Les Cahiers du GERAD ISSN: 0711–2440

Mitigating equipment overloads due to electric vehicle charging using customer incentives

F. Li, I. Kocar, A. Lesage-Landry

G–2023–01

January 2023
Revised: February 2023

La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2023
– Bibliothèque et Archives Canada, 2023

Legal deposit – Bibliothèque et Archives nationales du Québec, 2023
– Library and Archives Canada, 2023

GERAD HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal (Québec) Canada H3T 2A7

Tél. : 514 340-6053
Téléc. : 514 340-5665
info@gerad.ca
www.gerad.ca

Mitigating equipment overloads due to electric vehicle charging using customer incentives

Feng Li [a, b, d]

Ilhan Kocar [c]

Antoine Lesage-Landry [a, b]

[a] *GERAD, Montréal (Qc), Canada, H3T 1J4*

[b] *Département de Génie Électrique, Polytechnique Montréal, Montréal (Qc), Canada, H3C 3A7*

[c] *Department of Electrical Engineering, Hong Kong Polytechnic University, Hong Kong SAR, China*

[d] *CYME International T&D, Brossard (Qc), Canada J4Z 0N5*

feng.li@polymtl.ca
ilhan.kocar@polyu.edu.hk
antoine.lesage-landry@polymtl.ca

January 2023
Revised: February 2023
Les Cahiers du GERAD
G–2023–01

Abstract : This paper first presents a time-series impact analysis of charging electric vehicles (EVs) to loading levels of power network equipment considering stochasticity in charging habits of EV owners. A novel incentive-based mitigation strategy is then designed to shift the EV charging from the peak hours when the equipment is overloaded to the off-peak hours and maintain equipment service lifetime. The incentive level and corresponding contributions from customers to alter their EV charging habits are determined by a search algorithm and a constrained optimization problem. The strategy is illustrated on a modified version of the IEEE 8500 feeder with a high EV penetration to mitigate overloads on the substation transformer.

Keywords: Electric vehicles, power distribution networks, stochastic analysis, demand response

Acknowledgements: The authors would like to thank Eaton and CYME International T&D for support on this work.

1 Introduction

As electric vehicles are promoted as part of the electrification plan in the transportation sector, its penetration level in power systems is rapidly increasing. While EVs relax the dependency on fossil fuels and reduce the emission of greenhouse gases, power distribution networks are heavily burdened when EVs are being charged, especially in high penetration scenarios. Abnormal conditions such as overloading of crucial equipment like substation transformers, important voltage variations, phase unbalancing, harmonic distortions, etc. may occur due to EV charging [2, 8].

Stochastic impact analyses of EV charging which account for the uncertainties in locations of charging, starting time and duration, and charging power, may reveal abnormal conditions on the power networks that need to be addressed [6, 9, 11]. Mitigation plans and network optimization must be considered by utilities to maintain safe grid operations and provide good quality of service. While upgrades to the network infrastructure such as expansion of equipment capacity and installation of reactive power support devices can provide immediate relief to abnormal network conditions, they require high levels of capital investments. Alternatively, load shaping techniques have been proposed to reduce impacts of high penetration levels of EV charging to distribution networks. Demand response (DR) programs, whether incentive [14] or price-based [3, 15], are designed to shift EV charging loads to periods when grids are not heavily loaded. For example, in [14] an incentive-based DR program is proposed to minimize impacts of controllable loads to distribution networks. A constrained optimization problem is formulated to allocate a demand limit for each customer during a time period, and customers can select charging hours for their EVs as long as the demand limit is respected at all times. Effectiveness of the DR program is shown at different EV penetration levels; however, the relationship between the incentive and the demand limit is not clear. In [15], load shapes are studied when a DR strategy is implemented to non-critical loads (including EV charging) with time-of-use (TOU) rates. In [3], to reduce EV charging demand at the peak hours, an EV charging schedule is developed in response to the TOU rates to minimize users' charging costs. In both works, TOU rates are assumed to be pre-defined but not optimized considering load demands or other objectives. Finally, coordinated EV charging is another technique aiming for an optimal charging schedule of EVs connected to the network [5, 16].

In our previous work [11], we have proposed a rapid method to perform a stochastic analysis for impacts of EV charging on distribution networks at a specific time. In this paper, we extend this work to a time-series analysis such that we can assess impacts of EV charging to key network equipment, e.g., a substation transformer during a given period of time. We then propose an approach to mitigate the overloading issue identified, if any, by the stochastic impact analysis that could shorten equipment's service lifetime and cause premature failures. To account for the uncertainties in customers' EV charging habits, incentives are based on changes to customers' probabilities of the time when charging starts. Hence, our proposed method aims to reduce the probability of customers connecting and charging their EVs during hours when the equipment is overloaded, and increase the probability of having EV charged outside those hours. The amount of incentives offered to customers as well as the amount of changes to customers' charging probabilities are to be optimized.

