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Microsimulation of vehicle ownership decisions within an agent-based integrated urban model: An event-based hybrid of continuous and discrete simulation approach

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Abstract: This study presents vehicle ownership simulation (VOSim) within the STELARS (Simulator for Transportation, Energy, LAnd use for Regional System) framework. VOSim follows an event-based decision process adopting a hybrid of continuous and discrete time simulation techniques. In STELARS, each household agent subscribes to a list of events (e.g., childbirth) that makes the agent actively adjust his or her vehicle fleet. Being active, agents make two interconnected decisions: vehicle transaction and type choice. In the vehicle transaction stage, for households that never owned a vehicle, the timing of the first vehicle purchase decision is simulated. For households with vehicles, their decision to add, dispose, or replace a vehicle is simulated. In the vehicle type choice stage, an agent's decision to choose vehicles by body, vintage, fuel, and technology type is simulated. Vehicle transaction is simulated as a continuous-time decision using a hazard-based model. Once the timing of the transaction is determined, the vehicle type choice simulation transitions into a discrete-time step. This paper reports VOSim predictions and multi-year validation for the Okanagan region in Canada for the 2011-2021 period. Multi-year validation results confirm a satisfactory accuracy level. Prediction results suggest that a higher proportion of first-time vehicle purchasers reside in areas with lower accessibility to transit. A higher share of suburban dwellers is predicted to own alternative fuel vehicles. Overall, the VOSim adds capacity to integrated urban models to simulate vehicle ownership using a behaviorally realistic simulation procedure and be sensitive to plans and policies through an equity lens, such as who makes the first vehicle purchase decision.

Keywords: integrated urban model, vehicle ownership simulation, vehicle transaction, vehicle type, fuel type, advanced technology, agent-based model, validation, event-based simulation, continuous time simulation, discrete time simulation

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1 Introduction

Integrated Urban Models (IUMs) are large-scale regional models that serve as a critical tool for capturing the interplay between transportation and land-use decisions (Salvini & Miller, 2005). These models are designed to incorporate the complex dynamics of different elements of an urban system, including population socio-demographics, location choice, vehicle ownership, and travel activities, as well as their subsequent impacts on congestion, emissions, and energy consumption. The scope of IUMs makes it an essential tool to assist policymakers and planners in making informed decisions regarding sustainable transportation, land configuration, and urban

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environments (Anik & Habib, 2024; Miller, 2018; Shahrier et al., 2024). For example, decarbonizing the transportation sector is a priority for many countries around the world, including Canada. Many plans, policies, and incentive programs are developed to achieve these transportation decarbonization targets, such as how federal and provincial incentive programs in Canada are targeting the sale of new electric vehicles (Government of Canada, 2023). IUMs can be a fitting tool to test the impacts of such incentive programs on meeting emission reduction targets and vehicle ownership. However, to accurately test alternative scenarios and help develop unbiased policies, the simulation architecture and methodology of the IUMs need to represent the behavior of the population adequately.

A typical IUM contains several decision components, including long-term (e.g, demographic and residential changes), medium-term (e.g., vehicle ownership), and short-term (e.g., travel activities) decisions (Chingcuanco & Miller, 2018; Salvini, 2003). Some of the noteworthy existing IUMs are Integrated Land Use, Transportation, and Environment (ILUTE) (Miller et al., 2004); Predicting Urbanisation with Multi-Agents (PUMA) (Ettema et al., 2007); Urban Simulation Model (UrbanSim) (Waddell, 2002); Integrated Microscopic Mobility Simulator (SimMobility) (Adnan et al., 2016); and Comprehensive Econometric Microsimulator for Urban Systems (CEMUS) (Eluru et al., 2008).

Vehicle ownership is one of the crucial components of an IUM, as it can have a two-way interaction with other decision components. For example, it can affect long-term decisions such as choices for residential and work location, as well as short-term decisions such as travel mode choices, consequently impacting traffic congestion and emissions. ILUTE is one of the most comprehensive and operational IUMs, as it simulates vehicle ownership evolution as a two-stage interdependent decision of both vehicle transactions and type choices. Vehicle transaction decisions refer to the dynamic decisions of vehicle acquisition, trade, disposal, and doing nothing. The vehicle type choices in the second stage include different body types (e.g., compact and sport utility vehicles) and vintage types (e.g., new and old) preferences (Duivestein, 2013; Mohammadian & Miller, 2003). ILUTE modeled vehicle ownership using a nested logit structure and implemented this model with a discrete simulation time step of one year.

Another recently developed IUM is the integrated Transport Land Use and Energy (iTLE), which also simulates vehicle ownership as a two-stage decision of vehicle transaction and type choice decisions (Fatmi & Habib, 2018). Their simulation architecture follows a discrete time step. One of the important aspects of their model is to include first-time vehicle purchases as a component of the transaction decision. Their vehicle type choice component includes vehicle body type only. The current version of the iTLE only implemented the vehicle transaction decision, where the associated behavioral models include binary and multinomial logit models. The model simulates vehicle ownership evolution from 2007 to 2021, while validation was done for the single year of 2016.

Some other notable IUMs that included a vehicle ownership component are CEMUS (Eluru et al., 2008) and SimMobility (Adnan et al., 2016). In CEMUS, the vehicle ownership component simulates the number and type of vehicles owned by households. Households' vehicle fleets are updated in the simulation by their add, trade, sell, or do nothing decisions, while the vehicle types are determined in terms of the body types. The simulation follows a discrete time step of one year and was validated for one year (base year). Paleti et al (2011) proposed a vehicle fleet simulator that can be implemented within an IUM. The simulator includes vehicle transactions, type choices, and vehicle usage decisions. Additionally, it accounts for preferences regarding vehicle fuel types (e.g., gasoline, diesel, hybrid, electric, etc.), as well as their body and vintage types.

As discussed above, the majority of the IUMs simulate vehicle ownership evolution in a discrete-time step, such that every decision regarding vehicle ownership is simulated at every simulation time step (i.e., typically every year) for each agent (i.e., households or individuals). However, this might not be representative of the actual behavior, as the agents are unlikely to be active in the market to make vehicle transactions every year. In other words, people typically do not reassess the purchasing, trading, or disposal of their current vehicle(s) every year. Rather, they may become active in response to key events, such as the birth of a child or a relocation of residence (Adnan et al., 2016). This further introduces a continuous time dimension to the transaction decision process, emphasizing the need to capture when the decision of transaction is made, followed by the type choice decision. Therefore, appropriate behavioral representation in the simulation framework is necessary, which should not only improve the prediction accuracy but also ease the computational burden. Furthermore, limited studies have reported the validation of the vehicle ownership component, specifically because of the limited availability of observed data. Another limitation of the existing IUMs is their inability to forecast alternative fuel vehicles (e.g., hybrid and electric) and the availability of advanced technologies in vehicles (e.g., lane-keep assist, parking assist, emergency braking, and blind-spot detection).

This paper presents the microsimulation of vehicle ownership decisions within an IUM, adopting an event-based hybrid of continuous and discrete time simulation techniques. Specifically, vehicle ownership decisions have been microsimulated using the Simulator for Transportation, Energy, LAnd use for Regional System (STELARS). STELARS is an agent-based model that considers individuals and households as the agents. Agents are intelligent and autonomous entities that interact with each other and their environment, and exhibit certain behaviors based on their attributes. The decision-making unit for vehicle ownership decisions is the household agent. Vehicle ownership is simulated as a two-stage decision-making process of vehicle transaction and type choice, which are also interdependent. An event-based simulation approach is used, where the households are simulated to become active for making vehicle transactions in response to key life events, such as the birth of a child, addition of a job, residential relocation, etc. Once they are active, first their vehicle transaction decision is simulated, followed by vehicle type choice decisions. Vehicle transaction is simulated at a continuous time scale using a hazard modeling technique, whereas vehicle type choice is simulated at a discrete simulation time step. To adequately represent agents' behavior within the simulation framework, STELARS adopts a hybrid of continuous and discrete time simulation techniques. Vehicle transaction decisions include the acquisition, trade, and disposal of a vehicle. A key feature of this model is the ability to predict households' first vehicle purchase decisions, a significant decision that has several implications in determining their travel behavior and carbon footprint (Khan & Habib, 2021). A comprehensive set of vehicle type choices is accommodated in the framework, which includes vehicle body, vintage, fuel, and technology type choices. STELARS has been implemented for the Greater Okanagan region of British Columbia (BC) to micro-simulate vehicle ownership from 2011 to 2021. Furthermore, this paper represents a multi-year validation of the simulation results and prediction results of the vehicle fleet evolution over time, space, and by socio-demographic attributes.

2 STELARS framework

STELARS is an agent-based model (ABM) considering individuals and households as agents within its simulation framework, where each agent has their own attributes (e.g., individuals' attributes are age and marital status, and households' attributes are the number of people, number of children, and income). Additionally, each agent has their own set of behaviors that could be implemented within the simulation based on their attributes. For instance, individuals can marry, separate, attain higher education degrees, and die; and households can relocate to a new residence and make a vehicle transaction.

STELARS adopts an event-based approach that combines both continuous and discrete time simulation techniques. In other words, agents remain largely inactive until triggered by events, such as the birth of a child, the death of an existing member, or a member leaving the current household. Figure 1 shows the overall conceptual framework of STELARS, which encompasses three primary decision categories: long-term, medium-term, and short-term decisions. Each decision category has a set of modules, and each module consists of multiple models. STELARS requires three inputs: synthetic population, built-form layers, and transportation networks. The synthetic population represents a complete profile of individuals in the study area, including demographic attributes (age, education, marital status, children), socio-economic attributes (income, job status, number of vehicles), and residential details. This synthetic population, developed by Rahman & Fatmi (2022), uses the Bayesian network and generalized raking techniques.

