The model includes travel times and costs for each mode when relevant. For each possible destination, size variables, such as area, employment, population, and central business district (CBD) dummy, are included. They are incorporated using the aggregate spatial method outlined by Ben-Akiva and Watanatada (30). The model is estimated as a MNL or NL, where the order of nesting is determined empirically.

Tour Time-of-Day

Once the tour destination and mode are chosen, the Tour Time-of-Day models determine the start time and end time of the primary activity. The continuous 24-hour day is discretized into 48 half-hour segments. The full choice set includes all of the possible combinations of start and end times, leading to 1,176 alternatives. The alternative specific constants follow a continuous and cyclical form outlined by Ben-Akiva and Abou-Zeid (31) using a trigonometric utility functional form. Activity duration, travel times, and travel costs are also included. If there is no available time, the tour is removed. The number and duration of the time of day segments can be varied both in the simulation and in the model estimation in order to achieve accurate results. Ben-Akiva and Abou-Zeid, for example, use 35 time intervals consisting of half-hours in peak periods and longer intervals in off-peak periods. For simulation, departure times are randomly generated within the 30-minute interval selected. Logsums from the Tour Time-of-Day model can be included in the Tour Mode and Destination Model to capture the nested structure of the choice.

Work-based Subtour Generation

Subtours may be generated for work tours. The Work-based Subtour Generation is modeled as a quit/no-quit BL. While the individual chooses to not quit, they continue to schedule subtours. Individual characteristics and the tour mode are parameters in the model.

Work-based Subtour Mode and Destination

The Work-based Subtour Mode and Destination is modeled in the same manner as the primary activity Mode and Destination model. The modes, however, are limited based on the hierarchy described by Siyu (29), dictated by the work tour mode. In this hierarchy, an individual can only take the mode of their tour or others more readily available. Therefore, a person may not, for example, take a personal vehicle if they did not drive to work.

Work-based Subtour Time-of-Day

The Work-based Subtour Time-of-Day is modeled in the same manner as the Tour Time-of-Day. However, the availabilities of alternatives are determined by the duration of the primary work activity.

2.2.3 Intermediate Stop Level

In the Intermediate Stop Level, tours are divided into the inbound and outbound parts—before and after arriving at the primary activity respectively—and each of these parts is processed separately.

Intermediate Stop Generation

The Intermediate Stop Generation model is a NL quit/no-quit model, whereby a no-quit choice results in a new intermediate stop. While one of the nests includes only the quit option, the other includes the other activity purposes. Individual characteristics, tour purpose, and remaining time window—determined based on the start or end time of the primary activity, and preceding or successive stops—are included as variables in the model. Availability of stop purposes is determined based on the outputs of the Day Pattern Stops model. Stops are scheduled sequentially.

Intermediate Stop Mode and Destination

The Intermediate Stop Mode and Destination is modeled like the Tour Mode and Destination. For inbound and outbound stops, the travel time and travel cost being considered are those between the planned stop and the one succeeding or preceding it respectively. The mode availability follows the same hierarchy as that described in the Work-based Subtour Mode and Destination model.

Intermediate Stop Time-of-Day

Unlike the tour and subtour activities, intermediate stops are bound by adjacent activity start and end times. Therefore, their choice set is constructed out of the 48 half-hour time periods. The Intermediate Stop Time-of-Day still has the trigonometric functional forms, but are interacted for the different stop purposes. Travel time and travel cost are also included. The model is MNL and alternatives are defined similar to the window for generation.

3. ESTIMATION AND SIMULATION IN THE GREATER BOSTON AREA

The modeling framework defined above is applied to the GBA. The region has a population of 4.5 million individuals within 1.6 million households. Data from the 2010 Massachusetts Travel Survey (MTS) (32) and skim matrices for car and transit travel times and costs, provided by Boston's Central Transportation Planning Staff (CTPS), are used to estimate the models. The MTS includes activity diaries for 33,000 individuals belonging to 15,000 households. The data was collected between June 2010 and November 2011. Individuals were asked to fill out all activities they performed in a designated weekday (24 hours, Monday to Friday) in chronological order, and to provide the activity location, the transport mode used to arrive at this location, the arrival and departure times, and accompanying household or non-household members. The survey also collected individual and household characteristics for participants.

