Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Agent-based microsimulation of travel activity participation, mode choice, and vehicle allocation

Mahmudur Rahman Fatmi[a], Stephen McCarthy[b], Nazmul Arefin Khan[b], Muhammad Ahsanul Habib[b,]*

[a] The University of British Columbia, EME 3231, 1137 Alumni Avenue, Kelowna, BC, V1V 1V7, Canada
[a] Dalhousie University, Room B105, B Building, 1360 Barrington Street, P.O. Box 15000

Abstract

This paper presents the development of an agent-based travel activity simulator within an integrated Transportation Land Use and Energy (iTLE) modeling system. The following components of the simulator are implemented: transit pass ownership, driver's license ownership, activity participation, mode choice, activity organizer, and vehicle allocation. One of the key features of this simulator is the vehicle allocation component, which resolves conflict due to unavailability of vehicles at the time of intended activity. Another important dimension is to accommodate feedback among different decision components. Several advanced econometric models are developed to capture agents' behavior. For example, the mode choice component follows a random-parameters logit modeling technique. The activity simulator is implemented for Halifax considering 2006 as base year and forecasting for 2021. The simulation results are validated for 2006 and 2016. The simulation results for 2021 suggest that solo tours are predicted to increase by 7.92% compared to 2006. Mandatory tours are predicted to have a higher average number of stops compared to non-mandatory tours. A higher proportion of active modes are predicted to be used by urban dwellers. The share of suburban dwellers is higher for the use of auto mode. A higher proportion of larger vehicles are assigned to joint tours of high-income households. The model predicts VKT to be 22.06 km per individual per day. A higher proportion of smaller vehicles are predicted to be used for relatively shorter tours, whereas larger vehicles dominate longer tours.

Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

Keywords: Activity participation; mode choice; vehicle allocation; agent-based microsimulation; feedback mechanism

* Corresponding author. Tel.: +1-902-494-3209
E-mail address: ahsan.habib@dal.ca

Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY

1. Introduction

The development of activity-based models has emerged in travel behavior research since they offer the opportunity to accommodate the complexities embedded in scheduling and executing individuals' travel activities. Although activity-based travel modeling has advanced significantly to accommodate activity generation, scheduling, and mode choice decision processes; fundamental understandings regarding the interactions among household members and different decision processes, as well as validation and forecasting of the models, are limited in the exiting literature. Particularly, the following research questions need further attention: 1) how to address tour-specific vehicle assignment processes by resolving conflicts due to the unavailability of household vehicle at the time of intended activity; 2) how to integrate longer-term and shorter-term decisions and accommodate intra-household interactions within the simulation framework; and 3) how to advance activity-based modeling by implementing the model as a multi-year forecasting tool.

This study aims to address the above-mentioned research questions by developing an agent-based travel activity simulator within an integrated Transportation Land Use and Energy (iTLE) modeling system. This activity simulator implements the following model components: transit pass ownership, driver's license ownership, activity participation, mode choice, activity organizer, and vehicle allocation. This simulator accommodates inter-dependencies among different decisions. For example, intra-household interactions are accommodated and coupling within the shorter-term decision components and with the longer-term decision components are established. The model components are implemented by utilizing several advanced econometric and heuristic modeling methods. For example, the mode choice component follows a random-parameters logit modeling technique, and the vehicle allocation component utilizes a multinomial logit modeling technique. The simulator is implemented in Halifax, Canada, considering 2006 as base year and forecasting for 2021. The simulation results are validated for 2006 and 2016. This paper also presents the forecasting results of travel activity, mode choice, and vehicle assignment patterns for the year 2021.

2. Literature review

Several activity-based travel models have been developed in the past few decades, such as TASHA, CEMDAP, ALBATROSS, ADAPTS, CUSTOMS, and POLARIS, among many others. Some of the key components of the most activity-based travel models are activity generation, activity scheduling, mode choice, and destination choice. Activity model components in the majority of cases are developed by adopting econometric or rule-based or a hybrid of these modeling methods. For example, TASHA is an agent-based travel activity model, which utilizes a hybrid of econometric and rule-based modeling methods (Miller & Roorda, 2003). The model generates and schedules broad types of activities, such as work, school, and shopping, among others. These activity episodes and their corresponding characteristics, such as frequency, start time, and duration, are generated using random draws from the observed probability distribution. Activity scheduling is performed by organizing activities based on temporal order, pre-defined precedence, and conflict resolution heuristics. Finally, mode choice follows a random utility-based discrete choice modeling technique. CEMDAP is another activity-based microsimulation tool that extensively employs econometric models (Pinjari et al., 2008). CEMDAP first generates activities and associated attributes, including activity types, start time, end time, and accompanying travel arrangement. Following activity generation, travel modes, number of tours, number of stops, activity duration, travel time, and location, are determined. To represent individuals' behavior, several econometric models are developed, which can be categorized into the following six classes: binary logit, multinomial logit, hazard-duration, regression, ordered probit, and spatial location choice. ALBATROSS is a rule-based activity-travel simulation model (Arentze & Timmermans, 2004). The simulation process involves activity program generation, activity scheduling, location choice, transport mode choice, and choice of accompanying person, among others. Individuals' travel-activity behavior is simulated following a decision tree method.

ADAPTS simulates activity and travel planning, scheduling, and execution (Auld & Mohammadian, 2009, 2012). One of the key features of ADAPTS is to include the activity planning process. Activity planning accommodates time-dependency of decisions by determining different activity attributes, such as time of day, party composition, destination choice, and mode choice. Activity scheduling is performed by adding activities to the planned schedule and resolving scheduling conflicts. The model utilizes several econometric methods. For instance, the activity planning component follows an ordered probit modeling technique. CUSTOM is one of the new and emerging activity-based models that adopts a random utility maximizing econometric approach to model activity type, time expenditure, and location choice (Nurul Habib, 2018). Choice of time expenditure is assumed to be made by evaluating the time required for a scheduled activity with time savings from other activities. POLARIS is another emerging simulation model, developed with the focus on integrating and implementing several modeling components of different decision processes within a single platform in a computationally efficient manner (Auld et al., 2016). The current version of POLARIS integrates an activity-based travel demand model with a network simulation model. The travel demand component implements the ADAPTS model.

Based on a literature review, the following gaps can be identified. Limitations of existing models address how individuals' travel mode choice is made within the context of households' vehicle availability at different times of day. One of the existing models that attempt to capture such decision dynamics is TASHA. The mode choice component of TASHA explicitly addresses vehicle assignment conflicts among household members, when the number of household vehicles is less than the number of members searching for a vehicle (Miller et al., 2005). Several resolution mechanisms are developed to resolve these conflicts. In addition to resolving such conflicts regarding vehicle availability, vehicle assignment procedures also need to address how individuals choose a certain vehicle type from the household vehicle fleet when multiple vehicles are available. Behavioral models for vehicle assignment process need to be implemented to improve the understanding and forecasting accuracy.

Another important dimension that demands more attention is the interactions among household members' different decision processes. Recently, some advancements have been made in accommodating such decision dynamics, particularly focusing on intra-household interactions. For example, CEMDAP accommodates interactions among household members by determining travel arrangements, such as independent tours, joint tours and children drop-off and pick-up episodes (Pinjari et al., 2008). ALBATROSS addresses intra-household interactions by accommodating joint activities through flexible accompanying arrangements. TASHA accommodates interactions through the vehicle assignment component discussed above. Further effort is required to integrate longer-term decisions with shorter-term decisions; for example, integrating individuals' shorter-term travel activity with longer-term travel tool ownership decisions (i.e. vehicle ownership, transit pass ownership, and driver's license ownership). It is also crucial to accommodate interactions within shorter-term decisions. For example, establishing feedback from a lower-level mode choice decision to a higher-level decision of activity participation.