The long-term decision phase includes two modules: demographic dynamics and residential location. The demographic module models agents' life events such as aging, death, marriage, divorce, childbirth, education, and job (Khalil et al., 2024). The residential location module models household relocation decisions through a four-stage process: mobility, location search, bidding, and choice (Orvin et al., 2024; Orvin & Fatmi, 2023). The medium-term decision phase has three modules, among which vehicle ownership is one of the key modules and the primary focus of this research. The other two modules are information and communication technology (ICT) ownership and shared mobility services. The vehicle ownership module consists of two phases, including vehicle transaction and vehicle type choice. The ICT ownership module accommodates ownership of smartphones, computers, and other technologies. In the shared mobility module, the accessibility of transit passes and bikes, shared micro-mobility services, and car shares are simulated. Both ICT and shared mobility modules are still in development. Finally, the short-term decision phase mainly revolves around activity-based modeling in addition to traffic simulation. The activity-based model includes in-home activities as well as out-of-home activity generation, start time, frequency, and others (Khaddar et al., 2024; Shafie et al., 2024). Traffic simulation is being implemented using the MATSim platform (Saha et al., 2024). STELARS outputs include travel time, traffic flow, emissions, and energy consumption.

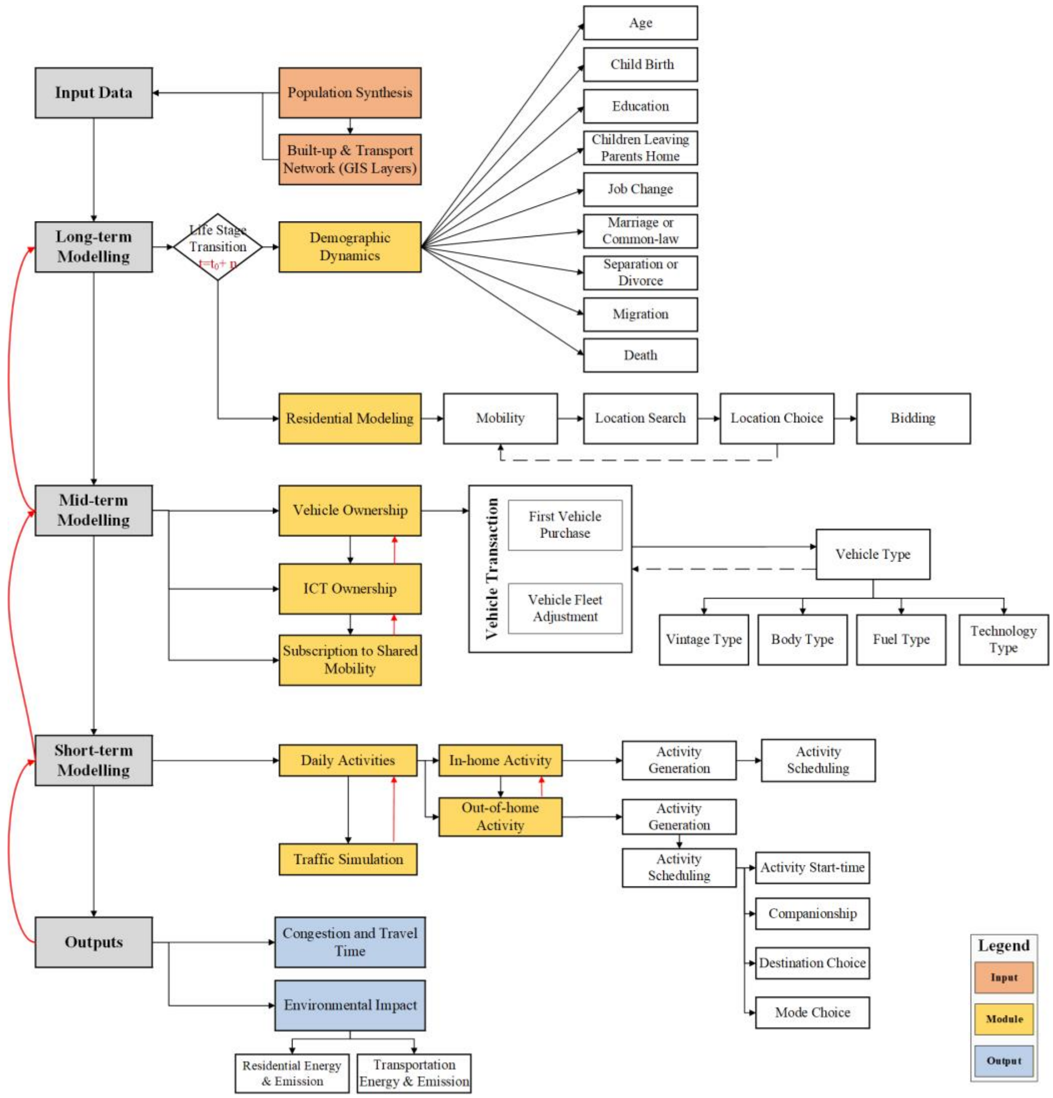


Figure 1. Conceptual framework of STELARS (Khalil et al., 2024)

3 Study area and data source

The vehicle ownership simulation exercise in this study is performed for the Greater Okanagan region of British Columbia (BC) (Figure 2). The study area includes the following five cities: Kelowna, West Kelowna, Lake Country, Vernon, and Peachland, which is the home of approximately 222,000 people (Regional District of Okanagan, 2021). The Travel Technology and Mobility Survey (TTMS) conducted in this region in 2019 is used to develop the core behavioral models incorporated in the VOSim module. TTMS is a retrospective survey that collected historical information at the household level, such as residential and employment records, history of vehicle ownership, and a life-cycle event diary. The residential record component collected retrospective information on residential location, household income, household composition, dwelling and tenure types, and technology ownership (e.g., smartphones, computers, Google Home, etc.), among others. This information was collected up to the three most recent residences.

The survey collected the vehicle ownership status of households for both currently and previously owned vehicles (up to ten most recent vehicles). In addition, the make, model year, model, trim level, fuel type, purchase and disposal year, purchase price, and types of technology features available were collected for each of those vehicles. Thus, the temporal evolution of household vehicle fleets was captured in the survey.

The data collected from the survey were later supplemented with land use, built-environment attributes, and neighborhood characteristics, leveraging some secondary data sources. For example, the accessibility to different points of interest, such as restaurants, shopping centers, schools, bus stops, etc., was collected from the Desktop Mapping Technologies Inc. (DMTI) enhanced point of interest (EPOI) dataset (Geospatial Centre, n.d.). The neighborhood characteristics were collected from the 2021 Census Canada (Statistics Canada, 2021). Furthermore, the land use-related information was extracted from the open data platform of the Okanagan region.

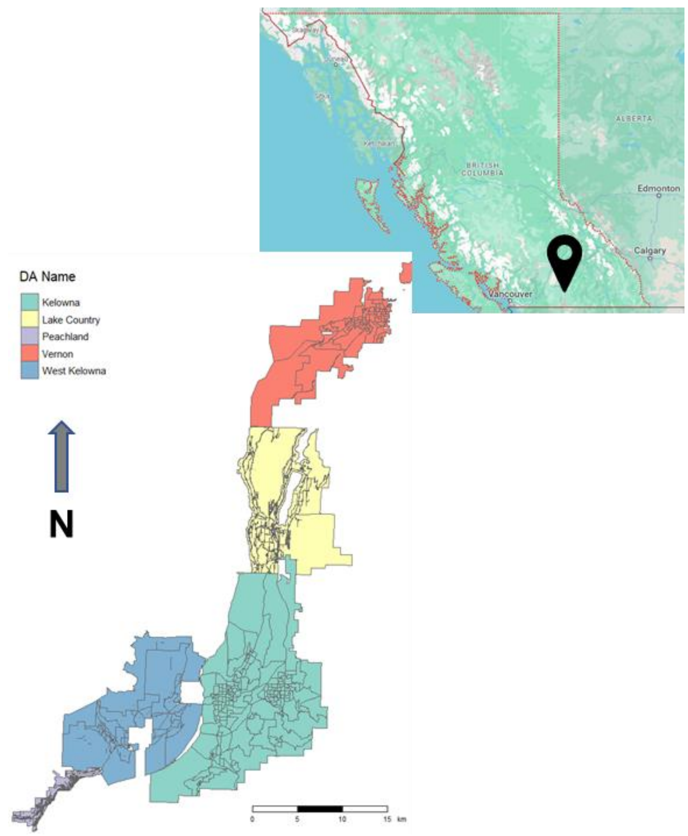


Figure 2. Map of greater Okanagan

4 Vehicle ownership simulation (VOSim) module

4.1 Event-based simulation

In VOSim, households are considered the agents – i.e., the decision-making unit. VOSim adopts an event-based simulation technique where the agents are mostly inactive (except in the base year) and are assumed to become active in the market to purchase or make changes in household vehicle fleets in response to key life-cycle events. Conceptually (Figure 3), agents can become active in anticipation of an event, in immediate response to an event, or as a consequence of an event. The events include residential relocation, addition or change of a job, birth of a child, marriage, and divorce, among others. The list of events comes from empirical evidence, reported in the next section, while discussing different model components and their estimation procedure.