Estimation for the models was done using PythonBiogeme (33). It was performed in two phases. First, all models were estimated using only the processed MTS and CTPS data. Before the second round of estimation, inclusive values from the lower level models were calculated. Models that included these were re-estimated in the second round. This estimation procedure allowed for partial simulation of the topmost levels to determine performance before continuing to lower levels.

3.1 Data Preparation

3.1.1 Tours, Subtours, and Intermediate Stops

MTS trip diaries were processed in order to identify tours, subtours, and intermediate stops. Activities in the MTS are classified into work, education, shopping, personal, recreation, or escort activities. The tour primary activity is determined based on the following hierarchy: (1) work, (2) education, (3) personal activities, (4) shopping, (5) recreation, and (6) escort. For full-time students, education is prioritized over work. If a tour includes two or more highest-priority activities of the same type, the primary activity is the one with the longest duration. All other activities within the tour are classified as intermediate stops. Work-based subtours are defined as trip chains starting and ending at the work location. Work activities before and after subtours are merged and considered as a single activity.

3.1.2 Day Patterns Models

Sixty-four activity patterns can be defined with the possible combinations of the six activity purposes. For example, a possible activity pattern is “work, recreation, and shopping”. After examining the MTS data, it was concluded that most individuals participated in at most four different primary activity purposes in a day, reducing the number of possible activity patterns from 64 to 56. Similarly, 56 activity patterns are identified from the data for intermediate stops, representing the different combinations of activities an individual engages in during the stops. For each individual, the number of tours for each activity type is determined. It was observed from the MTS data that individuals perform at most two tours per activity type per day—except for recreational tours, for which the maximum was three.

3.1.3 Tour Mode and Mode Destination Models

The tour mode is determined based on a hierarchy similar to that defined by Siyu (29): public transit, carpooling, driving alone, on-demand modes, motorcycle, biking and bike-sharing, and walking. Trips and tours with rare modes (e.g. ambulance, boat, airplane, etc.) are excluded. Walking, biking, driving alone, carpooling with two people, carpooling with three or more people, and public transit were empirically chosen as the available travel modes.

In the Mode and Mode and Destination choice models, walk and bike availability are determined based on the maximum walking and biking distances observed in the MTS: 5 miles and 15 miles respectively. Biking is available only for individuals whose households own at least one bike. Driving alone is available only for individuals who have a driver's license and at least one car in their household. Public transit availability is obtained from the CTPS skim matrices. Carpooling is assumed to be available to all individuals.

3.1.4 Time-of-Day Models

In Time-of-Day models, time availabilities are assigned in the order of activity priority. For example, a primary work activity is scheduled first, and all possible arrival and departure times are available for that activity. The second most important primary activity has all the times available, except those that are occupied by the primary work activity, and so on. Time availability for intermediate stops and work-based subtours are defined as specified in the framework (Section 2).

3.2 Simulation Implementation

The models estimated in this project follow the structure designated by Siyu (29) for integration into SimMobility. The software includes a Long-term Level, which deals with vehicle ownership and land-use; a Mid-term Level, which deals with daily travel patterns; and a Short-term Level, which is a microscopic traffic simulator (28).

The Mid-term Level of SimMobility is composed of three components: Pre-day, Within-day, and Supply (34). The Pre-day, which is presented in this paper, provides the initial demand for the simulator. The Supply Simulator contains the road and transit network and the capacities for each mode. It is interacted with the Within-day, which contains models that allow users to change their define their route and change their mode according to real-time network conditions, accounting for mode choice as a function of a set departure time.

Developed in C++, the simulator leverages performance improvements by relying on parallel processing and distributed computing. The lightweight, embeddable scripting language Lua is used to implement the above specifications (35). Implementation in Lua, combined with model framework's treatment of activity purposes, allows for easy addition of new modes and purposes. Furthermore, it makes implementing estimated models for different cities straightforward.

3.4.1 Synthetic Population

As an agent-based simulator, SimMobility requires detailed individual information as an input. Fournier and Christofa (36) describe the process through which the synthetic population is generated. A number of sources are used to produce and validate the synthesis:

1. Decennial data from the U.S. Census Bureau (2010)
2. 5-year American Community Survey (2010)
3. Massachusetts Travel Survey (2010)
4. Public Use Microdata Samples (PUMS; 2011)

While the census data (1 and 2) are aggregated totals, the PUMS and MTS data are disaggregated samples. A variety of methods were also used to generate the Synthetic Population, including different seeding approaches, iterative proportional fitting, integerization, iterative proportional updating, and Monte Carlo sampling. The developed synthetic population includes 1.7 million households with over 4.5 million individuals, which are inputs to SimMobility.

