Impact Analyses of Residential Electric Vehicle Charging on Distribution Networks

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***Abstract*—In this work, we present a flow of analysis processes to assess the risks of abnormal conditions on distribution networks with increasing penetration of residential electric vehicles (EVs). The load allocation technique is adopted to obtain reliable profiles for customers' baseload. Randomness in EV charging behaviors is characterized through probability distributions empirically determined from real charging data. A stochastic method based on Monte Carlo simulations and power flow analyses is proposed to analyze network conditions under the impacts of EV charging. Case studies on a real distribution network in the province of Ontario are performed using the proposed analysis framework. Network assets to which overloads likely to occur due to EV charging are identified. We also demonstrate how shifts in customers' charging behaviors under the time-of-use (TOU) pricing can help mitigate such overloads without early replacement of the equipment.**

***Index Terms*—Electric vehicles, distribution networks, stochastic analysis, Monte Carlo simulation.**

I. Introduction

As the adoption of electric vehicles (EVs) accelerates, the power demand increases significantly, which can affect the existing power distribution infrastructure. This surge in demand can lead to issues such as voltage instability, transformer overloads, and increased peak loads [1]. Without proper assessment and planning, these challenges can compromise the reliability of power distribution networks, potentially leading to power outages and increased operational costs. Moreover, understanding these impacts allows for the development of effective mitigation strategies, such as smart charging solutions and infrastructure upgrades, supporting the widespread adoption of EVs while maintaining a stable and resilient power grid.

To model EV loads and to simulate their impacts at different penetration levels, uncertainties such as charging locations of EVs, charging time and duration, charging power, etc., must be considered. In some early studies, deterministic methods are used to study EV impacts by using typical or worst-case scenarios [2], [3]. These deterministic simulation models are easier to implement, but analysis results may not be accurate because the uncertainty associated with EV charging is not fully characterized. In stochastic studies, randomness in variables such as locations of EV chargers and charging profiles should be included. Several Monte Carlo simulation-based studies have been performed due to the simplicity in the implementation. For example, [4] studies the impacts of voltage drops and loading levels of lines caused by EV charging, and changes to network losses, voltage variations and transformer loadings are studied at various penetration levels of EVs in [5]. The power quality is analyzed in [6], where not only locations of EVs and charging patterns are randomized, residential household loads also vary with time. Finally, impacts of multiple technologies including EVs and PVs to the distribution network in terms of abnormal voltages and transformer loading levels are studied in [7]. To obtain accurate results from Monte Carlo simulations, input data characterizing EV randomness need to be unbiased and represent the reality. While real EV charging profiles recorded by charging stations can be used [8], they are not always accessible to utilities. Alternatively, necessary input data can be estimated from EV usage and travel statistics [9], or extracted from historical smart meter data of EV owners [10].

In this paper, we present our methodology on analyzing impacts of EV charging on a distribution feeder of Hydro One, an electricity transmission and distribution utility serving the Canadian province of Ontario. The main contribution is to propose an analysis framework, which includes reliable allocation of customers' baseload, characterization of the randomness associated with EV charging in terms of probability distributions from real data, and an approach to reveal potential abnormal conditions on the network due to increasing EV penetration levels. We also explore how time-of-use (TOU) rates and demand response programs can help to mitigate EV charging impacts within the proposed analysis process.

II. Network model and data

In the study, we mainly focus on the residential EV owners, because they account for up to 80% of charging events with diversified and stochastic charging patterns [11]. A distribution network mainly servicing residential customers is to be selected, and time-series load data of the network are also required. More details are discussed in the following sections.

A. Distribution network

The one-line diagram of the targeted distribution network for the study is presented in Figure 1. The network is modelled in the CYME Power Engineering software (CYME) [12]. Not only does the network contain mainly residential customers, but some of them are also identified as EV owners. In addition, the majority of the distribution infrastructure is underground, making it more costly to replace or to upgrade. It is, therefore,

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Fig. 1: One-line diagram of the selected distribution network

more valuable to reveal potential risks to the network due to EV charging at an early stage to avoid costly repair work. The network has the following characteristics:

- Nominal voltage at the feeder head $V_{\text{nom}} = 27.6$ kVLL
- Operating voltage $V_{\text{op}} = 28.75$ kVLL (1.042 per-unit)
- 208 distribution transformers/loads servicing about 2,500 customers, and
- No photovoltaic systems (PVs) or battery systems are installed on the network, which allows to assess a "worst" baseline scenario.

