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# Flexible electric vehicle charging and its role in variable renewable energy integration

Robert Xu, Madeleine Seatle, Christopher Kennedy and Madeleine McPherson*

**Abstract**

Uptake of electric vehicles is accelerating as governments around the world aim to decarbonize transportation. However, swift and widespread electric vehicle (EV) adoption will require some degree of controlled charging to mitigate the adverse impacts of electric vehicle adoption. Simulating the interaction between transportation and power requires new modelling tools with operational detail and spatial-temporal granularity. This analysis evaluates the potential benefits of utility-controlled charging (UCC) with the objective of reducing variable renewable energy (VRE) curtailment in decarbonized power systems using a framework that links travel and power system models using an intermediate charging model. Results show that the addition of VRE generation infrastructure shows the most impact on electricity system operating emissions and costs, but EV charging plays a significant role as well. Within EV charging strategies, UCC charging decreases emissions by 7% compared to uncontrolled charging. UCC is proven to be most effective in the summer due to higher electric vehicle fuel economy. Finally, the type of VRE generation infrastructure on the grid may have implications for siting of EV charging infrastructure due to the typical temporal peaks of wind and solar energy. These findings demonstrate how the use of distinct but linked travel and power sector models can be deployed to reduce multi-sector emissions and costs.

**Keywords** Electric vehicles, Variable renewable energy, Smart charging, Utility controlled charging, Travel demand modelling, Demand response

## Introduction

The transportation sector is responsible for 21% of global $CO_2$ emissions (Climate Watch 2021), making it vitally important to focus greenhouse gas (GHG) mitigation efforts. 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 on non-emitting electricity, can facilitate this decoupling. As EV technology matures, battery prices fall, and the importance of reducing emissions becomes increasingly apparent, 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 Additional file 1: Tables S1, S2 and S3), find that policies support EV adoption through financial incentives (for both vehicles and chargers) and non-financial mechanisms (such as access to high occupancy vehicle lanes). However, there is a distinct lack of policies, regulations, or incentives that support controlled EV charging.

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This gap in the policy landscape is problematic: research demonstrates the perils of uncontrolled charging (UNC), and the benefits of controlled charging. Xcel Energy (2015) finds that if uncontrolled (i.e. vehicles charge as soon as they reach a destination), a significant amount of EV load coincides with the system peak, which drives up infrastructure requirements (generation capacity buildout) and costs. Similarly, Muratori (2018) shows that UNC leads to significant increases in peak residential power demand. On the other hand, the flexibility inherent to vehicle use presents a significant opportunity for electric utilities in the form of demand response (McPherson et al. 2018; Mwasilu et al. 2014). Demand-side policies could incentivize an EV owner to schedule their vehicle charging in an optimal way or give the utility (or a third-party entity) control of vehicle charging. Doing so can provide benefits to the utility, such as reducing peak generation (Debnath et al. 2020), and providing additional flexibility to facilitate VRE integration (McPherson et al. 2018). Ultimately, smart charging has the potential to lower emissions and costs of operating the electricity network. Accurately quantifying the value of flexible EV charging can help inform policy priorities around variable renewable energy (VRE) development, charging infrastructure siting, and 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, often 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. Wolinetz et al. (2018) use EV travel patterns and assumed charger availability to simulate utility-controlled charging (UCC) by linking with an electricity system operational model. Szinai et al. (2020) use an agent-based simulation linked with an electricity system operational model to evaluate the benefits of smart charging, using a similar approach as Wolinetz et al. (2018). Abbasi et al. (2019) use stochastic optimization to model the joint behaviour of an electric vehicle aggregator and a wind farm. Ray et al. (2021) use particle swarm optimization to maximize the profit of fast chargers while meeting electric vehicle demand in a system with variable renewable energy generation. Finally, Long et al. (2021) develop an ordinal optimization model to improve the computational efficiency of electric vehicle charging scheduling. In summary, these studies find that UCC leads to lower emissions, VRE curtailment, and charging cost for electric vehicles.

While these approaches make important and innovative contributions to modelling EV smart charging, previous analyses have suffered from a variety of limitations. First, several formulations (Knapen et al. 2011; Sterchele et al. 2020; Sun et al. 2018; Tu et al. 2020) do not link to a power system model that simulates generator dispatch and electricity network constraints. As a result, operational aspects of the power system, such as network congestion, unit commitment, and economic dispatch, are not considered when accounting for the impact of the introduction of EVs onto the system. The impact of EV adoption on system-wide costs and GHG emissions are of interest to utilities and policymakers as they devise and implement incentive schemes or controlled charging programs. Other studies suggest formulations or optimization procedures that may prove to be inconvenient for consumers. For example, the optimization procedures described by Kara et al. (2015), Szinai et al. (2020), Kam and Sark (2015), Long et al. (2021), and Ray et al. (2021) require EV owners to enter their vehicle departure times or daily travel schedules in advance so that a centralized optimization calculation can be performed. However, consumer acceptance of such a routine may be low, resulting in the overestimation of smart charging potential. Furthermore, it may be unrealistic to assume that the utility has perfect information given the unpredictable nature of travel routines.

This study quantifies the benefits of adopting controlled charging for EVs from a cost and GHG emissions perspective using a novel modelling framework that focuses on capturing the opportunity that controlled charging presents. In doing so, this paper makes two key contributions to the literature, first, by developing an innovative methodology for quantifying the impacts of EV charging on the power system, and second by producing multi-sector insights. The methodology proposed in this paper links two operational models of historically distinct sectors via UCC, 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 with the objective of reducing VRE curtailment as it might occur in real time between the utility and EVs. Insomuch, the proposed methodology overcomes several of the limitations seen in previous work. First, the prosed framework does not require the EV owner to provide trip information to the utility, which may face consumer acceptance barriers. Instead, the utility charges vehicles whenever it predicts that excess renewable energy will be produced. Second, the proposed framework accounts for the interaction between VRE variability and travel flexibility by simulating daily travel schedules chained together with carry-forward information. Finally, the proposed framework does not rely on historical travel patterns to estimate the spatial and temporal distribution of EV demand which fails to capture the changing nature of transportation systems being driven by technological, policy, behavioural factors. Rather, the proposed framework can leverage forecasted information on travel behaviour derived from mode choice and location choice simulations (Daina et al. 2017).

The second major contribution of this research comes from the insights that are produced by our multi-sector platform. Investigating the interactions between the design and operation of the transport system and power systems *in tandem* yields valuable insights into the co-evolution and decarbonization of both systems. The scenarios investigated in this paper probe the interaction between alternative EV charging paradigms combined with alternative variable renewable energy configurations to illuminate the value of EV flexibility alternative system configurations.

