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EV Overnight Charging Strategy in Residential Sector: Case of Winter Season in Quebec

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Abstract: Electric Vehicle (EV) technologies offer a leading-edge solution for clean transportation and have evolved substantially in recent years. The growing market and policies of governments predict EV massive penetration shortly; however, their large deployment faces some resistances such as the high prices compared to Internal Combustion Engine (ICE) cars, the required infrastructure, the liability for novelty and standardisation. During winter periods of cold countries, since the use of heating systems increases, the peak power may produce stress to the grid. This fact, combined with EVs high penetration, during charging periods inside of high consumption hours might overload the network, becoming a threat to its stability. This article presents a framework to evaluate load shifting strategies to reschedule the EV charging to lower grid load periods. The undesirable "rebound" effect of load shifting strategies is confirmed, leading us to our EV local overnight charging strategy (EV-ONCS). Our strategy combines the forecast of residential demand using probabilistic distribution from historical consumption, prediction of the EV expected availability to charge and the charging strategy itself. EV-ONCS avoids demand rebound of classic methods and allows a peak-to-average ratio reduction demonstrating the relief for the grid with very low implementation cost.

Keywords: battery chargers; distribution network; electric vehicles; Li–ion batteries; power electronics

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1. Introduction

Electric vehicles (EV) technologies, including hybrid, plug-in hybrid and full-electric cars, emerge as leading options to reduce the transport sector's carbon footprint through its electrification. Policymakers propose strategies oriented towards increasing sales and enhancing the capacity and availability of charging networks [1]. In the U.S., for example, the expectations (pre COVID-19) by 2025 are 50% of the car models sold in the region to have equivalent to Zero-Emission Vehicles (ZEV) [2]. In the same way, Canada plans ZEVs to be 10% of new passenger light-duty vehicle sales by 2025, 30% by 2030 and 100% by 2040 [3]. Specifically for the province of Quebec in Canada, where the percentage of electric cars and trucks is less than two per cent, the government has recently announced the ban on the sale of new gasoline-powered cars by 2035. This program includes small cars, sport utility vehicles (SUVs), vans and pick-up trucks for personal use. This strategy, followed by other provinces in Canada, is a part of the 2030 Plan for a Green Economy (PEV 2030) to help the province to meet emissions reduction targets [4]. For the case of Canada, 75% of the energy generated is electrical, and the electrification of transportation is presented as a promising solution for Greenhouse Gas (GHG) emissions reduction.

Achieving those mentioned outreach projections around EV technology represents, in practice, potential challenges; e.g., based on the expected EV market growth in the U.S. by 2025, approximately four times more public charging infrastructure is needed than what existed in 2017 [5]. The fast deployment of the EVs to cover the market projections could be affected by the high costs of the charger infrastructure considering that the estimated

average capital cost across 100 U.S. metropolitan areas, per public level-2 charger, is more than USD 5 k, and per DC fast charger is more than USD 80 k [5].

EV charging also brings challenges related to local weather conditions and cabling. Their massive utilization may intensify the conditions of peak power demand and power quality degradation [6]. It becomes evident that the utility grid's potential capacity must accommodate the increase in power and energy demand due to the high penetration of EVs [7,8]. In particular, the installation and operation to meet the high demand for electric vehicle charging points during the winter of Nordic countries will challenge the electricity grid. This issue appears especially on colder days when the use of space heating systems increases dramatically [9].

In this sense, and to cover the expected projections of the EV technology, massive integration is, and will definitely be, impacting the behaviour of EV owners and their consumption, which is reflected in the energy bill for them and on the power network for the electricity supplier [10]. Indeed, many studies have been carried out where the management of peak power consumption is a crucial issue for the electricity network [11,12], and the implementation of new strategies adapted to these new challenges are addressed [13]. The main problem lies in the fact that the demand can approach the maximum capacity of the electrical network, even for a short period, causing the energy supplier to pay for energy at a much higher cost to meet the demand and avoid power outages. It is known that, in countries such as Canada and the U.S., 30% of the causes of the total peak power consumption in the electric network is attributed to the residential sector [14]. This is happening in many countries such as Canada and the U.S. Thus, particular high-consuming loads that have been identified in the literature are now being managed to find a way to avoid peak power, e.g., space heating, air conditioning, washing machine, dryer, etc. It is easy to visualise that the electric vehicle, seen as a load, will contribute to the high-consumption periods when charging within the critical periods of the grid. The adaptation to these new scenarios requires the necessary measures to operate the electrical network correctly and to cover the demand and needs of the end-users.

Considering the issues mentioned earlier that are being faced by the network due to the near future high penetration of electric vehicle charging, new strategies that fit the impact on the electric network need to be developed. Thus, this paper provides a quick update of EV charging trends and proposes, on the one hand, a simulation framework permitting the study of the deployment of EV chargers in the residential sector, and on the other hand, a low-cost and low-complexity EV overnight charging strategy (EV-ONCS). The paper also includes a case study for the Quebec province of Canada during the winter season and the analysis of the impact of EV charging on the aggregated peak power as seen by the power grid.

Most of the literature works address particular cases and provide punctual solutions that are generally adapted to one side of the problem, while having at least two sides to consider. The first contribution of this paper is a simulation framework that provides a tool for analysing the impact of EV massive charging on the distribution grid and the customer interest, with the impact on the electricity bill, so both interfered sides are covered. Moreover, having in mind that the EV penetration has not been sufficiently analysed, the simulation framework offers the possibility to test new scenarios and different EV charging strategies. The strategies can be integrated as a part of an energy management system (EMS). The second contribution is the strategy proposed and applicable under realistic conditions with low complexity; there is no need to implement a complex communication system from the supplier side because the strategy can be applied locally. The EV is seen as a load or a source delivering energy to the grid. The paper also includes the analysis of the potential CO_2 emission saved while EVs' penetration increases.

The remainder of this paper is organised as follows: a short review of electric vehicles technology, trends and future directions, as well as the challenges and opportunities, are presented in Section 2. Section 3 describes the proposed simulation framework for the ecosystem of EV charging in the residential sector and the EV overnight charging strategy

(EV-ONCS). Section 4 presents the validation and the analysis of results, including the impact on the grid, on the electric bill and the CO_2 reduction assessment. The discussion and conclusions are presented in Sections 5 and 6, respectively.

2. Electric Vehicle Technology: Current Trends and Future Directions

The technology of EV has significantly evolved over the last two decades thanks to the improvements in batteries chemistry and materials, power electronics and power trains. This evolution has been strengthened by the contribution of the Internet of Things (IoT), Artificial Intelligence (AI), micro and nanoelectronics, computing and networking, embedded systems, telecommunication and information technologies.

2.1. Batteries and Technologies

From Ref. [15], in 2015, the driving range of commercially available EVs varies between 85 and 528 km. This is determined in part by the operational battery energy, which varies from about 20 kWh to 90 kWh. Indeed, the usable percentage of the battery can vary from 78% to 95% of the rated capacity, and by the energy consumption ranging from 117 to 166 Wh/km for small–large cars models. The battery voltage can vary from 277.5 V (iQ EV), which is relatively low, to up to high values such as 650 V (Concept One) or 740 V (Coupé); however, most of the cars sold use a voltage between 300 and 450 V. It is to be noticed that Li–ion technology is dominant in almost all cars that are sold. Types of Lithium batteries used in EVs include Li–ion phosphate, LiFePO4, Li–ion Mg, ternary lithium, Li–titan, Li–ion Pol, Li–ion Pri and Li–ion Lam. Recent progress related to Li–ion technologies has significantly increased the battery packs' energy capacity and extended the operating range of the latest available EVs.

2.2. Power Electronics Topologies and EV Chargers

EV charging technologies are numerous and continuously evolving. Their expansion needs some improvements in terms of cost minimisation, safety and interoperability. Among them, the main types of charging technologies are (1) conductive charging, which is mature and commercially available, and (2) wireless charging (inductive or capacitive), which is still in development, and that could be a promising technology for future charging infrastructure [16].

EVs with embedded chargers permit AC charging at different power levels from 3 to 22 kW, and DC fast chargers at higher power from 40 kW to 120 kW. In the residential sector (overnight) and institutional parking (office time), charging level 2 (240 VAC) is preferred; this is an unsurprising preference since the 240 V charger is almost twice as fast as a 120 V charger.