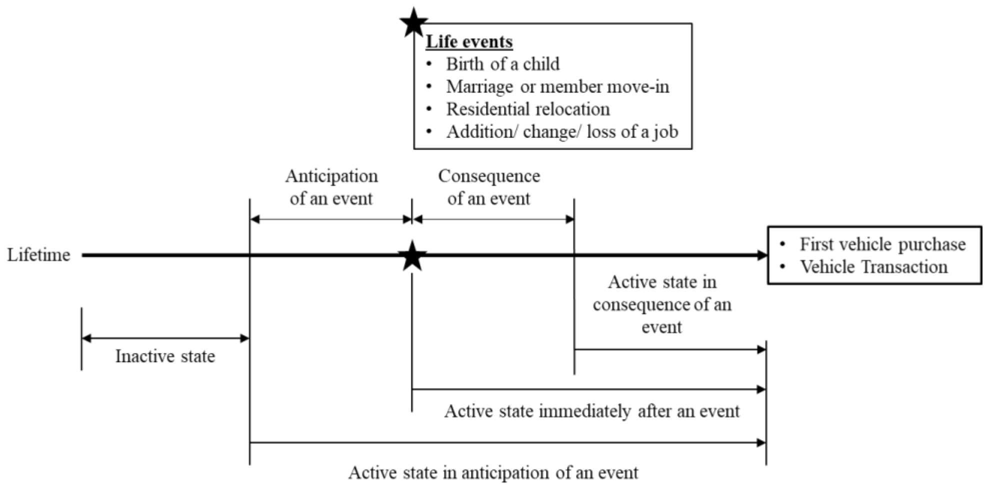


Figure 3. Concept of event-based simulation

4.2 Continuous-discrete simulation

Figure 4 below illustrates the conceptual framework utilized in implementing the Vehicle Ownership Simulation (VOSim) module within the STELARS. VOSim receives input from the long-term decision stage in STELARS, which includes demographic dynamics and residential locations over time. This VOSim module includes two interdependent phases, adopting a hybrid of continuous (phase 1: transaction timing) and discrete time (phase 2: vehicle type choice) simulation techniques. The two-way interactions between phases 1 and 2 have been accommodated in simulation using the expected maximum utility of the lower-level decision (phase 2). The first phase involves the simulation of the vehicle transaction timing decisions. In this phase, household agents are divided into two groups based on their vehicle ownership history. One group is identified as vehicle-free household agents, which refers to the households that have not owned a vehicle to this point in their simulated lifetime. The rest are identified as vehicle-owned households, who owned a vehicle in their lifetime. In the first phase, the first vehicle purchase timing decision is simulated for the vehicle-free households. In the case of vehicle-owned households, vehicle transaction decisions are simulated, which include: additions (adding another vehicle to an existing vehicle fleet of the household), disposals (selling an existing vehicle without purchasing another), or trades (selling an existing vehicle and acquiring another in the same year). Both the timing of the first vehicle purchase and vehicle transaction decisions are simulated at a continuous time scale using a hazard-based duration model. The baseline hazard function of the hazard-based duration model usually captures the increasing probability of a vehicle transaction as time progresses, while the life events accelerate the overall hazard. Consequently, in this phase, VOSim directly simulates the duration (in years) until a household agent's next vehicle transaction, instead of stepping through year by year to determine whether a transaction occurs. This method ensures a more efficient and behaviorally representative approach compared to the traditional models, where each agent's vehicle transaction probability is evaluated on a yearly basis.

In the second phase, vehicle type choice decisions are simulated only for those households who are making either a first vehicle purchase or a transaction decision. This vehicle type choice component runs at a discrete-time step for the year identified in the timing model. Vehicle type choice includes body type (i.e., subcompact, compact, midsize/large, SUV, and van/truck), vintage (new, used, and old), fuel type (gasoline, diesel, and AFV), and advanced technology (available or not). A brief description of the model estimation procedure and results is presented below.

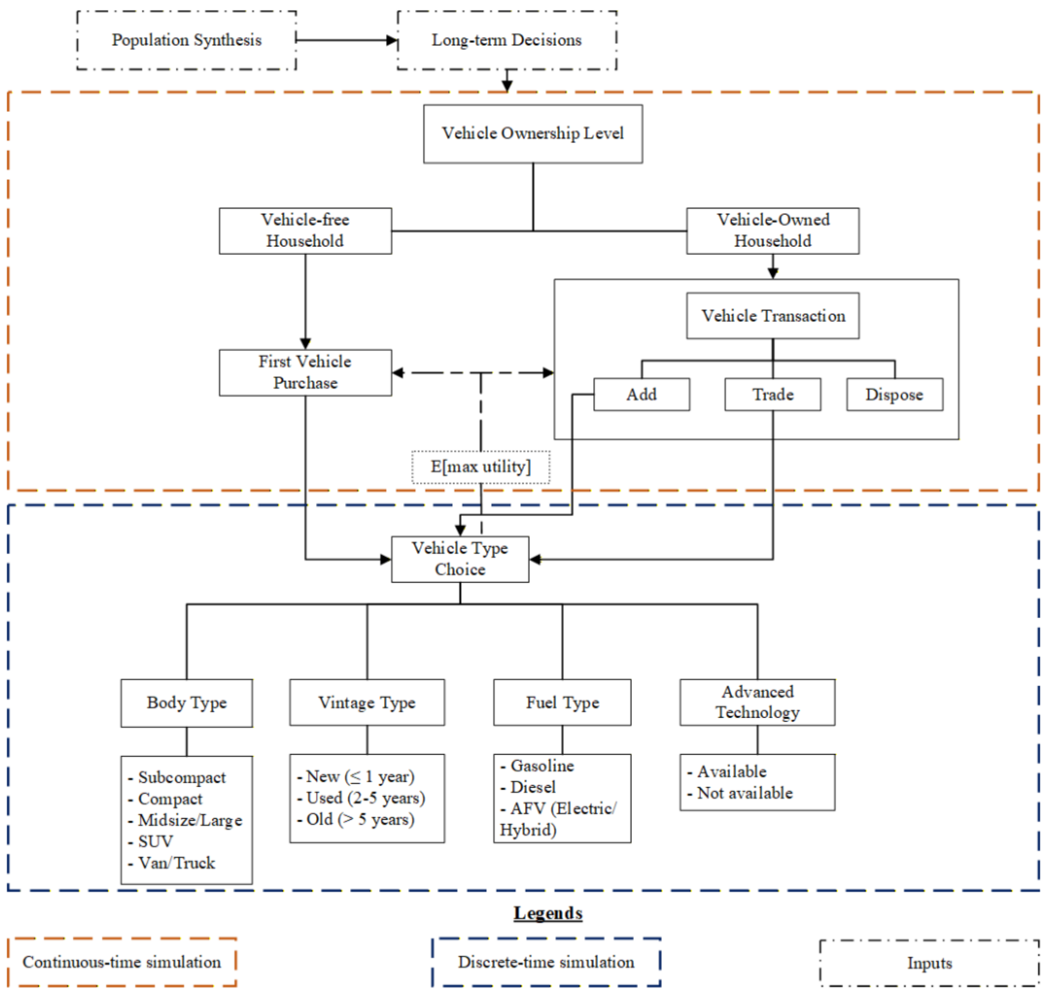


Figure 4. Microsimulation framework of the VOSim module of STELARS

4.3 Phase 1: Vehicle purchase timing

4.3.1 Modeling methodology

The first vehicle purchase timing and vehicle transaction duration, i.e., the duration to add, trade, and dispose a vehicle, are investigated using the hazard-based duration modeling technique. The probability of a household of failure $h(t)$ of a household q to survive without making a transaction until time t is as follows:

$$h_q(t) = \lim_{\Delta t \to 0} \left(\frac{P(t + \Delta t \geq T_q \geq t | T_q \geq t)}{\Delta t} \right) = h_{0q}(t) e^{-\beta x_q} \qquad (1)$$

where, household q survived without making a transaction until the duration T_q, h_{0q} is the baseline hazard function, x_q is the vector of explanatory variables, and β is the corresponding vector of coefficients. Assuming a Weibull distribution, equation (1) can be written as follows:

$$h_q(t) = \lambda t^{\lambda-1} e^{-\beta x_q} \quad (2)$$

where, λ denotes the shape parameter of the Weibull distribution. The survival function $S_q(t)$, which represents the probability of a household q surviving without making a transaction until time t takes the following form:

$$S_q(t) = e^{-\int_0^t h_q(\vartheta)d\vartheta} \quad (3)$$

Equations 2 and 3 are utilized to form the likelihood function, which is maximized to estimate the parameters. It is worth mentioning that the model was tested under different baseline hazard distributions, such as Weibull, log-logistic, and log-normal distributions. The distribution that results in the best model fit in terms of goodness-of-fit measures, such as the likelihood function, adjusted pseudo r-squared, and Bayesian Information Criterion (BIC), was considered for the final model.

4.3.2 First vehicle purchase timing

The first vehicle purchase timing is simulated for vehicle-free households (defined above), which predicts the timing at a continuous time scale. The underlying behavioral model developed to investigate the timing of first vehicle purchase is a hazard-based duration model. The model predicts the timing of when the car-free stage of the household is terminated following the first vehicle purchase. The model adopted an accelerated lifetime approach to reveal the effect of the covariates (Bhat & Pinjari, 2007). The log-logistic baseline hazard is considered for this model as it provides the best fit, and the survival probability is considered to be 50% to estimate the duration of termination (Qiao et al., 2019). For more details on model estimation and goodness of fit, see Hossain and Fatmi (2025). The list of variables retained in the final model is shown in Table 1.

Table 1. Variables in the first vehicle purchase timing model

Category	Variables
Life-cycle events	• Birth of a child in the household • Residential move • Addition of a job • Change of a job • Loss of a job
Built-environment attributes	• Land use index within 1000m radius of the residence • Percentage of residential area within 1000m radius of the residence • Employment rate in the residential dissemination area • No. of bus stops within 1000m radius of the residence • Bus stop distance < 1 km from the residence
Mobility tools	• No. of transit pass in the household • No. of bikes in the household
Socio-demographics	• Annual household Income ≥ 100,000 • No. of adults (age ≥ 18) in the household • No. of children • Dwelling type: semi-detached • Dwelling type: apartment • Dwelling type: townhouse
Expected maximum utility parameter	• Expected maximum utility of vehicle body type

This empirical exercise generates the list of events that activate a car-free household to make their first vehicle purchase. The events include the birth of a child, member move-in, residential relocation, addition of a job, and loss of a job. The results also confirm several other key factors that affect the timing of the first vehicle purchase, such as built-environment characteristics (e.g., land use index representing the land-use mix in the residential neighborhood), mobility tools (e.g., owning a transit pass), and socio-demographic attributes (e.g., income).

4.3.3 Vehicle transaction decisions

Vehicle transaction decisions are simulated for households owning a vehicle. This component simulates the timing for the addition, trading, and disposal of a vehicle. Similar to the first vehicle purchase model, it uses a hazard-based methodology to determine the year in which a household will make a transaction. Then, the vehicle type choice model is implemented to determine what type of vehicle to add or trade in. In the case of trading out or disposing a vehicle, this decision involves the removal of a vehicle from the household vehicle fleet.