The rest of the paper is organized as follows: in Section 2 the model to perform a time-series stochastic impact analysis in terms of EV penetration rate is presented. In Section 3, the mitigation strategy to shift customers' charging habits is proposed and how customers' probabilities of charging are modified accordingly is explained. A search algorithm along with an optimization problem to determine both the incentive level and the amount of changes to customers' charging probabilities is presented. Section 4 illustrates the results of the proposed mitigation strategy to an overloaded substation transformer due to EV charging on a modified IEEE-8500 test feeder, and finally we conclude in Section 5 and point out some future work directions.

2 Model for time-series stochastic EV impact analysis

We adopt the methodology from [11] due to its efficiency to analyse the impact to loading levels of power system equipment under various EV penetration rates. We then extend it to the time-series analysis case.

2.1 Assumption on input data

We assume that the input data for the analysis is gathered from either statistical surveys [4, 13, 17] or estimated from EV usage and travel data [7]. Hence, we have access to:

- Quantity probability $\mathrm{Pr}^i_{\mathrm{num}}$ that characterizes the probabilities of customer $i \in \{1, 2, \cdots, N_m\}$ of owning an EV, where N_m is the total number of customers.
- A set of charging profiles $\mathcal{L}_{\mathrm{EV}} = \{l^j_{\mathrm{EV}}(t), j = 1, 2, \cdots\}$, where $l^j_{\mathrm{EV}}(t)$ is a time-series EV charging profile during the discretized time horizon $\mathcal{T} = \{1, 2, \cdots, T\}$, where T is the length of the considered period.
- Adoption probability $\mathrm{Pr}^i_{\mathcal{L}}(j),\ j = 1, 2, \cdots$ attached to customer i to adopt a charging profile type j in $\mathcal{L}_{\mathrm{EV}}$.

In addition, the network model should also be available such that equipment data and network topology can be extracted to implement the stochastic analysis model.

2.2 Equipment loading levels

Let $x_t(p)$ denote the loading level of an equipment on the power distribution network at time t with an EV penetration rate p. The penetration rate is defined as the ratio of the total number of EVs n_{EV} over the the total number of customers on the network N_m, i.e., $p = n_{\mathrm{EV}}/N_m$. Let $m(x_t, p)$ denote the probability density functions (PDFs) of x_t at p, and the evolution of $m(x_t, p)$ is characterized by the following Fokker-Planck equation (FPE).

$$\frac{\partial m(x_t, p)}{\partial p} + \frac{\partial}{\partial x_t}\Big\{m(x_t, p)u(x_t, p)\Big\} = d\frac{\partial^2 m(x_t, p)}{\partial x_t^2}, \tag{1}$$

subject to $m_0 = m(x_t, p^0)$. Without loss of generality, $p^0 = 0$ hereinafter, i.e., the initial network does not have any EV connected. In (1), the diffusion velocity term d is a small positive constant, and the drift velocity term $u(x_t, p)$ specifies the rate of increase to equipment loading level at given p and t.

For distribution networks, the equipment loading level is computed by-phase. Let $g^{\phi}_{t,e}(p)$ denote the increased amount of loading to equipment e on phase $\phi \in \{A, B, C\}$ at EV penetration p and time t. We can approximate $g^{\phi}_{t,e}(p)$ by the following Equation [11].

$$g^{\phi}_{t,e}(p) \approx \frac{n_{\mathrm{EV}}\,\mathrm{Pr}^{\phi}_e(p)\mathbb{E}[S^{\phi}_e](t)}{S^{\phi}_e}, \tag{2}$$

where $\mathrm{Pr}^{\phi}_e(p)$ is the probability that EVs are connected to sections downstream of e on phase ϕ, $\mathbb{E}[S^{\phi}_e](t) \in \mathbb{R}$ is the expected charging power at t of an EV connected downstream of e and on phase ϕ, and $S^{\phi}_e \in \mathbb{R}$ is the rated power of e on ϕ, which is assumed to be known. The drift velocity $u(x^{\phi}_{t,e}, p)$ at t, therefore, is the derivative of $g^{\phi}_{t,e}(p)$ with respect to p.