In terms of standards, the deployment of electric vehicles must also address the fact that there are three dominant standards for fast charging (CHAdeMO, CCS, and GB/T). They are partially compliant with IEC 61851 and GB/T18487, there is still no universal agreement on the plug type, and cable specifications [17]. Table 1 presents a summary review of the main characteristics of actual EV charging standards. It is to be noted in Table 1, that even if fast chargers are available and allow an EV to fully recharge in a few minutes, their use is currently limited to strategic points on the roads and, at least for the moment, not suitable for use in the residential sector.

The outdoor temperature may also affect the regular operation of the chargers. For example, very high temperatures might pose difficulties in the charger manipulation, there might also be sand accumulation, and the critical temperature limits of the charging cables can be reached. Low temperatures also might present, for example, snow accumulation and frozen plug contacts [18,19]. Another view is how the outdoor temperature changes influence the energy consumption of electric vehicles [20], and by default, the operating EV range. For example, in colder periods, the EV rated range can be decreased by around 10%, and high temperatures may affect the battery health. It has also been found that the temperature might impact the charging time and driving behaviour of the EV owner. For

example, during winter, the same EV battery can take almost 4 h to be fully charged, while in the summer, it can be charged in 2.69 h [19].

Table 1. EV charging standards for passenger cars.

Standard	Type	Voltage [V]	Power [kW]	Connector
Level 1	AC	120	1.4	J1772 CSA 5-15R
Level 2 (1)	AC	240	3.6, 7.2, 11, 22	J1772
Fast charging (2)	DC	500–1000	<100	J1772 Combo
			<62.5	CHAdeMO 1.0
			<200	CHAdeMO 1.2
			<400	CHAdeMO 2.0
			<150	CCS HPC150
			<250	CCS HPC250
			<350	CCS HPC350

(1) Power levels vary for 208 VAC; (2) DC level 1 up to 80 A, and DC level 2 up to 200 A.

The recently introduced wireless power transfer (WPT) technology, as mentioned before, is promising for the massive deployment of EVs as expected by governments and communities around the world. This emerging way to recharge EVs offers several advantages over the established conductive charging. WPT for charging has the potential of being more reliable under extreme weather conditions and of offering a lower environmental impact and more safety benefits than conventional wired charging systems [16]; however, WPT has some technical issues that include the imperfect coupling or misalignment that impact the power transfer efficiency and are actually themes of research. The objective is to propose converter configurations and control methods with high misalignment tolerance to ensure a proper and efficient charging process [21,22].

2.3. Current and Upcoming Battery Electric Vehicles (BEVs)

Upcoming battery electric vehicles are offering battery packs with 100 kWh with over 400 m range. It is expected to offer a more extended operation range and high power charging capabilities in the coming years. New technologies are already using higher battery voltages (800 V) and enable fast charging modes. As presented in Table 2, current and upcoming passenger vehicles will offer greater autonomy than what is expected for ICE vehicles.

Table 2. Electric cars update.

Model	Release	Range EPA m (km)	Battery kWh (Volts)	Motor Power kW	Charging Power kW AC (DC fast)
SAIC Roewe Ei5	2020	261 (420)	52.5	86	7 (50)
Peugeot e-208	2020	200 (320)	50	100	7 (100)
Porsche Taycan TurboS	2020	192 (307)	93.4 (800)	560	22 (270)
Tesla Y	2020	338 (543)	62	—	7 (170/250)
Lexus UX 300e	2020	250 (400)	54.3	150	6.6 (50)
Jaguar I-PACE	2020	234 (377)	90	300	7 (50/100)
Hyundai Ioniq	2020	274 (170)	38.3	100	7.2 (44/100)
Mazda MX-30	2021	124 (198)	35.5	105	7 (50)
Volkswagen ID.4	2021	300 (482)	83	225	(125/150)
Mercedes EQ EQA	2021	217 (350)	60	200	11 (100)
BMW i4	2021	375 (600)	80	395	(150)
Audi Q4 e-tron	2022	281 (450)	82 (800)	225	7 (125)
Fisker Inc Ocean SUV	2022	300 (480)	80	225	—
BMW i7	2023	430 (700)	120 (800)	500	(up to 150)

Data updated on June 2020 from https://wattev2buy.com (accessed on 3 June 2021).

Likewise, increasing the energy capacity will undoubtedly help to improve the adoption of EVs in the near future. For this reason, utilities shall be prepared for the new challenges and require facilities to host the modernisation of the power grid, considering the integration of distributed storage systems and new charging modes to avoid voltage imbalance or frequency deviation problems.

Moreover, it is important to consider the costs of the Li–ion battery packs and the forecasts for the upcoming years, which show predictions of 94 USD/kWh by 2024 and 62 USD/kWh by 2030 [23,24]. Further, having in mind that the cost of the battery pack accounts for more than 40% of the total cost of the car, it is expected that by 2026, the average cost of a full electric vehicle will be less than an ICE average car.

2.4. EV Charging Challenges and Opportunities

This part of the paper seeks to emphasise the challenges that the EV charging system currently face that prevent its rapid deployment. More particularly, we focus on the strategies taking place in research to ease the drawbacks related to the future high penetration of EV. We touch on how different actors, such as EV owners, charging points suppliers and utilities, are facing and must face the inevitable deployment; however, our primary goal in this paper is to address the charging systems available in residential dwellings and the impact on the grid under the stress of cold weather conditions, considering the augmentation of space heating utilisation.

As we confirm in the next session, management strategies to regulate the charge are imposed in a necessary way to avoid the increase in peak electricity consumption. The idea is to achieve a good compromise among the EV owners' needs and satisfaction, the convenient cost of recharging, and the electric network's reliability.

In the first place, we can discuss the Vehicle to Grid (V2G) strategies. This means that the electric vehicles are seen as distributed energy sources that usually can have IP based communication between the EV owner and the grid operator [25,26]. This communication is required to remotely manage the vehicles to control the charging hours based on the grid conditions. Indeed, a reliable communication system is a must as those structures integrate the utilisation of specialised large quantities of sensors to manage them in the form of aggregated data. The collected information identifies the electricity regulation requirements and the state of charge (SoC) to achieve an optimal multi-cast scheduling, most of the time, under intermittent connections, which has become an extensive challenge to study [27].

Ancillary service is a category for power grid support to ensure its reliability through loss compensation, systems protection, dispatch of distributed sources or scheduling of loads. In this case, EV can be seen as a contribution load of the residential system by providing energy to the grid when needed in a bidirectional V2G structure. It is to remark that in this category, strategies such as the use of aggregated and clustering load management systems can deal with the voltage over-loading or under-loading situations, which have been identified as voltage instability problems for the grid [25,28].

Centralized control systems based on exchanging information through a cost-effective broadband network based on optical fibre and wireless technologies is a good possibility presented in [29]; however, the significant amount of calculations, additional to the required effectiveness of the communication system, might be barriers for their deployment.

Scheduling strategies have also been used to mitigate the load overcharging of the grid. These methods, mostly known as load shifting strategies, search to displace the peak demand to the periods where the load demand is lower using specific loads, i.e., space heating systems, water heaters and electric vehicles [30]; however, as the EV penetration is in augmentation, and combined with other loads, a rebound effect has been identified in literature, that can be seen as a new potential menace to overcharge the capacity of the grid during the periods identified as off-peak periods [31,32]. Further, these scheduling strategies require a representative amount of information (customer behaviour, outdoor temperature, etc.) to address customers' energy requirements and power network needs

optimally. In this category, we can also add grid support strategies using storage or renewable energy systems to shave the charging load during on-peak high electricity cost [29].

Smart-charging strategies directed to residential EV owners, considering the charging rates and the best time to recharge, are currently being investigated to improve the overall energy efficiency at home and in the network. Further, many other studies are being conducted in academic research and industry. This paper aims to propose strategies to support EV owners and utilities to achieve an optimal peak-to-average ratio by using low cost and low complexity decentralized EV charging strategies. Hence, the following section describes the proposed simulation framework. Since the load-shift strategy is widely used in the literature, we use it as a point of comparison with our proposal of overnight charging method as a potential solution, targeting the massive deployment of these new technologies.