4. ESTIMATION AND SIMULATION RESULTS

4.1 Estimation Results

Twenty-nine models are estimated for the GBA implementation. The significant values for the key models and model groups are discussed in this sub-section. For the Day Pattern Travel model, age, gender, education and employment, and inclusive values were significant. For the Day Pattern Tours and Day Pattern Stops models, in addition to the aforementioned variables, owning a transit pass, having a drivers' license, income, and purpose-interaction terms were also significant. In the majority of the Number of Tours models, the purpose-specific inclusive value of was significant. For the Mode and Mode-Destination models, travel time and costs, as well as zone-specific population, area, and employment tended to be significant. While each Time-of-Day model had a different number of trigonometric components, travel time and cost were significant. Finally, for Intermediate Stop Generation, the remaining time window in the day, combined with how many stops were already performed for that half-tour, was significant. The tour purpose was also significant. For full estimation results, model specifications, and Lua implementation files, please refer to the GitHub repository (37).

4.2 Simulation Results

The value of the ABM approach is twofold: it can be used to get aggregate metrics of the demand and to simulate demand on a network. While the latter is outside of the scope of this paper, the former is presented below. For all figures, simulated results to the MTS are compared.

The simulation was done in two phases. The calculation of the inclusive values for all individuals was done on 20 cores within 21 hours and the simulation of the DAS itself was done on 20 cores in 23 hours. 5,096,606 tours and 10,548,458 stops—including primary activities, sub-tours, and intermediate stops—were simulated for 4,142,068 people, of which 720,924 did not travel. Note that, since SimMobility allows for parallelization and distributed processing, the run-time can be improved significantly by allocating more cores, or by using High Performance Computing (HPC).

Figure 2 (a) shows the split of the tour purposes. The models are overall consistent with the MTS. While work is slightly overestimated, personal, recreation, and escort are slightly underestimated. Education, however, is overestimated by 5%. This can be explained by the underrepresentation of students in the MTS. Of the existing students in the MTS, 90.8% do at least one education tour in a day. Therefore, the Synthetic Population leads to more education tours.

Similarly, Figure 2 (b) shows the comparison between the modal split of the MTS and the simulated DAS. Overall, the framework properly models the tour modes. Driving alone is underestimated by 5% while two-person carpool and three or more-person carpool are both overestimated by only 1%. Public transit was as prevalent in the DAS as in the MTS. 10% of the simulated tours have walking as the primary mode, while only 7% of the tours in the MTS are walking tours. Biking, although selected for 1449 tours, it is underestimated. The differing mode share is a result of the differing purpose share: since each tour purpose has its own mode (or mode and destination) choice model, the produced modal splits are different.