Finally, validating and forecasting exercises for travel activity models are limited in existing literature. Some studies have verified the accuracy of their models by comparing simulation results with base year information. For example, CEMDAP is implemented for the Dallas-Fort Worth (DFW) area and the simulation results are verified for the base year 2000 (Pinjari et al., 2008). ADAPTS results are verified for the base year 2000 for the Chicago region (Auld & Mohammadian, 2013). ALBATROSS is implemented in the Netherlands for a baseline scenario of 2000 and then tested alternative scenarios from 2020 to 2040 (Timmermans & Arentze, 2011). Very few studies have focused on validating the forecasting capacity of the activity-based models. Among the few, TASHA performs a 24-hour verification for the base year 1996 and a validation of the forecasting results for 2001 (Roorda et al., 2008). However, the majority of these validations are performed using an observed or synthesized population. It is important to validate the simulation results using a forecasted population. Further effort is required to implement travel activity models as multi-year forecasting tools to predict the evolution of travel and vehicle use patterns.

2.1. Contributions of the study

This study focuses on developing an agent-based travel activity simulator. The contributions of this study are three-fold. 1) A vehicle allocation component is introduced within the simulator, which primarily assigns household vehicles to individuals based on the vehicle availability at different times of day. This component also involves the allocation of specific type of vehicles from the household vehicle fleet when multiple vehicles are available. Micro-behavioral models for the vehicle allocation component are developed and implemented. 2) Interactions among household members and their different longer-term and shorter-term decision processes are accommodated. For example, inter-dependencies among decisions are accommodated by introducing coupling among multi-domain choice dimensions, such as coupling longer-term decisions of travel tool ownership with shorter-term decisions of travel activity and coupling lower-level mode choice decision with higher-level activity participation. Moreover, a household tour organizer component is embedded to address household members' interactions in making solo and joint tours. 3) The activity-based travel simulator is implemented within an integrated Transportation Land Use and Energy (iTLE) modeling framework for a multi-year period. The simulation results present how travel tool ownership, activity participation, mode choice, and vehicle assignments evolve over time and space.

3. Conceptual model

This study develops a travel activity simulator within an integrated Transportation Land Use and Energy (iTLE) modeling system. The iTLE is an agent-based microsimulation platform, which considers individuals and households as the agents and micro-spatial unit of parcels as the objects. To generate the input information for simulation, a population synthesis procedure is performed (Fatmi & Habib, 2017). The core of iTLE consists of the following three modules: a longer-term decision simulator (LDS), a shorter-term decision simulator (SDS) and a traffic simulator (TFS). The conceptual framework of the iTLE model is presented in Figure 1. LDS includes the following components: life-stage transition, residential location, and travel tool ownership. The life-stage transition module simulates the following demographic events: aging, death, birth, out-migration, in-migration, household formation, and employment status (Fatmi & Habib, 2018a). Residential location is modelled as a three-stage process of: 1) mobility, 2) location search, and 3) location choice (Fatmi & Habib, 2018a). Travel tool ownership refers to the ownership of a vehicle, a driver's license, and a transit pass. Vehicle ownership is simulated as a process of vehicle transaction and vehicle type choice (Fatmi & Habib, 2018b). Driver's license and transit pass ownership are simulated as binary choice decision.

The SDS module includes the following components: activity participation, mode choice, activity organizer, and vehicle allocation. A brief description of these components is given below:

- *Activity participation* involves individuals' engagements into the following three broad categories of activities: mandatory, maintenance, and discretionary. This module generates activity types and associated activity attributes for each individual by adopting a tour-based approach. Activity attributes include tour time allocation, starting time, number of intermediate stops, and destination location. In the component's micro-behavioral models, activity participation and time allocation are modelled following a random utility-based modeling technique (Khan et al., 2018). Tour attributes are generated following a heuristic modeling approach.
- *Mode choice* is simulated at the tour level considering the following four categories of modes: auto, transit, walk, and bike. The mode choice component is constrained by the availability of a vehicle in the household, where auto is considered in the choice set of those individuals who own at least one household vehicle. The travel tool ownership component simulates this vehicle ownership information. Separate mode choice models are estimated for mandatory and non-mandatory activities. The mode choice model follows a mixed logit modeling method (Khan & Habib, 2018). A feedback mechanism is established by coupling lower-level mode choice decisions with higher-level activity participation decisions through logsum estimates.
- *Household-level activity organizer* operates at the household-level to determine whether a tour is performed solo or joint with another tour. Joint tours refer to traveling with household/non-household members to the activity destination. Solo tours refer to traveling alone to the activity destination. This component is developed following a heuristic modeling method.
- *Vehicle allocation* simulates the assignment of vehicles from the household vehicle fleet to specific tours with auto mode choice. One of the key features of this component is a conflict resolution manager, which resolves conflicts when multiple individuals need the same vehicle at the same time. In addition, in cases when no conflict exists due to the availability of multiple vehicles at the time of intended activity, the vehicle allocation component also deals with the choice of a tour-specific vehicle type from the household vehicle fleet. The micro-models for this component are developed utilizing a Latent segmentation-based random parameter logit (LSRPL) modeling technique. The following five types of vehicles are considered: subcompact, compact, midsize, SUV (Sport Utility Vehicle), and van (including trucks). A total of four LSRPL models are developed for mandatory and non-mandatory tours based on accompanying travel arrangement of solo tour or joint tour (Khan & Habib, 2018). The conflict resolution manager follows a heuristic modeling technique. A feedback mechanism is established with activity participation, activity organizer, and mode choice components for conflict resolution.

The purpose of this coupling is to accommodate rescheduling, re-evaluating for accompanying travel arrangement, or re-assessing mode choice for tours with conflict for vehicle assignments.

