Linkage of transportation demand model and production cost model to investigate flexibility benefits of electric vehicles for the electricity grid

by

Robert Xu

BASc, University of Alberta, 2019

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Abstract

Uptake of electric vehicles (EVs) is accelerating as governments around the world aim to decarbonize transportation. While EV adoption is widely promoted in Canada, swift and widespread EV adoption will require some degree of controlled charging to mitigate the challenges that EV charging imposes onto the power system, such as increased cost and emissions from electricity generation. In this analysis, the potential benefits of utility controlled charging (UCC) are evaluated for the city of Regina, Saskatchewan, which aims to be 100% renewable by 2050. The flexibility that UCC can contribute, and its effectiveness for integrating variable renewables is tested in configurations with solar resources, wind resources, and a mix of both. A novel modelling methodology is developed to do so, which links a travel demand model (TASHA) and an electricity system production cost model (SILVER), using a novel intermediate charging model to simulate electric vehicle travel behaviour and utility controlled charging. The use of operational models allows for an accurate representation of both travel demand and electricity system operating costs and emissions at a high spatial and temporal resolution. By linking sectoral models in this way, the interactions between the two sectors - transportation and power – can be investigated simultaneously with detailed insight into the two individual sectors. Results show that uncontrolled charging will increase average emissions from the electricity grid, but controlled charging decreases both greenhouse gas emissions as well as operating costs. By shifting vehicle charging to times when renewable energy production is high, UCC reduces operating costs and emissions by 7% compared to uncontrolled charging, without requiring changes to travel scheduling and behaviour. The temporal characteristics of wind generation is found to be more compatible with controlled charging than solar PV, due to its longer generation periods and higher capacity factor in the winter, when demand is also high.

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Author Contributions

Chapter 2 of this thesis will be submitted as a peer-reviewed manuscript. Below, the author list, title and author contributions are clarified.

Xu, R., McPherson, M. Flexible EV charging and its role in VRE integration: a case study of Regina, Saskatchewan

> R.X. developed the methodology - building the Regina TASHA model and writing the charging model – and wrote the manuscript. M.M. supervised and contributed to editing the manuscript, as well as providing insight and analysis on modelling results. Chapter 2 of this thesis further develops a model which was used to model electric vehicle charging impacts by Seatle et al. (2021). R.X. is also a co-author of Seatle et al. (2021)
>
> While Madeleine Seatle is not listed as an author of Chapter 2, she contributed by assisting with modelling.

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Chapter 1:
Introduction

In the face of issues such as climate change and energy security, as well as falling battery costs and advancements in technology, zero emission vehicles, which include electric vehicles (EVs) and fuel cell vehicles have become prominent in recent years as an alternative to the dominant internal combustion vehicle. Globally, governments have set a range of targets for transitioning towards zero emission transportation, and a compilation of various policies and targets from countries around the world is presented by the IEA (IEA, 2021).

At the national level, Canada's transportation is responsible for 30% of national greenhouse gas emissions, nearly 70% of which can be attributed to road transport (Environment and Climate Change Canada, 2021). The large energy demand of the on-road transportation sector is driven by the need to transport people and goods across Canada's large geographic area (Government of Canada, 2021a).

This thesis is concerned with passenger transportation, an area in which electric vehicle technology is more mature and widespread the fuel cell technology. As a result, this thesis is focused on electric vehicles. Given that Canadian electricity supply is dominated by hydropower (Natural Resources Canada, 2019), electrification of the transport sector offers an opportunity to decrease greenhouse gas emissions, particularly in areas which are powered by non emitting electricity such as British Columbia. In recognition of this, governments at all levels in Canada have begun to offer financial and non-financial incentives towards the purchase of electric vehicles. The findings of a review of such policies at a national, provincial, and municipal level can be found in tables A1, A2, and A3 in the appendix.

A clear finding from the review is the broad focus on promoting EV adoption, while strategies for controlling EV charging are lacking. Studies of EV charging find that left uncontrolled, EV charging coincides with system load peaks, requiring additional investments in generation capacity (Xcel Energy, 2015). In provinces such as Alberta and Saskatchewan which rely on fossil fuel resources (Government of Canada, 2021b), EV charging demand will increase total emissions from electricity generation. At the same time, the inherent flexibility of EV charging presents an opportunity for EVs to aid in decarbonizing the grid, by helping to integrate variable renewable energy (VRE). By implementing or incentivizing controlled charging for EVs, EV charging can be scheduled to achieve multiple objectives such as: reduction of peak load, reducing VRE curtailment, or minimizing GHG emissions/cost (McPherson et al., 2018; Sun et al., 2018; Szinai et al., 2020).

The key objective of this thesis is to develop a modelling framework to study how controlled EV charging could be used to integrate large amounts of VRE in Regina, which currently draws power from Saskatchewan's carbon intensive grid, but which is also located in an area rich with solar and wind resources. Regina recently adopted a target of achieving 100% of their energy from renewable sources by 2050 (Regina Energy Futures Project, 2020), motivating the use of Regina as a case study. In addition, the developed framework is applicable to cities across Canada and provide metrics of interest to municipal policymakers, planners, and other stakeholders. Developing a model framework to meet these criteria was achieved through the following milestones:

1. **Constructed a travel demand model for the city of Regina**. A travel demand model is used to predict the travel behavior of a population, given population and infrastructure characteristics. In the context of EV charging, we model vehicle use, including EVs, in Regina using the travel demand model, making the implied assumption that EVs travel similarly to conventional vehicles. With the help of the University of Toronto Travel Modelling Group, the travel demand model for Regina is built and calibrated using data from Regina's 2009 Household Travel Survey.

2. **Link travel model outputs to an electricity system production cost model assuming uncontrolled charging**. SILVER, a production cost model, simulates optimal dispatch of electricity generators to meet a given demand. A SILVER implementation for Regina was developed by Seatle et al. (2021) to account for the GHG emissions and cost impact of EV integration. To translate the travel demand model outputs into spatially and temporally disaggregated load curves used in SILVER, a charging model, written in Python, is used to simulate EV charging behavior in uncontrolled scenarios. The methodology for the model is described in the attached paper, and section A2 of the Appendix includes a detailed description of the process to translate travel demand model outputs into a format usable by the charging model. This contribution is a precursor to modelling utility-controlled charging of EVs, which requires information flow from SILVER to the charging model.

3. **Extend the charging model to simulate utility controlled charging (UCCs) of EVs**. To represent utility controlled charging, a bidirectional linkage between SILVER and the charging model is implemented. In designing the controlled charging simulation, we wanted to overcome some of the limitations inherent in other smart charging formulations including: representing only a single day in the modelling period, which constrains energy delivered to be equal to energy consumed; and assuming that vehicle drivers can predict and share their travel schedules with the entity in charge of controlling vehicle charging. In contrast, we assume that the utility must react to consumer travel behaviour, which it has no information of. To control charging of EVs, we first needed to select an objective, such as –reducing peak load, minimizing cost, or minimizing curtailment. Optimizing such metrics in the charging model requires information from SILVER. To simulate controlled charging, we model the utility as having direct control of individual vehicle chargers, rather than a system with EV aggregators. Addressing these limitations resulted in the simulation model described in the methodology section of Chapter 2.

The result of these contributions is the manuscript which serves as Chapter 2 of this thesis. An important contribution of the research is demonstrating a link between operational transportation and electricity system models. Linking these two model types allows for the simultaneous exploration of policy directions in both the transportation and electricity sector. Though there are many intersection points between the electricity and transportation sectors (such as electricity demand from light rail transit and electric bus charging), this analysis focuses on passenger electric vehicles.

Chapter 2:
Flexible EV charging and its role in VRE integration: a case study of Regina, Saskatchewan

Introduction

With the transportation sector responsible for 21% of global CO2 emissions (Climate Watch, 2021), it is vitally important to reduce greenhouse gas emissions from the sector. According to the Intergovernmental Panel on Climate Change, reducing emissions from the transport sector will require the decoupling of GDP and transportation emissions. Electric vehicles (EVs), which can operate exclusively on an electric battery, can facilitate this decoupling if they are charged with non-emitting electricity. As technology matures, battery prices continue to fall, and the importance of reducing emissions becomes increasingly apparent, encouraging the adoption of "zero emission vehicles" has become the focus of governments around the world (IEA, 2021).

In 2021, Canada adopted a requirement that 100% of new passenger vehicle and light truck sales be zero emission vehicles by 2035 (Transport Canada, 2021). The options for passenger vehicles include battery electric vehicles, which run exclusively on electricity, and plug-in hybrid electric vehicles, which can run on both gasoline and electricity. Our review of EV adoption policies and incentives at the federal, provincial, and municipal level (summarized in appendix tables A1, A2, and A3), find that EV adoption is broadly supported by policies that focus on incentivizing EV adoption through financial mechanisms (for both vehicles and chargers) and nonfinancial mechanisms (such as access to high occupancy vehicle lanes). However, there is a distinct lack of policies and incentives supporting controlled EV charging.

This gap in the policy landscape is problematic, since research demonstrates the perils of uncontrolled charging, and the benefits of controlled charging. Xcel Energy (2015) finds that if uncontrolled (with vehicles charging as soon as they reach a destination), a significant amount of EV load coincides with the system peak, which may drive infrastructure costs (generation capacity buildout) to accommodate EV adoption. Similarly, Muratori (2018) show that uncontrolled charging may lead to significant increases in peak residential power demand. On the other hand, the inherent flexibility in vehicle use, which can be deemed a form of demand response, presents a significant opportunity for electric utilities through EV smart charging (McPherson et al., 2018; Mwasilu et al., 2014). Smart charging incentivizes an EV owner to schedule their vehicle charging in a certain way, or gives a utility or other entity control of vehicle charging. Smart charging can provide benefits to the utility such as reducing peak generation (Debnath et al., 2020), and providing the additional flexibility facilitate VRE integration (McPherson et al., 2018). Ultimately, smart charging can result in lower emissions and costs of operating the electricity network. Accurately quantifying the value of flexible EV charging can help inform policy priorities around VRE development, charging infrastructure siting, and incentive programs for participation in smart charging programs.

There is a large body of research addressing optimal strategies for utilities to control or incentivize EV charging patterns that reduce system emissions (Wang et al., 2016). A common approach to model EV charging demand is by simulation of vehicle schedules, commonly derived from travel surveys (Kelly et al., 2012; Wood et al., 2018). Modelling approaches differ, however, in their treatment of charging behaviour and EV scheduling from a utility or EV owner perspective. Tu et al. (2020) optimize vehicle charging schedules to minimize GHG emissions, using a genetic algorithm populated with travel survey data from Toronto to find the optimal schedule for all vehicles. Tushar et al. (2012) utilize a game theoretic approach to demonstrate smart charging from an individual EV owner's perspective. Sun et al. (2018) utilize convex optimization principles to schedule EV charging to achieve a valley filling effect. In general, these studies find that smart charging leads to lower emissions and VRE curtailment.

Despite the breadth in approaches to modelling smart charging, several limitations can be identified. First, many formulations do not directly link to an operational electricity system model (Knapen et al., 2011; Sterchele et al., 2020; Sun et al., 2018; Tu et al., 2020). As a result, operational aspects of the system such as network congestion, unit commitment, and economic dispatch are not considered, and important power systems operations, which drive GHG emissions and cost, are not accurately captured. Such insights are of interest to utilities, which might implement any controlled charging program or incentive scheme for customers, as well as to policy-makers, who are pursuing evidence-based decision making.

Second, the optimization procedures described in many studies may be inconvenient for consumers. Optimization procedures described by Kara et al. (2015), Szinai et al. (2020) and van der Kam & van Sark (2015) require EV owners to enter vehicle departure times or entire daily travel schedules in advance to perform the centralized optimization. Although these approaches assume that the utility or entity in control of smart charging has perfect information, unpredictability of travel routines and uncertainty surrounding consumer acceptance may result in the overestimation of smart charging potential.

Third, many models of smart charging only optimize for a single day. This could be due to a lack of data on the multi-day travel behaviour of vehicles, computational limitations, or an implicit assumption that travel behaviour can only be defined one day in advance. However, when only a single day is considered, models often impose constraints specifying that the vehicle battery level at the end of day must be greater than or equal to the battery level at the start of the day (Tu et al., 2020; Wolinetz et al., 2018). This constraint limits the usability of EV flexibility to the duration of a single day. In reality, consumers with appropriate incentivization may accept a partially charged vehicle at the end of an activity or end of day.

In this study, the benefits of adopting controlled charging for EVs, from an electricity cost and GHG emissions perspective, are presented. To do so, we develop a novel modelling framework which focuses on improving the representation of EV charging, specifically as it pertains to capturing the opportunity which controlled EV charging presents. This analysis focuses on the utility controlled charging (UCC) method of smart charging, in which the utility has direct control over EV charging for a city fleet. More specifically, a power system production cost model is linked to a travel demand model, with an intermediate EV charging simulation model to model UCC as it might occur in real time between the utility and EVs. To respect driver convenience, the modeling framework does not require the EV owner to provide trip information to the utility. Instead, the utility charges vehicles whenever it predicts that excess renewable energy will be produced. The model simulates an arbitrary number of days by chaining daily travel schedules together and does not require constraints on a daily energy balance for EVs. This allows the model to account for a more accurate interaction between temporal variation in VRE and the flexibility in travel schedules. The model is applied to a case study of Regina, Saskatchewan, and results from the model compare electricity system cost and emissions with controlled and uncontrolled charging. Battery electric vehicles are the focus of the modelling work; EV is used to refer to vehicles which exclusively use electricity throughout this paper.

The first major contribution of this research work is the methodological innovation of linking two operational models of historically distinct sectors. Many studies of renewable energy integration which consider EV charging rely on historical travel patterns to estimate spatial and temporal distribution of EV demand. However, transportation systems are changing, with transportation policy trending in the direction of increased active transportation, public transportation, and zero emissions vehicles. As a result, historical travel patterns do not capture the technological and policy directions changing travel behaviour. To better forecast travel behaviour, operational transportation models, which focus on representing behavioural decisions such as mode choice and location choice, can be employed (Daina et al., 2017). Simultaneously representing changes in the electricity and transportation sectors can be best achieved by utilizing the operational models of each sector and the present study seeks to do so by focusing on one such intersection point of the two systems: passenger EV charging.

The second major contribution of this research is the insights that can be produced by our multi-sector platform. Investigating the interactions between the design and operation of the transport system and power systems yields valuable insights on the co-evolution of both systems for a more holistic perspective on decarbonization pathways. In this analysis, we focus on the interaction between controlled charging under alternative variable renewable energy configurations. Namely, we quantify the value of EV flexibility under high wind and solar scenarios. The effectiveness of utility controlled charging is quantified by the ratio of controlled to uncontrolled EV load.

Methods

To assess the value of flexibility in EV charging behaviour on the electricity grid, the operations of the transportation and electricity systems are modelled with a high degree of spatial, temporal, and operational detail. The Travel and Activity Scheduler for Household Agents (TASHA), a travel demand model, and SILVER, a production cost model of the electricity system, are linked through a charging model to capture the interaction between both sectors. TASHA produces travel schedules for individuals, which are then simulated in the charging model. The charging model produces spatially disaggregate load curves from EV charging, which are input to SILVER. SILVER then aggregates the EV load with the non-EV load for the region of interest, simulates optimal dispatch of electricity generation to meet demand, and outputs cost and emission profiles.

By implementing a bidirectional flow of data between SILVER and TASHA, utility controlled charging is simulated in the charging model, with a utility entity controlling vehicle charging. In the implementation of UCC, the utility aims to maximize local use of VRE generation and reduce system GHG emissions and cost by initiating vehicle charging during time intervals when excess VRE is produced, while EV drivers are assumed to delay charging until their EV battery falls below a certain threshold. A high-level representation of the linkage is shown in Figure 1. In this section, the formulation and relevant inputs and outputs for TASHA, SILVER, and the charging model will be described in further detail.

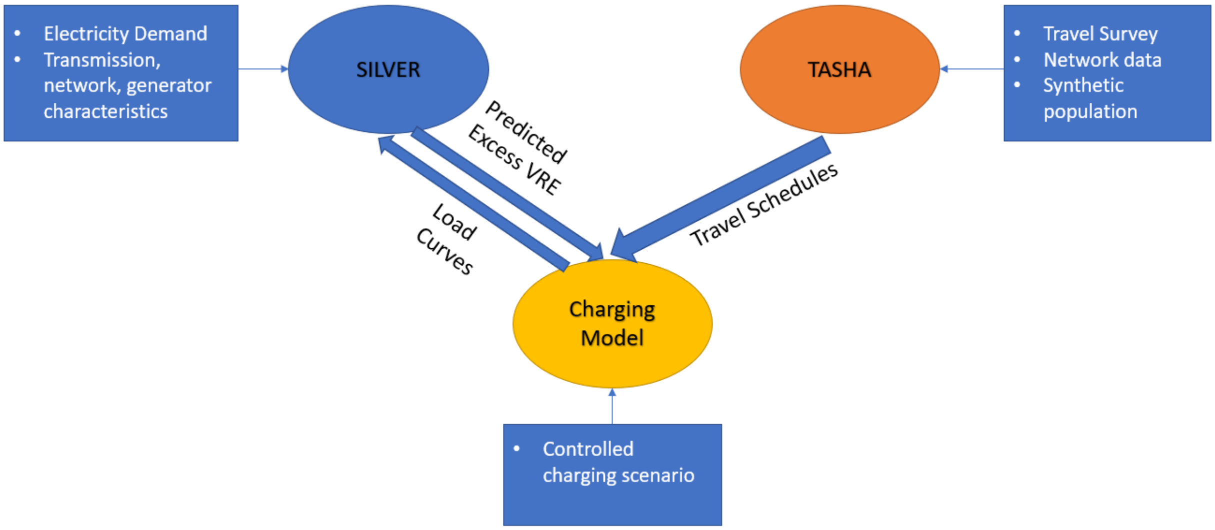


Figure 1: High level overview of model linkage

TASHA

TASHA predicts travel schedules for a synthetic population (i.e., a population set replicated to represent a given study area) of households and individuals. TASHA has been used to evaluate impacts of transportation policy and infrastructure changes on travel behaviour in the Toronto area (Miller et al., 2015), as well as Montreal (Yasmin et al., 2015) and Cape Town (Diogu, 2019). TASHA schedules activities (i.e. mode choice and location choice) as a function of travel time, distance, and employment status, among other variables, as well as spatiotemporal and resource constraints. A detailed flowchart showing the data sources and processes in TASHA as well as linkages to the charging model and SILVER is shown in Figure 2. The detailed formulation of TASHA is described by (Miller & Roorda, 2003).

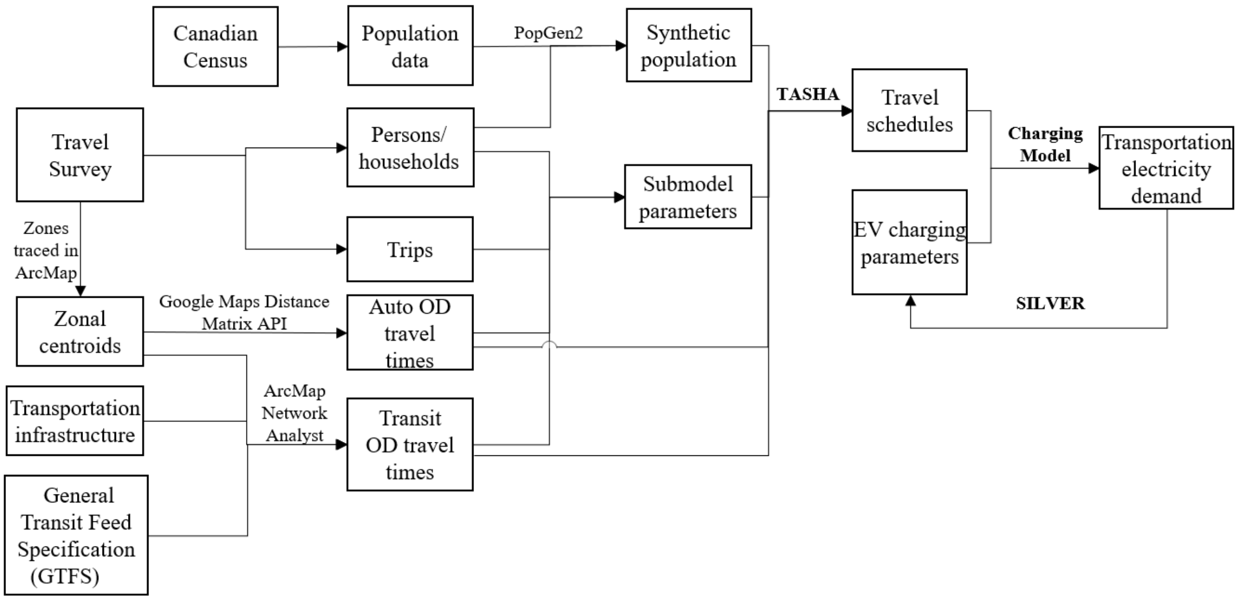


Figure 2: Detailed flowchart for building TASHA as used in this study

TASHA requires several input types, as shown on the left-hand side of Figure 2. The three key inputs include the origin-destination travel times for modes throughout the network, which can be obtained either from a city's existing transportation model or from commercial software such as Google Maps and ArcGIS. The synthetic population consisting of households and persons, for which travel schedules are assigned, must be generated, as described by National Academies Press (2014). This analysis employs the PopGen2 synthetic population synthesizer (Bar-Gera et al., 2009; Konduri et al., 2016; Mobility Analytics Research Group, 2016; Ye et al., 2009). Finally, a local travel survey is used for calibration. Results from validation of TASHA for the case study are presented in section A5 in the appendix.