When households own multiple vehicles, the decision of which vehicle to remove from the fleet follows a systematic, hierarchical approach based on three key criteria. The vehicle's vintage serves as the primary selection factor for disposal, with the oldest vehicle in the household fleet prioritized for removal. Existing literature consistently identifies age as the most critical determinant in vehicle disposal decisions (Jin et al., 2022), as vehicles experience declining reliability and increasing maintenance costs over time. These factors naturally drive vehicle owners towards replacement decisions.

When multiple vehicles share the same vintage, the presence of advanced technology becomes the deciding factor. Vehicles lacking advanced technology features are prioritized in this case for disposal over those equipped with them. The tangible benefits of advanced technology, including enhanced safety features, improved driving convenience, and stronger resale values, make vehicles with advanced technology more valuable to retain in the household fleet. Furthermore, if both vehicle age and technology types are identical, fuel types serve as the final criterion for disposal. Gasoline and diesel vehicles are selected for disposal before AFVs, assuming the long-term environmental benefits and lower operating costs associated with AFVs.

Table 2 shows the model results for vehicle transaction decisions. The results provide empirical evidence regarding a subscribed list of events that trigger the decision to make a vehicle transaction. The events include the birth of a child, a member moving in, marriage, residential move, and addition or change of a job. For instance, following the birth of a child, households are more likely to add a vehicle. Immediately after a residential move, households have a higher likelihood of both adding and trading a vehicle. However, they are less likely to dispose of a vehicle. Following a change of job, households show a higher likelihood of vehicle disposal. The results further reveal that households living farther from the urban center are more likely to add vehicles to the fleet. On the other hand, living closer to school is found to accelerate vehicle disposal. In the case of mobility tool ownership, a higher number of vehicles is found to accelerate vehicle disposal from the household. Interestingly, households owning bikes are less likely to add or trade a vehicle. Furthermore, high-income households are more likely to add and trade a vehicle, whereas they are less likely to dispose a vehicle. Finally, to capture interdependencies between transaction and vehicle type choice decisions, expected maximum utility parameters from vehicle type choice dimensions, such as vehicle technology and vintage type models, are tested and found to be significant for vehicle addition and trading.

Table 2. Vehicle transaction model results

Variables	**Addition Coeff.**	**Addition *t*-stat**	**Trade Coeff.**	**Trade *t*-stat**	**Disposal Coeff.**	**Disposal *t*-stat**
Constant	1.77	10.05	1.61	15.45	2.21	16.61
Life-cycle events and longer-term changes						
Birth of a child same year	-0.77	-5.44	-	-	-	-
Member move in the same year	-	-	0.33	2.06	-	-
Member move in or marriage in the same year	-0.28	-1.75	-	-	-	-
Residential move in the in the same year	-0.84	-2.93	-0.78	-7.71	0.75	6.43
Addition of a job in the same year	-0.25	-1.91	-0.67	-4.01	-	-
Change of a job in the same year	-	-	-	-	-0.81	2.06
Built-environment						
Land use index	-	-	0.58	4.24	-	-
Distance to urban core	-0.02	-1.63	-	-	-	-
Bus stop distance < 1km	0.29	2.94	-	-	-	-
Distance to school<3 km	-	-	-	-	-0.16	-3.64
% of residential area	-0.36	-1.69	-0.58	-4.25	-	-
Mobility tools						
No. of vehicles	-	-	-	-	-0.08	-2.97
Vehicle per adult	-	-	0.28	6.06	-	-
Owns bike	0.73	11.17	0.29	2.91	-	-
Owns transit pass	-	-	-	-	-0.80	-9.00
Socio-demographics						
Income 50,000-99,999	-0.36	-4.40	-	-	-	-
Income ≥ 100,000	-0.04	-0.56	-0.32	-3.86	0.22	2.26
No. of children	-	-	-0.17	-5.36	-	-
Number of individuals in the household	-	-	-	-	0.08	2.97
Owned house	-	-	-	-	0.73	6.51
Expected maximum utility parameters						
For technology type	-0.36	-2.32	-0.001	-5.40	-	-
For vintage type	-	-	-0.11	-3.85	-	-
Other parameters						
Shape Parameter	0.72	29.25	0.46	18.82	0.49	21.00

4.4 Phase 2: Vehicle type choice decisions

4.4.1 Modeling methodology

The vehicle type choice decisions at this phase are investigated using a multi-dimensional probit modeling technique. The vehicle type dimensions considered are vehicle body, vintage, fuel, and technology types. The model accommodates the unobserved correlation that exists across different vehicle choice dimensions. For a household h, the utility function for a choice alternative of a vehicle type dimension is expressed as follows:

$$U_{ki_kh} = \beta'_{ki_k} x_{ki_kh} + \varepsilon_{ki_kh}$$

Here,
i_k = index denoting the alternatives of k^{th} vehicle type dimension = 1, 2, …, I_K
x_{ki_kh} = the vector of explanatory variables
β_{ki_k} = the vector of the corresponding coefficient
ε_{ki_kh} = normal error term with a mean of zero and variance of one
The error term in the above utility equation ε_{ki_kh} is assumed to have a covariance structure that captures the unobserved correlation among the alternatives within and across vehicle type dimensions k.

The above utility function is used to form the likelihood function that is maximized using the maximum approximate composite marginal likelihood (MACML) proposed by Bhat (2011) to estimate the parameters associated with different vehicle type choices.

4.4.2 Vehicle types

In the second phase, the vehicle type choice decision is simulated for households purchasing the first vehicle or making a vehicle transaction. For the first vehicle purchase, the following vehicle types are considered: vehicle body, vintage, and technology types. Vehicle body type alternatives include subcompact, compact, midsize/large cars, SUVs, and van/trucks. Vehicle vintage is categorized as new (vehicles not older than 1 year), used/old (more than 1 year old). Additionally, for technology type, the choice is between vehicles with advanced technology features (e.g., parking assist, lane-keep assist, blind-spot detection, or autonomous emergency stop) and those without.

The list of variables of the vehicle type choice model results is presented in Table 3. The key factors affecting vehicle type preference during the first vehicle purchase are life-cycle events (e.g., birth of a child, addition of a job, etc.), built environment attributes (e.g., land-use mix), mobility tools (e.g., bikes and transit pass), technology ownership (e.g., owning a computer), and socio-demographic characteristics (e.g., income, age, number of children, etc.), among others. A detailed discussion of the modeling technique and results can be found in Hossain and Fatmi (2025).

Table 3. Variables in the first vehicle type choice model

Category	Variables
	Vehicle Body Type
Life-cycle	• Birth of a child in the household • Member moving in the household • Addition of a job
Built-environment attributes	• Land use index within 1000m radius of the residence • Urban core distance from the residence < 3 km • Bus stop distance from the residence < 1 km • Commute distance < 3 km
Mobility tools	• No. of transit pass in the household • No. of bike in the household
Socio-demographics	• Annual household income 30,000-79,999 • Annual household income ≥ 80,000 • Avg. age of adults (age ≥ 18) • No. of children =1 • No. of children > 1 • Rented house • Dwelling type: single-detached
	Vehicle Vintage Type
Life-cycle	• Birth of a child in the household • Member moving in the household • Residential move • Addition of a job
Built-environment attributes	• Land use index within 1000m radius of the residence • Bus stop distance from the residence < 1 km

Category	Variables
Socio-demographics	• Annual household income < 50,000 • Annual household income 50,000-79,999 • Annual household income ≥ 150,000 • Rented house • Dwelling type: semi-detached • Dwelling type: apartment • Dwelling type: townhouse
Technology Type	
Life-cycle	• Birth of a child or member moving in the household • Change of job
Technology ownership	• Owns a computer in the household: yes • Owns Google home in the household: yes
Built-environment attributes	• Land use index within 1000m radius of the residence • Dwelling density in the residential dissemination area • Commute distance < 3 km
Socio-demographics	• Annual household income < 30,000 • Log of avg. age of adults (age ≥ 18) • Owned house • Dwelling type: single-detached • Dwelling type: townhouse • Dwelling type: apartment

Note: Base alternative for body type: van or truck; Base alternative for vintage type: used/old vehicles; and Base alternative for presence of technology: technology not available

In the case of vehicle transactions, the vehicle type dimensions include vehicle body, vintage, and technology type, similar to the first vehicle purchase. Additionally, the vehicle fuel type dimension is considered during this transaction, which includes gasoline, diesel, and AFV alternatives. The list of variables used in the vehicle type models during vehicle transactions is presented in Table 4. The key factors affecting vehicle type preference during vehicle transactions are socio-demographic characteristics (e.g., income, age, number of children, etc.), mobility tools (e.g., bikes and transit passes), and built environment attributes (e.g., land-use mix), among others. One of the key findings from the vehicle type choice models is the significant effect of historical exposure on vehicle preferences. For example, vehicle body, vintage, and fuel type choices are found to be influenced by the current vehicle fleet composition. Additionally, vehicle technology preference is found to be influenced by historical exposure to technology. A detailed discussion and interpretation of model results can be found in Hossain et al. (2023).