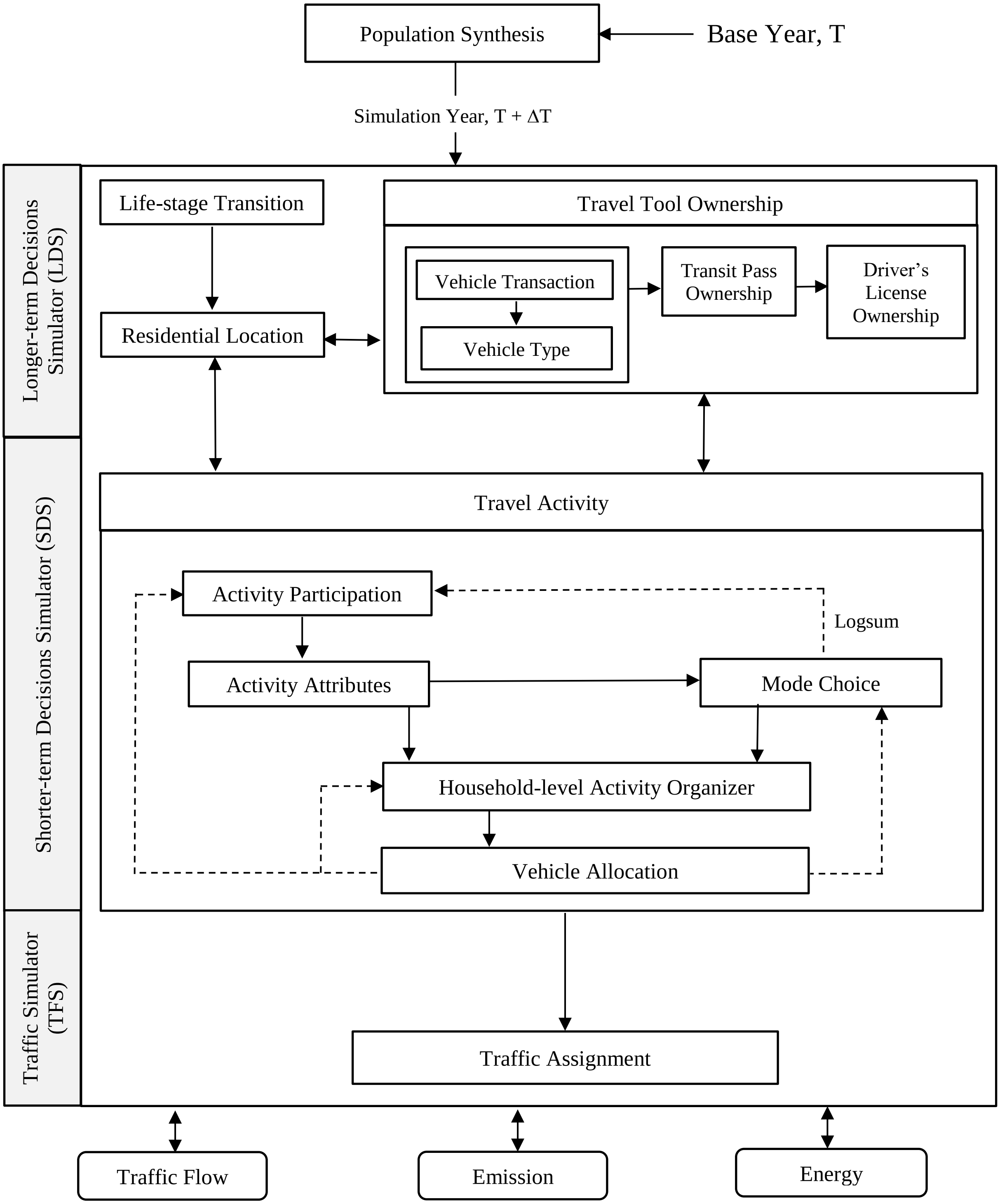

Fig. 1. Conceptual Framework of the Travel Activity Simulator within the integrated Transportation Land Use and Energy (iTLE) Model

One of the key features of iTLE is to operate at a varying temporal-level for different decision components. For example, LDS simulates at a yearly time-step. In the case of SDS, the model simulates over a 24-hour time-step. The population synthesis and majority of the LDS components are already implemented for Halifax (Fatmi & Habib, 2017, 2018a, 2018b, Fatmi, 2017). The traffic simulator is currently under development. The focus of this paper is to implement the SDS module within the iTLE framework. This paper also implements the transit pass and driver's license ownership components of the LDS module.

4. Data

The primary data source for this study is Nova Scotia Travel Activity (NovaTRAC) survey. NovaTRAC is a travel survey conducted for Nova Scotia in 2015-2016. The survey asked respondents to provide a 24-hour travel log for a typical weekday for each member of the household. The 24-hour travel log includes information regarding travel location, purpose, arrival and departure time, and mode. This component also includes vehicle type and accompanying person for the travel. In addition, the survey collected individual-level and household-level socio-demographic characteristics, vehicle ownership and type choice, and health and attitudinal information. The survey yielded a total sample size of 1268. NovaTRAC data is utilized to develop micro-behavioral models for different components of the travel activity simulator. NovaTRAC is also used to generate the probability density functions the heuristic generation of different tour attributes, including time allocation for the tour, starting time, and number of stops.

The simulation results are validated for the year 2006 and 2016 using the Census data for Halifax. The sample size of the Census 2006 includes 372,679 individuals and 155,060 households in Halifax. In the case of Census 2016, the data includes 403,390 individuals and 173,460 households. In addition, baseline population information for Halifax is generated through a synthesis procedure using Public Use Microdata File (PUMF) and Census data for the year 2006.

5. Methods

A summary of the methods utilized to develop and implement the SDS is presented in Table 1. A brief description of the methods is discussed below.

5.1. Travel tool ownership

The travel tool ownership component involves the simulation of vehicle ownership, transit pass ownership, and driver's license ownership. Vehicle ownership simulation results can be found in Fatmi and Habib (2018a) and Khan et al. (2019). This paper reports the simulation of transit pass and driver's license ownership. In the case of transit pass ownership, the decision is simulated as a binary choice to own a transit pass or not. A binomial logit (BL) model is developed to simulate individuals' ownership of transit pass (Table 1). The probability of choosing transit pass ownership is estimated utilizing the choice probability equation for the BL model reported in Table 1. Transit pass is assigned to individuals by comparing the probability estimates of the model with a uniformly distributed randomly generated number between 0 and 1. Independent variables retained in the BL model is also reported in Table 1. Due to space limits, a description of the model estimation results is not provided in this paper. In the case of driver's license ownership, a binomial logit model is developed (Table 1). Simulation procedure for the driver's license ownership is similar to the model discussed above for the transit pass ownership. The independent variables retained in the final model of driver's license ownership is reported in Table 1.

5.2. Activity participation

The activity participation component simulates individual's daily engagement in different types of activities. Travel associated to perform activities is formulated by adopting a tour-based approach. A tour originates and returns to the individual's home location with a series of embedded stops. A tour is assumed to have at least one primary stop and might have several secondary stops. At each stop, individuals perform at least one activity. The activity associated with the primary stop is assumed to be the purpose of the tour. Tours are generated for the following three activity purposes: 1) *mandatory*: work/job activities and school activities, 2) *maintenance*: routine shopping, household and work-related errands, personal business, healthcare, and escorting (i.e. drop-off or pick-up passenger in car), and 3) *discretionary*: eating out, civic or religious activities, recreation, entertainment, and visiting friends. The current version of the model simulates activities for a typical weekday.

The first step of the activity participation process is to generate the number of tours for each individual in a typical weekday. Each individual is assigned a number of tours using a random draw from the probability density distribution derived from the NovaTRAC 2016 data. Following the generation of the number of daily tours, the primary activity to perform in a tour is simulated. A simplified multinomial logit (MNL) version of the model developed by Khan et al. (2018) is implemented (Table 1). The model considers the following four activity participation categories: mandatory activity tour 1, mandatory activity tour 2, maintenance activity tour, and discretionary activity tour.

The choice probability equation for MNL model is reported in table 1. Individuals are assigned to participate in different activity types by comparing the model generated probability estimates with a random draw made from the probability distribution of activity types. When an activity type is selected, that type is removed from the distribution for the remaining draws. Note that the selection of '2 mandatory activities' counts as two separate tours toward the individual's number of tours.