TASHA outputs a complete daily travel schedule for every individual in the synthetic population. The schedule consists of a series of trips, with each trip having an associated origin zone, destination zone, arrival time, departure time, origin activity type, and destination activity type. To account for household vehicle sharing, the individual travel schedules are combined to form vehicle travel schedules. The procedure for converting the TASHA output to vehicle schedules is described detail in section A2.1 of the appendix. An example of the type of data produced by this process is provided in Table 1.

Table 1: Sample vehicle schedule

Household #	Vehicle #	Origin activity	Origin zone	Destination activity	Destination zone	Depart time	Arrive time	Distance (m)
20034	1	Home	2	Other	35	401	420	19360
20034	1	Other	35	Home	2	480	499	19809
20034	1	Home	2	Work	46	521	540	15438
20034	1	Work	46	Home	2	1020	1037	15234

SILVER

SILVER, a production cost model with a high spatiotemporal resolution of power system operations is used to represent the effect of EV charging on GHG emissions and operating cost. A detailed description of SILVER is found in McPherson & Karney (2017), and SILVER has been used to model storage asset deployment (McPherson & Tahseen, 2018). SILVER optimizes for the least cost dispatch of generation and transmission assets to meet electricity demand at each time step. SILVER also includes a day ahead and real time model, allowing the model to account for imperfect future knowledge of electricity demand and renewable energy generation.

Inputs for SILVER include electricity demand profiles, and transmission network configuration, and generator characteristics, such as ramping constraints, operating costs, and renewable energy generation profiles. SILVER outputs generator dispatch, operating cost, emissions and VRE curtailment at a user defined time step. Emissions and generator dispatch outputs from SILVER are used to implement UCC within the charging model.

For this study, a SILVER implementation was designed following the formulation outlined in Seatle et. al (2021), using a fifteen-minute time step to capture the high temporal resolution of EV charging behaviour and variability in VRE generation. Seatle et. al (2021) also describes the procedure for assigning EV load from the zonal resolution used in TASHA and the charging model to the substation resolution used within SILVER. Operational costs and emissions of VRE resources are assumed to be zero.

Charging model

To illustrate the value of flexible charging behaviour, the charging model runs with two different configurations: uncontrolled charging (UNC), and utility-controlled charging (UCC). The methodology for both configurations are described in the following sections.

Uncontrolled Charging (UNC)

In uncontrolled charging scenarios, EVs begin charging as soon as they arrive at their destination, regardless of where the destination is or the type of location (e.g. work, home). The implicit assumption is that EV owners do not have incentive to charge at particular times or locations, or according to a particular strategy. The charging process uncontrolled charging is described by the following set of rules and equations.

Each time an EV makes a trip, its battery level (or state of charge, SOC) is updated based on the trip distance to the next activity location, and the depletion rate, such that:

$$SOC_a = SOC_d - D * d \tag{1}$$

where SOC_a (in kWh) is the battery level upon arrival to its next activity, SOC_d is the battery level upon departure from the previous activity, d is the distance between the zones in which the arrival and departure activities are located (in km), and D is the battery depletion rate (kWh/km) which is modelled as a function of temperature and thus varies by season. This is a simplifying assumption made in the model, as depletion rate also varies with terrain changes and speed, which are not modelled.

When the vehicle arrives at its activity, it immediately begins charging, and continues to charge until the battery reaches full capacity, or the vehicle departs for the next activity. The battery level upon departure from the current activity is given as:

$$SOC_d = min\left(SOC_a + \frac{(t_d - t_a)}{60} * R, SOC_{max}\right) \quad (2)$$

where t_d is the departure time in minutes from the current activity, t_a is the time at which the vehicle arrived at the current activity, R is the user defined charging power (in kW), and SOC_{max} is the vehicle battery capacity.

The arrival and departure cycle represented by equations 1 and 2 is repeated until the entire daily schedule of the vehicle is completed. This daily schedule is then cycled through until the time horizon of the simulation period (e.g. one week) is completed. EV charging load curves, which are disaggregated by spatial zone and activity type, are generated by simulating a collection of EVs within the spatial boundaries modelled and summing the results. For uncontrolled charging scenarios, these load curves are assigned to substations and combined with non-EV load using a process described by Seatle et. al (2021). The total load curve is then run through SILVER to determine operating cost, emissions, and curtailment.

Utility Controlled Charging (UCC)

Under a paradigm with utility controlled charging (UCC), it is assumed that vehicle owners are incentivized to delay charging their vehicle until they reach a minimum battery threshold, thereby providing a flexible resource for the utility to control. In this analysis, the goal of UCC implementation is to maximize the amount of renewable energy used, thus minimizing the amount curtailed. To achieve this, UCC events occur when VRE generation exceeds the non-EV load, which then triggers the utility to charge vehicles to utilize the excess generation. Vehicle owners only initiate charging, outside of utility control, when the battery falls below a minimum capacity threshold. All other charging occurs through utility control.

When installed VRE generates excess electricity, the utility needs to quantify the amount of excess generation which can be used to charge vehicles through UCC. In this analysis, this quantity is referred to as excess renewable generation (ERG) and is estimated by the utility based on the non-EV load and the renewable production at each time step. Within the charging model, ERG is an input (the methodology for determining ERG is described in the next section) and serves as an upper bound for the EV load during a UCC event, as shown in equation 3:

$$Load_{EV}(t) \leq ERG(t) \quad (3)$$

where $Load_{EV}(t)$ refers to the marginal EV load (in addition to the baseline non-EV load) in kWh during the time step t. $Load_{EV}(t)$ is the sum of charging occurring via UCC and the charging of vehicles whose battery level fell below threshold. This study uses a time interval of 15 minutes for UCC.

In the controlled charging scenarios, this study uses a discrete time simulation approach, in which vehicle travel, charging, and UCC occur in parallel. Like the uncontrolled approach, the departure, arrival, and charging of individual vehicles is simulated. When a vehicle arrives at its activity, the owner first evaluates whether the battery is below its threshold. For this study, the threshold is determined on an individual vehicle basis, and is equal to twice the vehicle's daily driving distance:

$$SOC_{threshold,v} = 2 * d_{daily,v} * D \quad (4)$$

Where vehicles which are more heavily driven have a higher threshold than vehicles which are not, and all vehicles will have a lower threshold in the summer, due to the lower depletion rate.

If a vehicle arrives at its destination with a battery level below its threshold, it charges according to equation 2, with the associated demand labeled as “threshold charging”. If the battery level is above the threshold, the vehicle does not charge immediately and is labelled “UCC eligible”.

At the start of each 15 minute interval, the utility estimates the ERG in the time interval. If the ERG is greater than zero, then a UCC event will occur if the system wide threshold charging EV load is less than the ERG. Specifically, a UCC event will occur if $ERG_{UCC}(t)$ is positive, given by the following equation:

$$ERG_{UCC}(t) = \begin{cases} 0\,, if ERG(t) = 0 \\ \max\big(0, ERG(t) - L_{threshold}(t)\big), if\ ERG(t) > 0 \end{cases} \tag{5}$$

Note that the threshold charging load and UCC load are tracked separately. During a UCC event, the utility will continually select random eligible vehicles and charge them for a duration given by

$$duration_{UCC,v} = \min\big(15, duration_{depart,v}, duration_{full,v}\big) \tag{6}$$

where $duration_{depart,v}$ is the time until vehicle v departs, given in minutes by

$$duration_{depart,v} = t_d - t \tag{7}$$

where t is the current time and $duration_{full,v}$ is the time it would take for vehicle v to reach SOC_{max}, given by

$$duration_{full,v} = \frac{SOC_{max} - SOC(t)}{R} * 60 \tag{8}$$

Equation 5 implies that a vehicle being charged by the utility may charge for less than 15 minutes because the vehicle must depart, or because it has reached a full charge. When vehicle v departs for its next trip, its battery level now reflects any charging through utility control that may have occurred while it was parked. Because the utility is unaware of the vehicle’s departure time, it assumes that the charging duration is 15 minutes, and updates $ERG_{UCC}(t)$ such that

$$ERG_{UCC}(t)' = ERG_{UCC}(t) - 15 * \frac{R}{60} \tag{9}$$

where $ERG_{UCC}(t)'$ is the updated prediction of ERG for UCC after just having charged a vehicle in the UCC eligible pool. EVs leave the UCC eligible pool when they depart from an activity, or when their battery is charged to capacity. A pseudocode for the charging model is provided in the appendix in section A3.

Determining Excess Renewable Energy Generation (ERG)

While SILVER outputs VRE curtailment, it was found to be an unsuitable metric to use as ERG. Curtailment can occur for reasons besides oversupply, such as transmission and ramping constraints, and therefore the amount of curtailment during a time interval does not necessarily indicate the amount of excess VRE which can be used to charge vehicles. In other words, while curtailment can occur when the VRE generation is less than demand, ERG must only be positive when VRE generation is greater than demand.

Because ERG is not a direct output of SILVER, a methodology was developed to iteratively refine an initial ERG estimate. In context of the linkage between models, this procedure is shown by the dual arrows between SILVER and the charging model in Figure 1. The goal of the iteration procedure is to ensure that UCC events do not utilize non-VRE generation to charge vehicles. For the initial iteration of a UCC model run, the ERG estimate is determined using the output of a SILVER run using only non-EV load. Specifically, the initial estimate can be given by:

$$ERG(t,0) = \max\big(0, VRE_{available}(t) - Non\ EV\ Load(t)\big) \tag{10}$$

where $ERG(t,0)$ indicates the 0th, or initial, iteration. $Non\ EV\ Load(t)$ is a model input, which can be sourced from a utility and is iteration-independent, and $VRE_{available}(t)$ is the installed capacity of VRE multiplied by the capacity factor at time t.

For subsequent iterations, the generator dispatch and carbon intensity outputs from SILVER for the previous iteration and non-EV run are utilized to adjust the ERG estimate. The adjustment procedure proceeds as follows for the next iteration, and a pseudocode for the procedure can be found in section A4 in the appendix. Figure 3 shows the iterative convergence procedure as a flowchart.

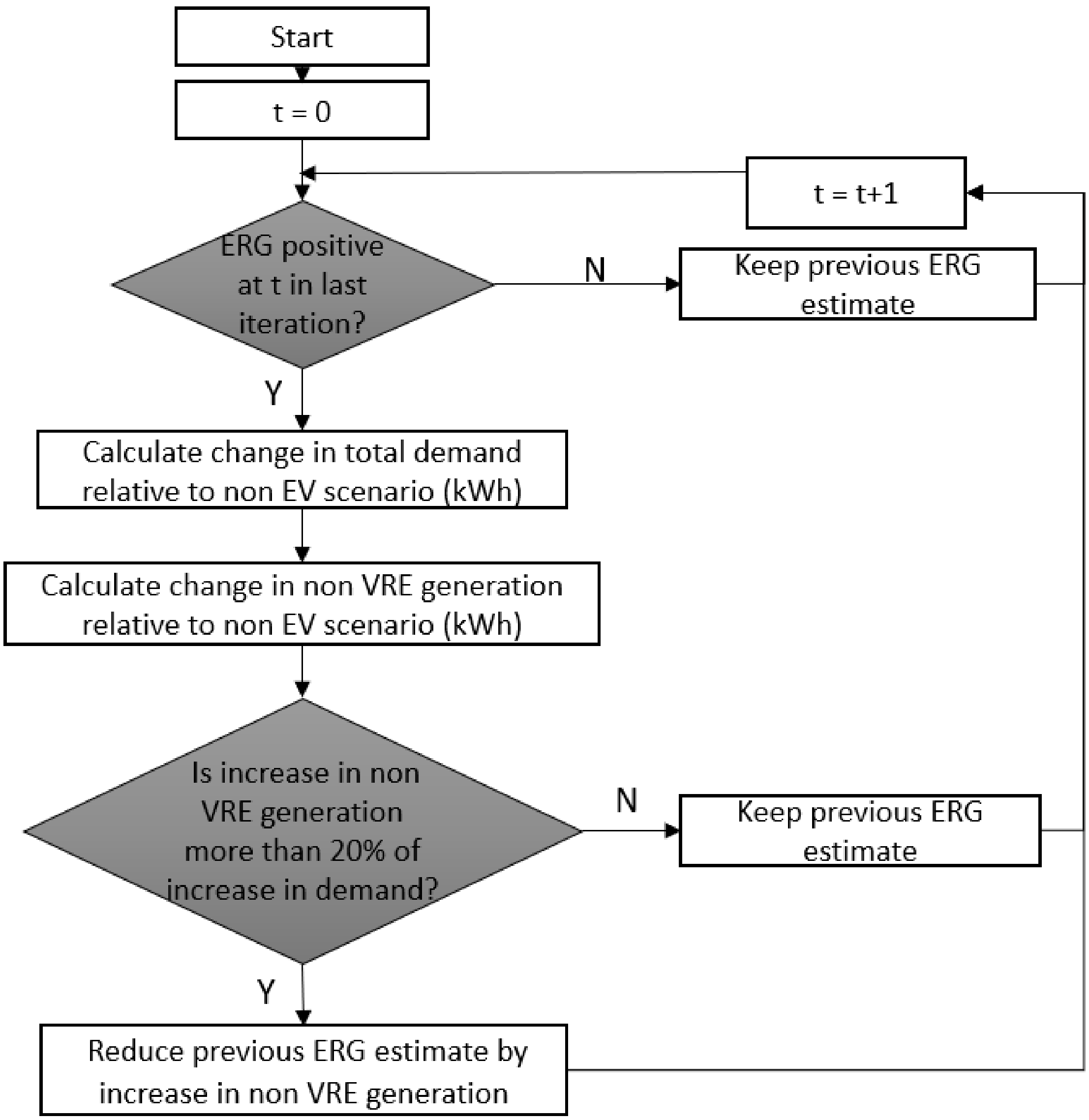


Figure 3: Flowchart for iterative procedure linking SILVER with charging model to ensure utility controlled charging only uses renewable generation

Convergence is reached when there are no intervals during which the increase in non VRE generation accounts for greater than 20% of the load increase during a UCC event. If convergence is not reached, the updated ERG estimate is used as an input to the charging model to rerun UCC, with the subsequent load curves passed into SILVER. The SILVER output is then used to determine whether further iterations are required.

Case Study

The City of Regina recently committed to becoming a renewable city (City of Regina, 2020), and is currently exploring pathways towards meeting 100% of the city's energy demand with renewable sources, including passenger transportation, public and private buildings, and industrial processes. A recent survey indicates that a majority of Regina residents support a wind farm outside city limits, and 25% of residents would consider installing rooftop solar with no financial incentive (Regina Energy

Futures Project, 2020). This analysis explores the implications of highly electrified passenger vehicles in the City of Regina, focusing on the effectiveness of controlled EV charging behaviour in various configurations of added wind and solar generation capacity.

Several assumptions are made for the case study. It is assumed that the added VRE is operated by the city, and that Regina can import electricity from the provincial grid when VRE generation is insufficient to meet demand. Data inputs used to parameterize TASHA and SILVER implementations for the case study can be found in Seatle et. al (2021). Mode shares within TASHA are based on a local travel survey, and therefore do not account for changes in transportation behaviour. Assumptions within the charging model can be found in Table 2 and are consistent between UNC and UCC scenarios. The assumptions made can influence results – assumption of a low EV charging power that is homogeneous across all vehicle chargers affects the flexibility of charging. EVs are assumed to be randomly distributed across Regina households. The spatial scope of Regina's traffic zone system, as well as substation locations and wind farm location, is shown in Figure 4. The wind farm site was chosen to be close to Regina, such that direct transmission of wind power to the city would be feasible. Wind generation capacity factors are based on the methodology of (Staffell & Pfenninger, 2016), accessed using the website interface to retrieve data (Staffell, 2021). Capacity factors are based on a Vestas V90 2000 model wind turbine at an 80m hub height. Rooftop solar capacity factors were determined following the methodology described in Seatle et al (2021).

Table 2: Assumed parameters for Regina case study

Parameter	Value
EV Charging Power (kW)	2
Summer/Winter Depletion Rate (kWh/km)	0.16/0.32 (Geotab, 2021)
EV Battery Capacity (kWh)	40

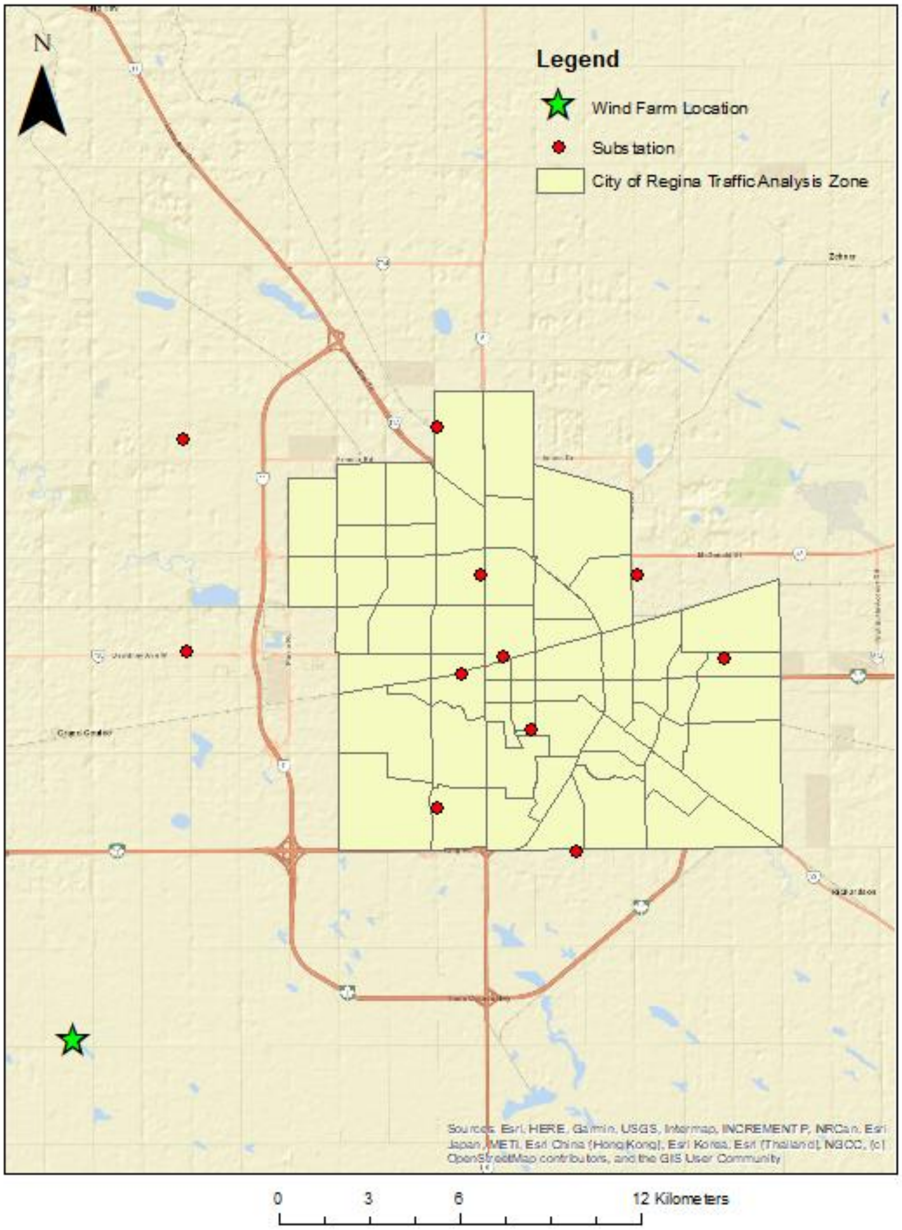


Figure 4: Extent of study area, substation locations used in SILVER, and location of wind farm

The central scenario matrix used to support the Regina analysis is shown in Table 3. To capture seasonal effects, each scenario is simulated for a representative week in January and July. In all scenarios, 400MW of VRE is added to the system (except for the business-as-usual (BAU) scenario). The 400MW figure is based on the amount of rooftop solar capacity with 25% of Regina households installing rooftop solar. Wind has a significantly higher capacity factor than solar and keeping a constant capacity of added VRE (400 MW) has implications for electricity system operating cost, emissions, and curtailment, which will be seen in the results section. Installed capacity was kept constant as this was found to highlight the effect of utility controlled charging. A smaller sized wind farm would have produced less VRE, decreasing the potential availability of controlled charging. Because Regina residents are accepting of both rooftop solar and a wind farm outside city limits, additional scenarios are explored for the solar/wind hybrid configuration by varying the EV penetration rate between 0, 25, 50, and 100 percent. Aside from the solar/wind configuration, a 50% EV penetration rate is simulated to illustrate the potential flexibility of a relatively large fleet of passenger EVs. Note that for all scenarios, regardless of adoption rate, we assume that the baseload does not change, and is based on data from the provincial utility (Seatle et. al, 2021).