3. Simulation Framework and EV Overnight Charging Strategy (EV-ONCS)

The proposed simulation framework of EV charging, focusing on the residential sector ecosystem, includes the following aspects: (i) the battery pack and charger; (ii) the EV energy needs; (iii) the residential load demand; and (iv) the strategy for EV charging.

3.1. Simulation Framework

The proposed framework can accept different EV charging strategies, which can be integrated as a part of an EMS. The management system can operate using only local information. It can also be seen as an agent in a multi-agent configuration sharing information with other agents in the neighbourhood or at different distribution network levels. Figure 1 presents a simplified diagram of the proposed simulation framework. As illustrated, the main inputs of this framework are the power measurements database, the information of meteorological conditions and the heat loss characteristics of the park of residential buildings.

It should be noted that even if, for this study, the proposed framework is used for the case of Quebec, it can be adapted and extended to the study of the problem of EVs high penetration into distribution networks in the context of other countries. The only condition for doing this is the availability of information on the characteristics of the buildings (heat loss coefficients and construction standards) in the area, the meteorological conditions, the typical profiles of energy consumption and the characteristics of the electrical network.

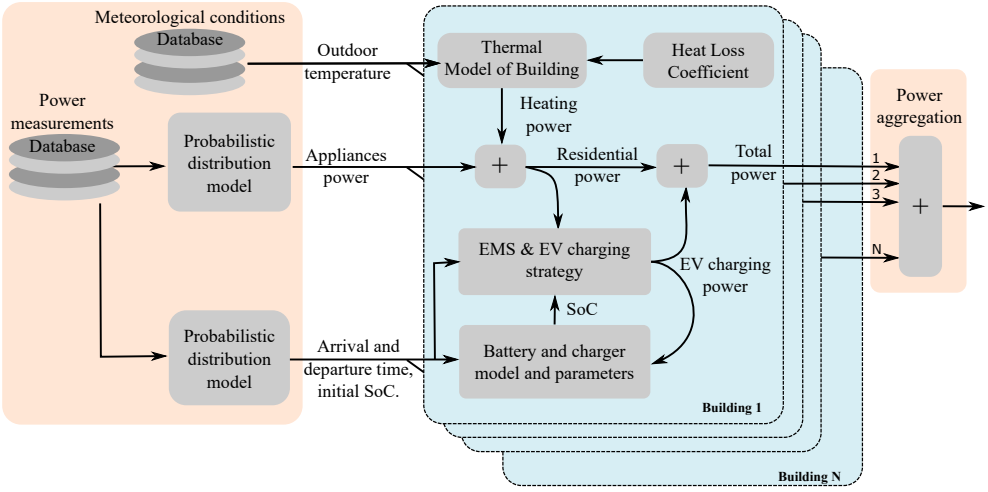


Figure 1. Simulation framework.

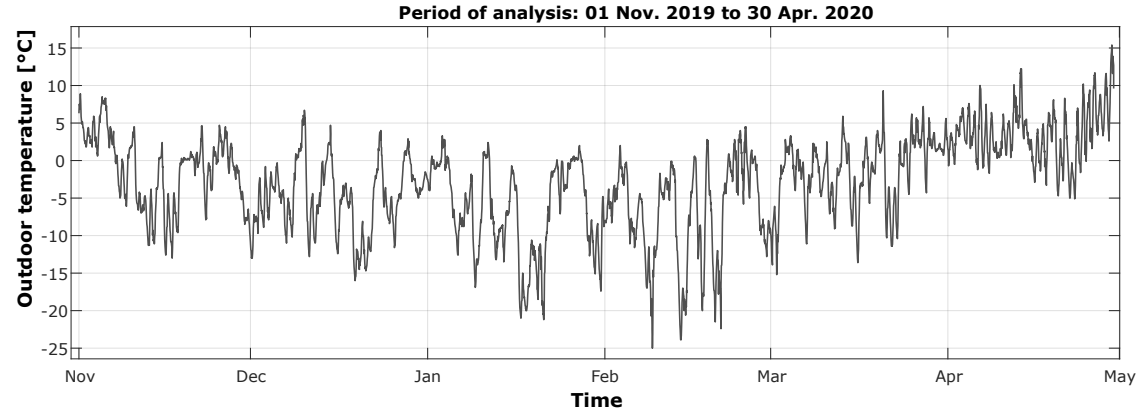
It is to be noticed that the studied scenarios are focused on assessing a mostly cold environment, so the framework integrates probabilistic models based on measurements of occupied houses in the Quebec province and thermal models from the real-time emulation

system proposed in [14,33]. Thus, the framework provides the power profiles for a number N of buildings from the thermal and probabilistic distribution models. The profiles of heating (or cooling) power are obtained separately, depending on the outdoor temperature and thermal characteristics of each building and the ones related to appliances usage depending on historical behaviour.

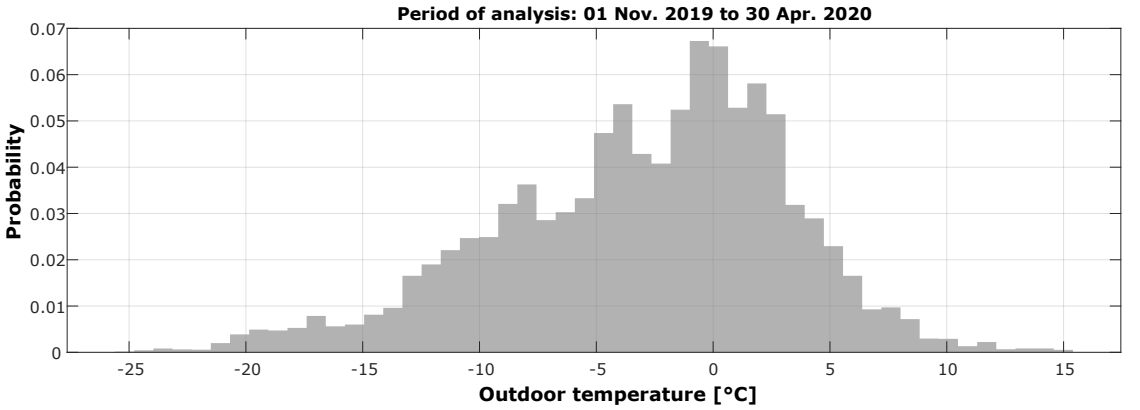
The framework also provides, through a probabilistic distribution model, the profiles of the arrival and departure time and the state of the charge (SoC) at the arrival time for each vehicle. To simplify the analysis, only one, or the equivalent of one electric vehicle per household, is considered. This information is used to feed a battery and charger model, which provides the SoC and the power demand of EV charging for each vehicle, depending on the implemented strategy.

3.2. Case Study

In this study, we consider the consumption profile of one hundred detached houses located in the Quebec province with the possibility of owning one EV with distributed overnight recharging. The analysis was conducted strategically, including the typical coldest periods of Quebec between 1 November 2019, to 30 April 2020. This analysis period permits us to capture the impact of the low temperature on the overall residential energy consumption. Figure 2 shows the outdoor temperature and distribution observed during the period of analysis for the city of Trois-Rivieres in Quebec, Canada. We can see that the measured outdoor temperature can drop below -25 °C during the analysis period. The heat loss coefficients and time constants used in the simulation of the park of buildings correspond to typical values for Canadian detached houses as confirmed by field measurements reported in [14,33,34] and illustrated by Figure 3.



(**a**) Profile of the outdoor temperature



(**b**) Distribution of the outdoor temperature

Figure 2. Outdoor temperature profile and distribution for the period of analysis (Data from: Simeb-HydroQuébec, https://www.simeb.ca/, accessed on 8 June 2020).

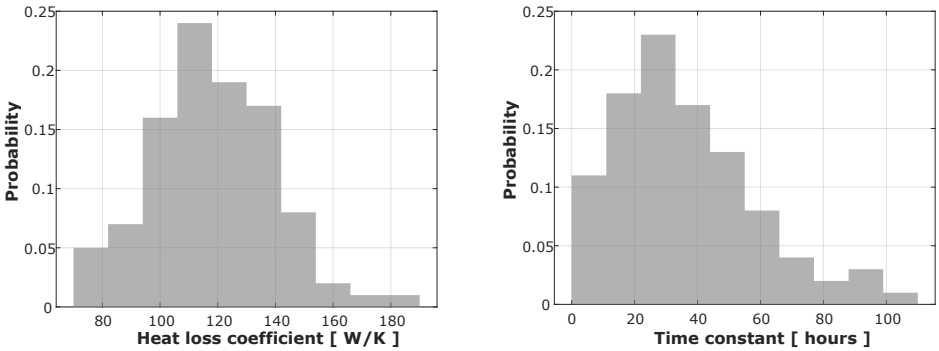


Figure 3. Heat loss coefficients and time constants distribution for the emulated park of residential buildings (from [14,33,34]).