Table 1. Summary of modelling methods

Model Components	Method	Choice Alternatives	Choice Probabilities*	Independent Variables
Transit Pass Ownership	Binomial Logit Model	Yes, No	$P(U_j) = \dfrac{e^{b+\alpha X_j}}{1+e^{b+\alpha X_j}}$	Gender, age, employment status, income, household size, household vehicle fleet size, tenure type, and home distance from CBD.
Drivers License Ownership	Binomial Logit Model	Yes, No	$P(U_j) = \dfrac{e^{b+\alpha X_j}}{1+e^{b+\alpha X_j}}$	Gender, age, employment status, income, household vehicle fleet size, dwelling type, home distance from CBD, home distance to the closest bus stop, population density of the neighbourhood
Activity Participation	Multinomial Logit Model	Mandatory, Maintenance, Discretionary	$P_{ij} = \dfrac{b_i + \alpha_i X_{ij}}{\sum_j b_i + \alpha_i X_{ij}}$	Gender, age, employment status, income, household size, household vehicle fleet size, driver's license ownership, transit pass ownership, and mode choice logsum
Activity Attributes	Heuristic Method	-	-	-
Mode Choice**	Random-parameters Logit Model	Auto, Transit, Walk, Bike	$P_{ij} = \int \dfrac{b_i + \alpha_i X_{ij}}{\sum_j b_i + \alpha_i X_{ij}} f(\alpha_i \mid \mu, \vartheta) d\alpha_i$	Number of activity stops in the tour, tour duration, tour distance, transit pass ownership, driver's license ownership, gender, age, income, household size, household vehicle fleet size, land use index, distance to bus stop
Household-level Activity Organizer	Heuristic Method	-	-	-
Vehicle Allocation***	Multinomial Logit Model	Sub-compact, Compact, Mid-size, SUV, Van	$P_{ij} = \dfrac{b_i + \alpha_i X_{ij}}{\sum_j b_i + \alpha_i X_{ij}}$	Number of activity stops in the tour, tour duration, tour accompanying arrangement, gender, land use index, distance to business park, dwelling density

***** j = individual, i = alternative, b = constant term, α = coefficient vector, X = vector of observed characteristics, ϵ = random error term, $f(\alpha_i|\mu, \vartheta)$ = density function assumed to have a normal distribution with a mean and standard deviation of μ and ϑ.

**Two models are estimated for mandatory and non-mandatory activities

***Four models are estimated for mandatory and non-mandatory activities involving solo and joint tours

5.3. Activity attributes

Activity attributes refers to determining the characteristics of activities, which include the tour start time, total time allocation, number of stops, and destination location. The current version of the model heuristically determines tour attributes. For example, start time for tours is determined by drawing randomly from the probability density functions (PDF) from the NovaTRAC data. The distribution for start time is conditioned on the tour type (i.e. mandatory, maintenance, and discretionary). Conflicts occur when two or more tours made by the same individuals are assigned the same start time. In such cases, precedence is given in the following order: mandatory tour followed by maintenance tour followed by discretionary tour. Similarly, number of stops in a tour is generated with a random draw from the NovaTRAC distribution. Stops represent the secondary activities that are performed in the tour. In the case of duration, and destination location, the distribution is generated conditioned on the tour type as well as time of day (i.e. AM peak, PM peak). In the current version of the model, distance is used as a proxy to represent destination location.

5.4. Mode choice

The mode choice component assigns a mode to each tour. A random-parameters logit (RPL) model is developed to simulate the mode choice decisions of the individuals (Khan et al., 2018). Separate RPL models are developed for mandatory and non-mandatory tours. The following four modes are considered: auto, transit, walk, and bike. The choice probability equation of RPL model is reported in table 1. The independent variables retained in the final model is also presented in Table 1.

One of the key features of the mode choice model is to establish coupling among different decision components of the activity simulator. For example, a logsum from tour mode choice model is calculated for each individual (Khan et al., 2015). This logsum is used to estimate the activity participation model, thus creating a feedback mechanism. In addition, transit pass ownership, and driver's license ownership determined within the travel tool ownership component is used in simulating the mode choices. Similarly, tour mode choice simulation considers tour attributes, such as the number of activity stops in the tour, tour duration, and tour distance (Table 1). These tour characteristics are determined during the tour attribute simulation stage.

Mode is assigned to each tour by comparing the model generated probability estimates with a random draw made from the probability distribution of mode types. Note that the simulation procedure is conditioned on the availability of auto. Therefore, auto is not considered as an alternative mode for individuals who do not own a household vehicle.

5.5. Household-level activity organizer

This component explicitly accommodates intra-household interaction by simulating whether two or more household members can travel together or not. To this point, it is assumed that all tours are made solo, which means that individuals are traveling alone. Whereas in reality, individuals might interact with their friends and family and travel together, in other words make joint tours. To mimic such interactions, the activity organizer component assesses whether a solo tour can be made joint or not. This component is developed by following a heuristic modeling method. The eligibility of an individual to make a joint tour with another individual is assessed based on whether both the tours satisfy the following criteria: 1) the start time of both tours is within one hour, and 2) both tours have the same travel mode. Finally, tours satisfying the above criteria are assigned as joint tours probabilistically. The probability is conditioned on the relative duration of the tours, which is obtained from NovaTRAC. For example, tours with shorter difference in duration are assumed to have a higher probability to be joint tours. Note that the current version of the model only accommodates joint tours among household members. Following this procedure, the tour status is updated accordingly as joint or solo.

5.6. Vehicle allocation

The vehicle allocation component determines the choice of vehicle for a tour from the household vehicle fleet. Therefore, only tours with mode 'auto' are considered in this stage. A simplified multinomial logit (MNL) version of the model developed by Khan and Habib (2018) is implemented. The model considers five types of vehicles as alternatives: subcompact, compact, midsize, SUV, and van (including trucks). Four MNL models are developed for the following four combinations of tours: solo-mandatory, joint-mandatory, solo-discretionary, and joint-discretionary. The choice probability equation and predictors retained in the final model are reported in table 1.

During the assignment of vehicles to specific tours, conflicts may occur when multiple individuals require the same vehicle at the same time. To address such conflicts, a conflict resolution manager is introduced to generate strategies in two stages. In the first stage, vehicles are assigned on the basis of tour types and accompanying travel arrangement types. For example, mandatory tours are given priority over non-mandatory tours. In the case of travel arrangements, joint tours are given priority over solo tours. All available vehicles are assigned to tours following the above order of precedence. After the first stage of vehicle allocation, the second stage deals with those tours which did not get a vehicle assigned in the first stage. At this stage, no vehicle is available. Strategies in the following order are adopted to accommodate this conflict:

1. Re-schedule the tours to a new starting time when a vehicle is available.
2. If strategy 1 does not work, re-evaluate the accompanying travel arrangement by assessing the potential for the tour to be joined with another tour which has vehicle assigned.
3. If strategy 2 does not work, re-evaluate tour mode choice.

To implement the above-mentioned strategies, feedback mechanisms among different components of the activity simulator are established. For instance, in the case of strategy 3 regarding the re-assessment of mode choice, the mode choice model described in section 5.4 is re-implemented, excluding the ‘auto’ mode.

6. Software architecture and proto-type implementation

This study presents the implementation of the proposed travel activity simulator known as a short-term decision simulator (SDS). The SDS is designed and implemented within the iTLE model architecture. The program code of iTLE is written using C# DotNET programming language. The SDS is designed as a modular-based system and written in PHP. One of the critical features of the SDS is to maintain data integrity, as it handles a large amount of data concerning population, built environment, and transportation systems of an entire urban region. Therefore, SDS uses a MySQL database to upload, store, retrieve, and update data. The MySQL database includes several data tables such as household file, individual file, tour file, model parameter file, and probability distribution file, among others. This database loads the input file, and updates data tables accordingly following the simulation run. The SDS simulates travel activities at a 24-hour time-step. The run-time of the SDS model for each simulation time-step is around 9 minutes on a computer with Core i7-4770 processor and 16 GB of RAM, running on a 64-bit Windows 7 operating system.

A prototype version of the iTLE software is implemented for Halifax, Canada. The prototype model generates a 100% synthetic population for Halifax and runs the simulation for a 10% sample. The LDS component of iTLE runs for a 15-year period, starting from the base year 2006 to 2021. The description of the LDS implementation is documented in Fatmi and Habib (2017, 2018a, 2018b). In the case of SDS, this component operates over a 24-hour period for a typical weekday. The current SDS version implements the following components: transit pass and driver’s license ownership, activity participation, tour attributes, mode choice, activity organizer, and vehicle allocation. The simulation results are validated for the years 2006 and 2016. Finally, a brief discussion of the simulation results for the year 2021 is presented.