Table 3: Scenario matrix

<table>
<tr><th>Scenario Name</th><th>VRE Configuration</th><th>Adoption rate (%)</th><th>Controlled or Uncontrolled</th></tr>
<tr><td>BAU</td><td rowspan="2">None added</td><td>0</td><td>N/A</td></tr>
<tr><td>BAU-UNC</td><td>50</td><td>Uncontrolled</td></tr>
<tr><td>S</td><td rowspan="3">400MW Solar</td><td>0</td><td>N/A</td></tr>
<tr><td>S-UNC</td><td rowspan="2">50</td><td>Uncontrolled</td></tr>
<tr><td>S-UCC</td><td>Controlled</td></tr>
<tr><td>W</td><td rowspan="3">400MW Wind</td><td>0</td><td>N/A</td></tr>
<tr><td>W-UNC</td><td rowspan="2">50</td><td>Uncontrolled</td></tr>
<tr><td>W-UCC</td><td>Controlled</td></tr>
<tr><td>SW</td><td rowspan="3">200MW Solar/200MW Wind</td><td>0</td><td>N/A</td></tr>
<tr><td>SW-UNC</td><td rowspan="2">50</td><td>Uncontrolled</td></tr>
<tr><td>SW-UCC</td><td>Controlled</td></tr>
</table>

Limitations

There are several limitations associated with this study. Due to a lack of data, differences between weekday and weekend travel are not accounted for, as well as daily variations in travel demand. This may lead to inaccuracies in the representation of times and locations during which vehicles are charging/travelling. Similarly, the model does not account for changes in travel behaviour due to switching to an EV, or due to UCC participation, which leads to inaccuracies in predicting vehicle use. Travel distances and times between zones are based on the path with the shortest travel time between zonal centroids, which may not be an accurate representation of driving distance or travel times, leading to an underestimation of actual driving distances. Chargers are assumed to be abundant, while in reality limited number of chargers will constrain the number of actively charging and plugged in EVs, which limits the extent to which UCC can control fleetwide charging. This analysis only considered local travel within Regina, and does not consider longer range, inter-city travel - which may result in an underrepresentation of EV demand. Because installed capacity is chosen to be constant across VRE configurations, significant VRE curtailment is observed in scenarios of the 400MW wind configuration. While UCC is found to be quite effective in shifting EV charging in the wind configuration, high levels of curtailment indicate that the system is overbuilt with the assumed wind capacity. In this analysis, we assumed that Regina would use VRE when it was produced, but otherwise would draw from the provincial utility. This assumption may not accurately represent the relationship between the city of Regina and the provincial utility, and further study into this area would be helpful to determine how city level demand affects generation dispatch of the provincial utility.

Results

Results of this analysis show that adding uncontrolled EV charging, as well as controlled charging, can have significant impacts on system operating cost and emissions. This section explores results by comparing non EV, UNC, and UCC scenarios for the various configurations. First, the effect of adding EV charging, either uncontrolled or controlled, onto the system is described. Next, we delve into how the controlled charging influences the shape of the EV load curve, as compared to uncontrolled charging. Some of the nuance around the effectiveness of UCC will be quantified through explorations around VRE configuration and season where 'effectiveness' is measured by the ability to shift charging to high VRE generation periods. More importantly though, the effect of EV charging and UCC on electricity system operating cost, emissions, and VRE curtailment will then be quantified. Finally, the impacts of increasing degrees of EV penetration rate will be illustrated.

Effect of EV Charging on System Load

When 50% of the vehicle feet is electrified, vehicle charging load represents approximately 8% of total electricity demand in a January week, and 4% in a July week. While the net load may be relatively small, EV charging has notable effects on the shape of the load curve. Figure 5a and 5b respectively show the load and generation profiles for a January week for the wind configuration when charging is controlled. Uncontrolled charging results in two demand peaks, one in the morning as people arrive at work, and one in the late afternoon as they arrive home. As seen in Figure 5a, the afternoon peak occurs at the same time as the daily non-EV load peak, thus exacerbating the existing system peak.

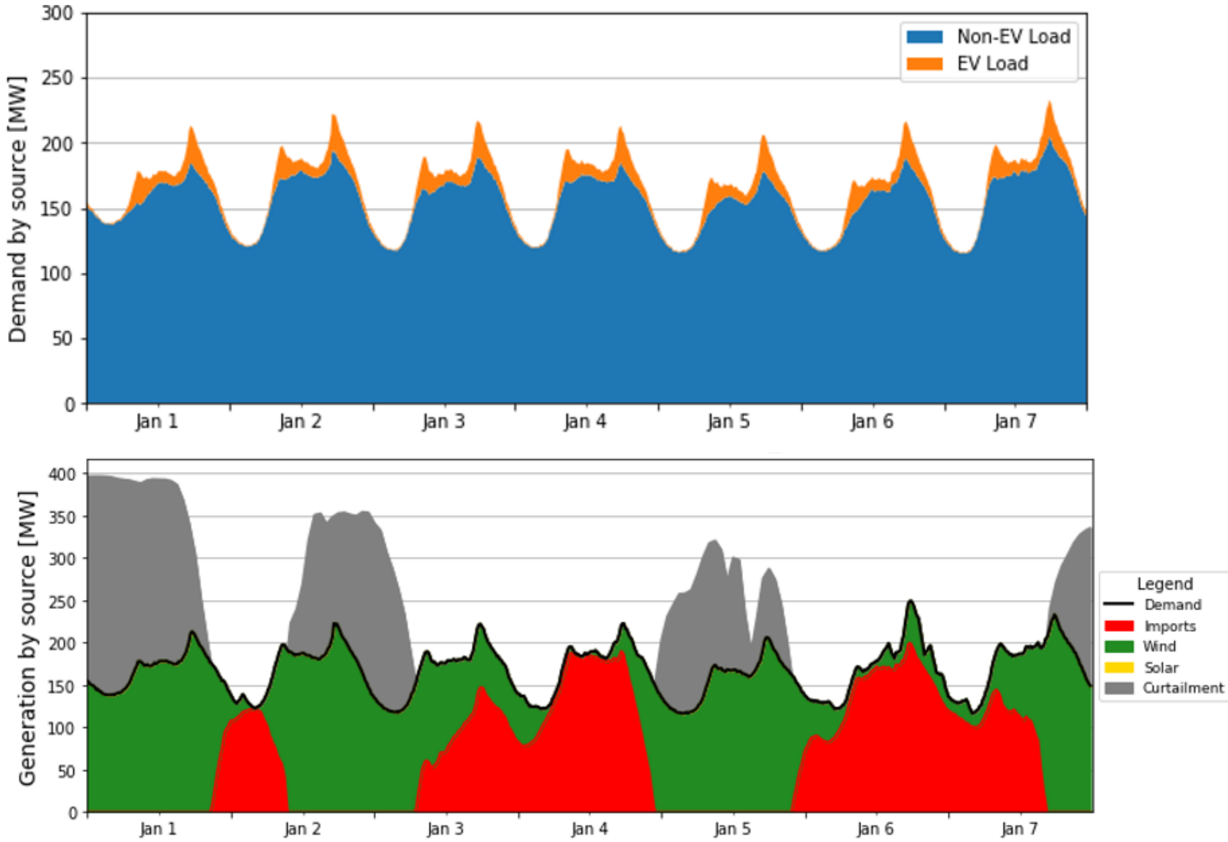


Figure 5: Regina's electricity demand for wind only configuration with uncontrolled charging in January, shown by a) demand type (top) and b) generation type (bottom). Note that "imports' refer to electricity supply from the provincial grid, which have been aggregated by generation type but include coal and natural gas.

When EV load can be shifted through UCC, the EV demand peaks when wind generation is high, which in turn increases the utilization of VRE (reduces VRE curtailment, as shown in Figure 6a and 6b. Although the system load peak is 25% higher when charging is controlled as opposed to uncontrolled, the generation during that peak is met entirely through wind generation. Despite the positive effects of UCC, VRE generation far exceeds the EV demand, indicating a large amount of energy that would need to be exported, converted to storage, or curtailed.

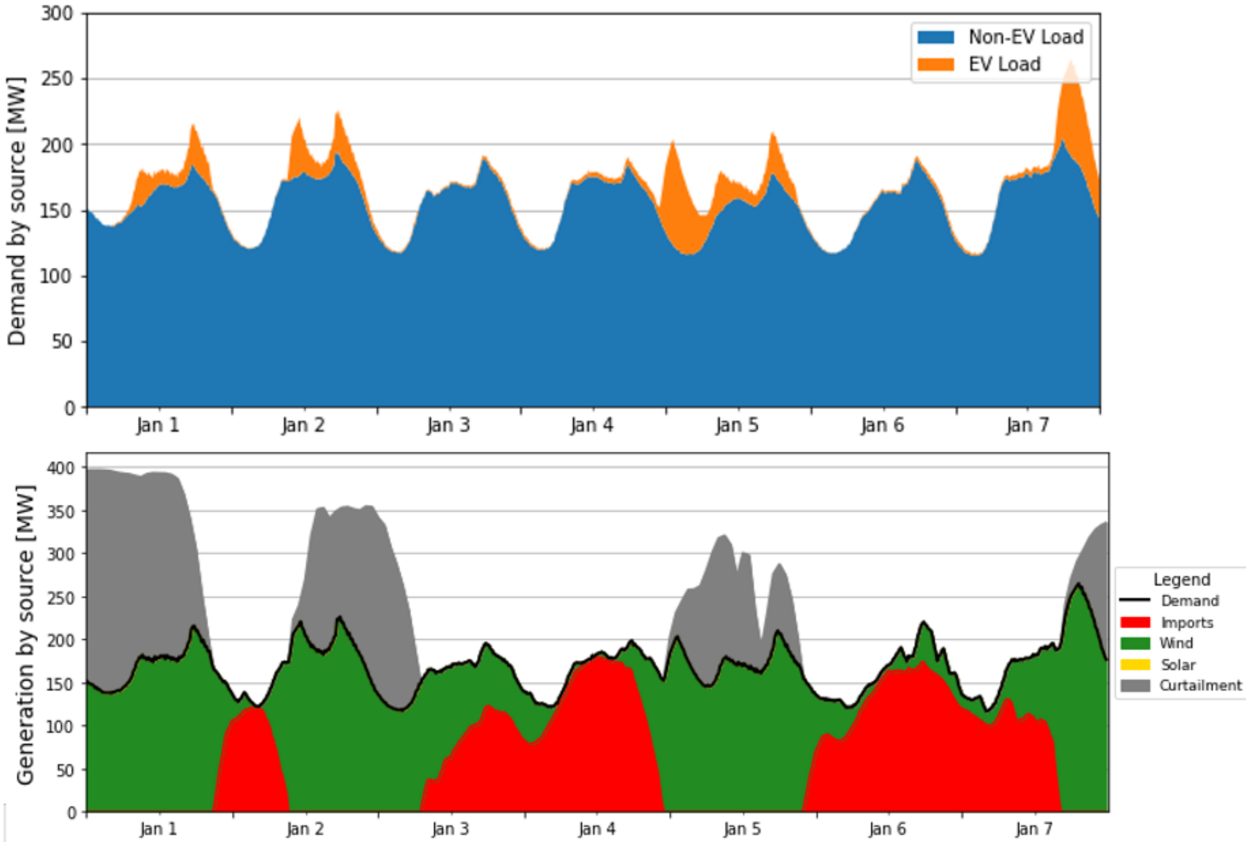


Figure 6: Regina's electricity demand for wind only configuration with utility controlled charging in January, shown by a) demand type (top) and b) generation type (bottom)

Figure 7 presents a closer look of the relationship between controlled EV demand and the ERG estimate during a January week (again, in the wind scenario). The UNC curve shows when uncontrolled charging occurs relative to VRE production. When charging is controlled, the EV demand peak shifts to the beginning of a ERG period, as UCC occurs whenever excess VRE generation is predicted. Following this peak, EV demand drops as parked vehicles are fully charged. During the January week, periods of excess VRE generation last around 24 hours, due to the nature of the underlying wind regime. During these periods, the controlled EV load partially matches the uncontrolled EV load: vehicles charge as soon as they arrive at their destination. However, four distinctions are observed, when comparing the controlled and uncontrolled EV load profiles. In the two-day period following January 2nd, the EV demand with controlled charging is much less than in the uncontrolled scenario: with batteries fully charged, EVs can travel multiple days without requiring charging, allowing them to delay charging until another excess VRE generation period on January 5. The same effect occurs between January 5th and 7th. The net result is that under UCC, most EV charging occurs during excess VRE generation periods. In the UNC scenario, some EV charging happens to line up with periods of excess VRE generation, but a significant portion of EV charging occurs outside of these periods.

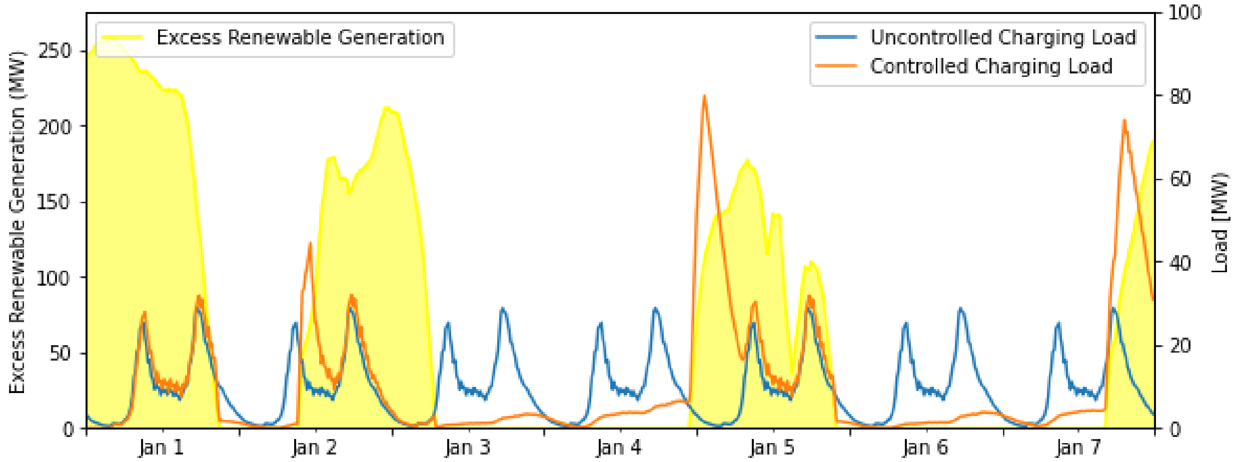


Figure 7: Correlation between excess renewable energy generation (ERG; left axis, in yellow area) and total electric vehicle load (right axis) for scenarios of uncontrolled charging (W-UNC) and utility controlled charging (W-UCC) for a January week in Regina in the wind only configuration.

Effectiveness of UCC

Although EV load may be relatively small compared to total system load, the ability to shift charging has important implications for emissions. Here, we define the 'effectiveness of UCC' as the ratio of energy shifted through utility control to the total energy demand of the EV fleet. As shown in Figure 8, the percent of EV energy met through utility control differs across VRE configuration scenarios, along with the timing and quantity of VRE generation. The seasonal effect is most drastic for the solar scenario; in the winter, there is no excess VRE available. It is in fact the wind generation that facilitates UCC in both seasons. In addition, the timing of wind generation appears to be more suitable for UCC: the long periods of excess wind generation allow vehicles to fully charge through utility control in the winter. In contrast, solar generation, particularly in the winter, occurs for only a few hours each day, which, when combined with the slow rate of charging and low fuel economy, diminishes the overall effectiveness of UCC. Wind also has a seasonal advantage: wind capacity factors are higher in the winter than in the summer, which corresponds well to a higher demand from EVs in the winter than in the summer. In July, more than 80% of EV demand through UCC regardless of VRE configurations.

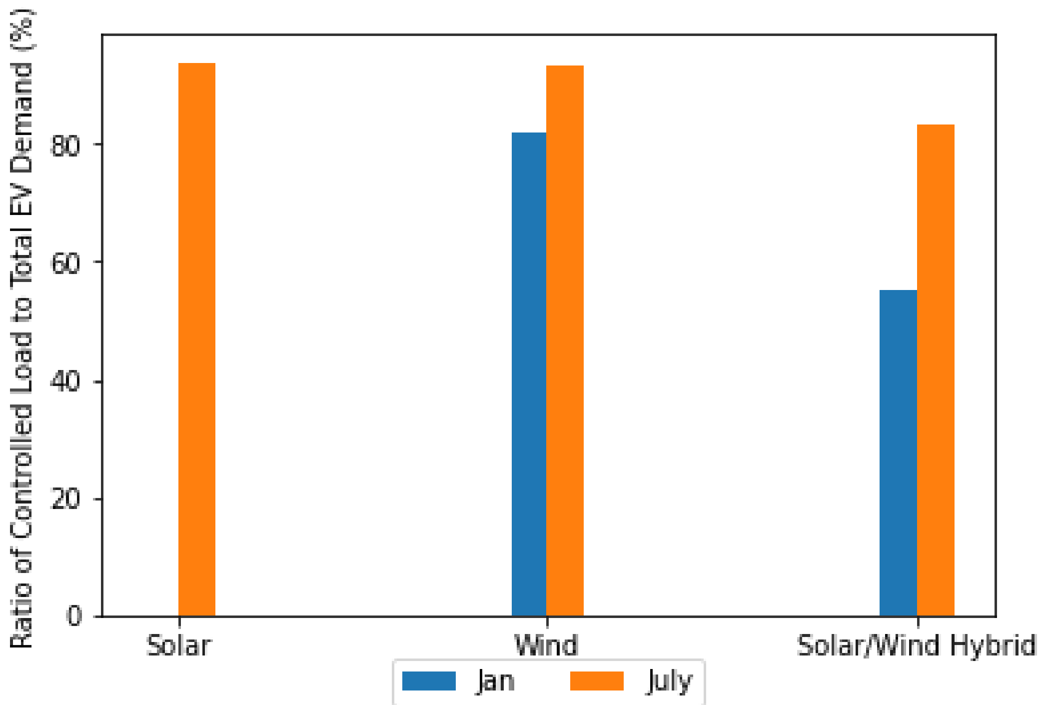


Figure 8: Ratio of utility controlled charging demand to total demand from electric vehicles for solar, wind, and solar/wind configurations. Utility controlled charging demand is the electric vehicle charging energy shifted to periods of renewable energy generation

The modelling in this analysis also allows EV load to be disaggregated by activity type, thus charging demand at home nodes to be separated from the charging demand at work nodes, as well as the other activity types. Different VRE configurations result in different allocation of load to activity types when UCC is involved, as shown in Figures 9a (S-UCC) ,9b (W-UCC), and 9c (SW-UCC) for a July week. Note that because there is no constraint on energy balance, the total demand from EVs is not equal in all configurations. In other words, the aggregate battery level of the fleet at the end of the simulation week is not equal across scenarios. The removal of this constraint allows for multi-day flexibility of EV charging to be explored, rather than charging flexibility within a single day. These results highlight the entanglement between power system planning and transportation planning. When the power grid is dominated by solar, most EV charging (with UCC) takes place at work locations in July, suggesting that chargers located at 'work' nodes will be necessary for EV charging to take advantage of solar production. In contrast, when wind is present (W and SW) in the generation mix, EV charging primarily takes place at 'home' nodes, and workplace charging plays a lesser role. In sum, infrastructure planning should prioritize EV charging stations at home when the power system includes wind generation but should prioritize EV charging stations at work when solar dominates the generation mix. In all configurations, charging at other and shopping type activities play a minor role, indicating that infrastructure that enables UCC is a lower priority.