The data of typical residential load demand for Quebec are generated using the model of real-time emulation system proposed in [33]. We consider that the residential installations have an electric vehicle recharge using level 2 connections with different nominal power depending on the size of the battery pack, for example, 3.6 kW for a battery of 25 kWh, 7.2 kW for 50 kWh, 11 kW for 60 kWh and 22 kW for 90 kWh. The charging process starts with constant current mode and finishes with constant voltage, and follows the typical open circuit voltage—state of charge (OCV-SoC) behaviour of Li–ion batteries [35]. The profile of OCV versus SoC is presented in Figure 4.

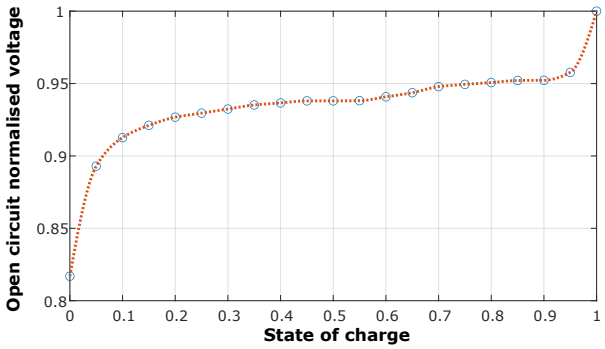
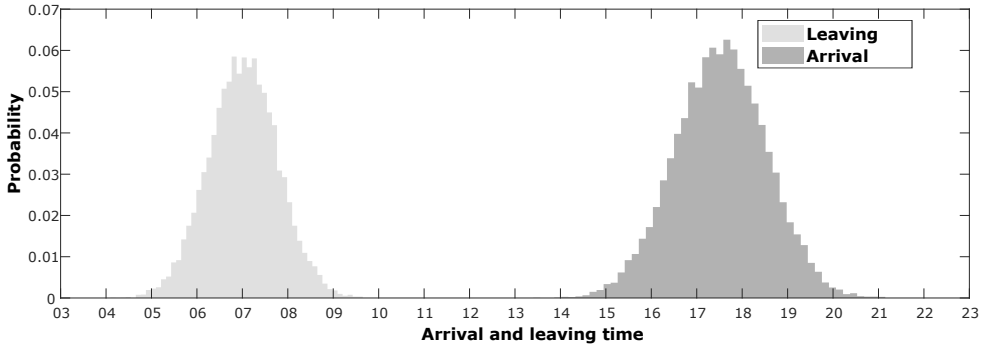


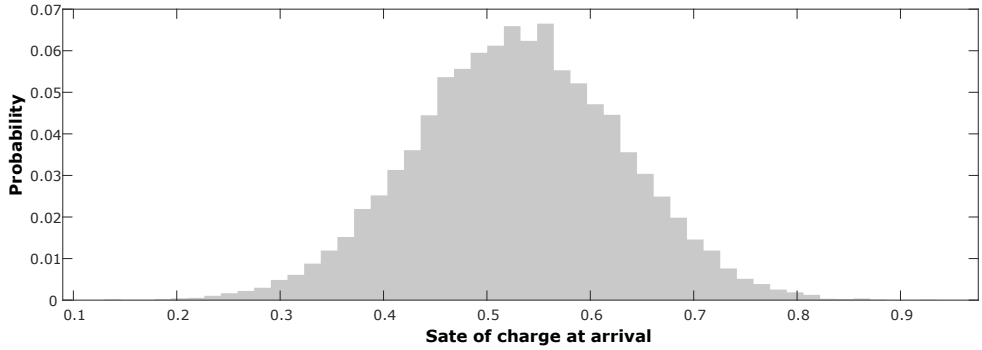
Figure 4. Open circuit voltage (OCV) versus state of charge (SoC) of Li–ion batteries [35].

According to the typical profiles of the household electricity consumption in Quebec, Figure 5a presents the Gaussian distributions for leaving and arrival times with mean values around 7H15 and 17H30, respectively. Similarly, in Figure 5b, a Gaussian distribution is employed to model the expected state of charge at the moment of arrival. As in a real scenario, we consider that some vehicles can be partially recharged at the workplace or public charging facilities.

As stated by the utility provider Hydro-Quebec, about 90% of the EV charging needs are covered at home and at work rather than at public charging stations. It is also reported since 2009 that 89% of the households that owned or intended to buy an EV had access to an external 120 V AC outlet for EV charging [36]; however, it is recognized that with the installation of a 240 V outlet, the user can benefit from charging level 2, which reduces to less than one half of the regular time it takes to charge the EV.



(**a**) Leaving and arrival time



(**b**) State of charge at arrival

Figure 5. Leaving and arrival time, and state of charge at arrival using typical profiles of household consumption in Quebec.

As mentioned before, in this analysis, we consider that the user has access to level 2 charging for the overnight recharging. The fleet of 100 EVs is distributed differently, by battery size (and charging power), to define four cases as detailed in Table 3. Case 1 involves the majority of the EV population with low battery size and uses low charging power. Instead, case 2 considers the medium battery size and medium charging power. For case 3, the number of cars is equally distributed among low, medium, and high battery size and power, respectively. For case 4, the majority of the vehicles have a bigger battery capacity and use high power for recharging.

Table 3. EV fleet composition.

Battery Size (Charging Power)	% of Cars			
	Case 1	Case 2	Case 3	Case 4
25 kWh (3.6 kW)	40	17	25	5
50 kWh (7.2 kW)	38	40	25	17
60 kWh (11 kW)	17	38	25	38
90 kWh (22 kW)	5	5	25	40

Only level 2 charging at 240 VAC (or 208 V) is considered.

The idea is to represent a fairly diverse population of EVs that takes into account the changing evolution of present and future conditions, in which small cars may be preferred, as well as scenarios in which SUVs, with large batteries, can occupy the market share of EVs. As mentioned, we consider 100% penetration of EV with one vehicle per household for all four scenarios.

A typical real-world radial distribution system is considered for the evaluation with service voltage connection of three-wire 120/240 V single phase, through distribution step-down 25 kV transformers serving a group of clients as illustrated in Figure 6. In our simulation, the primary transformer provides voltage regulation with on-load tap-changer (OLTC), and each distribution transformer is properly sized to supply ten users. It

should be noted that in the United States and Canada, distribution transformers (service transformers) generally range from 35 kV or less and single-phase power can range from 15 kVA to 833 kVA. IEEE Std C57.12.20-2017 defines the specifications for Overhead-Type Distribution Transformers 500 kVA and Smaller with High Voltage of 34,500 V and below and Low Voltage of 7970/13 800Y V and below.

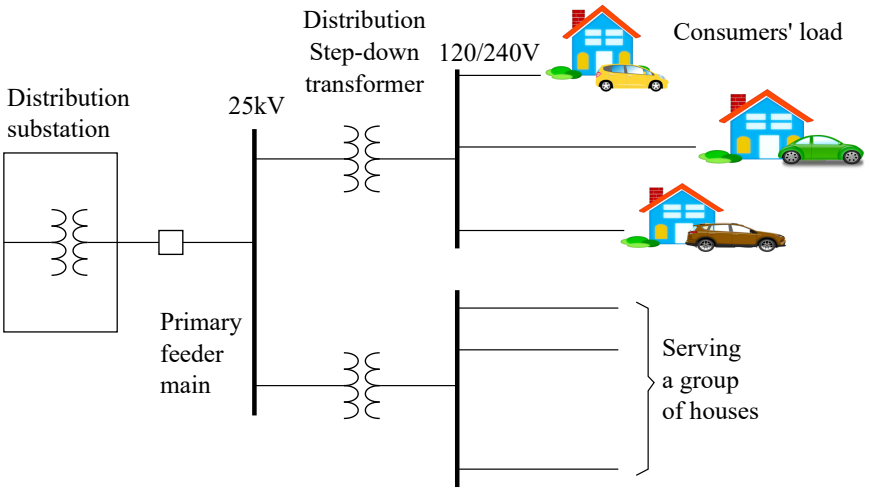


Figure 6. Simplified diagram of power system.