B. Customer load

In the network model, rather than modelling each individual customer, a single load is used to model each of the 208 distribution transformers which includes all customers serviced by the same transformer. Correspondingly, we aggregate the data measured by customers' meters at each hour so we have hourly consumption of each load. However, to Hydro One's knowledge, these aggregated consumption data are not always accurate due to the errors in transformer-meter connectivity information. To make the load profiles more reliable for the study, we leverage the demands measured in ampere at each time $t \in \mathcal{T}$ at the feeder head, denoted by $I_\phi^t \in \mathbb{R}$, where $\phi \in \{a, b, c\}$. The power factor is not measured, therefore, it is assumed at $pf = 0.95$ lagging. The demands in kVA at the feeder head $S_{\text{total}}^\phi \in \mathbb{C}$ can then be calculated as:

$$S_{\phi,\text{total}}^t = \left(pf + j\sqrt{1 - pf^2}\right) I_\phi^t V_{\text{op}}. \tag{1}$$

We then allocate the computed $S_{\phi,\text{total}}^t$ into all loads on phase ϕ using a top-down approach, where the daily consumption of each load is used as the allocation weight. Because losses and line charging need to be considered, the process is iterative using power flow analyses until the demands in kVA allocated to all loads on each phase sum up to $S_{\phi,\text{total}}^t$ within an acceptable tolerance at each time t. In this way, we obtain

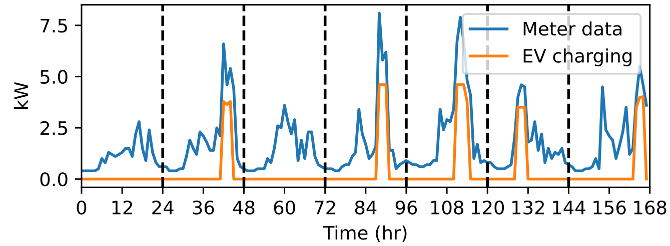

Fig. 2: Customer's meter and EV charging data for one week

time-series load profiles of each load in the network, while the total load matches the measured demand at the feeder head.

C. EV charging data

To characterize the EV charging behavior on the targeted network, we need charging data of existing EVs. As the charging occurs behind-the-meter (BTM), direct access to the data is difficult, but they can be disaggregated from customers' meter data which are available. This has been done internally at Hydro One, and 25 active EV owners are identified on the targeted network. Figure 2 shows an example of the EV charging data disaggregated from the meter data for an EV owner during a week, where 5 charging events are identified. For each of the charging events k, we can extract the information of start time, duration, and energy consumed, which are denoted as $t_{\text{s}}^k, t_{\text{d}}^k$, and e^k, respectively. The uncertainty with EV charging lies in the fact that $t_{\text{s}}^k, t_{\text{d}}^k$, and e^k do not have same values for different charging events, even for the same customer as observed in Figure 2. Hence, they are considered as three random variables of EV charging. From a sufficiently large number of charging events, we are able to determine the probability mass functions (PMFs) of the random variables from their respective empirical distributions based on the law of large numbers.