The remainder of this paper is organized as follows. The "Methods" Section introduces the modelling methodology, including the two distinct transportation (TASHA) and power system (SILVER) models, as well as the charging model that links them. The model is applied to a case study of Regina, Saskatchewan, the characteristics of which are described in the "Case study" Section. The "Results" Section then presents the results, which center on comparing electricity system cost and emissions with controlled and UNC. The "Discussion" Section then contextualizes the results and contributions within the context of the literature, along with discussing limitations and areas for further research, and the "Conclusion and Policy Implications" Section concludes.

## 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, UCC 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 Fig. 1. In this section, the formulation and relevant inputs and outputs for TASHA, SILVER, and the charging model will be described in further detail.

### 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 and has been used to evaluate the 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 Fig. 2. The detailed formulation of TASHA is described by Miller and Roorda (2003).

TASHA requires several input types, as shown on the left-hand side of Fig. 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 (Google Maps Platform 2021) and ArcGIS (GEOFABRIK 2020). 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. The travel survey was conducted on weekdays over a one month period in the fall of 2009. Results from the validation of TASHA for the case study are presented in Additional file 1: Section S5.

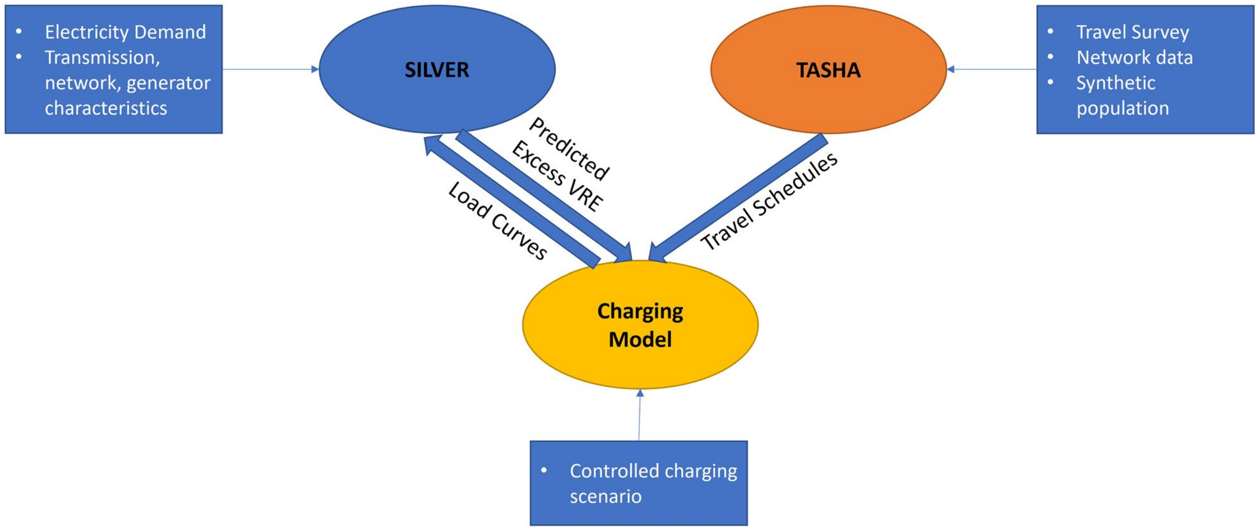


**Fig. 1** High level overview of model linkage

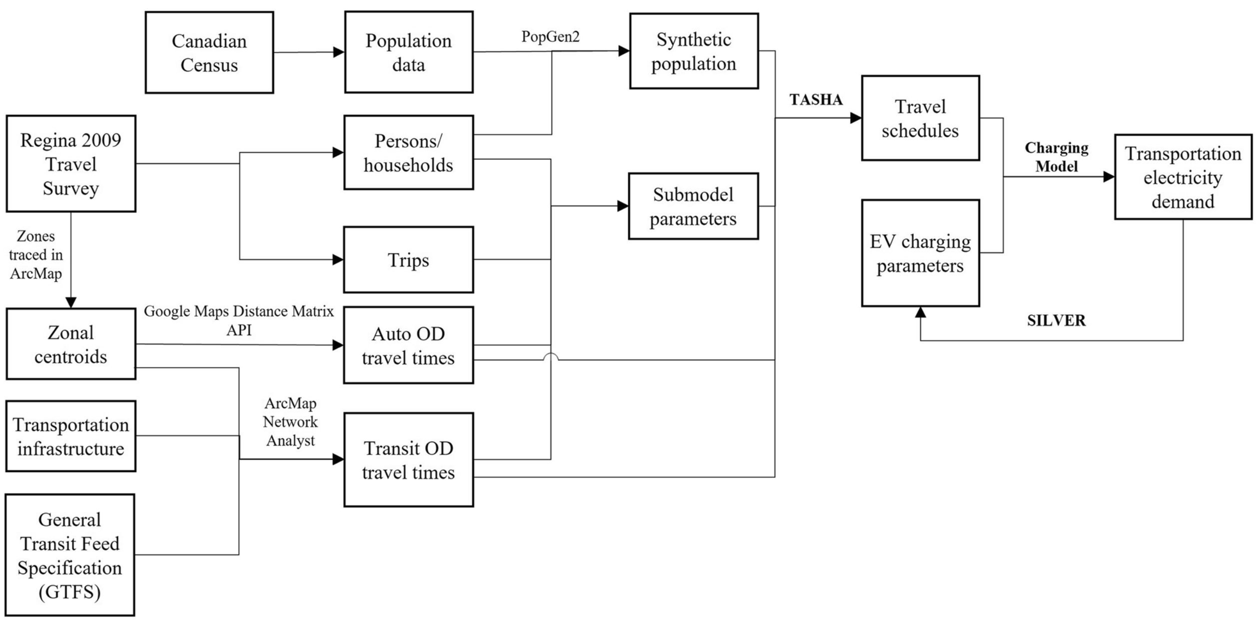


**Fig. 2** Detailed flowchart for building TASHA as used in this study

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. The individual travel schedules are combined to form vehicle travel schedules to account for household vehicle sharing. The procedure for converting the TASHA output to vehicle schedules is described in detail in Additional file 1: Section S2.1. An example of the type of data produced by this process is provided in Table 1.

## 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 costs. SILVER has been used to model storage asset deployment (McPherson and Tahseen 2018). A detailed description of SILVER's methodology

**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 |

can be found in McPherson and Karney (2017). 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, 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 for the City of Regina 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 describe the procedure for assigning EV load from the zonal resolution used in TASHA and the charging model to the substation resolution used within SILVER. Provincial electricity generation infrastructure is modelled as external to the city, with transmission within the city not being a constraint. City-wide baseline electricity demand profiles are taken from the 2018 reference year. Operational costs (U.S. Energy Information Administration 2019) are optimized for within the SILVER model, while GHG emissions (Canada Energy Regulator 2020) are calculated external to the SILVER model.