3.3. Local EV Overnight Charging Strategy EV-ONCS

We propose a strategy that uses only local information of the buildings owning an electric vehicle for the planning of EV charging; this information can be provided by any energy management or local measurement system and includes:

- The arrival time or connecting detection of the EV (EVCD);
- The historical of leaving time or disconnecting detection of the EV (EVDD);
- The actual (and historical) state of charge (SoC) at the arrival time of the EV;
- The actual (and historical) residential power demand (P_R);

We consider that 240 V (or 208 V) outlets are available in each residential building and allow each user to plug in and recharge the EV at the power defined by the onboard charger. The rated power of EV chargers are defined as 3.6 kW, 7.2 kW, 11 kW or 22 kW, depending on the type of vehicle, from small cars preferred for short daily driving cycles (<50 km) to SUVs preferred for longer driving cycles (>100 km). We also consider that all EV chargers offer the possibility of bidirectional and modulated power. They can communicate and exchange information with the local energy management or measurement system of each residential building.

The EV charging strategy is based on the use of Gaussian kernel modelling to estimate the probabilistic distribution of residential demand from the historic consumption as presented in (1).

$$\psi_H(k,a) = \frac{1}{\sqrt{2\pi}\cdot a}\cdot e^{\frac{-k^2}{2a^2}}, \quad (1)$$

where a is the standard deviation of the distribution, the index of each coefficient is $-l \leq k \leq l$, and $2l+1$ is the dimension of the kernel. The value of l is fixed to be equivalent to one hour of data. The estimated demand $\hat{P}_R$ is defined by (2)

$$\hat{P}_R(n) = \lambda_T \cdot \sum_{k=-l}^{l} [\psi_H(k,a)\cdot P_R(n-T+k)] + \lambda_{2T}\cdot \hat{P}_R(n-2T) + \lambda_{3T}\cdot \hat{P}_R(n-3T), \quad (2)$$

where T represents the periodicity of estimation, in this case, defined as a 24 h delay. The coefficients $[\lambda_T, \lambda_{2T}, \lambda_{3T}] \in (0,1)$ and $\lambda_T + \lambda_{2T} + \lambda_{3T} = 1$. Similarly, the mean behaviour of the power demand $\tilde{P_R}$ is estimated using (3) and (4),

$$\psi_D(k,b) = \frac{1}{\sqrt{2\pi}\cdot b}\cdot e^{\frac{-k^2}{2b^2}}, \tag{3}$$

$$\tilde{P}_R(n) = \alpha\cdot\sum_{k=-m}^{m}[\psi_D(k,b)\cdot P_R(n-T+k)] + (1-\alpha)\cdot\tilde{P}_R(n-T), \tag{4}$$

where b is the standard deviation of the distribution, the index of each coefficient is $-m \leq k \leq m$ and $2m+1$ is the dimension of the kernel matrix. The value m is fixed to be equivalent to one day of data. The coefficient $\alpha \in (0,1)$. Any instant n is considered inside an expected period of low local power demand if $\tilde{P_R}(n)$ is higher than $\hat{P_R}(n)$, and a low power demand flag LPD becomes true.

Similarly to the models for the estimation of instantaneous and mean power demand, $\hat{P}_R(n)$ and $\tilde{P}_R(n)$ described by the Equations (1)–(4), the information of arrival or connecting detection (EVCD) and leaving time identified as disconnecting detection (EVDD) are used to build a model of availability periods (EV_{AT}) for each vehicle in hours. This is performed based on a Gaussian kernel algorithm to predict the expected periods of availability for recharging each vehicle. This information is used to estimate the power EV_{CP} to be used for the actual recharging session. Thus, this value is defined by Equation (5) and based on the nominal power of the charger EV_{NP} in kW, the battery size EV_{BS} in kWh, the state of charge at arrival SoC_A and a safety margin factor $\delta < 1$, which is used to compensate the error of estimation of EV_{AT}.

$$EV_{CP} = \left[\min\left(\frac{(1-SoC_A)\cdot EV_{BS}}{\delta\cdot EV_{AT}\cdot EV_{NP}}, 1\right)\right]\cdot EV_{NP} \tag{5}$$

Depending on the state of charge at arrival SoC_A, some EVs can contribute to balance the power demand during the locally estimated peak periods ($\tilde{P_R}(n) < \hat{P_R}(n)$) while others can start their recharge earlier. Thus, a state of charge threshold SoC_{TH} can be defined to start the SoC balancing action. In this way, EV with $SoC < SoC_{TH}$ can be recharged once the vehicles under this condition are available, and the EV with $SoC > SoC_{TH}$ can contribute with its available energy. The power contribution in discharging mode is defined as a portion of the nominal charging power $EV_{DP} = -\gamma\cdot EV_{NP}$, with $\gamma \in (0, 0.5)$.

Recharging or V2G contribution during high power demand stops when the battery of the EV reaches the condition of $SoC = SoC_{TH}$; and recharging restarts during the locally estimated low consumption periods after a delay $\hat{D}$ defined by (6).

$$\hat{D} = \frac{SoC_A\cdot EV_{BS}}{EV_{NP}}\cdot SPH. \tag{6}$$

where, SPH is the number of samples per hour. Typically, the smart meters and weather forecast services provide at least four samples per hour. Still, technically such information can be accessible at a higher sampling rate at low cost, e.g., a measurement period of one or five minutes. This delay $\hat{D}$ is generated for each vehicle based on the state of charge at the arrival (SoC_A), the battery capacity EV_{BS} and the nominal charging power EV_{NP}. Essentially, it helps to avoid the power demand rebound appearing in most of the strategies based on modulated electricity tariffs and load shift. The logic permitting to compute the charging (or discharging) power at any instant n can be defined by the Algorithm 1 in terms of $\hat{D}$, LPD, EV_{CP} and EV_{DP} as follows.

As illustrated in Figure 7, the Algorithm 1 is executed while the electric vehicle is available and takes information from a complementary process that establishes the condition (or flag) of low power demand LPD. This process is based on the Gaussian kernel models that are updated continuously based on the information coming from the EMS or the measurement system of the building. Algorithm 1 produces the information of power (P) to be used by the charger. Depending on the condition of SoC and LPD, P represents the power to recharge or discharge the battery.

Algorithm 1: EV charging strategy.

$C \leftarrow 0$;
Read $EV_{AV}(n)$;
while $EV_{AV}(n)$ **do**
  Read $LPD(n)$, $SoC(n)$,EV_{DP}, EV_{CP}, $\hat{D}$;
  if $NOT(LPD)$ **then**
    if $SoC(n) < SoC_{TH}$ & $SoC(n-1) < SoC_{TH}$ **then**
      $P \leftarrow EV_{CP}$;
    else
      if $SoC(n) > SoC_{TH}$ & $SoC(n-1) > SoC_{TH}$ **then**
        $P \leftarrow EV_{DP}$;
      else
        $P \leftarrow 0$;
      end
    end
  else
    if LPD & $\left(C > \hat{D}\right)$ & $(SoC(n) < SoC_{MAX})$ **then**
      $P \leftarrow EV_{CP}$;
    else
      $P \leftarrow 0$;
    end
  end
  Read $EV_{AV}(n)$;
  $C \leftarrow C + 1$;
end