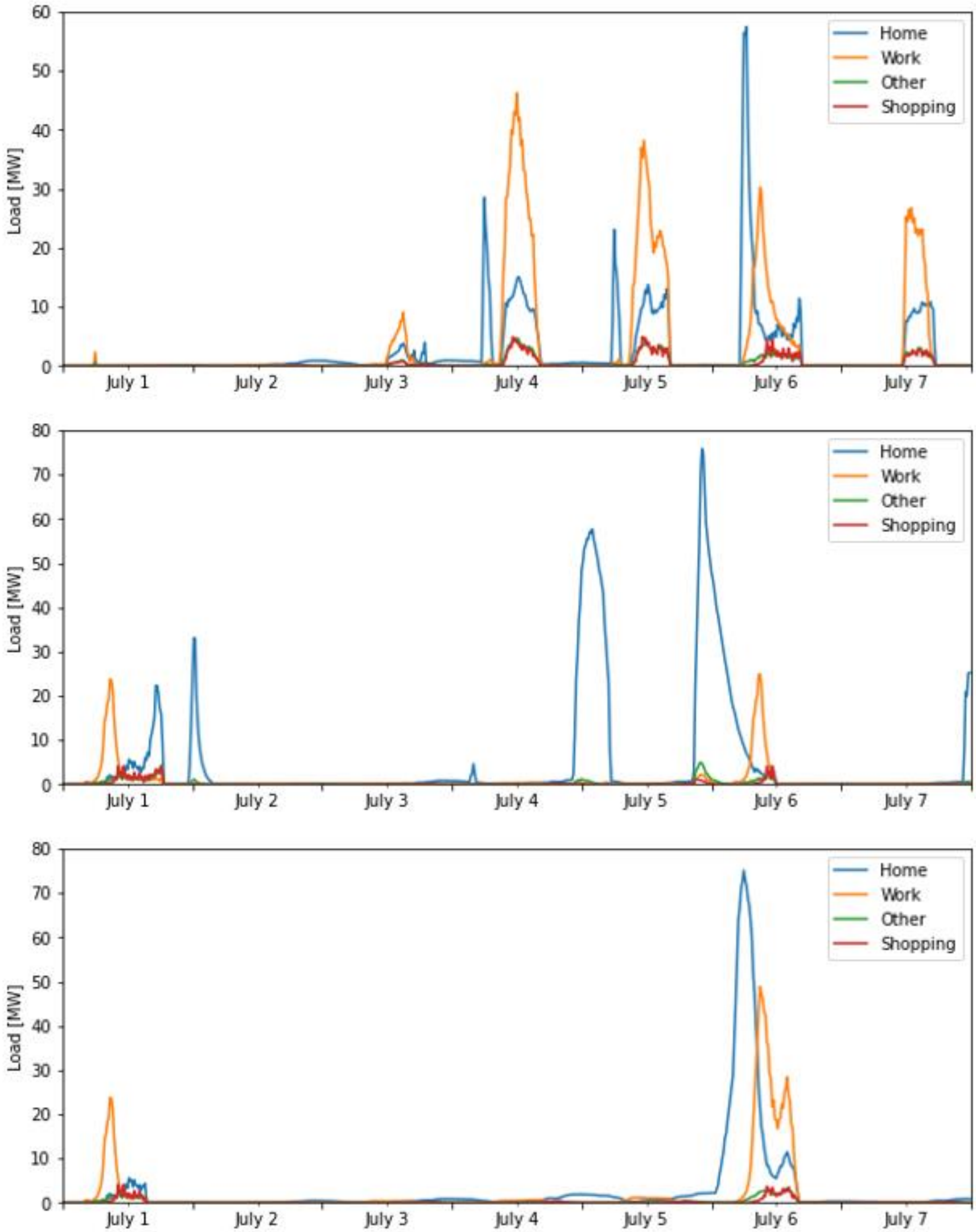
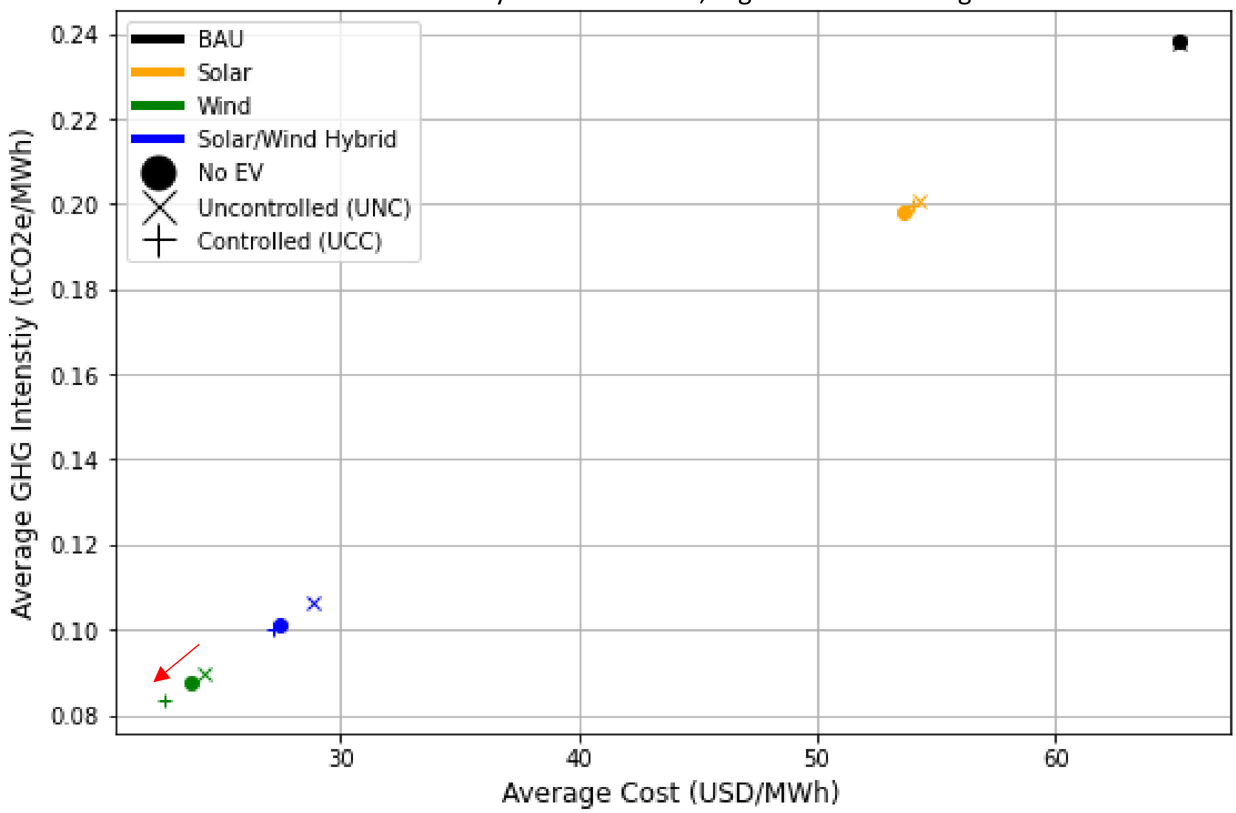


Figure 9: Electric vehicle load breakdown by activity for utility controlled charging occurring in a July week in the a) solar (top) b) wind (middle) and c) solar-wind hybrid (bottom) configurations

Electricity system operating cost and GHG emissions

Unsurprisingly, the high- VRE configurations investigated in this analysis result in significant reductions in average operational cost and GHG intensity of electricity production as compared to the BAU configuration. Figure 10 compares scenarios' GHG intensity (tCO2e/MWh) and operational electricity cost (USD/MWh) in January and July. Average operational cost varies significantly between scenarios and seasons. Solar generation is the most expensive among VRE configurations in the winter due to its low capacity factor, but it performs well in the summer. Both the wind and solar/wind hybrid scenario offer both low cost and emissions intensity in both seasons, regardless of EV integration and UCC.



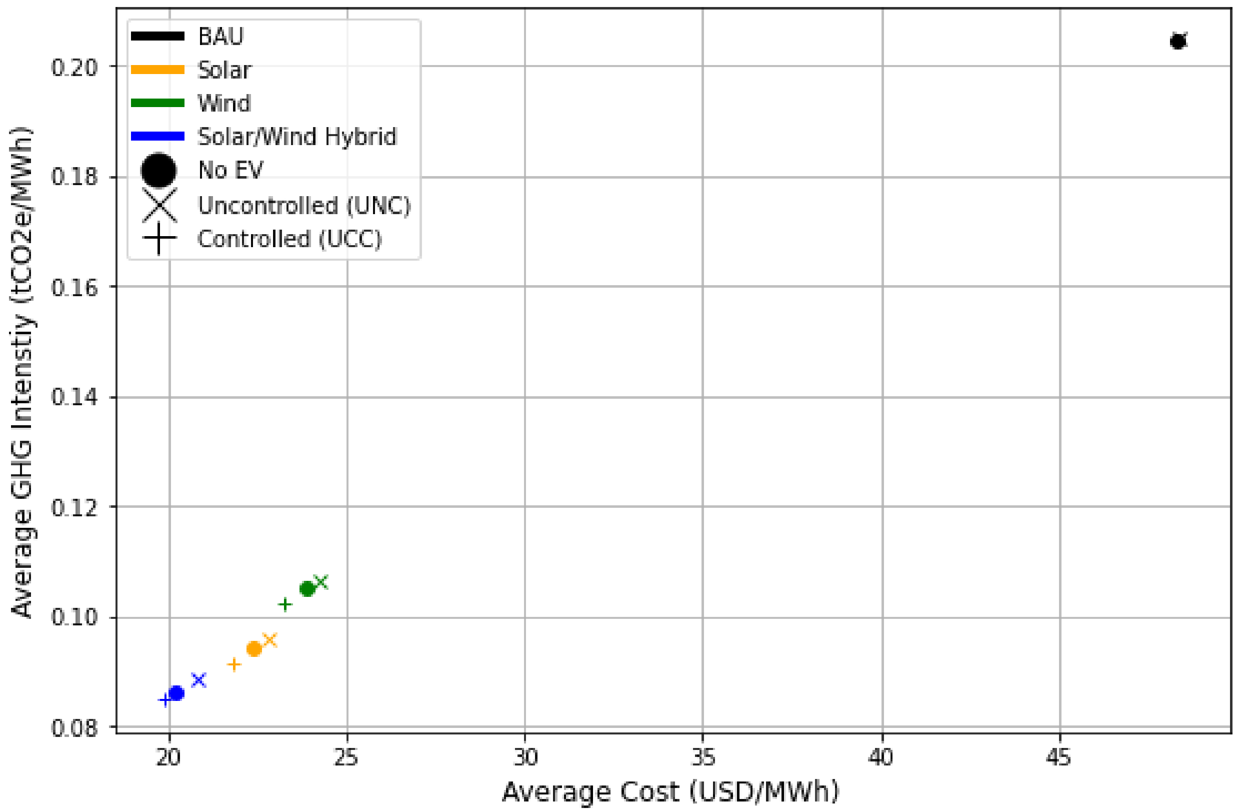


Figure 10: Average operational cost vs average operational greenhouse gas emissions intensity from electricity generation for a) January week (top) and b) July week (bottom)

Uncontrolled charging results in 1%-5% higher GHG intensity of electricity generation and costs when compared to non-EV scenarios. The increase in GHG intensity of generation across scenarios indicates that EV charging (when uncontrolled) relies more on fossil fuel generation than the non-EV load, regardless of VRE configuration or seasonal effects. This observation highlights the need for controlled charging, or incentive programs to shift EV charging.

In contrast, UCC decreases GHG intensity and operational cost relative to UNC scenarios as well as the no EV scenarios. UCC decreases operational cost and average GHG intensity by 7% in the wind configuration in January (shown by the red arrow in Figure 10a) and 5% in the summer. The largest change in average cost and GHG intensity in the solar dominated scenarios occur in the summer, due to a significantly higher capacity factor. Long lasting periods of VRE generation help to facilitate UCC more than VRE which peaks and diminishes rapidly (within the span of a few hours), as is the case with solar generation, incentivizing wind deployment in tandem with the UCC charging paradigm.

VRE curtailment

Due to the mismatch in timing between VRE generation and EV demand, VRE curtailment remains high when charging is uncontrolled. By implementing UCC, VRE curtailment is reduced by utilizing the VRE more effectively. Though UCC decreases curtailment, demand from passenger EV charging alone is too small to eliminate the curtailment from 400 MW of new VRE. The effect of uncontrolled and controlled charging on total system curtailment is shown in Figure 11 winter (11a) and summer (11b) periods, for the three VRE configurations. Again, we note that no curtailment occurs in the winter in a solar-dominated grid, due to lower solar capacity factors and a typically higher electricity demand in the winter. The high capacity factor of wind led to very high curtailment rates in the wind dominated configuration. In contrast, curtailment rates are more reasonable in the solar/wind hybrid configuration, which achieves low cost, emissions, and curtailment through the implementation of UCC in both the January and July weeks.

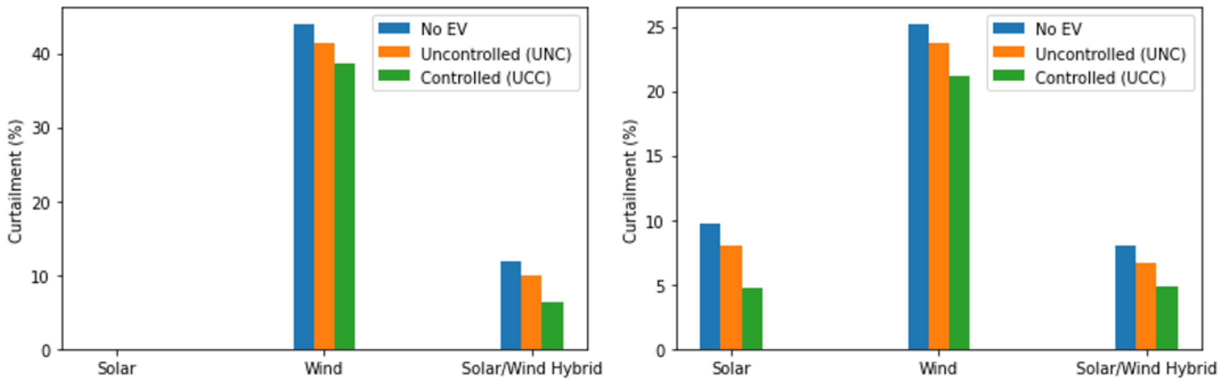


Figure 11: Total system curtailment for solar, wind, and solar-wind configurations for a) the January week (left) and b) the July week (right)

EV Penetration Rate Sensitivity

As EV penetration increases, VRE curtailment noticeably plateaus with 200MW each of solar and wind generation, as shown in Figure 12. This plateau is accompanied by a drop in the effectiveness of UCC, indicating that the amount of generation may not be sufficient to use UCC to its full potential, and the EV fleet can be considered as "saturated". However, it is evident that UCC can keep VRE curtailment rates within 10% and still be relatively effective in shifting EV charging.

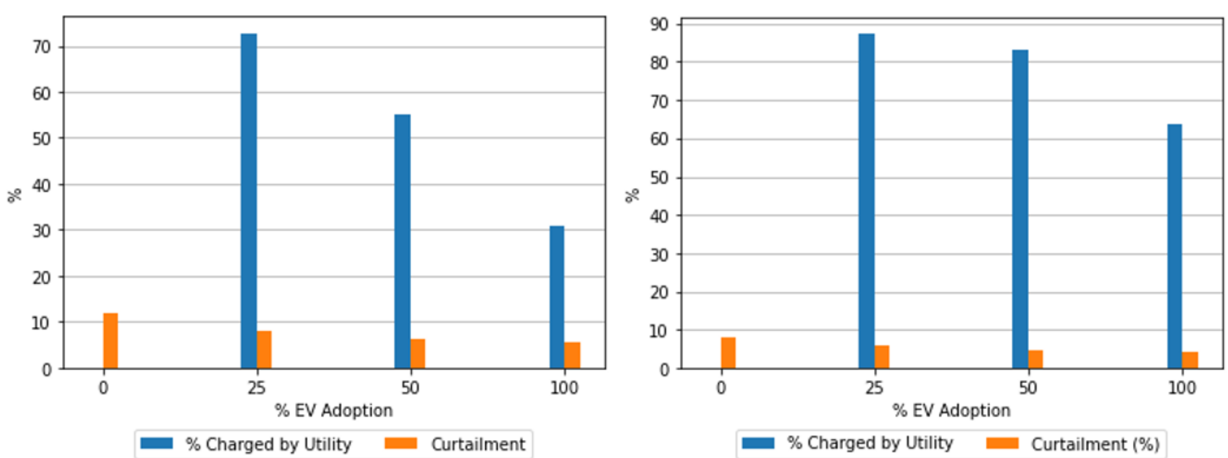


Figure 12: Comparison between curtailment and percent of electric vehicle demand shifted via utility controlled charging as electric vehicle penetration increases for a) January (left) and b) July (right) for the solar-wind configuration

Discussion

This analysis describes the linkage of operational models for the transportation sector and electricity sector, using an intermediate charging model to simulate uncontrolled and controlled vehicle charging. The modelling framework is intended to serve as a scenario exploration and evaluation tool, not as a tool to predict the future system configuration. Potential configurations of VRE generation local to

Regina were investigated and had the greatest impact on system cost, emissions, and curtailment when compared to the addition of EVs and UCC, though the latter were found to have significant effects as well.

Utility controlled EV charging results in cost, emissions, and VRE curtailment reductions across all the scenarios that we investigated. However, the benefit of UCC is not uniform across VRE configurations and seasons. In the winter, reductions in emissions and cost are higher when UCC is implemented with wind generation, due to longer lasting generation events and a higher capacity factor. Our findings are consistent with previous analyses by Szinai et al. (2020) and Wolinetz et al. (2018) who integrate UCC within production cost models of the electricity system in an optimization approach using a comparable approach to this analysis. (Wolinetz et al., 2018) find that UCC can reduce electricity prices by 4.2% relative to uncontrolled charging in Alberta, when nearly the entire LDV stock is electrified. (Szinai et al., 2020) report system operating cost reductions 2%-10% reduction when 0.95-5 million EVs participate in smart charging and up to 40% reduction in VRE curtailment, in a California grid 50% solar installed capacity. This study finds that with 50% EV penetration, a 5-7% reduction in operational cost can be achieved through UCC, which is on a similar scale to that reported in the other studies. Like Wolinetz et al. (2018), we find that the operational cost savings from implementing controlled charging is on the order of tens of dollars per vehicle, per year. While this may seem low, the financial benefits of controlled charging can be realized with minimal inconvenience to EV owners.

In contrast to (Szinai et al., 2020; Wolinetz et al., 2018), this analysis employs an approach to UCC where no travel information is provided to utilities by travellers. More specifically, the utility or entity controlling vehicle charging is only aware of whether a vehicle is plugged in or not. Amongst the diverse approaches to modelling smart and controlled EV charging, one should consider consumer acceptability when devising the formulation of controlled charging. Drivers may be unwilling to accept a controlled charging scheme which allows utilities to stop vehicle charging during peak hours, or which requires them to share departure times or travel schedules. The results of this study show that UCC can lead to cost reductions with minimal information from the vehicle driver. However, the proper incentives for participating in UCC must be in place. For example, the utility could provide a discount on electricity rates when VRE generation is high, or offer a rebate depending on participation in a UCC program. Other models of smart charging may evolve as EV adoption increases – such as the decentralized approach where EVs individually bid into purchasing charging services upon receiving a price signal from the utility (Galus et al., 2012).

As Regina seeks to meet its energy demand through renewable sources, the role of local, community owned generation may become larger. While technologies such as rooftop solar increase the decentralization of the electricity grid, this analysis shows that at 400MW installed capacity, the low capacity factor of rooftop solar is not effective in facilitating UCC in the winter, while still resulting in curtailment in the summer. This poses a dilemma for solar integration with UCC in particular: building enough capacity for UCC in the winter would result in a large amount of excess VRE in the summer. On the other hand, as shown in this analysis, not building enough solar can lead to ineffective UCC in the winter. A possible solution is seasonal storage of hydrogen, which would incur additional complexity and cost to the system. In contrast, wind generation has the advantage of a higher capacity factor in the winter than in the summer. Both EV demand and electricity demand are higher in the winter than in the summer in Regina, and this characteristic of wind may somewhat offset the need for system storage or VRE curtailment at appropriate levels of installed capacity.

In terms of future work, there are several potential advancements to build on the results of this analysis. Research is ongoing to link the municipal and provincial system models to provide a more realistic representation of the electricity system. This analysis did not consider the effect of EV adoption on travel patterns and assumed EV penetration rates and VRE capacity – future work could incorporate more realistic EV adoption rates as well as explore the potential for using EV travel schedules. Future work could also address temperature dependent effects such as heating and cooling, which would increase electric vehicle charging demand. While potential configurations of the transportation system were not modelled - such as different scenarios of land use growth, public transit infrastructure, and vehicle ownership - the framework developed in this analysis can be used to explore these scenarios using TASHA. Finally, while this study explored the benefits of controlled charging at the transmission level, future work could explore controlled charging schemes to avoid negative effects on the electricity distribution grid.