Once $u(x^{\phi}_{t,e}, p)$ is computed, (1) is numerically solved by finite-volume method (FVM) using an implicit scheme [10]. The solution is a sequence of PDFs indexed by p at a given t, from which the mean or any percentile value of $x^{\phi}_{t,e}(p)$ can be computed to indicate whether the equipment is overloaded or not at t. To evaluate equipment loading levels at multiple times during the period $\mathcal{T}$, the analysis must be repeated for each $t \in \mathcal{T}$. By such a time-series analysis, if the equipment is frequently overloaded or the overload lasts long, the risk of premature equipment failure is higher which increases the operating and maintenance costs for utilities. Hence, a mitigation strategy becomes necessary to manage equipment loading levels.

3 Mitigation strategy

For a distribution network with high penetration of residential EVs, equipment is most likely overloaded during the peak hours when most EVs are connected and start charging around the same time. In such a case, the expected EV charging power $\mathbb{E}[S_e^\phi](t)$ during the peak hours will be high, and according to (2) the extra loading due to EV charging will be high. Conversely, if a control mechanism is in place to limit $\mathbb{E}[S_e^\phi](t)$ during the peak hours, the overloading on the equipment can be mitigated.

The expected charging power for $t \in \mathcal{T}$ of an EV connected downstream of e on phase ϕ can be expressed by the following equation:

$$\mathbb{E}[S_e^\phi](t) = \frac{1}{|\mathcal{K}_e^\phi|} \sum_{i \in \mathcal{K}_e^\phi} \sum_j l_{\mathrm{EV}}^j(t) \, \mathrm{Pr}_{\mathcal{L}}^i(j), \tag{3}$$

where $\mathcal{K}_e^\phi$ is the set of customers who are downstream of e on phase ϕ, and $|\mathcal{K}_e^\phi|$ is its cardinality. Considering (3), to reduce $\mathbb{E}[S_e^\phi]$ during the peak hours, we can modify $\mathrm{Pr}_{\mathcal{L}}^i(j)$ of each customer such that their probabilities of adopting charging profile types $l_{\mathrm{EV}}^j(t)$ that are activated during the peak hours are reduced by a certain amount. On the other hand, when the probabilities of profiles that are activated during the off-peak hours are increased by the same amount, $\mathbb{E}[S_e^\phi](t)$ is increased during the off-peak hours while the sum of $\mathrm{Pr}_{\mathcal{L}}^i(j)$ is conserved to be 1. In the following section, we discuss how modification is made to $\mathrm{Pr}_{\mathcal{L}}^i$.

3.1 Modification to charging profile probabilities

Let the set of the peak hours be $\mathcal{T}^{\mathrm{pk}} \subseteq \mathcal{T}$ and that of the off-peak hours be $\mathcal{T}^{\text{off-pk}} \subseteq \mathcal{T}$. Then, let $\mathcal{L}_{\mathrm{EV}}^{\mathrm{pk}} = \{l_{\mathrm{EV}}^j(t) |$ EV charging start hour $\in \mathcal{T}^{\mathrm{pk}}\}$ and $\mathcal{L}_{\mathrm{EV}}^{\text{off-pk}} = \{l_{\mathrm{EV}}^j(t) |$ EV charging start hour $\in \mathcal{T}^{\text{off-pk}}\}$. Hence $\mathcal{L}_{\mathrm{EV}}$ is partitioned into $\mathcal{L}_{\mathrm{EV}} = \mathcal{L}_{\mathrm{EV}}^{\mathrm{pk}} \bigcup \mathcal{L}_{\mathrm{EV}}^{\text{off-pk}}$. Let $\boldsymbol{Y} \in \mathbb{R}^L = [y_j, j = 1, 2, \cdots L]^\top$ be an indicator vector where $y_j = 1$ if $j \in \mathcal{L}_{\mathrm{EV}}^{\mathrm{pk}}$ and $y_j = 0$ otherwise. Let $\mathbf{Pr}_{\mathcal{L}} \in \mathbb{R}^{N_m \times L}$ denote the EV charging profile probabilities for all N_m customers. Note that $\mathbf{Pr}_{\mathcal{L}}$ can be of any arbitrary probability distribution. We can extract the probabilities of profiles in $\mathcal{L}_{\mathrm{EV}}^{\mathrm{pk}}$ for all customers by,

$$\mathbf{Pr}_{\mathcal{L}}^{\mathrm{pk}} = \mathbf{Pr}_{\mathcal{L}} \, \mathrm{diag}\{\boldsymbol{Y}\},$$

where $\mathrm{diag}\{\boldsymbol{Y}\} \in \mathbb{R}^{L \times L}$ is a square matrix with $\boldsymbol{Y}$ on the diagonal elements. Let $\Sigma^i = \mathrm{Pr}_{\mathcal{L}}^{i,\mathrm{pk}} \boldsymbol{Y} \in \mathbb{R}$ be the sum of all elements in $\mathrm{Pr}_{\mathcal{L}}^{i,\mathrm{pk}}$, which is customer i's total probability of starting EV charging during the peak hours. Suppose that we would like to adjust Σ^i by an amount $\Delta_{\mathrm{prob}}^i \in \mathbb{R}$, then the resulting probabilities during peak hours become,

$$\widetilde{\mathrm{Pr}}_{\mathcal{L}}^{i,\mathrm{pk}} = \mathrm{Pr}_{\mathcal{L}}^{i,\mathrm{pk}} + \frac{\Delta_{\mathrm{prob}}^i}{\Sigma^i} \mathrm{Pr}_{\mathcal{L}}^{i,\mathrm{pk}} . \tag{4}$$