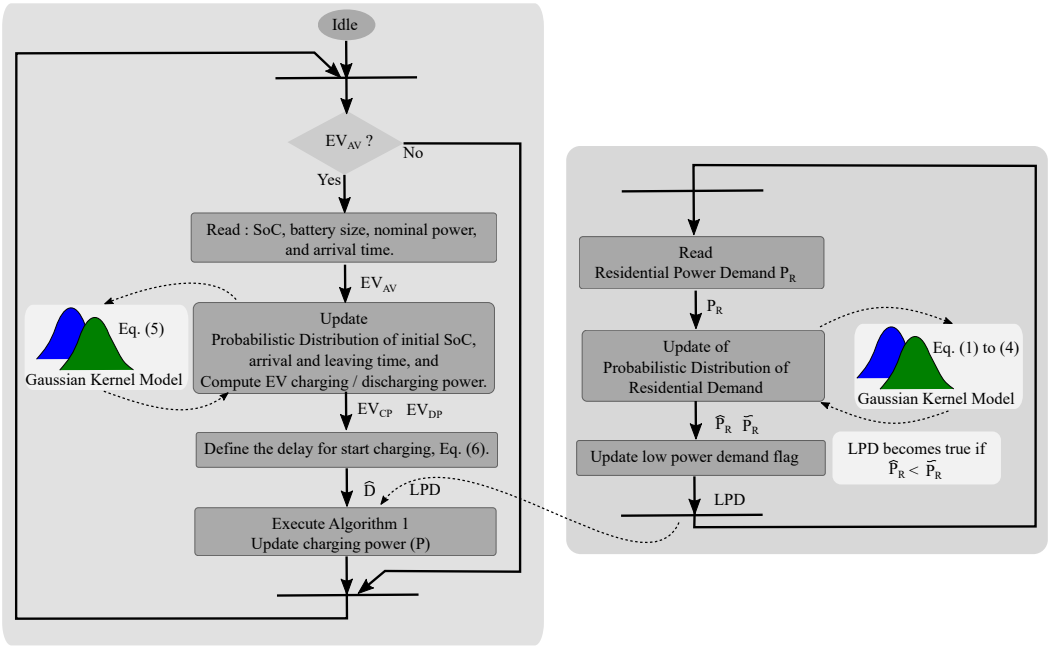


Figure 7. Simplified diagram of the local EV charging strategy.

3.4. Description of the Scenarios

To illustrate the outstanding of our proposition for each case defined in Table 3, we consider three scenarios, which are listed below.

- **First scenario:** each vehicle is plugged and recharged following the arrival time;
- **Second scenario:** the recharge of each vehicle begins following the low power demand (LPD) information, to shift the load (Load-shift strategy);

- **Third scenario:** the proposed strategy EV-ONCS enables vehicles with high initial SoC to contribute with V2G power transfer, while the vehicles with low initial SoC starts recharging earlier.

4. Results

The load-shift and the EV-ONCS strategies impact three important aspects. The first one is related to the Distribution System Operators (DSO), the second to the customers, determining their acceptance and enrolment to the programs (for energy savings) and the third is related to emissions avoidance. Concerning the distribution operator, the vital aspect is the power profile, while the electricity bill is more significant for the customer. On the environmental side, we want to affect the amount of CO_2 we want to avoid; therefore, depending on the level of integration of EV, there is an impact on the reduction in CO_2 and is essentially related to fossil fuel, e.g., litres of gasoline or diesel avoided by replacing conventional cars with electric vehicles. We present in this section the analysis of these three aspects.

4.1. Impact on the Profile of Power Demand

Figure 8 shows an example of the results obtained for the house # 6 that has assigned an EV with a battery of 50 kWh and 7.2 kW charging power characteristics. From these results, we observe the peak demand which has significantly increased for all cases after the integration of EVs.

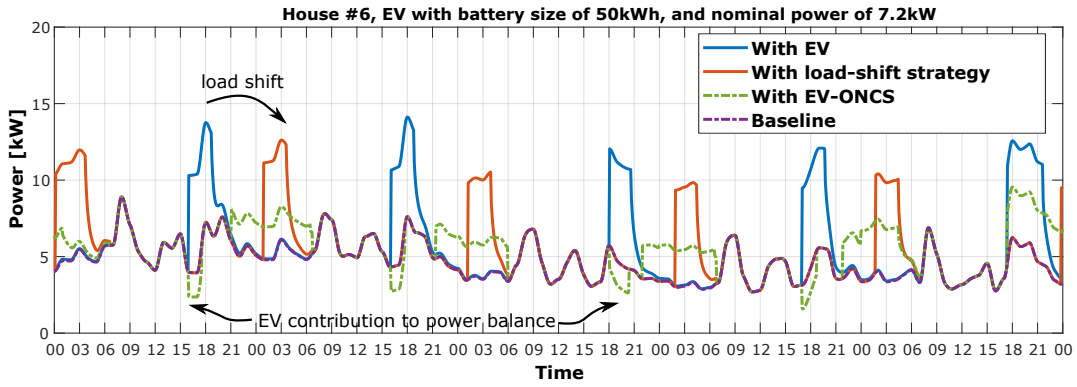


Figure 8. Example of results for house # 6 during five days in January 2020.

We can also evidence in the same figure that by applying only the load-shift strategy, the solution fails, considering that the peak power is relocated, generating important power rebound. Instead, the proposed strategy EV-ONCS produces a better performance from the local point of view reducing significantly the peak of power. Further, in this example, it is to be noticed that the EV contributes to the power balance in some days, which allows EVs with a low SoC to start recharging. The proposed strategy does not produce the increase (or "rebound" effect) in peak demand compared to the scenario with the load-shift strategy.

We also present, in this section, the results of the analysis of the possible effect of the EVs overnight recharging on the aggregated power as faced by the power network for the cases 1 and 4. Figure 9 shows the results during high power demand in a period of five days in January where the recorded outdoor temperatures were particularly low. This effect can be corroborated in Figure 10 where the peak-to-average ratio (PAR), which is an important parameter to minimize the grid congestion events and maintain the desired stability, is calculated by week and plotted for scenario case 4. With these results, we confirm that the use of the load-shifting strategy does not improve the balance of the grid, and contrarily in some cases, produces negative effects or higher peak power as the problem is moving elsewhere to be faced later. Instead, the proposed strategy, EV-ONCS, reduces the negative impact of the EV's integration and permits to improve the PAR compared to the baseline

case without EV. This means that the power demand is well distributed over time, the difference between the peak and the average profile decreases and the stability of the network can be guaranteed.

Table 4 provides the information of the mean peak-to-average ratio for the period of analysis considering the four scenarios of the EV fleet composition presented in Table 3. We can notice from these results that the PAR is improved by using the proposed strategy. Specifically, the index is reduced by 16% in cases 1, 2 and 3, and by 21% in case 4. This means that the strategy helps to mitigate the negative impact of EV in the residential sector and contributes to demand-side management. We highlight that the load-shift strategy could help in cases 1 and 2 but becomes unsuitable in case 4.

Table 4. Peak-to-average ratio of aggregated power demand.

Scenario / Case	Mean Peak-to-Average Ratio			
	Case 1	**Case 2**	**Case 3**	**Case 4**
Baseline	1.9	1.9	1.9	1.9
With EV	2.2 (+16%)	2.4 (+26%)	2.6 (+37%)	2.9 (+53%)
With load-shift strategy	1.9 (+0%)	2.1 (+10%)	2.3 (+21%)	2.9 (+53%)
With EV-ONCS	1.6 (−16%)	1.6 (−16%)	1.6 (−16%)	1.5 (−21%)

Values for the period from 20 January to 25 January 2020.