Conclusion

Following the results presented in this study, the following conclusions can be made:

1. Adding variable renewable energy generation has the most meaningful impact on electricity system operating emissions and cost, when compared to other toggled variables. However, electric vehicle charging, controlled and uncontrolled, play a significant role as well.

Relative to the business-as-usual configuration, addition of 400 MW of VRE generation reduces emissions intensity by 60 -70 %. Imposing UCC in a future where 50% of vehicles are electric reduces operational greenhouse gas emissions and cost by 5-7 % compared to uncontrolled charging. Configurations with wind generation are the least expensive across both seasons and achieve more significant reductions in emissions in the winter, due to its compatible capacity factor across seasons. These are results specific to the case study of Regina, although similar travel patterns and wind/solar generation capacity factors would lead to similar results in other jurisdictions.

2. The profile for uncontrolled electric vehicle charging does not correspond with either the solar or wind generation profiles, and thus results in higher emissions intensity when compared to scenarios without electric vehicles

Some measure of controlled charging is necessary to prevent an increase in emissions from the introduction of electric vehicles. As shown in this analysis, the timing of vehicle arrivals coincides with the system peak demand. Even if charging is not directly controlled by the utility, preferable charging behaviour could be incentivized through indirect control of charging through price signalling such as time-of-use rates. In this analysis, the utility could shift nearly all vehicle charging to high VRE generation times in the summer and could shift up to 83% of EV demand in a winter week with 400MW of added wind generation. Even with significantly less wind on the system (as high curtailment rates were observed), utility controlled charging would still be able to shift charging so that most electric vehicle demand is met through VRE.

3. Seasonal effects play a large role in the effectiveness of utility controlled charging, with summer being optimal due to higher electric vehicle fuel economy.

While UCC effectively reduces both average emissions and operational costs, the variability of renewable resource profiles across seasons affects utility controlled charging effectiveness. Regardless of electric vehicle adoption in Regina, VRE integration faces a supply and demand balancing problem, particularly in high-solar scenarios: solar generation peaks in the summer when demand is lower. While controlled electric vehicle charging can somewhat mitigate this issue, the incremental demand of electric passenger vehicles on the system may not be sufficiently large enough to fully offset the balancing problem. Other solutions such finding export markets, or energy storage, may be required.

4. The choice of VRE configuration may have implications for prioritizing siting of electric vehicle charging infrastructure, due to the temporal variation of generation between wind and solar energy.

In wind dominated configurations, controlled electric vehicle charging can rely more on home charging infrastructure, while solar configurations may require more charging infrastructure at workplaces. This is an important consideration for utilities and municipal governments, as infrastructure costs could potentially be avoided depending on plans for VRE integration. Because most electric vehicle owners would be expected to have chargers at home, integration of wind energy with utility controlled charging may result in decreased infrastructure costs, though further analysis on the costs of charger installation would be required. This is a finding which highlights the importance of co-modelling of different sectors, which can reveal interactions between electricity generation characteristics and characteristics of other sectors.

Chapter 3: Conclusions

Understanding the extent of electric vehicle charging flexibility can help to inform planning related to both the transportation and electricity sectors. As demonstrated in Chapter 2, flexible charging can provide benefits including reduced renewable energy curtailment, operational cost and emissions, thereby aiding the decarbonization of the transportation sector.

The objective of this thesis was to develop a modelling framework which can be used to estimate these benefits of EV flexibility, especially in the context of VRE integration. To achieve this objective, the City of Regina was used as a case study. A travel demand model was built for the city, allowing vehicle travel schedules to be determined. The charging and travel behaviour of the vehicles represented by these schedules were then simulated in a charging model to output EV charging load curves. Finally, these load curves were aggregated with the non-EV load for Regina, and the production cost model SILVER was used to model electricity system operating cost and emissions.

Results from this work show that while the choice of VRE configuration (installed solar and wind capacity) has the most noticeable effect, electric vehicle charging can influence electricity operating cost and emissions either negatively or positively, depending on whether charging is controlled. Left uncontrolled, EV charging increases cost and emissions, regardless of the type of the VRE configuration. In contrast, controlled EV charging decreases cost and emissions by up to 7% relative to uncontrolled charging, and up to 5% relative to scenarios with no EV penetration. Furthermore, by utilizing excess renewable energy, utility controlled charging reduces VRE curtailment. Wind generation was found to be better suited to facilitate controlled charging than solar PV, due to its higher capacity factor, longer duration of generation events, and ability to produce electricity overnight, when parked vehicles have the greatest flexibility. Our analysis shows that utility controlled charging can effectively shift EV charging regardless of generation type in the summer, as higher EV fuel economies when temperature is higher reduces the need for vehicles to charge.

An important motivation for this work was the desire to represent realistic consumer behaviour in the context of UCC. As a result, we did not allow the utility to have perfect information on driver schedules and did not enforce a daily energy balance constraint on EV charging. Even without posing an inconvenience to consumers, utility controlled charging lead to significant decreases in cost and emissions.

Finally, while this thesis has presented some potential benefits of EV charging in terms of electricity system operations, EVs are not necessarily a silver bullet to the issue of transportation system decarbonization. Lifecycle analysis of EVs by Hawkins et al. (2013) and Milovanoff et al. (2020) shows that EVs have drawbacks from a materials use and environmental degradation perspective. As such, there remains a need for policies that reduce vehicle usage, such as making public and active transportation more attractive. Electric vehicles will be one technology in a mix of different policies and technologies aimed at reducing emissions from the transportation sector.

There are several future avenues for further research for investigating the role of demand side flexibility in decarbonization. In terms of modelling techniques, the work in this thesis represented an iterative linkage between SILVER and the charging model. Future work could involve programming the charging model as a module of SILVER, removing the need to pass information manually between the two models. In addition to the transportation sector, the building sector plays a large role in municipal energy demand. Seatle. et al (2021) present an approach for linking transportation energy demand model (as described in this thesis) and a building energy demand model with an electricity production model such as SILVER to generate multisector insights The proposed modelling framework can be applied different cities across Canada, revealing different pathways towards decarbonization for different cities.

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Appendix

A1. EV Policy Review

The tables in this section were contributed to a Canadian Institute of Climate Choices White Paper on Grid Modernization, within the transportation analysis section. The White Paper is embargoed at the time of submission of this thesis.

Table A-1: Federal Level ZEV policies and incentives

Policy name	Category	Target	Description	Link
iZEV Program	Financial rebate	Prospective EV purchasers	Up to $5000 rebate for the purchase of a new electric vehicle	https://tc.canada.ca/en/road-transportation/innovative-technologies/zero-emission-vehicles
Tax Write-off	Tax benefit	Businesses	Budget 2019 proposed a 100-per-cent write-off for zero-emission vehicles to support business adoption. Cannot receive both federal rebate and write-off	https://tc.canada.ca/en/road-transportation/innovative-technologies/zero-emission-vehicles
Electric Vehicle and Alternative Fuel Infrastructure Deployment Initiative (EVAFIDI)	Funding for charging infrastructure	Utilities/ Companies/ Governments/ Institutions	Offers repayable contributions to support the construction of an electric vehicle (EV) fast charging, coast-to-coast network	https://www.nrcan.gc.ca/energy-efficiency/transportation-alternative-fuels/electric-and-alternative-fuel-infrastructure/electric-vehicle-alternative-fuels-infrastructure-deployment-initiative/18352
Zero Emission Vehicle Infrastructure Program (ZEVIP)	Funding for charging infrastructure	Utilities/ Companies/ Governments/ Institutions	Targets ZEV infrastructure projects in public places, on-street, multi-unit residential buildings, workplaces and light-duty vehicle fleets Focus on local charging as opposed to coast to coast (EVAFIDI)	https://www.nrcan.gc.ca/energy-efficiency/transportation-alternative-fuels/zero-emission-vehicle-infrastructure-program/21876

Policy name	Category	Target	Description	Link
Zero Emission Vehicle Awareness Initiative	Funding for awareness projects	Utilities/ Companies/ Governments/ Institutions	Supports projects that aim to increase awareness of ZEVs, and public charging and refueling infrastructure, through education and capacity-building activities to ultimately support a greater adoption of ZEVs by Canadians	https://www.nrcan.gc.ca/energy-efficiency/transportation-alternative-fuels/electric-and-alternative-fuel-infrastructure/zero-emission-vehicle-awareness-initiative/22209
100% ZEV passenger vehicle sales by 2035	Mandatory target	Government	Mandatory target for new light-duty cars and passenger truck sales to be 100% zero emission by 2035	https://www.canada.ca/en/transport-canada/news/2021/06/building-a-green-economy-government-of-canada-to-require-100-of-car-and-passenger-truck-sales-be-zero-emission-by-2035-in-canada.html

*Table A-2: Provincial level ZEV policies and incentives - Governmental/**Non Governmental***

Province	Policy name	Category	Target	Description	Link
BC	Go Electric Public Charger Program	Financial Rebate	Indigenous communities, rural and northern areas, and city centers experiencing long queues	Rebates for fast charger installation, amount depending on charger power ranging from $20000 to $130000	https://pluginbc.ca/publiccharger/#:~:text=The%20CleanBC%20Go%20Electric%20Public%20Charger%20Program%20is,the%20growing%20number%20of%20ZEVs%20on%20the%20road
	ZERO Emission Vehicles act	Legal requirement	Automakers	Requires automakers to meet an escalating annual percentage of new light-duty ZEV sales and leases, reaching: 10% of light-duty vehicle sales by 2025, 30% by 2030 and 100% by 2040 (Harmonized with federal target). Sales of ICEs banned by 2040	https://www2.gov.bc.ca/gov/content/industry/electricity-alternative-energy/transportation-energies/clean-transportation-policies-programs/zero-emission-vehicles-act
	SCRAP-IT	Financial Rebate	Prospective EV purchasers	Up to $6000 rebates for purchasing a new EV after trading in an older gas vehicle, $3000 for purchase of a used EV (BC only)	https://scrapit.ca/
	Go Electric Vehicle Rebates (Passenger, Commercial, and Fleet vehicles)	Financial Rebate	B.C. residents, businesses, non-profit organizations and local government organizations	Various rebates depending on the category (passenger, commercial, fleet) Funding for infrastructure/assessments for fleet program only	https://www2.gov.bc.ca/gov/content/industry/electricity-alternative-energy/transportation-energies/clean-transportation-policies-programs/clean-energy-vehicle-program

Province	Policy name	Category	Target	Description	Link
BC	Go Electric Home and Workplace Charger Rebates	Financial rebate	Charger installations	Financial support for Level 2 charging, and funding for electrical upgrades/assessments (up to $300 for homes, $2000 for apartments)	https://www2.gov.bc.ca/gov/content/industry/electricity-alternative-energy/transportation-energies/clean-transportation-policies-programs/clean-energy-vehicle-program/charging-infrastructure
	Use of HOV lanes	Non Financial Incentive	EV Drivers	EVs allowed to use provincial highway HOV lanes	https://www2.gov.bc.ca/gov/content/transportation/driving-and-cycling/traveller-information/routes-and-driving-conditions/hov-lanes/electric#:~:text=Electric%20vehicles%20%28EVs%29%20displaying%20an%20official%20decal%20are,vehicle%20list%20before%20a%20permit%20will%20be%20issued.
AB	Electric Vehicles for Municipalities Program	Funding for various initiatives	Municipalities within Alberta	Funding for municipalities (not individuals) including EV feasibility studies; variety of EVs such as passenger vehicles, medium-heavy duty vehicles, and Zambonis.	https://mccac.ca/programs/electric-vehicles-for-municipalities-program/

Province	Policy name	Category	Target	Description	Link
SK	Tax on EVs	Financial disincentive	EV Owners	$150 annual tax on passenger electric vehicles (EVs)	https://www.saskatchewan.ca/government/news-and-media/2021/april/06/202122-budget-will-protect-build-and-grow-saskatchewan#:~:text=The%202021-22%20Budget%20includes%20%241.5%20billion%20to%20help,years%2C%20for%20a%20multi-year%20commitment%20of%20%244.8%20billion.
MB	Electric vehicle roadmap	Strategic Plan	Various	Key actions include creating partnerships with companies and institutions to demonstrate technology and raise public awareness; creating an EV advisory committee; and developing an EV learning and Demonstration Center	https://www.gov.mb.ca/sd/environment_and_biodiversity/energy/pubs/elec_vehicle_road_map.pdf
ON	Green Vehicle Licence Plate Program	Non Financial Incentive	EV Drivers	Vehicles with green plates can access HOV lanes and free access to High Occupancy Toll (HOT) lanes on 400-series highways and the Queen Elizabeth Way (QEW)	http://www.mto.gov.on.ca/english/vehicles/electric/green-licence-plate.shtml#:~:text=Ontario%27s%20Green%20Vehicle%20Licence%20Plate%20Program.%20Your%20Green,there%20is%20only%20one%20person%20in%20the%20car.
	Used Electric Vehicle Incentive	Financial rebate	Prospective EV purchasers	Ontario drivers qualify for $1,000 toward the purchase of a used fully electric car	https://www.plugndrive.ca/used-electric-vehicles-incentive/
	Scrappage Incentive Program	Financial rebate	Prospective EV purchasers	Rebate for purchasing an EV after trading in an older gas vehicle (ON only)	https://www.plugndrive.ca/used-electric-vehicles-scrappage/

Province	Policy name	Category	Target	Description	Link
QC	New vehicle rebate	Financial Rebate	Individuals, Businesses, Municipalities	Rebate of up to $8,000 on the purchase or lease of a new electric vehicle	https://vehiculeselectriques.gouv.qc.ca/english/rabais/ve-neuf/programme-rabais-vehicule-neuf.asp
	Used vehicle rebate	Financial Rebate	Individuals, Businesses, Municipalities	Rebate of up to $4,000 towards purchase of a used electric vehicle	https://vehiculeselectriques.gouv.qc.ca/english/rabais/ve-occasion/programme-rabais-vehicule-occasion.asp
	Charging station rebates	Financial Rebate	Charger installations	Varying amount of rebate depending on program (Home, Multi Unit Residential Building, Workplaces)	https://vehiculeselectriques.gouv.qc.ca/english/rabais/domicile/programme-remboursement-borne-recharge-domicile.asp
	Toll Free Bridges and Ferries	Financial Incentive	EV Drivers	Free access to toll bridges highways 25 and 30 and ferry services of the Society of Quebec ferries	https://www.transports.gouv.qc.ca/fr/ministere/role_ministere/electrification/Pages/electrification.aspx
	Access to HOV Lanes	Non Financial Incentive	EV Drivers	Use of HOV reserved lanes in provincial highways	https://www.transports.gouv.qc.ca/fr/ministere/role_ministere/electrification/Pages/electrification.aspx
	Zero Emission Vehicle Standard	Legal requirement	Vehicle manufacturers	Manufacturers accumulate credits for the sale of zero emissions vehicles in QC	https://www.environnement.gouv.qc.ca/changementsclimatiques/vze/index.htm
	Ban of ICE sales by 2035	Legal requirement	Dealerships	Part of Quebec's Green Economy initiative, applies to new vehicle sales	https://electricautonomy.ca/2020/11/16/quebec-ban-new-gas-vehicles-2035/#:~:text=Quebec%E2%80%99s%20ICE%20ban%20is%20a%20move%20that%20is,federal%20level%20to%20create%20a%20Canada-wide%20electrification%20minimum.

Province	Policy name	Category	Target	Description	Link
NL	-	-	-	No major available rebates or incentives in the province	-
NB	-	-	-	No major available rebates or incentives in the province	-
NS	Electric Vehicle Rebate program	Financial rebate	Prospective EV purchasers	Rebates for the purchase or lease of BEVs, PHEVs and e-bikes (up to $3000 for new vehicles, $2000 for used)	https://evassist.ca/rebates/
PEI	Electric Vehicle Incentive and free charger	Financial rebate	Prospective EV purchasers	Rebate for purchase of a new EV from licensed dealership, plus free level 2 charger (up to $5000)	https://www.princeedwardisland.ca/en/information/environment-energy-and-climate-action/electric-vehicle-incentive
YK	Electric vehicle rebate	Financial rebate	Prospective EV purchasers	Rebate for purchase or lease of a new EV (up to $5000)	https://yukon.ca/en/driving-and-transportation/apply-rebate-new-zero-emission-vehicle
	Charger rebate	Financial rebate	Charger installations	Rebate available for personal level 2 chargers at residences and commercial/apartment buildings, amount depending on building and charger type	https://yukon.ca/en/driving-and-transportation/clean-energy-rebates/apply-rebate-install-level-2-electric-vehicle
NWT	Electric vehicle and charger rebate	Financial rebate	Prospective EV purchasers and charger installations	New EV, PHEV, and Level 2 charging stations are eligible for rebate (up to $5000 for vehicle, $500 for charger)	https://aea.nt.ca/program/electric-vehicles/
NU	-	-	-	No major available rebates or incentives in the province	-

Table A-3: Municipal level ZEV policies and incentives

City	Policy name	Category	Target	Description	Link
Toronto	City of Toronto EV Strategy	Strategic Plan	Various	Identifies opportunity areas that the City will take advantage of to become an EV-ready city, such as on street charging pilot programs	https://www.toronto.ca/wp-content/uploads/2020/02/8c46-City-of-Toronto-Electric-Vehicle-Strategy.pdf
Montreal	Montreal 2020-2030 Climate Plan	Strategic Plan	Various	Identifies key action items related to transportation electrification, such as setting targets for EV registration in the city	https://portail-m4s.s3.montreal.ca/pdf/climate_plan_2020-2030_executive_summary.pdf
Edmonton	City of Edmonton EV Charger Rebate	Financial rebate	Homeowners and Businesses	Maximum of $600 for existing residential properties and $2,000 for existing commercial properties	https://www.edmonton.ca/city_government/environmental_stewardship/electric-vehicles.aspx#:~:text=The%20City%20of%20Edmonton%20has%20a%20rebate%20to,residential%20properties%20and%20%242%2C000%20for%20existing%20commercial%20properties.
	City of Edmonton EV Strategy	Strategic plan	Various	Identifies opportunity areas that the City will take advantage of to become an EV-ready city	https://www.edmonton.ca/city_government/documents/PDF/EdmontonElectricVehicleStrategy.pdf
Calgary	City of Calgary EV strategy	Strategic plan	Various	Identifies actions related to increasing EV adoption such as partnering with organizations to improve charging infrastructure, raising awareness, and implementing charging infrastructure requirements for new buildings	https://www.calgary.ca/transportation/tp/strategy/electric-vehicle-strategy.html

City	Policy name	Category	Target	Description	Link
Vancouver	Charger requirements for new buildings	Legal requirement	Developers	As of January 1, 2019, all new development permit applications require that 100% of residential parking stalls, except visitor stalls, must be EV-ready.	https://vancouver.ca/files/cov/2019-006-electric-vehicle-charging-for-buildings.pdf
	Dedicated Parking	Non Financial Incentive	EV Owners	Dedicated zero emission vehicle parking stalls in parking lots across the city	https://vancouver.ca/streets-transportation/electric-vehicles.aspx
	HOV Lane access	Non Financial Incentive	EV Owners	EVs allowed to use municipal HOV lanes in addition to provincial ones	https://vancouver.ca/streets-transportation/electric-vehicles.aspx
Surrey	City of Surrey EV Strategy	Strategic Plan	Various	In development, identifies actions to accelerate EV adoption in the City and supports a long-term vision for Surrey where all vehicles are zero-emission	https://www.surrey.ca/services-payments/parking-streets-transportation/electric-vehicles/electric-vehicle-strategy
Burnaby	Electric Vehicle (EV) Charging Bylaw	Legal requirement	Developers	Requires all required parking spaces for new dwelling units to provide Level 2 electric charging	https://www.burnaby.ca/Assets/city+services/building/Brochures+$!26+Bulletins/Building+Technical+Information/Electrical+Vehicle+(EV)+Charging+Bylaw.pdf

A2. Vehicle scheduling

Predicting EV charging at a disaggregate level requires vehicle schedules. Converting the TASHA output to vehicle schedules requires consideration of two factors in household vehicle travel modelled by TASHA: Ridesharing/passenger facilitation, and household vehicle sharing. The procedure for mode share in TASHA can be found in Roorda and Miller (2003). The methodology described in this section attempts to “reverse engineer” the TASHA output to produce vehicle schedules. TASHA outputs three file types related to trip modes and timing: trips.csv (Table S1), trip_modes.csv (Table S2), and facilitate_passenger.csv (Table S3). Because TASHA operates at a household level, all tables show TASHA outputs for a single household. Additionally, TASHA activity types have been aggregated into 4 categories (Work, Home, Shopping, and Other) for ease of analysis in the study.