7. Validation results

A multi-year validation of the simulation results is performed for the year 2006 and 2016. For the year 2016, validation results for the activity participation type suggests that the simulator performs reasonably well (Figure 2a). For example, mandatory activities are over-represented by 1.6% only. Similarly, maintenance activities are slightly over-represented. The model under-represents discretionary activities by 5.1%. This result is expected, as discretionary activities are assumed to be of lower priority than mandatory and maintenance activities, therefore they might have been rejected while resolving the scheduling conflicts within the tour organizer and vehicle allocation components. The validation results for mandatory tour distance suggests that the majority of the simulated distance bands represent the observed distribution within a difference of 2% (Figure 2b). In the case of tour start time, the simulator predicts that the majority of mandatory activity tours start between 7-9 am, which is similar to the observed start time (Figure 2c). The simulator over-represents mandatory tours between 7-8 am and 8-9 am. One of the attributing factors for this error might be the overall over-representation of mandatory tours by the simulator. The validation for tour mode choice is presented in Figure 2d. The analysis suggests that the predicted mode share is within a difference of around 2% from the observed distribution in the case of majority of the modes.

For the year 2006, the validation results suggest that the majority of categories lie within a few percentage points from the observed distribution. For example, in the case of mandatory tour mode choice, share of auto and transit mode is over-represented by 0.8% and 0.6% respectively (Figure 3a). Similar observations can be made for mandatory tour distances (Figure 3b). In summary, it can be concluded that the proposed activity-based model performs reasonably well and generates satisfactory travel activity distribution.

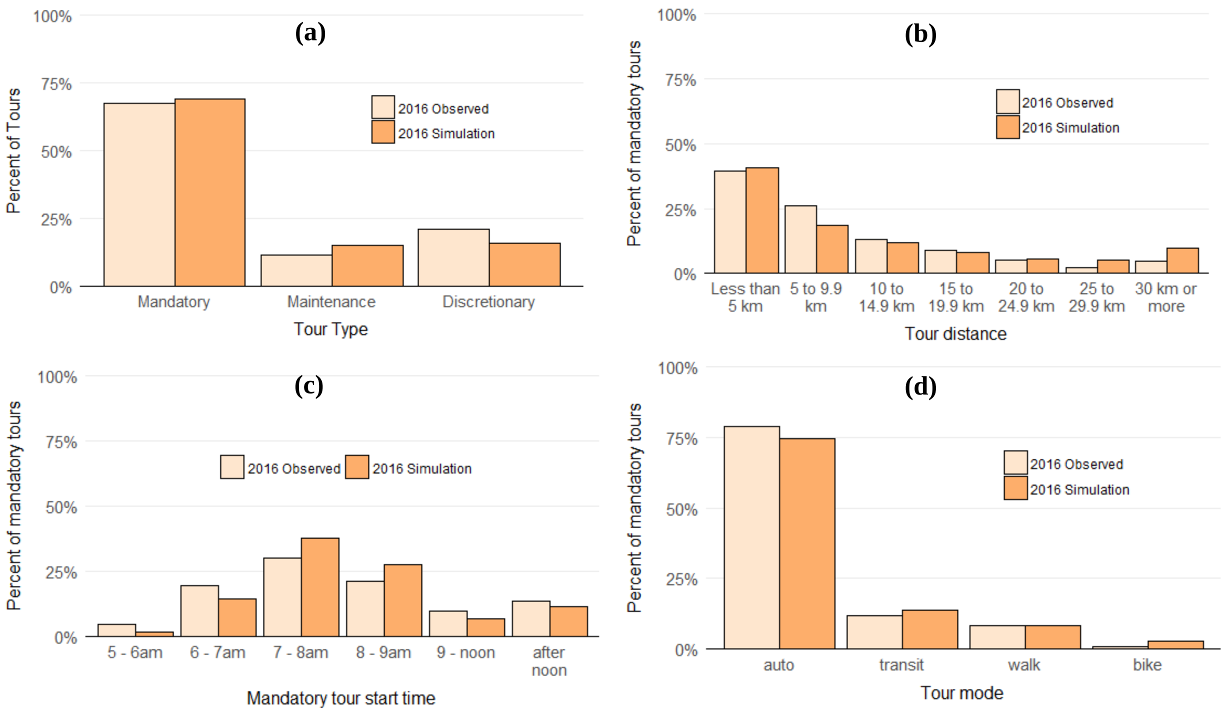

Fig. 2. (a) Activity tour types; (b) Mandatory tour distance; (c) Mandatory tour start time; (d) Mandatory tour mode choice.

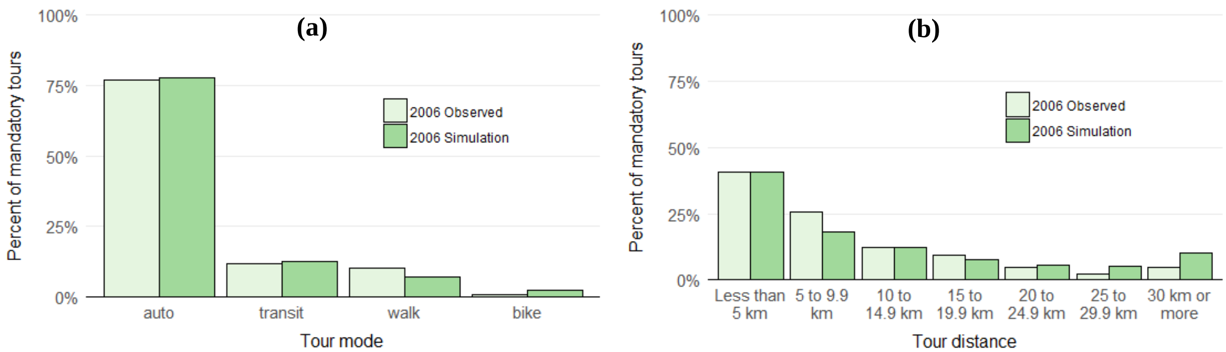

Fig. 3. (a) Mandatory tour mode choice; (b) Mandatory tour distance

8. Microsimulation results for the year 2021

The simulator predicts an average of 1.19 tours/person on a daily-basis for the year 2021. Among these tours, around 69.7% are mandatory, 13.5% are maintenance, and 16.8% are discretionary. Around 66.2% of the tours are made solo, which is an increase of 7.9% compared to 2006. The rest, 33.8%, are predicted as joint tours. The average number of stops per mandatory tour is 2.22. In the case of maintenance and discretionary tours, the average number of stops is 1.14 and 1.16 per tours respectively. Joint tours have a higher number of stops than solo tours for all three activity types. For example, the average number of stops for joint mandatory tours is 2.41, whereas it is 2.07 for solo mandatory tours. The share of predicted tour mode choice over the simulation period is presented in Figure 4. In 2021, the majority of tours are predicted to be made with auto mode, to be specific, around 69.6% of total tours. In comparison to 2006, the share of auto tours is predicted to decrease by around 5.2%. Interestingly, the share of transit tours is predicted to be 12.1% in 2021, which is an increase of 2.9% in comparison to 2006. Among other modes, in 2021, the share of walking and biking is 10.5%, and 7.8% respectively. In-terms of travel tool ownership, the simulator predicts that around 20.9% of individuals own a monthly transit pass and 77.8% own a driver's license. In the case of vehicle type assignment, around 45.0% of auto tours involve subcompact cars. Midsize and SUVs are assigned to around 9.8% and 9.7% of auto tours. This simulator advances activity-based travel modeling by maintaining feedback within the SDS and LDS components. The flexibility added through this coupling mechanism facilitates the opportunity to predict how travel activities, mode choice, vehicle types, and vehicle kilometers traveled evolve with travel tool ownership, and socio-economic distribution of the population. Further analysis of the simulation results is discussed below.