## Charging model

To illustrate the value of flexible charging behaviour, the charging model runs with two different configurations: UNC and UCC. The methodologies for both configurations are described in the following sections. Battery electric vehicles are the focus of the modelling work; EV is used to refer to vehicles that exclusively use electricity throughout this paper. Universal access to charging stations is assumed within the charging model for the purpose of evaluating the most beneficial placements.

### *Uncontrolled charging (UNC)*

In UNC 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 an incentive to charge at specific times or locations or according to a particular strategy. The charging process UNC 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 the 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:

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

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 constant user-defined charging power (in kW), and $SOC_{max}$ is the vehicle battery capacity.

The arrival and departure cycle represented by Eqs. 1 and 2 are 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 UNC 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 the costs, emissions, and curtailment.

### *Utility controlled charging (UCC)*

Under a paradigm with 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. UCC events occur when VRE generation exceeds the non-EV load, which then triggers the utility to charge vehicles to utilize the excess generation to achieve this. 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 Eq. 3:

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

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 the threshold. This study uses a time interval of 15 min 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 are 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:

$$SOC_{threshold,v} = 2 * d_{daily,v} * D \tag{4}$$

where vehicles that are more heavily driven have a higher threshold than vehicles that 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 Eq. 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 min 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:

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

This formulation means that at times, all available EVs may be charging, or just a subset, depending on the value of the *ERG*.

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

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

where $duration_{depart,v}$ is the time until the 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 the vehicle $v$ to reach $SOC_{max}$, given by

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

implies that a vehicle being charged by the utility may charge for less than 15 min 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 min 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 Additional file 1: Section S3.

#### *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 the context of the linkage between models, this procedure is shown by the dual arrows between SILVER and the charging model in Fig. 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:

$$ERG(t, 0) = \max\left(0, VRE_{available}(t) - NonEVLoad(t)\right) \tag{10}$$

where $ERG(t, 0)$ indicates the $0^{th}$, or initial, iteration. $NonEVLoad(t)$ 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 Additional file 1: Section S4. Figure 3 shows the iterative convergence procedure as a flowchart.

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. Note that the 20% threshold was selected to be a midpoint between the optimality of UCC utilization and the innate unpredictability of VRE generation. 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 (Bardutz and Dolter 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 (Bardutz and Dolter 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[1] 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—the 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

[1] Modelled provincial grid mimics 2018 Saskatchewan grid, with the generation capacity split as follows:

- 40% natural gas,
- 37% coal,
- 23% hydro,
- 0.5% wind,
- 0.4% biogas and
- < 0.1% solar.

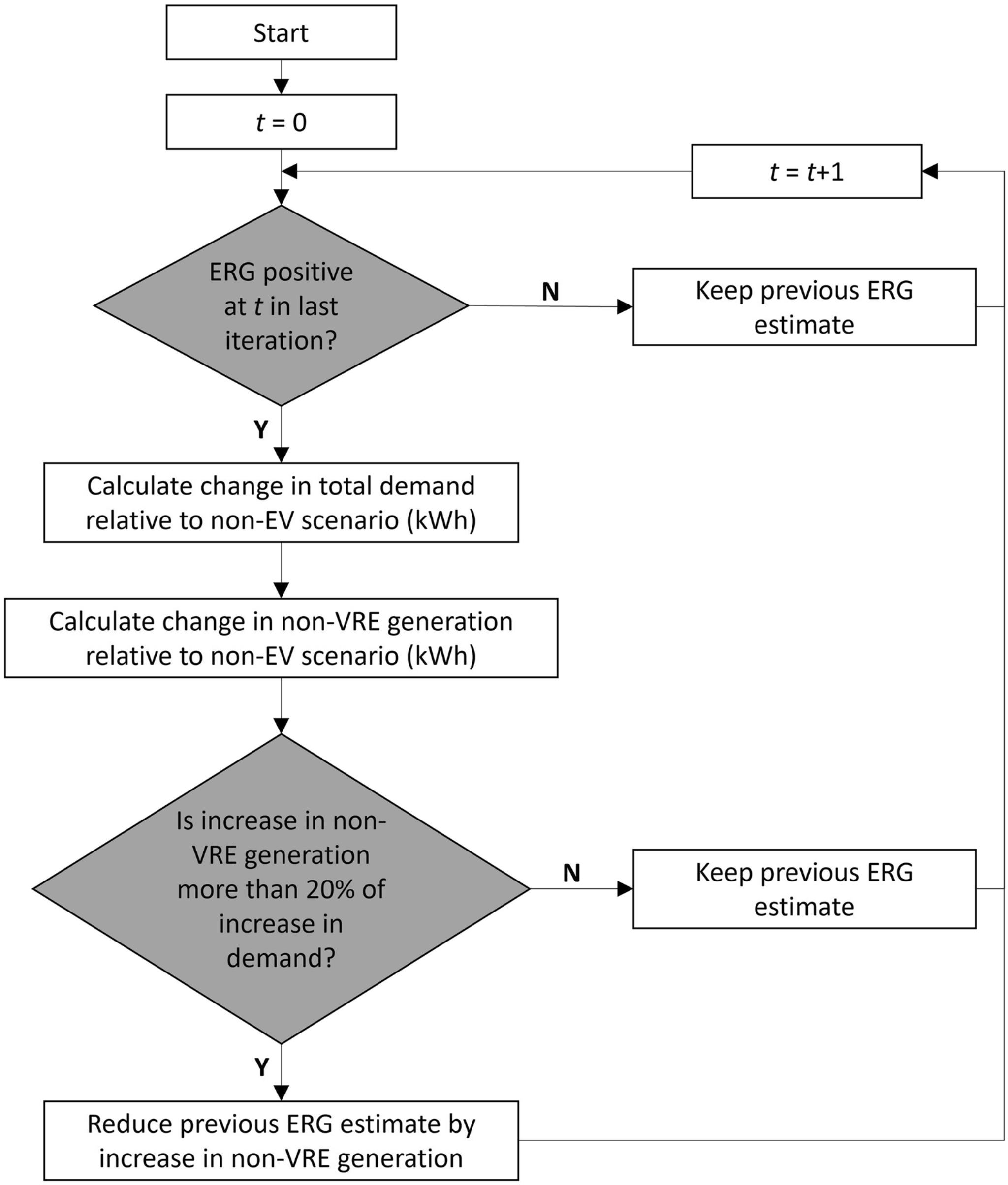


**Fig. 3** Flowchart for iterative procedure linking SILVER with charging model to ensure UCC only uses renewable generation

zone system, as well as substation locations and wind farm location, is shown in Fig. 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 80 m hub height. Rooftop solar capacity factors were determined following the methodology described by 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 |