We collect a total of 1,907 charging events (1,350 on weekdays and 557 on weekends) for these 25 EV owners during 11 months in 2023, and we obtain the following multisets: $\mathcal{E} = \{e^k\}_{k=1}^{1907}$, $\mathcal{T}_{\text{s}} = \{t_{\text{s}}^k\}_{k=1}^{1907}$, and $\mathcal{T}_{\text{d}} = \{t_{\text{d}}^k\}_{k=1}^{1907}$. We have observed that charging patterns of these EV owners during holidays are similar to those on weekends. Therefore, we consider holidays as weekends, even if they occur on weekdays. We then empirically determine the PMFs of daily energy consumption during weekdays vs. weekends, as shown in Figure 3. To maintain the consistency between e and $t_{\text{s}}, t_{\text{d}}$, we compute the joint PMFs of $(t_{\text{s}}, t_{\text{d}})$ and visualize them in Figure 4 for weekdays vs. weekends. The following observations on charging behaviors can be made from the figures:

- PMFs of daily energy consumptions are similar on weekdays vs. on weekends
- On weekdays, many charging events start during the evening (e.g., from 4PM to 9PM), which coincides with the peak period of other household loads (e.g., cooking, heating/cooling), and
- On weekends, more charging events start outside of evening hours than on weekdays.

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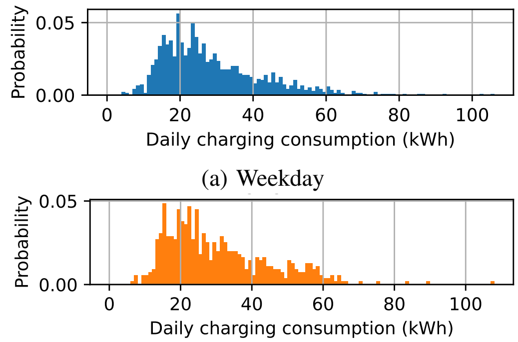
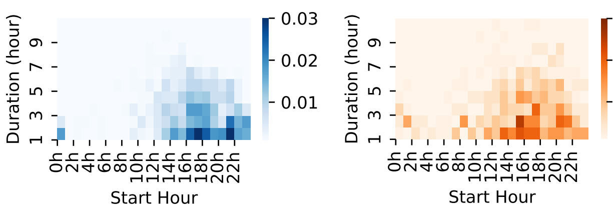


(a) Weekday

(b) Weekend

Fig. 3: PMFs of daily charging consumption during weekdays and weekends



(a) Weekday (b) Weekend

Fig. 4: Joint PMFs of charging profiles during weekdays and weekends

Lastly, we also need the information of charging power levels, which are not deterministic either. Based on the values of t_d^k and e^k, we can calculate the power P^k by $P^k = e^k/t_\mathrm{d}^k$ for each event k. By doing this to all 1,907 events regardless of day type, we obtain a set of power levels, denoted as $\mathcal{P}$. To determine the representative power levels and their percentages, we perform KMeans clustering to $\mathcal{P}$, using numbers of clusters from 2 to 6. It is determined that the Silhouette score is the highest with 3 clusters. Therefore, we have the following distribution of power levels: 6.5 kW (52%), 7.1 kW (32%), and 7.5 kW (16%).

III. Methodology of Analysis

We first define the EV penetration rate p as:

$$p \triangleq \frac{N_\mathrm{EV}^0 + N_\mathrm{EV}}{N_\mathrm{m}}, \tag{2}$$

where N_EV^0 is the existing number of EVs identified on the network (e.g., $N_\mathrm{EV}^0 = 25$ for our selected network), $N_\mathrm{EV} \in \mathbb{N}$ is the number of the new EVs to add, and N_m is the number of customers on the network. To assess the impacts of EV charging to the network at penetration p, we need to add N_EV EV loads to the network and perform power flow analyses. Given that charging patterns of these new EV loads are not deterministic, a stochastic approach is required.

A. Stochastic analysis using Monte Carlo

In this section, we describe the Monte Carlo-based stochastic method that is used in the case studies. We first denote the distribution network as $\mathcal{N}$, and the allocated customer loads obtained in Section II-B as $\mathbf{S} = \{S_L^t\}_{L=1}^{208}$ where $S_L^t \in \mathbb{C}^{|\mathcal{T}|}$ is the time-series complex power demand of load L and $|\mathcal{T}|$ is the cardinality of the time horizon $\mathcal{T}$. We also denote the (joint) distributions obtained in Section II-C as f_e, $f_\mathrm{s,d}$, and f_P for daily charging energy, charging start time and duration, and charging power level, respectively. The set of residential customers who will have EVs is denoted by $\mathcal{C}$, which excludes the 25 existing EV owners. Algorithm 1 is proposed below to construct one Monte Carlo sample and we analyze the EV charging impacts of this sample during a day, i.e., $\mathcal{T}$ for 24 hours. By using Algorithm 1 to construct multiple Monte Carlo samples, we assess the likelihood and severity of abnormal conditions on the network at the given EV penetration rate through statistical analyses of the saved power flow results on the samples, e.g., we check whether the mean load of a device exceeds the device rating, or whether the mean voltage level of a node violates the voltage limits.