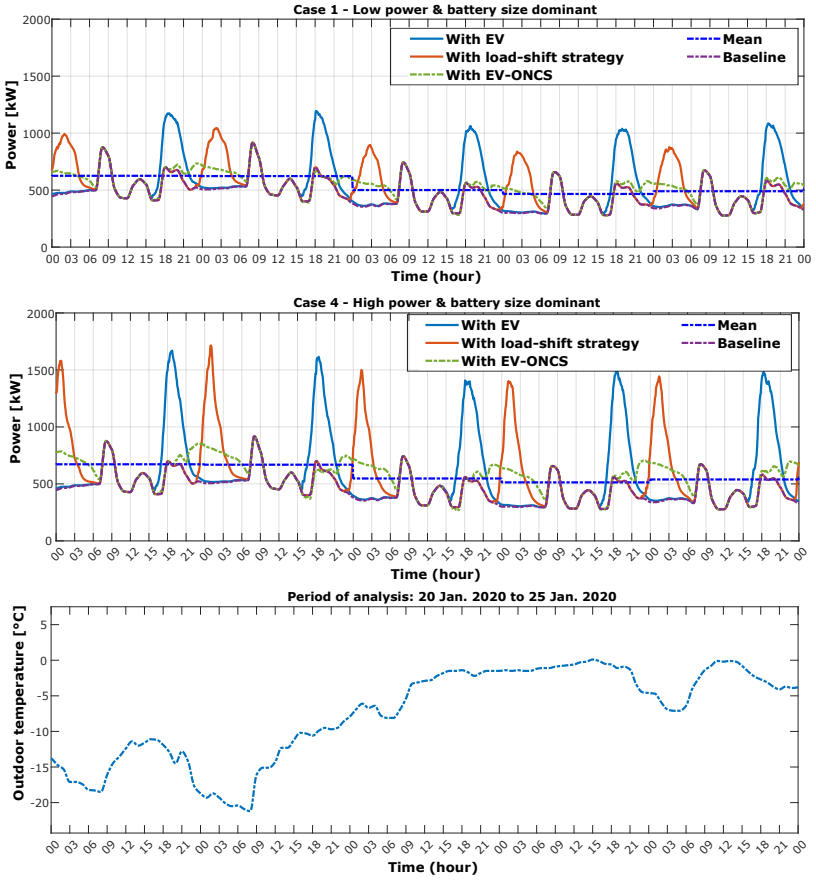


Figure 9. Aggregated power demand for cases 1 and 4 during five days in January 2020 and outdoor temperature for the same period.

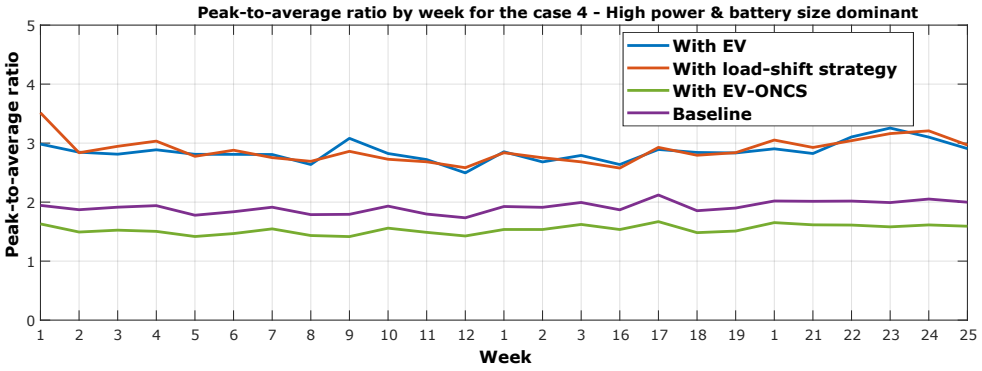


Figure 10. Peak-to-average ratio computed weekly for the period of analysis under the case 4.

We have assessed the effect of EV integration on the power seen by the distribution transformers 1 (DT-1), 5 (DT-5) and 10 (DT-10) with the configuration proposed in Table 5. We considered for this test the same week of January 2020, and the results are gathered in Table 6. The DT-1 supplies, in most cases, EVs with low charging power, while DT-5 and DT-10 with medium and high charging power, respectively. As expected, the load-shift strategy works properly for the DT-1; its performance is degraded in DT-5 and does not work for DT-10. It is to be noted that the peak power is increased by almost +200% in cases 3 and 4 for DT-10. The proposed strategy EV-ONCS works properly for the three transformers with a slight increase in peak power demand or enabling the peak reduction.

Table 5. EV fleet composition for DT-1, DT-5 and DT-10.

Battery Size (Charging Power)	Number of Cars			
	Case 1	Case 2	Case 3	Case 4
		Transformer # 1		
25 kWh (3.6 kW)	10	10	10	5
50 kWh (7.2 kW)	0	0	0	5
		Transformer # 5		
50 kWh (7.2 kW)	10	10	10	0
60 kWh (11 kW)	0	0	0	10
		Transformer # 10		
60 kWh (11 kW)	5	5	0	0
90 kWh (22 kW)	5	5	10	10

Table 6. Aggregated peak power demand seen by distribution step down transformers 1, 5 and 10.

Scenario Case	Peak Demand in kVA			
	Case 1	Case 2	Case 3	Case 4
		Distribution Transformer # 1		
Baseline	90	90	90	90
With EV	101 (+12%)	105 (+17%)	106 (+18%)	122 (+36%)
With load-shift strategy	91 (+1%)	91 (+1%)	90 (+0%)	104 (+16%)
With EV-ONCS	89 (−1%)	89 (−1%)	88 (−2%)	90 (+0%)
		Distribution Transformer # 5		
Baseline	94	94	94	94
With EV	134 (+43%)	137 (+46%)	137 (+46%)	164 (+74%)
With load-shift strategy	119 (+27%)	119 (+27%)	119 (+27%)	153 (+63%)
With EV-ONCS	96 (+2%)	93 (−1%)	94 (+0%)	95 (+1%)

Table 6. *Cont.*

Scenario Case	Peak Demand in kVA Case 1	Case 2	Case 3	Case 4
	Distribution Transformer # 10			
Baseline	87	87	87	87
With EV	201 (+131%)	202 (+132%)	238 (+174%)	235 (+170%)
With load-shift strategy	192 (+121%)	193 (+122%)	242 (+178%)	244 (+180%)
With EV-ONCS	87 (+0%)	86 (−1%)	93 (+7%)	93 (+7%)

Values for the period from 20 January to 25 January 2020.

4.2. Impact on the Electricity Bill

As mentioned previously, the customers' saving energy affecting the amount to be paid or reducing the electricity bill is key for adopting energy management programs. In terms of awareness of climate change, consumers also want to contribute to the common well-being for current and future generations. To cover environmental issues, the energy suppliers and operators allied with researchers work out potential solutions to high energy consumption and power peaks. Since the residential sector contributes enormously, these programs propose the segregation of energy rates to encourage the residential customer to avoid synchronized energy consumption; an example of a widely used program is the Time-of-Use (TOU), also called Time-Varying Rates (TVR). In this program, the operators have identified the high, medium and low consumption schedules and charge more according to the periods of stress for the network. Many countries such as the U.S. and Canada have adopted the critical-peak pricing rates; however, they are optional in some provinces. For example, the Quebec DSO, Hydro-Quebec, does not yet employ time modulated tariffs, but two rates depending on the daily energy consumption, the first 40kWh are billed at a low rate, and the exceeding kWhs at a higher rate [37]. Thus, if the energy consumption remains the same, there is no difference in the electricity bill while using one or another strategy. To compare the possible impact of each strategy on the electricity bill, we consider the Time of Use (TOU) tariffs used in Ontario (Canada) specified in Table 7.

Table 7. Time of Use tariffs for winter season from Ontario Energy Board (In CAD$).

Tariff	(Cents/kWh)	Weekdays	Weekend and Holidays
Off-peak	8.2	19h00-06h59	00h01-23h59
Mid-peak	11.3	11h00-16h59	-
On-peak	17.0	07h00-10h59	-
		17h00-18h59	-

From: https://www.oeb.ca/rates-and-your-bill/electricity-rates, accessed on 16 August 2021.

Figures 11–13, respectively, present the results of the mean daily cost of electricity for each house in the study, applying the TOU rate of Table 7. Further, to have the individual sight, we have plotted the daily cost of electricity for house # 6 during two weeks from 20 January to 1 February 2020, and the daily cost for the house # 80 during the same observation period.

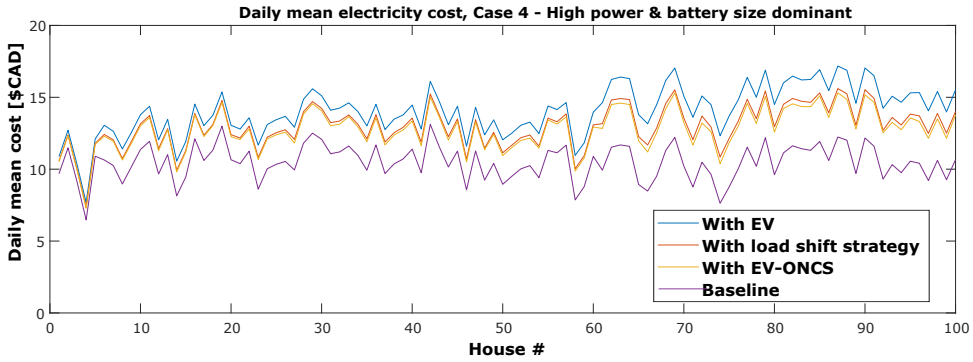


Figure 11. Daily mean cost of electricity by house for the period of analysis under the case 4.