The central scenario matrix used to support the Regina analysis is shown in Table 3. Each scenario is simulated for a representative week in January and July to capture the seasonal effects. In all scenarios, 400 MW of VRE is added to the system (except for

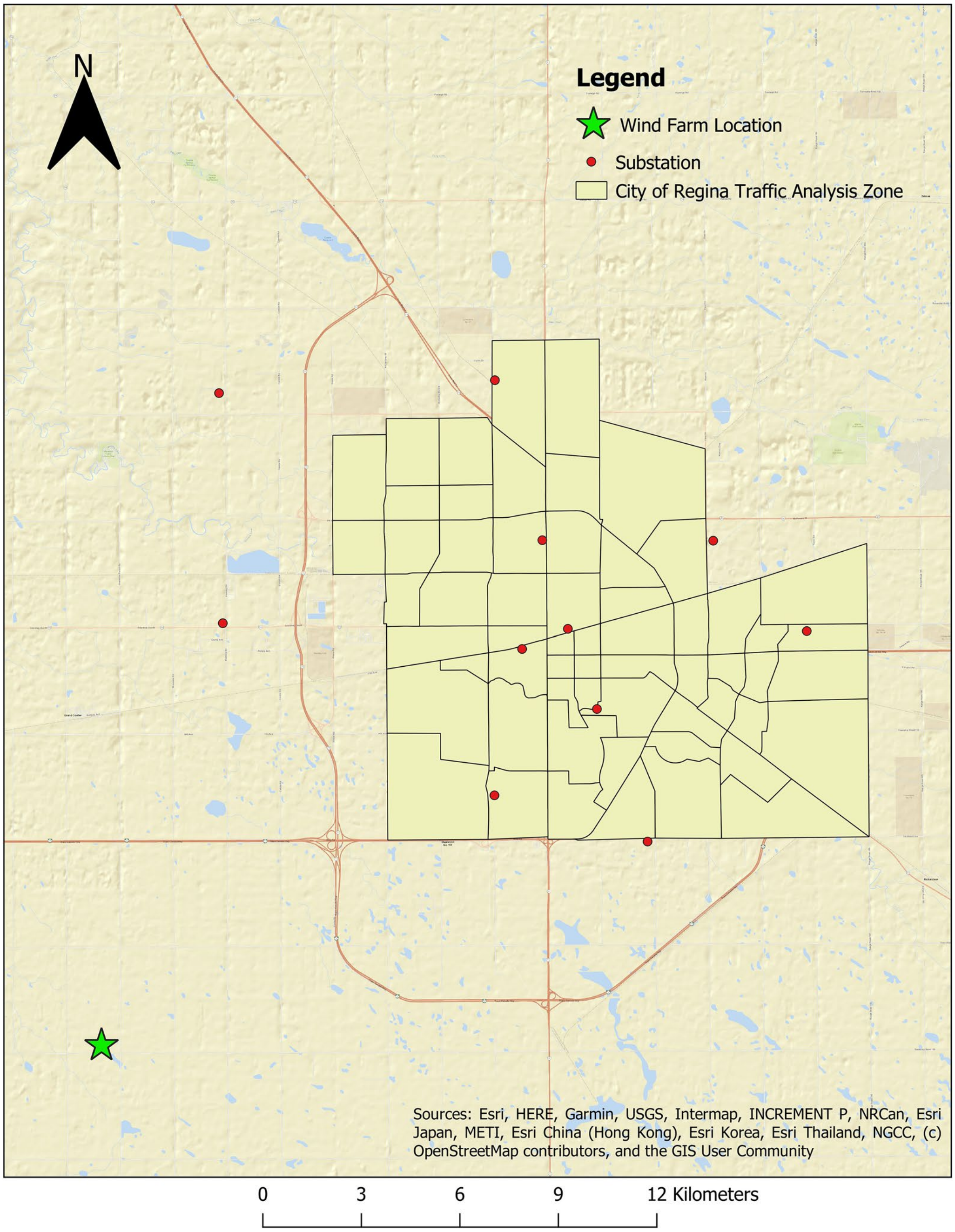


**Fig. 4** Extent of study area, substation locations used in SILVER, and location of wind farm

the business-as-usual (BAU) scenario). The 400 MW figure is based on the amount of rooftop solar capacity with, 25% of Regina households installing rooftop solar (Bardutz and Dolter 2020). 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 UCC. This amount of additional wind capacity is also in line with the provinces' future grid expansion (SaskPower 2021). 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

**Table 3** Scenario matrix

| Scenario name | VRE configuration | Adoption rate (%) | Controlled or uncontrolled |
|---|---|---|---|
| BAU | None added | 0 | N/A |
| BAU-UNC | | 50 | Uncontrolled |
| S | 400 MW Solar | 0 | N/A |
| S-UNC | | 50 | Uncontrolled |
| S-UCC | | | Controlled |
| W | 400 MW Wind | 0 | N/A |
| W-UNC | | 50 | Uncontrolled |
| W-UCC | | | Controlled |
| SW | 200 MW Solar/200 MW Wind | 0 | N/A |
| SW-UNC | | 50 | Uncontrolled |
| SW-UCC | | | Controlled |

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).

## Results

Results of this analysis show that adding uncontrolled EV charging, as well as controlled charging, can have significant impacts on system operating costs 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 controlled charging influences the shape of the EV load curve, as compared to UNC. Some of the nuances 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 fleet is electrified, vehicle charging load represents approximately 8% of total electricity consumption 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. Figures 5a and b, respectively, show the load and generation profiles for a January week for the wind configuration when charging is controlled. UNC 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 Fig. 5a, the afternoon peak occurs at the same time as the daily non-EV load peak, thus exacerbating the existing system peak.

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 Fig. 6a and b. 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 7 presents a closer look at the relationship between controlled EV demand and the *ERG* estimate during a January week (again, in the wind scenario). The UNC curve shows when UNC occurs relative to VRE production. When charging is controlled, the EV demand peak shifts to the beginning of an *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 h, 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 2-day period following January 2, 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.