To reduce the loading during peak hours, we should impose $-\Sigma^i \leq \Delta_{\mathrm{prob}}^i \leq 0$, where the lower bound is necessary to make sure that all elements of $\widetilde{\mathrm{Pr}}_{\mathcal{L}}^{i,\mathrm{pk}}$ are non-negative. Further, the aspect ratios among EV charging profile probabilities are maintained following the adjustment Δ_{prob}^i. We can write (4) in a matrix form for all customers:

$$\widetilde{\mathbf{Pr}}_{\mathcal{L}}^{\mathrm{pk}} = \mathbf{Pr}_{\mathcal{L}}^{\mathrm{pk}} + \boldsymbol{\Sigma}^{-1} \, \mathrm{diag}\{\Delta_{\mathrm{prob}}^i\} \, \mathbf{Pr}_{\mathcal{L}}^{\mathrm{pk}}, \tag{5}$$

where $\boldsymbol{\Sigma} = \mathrm{diag}\{\mathbf{Pr}_{\mathcal{L}}^{\mathrm{pk}} \boldsymbol{Y}\},\ \mathrm{diag}\{\Delta_{\mathrm{prob}}^{i}\} \in \mathbb{R}^{N_m \times N_m}$. Similarly, we can write the adjusted probabilities for off-peak profiles after adding Δ_{prob} to them.

$$\widetilde{\mathbf{Pr}}_{\mathcal{L}}^{\text{off-pk}} = \mathbf{Pr}_{\mathcal{L}}^{\text{off-pk}} + (\mathbb{I}_{N_m} - \boldsymbol{\Sigma})^{-1}\, \mathrm{diag}\{-\Delta_{\mathrm{prob}}^{i}\}\, \mathbf{Pr}_{\mathcal{L}}^{\text{off-pk}}, \tag{6}$$

where $\mathbb{I}_{N_m}$ is the $N_m \times N_m$ identity matrix. Summing (5) and (6), we obtain the modified charging profile probabilities,

$$\widetilde{\mathbf{Pr}}_{\mathcal{L}} = \widetilde{\mathbf{Pr}}_{\mathcal{L}}^{\mathrm{pk}} + \widetilde{\mathbf{Pr}}_{\mathcal{L}}^{\text{off-pk}} \tag{7}$$

In the next section, we formulate an optimization problem to determine the appropriate $\Delta_{\mathrm{prob}}^{i}$ values for all customers.

3.2 Determination of optimal $\Delta_{\mathrm{prob}}^{i}$ adjustment

Values of $\Delta_{\mathrm{prob}}^{i}$ should be determined such that (a) the equipment usable lifetime should not be reduced due to extensive overloading and (b) incentives should be given to customers to change their charging habits according to the adjusted EV charging profile probabilities $\widetilde{\mathbf{Pr}}_{\mathcal{L}}$ without leading to unmotivated costs.

3.2.1 Constraint on $\mathbb{E}[S_e^{\phi}](t)$

As equipment loading levels are computed from the stochastic analysis model with respect to EV penetration, it is difficult to directly impose a constraint on them. Alternatively, constraints can be made on $\mathbb{E}[S_e^{\phi}](t)$ which implicitly limit the extra equipment loadings due to EV charging. Let $\bar{S}^{\mathrm{pk}}$ and $\bar{S}^{\text{off-pk}}$ be given limits of $\mathbb{E}[S_e^{\phi}](t)$ during $\mathcal{T}^{\mathrm{pk}}$ and $\mathcal{T}^{\text{off-pk}}$, respectively. We have,

$$\mathbb{E}[S_e^{\phi}](t) \leq \bar{S}^{\mathrm{pk}}, t \in \mathcal{T}^{\mathrm{pk}} \tag{8}$$

$$\mathbb{E}[S_e^{\phi}](t) \leq \bar{S}^{\text{off-pk}}, t \in \mathcal{T}^{\text{off-pk}}. \tag{9}$$