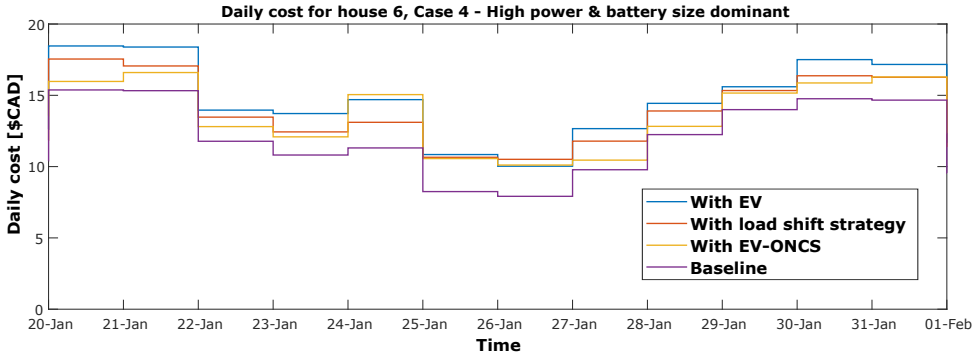


Figure 12. Daily cost of electricity for house #6.

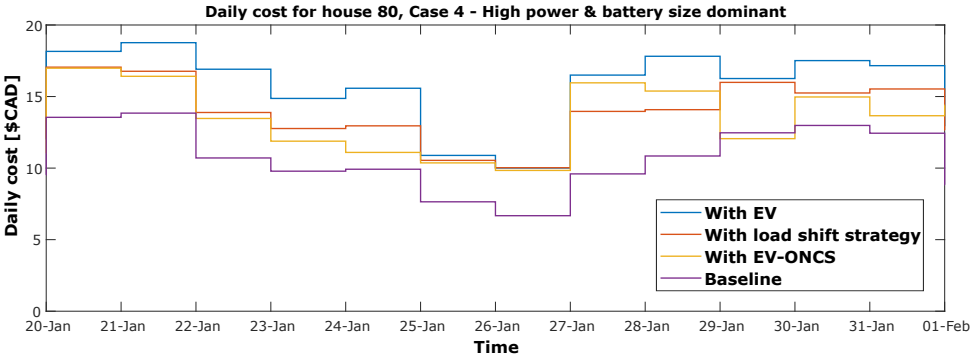


Figure 13. Daily cost of electricity for house #80.

We can conclude from these results that the EV-ONCS offers similar or better performance than a classic load-shift strategy based on the bill's reduction, independently of the size of the battery. Considering the example of case 4, the vehicle of house # 6 uses a battery of 50 kWh, and the one of house # 6 has a battery of 90 kWh. Further, we should highlight that both strategies can be used with the objective of electricity bill reduction when time modulated tariffs exist.

4.3. Impact on CO_2 Emissions Reduction

The main objective of the massive EVs integration in distribution networks is the reduction in CO_2 emissions. In the particular case of the study, almost 100% of electricity in Quebec comes from hydropower. Thus, we can consider that each kWh used by each EV permits to reduce the equivalent of emissions produced by the combustion of the equivalent litres of gasoline used by its counterpart ICE vehicle. From [38], the mean efficiency of ICE and BEV are 13.2 km/L and 5.75 km/kWh, respectively. This means that a mean equivalence factor of 0.4356 L/kWh can be used to estimate the litres of gasoline used by an ICE vehicle with a similar duty cycle. Finally, from the U.S. Energy Information

Agency (https://www.eia.gov/, accessed on 12 August 2021) , the equivalent emissions of CO_2 associated to automotive gasoline is estimated as 2.31 kg/L (or 8.89 kg/gallon). Further and according to the U.S. Environmental Protection Agency (EPA) in a study of 2018 explains that an average gasoline passenger car running 11,500 m (18,507 km) per year can produce the equivalent to 4.6 metric tons of CO_2 yearly [39].

Based on the information mentioned above and the results of this work, the expected mean reduction in CO_2 emissions by household could vary from 11 to 42 kg/day depending on the battery size of the EV. Figure 14 presents the simulated daily reduction for the houses #6 and #80 from 20 January to 1 February 2020. These results can vary depending on the driving cycle, each vehicle's efficiency and the number of vehicles by household.

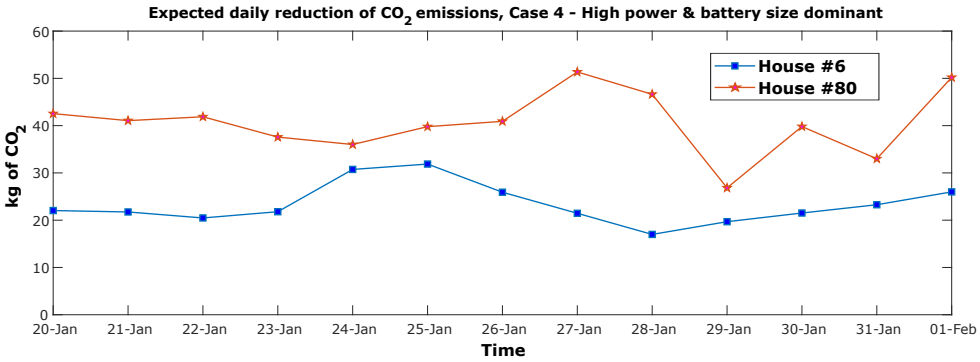


Figure 14. Expected daily reduction in CO_2 emissions for houses #6 and #80.

5. Discussion

It is worth highlighting in quite general terms that the load-shift strategy is less efficient in reducing the peak power demand. This loss of efficiency is more evident when a drop in the outdoor temperature occurs during the night (e.g., 21 January in Figure 9). In such cases, it could be necessary to consider energy storage to enable the integration of EV recharging without significant impact on the distribution network.

Based on local consumption information and the detection of the state of charge of the EV on arrival, the proposed strategy produces promising results for better integration of the EV into distribution networks. This strategy does not require the use of energy storage. It allows good integration of EVs with night charging and contributes to demand-side management, which results in a significant reduction in the peak-to-average ratio. Thus, it helps to improve the load factor and therefore the efficiency of the electrical system. We would like to remark that the deployment of the proposed local EV charging strategy requires chargers with bidirectional and modulated power; however, it can be implemented without complex communication infrastructure and using low-cost processors.

The potential of reduction in emissions can vary depending on the use of the vehicle, the vehicle itself and the primary source. In the case of Quebec, the main energy source is renewable hydropower. In this sense, it is an advantage to promote the massive use of EVs; however, evaluating emissions for other jurisdictions with different types of primary sources requires reevaluating the equivalence factors.

6. Conclusions

This paper provides an analysis of the possible impact of overnight recharging in the perspective of the upcoming massive deployment of EVs in the residential sector. A simulation framework is proposed to enable the analysis of energy management strategies to reduce the peak power demand seen by the distribution network. Considering that the scenarios proposed and implemented in the framework reflect the effects of the low outdoor temperatures of Canada with the combination of space heating and electric vehicles, the proposed solution is realistic and valuable for similar real-life scenarios.

The study reveals that the deployment of electric vehicles offering a low autonomy range could be handled using the existing distribution infrastructure and classic load-shift strategies without energy storage integration; however, it also shows the limitations of load-shift strategies faced to the massive deployment of EVs with high capacity batteries and high recharging power, and in the presence of low temperatures.

The proposed local overnight EV charging strategy (EV-ONCS), based on the estimation of the EV and residential building needs by Gaussian-core kernel models, permits the proper integration of electric vehicles taking into account different sizes of electric vehicles and without negative impact on peak-to-average ratio. This strategy permits, by the way, to improve the load factor without the necessity of additional energy storage systems. Coordinated optimal management strategies, including local or distributed energy storage, can be complementary solutions for implementing ancillary services; however, they entail additional and non-negligible capital and maintenance costs.

Future works include the analysis of integrating energy storage systems, either in the residential, industrial or commercial sector and the analysis of emerging EVs recharging technologies and the impact of their deployment on the power quality.

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