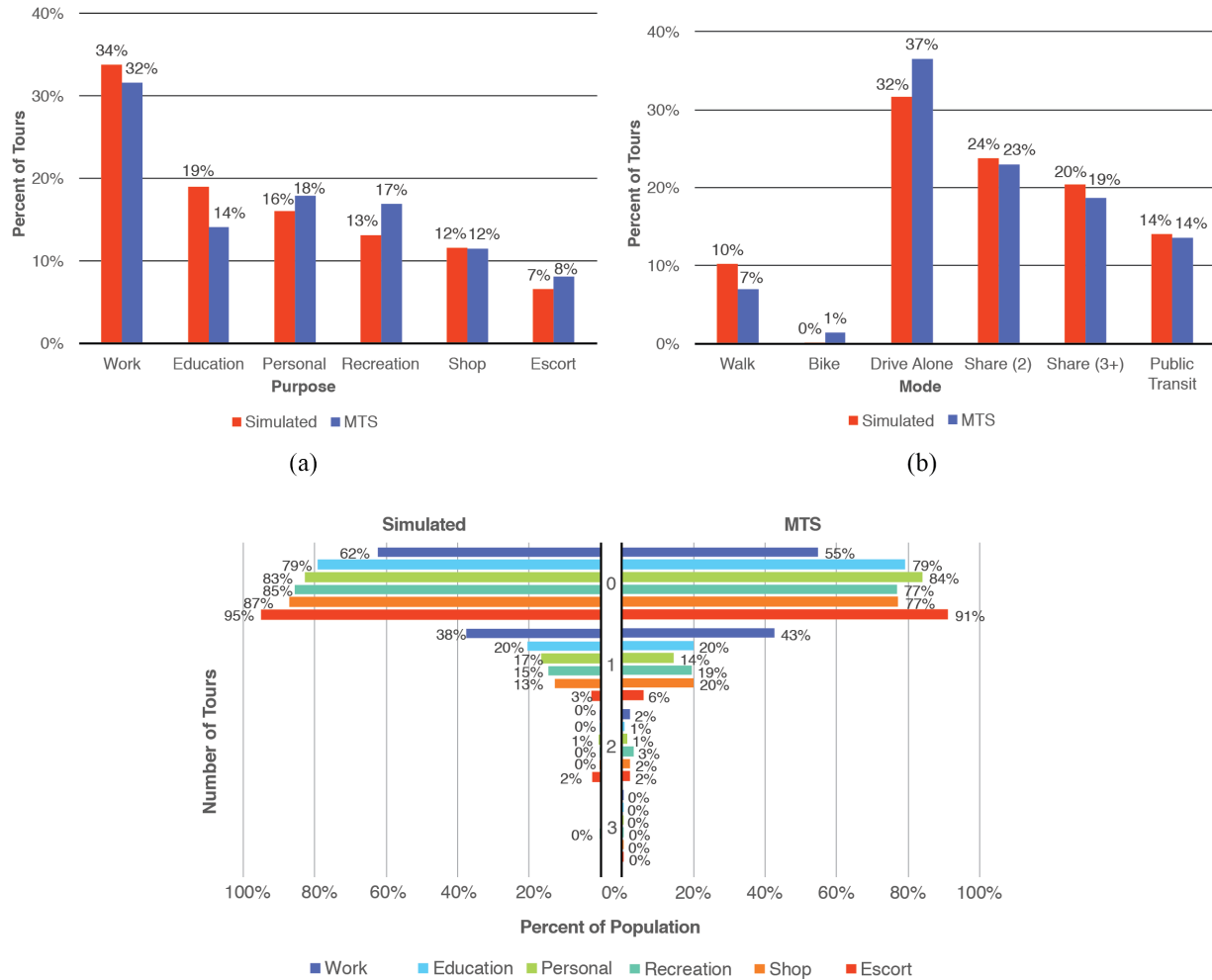


FIGURE 2 Tours by (a) purpose, (b) mode, and (c) number of tours per person per mode.

Figure 2 (c) displays how many trips of a given purpose each individual performs. It shows that the Synthetic Population and models, despite reproducing modal trends well, are slightly underrepresenting work, shop, and recreational tours. More importantly, it shows that traveling is underrepresented. This corresponds to the difference of 1.12 tours per capita in the simulation, versus 1.21 tours per capita observed in the MTS.

Figure 3 shows the times at which people travel to and from their primary activity. The temporal peaks for work and education are clearly visible in both the simulation and the MTS. It has been broken down by activity purpose. As mentioned, education is higher in the simulated results because of the underrepresentation of students in the MTS. It is also noticeable that, as a consequence of the hierarchy of tour purposes for simulation, lower tours are being pushed to later in the day, such as recreation and escort.