Table S1 contains the trip schedule for each person, including origin and destination zone and activities for each trip. Table S2 links each trip with a departure/arrival time, as well as a mode choice. Finally, Table S3 contains information on those trips which have “Passenger” as the mode choice. Specifically, for each trip with “Passenger” mode, Table 3 records the person ID of the household member driving the passenger, as well as which trip the driver is diverting away from in order to drive the passenger on that trip. Facilitate passenger trips are included in the overall trip distance when scheduling vehicles, in a methodology which is further described in the next section.

Table A-4: Sample person level trip schedule for Household 42

Household ID	Person ID	Trip ID	Origin Activity	Origin Zone	Destination Activity	Destination Zone
42	1	1	Home	15	IndividualOther	27
42	1	2	IndividualOther	27	Home	15
42	1	3	Home	15	PrimaryWork	27
42	1	4	PrimaryWork	27	Home	15
42	1	5	Home	15	IndividualOther	27
42	1	6	IndividualOther	27	Market	27
42	1	7	Market	27	Home	15
42	2	1	Home	15	Market	15
42	2	2	Market	15	Home	15
42	3	1	Home	15	PrimaryWork	27
42	3	2	PrimaryWork	27	IndividualOther	27
42	3	3	IndividualOther	27	SecondaryWork	15
42	3	4	SecondaryWork	15	IndividualOther	14
42	3	5	IndividualOther	14	Home	15
42	5	1	Home	15	IndividualOther	69
42	5	2	IndividualOther	69	Home	15

Table A-5: Mode choice for each trip made in Household 42

household_id	person_id	trip_id	mode	o_depart	d_arrive
42	1	1	Auto	345.7167	360
42	1	2	Auto	480	493.8167
42	1	3	Auto	510.7167	525
42	1	4	Auto	1020	1034.467
42	1	5	Auto	1096.35	1110
42	1	6	Auto	1230	1230.35
42	1	7	Auto	1365.35	1378.017
42	2	1	Passenger	974.0333	975
42	2	2	Passenger	1080	1080.967
42	3	1	Auto	420.9	435.1833
42	3	2	Auto	945.1833	945.5333
42	3	3	Auto	1020.533	1035
42	3	4	Auto	1080	1086.483
42	3	5	Auto	1326.483	1333.65
42	5	1	Carpool	1202.9	1215
42	5	2	Passenger	1335	1342.383

Table A-6: Facilitate passenger table for Household 42

household_id	passenger_id	passenger_trip_id	driver_id	driver_trip_id
42	2	1	3	3
42	2	2	1	5
42	5	2	1	7

A2.1 Facilitate Passenger

TASHA models facilitate passenger trips, which involve a driver and a passenger, and occur when the timing of a passenger's trip is close to the timing of the driver's trip. If a driver facilitates a passenger, the EV driving distance increases, and additional charging will be required to compensate. When facilitating a passenger, the driver diverts away from their original destination, drives to the passenger's location, and drives them to their next activity, and then resumes their original travel schedule. Multiple passengers may require facilitation around the same time, causing the driver to make multiple facilitations before returning to their original schedule. Using Table S1, S2, and S3 as an example (Household ID 42), there are 3 faciliatate pasenger trips made. Person 2 trip 1 requires Person 3 to divert from trip 3. Person 2 trip 1 has an origin of Zone 15 and destination of zone 15, while Person 3 trip 3 has an origin and destination zone of 27 and 15 respectively. The total distance required to facilitate the passenger and complete the original trip is based is calculated assuming the driver begins at zone 27, drives to the passengers origin location (15), drives to the passengers destination location (15), and finally drives to their original destination location. This can be shown in Figure S1.

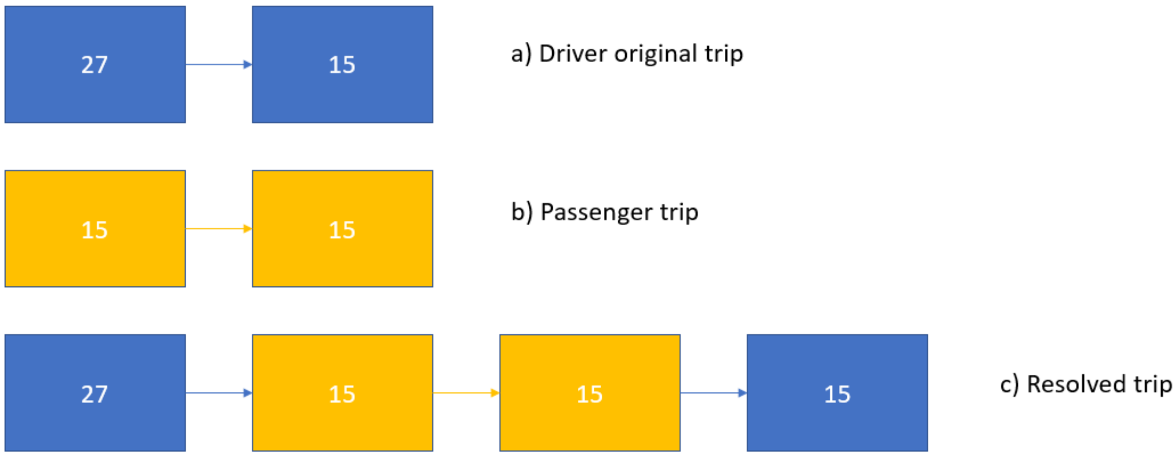

Figure A13: Facilitate passenger resolution

The diversions away from the original trip directly affect the distance driven on the auto driver's original trip, but not the start and end times of the driver's trip, as doing so could cause inconsistencies with the trip schedule. TASHA may schedule trips such that multiple passenger trips require the driver to divert from the same trip. In this case, the assumption is that the driver facilitates one passenger at a time, dropping a passenger off at their destination before picking up another passenger. The final distance of the vehicle trip is simply calculated as the sum of origin destination pairs, as shown in equation S1.

$$d_{fp} = \sum_{n=0}^{n} d(i,j)_n \qquad (S1)$$

Where d_{fp} is the total distance, n is the number of pairs on the resolved trip chain, and $d(i,j)_n$ is the distance between zone i and zone j of the nth pair. After facilitate passenger trips are considered, each vehicle trip will now have an associated distance. At this point, vehicle allocation can be considered.

A2.2 Vehicle allocation

TASHA considers vehicle availability when determining household travel schedules, as the number of vehicles in a household is limited. In TASHA, vehicles start and end the travel day at the home location; household vehicle sharing must respect spatiotemporal constraints; and vehicle swapping only occurs at the home location. Figure S2 shows potential configurations for vehicle allocation using a TASHA schedule output.

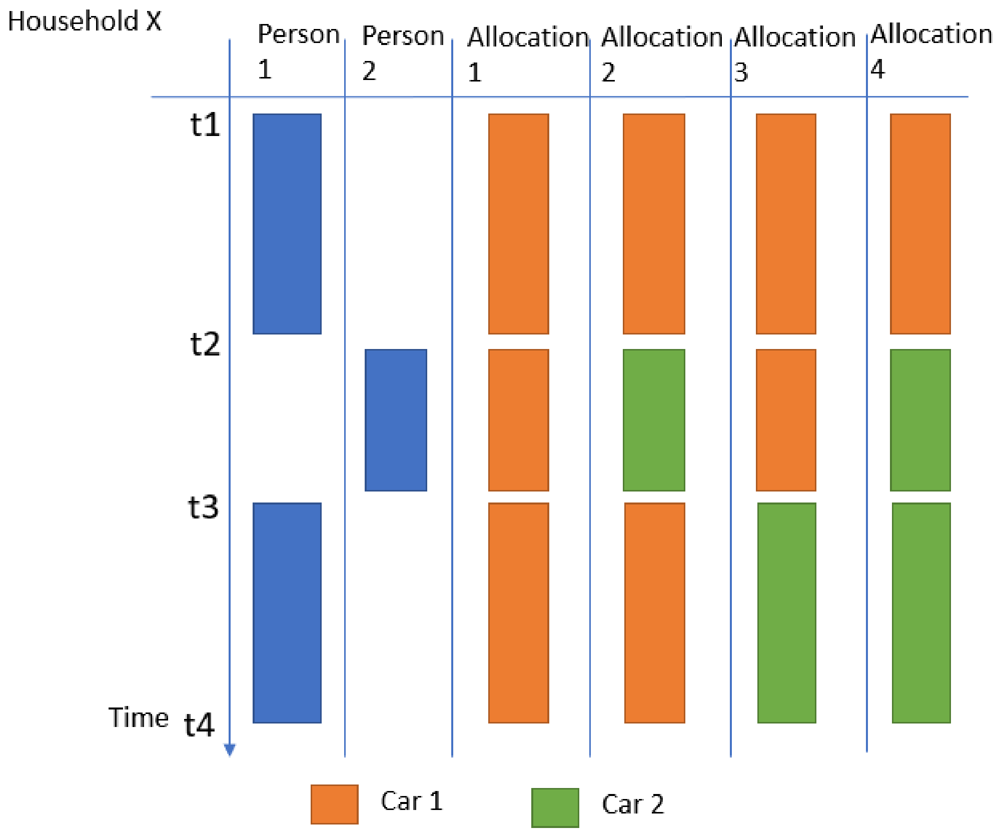

Figure A14: Household vehicle allocation

The blue bars are the TASHA output: based on the output, only the person schedules are known. The labelled times indicate blocks of time that a person has driven out of home: for example person 1 makes a vehicle trip starting from home at t1, and returns the vehicle to home at t2. Given that the example household has 2 vehicles, some potential allocation patterns are shown using the orange and green bars on the right. Allocation 1 shows all trips being made with the same vehicle, while Allocation 2 shows the two people using the same vehicle for their respective trips. Clearly, any of the allocations are possible, however the choice of allocation has implications for when and where a vehicle charges. To select a single vehicle allocation pattern for a household schedule, a simulation procedure was employed, which the following simplified pseudocode describes.

```
For each Household:

        Create household vehicle pool (stack structure) with length equal to number of household
        vehicles (model input);

        Filter and sort household vehicle trips by ascending order of departure time;

                For each vehicle trip:

                        If trip start purpose is Home:

                                Pop vehicle from back of vehicle pool stack, and mark trip as
                                completed by popped vehicle;

                        If neither trip start purpose or trip end purpose is Home:

                                Mark trip as completed by the last vehicle used by person;


                If trip end purpose is Home:
```

Using the above procedure, the household travel schedule described by Tables S1, S2, and S3 is added becomes Table 1 (in actual article), which contains trip distances and a vehicle ID label for each trip.

A3. UCC Pseudocode

```
Initialize empty UCC eligible pool
Initialize Simulation time step array
Initialize Load curve arrays

## Preprocessing step and simulation initialization
For each unique household vehicle:
        Insert (vehicle ID, “Departure”) event into simulation time array at index i = departure time of vehicles
        first trip;
        Set Battery Level = Full Capacity;
        Calculate Threshold;
        Set Trip Index parameter to 0;

## Simulation stage
For each minute t in simulation horizon:
        If t mod 15 = 0: ##UCC occurs every 15 minutes;
                Read ERG(t) from input file;
                Calculate ERG for UCC(t);
                While ERG for UCC(t) > 0:
                        Select Vehicle from UCC eligible pool;
                        Increment Load curve associated with vehicles activity location and
                purpose by charge rate from t to t + t_charge (UCC Charging);
                        Remove vehicle from UCC eligible pool if battery level = Full Capacity;
                        Update ERG for UCC(t);

        For each (Vehicle ID, event) in Simulation time step array[t]:

                If event is “Departure” type:
                        Update vehicle battery level;
                        Discard vehicle from UCC eligible pool;
                        Insert (vehicle ID, “Arrival”) event into simulation time array at index
                i = arrival time of vehicles current trip;

                Else if event is “Arrival” type:
                        Increment vehicle trip index parameter by 1;
                        If battery level is below threshold:
                                Increment Load curve associated with vehicles activity location and
                                purpose by charge rate from t to t + t_charge (non UCC Charging);
                        Else:
                                Add vehicle to UCC eligible pool;

                        Increment trip index for vehicle by 1;
                        Insert (vehicle ID, “Depart”) event into simulation time array at index
```

A4. ERG adjustment pseudocode

```
FOR each interval t:
    IF ERG(t, i-1) > 0: (indicating a UCC event during period t during last iteration)
        Demand increase = demand(t, i-1) – demand(t, 0)
        Non VRE increase = non vre generation (t, i-1) – non vre generation (t,0)
        IF Non VRE increase/Demand increase > 0.2:
            ERG (t, i) = ERG (t, i-1) – Non VRE increase
        ELSE:
            ERG (t, i) = ERG (t, i-1)
    ELSE:
        ERG (t, i) = 0
```

A5. TASHA Validation

This section compares results from TASHA to those observed in the 2009 Regina Travel Survey, which was used to calibrate TASHA. Figures S3 – S7 compare the start times of activities between TASHA and the survey, for the following activity types: Work, Shopping, School, Other, and Return Home. In the main analysis, “School” activities are grouped with the “Home” activity type, due to the typical proximity between Home and School locations.