8.1. Tour mode choice

To evaluate how the choice of mode varies by travel tool ownership, a cross-distribution for the year 2021 is presented in Figure 5. In the case of individuals who do not own any travel tool, the majority of their tours are predicted to be made using transit, more specifically, around 43% of their total tours. The share of walk and bike for this group is around 35% and 22% respectively. As individuals' number of travel tool ownership increases, the share of auto tours increases as well. For example, individuals with the ownership of a transit pass, a driver's license, and multiple household vehicles choose auto for approximately 91% of their tours. Individuals owning a monthly transit pass with different combinations of other travel tools are predicted to have a higher share of transit tours than those without a transit pass. For instance, individuals who own a transit pass and a license but do not own a household vehicle, are predicted to use transit for around 59% of their tours. The share of transit tours drops to 48% for individuals who do not own a transit pass with the rest of the combination remaining the same. The choice of auto mode is predicted to increase as the number of household vehicles increases. The auto mode share is higher for licensed individuals compared to not licensed ones.

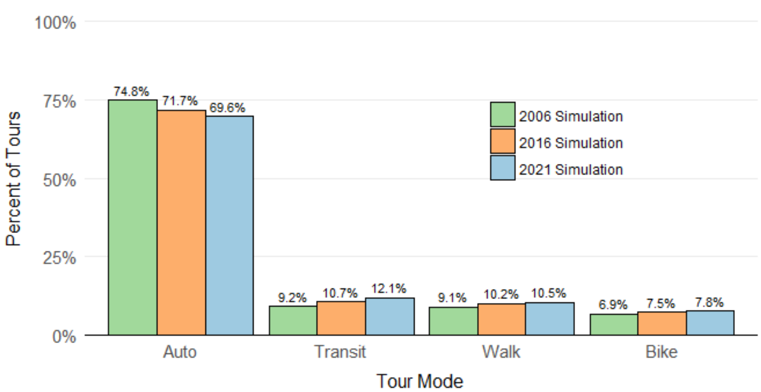

Fig. 4. Predicted Mode Choice Distribution for the Years 2006, 2016, and 2021

Figure 6 adds another layer to the mode choice analysis by representing how tour mode choice is predicted to vary by age. The results suggest that the 25th percentile, median, and the 75th percentile of individuals' age for auto mode is consistently predicted to be higher than other modes for mandatory, maintenance and discretionary activities. For example, in the case of discretionary activities, the median age of individuals choosing auto mode is 47 years, which is higher than that of transit (which has a median age of 27 years). This implies that the choice of auto mode involves a higher proportion of older individuals compared to other modes. In the case of transit, the 25th percentile, median, and the 75th percentile of age is found to be lower than other modes for the three activity types. For example, for maintenance activities, the median age is 27 years. This implies that a higher proportion of relatively younger population chooses transit to perform different activities.

Figure 7 presents the kernel density of home to CBD distance by mode choice for different activity types. The analysis reveals that density for active modes such as transit, walk, and bike are skewed to the left of 5 km for mandatory tours. These are urban dwellers as locations within 5 km from CBD are core downtown areas. Interestingly, the auto mode is observed to show a secondary peak within 10-15 km and another small peak around 20 km. In the context of Halifax, locations above 10 km are suburban areas. For non-mandatory tours such as maintenance tours, the distribution of active transportation modes reveals a similar distribution to that of mandatory tours. However, the auto mode shows more variability and is skewed to the left of 10 km.

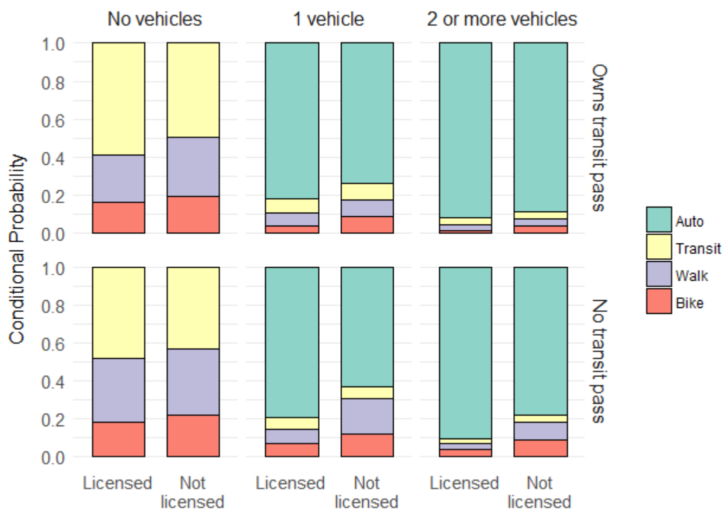

Fig. 5. Predicted Distribution of Tour Mode Choice by Travel Tool Ownership Type for the Year 2021

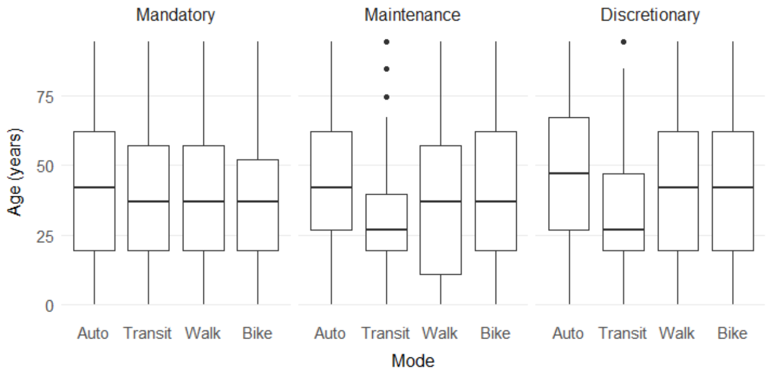

Fig. 6. Predicted Distribution of Individuals' Age by Mode Choice for Different Activity Types for the Year 2021

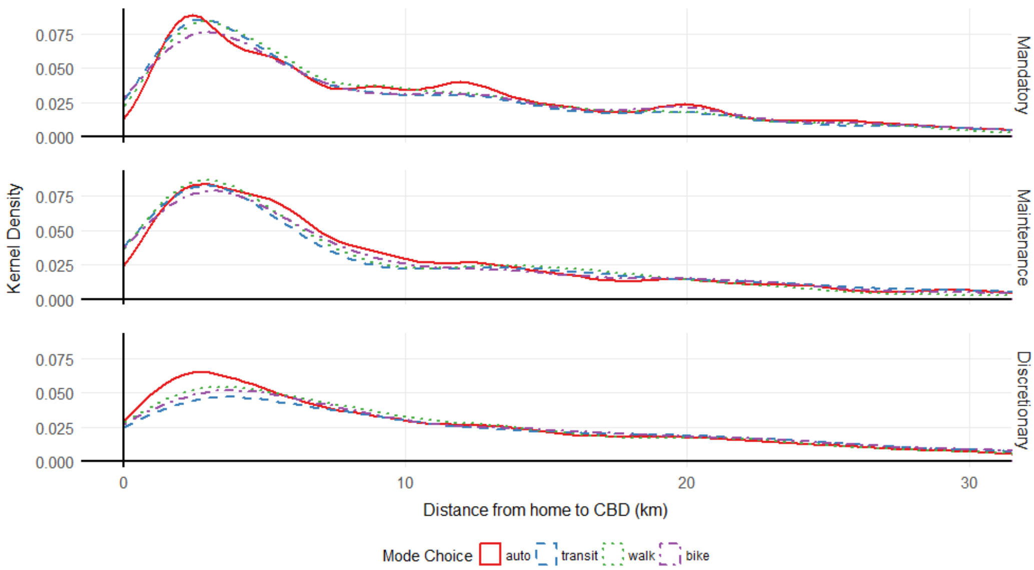

Fig. 7. Predicted Distribution of Home to CBD Distance by Tour Mode Choice for Different Activity Types for the Year 2021