### Effectiveness of UCC

Although the EV load may be relatively small compared to the 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 Fig. 8, the percent of EV energy

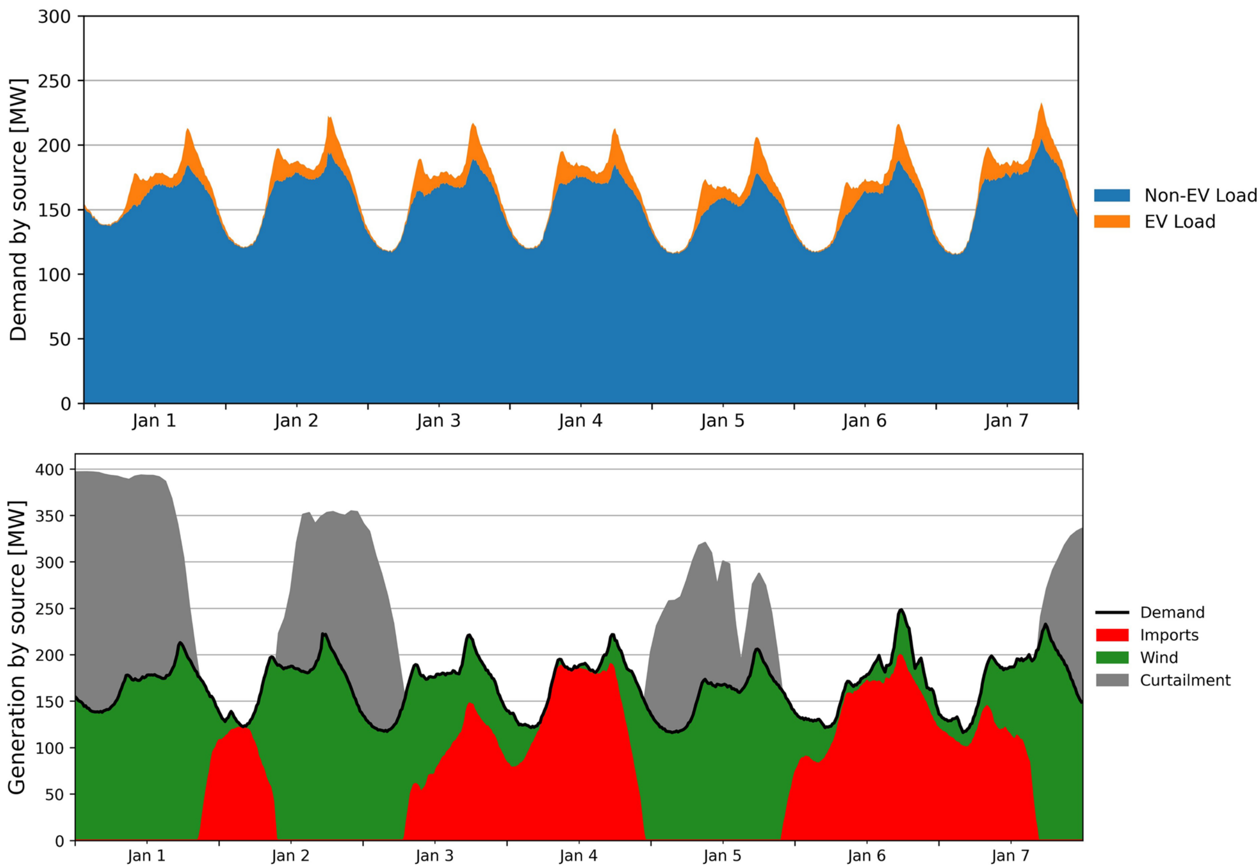


**Fig. 5** Regina's electricity demand for wind-only configuration with UNC in January, shown by **a** demand type (top) and **b** generation type (bottom). Note that "imports" refer to electricity supply from the provincial grid, which have been aggregated by generation type but include coal and natural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

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 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.

The modelling in this analysis also allows EV load to be disaggregated by activity type; thus, charging demand at home nodes be separated from the charging demand at work nodes, as well as the other activity types. Different VRE configurations result in a different allocation of load to activity types when UCC is involved, as shown in Fig. 9a (S-UCC),b (W-UCC), and c (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, Regina's infrastructure planning should

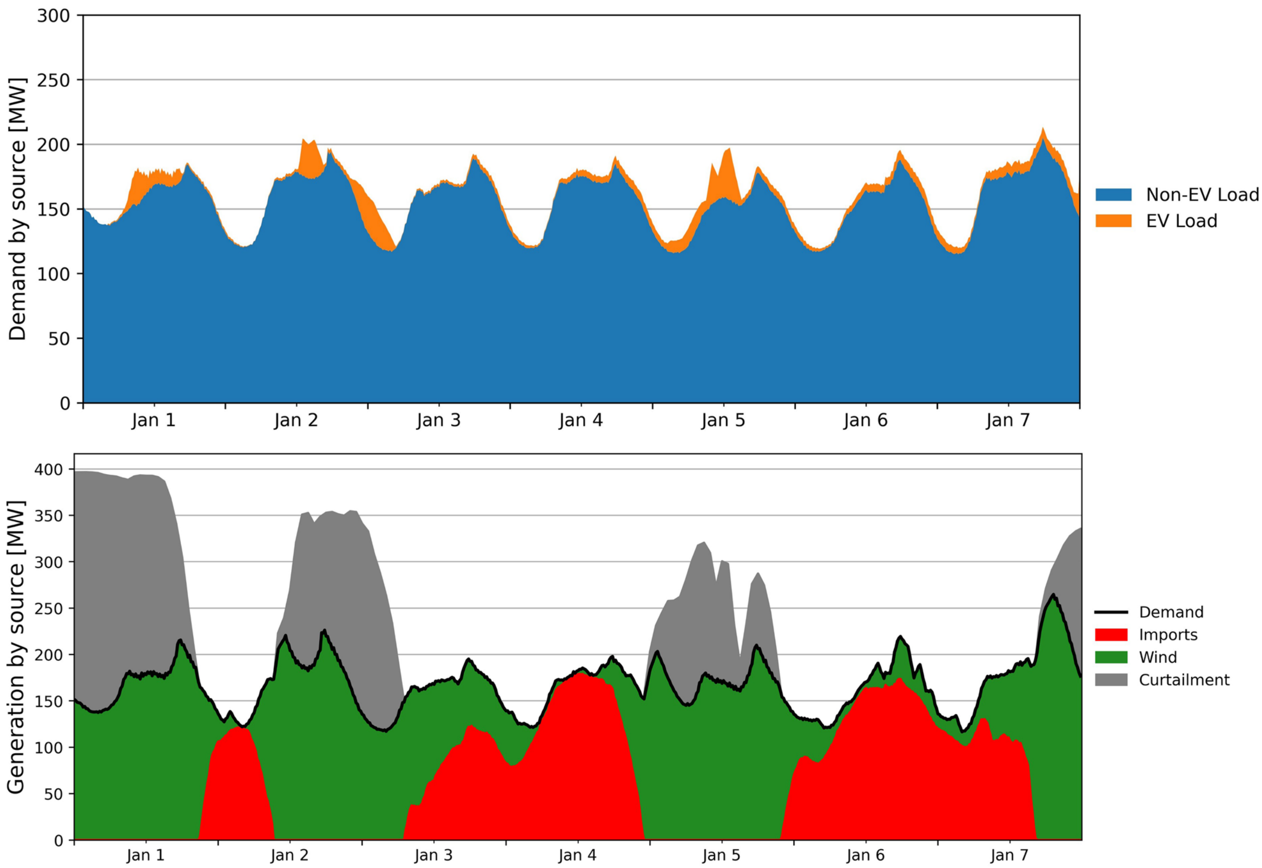


**Fig. 6** Regina's electricity demand for wind-only configuration with UCC in January, shown by **a** demand type (top) and **b** generation type (bottom)