Table 4. Variables in the vehicle type model

Category	Variable
Vehicle Body Type	
Historical exposure to vehicles	• Currently own subcompact • Currently own compact • Currently own midsize/large • Currently own SUV • Currently own van/truck
Mobility tools	• No. of vehicles in the household • No. of bikes in the household
Built-environment attributes	• Land use index within 1000m radius of the residence • Percentage of residential area within 1000m radius of the residence

Category	Variable
Socio-demographics	• Annual household income < 50,000 • Annual household income 50,000-79,999 • Annual household income 80,000-99,999 • Presence of children in the household: no • No. of children in the household • No. of adults (age ≥ 18) in the household • Rented house • Dwelling type: semi-detached • Dwelling type: apartment
	Vehicle Vintage Type
Historical exposure to vehicles	• Currently own new • Currently own used • Currently own old
Mobility tools	• No. of vehicles
Socio-demographics	• Annual household income 80,000-99,999 • Annual household income ≥ 100,000 • Average age of adults (age ≥ 18) in the household • Owned house • Dwelling type: owned & single-detached • Dwelling type: single-detached • Dwelling type: townhouse • Dwelling type: apartment
	Vehicle Fuel Type
Historical exposure to vehicles	• Currently own alternative fuel vehicle (AFV) • Currently own gas vehicle
Mobility tools	• Vehicle per adult • Vehicle price • Bike ownership: yes • Transit pass ownership: yes
Built-environment characteristics	• Commute distance • Distance to the nearest school • Distance to the nearest eating/drinking place
Socio-demographics	• Annual household income < 50,000 • Annual household income 50,000-79,999 • Annual household income ≥ 150,000 • Average age of adults (age ≥ 18) in the household • Dwelling type: single-detached
	Technology Type
Historical exposure to technology	• No. of smartphones per person • No. of laptops per person • Historically own advanced technology in vehicles • Historically own AFV
Socio-demographics	• Annual household income 80,000-99,999 • Annual household income ≥ 150,000 • Average age of adults (age ≥ 18) in the household • Dwelling type: owned & single-detached • Rented house

Note: Base alternative for body type: van or truck; Base alternative for vintage type: old vehicles; Base alternative for fuel type: diesel; and Base alternative for presence of technology: technology not available

The vehicle type choice models are linked to vehicle transaction duration models through expected maximum utility. The expression of expected maximum utility in the MNP model is not in closed form, unlike the GEV-based model. Hence, it is approximated using the Monte carlo Simulation technique. In this process, the maximum utility is calculated for a repeated number of draws taken from the multivariate normal distribution, and then averaged across the draws. Finally, the resulting simulated expected maximum utility is included as the independent variable in the vehicle transaction model to capture the interdependencies between vehicle type choice and vehicle transaction decisions.

5 VOSim microsimulation and validation

The VOSim module of STELARS has been implemented for the greater Okanagan (Kelowna, West Kelowna, Lake Country, Peachland, Vernon) population from 2011 to 2021. The Python programming language is used to code the VOSim module. The current runtime for a 10-year simulation of approximately 85000 households (i.e., 100% population for Okanagan) is only about 10 seconds using a computer equipped with an Intel ® Core ™ i7-10750H CPU @ 2.60 GHz processor and 32GB RAM. This significantly faster simulation is achieved by using the vectorization technique in Python (Khalil et al., 2024).

To assess the accuracy of the vehicle ownership simulation results, a multi-year validation was conducted. This validation utilized an independent travel survey dataset obtained from city authorities, which had not been incorporated during the model training phase. The validation dataset was sourced from the Okanagan Travel Survey data, which contains a representative sample of the Okanagan population (Regional District of Central Okanagan, 2013; Regional District of Central Okanagan, 2018). Firstly, the VOSim Module is validated by comparing the observed and predicted number of vehicle ownership of the households for the years 2013 and 2018 (Figure 5).

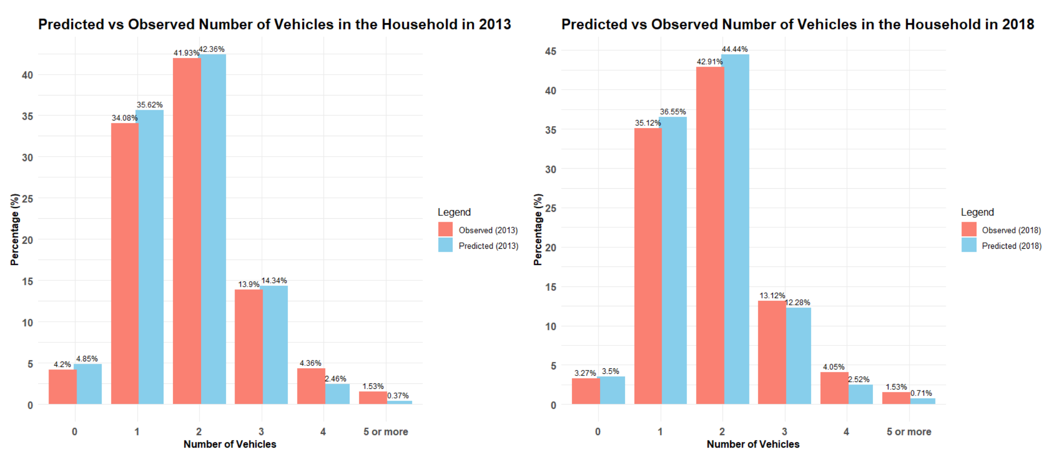


Figure 5. Observed vs. predicted number of vehicles in the household for the years 2013 and 2018

The comparison reveals very minor differences in the observed and predicted levels of vehicle ownership for both years. For instance, zero-vehicle households are over-predicted both in 2013 and 2018 by 0.65 percentage points and 0.23 percentage points, respectively. A similar trend is observed for households owning 1, 2, and 3 vehicles, where the maximum difference between the predicted and observed share of households is 1.9 percentage points. On the other hand, households owning 3, 4, and 5 or more vehicles show a difference of <2 percentage points for both simulation years.

Further validation is performed for the vehicle body and fuel types for the year 2018 (Figure 6). For vehicle body type validation, several categories, such as subcompact, compact, and midsize/large cars, were aggregated into "passenger cars" in order to match the categories available in the 2018 OTS data. The observed and predicted share of passenger cars in 2018 is 45.36% and 43.91%, with a minor difference of 1.45 percentage points. The VOSim slightly over-predicts SUVs and van/trucks with a margin of less than 1 percentage points. Finally, the fuel type prediction results show that gasoline vehicles are slightly under-predicted, while diesel and AFVs are over-predicted by a narrow margin. Overall, the validation results illustrate that the prediction of VOSim reasonably fits the observed data and, therefore, the prediction performance of the model is considered satisfactory. However, vehicle type validation for 2013 could not be performed due to data unavailability.

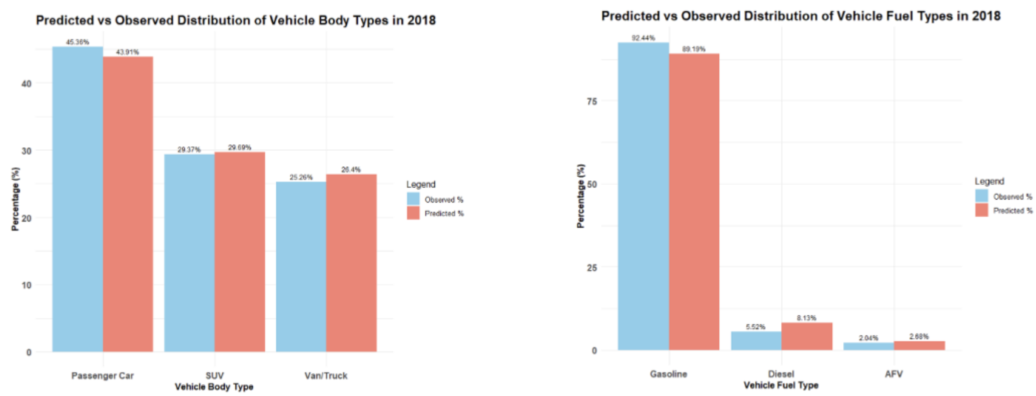


Figure 6. Observed vs. predicted vehicle body and fuel types in the household for the year 2018

6 Analysis of the prediction results

In this section, we highlighted the key insights derived from the VOSim outputs. Initially, we did the spatio-temporal analysis to reveal the characteristics of the households with different vehicle ownership levels. Next, we presented the predicted vehicle type distribution for the study region. Finally, we leveraged the STELARS framework to explore the characteristics of the households making different vehicle transactions, such as their socio-economic attributes and the characteristics of the built environment where these households reside.

6.1 Vehicle ownership level

In this section, the prediction of the vehicle ownership levels over the 10-year period is discussed. The average vehicle ownership per household is predicted to range between 1.70 to 1.80 over the years, which demonstrates relatively stable prediction results. This study further delves into exploring the vehicle ownership level of households by the distance of their residence from the urban centers (Figure 7). The results are generated for the simulation years 2012-2021. The distribution for the 10-year period again shows that the simulation results are relatively stable over the years. One of the important findings from this distribution is that the share of zero-vehicle and single-vehicle households is significantly higher in areas within 5 kilometers of the urban centers. In the case of multi-vehicle households, the distribution starts to skew towards locations farther away from the urban centers.

To further understand the predicted spatial distribution of different vehicle ownership levels, Figure 8 presents this result visually in maps, with 2021 shown as an example. In the case of the City of Kelowna, there are five urban centers: Downtown, Capri Landmark, Pandosy village, Midtown, and Rutland centers (City of Kelowna, 2022). The visualization reveals that the density of zero-vehicle households is predicted to be the highest within these five urban centers, which have good transit facilities, bike infrastructures, and nearby destinations. Interestingly, in the case of single-vehicle households, the density is higher within and in the peripheral areas of these urban centers. In the case of multi-vehicle households, the density is found to be relatively higher in areas farther from the urban centers; specifically, suburban neighborhoods such as Upper Mission and Kettle Valley neighborhoods.