3.2.2 Incentives received by customer

As customer i contributes to reducing loadings of network equipment during the peak hours by changing their EV charging habits from the associated probabilities $\mathbf{Pr}_{\mathcal{L}}$ to $\widetilde{\mathbf{Pr}}_{\mathcal{L}}$, an incentive R^i should be rewarded. We define the incentive R^i as:

$$R^i = \sum_{t \in \mathcal{T}^{\mathrm{pk}}} r \left(\sum_j l_{\mathrm{EV}}^{j}(t) \left(\mathrm{Pr}_{\mathcal{L}}^{i}(j) - \widetilde{\mathrm{Pr}}_{\mathcal{L}}^{i}(j) \right) \right) \Delta t, \tag{10}$$

where Δt is the time step, and $r \in \mathbb{R}$ (\$/kWh) is the unit reward applicable to all customers which is also to be determined by the optimization problem. Note that $R^i \geq 0$ due to $\Delta_{\mathrm{prob}}^{i} \leq 0$.

3.2.3 Objective function and constraint on incentives

The objective function is the total incentives given to all customers, which is,

$$f_{\mathrm{obj}} = \sum_{i=1}^{N_m} R^i. \tag{11}$$

Utilities cannot offer unlimited amount of incentives which does not make economic sense. For example, if the total incentives exceed the increased costs incurred due to shortened equipment lifetime caused by overloads, then utilities' best option is to keep operating at higher costs without paying any incentives to customers to change their charging habits. Hence, we take the incurred costs due to the shortened equipment lifetime, denoted as $c(F_{\text{life}})$, as a "budget" for the incentives. Here, F_{life} is a factor indicating the expected equipment lifetime which can be computed from the equipment loading levels obtained from the model in Section 2.2. When $F_{\text{life}} > 1$, equipment lifetime is reduced, and $c(F_{\text{life}}) > 0$. Hence, we impose the following constraint to the total incentives:

$$0 \leq f_{\text{obj}} \leq c(F_{\text{life}}). \tag{12}$$

3.2.4 Calculation of $c(F_{\text{life}})$

As overloading often results in higher operating temperature of the equipment, a thermal-aging model is utilized to compute F_{life} from equipment load levels with time. Thermal-aging models for different types of equipment are described in the literature and in IEEE standards. For example, IEEE standard C57.91 describes the thermal-aging model for transformers [1]. The cost $c(F_{\text{life}})$ is then the increased amount to the annual cost (depreciation, operating & maintenance, etc.) due to the shortened lifetime, i.e.,

$$c(F_{\text{life}}) = c_{\text{annual}}(\max\{1, F_{\text{life}}\} - 1), \tag{13}$$

where c_{annual} is the total annual cost at the nominal lifetime.

Note that when $F_{\text{life}} \leq 1$, the equipment is expected to have its nominal lifetime hence $c(F_{\text{life}} \leq 1) = 0$. In such a case, no mitigation strategy is required.

3.2.5 Constrained optimization problem formulation

The optimization problem to determine Δ^i_{prob} and the unit reward r can be written as,

$$\begin{aligned} \min_{\Delta^i_{\text{prob}}, r} \quad & f_{\text{obj}} \\ \text{subject to} \quad & -\Sigma^i \leq \Delta^i_{\text{prob}} \leq 0 \\ & (7), (8), (9), (10), (12) \end{aligned} \tag{14}$$

Solving the optimization problem (14) gives the optimal values of Δ^i_{prob} and r for given limits $\bar{S}^{\text{pk}}$ and $\bar{S}^{\text{off-pk}}$. In the following section, how the values for $\bar{S}^{\text{pk}}$ and $\bar{S}^{\text{off-pk}}$ are determined is discussed.

3.3 Determination of $\bar{S}^{\text{pk}}$ and $\bar{S}^{\text{off-pk}}$

3.3.1 Calculation of $\bar{S}^{\text{off-pk}}$

Equipment loading level at time t can be written as,

$$x^{\phi}_{t,e}(p) = x^{\phi}_{t,e}(p^0) + g^{\phi}_{t,e}(p),$$

where $x^{\phi}_{t,e}(p^0)$ is the *baseline* loading levels without any EV connected on the network and can be obtained from power flow analysis. If we impose that the equipment during the off-peak hours should never be overloaded, we have,

$$\begin{aligned} x^{\phi}_{t,e}(p^0) + g^{\phi}_{t,e}(p) &\leq 1, \\ g^{\phi}_{t,e}(p) &\leq 1 - x^{\phi}_{t,e}(p^0), \quad t \in \mathcal{T}^{\text{off-pk}}. \end{aligned} \tag{15}$$