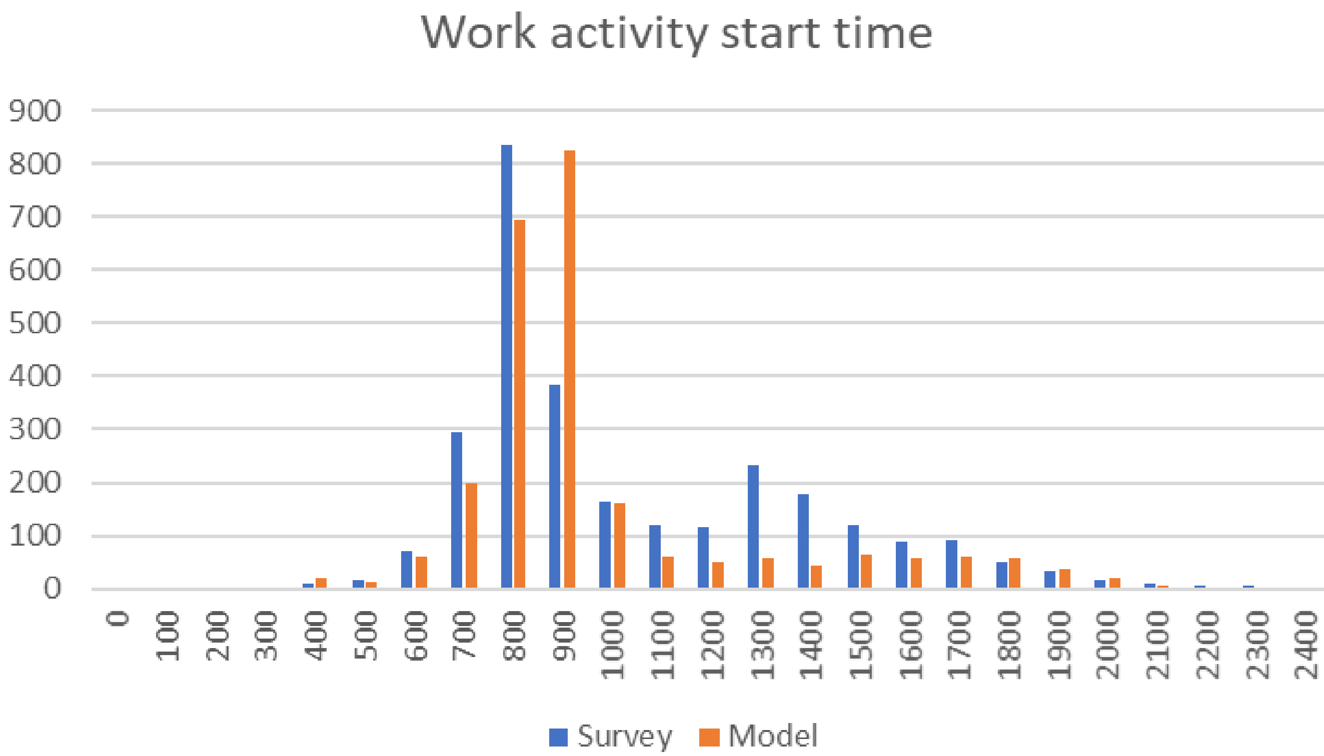

Figure A15: Work activity start time comparison

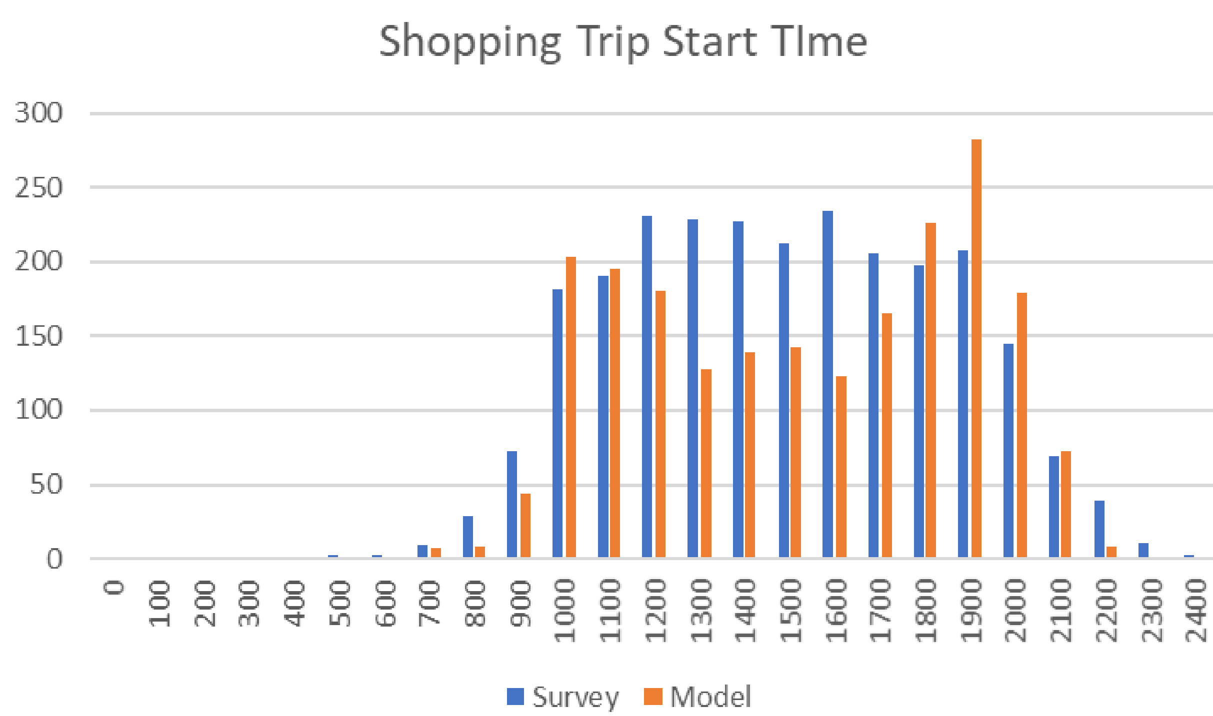

Figure A16: Shopping activity start time comparison

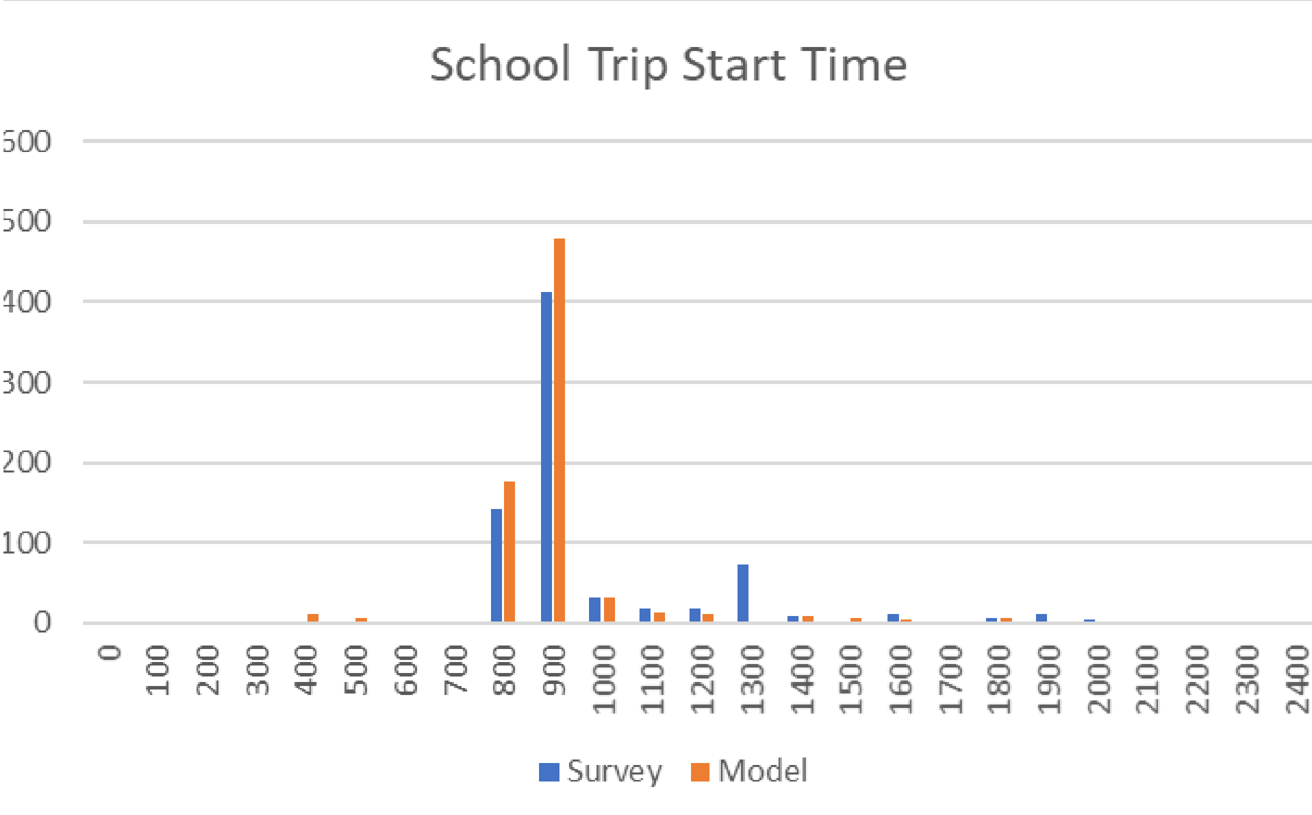

Figure A17: School activity start time comparison

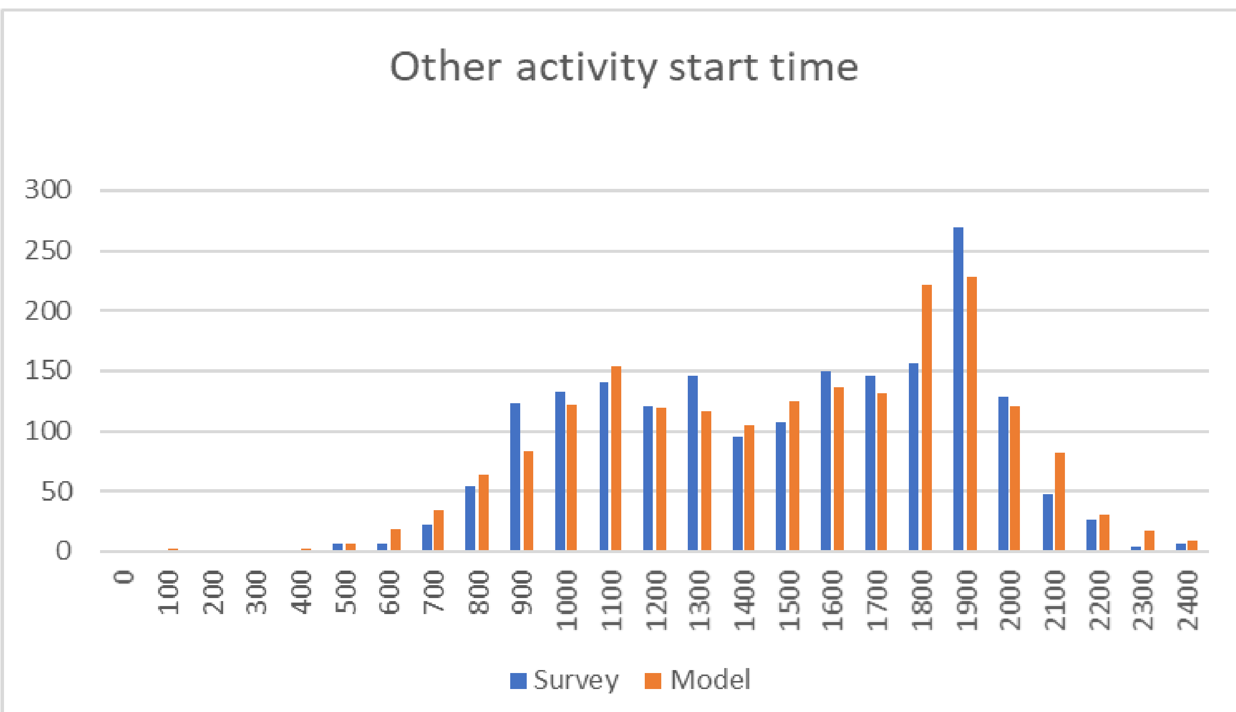

Figure A18: Other activity start time comparison

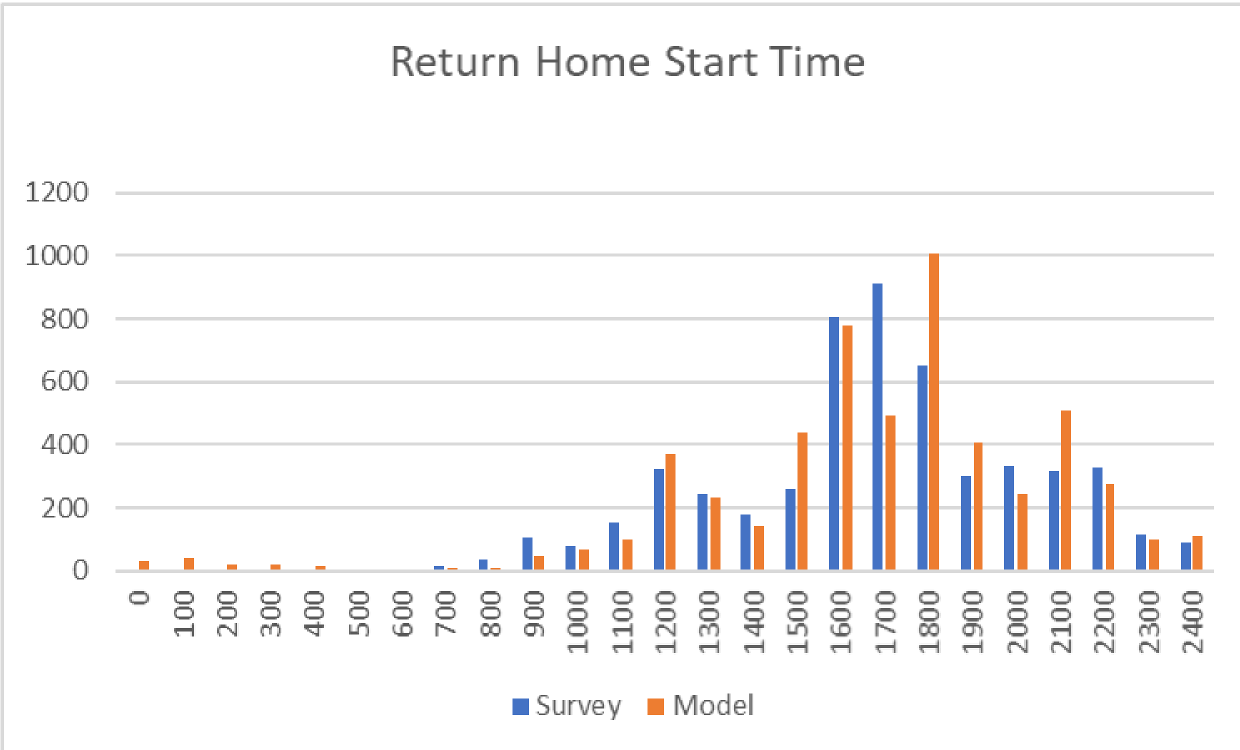

Figure A19: Return Home activity start time comparison

Figures A8-A11 plot start time versus activity duration for Work, School, Other, and Shopping activities.

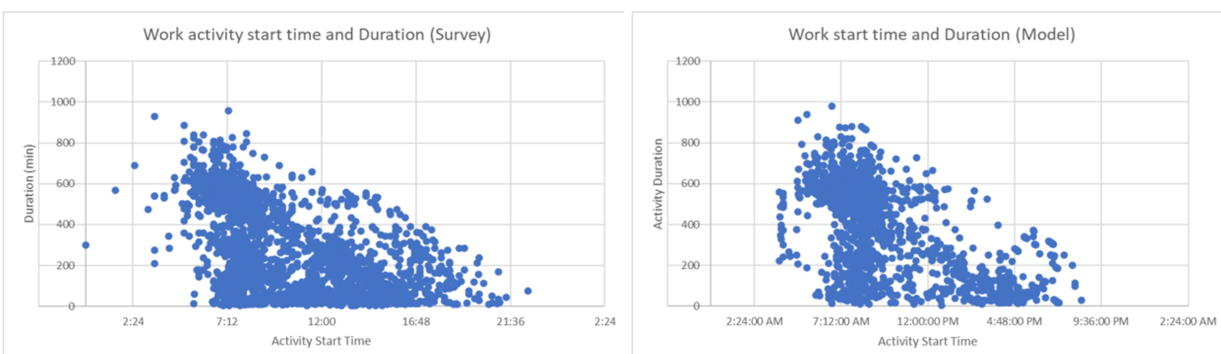

Figure A20: Work activity start time vs duration for survey (left) and model (right)

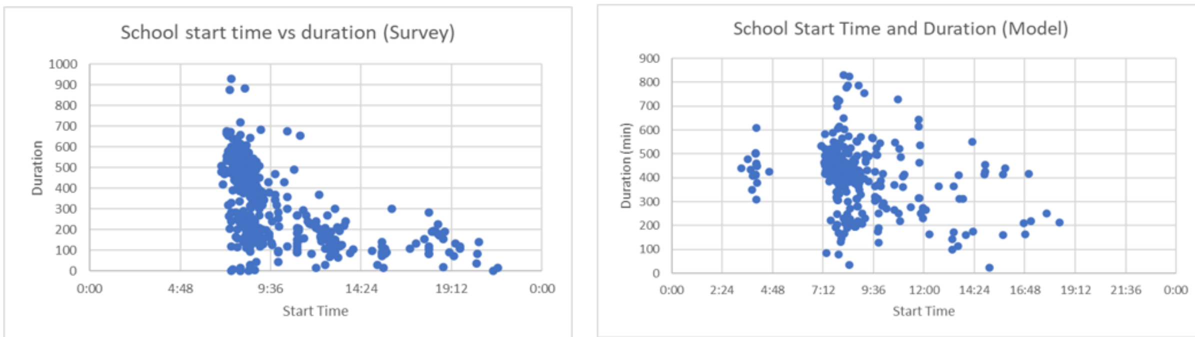

Figure A21: School activity start time vs duration for survey (left) and model (right)

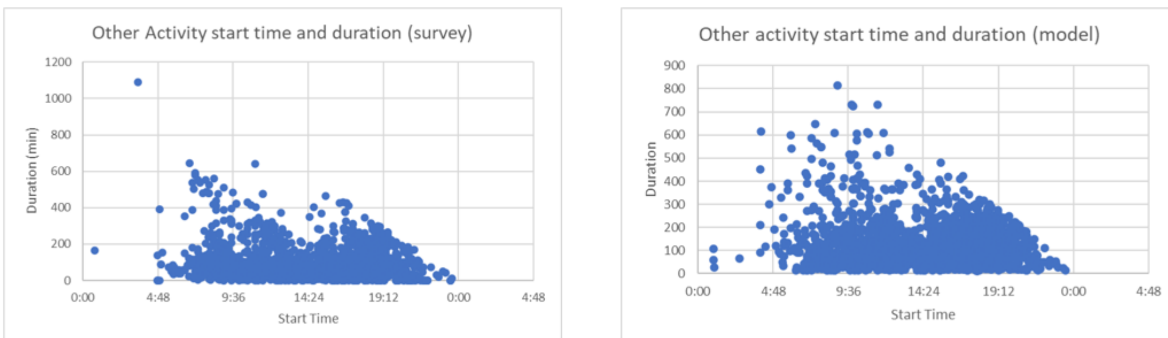

Figure A22: Other activity start time vs duration for survey (left) and model (right)

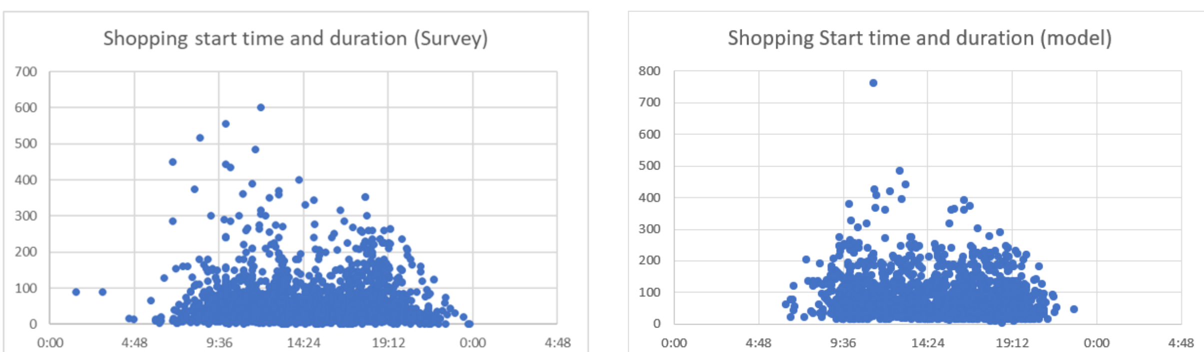

Figure A23: Shopping activity start time vs duration for survey (left) and model (right)

Table A7 compares average travel distances by activity type.

Table A7: Survey distance vs Model distance for various activity types

Activity	**Survey distance , km (avg)**	**Model distance, km (avg)**	**Distance error (%)**
Work	6.3	5.4	-14

School	4	3.8	-5
Shopping	4.3	2.4	-44
Other	5.8	2.9	-50

Figure A12 – A16 show modal split (% of trips) by period of day – Peak AM (6am – 9am), Midday (9am – 3pm), Peak PM (3pm – 7pm), Late PM (7pm – 12am) and Overnight (12am – 6am). Note that WAT indicates Walk-Access Transit (Bus in the case of Regina).