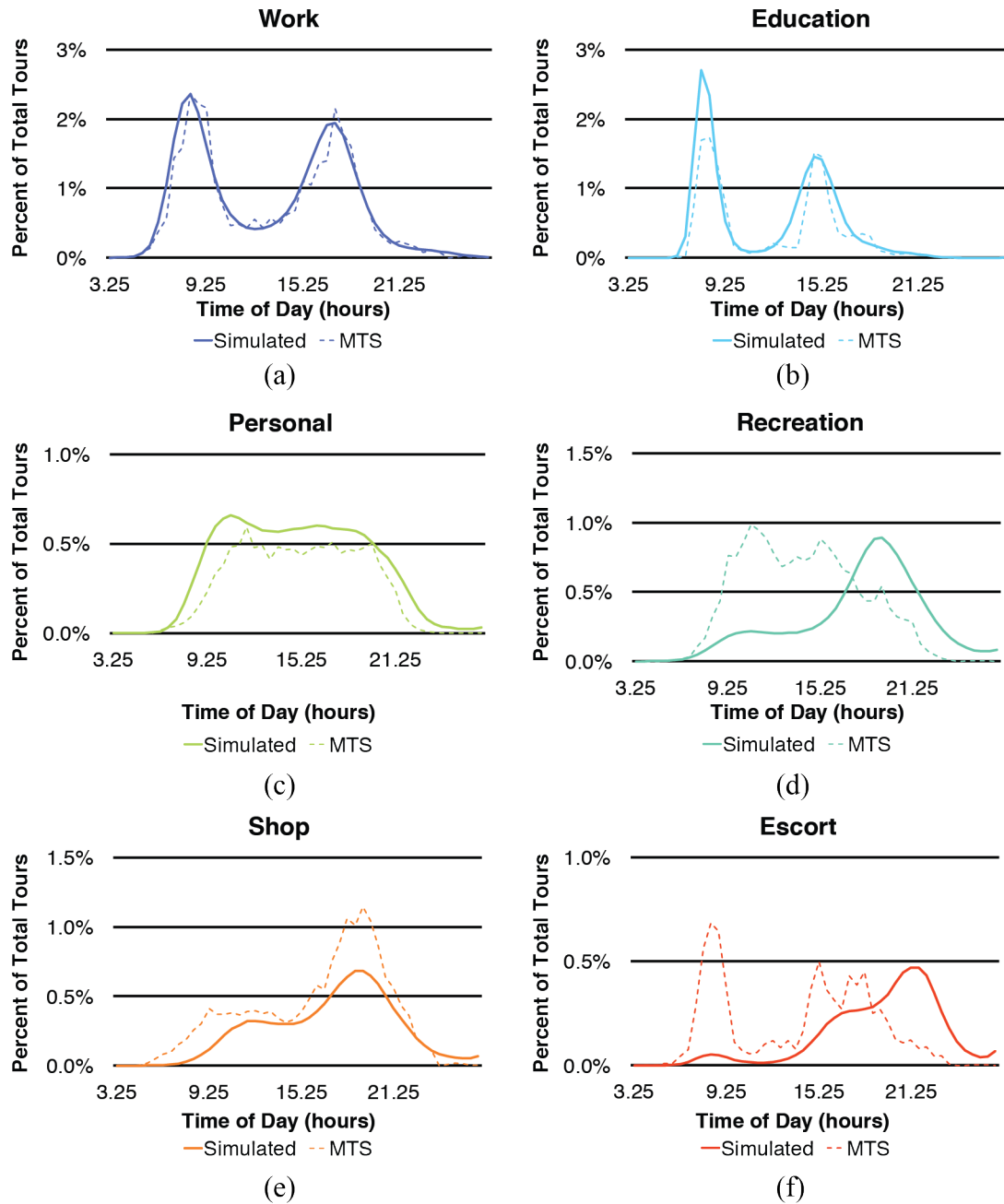


FIGURE 3 Tours by time-of-day for (a) work, (b) education, (c) personal, (d) recreation, (e) shop, and (f) escort.

Finally, Figure 4 shows the special distribution of the tour destinations. As expected, the CBD—located at the center of the figure—has the highest tour density.