Substituting (2) into (15) we get,

$$\begin{aligned} \frac{n_{\text{EV}} \Pr^{\phi}_e(p) \mathbb{E}[S^{\phi}_e](t)}{S^{\phi}_e} &\leq 1 - x^{\phi}_{t,e}(p^0), \\ \mathbb{E}[S^{\phi}_{\text{EV}}](t) &\leq \frac{S^{\phi}_e \left(1 - x^{\phi}_{t,e}(p^0)\right)}{n_{\text{EV}} \Pr^{\phi}_e(p)}, \quad t \in \mathcal{T}^{\text{off-pk}}. \end{aligned}$$

By taking the maximum level of $x^{\phi}_{t,e}(p^0)$ over $t \in \mathcal{T}^{\text{off-pk}}$, we can compute $\bar{S}^{\text{off-pk}}$ by,

$$\bar{S}^{\text{off-pk}} = \frac{S^{\phi}_{e}\left(1 - \max_{t\in\mathcal{T}^{\text{off-pk}}} x^{\phi}_{t,e}(p^0)\right)}{n_{\text{EV}}\,\text{Pr}^{\phi}_{e}(p)}. \tag{16}$$

3.3.2 Search for $\bar{S}^{\text{pk}}$

Unlike $\bar{S}^{\text{off-pk}}$, the limit $\bar{S}^{\text{pk}}$ cannot be analytically computed. Rather, an appropriate value should be selected such that two conditions are satisfied: (a) the optimization problem (14) is feasible, and (b) the equipment's lifetime should be as close as possible to its nominal value, i.e., $|F_{\text{life}} - 1|$ is minimized. A basic search algorithm is proposed below to find an appropriate value for $\bar{S}^{\text{pk}}$ at given p.

Algorithm 1 **A search algorithm for $\bar{S}^{\text{pk}}$**

Initialize $n \leftarrow 0$, $\bar{S}^{\text{pk}}_{n} \leftarrow \max_{t\in\mathcal{T}} \mathbb{E}[S^{\phi}_{\text{EV}}]$, $\delta_n \leftarrow \bar{S}^{\text{pk}}_{n}$
Compute $\bar{S}^{\text{off-pk}}$ by (16), $F_{\text{life},n}$, and $c(F_{\text{life},n})$
while $n < N$ or $\delta_n > 0.001$ **do** ▷ N is a large number
  Solve the optimization problem (14)
  $n \leftarrow n + 1$
  if there exists a feasible solution to (14) **then**
    Compute equipment loading under the solution
      from the model in Section 2.2
    Compute the resulting $F_{\text{life},n}$ and $c(F_{\text{life},n})$
    if $F_{\text{life},n} > 1$ **then**
      $\bar{S}^{\text{pk}}_{n} \leftarrow \bar{S}^{\text{pk}}_{n-1} \exp(-1/n)$
    else if $F_{\text{life},n} \leq 1$ **then**
      $\bar{S}^{\text{pk}}_{n} \leftarrow \bar{S}^{\text{pk}}_{n-1} \exp(1/n)$
    end if
  else if there exists no feasible solution to (14) **then**
    $\bar{S}^{\text{pk}}_{n} \leftarrow \bar{S}^{\text{pk}}_{n-1} \exp(1/n)$
  end if
  $\delta_n \leftarrow |\bar{S}^{\text{pk}}_{n} - \bar{S}^{\text{pk}}_{n-1}|$
end while

The main idea of the search algorithm is to try a higher $\bar{S}^{\text{pk}}$ value when (14) is infeasible or when (14) is feasible but $F_{\text{life},n} \leq 1$, and try a lower $\bar{S}^{\text{pk}}$ value when (14) is feasible and $F_{\text{life},n} > 1$. The algorithm is expected to converge when N is sufficiently large and δ_n vanishes due to the exponential factor used in each iteration. The convergence proof is omitted here due to the space limitation.

4 Numerical study

For the numerical simulation to illustrate the proposed mitigation strategy, we use the modified IEEE-8500 test network as in [11] where the substation transformer has a nominal rating of 27.5 MVA. The following information are assumed:

- $\mathcal{L}_{\text{EV}}$**:** Charging may start at each hour and lasts for 4 hours, and 4 levels of EV charging power are considered (1.8kW, 3.6kW, 6.6kW, 7.2kW, with unity power factor).
- $\text{Pr}_{\mathcal{L}}$**:** uniform probabilities are assumed for simplicity, and customers have much higher probabilities of starting charging between noon and midnight.