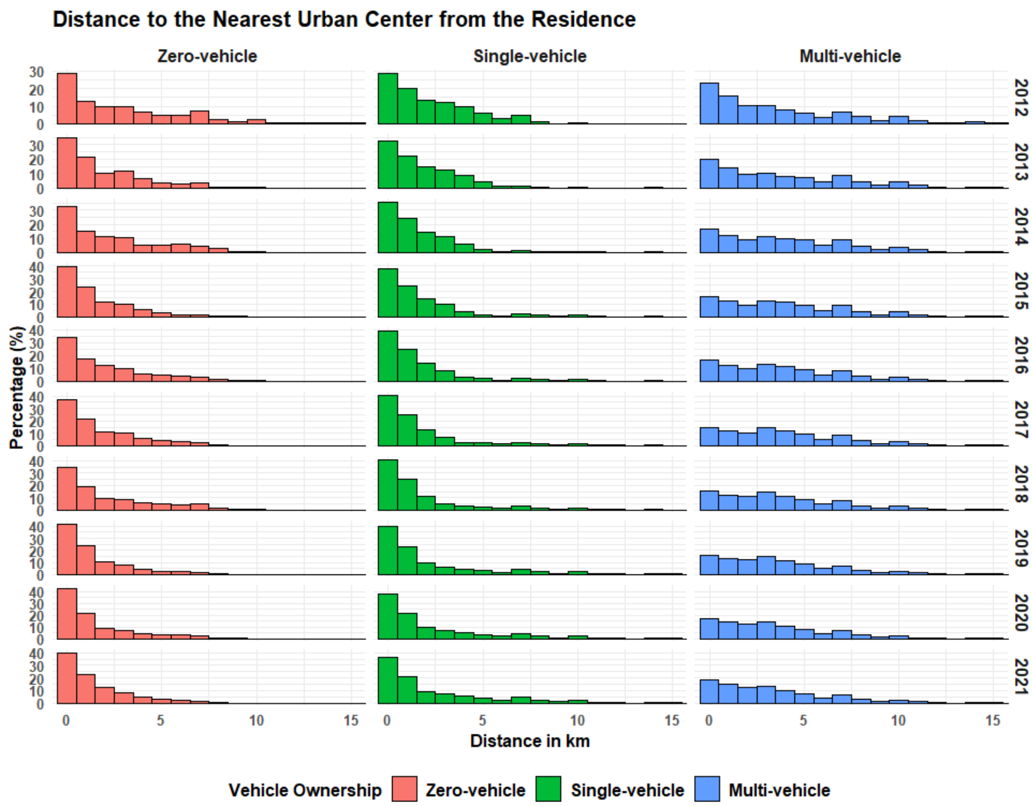


Figure 7. Predicted distribution of households' vehicle ownership level by the distance of residence from the urban centers in 2021

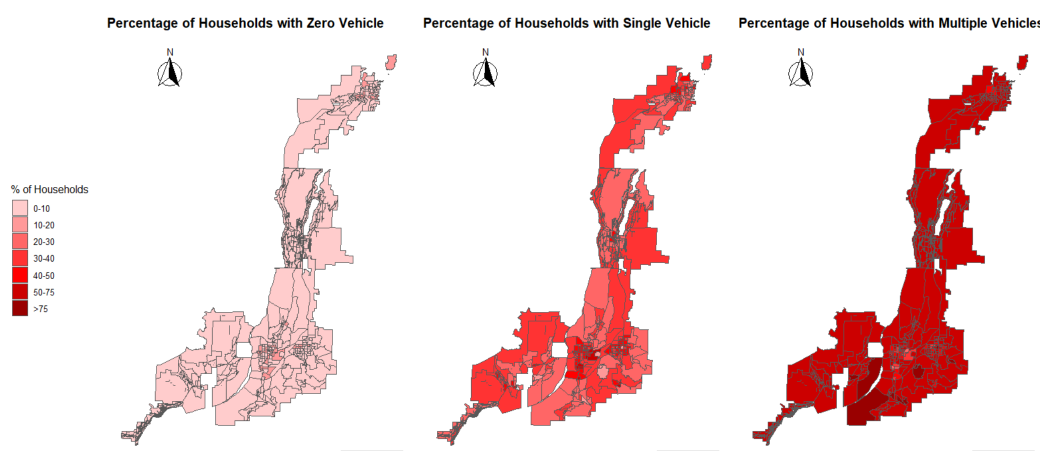


Figure 8. Spatial distribution of vehicle ownership level in 2021

6.2 Vehicle types

In Figure 9, the overall predicted shares of different vehicle types are presented for the year 2021. Among the vehicle types, the share of larger vehicles such as SUVs and vans/trucks is found to be the highest, and as the size decreases, the share of the vehicles also decreases. The predicted share of vehicles by their vintage shows that half of the vehicles owned by households are new, whereas the other half of the vehicles are either used or old, with older vehicles having a slightly larger share.

In the case of vehicle fuel types, the majority of the vehicles are predicted to be gasoline vehicles (88%), followed by a small share of diesel vehicles (10%) and AFVs (3%). Furthermore, about 78% of the vehicles owned are predicted not to have advanced vehicle technology, whereas the rest 22% include advanced technology.

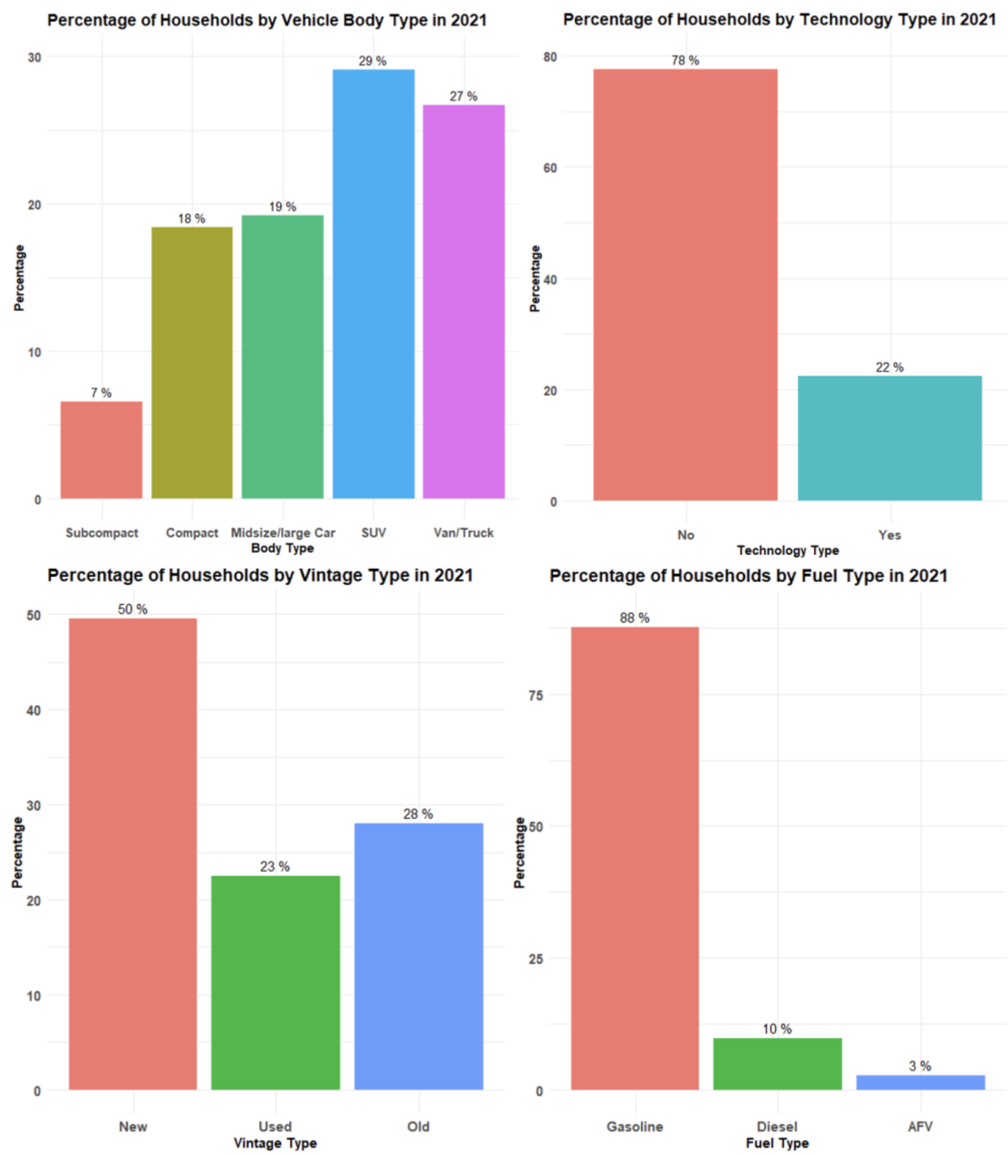


Figure 9. Distribution of different vehicle types owned by households

6.3 First vehicle purchase

6.3.1 Predicted characteristics of the households purchasing their first vehicle

The prediction results reveal consistent characteristics of the first vehicle purchasers over the 10-year simulation period in terms of their socio-demographic and built-environment attributes. Figure 10 illustrates the prediction results of the households that purchased their first vehicle in 2021. The histograms in Figures 10(a) and 10(b) depict the characteristics of the households that have purchased their first vehicle, based on annual household income and the average age of the household members. The largest share of the first vehicle purchasers is predicted to be mid-income (annual income $40,000 - $49,999) households. The distribution of age suggests that a higher share of relatively younger and middle-aged households is predicted to purchase their first vehicle.

Figures 10(c) and 10(d) show the relative frequency of these households in terms of where they live. The results indicate that the number of households purchasing their first vehicle is living in neighborhoods having a higher share of residential areas, longer commutes, and fewer bus stops. These results imply that households purchasing their first vehicle are mostly living in a more residential area-oriented neighborhood, which is usually the case in suburban areas with less accessibility to alternative transportation modes.