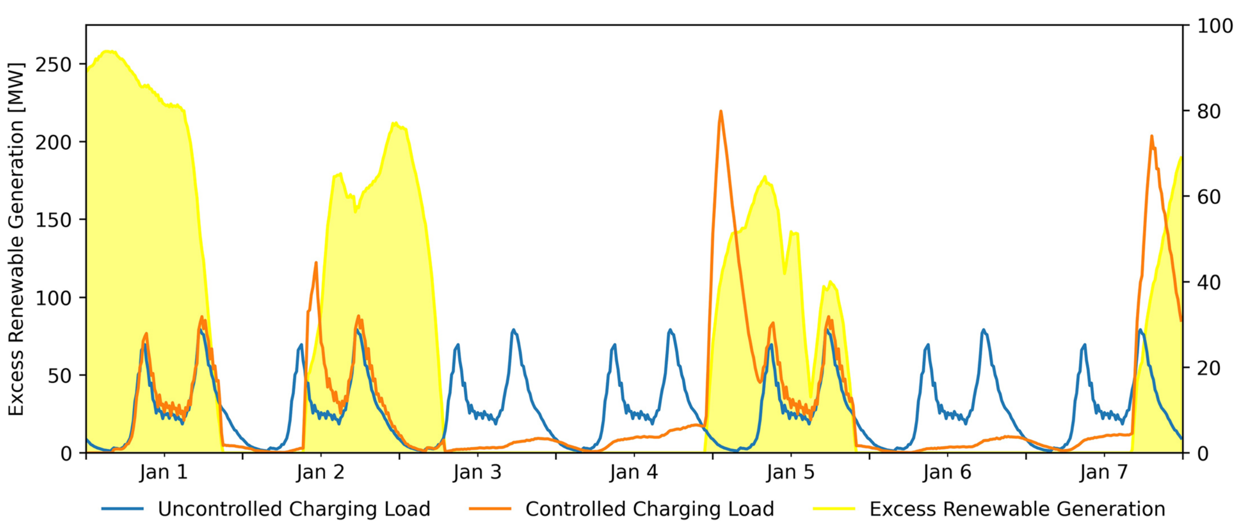


**Fig. 7** Correlation between excess renewable energy generation (ERG; left axis, in the yellow area) and total electric vehicle load (right axis) for scenarios of UNC (W-UNC) and UCC (W-UCC) for a January week in Regina in the wind-only configuration

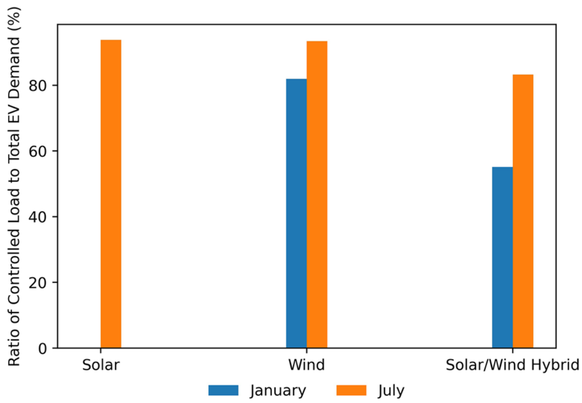


**Fig. 8** Ratio of UCC demand to total demand from electric vehicles for solar, wind, and solar/wind configurations. UCC demand is the electric vehicle charging energy shifted to periods of renewable energy generation

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.

#### 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 scenarios offer both low cost and emissions intensity in both seasons, regardless of EV integration and UCC. Carbon pricing is not factored into the operational costs, but due to the low emissions and low operational costs associated with VRE production, would assume to further decrease the operational costs of high-VRE configurations.

UNC 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 Fig. 10a) and 5% in the summer. The largest change in average cost and GHG intensity in the solar-dominated scenarios occurs 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 (measured as a % of total available VRE not utilized) 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 Fig. 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 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.

#### EV penetration rate sensitivity

As EV penetration increases, VRE curtailment noticeably plateaus with 200 MW each of solar and wind generation, as shown in Fig. 12. This plateau is accompanied by a drop in the effectiveness of UCC, indicating that the amount of VRE generation exceeds the amount of UCC "storage" available, 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.