Algorithm 1 Construction of a Monte Carlo sample

Collect $\mathbf{S}$, f_e, $f_\mathrm{s,d}$, f_P, and $\mathcal{C}$, and calculate N_EV using (2)
Initialize $n \leftarrow 0$, and assign $\mathbf{S}$ to all loads on $\mathcal{N}$
while $n < N_\mathrm{EV}$ **do**
  Randomly select a customer $c \in \mathcal{C}$
  Randomly select an energy $e \sim f_\mathrm{e}$
  Randomly select a charging power level $P \sim f_\mathrm{P}$
  Randomly select a set of tuples $\{(t_\mathrm{s}, t_\mathrm{d}) \sim f_\mathrm{s,d}\}$
    such that $|e - P\sum_{\{(t_\mathrm{s},t_\mathrm{d})\}} t_\mathrm{d}| \leq \varepsilon_\mathrm{e}$
  Add an EV load to c on $\mathcal{N}$
  Attach charging profiles to it using P and $\{(t_\mathrm{s}, t_\mathrm{d})\}$
  Remove this c from $\mathcal{C}$, and $n \leftarrow n + 1$
end while
Perform a power flow analysis to $\mathcal{N}$ at each time $t \in \mathcal{T}$
Save the deterministic analysis results of this sample
Restore $\mathcal{C}$ and $\mathcal{N}$ by removing all N_EV loads

B. Condition for convergence

While Algorithm 1 is very efficient in constructing a Monte Carlo sample by choosing customers to add EVs and attaching charging profiles at random, it takes efforts to run the time-series power flow analyses on the sample because the power flow at each time step is an iterative process to solve a system of nonlinear equations [13]. Therefore, it is necessary to determine a sufficiently large number of samples such that we can be confident that the simulation results are converging.

Suppose that $y_1, y_2, \cdots, y_n$ are sampled values for the random variable Y, then based on the central limit theorem, the error ϵ between the true mean of Y and the sampled mean follows a normal distribution [14]. Hence, we have $\mathrm{Prob}\left(\sqrt{n}\epsilon/\sigma \leq z\right) \rightarrow \Phi(z)$, where σ is the sampled variance, z follows the normal distribution, and $\Phi(z)$ is its CDF. Assuming a confidence level of 95%, corresponding to $z = 1.96$, we need at least n_c samples for a specified ϵ, where

$$n_c = \left(\frac{1.96}{\epsilon}\sigma\right)^2. \tag{3}$$

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To check the convergence, we calculate n_c using (3) for the following random variables after constructing N_{MC} samples:

1) The time-independent number of EVs added downstream of each distribution transformer, denoted as n_{numEV}, and
2) The average kW of EV load downstream of each distribution transformer at each time step t, denoted as n^t_{kW}.

If the following condition holds, then we claim that we have run enough samples and results are converging to our specified tolerance of errors.

$$N_{\mathrm{MC}} > \max\left\{n_{\mathrm{numEV}}, \max_{t\in\mathcal{T}}\{n^t_{\mathrm{kW}}\}\right\}. \tag{4}$$