8.2. Vehicle type assignment

Analysis of vehicle assignments with travel arrangement types suggests that solo tours are dominated by the choice of subcompact and compact vehicles. The proportion of midsize and SUV use is predicted to be higher for joint tours. In the case of analysis regarding vehicle assignments with income, results suggest that smaller-sized vehicles are predicted to be assigned to a higher proportion of tours made by individuals in lower income households. The size of the vehicle is predicted to increase with household income. Figure 8 represents a cross-distribution of vehicle type by household income and travel arrangements. The analysis reveals that larger-sized vehicles (i.e. SUV) are assigned to a smaller proportion of the solo tours made by low income individuals. For example, SUV is assigned to around 5.98% of the solo tours made by individuals with income below $20,000. Interestingly, the proportion of SUV assignment increases to around 18.6% for joint tours with incomes $100,000 and above. The proportion of such larger vehicle assignment is predicted to be even higher for high income households if joint tours include children.

8.3. Vehicle kilometers traveled (VKT)

The average vehicle kilometers traveled (VKT) per individuals is predicted to be 22.1 km on a typical weekday for the year 2021. The mean VKT per individual is predicted to increase with age (Figure 10). The mean VKT is predicted to range from around 17 km for younger population to approximately 22 km for older adults. Interestingly, a drop in the mean VKT is predicted for individuals over the age of 80 years. Figure 9 shows vehicle kilometers traveled by vehicle type for different activities. A kernel density estimation technique is utilized to plot the VKT. The results suggest that VKT density is skewed to the left of 5 km for smaller-sized vehicles, such as subcompact cars for mandatory tours. This implies that a higher proportion of smaller-sized vehicles are assigned to shorter mandatory tours. For larger-sized vehicles such as vans, density is more variable and skewed to the left of 15km. This implies that larger-sized vehicles are assigned to relatively shorter as well as longer mandatory tours. Interestingly, for non-mandatory activities such as maintenance activities, the VKT for subcompact cars is more variable than that of mandatory activities. The distribution is skewed to left of 10km. Kernels for SUV and vans show a higher degree of variability and skewness to the left of 15km. For discretionary tours, the VKT distribution for vans is skewed within 5-20 km. Interestingly, a secondary peak is observed between 25-40km.

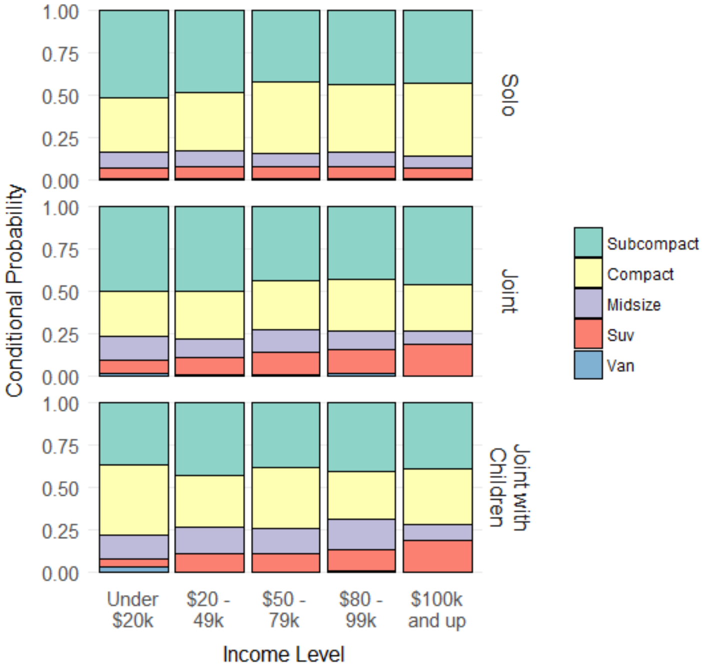

Fig. 8. Predicted Distribution of Vehicle Type by Household Income for Different Tour Accompanying Arrangements for the Year 2021

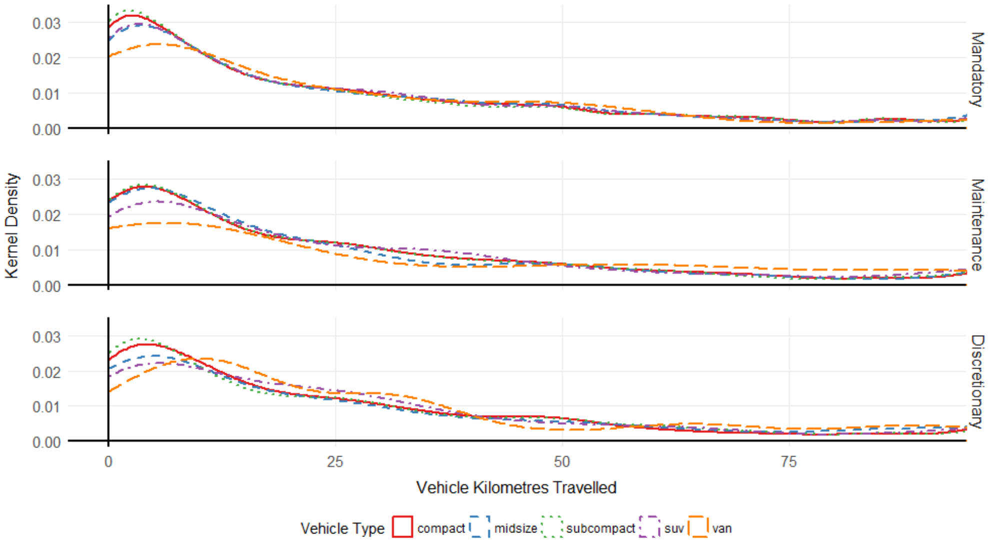

Fig. 9. Predicted Distribution of Vehicle Kilometer Traveled (VKT) by Vehicle Type for Different Activity Types for the Year 2021

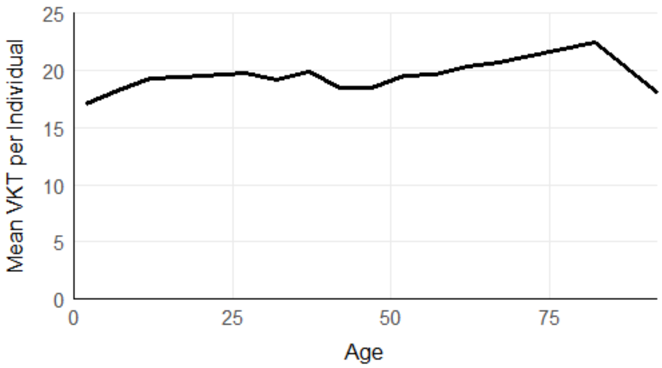

Fig. 10. Predicted Distribution of Vehicle Kilometer Traveled (VKT) by Age of Individuals for the Year 2021

9. Conclusions

This study presents the implementation of a travel activity simulator within an agent-based integrated Transportation Land Use and Energy (iTLE) modeling system. The activity simulator includes the following components: driver's license ownership, transit pass ownership, activity participation, activity attributes, mode choice, activity organizer, and vehicle allocation. One of the key features of this simulator is to simulate the vehicle allocation procedure for individual tours. Vehicle allocation involves assignment of vehicles from household vehicle fleet utilizing a micro-behavioral model. In the case of vehicle unavailability, several strategies are adopted to resolve the conflict, such as rescheduling the tour, reassessing accompanying arrangements, or reestimating mode choice. Another important feature of the simulator is to accommodate feedback among and within different shorter-term and longer-term decision processes by adopting coupling mechanisms. For example, coupling is established between mode choice and activity travel participation models using a logsum component. The simulator also addresses interactions among household members' decision processes. For instance, intra-household interaction is addressed through the formation of solo or joint tours within the tour organizer component. The simulation involves the implementation of several advanced econometric methods, such as random-parameters logit model, multinomial logit model and binomial logit model.