## 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

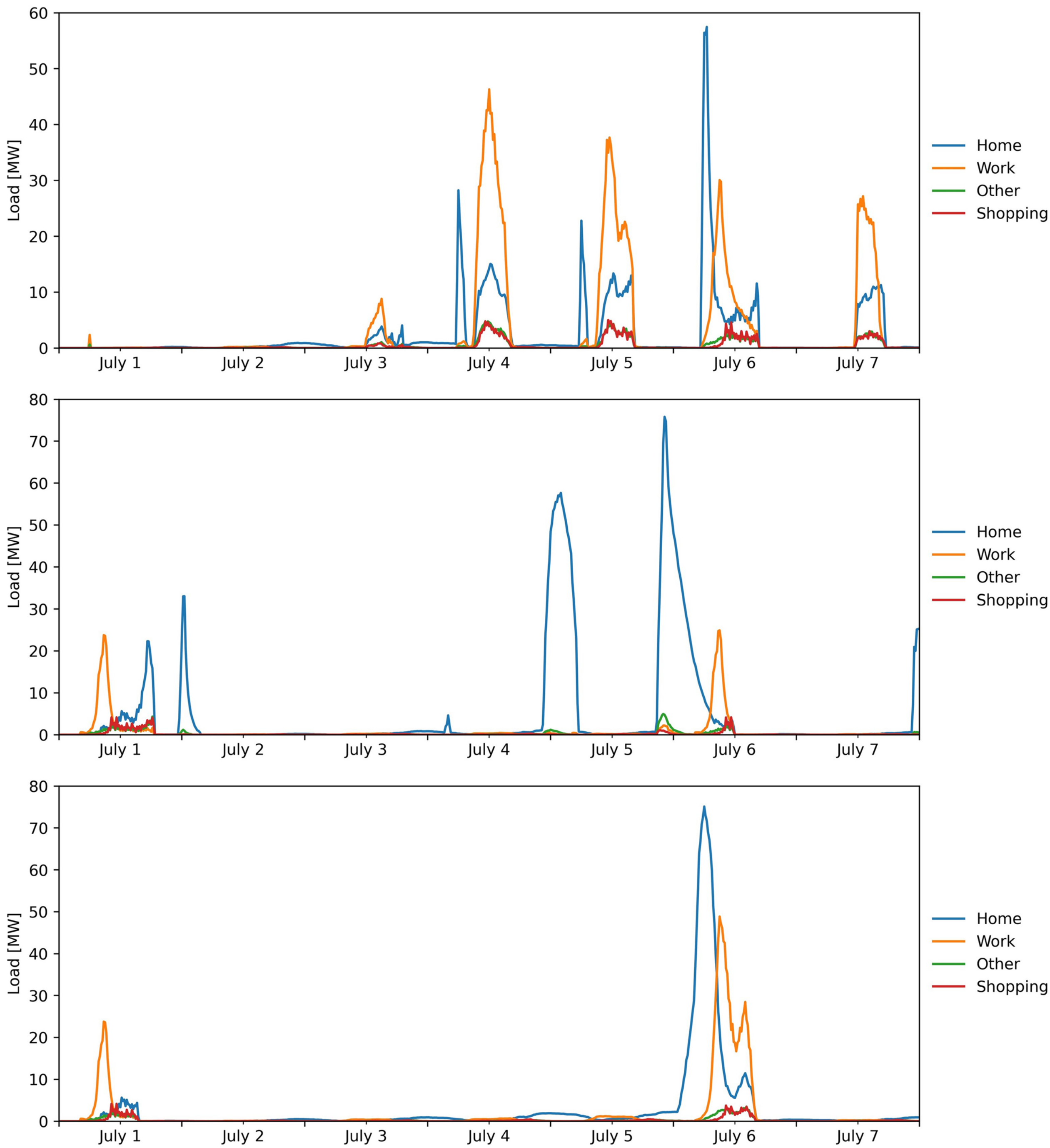


**Fig. 9** Electric vehicle load breakdown by activity for UCC occurring in a July week in the **a** solar (top) **b** wind (middle) and c) solar-wind hybrid (bottom) configurations

evaluation tool, not as a tool to predict 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

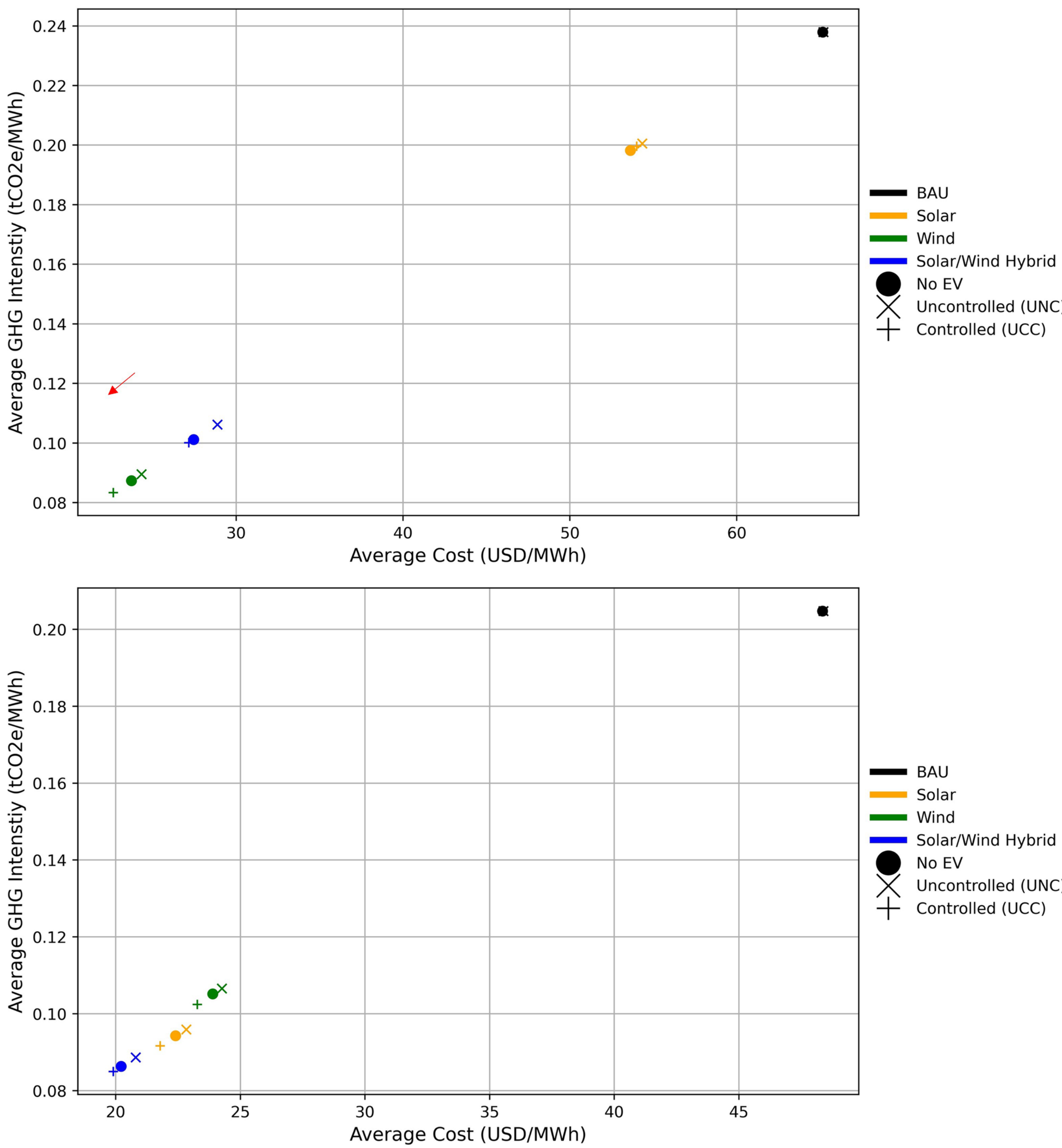


**Fig. 10** Average operational cost vs. average operational GHG emissions intensity from electricity generation for **a** January week (top) and **b** July week (bottom)

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 UNC 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 with 50%