C. Managed charging

In case that devices on the network are frequently overloaded due to the high EV charging loads, mitigation plans need to be prepared. One potential solution is to encourage EV owners to participate in the Time-of-Use (TOU) or Ultra-low Overnight (ULO) rate plans in Ontario [15] so they charge their vehicles when the electricity price is low. This not only saves EV owners' costs of charging, but also help reduce EV loads during the peak time. To model such shift in charging behaviors, the following is proposed. We denote $\mathcal{T}^{\mathrm{P}}, \mathcal{T}^{\mathrm{OP}} \subset \mathcal{T}$ as the peak and off-peak period, respectively. While we do not characterize customers' response to the published TOU/ULO rates, we assume that EV owners' participation factor in TOU/ULO is $\rho \in [0, 1]$, and on average they reduce their probability of charging during $\mathcal{T}^{\mathrm{P}}$ by $\Delta \in (0, 1]$ and increase the probability of charging during $\mathcal{T}^{\mathrm{OP}}$ by Δ. Under this setup, $f_{\mathrm{s,d}}$ is modified to $f^{\Delta}_{\mathrm{s,d}}$ using a similar approach as in [16], while f_{e} and f_{P} remain unchanged. Accordingly, the following modifications to Algorithm 1 are necessary:

1) When selecting c to add an EV load, also generate a random number $r \sim \mathcal{U}[0, 1]$, and
2) If $r \leq \rho$, then all charging profile tuples should be randomly selected according to $f^{\Delta}_{\mathrm{s,d}}$; otherwise, use $f_{\mathrm{s,d}}$.

IV. Case Study

Given the limitation of the space, we consider the following setup for the case study.

- It is projected that EVs on the road in Canada will reach 40% by 2035 [17], which we use as the penetration rate p.
- To consider natural load growth, we use a compound annual growth rate (CAGR) of 1% to forecast the demands in 2035, i.e., all customer loads are scaled up by 113%.
- Assuming that the peak demand in 2035 will occur on a weekday, we use the probabilities distributions for the weekday to simulate the EV charging behaviors.

We first run power flow analyses at each hour to the network without any additional EV loads as the baseline case. Given that the operating voltage is at 1.042 per-unit, no under-voltage is observed on the network but three distribution transformers are slightly overloaded. Their overload patterns are shown in Figure 5, with transformers' nominal ratings indicated.

We then follow Algorithm 1 to construct and analyze up to $N_{\mathrm{MC}} = 200$ samples with 40% EV penetration,

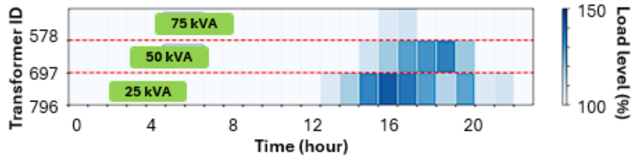


Fig. 5: Overloaded transformers – baseline

and compare with the required number of samples for convergence using $\epsilon = 0.4$. Figure 6 shows the computed n_{numEV} (left) and $\max_{t\in\mathcal{T}}\{n^t_{\mathrm{kW}}\}$ (right) versus N_{MC}, and it is determined that the condition in (4) holds with $\max\left\{n_{\mathrm{numEV}}, \max_{t\in\mathcal{T}}\{n^t_{\mathrm{kW}}\}\right\} = 187$. It is observed that in all samples all nodal voltages are within the range of $[0.95, 1.05]$ per-unit at all times, hence we do not have any over/under-voltage risks on the network. For device loadings, we look at the mean values of hourly loadings from the results of all samples, and the overloaded transformers are shown in Figure 7. We observe that an additional 18 transformers on the network are overloaded at 40% EV penetration, and the overloads mainly occur between late afternoon and early evening. For the three transformers that are initially overloaded in the baseline case, their overload conditions are even worse which could lead to reduced lifetime and premature failure.