This travel activity simulator is implemented for Halifax, using2006 as the base year and predicting for 2021. The simulation results are validated for the years 2006 and 2016. The validation results suggest that the simulator generates reasonably satisfactory estimates of the population travel activities, including activity type, start-time, duration, and mode choice. Based on these results, the simulator is implemented to predict the evolution of travel tool ownership, activity participation, mode choice, and vehicle assignments for the year 2021. The simulation results suggest that a person will perform an average of 1.19 tours on a daily-basis in 2021. The majority of tours are predicted to be mandatory (around 69.7%). Solo tours dominate the distribution with a percentage of 66.2%, which is an increase of 7.9% when compared to 2006. Mandatory tours are predicted to have a higher average number of stops (around 2.22) compared to non-mandatory tours (around 1.14 and 1.16 for maintenance and discretionary respectively). Joint tours also have a higher number of stops than solo tours. The majority of tours are predicted to be made with auto, specifically, around 69.6%. Approximately 20.9% of individuals own a monthly transit pass and 77.8% own a driver's license. A cross-distribution of different combinations of travel tool ownership and mode choice show that the use of transit is higher for individuals owning a transit pass than that of those not owning a transit pass. For example, for individuals who do not own a household vehicle, around 59% of their tours involve transit use if they own a transit pass. Interestingly, the percentage of transit use drops to 48% if they do not own a pass. A higher proportion of tours made by auto is predicted to include older adults compared to their younger counterparts, who are found to use transit more frequently. The kernel density plots for home to CBD distance by mode choice suggest that a higher proportion of active modes will be used by urban dwellers. Car mode is predicted to be dominated by suburban dwellers as well as urban dwellers (with presumably high income). In the case of vehicle allocation, the proportion of larger vehicle assignment is predicted to be higher for the joint tours of high-income households. The simulator also forecasts VKT, which is on an average 22.1 km per individual for a typical weekday of 2021. Mean VKT per individual is predicted to increase with age. The kernel density plots of VKT for different types of vehicle use suggest that the majority of smaller vehicle assignments include relatively shorter tours. A higher proportion of larger vehicle assignments involve relatively longer tours. In summary, the implementation of this travel activity simulator advances activity-based modeling and forecasting literature in many folds. This simulator adds the capacity to activity-based models to simulate tour vehicle assignments, and travel accompanying arrangements, among others. Future research should focus on using this simulator to test individuals' travel activity and vehicle use pattern under alternative land use and transportation scenarios.

Acknowledgements

The authors would like to thank the Natural Sciences and Engineering Research Council (NSERC) - Discovery Grant, and Nova Scotia Department of Energy for their financial support. The authors would also like to thank Mitch Gold, Rachel Lynn and Katie Walker for editing the manuscript.

References

Arentze, T.A., Timmermans, H.J., 2004. A Learning-based Transportation Oriented Simulation System. Transportation Research Part B: Methodological 38: 613–633.

Auld, J., Hope, M., Ley, H., Sokolov, V., Xu, B., Zhang, K., 2016. POLARIS: Agent-based Modeling Framework Development and Implementation for Integrated Travel Demand and Network and Operations Simulations. Transportation Research Part C: Emerging Technologies 64: 101–116.

Auld, J.A., Mohammadian, A.K., 2009. Framework for the Development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) Model. Transportation Letters 1: 245–255.

Auld, J.A, Mohammadian, A.K, 2012. Activity Planning Processes in the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) Model. Transportation Research Part A: Policy and Practice 46: 1386–1403.

Auld, J.A., Mohammadian, A.K., 2013. Development and Implementation of the ADAPTS Integrated Activity-travel Model, in "Travel Behaviour Research: Current Foundations, Future Prospects". In: Roorda, M., Miller, E. (Ed.). Lulu Publishers, USA.

Fatmi, M.R., 2017. Development of Integrated Urban System Models: Population Life-transitions, Household location, and Vehicle Transaction Decisions. Doctoral Dissertation.

Fatmi, M.R., Habib, M.A., 2017. Baseline Synthesis and Microsimulation of Life-stage Transitions within an Agent-based Integrated Urban Model. Procedia Computer Science 109: 608–615.

Fatmi, M.R., Habib, M.A., 2018a. Microsimulation of Life-stage Transitions and Residential Location Transitions Within a Life-oriented Integrated Urban Modeling System. Computers, Environment and Urban Systems 69: 87–103.

Fatmi, M.R., Habib, M.A., 2018b. Microsimulation of Vehicle Transactions Within a Life-oriented Integrated Urban Modeling System. Transportation Research Part A: Policy and Practice 116: 497–512.

Khan, N.A., Enam, A., Habib, M.A., Konduri, K.C., 2018. Investigation of Tour Participation, Time Allocation, and Mode Choice: An Application of Multiple Discrete-Continuous Extreme Value-Mixed Multinomial Logit Modeling Approach. 97th Annual Meeting of the Transportation Research Board, Washington D.C., No. 18-06704.

Khan, N.A., Habib, M.A., 2018 (under review). Understanding Variations in Tour-level Vehicle Allocation for Solo and Joint Activities: A Latent Segmentation-based Random Parameter Logit Modeling Approach. Transportation.

Khan, N.A., Fatmi, M.R., Habib, M.A., 2019 (submitted). Proto-type Microsimulation Modeling of Vehicle Type Choice within the iTLE Urban Systems Model. Transportation Research Record: Journal of the Transportation Research Board, 2019.

Miller, E.J., Roorda, M.J., 2003. Prototype Model of Household Activity-travel Scheduling. Transportation Research Record: Journal of the Transportation Research Board 1831: 114–121.

Miller, E.J., Roorda, M.J., Carrasco, J.A., 2005. A Tour-based Model of Travel Mode Choice. Transportation 32: 399–422.

Nurul Habib, K.A., 2018. Comprehensive Utility-based System of Activity-travel Scheduling Options Modelling (CUSTOM) for Worker's Daily Activity Scheduling Processes. Transportmetrica A: Transport Science 14: 292–315.

Pinjari, A., Eluru, N., Srinivasan, S., Guo, J. Y., Copperman, R.B., Sener, I.N., Bhat, C.R., 2008. Cemdap: Modeling and Microsimulation Frameworks, Software Development, and Verification. 87th Annual Meeting of the Transportation Research Board, Washington D.C.

Roorda, M.J., Miller, E.J., Habib, K.M., 2008. Validation of TASHA: A 24-h Activity Scheduling Microsimulation Model. Transportation Research Part A: Policy and Practice 42: 360–375.

Timmermans, H., Arentze, T.A., 2011. Transport Models and Urban Planning Practice: Experiences with Albatross. Transport Reviews 31: 199–207.