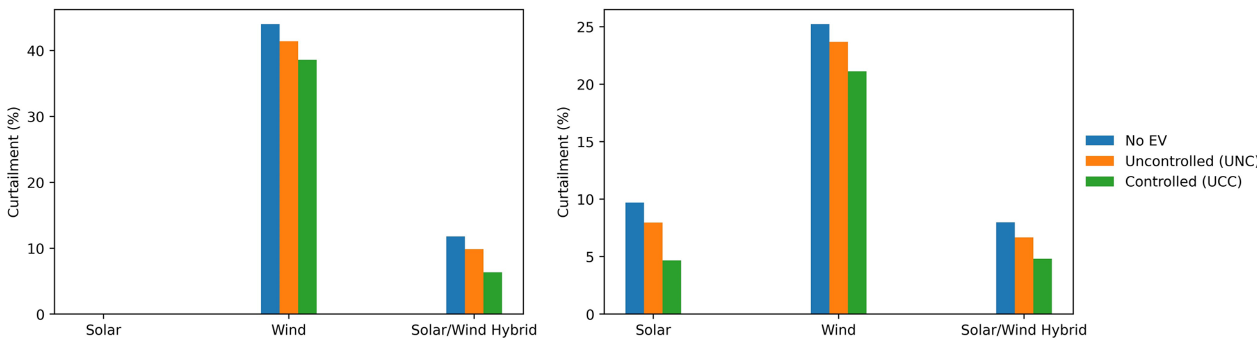


**Fig. 11** Total system curtailment for solar, wind, and solar-wind configurations for **a** the January week (left) and **b** the July week (right)

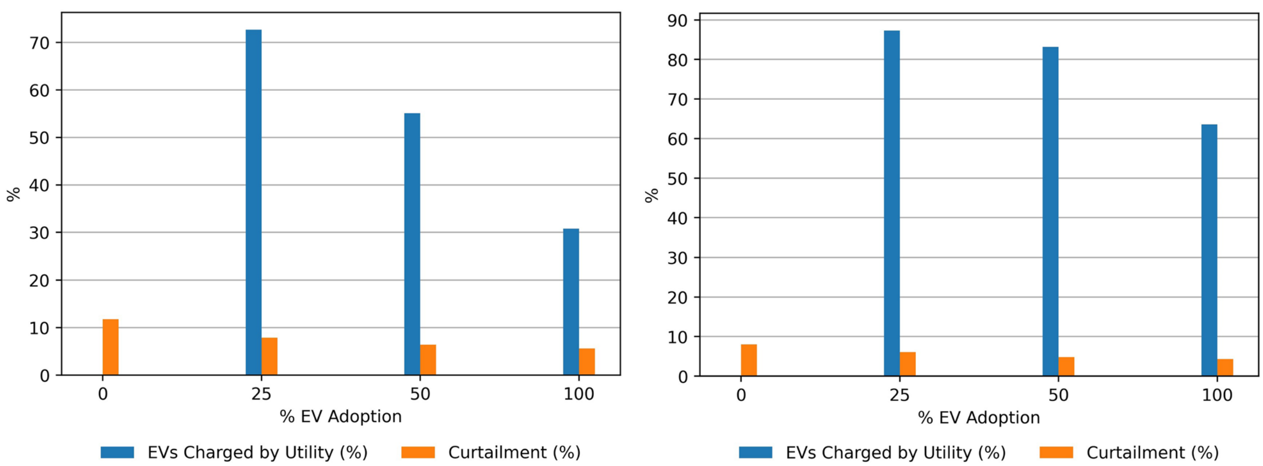


**Fig. 12** Comparison between curtailment and percent of electric vehicle demand shifted via UCC as electric vehicle penetration increases for **a** January (left) and **b** July (right) for the solar-wind configuration

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 are 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.

Differing from Szinai et al. (2020) and 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 that allows utilities to stop vehicle charging during peak hours or 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 400 MW 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 the 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.

#### Limitations and future work

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. However, these limitations can be addressed by using updated datasets as EV adoption becomes more widespread. 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. This implies that UCC may be more effective than found in this study, as this would suggest more EV battery capacity is able to be utilized. 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. As EVs become more viable for long-range trips, inter-city travel may need to be considered. Because installed capacity is chosen to be constant across VRE configurations, significant VRE curtailment is observed in scenarios of the 400 MW 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 available 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 the generation dispatch of the provincial utility.

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. Similarly, within the charging model, charging stations are assumed to be universal; however, the 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. Future work may leverage the general findings of where EV chargers are most effective and find the optimal number and location of chargers within the city. 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 and policy implications

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, the addition of 400 MW of VRE generation reduce emissions intensity by 60–70%. Imposing UCC in a future where 50% of vehicles are electric reduces operational GHG emissions and cost by 5–7% compared to UNC. 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 emis-

sions 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's 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 400 MW of added wind generation. Even with significantly less wind on the system (as high curtailment rates were observed), UCC 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 UCC, 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 UCC's 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 for 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 UCC may result in decreased infrastructure costs, though further analysis of 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.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40068-023-00293-9.

**Additional file 1: A1**: EV Policy Review at the Federal (A-1), Provincial (A-2), and Municipal (A-3) scales. **A2**: Vehicle scheduling parameters including facilitate passenger (A2.1) and vehicle allocation (A2.2). **A3**: UCC Pseudocode. **A4**: ERG adjustment pseudocode. **A5**. TAHSHA Validation. **Table S1**. Federal Level ZEV policies and incentives. **Table S2.** Provincial level ZEV policies and incentives—Governmental/Non Governmental. **Table S3.** Municipal level ZEV policies and incentives. **Table S4.** Sample person level trip schedule for Household 42. **Table S5.** Mode choice for each trip made in Household 42. **Table S6.** Facilitate passenger table for Household 42. **Figure S1.** Facilitate passenger resolution. **Figure S2.** Household vehicle allocation. **Figure S3.** Work activity start time comparison. **Figure S4.** Shopping activity start time comparison. **Figure S5.** School activity start time comparison. **Figure S6.** Other activity start time comparison. **Figure S7.** Return Home activity start time comparison. **Figures S8.** plot start time versus activity duration for Work, School, Other, and Shopping activities. **Figure S9.** Work activity start time vs duration for survey (left) and model (right). **Figure S10.** School activity start time vs duration for survey (left) and model (right). **Figure S11.** Other activity start time vs duration for survey (left) and model (right). **Figure S12.** Shopping activity start time vs duration for survey (left) and model (right). **Table S7.** Survey distance vs Model distance for various activity types. **Figure S13.** show modal split (% of trips) by period of day – Peak AM (6am – 9am), Midday (9am – 3 pm), Peak PM (3 pm – 7 pm), Late PM (7 pm – 12am) and Overnight (12am – 6am). Note that WAT indicates Walk-Access Transit (Bus in the case of Regina). **Figure S14.** Peak AM modal split. **Figure S15.** Midday modal split. **Figure S16.** Peak PM modal split. **Figure S17.** Late PM modal split. **Figure S18.** Overnight modal split. **Figure S19.** Work trip modal split. **Figure S20.** School trip modal split. **Figure S21.** Other trip modal split. **Figure S22.** Shopping trip modal split.

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**Author contributions**
RX—writing original draft, developing model, data collection. MS—paper revision. MM—paper review, model guidance, analysis. CK—paper review, model guidance, analysis. All authors read and approved the final manuscript.

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