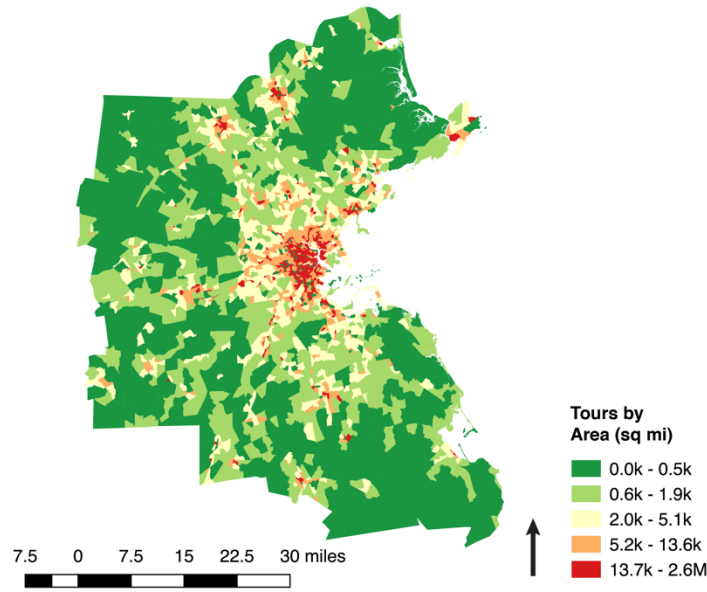


FIGURE 4 Tour destinations per TAZ

Overall, the framework and the Synthetic Population successfully replicate the major trends in travel demand in the GBA.

5. CONCLUSION AND DISCUSSION

This paper presents an application of an updated approach for modeling activity patterns in an activity-based, agent-based simulator. Compared to the existing approaches, this framework allows for more flexibility in representing different day patterns. In line with the DaySim modifications to the Bowman structure, the proposed structure allows for a larger set of combinations of different tour purposes and numbers of tours. By including the interaction terms at the Day Pattern Level in the Day Pattern Tours and Day Pattern Stops models, the model captures the added utility of performing different activities in combination—a behavioral trait often ignored. This is further enforced in the Intermediate Stop Generation model, which takes in the primary purpose as one of the inputs.

Furthermore, the inclusion of the trigonometric functional forms in the Time-of-Day models allows for smoother scheduling of activities. This method was chosen over the use of multiple discrete-continuous models, which would have been combined with the Day Pattern Level as generation models. This Time-of-Day formulation can account for time periods where travel data is not available, and can be modified to model time periods of unequal length. More importantly, the structure captures the cyclical properties of time preferences (31). The current framework allows for the effective implementation of interaction terms between tour purposes to create diversified activity patterns and for the consideration of the time-of-day dependence of the value of an activity duration.

However, there are a number of improvements that can be made to this application. First of all, the data used in this paper were collected in 2010-2011, and thus are relatively old. Vehicle ownership, as well as modal shares in MTS are different from those observed today due to the pervasiveness of on-demand services, such as Uber, Lyft, ZipCar, etc. Additionally, the MTS lacks information on weekend travel and under samples university students, even though they represent a significant fraction of the GBA population.

1 To correct for all of these data limitations, a data collection effort is planned in the GBA.
2 During the data collection, 500 subjects are expected to validate their trips for multiple weeks and
3 fill out the stated preference surveys (SP) using the Future Mobility Sensing (FMS) app-based
4 survey platform (38). Subjects will install FMS and fill out a pre-survey, daily validation surveys,
5 and daily SP surveys for three consecutive weeks.

6 Undergoing research is focusing on calibrating the DAS models using traffic counts. In
7 addition, a Within-day framework is developed in order to represent how agents change their Pre-
8 day DAS as the simulation advances due to network changes, delays, and unforeseen events. This
9 framework currently includes route-choice and mode-choice models, which account for the
10 potentially incorrect behavioral assumption that individuals choose their activity mode and
11 destination before the start and end time. These models are being extended to account for re-
12 scheduling activities and re-planning the rest of the day. Currently, the Within-day framework is
13 also useful to model the effect of real-time information (e.g. travel advisors) and incidents.

14 In this framework, escort activities are modeled separately without accounting for any
15 household interactions. These activities are supposed to capture pick-ups, drop-offs, and trips that
16 are performed to accompany someone. Undergoing research is focusing on modeling social
17 interactions particularly through joint household activities. A household DAS framework to be
18 integrated into the Day Pattern Level is being proposed. The sequential models in this framework
19 represent whether or not the household will have any joint activities during the day, what types of
20 activities, the number of tours associated with each of these activities, which household members
21 are participating in these tours, and whether or not the participating members travel together (e.g.
22 carpooling). The output of the joint household models will then feed into the individual Day Pattern
23 Level models.

24 Overall, the presented and implemented model benefits from its framework and
25 implementation environment. The model allows for complex activity patterns and activity purpose
26 interaction, and takes into account the time-dependence of the value of duration. The simulation
27 software it is implemented in, SimMobility, is streamlined with Lua files, which allow for the
28 facilitated addition of new purposes and modes.
29

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