We look at the impact to the substation transformer loading levels on phase A at 80% EV penetration for $\mathcal{T} = 24$ hours with a time step of $\Delta t = 1$ hour. We take the mean loading levels computed from the time-series stochastic analysis model. As observed in Figure 1, the substation transformer starts to be overloaded from 3PM until 9PM. Assuming that this loading pattern occurs for an entire year, from the thermal-aging model we can calculate the lifetime factor $F_{\text{life}} = 1.09$. Suppose that the annual cost of the transformer at the nominal lifetime is $c_{\text{annual}} = \$500{,}000$, then from (13) utilities are incurred an extra cost of $c(F_{\text{life}}) = \$45{,}000$ per year due to the shortened lifetime, which serves as the budget for customer incentives.

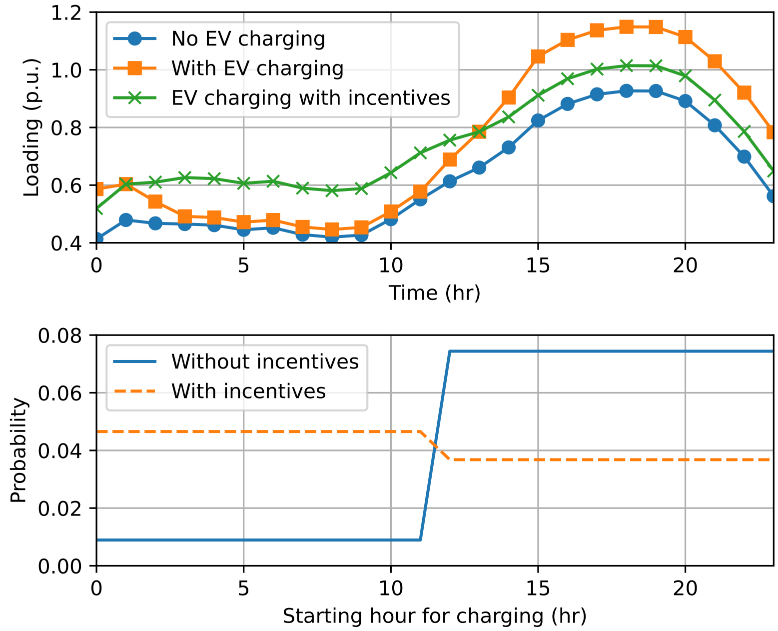

Figure 1: Mitigation of the substation transformer overload by giving incentives to change customers' EV charging habits (probabilities of charging hours)

We rewrite (14) as a convex optimization problem to reduce computational efforts and find a global optimum. We reformulate constraint (10) which is non-convex. To do so, we use the price elasticity [12, 18] to model customers' response to the incentive offered. Hence

$$R^i = -\varepsilon^i r^2, \tag{17}$$

$$-\varepsilon^i r = \sum_{t \in \mathcal{T}^{\text{pk}}} \left(\sum_j l^j_{\text{EV}}(t) \Big(\Pr^i_{\mathcal{L}}(j) - \widetilde{\Pr}^i_{\mathcal{L}}(j) \Big) \right) \Delta t, \tag{18}$$

where $\varepsilon^i < 0$ ($[\text{kWh}]^2/\$$) is the price elasticity which is randomly generated in our numerical example. The constraint (10) in the optimization problem (14) is then replaced by (17) and (18), and `cvxpy` with the `MOSEK` solver is used to find an optimal solution.

Figure 2 shows $\bar{S}^{\text{pk}}$ value for each iteration of Algorithm 1, as well as the corresponding total yearly incentives rewarded to all customers (total cost to utilities) and the unit reward value. It is observed that at convergence, $\bar{S}^{\text{pk}} = 0.55$ kVA, the unit reward $r = 1.7$ ¢/kWh, and the total extra cost to utilities reduces from \$45,000 to around \$30,000 per year (a 33.3% saving). As shown in Figure 1, with the incentive, a customer's probabilities of starting charging during the midnight to noon period have been greatly increased. Collectively, the overload of the substation transformer is mitigated such that its lifetime of service is maintained at the nominal value.