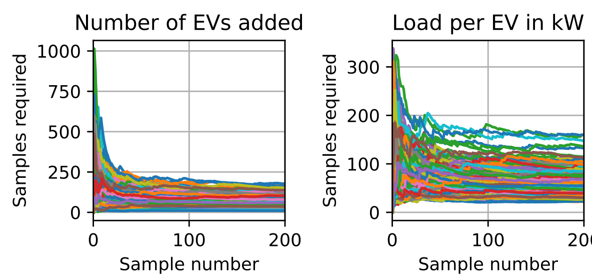


Fig. 6: Number of samples required to reach the desired error vs. the number samples simulated

In an attempt to mitigate the transformer overloads rather than replacing them to higher rating units, EV owners are encouraged to participate in TOU or ULO rate plans, where 4PM – 21PM is considered as the peak period and 11PM–7AM is the off-peak period. We model customers' charging behaviors under the TOU/ULO plans using the process in Section III-C assuming that they reduce the probability of charging during the peak period by $\Delta = 0.75$. We show the resulting shifted probabilities of charging in Figure 8, and the overloaded transformers on the network in Figure 9. We remark that as the probabilities of charging during the off-peak period are higher, the number of overloaded transformers is reduced to 9 with 50% customer participation, and no additional transformer is overloaded at 100% customer participation other than those in the baseline case. Hence, it is feasible to mitigate overloads caused by EV charging by shifting customers' charging behaviors without changes to transformer sizing.

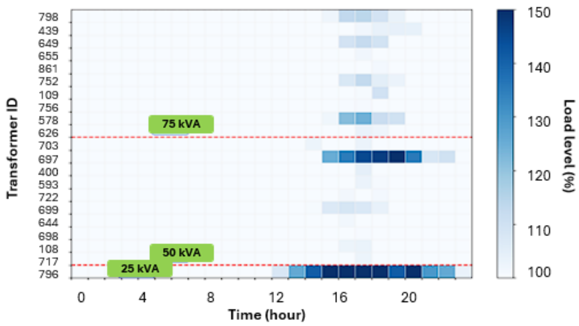
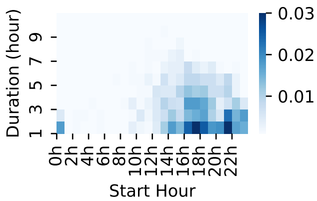
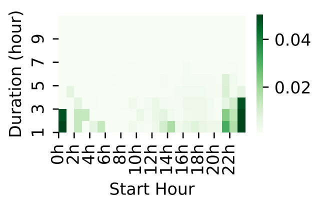


Fig. 7: Overloaded transformers without managed charging

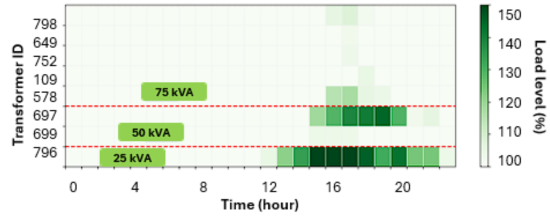


(a) Weekday

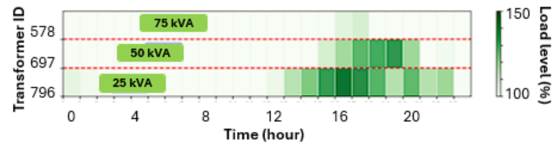


(b) Weekday under TOU/ULO

Fig. 8: Joint probability of charging profiles on weekdays with vs. without managed charging



(a) At $\rho = 50\%$ participation rate



(b) At $\rho = 100\%$ participation rate

Fig. 9: Overloaded transformers under managed charging

V. Conclusion

In this work, we present an analysis methodology to study impacts of EV charging on a real Canadian distribution network, utilizing scaled historical load data and considering uncertainty in EV charging profiles. Distribution transformers having risks of being overloaded are identified, and such overloads can be mitigated by encouraging customers to shift charging behaviors under TOU/ULO rates.

We remark that over 90% of time is spent on running power flow analyses of Monte Carlo samples. In future, we wish to develop parallelization and acceleration techniques to improve the computational efficiency, which enables the simulation of EV impacts on network states over a full year. In addition, other networks and scenarios are to be simulated to check whether abnormal voltage conditions and/or new overloads during off-peak periods under TOU/ULO rates could occur.

To extend the scope of the methodology, other EV control such as centralized/direct and decentralized strategies, can be incorporated. Other analyses than power flow can also be embedded into the process flow, e.g., harmonics and hosting capacity analyses, while uncertainty in EV loads is considered.

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