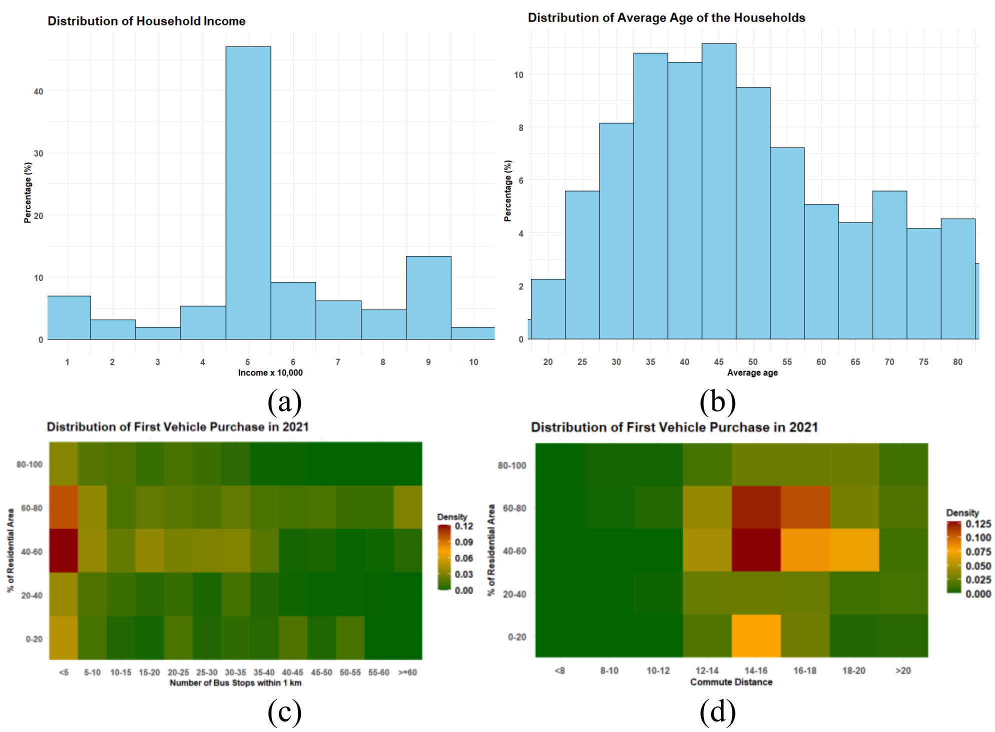


Figure 10. Predicted distribution of the households purchasing their first vehicle in 2021 by their demographic and built-environment attributes

6.3.2 Predicted vehicle types and the households

The study analyzes the characteristics of the first vehicle purchasers for different vehicle types. A distribution of the prediction results for the vehicle types that the households choose as their first vehicle is presented in Figure 11. The majority of households purchasing passenger cars, such as subcompact, compact, and midsize/large cars are predicted to live closer to the urban core but commute longer distances. On the other hand, the highest density of households purchasing larger vehicles such as SUVs and vans/trucks is predicted to live farther from the urban core. Interestingly, they are predicted to commute longer distances compared to passenger car owners.

The kernel density plots in Figures 11(c) and 11(d) illustrate the spatial distribution of the predicted households purchasing their vehicles by vintage and technology types. The results indicate that the density of households living closer to the bus stops is higher for used/old vehicle owners compared to new vehicle owners. Additionally, the density of households living closer to the urban centers and purchasing advanced vehicle technology is predicted to be lower compared to others. These results might imply that households living closer to the urban core and closer to bus stops have access to alternative transportation modes and require less driving. Hence, they are reluctant to invest more to purchase newer vehicles with advanced technology.

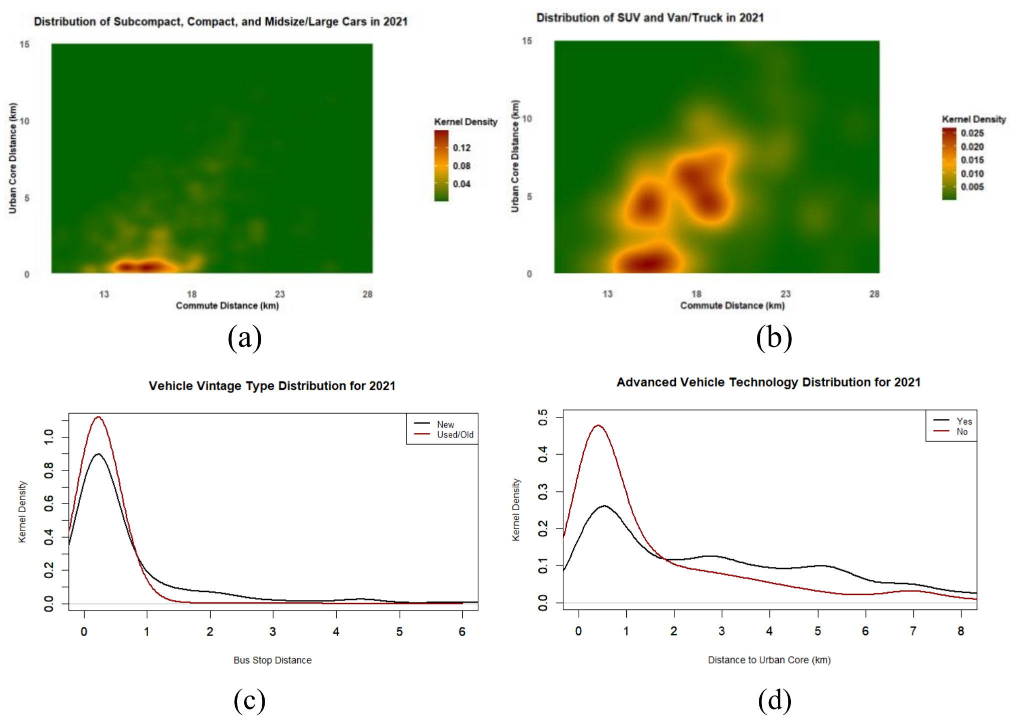


Figure 11. Predicted distribution of vehicle body (a & b), vintage (c), and technology type (d) households purchasing their first vehicle in 2021

6.4 Vehicle transaction of vehicle-owned household

6.4.1 Characteristics of vehicle-owned households making vehicle transactions

The predicted distribution of households making vehicle transactions by adding, trading, and disposing a vehicle (in 2021) by their household income and average age of the members is presented in Figure 12. Overall, the middle-aged group of people (average age ranging from 30 to 50) is predicted to be mostly active in the market, making different types of vehicle transactions. While focusing on annual household income, higher-income households are predicted to be adding and trading vehicles. On the other hand, the plot for disposal shows higher density for the lower- and middle-income groups. These households might have lower affordability, which led them to dispose their vehicles. However, a secondary cluster among the higher-income people is predicted to dispose their vehicles also. One possible reason for such observation might be that these high-income people are more environmentally conscious and thus might be disposing their vehicles.

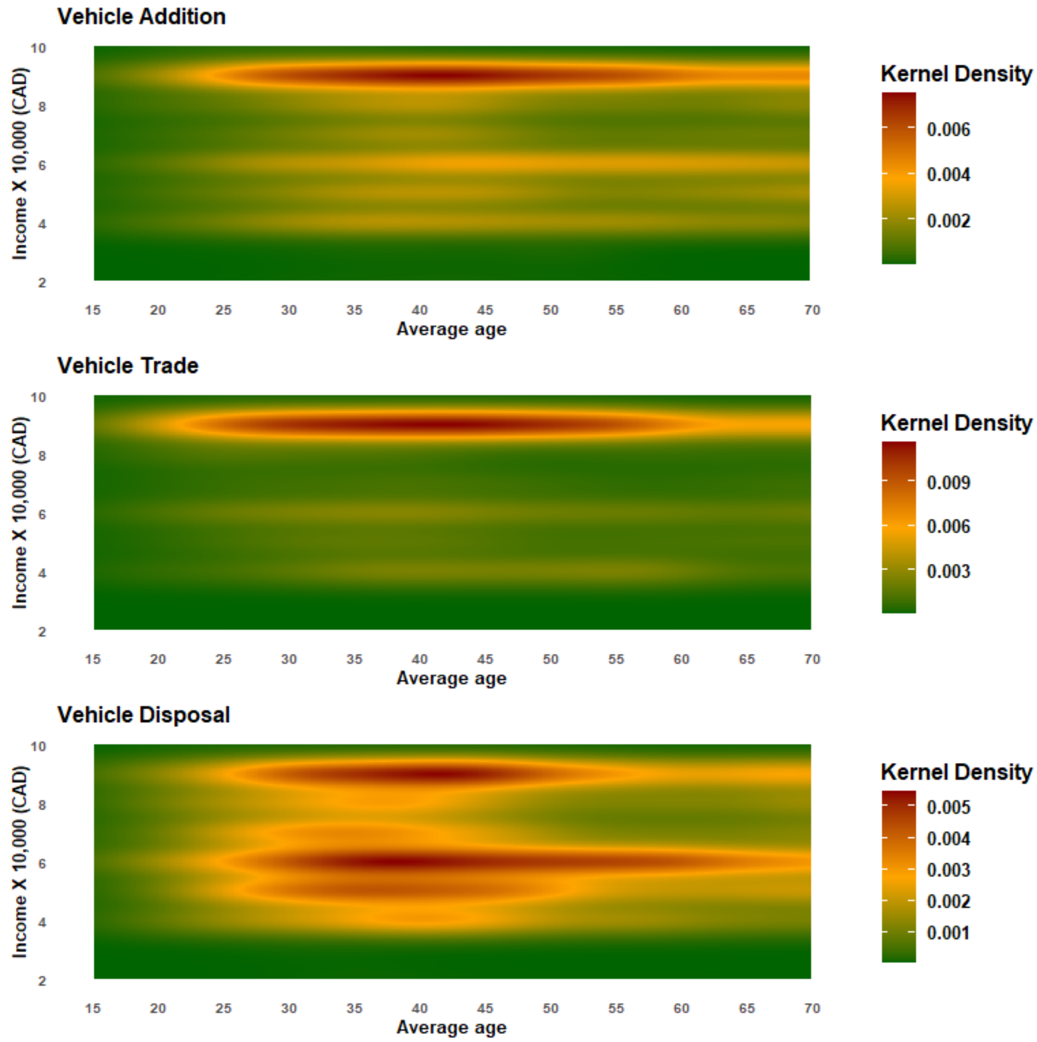
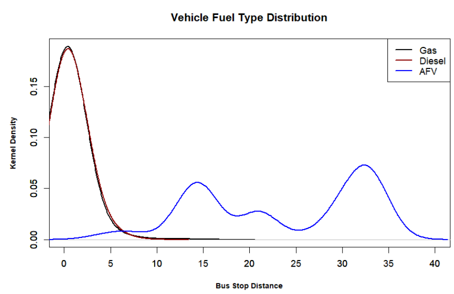


Figure 12. Predicted distribution of age and household income for vehicle addition, vehicle trading, and vehicle disposal in 2021

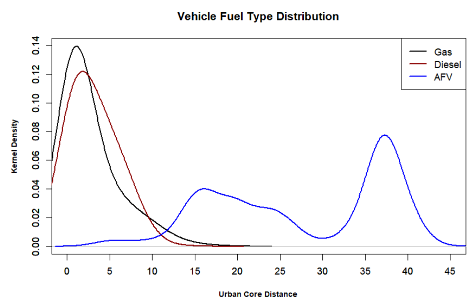
6.4.2 Predicted vehicle types

The prediction results for vehicle types, specifically, the fuel types in the case of adding or trading in a vehicle by households, are illustrated in Figure 13. The kernel density plots indicate that households living in low-density areas, farther from the urban centers and bus stops, are predicted to purchase more AFVs compared to gasoline or diesel vehicles.