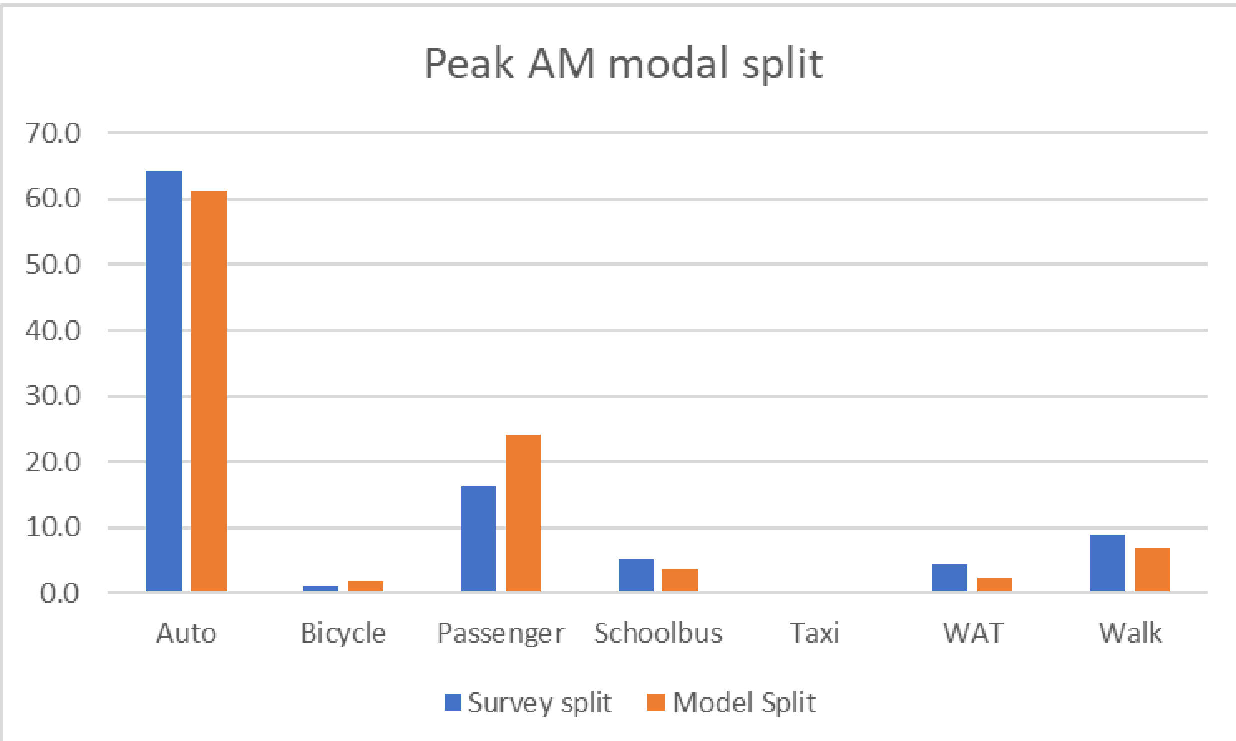

Figure A24: Peak AM modal split

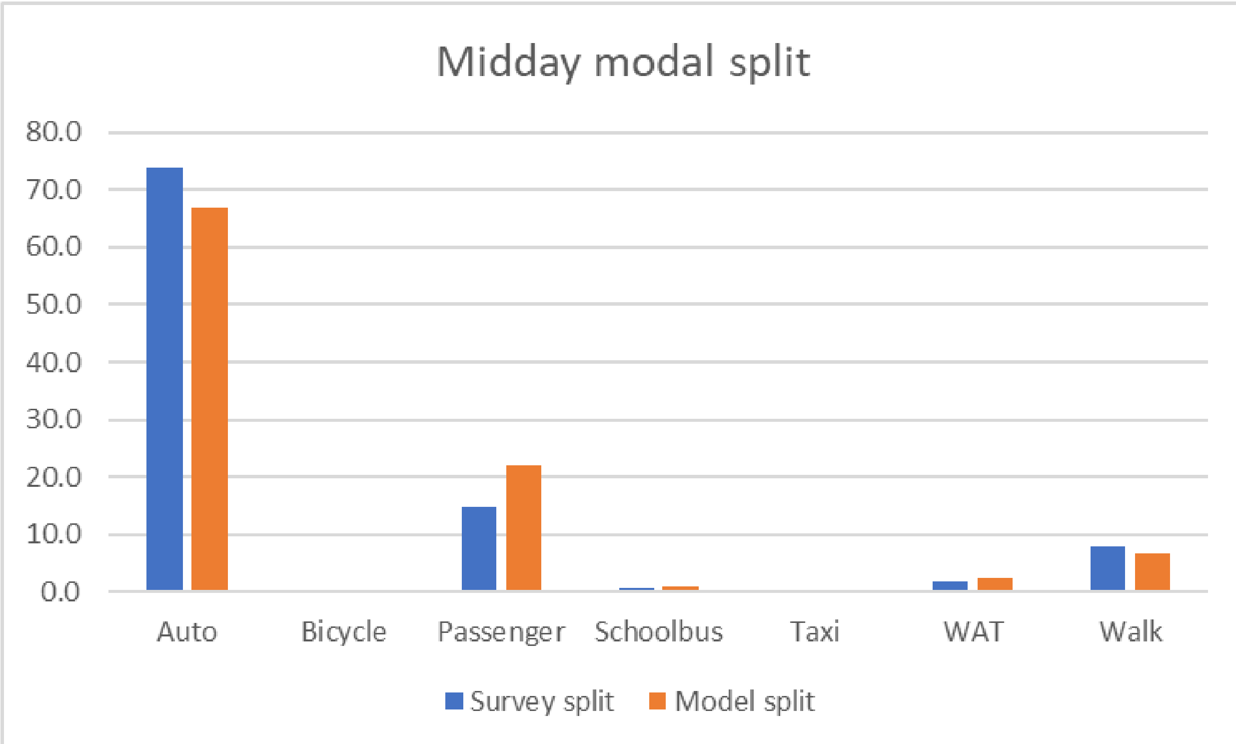

Figure A25: Midday modal split

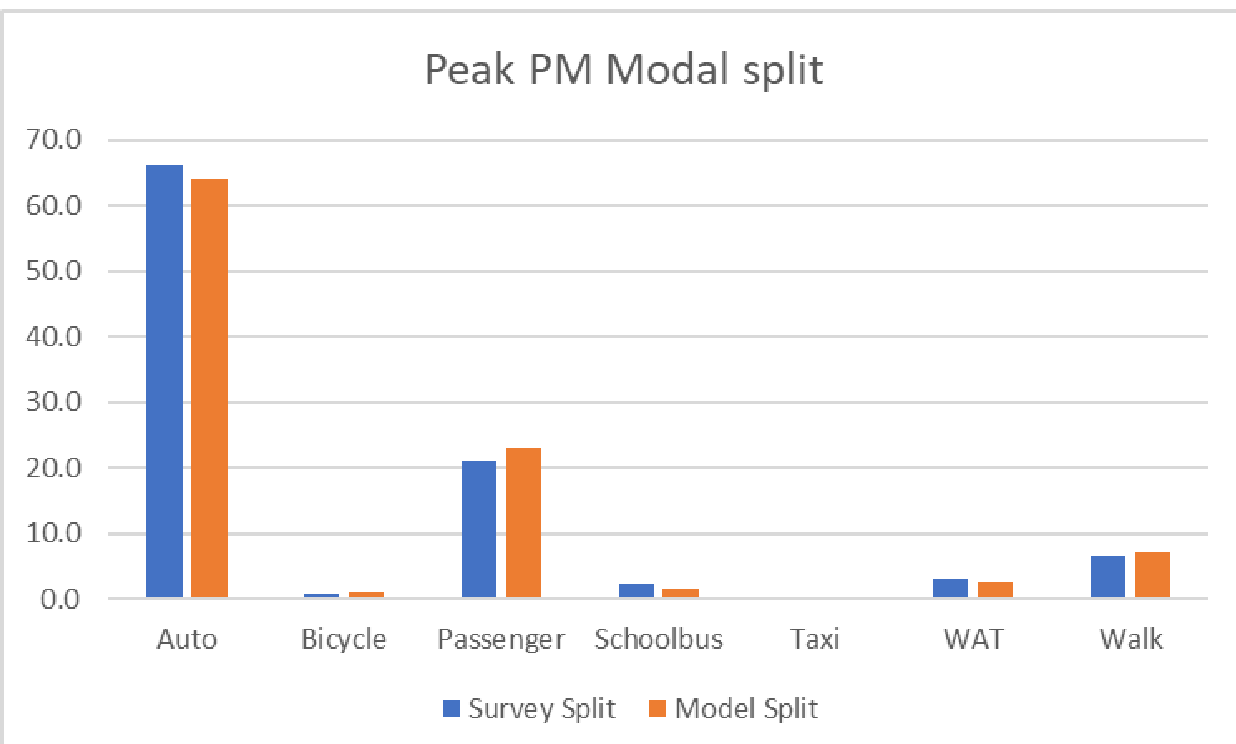

Figure A26: Peak PM modal split

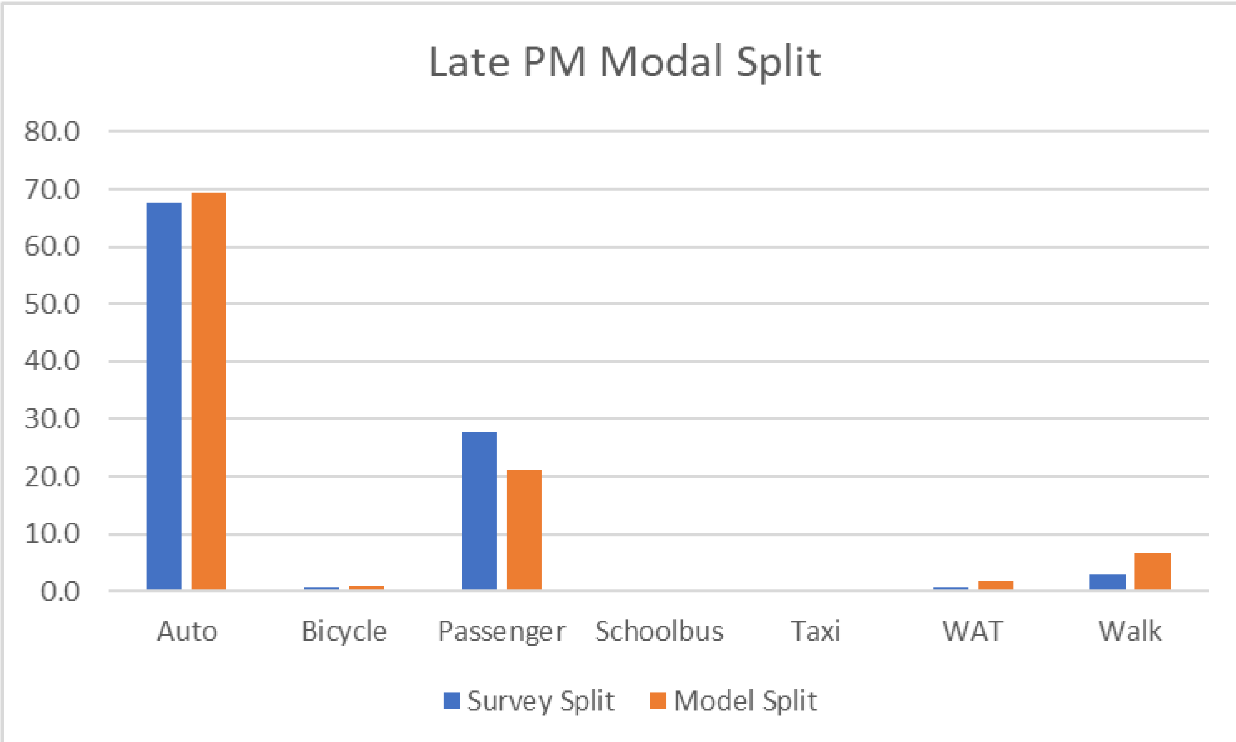

Figure A27: Late PM modal split

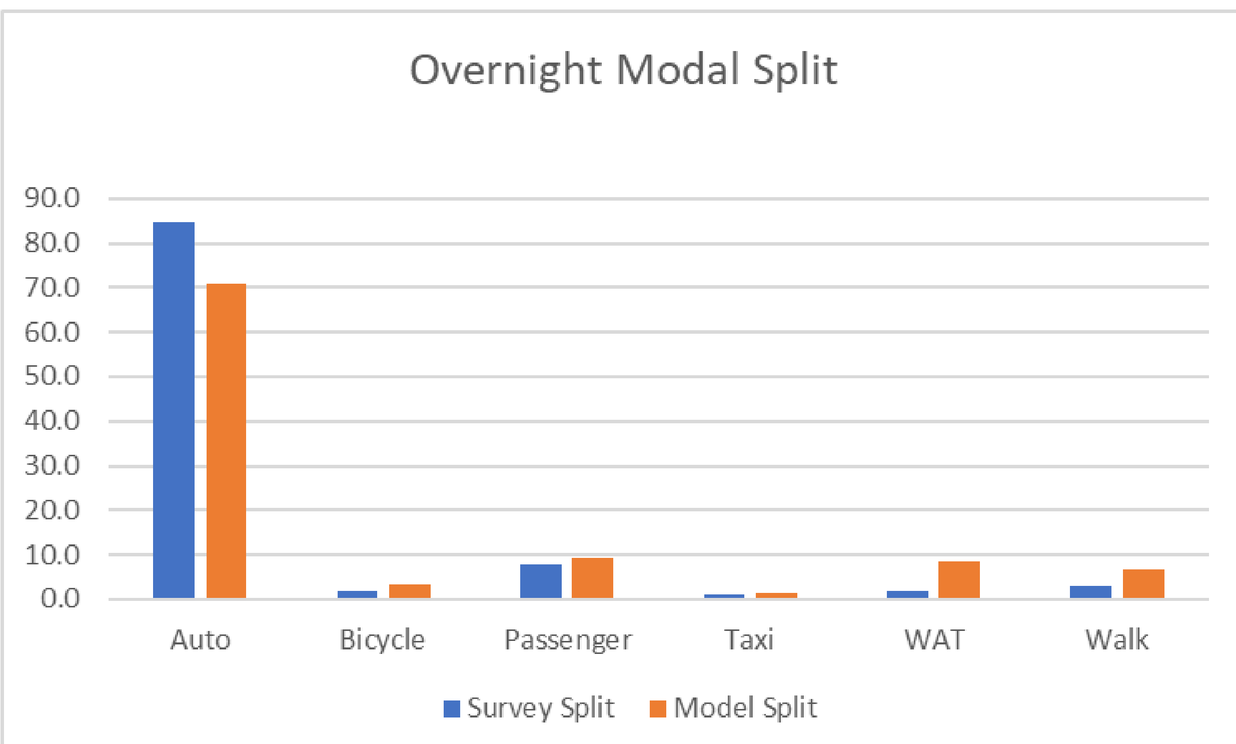

Figure A28: Overnight modal split

Similarly, Figures S17-S20 display mode split by activity type for Work, School, Other, and Shopping.

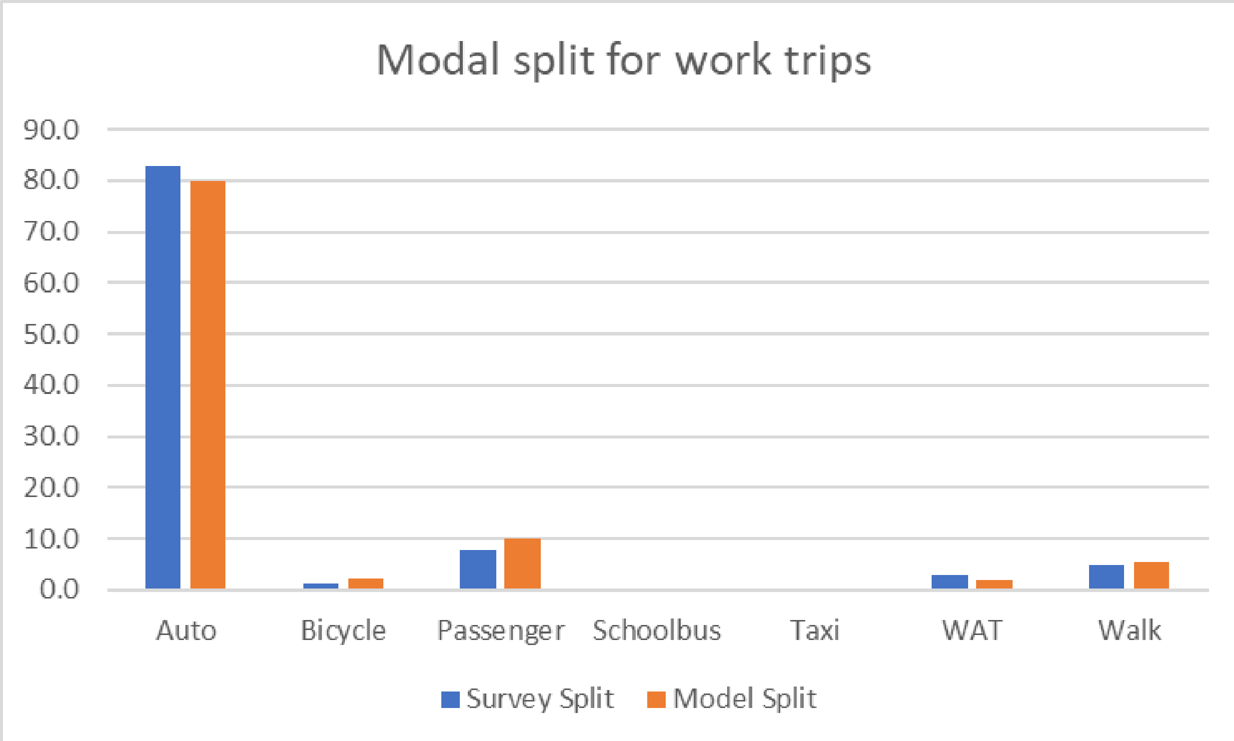

Figure A29: Work trip modal split

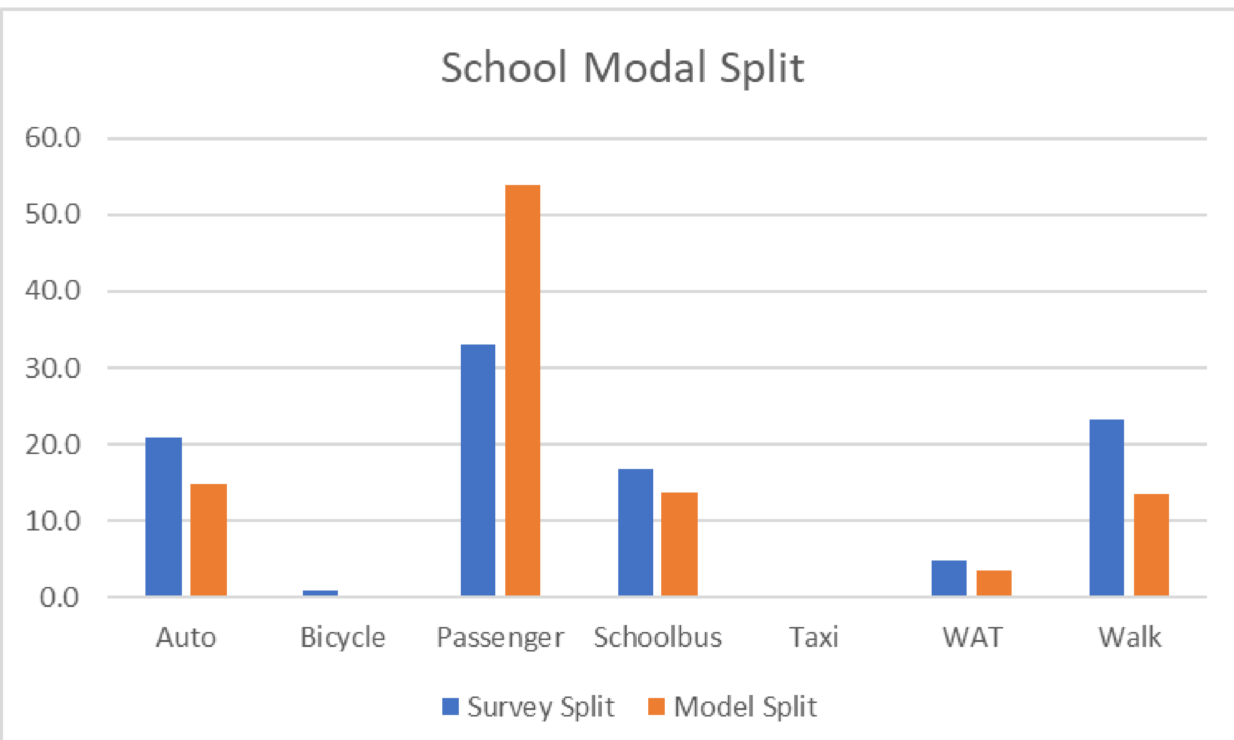

Figure A30: School trip modal split

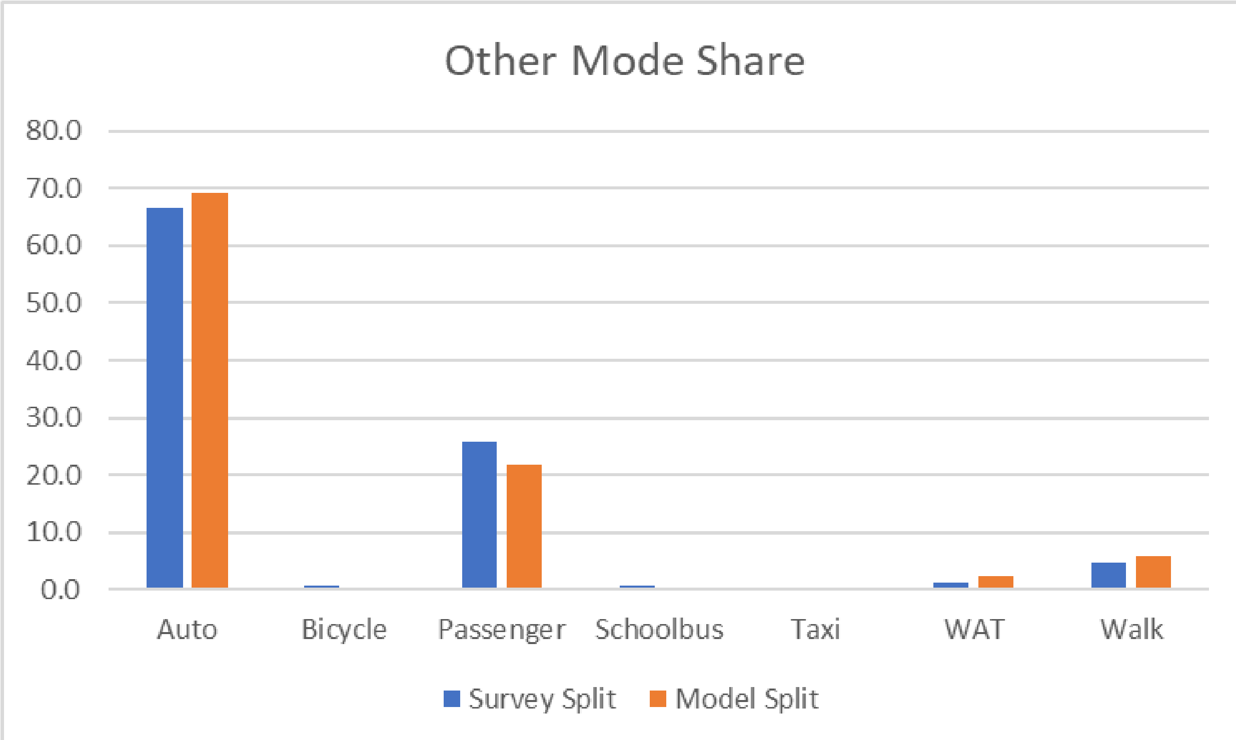

Figure A31: Other trip modal split

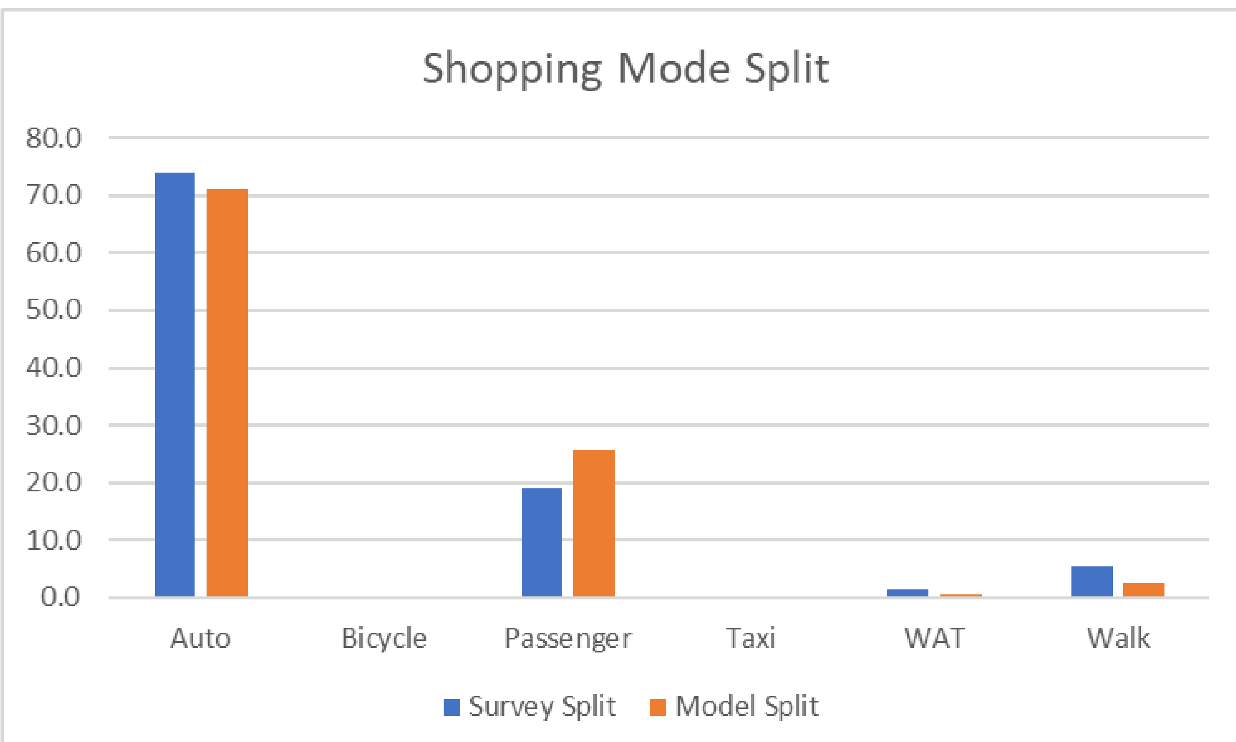

Figure A32: Shopping trip modal split