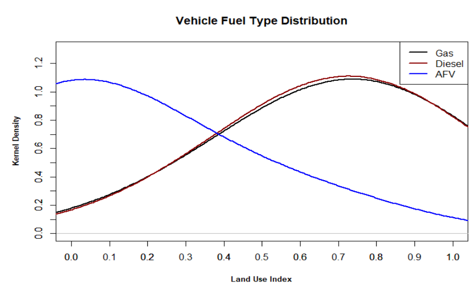
Figure 14 represents the prediction results of the households purchasing advanced vehicle technology using two-dimensional kernel density plots. The density of the households purchasing advanced vehicle technology is found to be higher among the high-income households living in lower land-use mix areas and living in a neighborhood with a very high proportion of single-detached houses. These results might represent the suburban dwellers who often drive more. They might prefer such vehicles because of the safety and comfort provided by these while driving. Additionally, Figure 15 shows the purchasers of vehicles with advanced technology by their home ownership types and dwelling types. The results illustrate that the majority of the households that are purchasing advanced vehicle technology are predicted to live in owned and single-detached dwellings. These results again represent the well-off households who have the affordability to purchase such a vehicle, which often has higher prices compared to other vehicles.



(a)

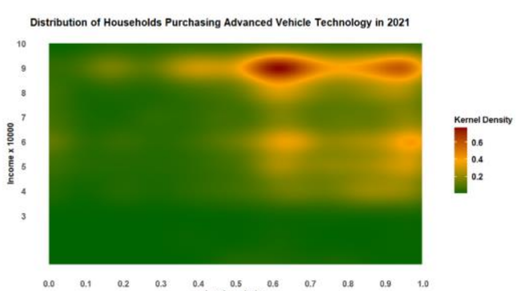


(b)

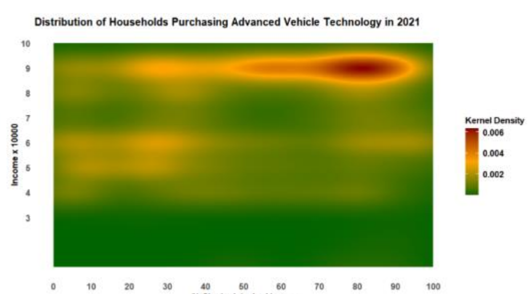


(c)

Figure 13. Predicted distribution of vehicle fuel type in 2021

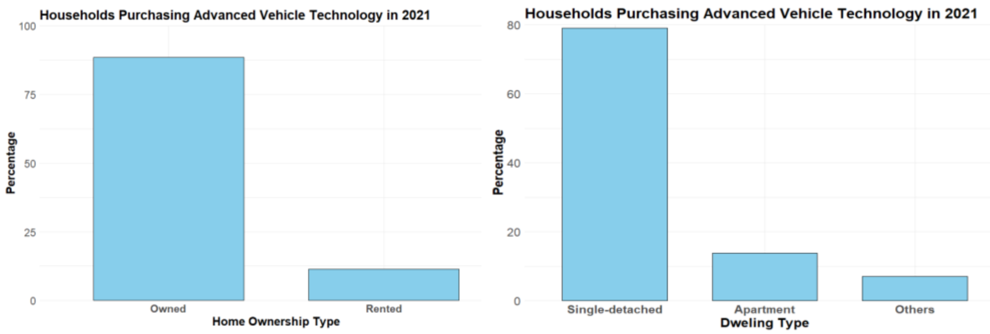


(a)



(b)

Figure 14. Predicted distribution of households purchasing vehicles with advanced technology in 2021



(a) (b)

Figure 15. Predicted distribution of households purchasing vehicles with advanced technology in 2021

7 Conclusions

This study presents the implementation of the VOSim module within an agent-based IUM, known as STELARS. VOSim is conceptualized as an event-based hybrid simulation approach where the vehicle transaction decisions are simulated in a continuous time dimension, and type choices are simulated in discrete time steps. As an event-based approach, agents are assumed to become active in the vehicle market to terminate the zero-vehicle stage or to modify the vehicle fleet in response to key life events, such as the birth of a child. One of the key features of VOSim is its ability to simulate the first vehicle purchases of households. Households that never owned a vehicle in their simulated lifetime are considered in this stage, and their decision to purchase a vehicle, followed by vehicle type choice decisions, is simulated. For the rest of the households, the vehicle transaction model is run to simulate the timing of adding, trading, or disposing of a vehicle, followed by the corresponding vehicle type choices, including body, vintage, fuel, and technology type choices.

The VOSim module currently simulates vehicle ownership for the entire greater Okanagan population for the years 2011 to 2021. Multi-year (i.e., 2013 and 2018) and multi-dimensional (i.e., vehicle ownership levels, body type, and fuel type) validations are performed to assess the performance of the VOSim module. The results demonstrate satisfactory predictive accuracy, with simulated distributions of vehicle ownership levels and vehicle types closely matching observed data within a few percentage points over the analyzed years.

The simulation results reveal that households purchasing AFVs are predominantly high-income and commute longer distances. This finding underscores the need to address equity concerns by supporting low-income households, such as through policies that make AFVs more affordable and enhance their market accessibility. Additionally, the results indicate that households transitioning from zero-vehicle to vehicle-owning status are typically located in areas characterized by a higher proportion of residential developments with limited access to public transit. Enhancing the diversity of housing options in mixed-use areas and improving accessibility to alternative transportation modes could help sustain zero-vehicle lifestyles.

While these insights on vehicle ownership are consistent with existing literature, the true value of VOSim lies in its added capacity to the integrated urban model to simulate vehicle ownership using a behaviorally realistic simulation procedure, providing temporally and spatially disaggregated predictions. This enhanced capacity enables more precise and equitable policy interventions, supporting the development of targeted transportation and land-use strategies across the region. Traditional simulation models typically rely on aggregate forecasting approaches, such as forecasting vehicle ownership levels. These approaches have limited capacity to address critical questions that policymakers might face, such as: When will specific households become active in the vehicle market to make vehicle transactions? Where are these households spatially distributed in a region? What combination of life-cycle events and socio-demographic attributes triggers vehicle ownership decisions? By addressing these concerns, this study predicts vehicle ownership dynamics both spatially and at the household level. This knowledge might help the government and policy planners in introducing actionable policies to address mobility needs and reach sustainability goals. Additionally, VOSim can be utilized to forecast the vehicle ownership evolution under alternative transportation policy scenarios, such as future market sales of AFVs under different incentive scenarios. Thus, VOSim could be an effective tool for the Canadian government to evaluate and compare policy options in support of their future AFV adoption targets.

The VOSim module presented in this study has some limitations. For instance, the unit of time in VOSim is currently represented in calendar years (e.g., 2012, 2013, etc.) rather than in months. As a result, the model cannot identify the specific time of year in which a vehicle transaction occurs. To capture transaction timing and intervals more accurately, future work should focus on developing and integrating behavioral models for vehicle transactions that simulate duration on a monthly basis. Another limitation concerns the lack of consistency among the variable categories across the behavioral models implemented in VOSim. Despite extensive efforts, it was not possible to maintain consistency in the variable categories across the models. Variables were selected based on theoretical justification and statistical significance, which naturally led to model-specific specifications. The primary objective was to estimate the best-fit models within its own context based on the theoretical and empirical evidence rather than prioritizing the consistency of the variable categories. Hence, evaluating how this lack of consistency may influence interactions among the interdependent models falls outside the scope of this study.

Alternative fuel vehicles, such as hybrid, plug-in hybrid, and plug-in electric vehicles, are currently aggregated in the simulation framework. The data used to develop the behavioral models comes from 2019, when the share of these vehicles was substantially small in the study region; hence, they could not be considered as separate categories in the behavioral models implemented in VOSim. The share of different categories of alternative fuel vehicles has substantially increased in the study region over time. Recently, a survey by the same research team has collected this fuel type information, and one of the future research avenues is to use this data to update the model with the disaggregated fuel type categories. Another limitation of this study is the deployment of the anticipation of life-cycle events into the VOSim module. STELARS simulates life cycle events through its demographic dynamics module, which simulates the occurrence of life events on a yearly basis. A key limitation of the current simulation architecture of this module is that it operates in discrete yearly time steps and cannot anticipate or forecast events beyond the current simulation year. This sequential, year-by-year progression restricts the model's ability to generate forward-looking demographic trajectories. Consequently, while the immediate effects and consequences of events can be simulated, the anticipation of future events cannot be incorporated into VOSim- even though, conceptually, the anticipation of a life event might influence vehicle transaction. One of the immediate future research directions would be to develop an event anticipation model and integrate it with the STELARS framework to enable simulation of anticipated events.

In the current version of VOSim, households that become vehicle-free after previously owning vehicles are treated similarly to those that have never owned a vehicle. However, these two groups may differ in their underlying motivations, travel behavior, and subsequent re-entry into the vehicle-owning state. One of the immediate future directions for research would be to implement separate behavioral models within VOSim for these two groups, thereby enabling a more nuanced analysis of their respective behaviors and policy sensitivities. Furthermore, VOSim currently employs a systematic hierarchical process for the disposal of a vehicle (i.e., what type of vehicle would be disposed from the fleet) rather than relying on a behavioral model for this particular decision. Due to limited data on vehicle disposal, a behavioral model could not be developed or implemented in the current version of VOSim. However, with sufficient data on disposed vehicles in the future, such a model could be developed and integrated into the simulation to better capture real-world behavior and to evaluate alternative policy scenarios.

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Author contribution

The authors confirm contribution to the paper as follows: study conception and design: M.S. Hossain, M.R. Fatmi, M. A. Khalil; data collection: M.R. Fatmi; analysis and interpretation of results: M.S. Hossain, M.R. Fatmi, M. A. Khalil; draft manuscript preparation: M.S. Hossain, M. A. Khalil, M.R. Fatmi. All authors reviewed the results and approved the final version of the manuscript.

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