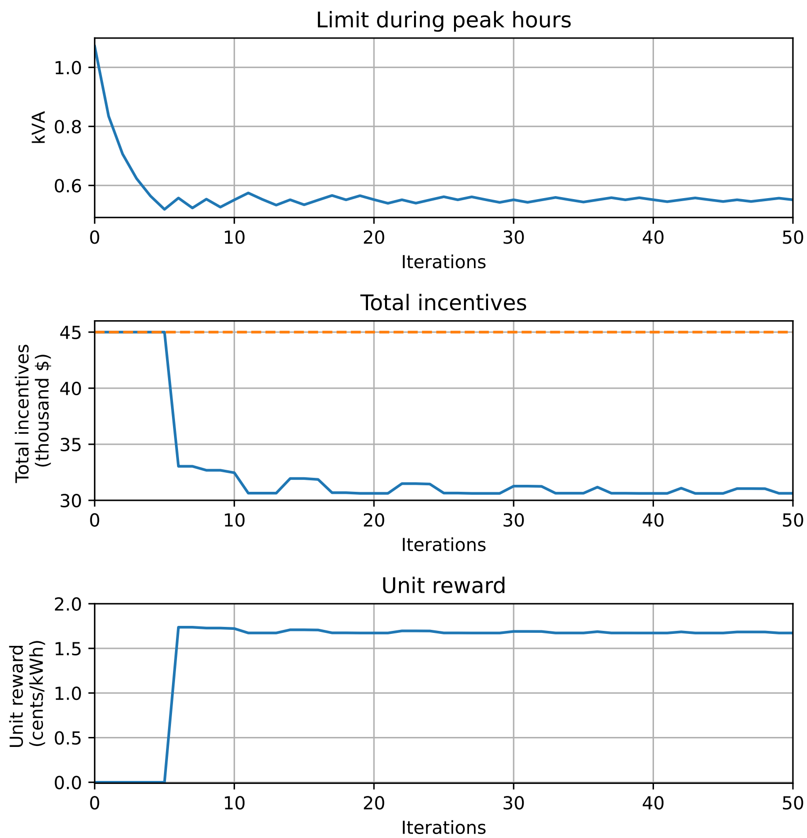

Figure 2: Total incentives f_{obj}, the unit reward r, and the $\bar{S}^{\text{pk}}$ value during the search algorithm iterations

5 Conclusion

In this paper, we propose a model to perform a time-series impact analysis of EV charging on power distribution networks. When such an analysis indicates potential overloading issues to network equipment, a mitigation strategy is designed based on shifting customers' probabilities of charging their EVs from peak hours to off-peak hours. Customers receive incentives from utilities to make these changes to their charging habits. The proper incentive amount and customers' changes required are determined from a search algorithm embedded with a convex constrained optimization problem. Due to the stochastic nature of EV usage and charging needs, customers are not required to follow any specific daily charging schedule; rather, they still have the freedom to charge their EVs during the peak hours when needed as long as the modified probabilities of charging hours are followed.

As a next step, a new search algorithm with a faster rate of convergence can be looked at. Its convergence needs to be proved and the optimality of the converged value will also be studied. As the stochastic analysis model can also indicate abnormal voltage conditions on the network [11], another topic of future work is to extend our approach to including voltage constraints in designing corresponding mitigation strategies.

References

[1] IEEE guide for loading mineral-oil-immersed transformers and step-voltage regulators. IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995), pages 1–123, 2012.

[2] Muhammad Ashfaq, Osama Butt, Jeyraj Selvaraj, and Nasrudin Rahim. Assessment of electric vehicle charging infrastructure and its impact on the electric grid: A review. International Journal of Green Energy, 18(7):657–686, 2021.

[3] Yijia Cao, Shengwei Tang, Canbing Li, Peng Zhang, Yi Tan, Zhikun Zhang, and Junxiong Li. An optimized EV charging model considering TOU price and SOC curve. IEEE Transactions on Smart Grid, 3(1):388–393, 2012.

[4] Sanya Carley, Rachel M Krause, Bradley W Lane, and John D Graham. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transportation Research Part D: Transport and Environment, 18:39–45, 2013.

[5] Kristien Clement-Nyns, Edwin Haesen, and Johan Driesen. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Transactions on Power Systems, 25(1):371–380, 2010.

[6] Salman Habib, Muhammad Mansoor Khan, Farukh Abbas, Muhammad Numan, Yaqoob Ali, Houjun Tang, and Xuhui Yan. A framework for stochastic estimation of electric vehicle charging behavior for risk assessment of distribution networks. Frontiers in Energy, 14(2):298–317, 2020.

[7] Salman Habib, Muhammad Mansoor Khan, Farukh Abbas, Muhammad Numan, Yaqoob Ali, Houjun Tang, and Xuhui Yan. A framework for stochastic estimation of electric vehicle charging behavior for risk assessment of distribution networks. Frontiers in Energy, 14(2):298–317, 2020.

[8] Salman Habib, Muhammad Mansoor Khan, Farukh Abbas, Lei Sang, Muhammad Umair Shahid, and Houjun Tang. A comprehensive study of implemented international standards, technical challenges, impacts and prospects for electric vehicles. IEEE Access, 6:13866–13890, 2018.

[9] Rong-Ceng Leou, Chun-Lien Su, and Chan-Nan Lu. Stochastic analyses of electric vehicle charging impacts on distribution network. IEEE Transactions on Power Systems, 29(3):1055–1063, 2014.

[10] Randall J LeVeque et al. Finite volume methods for hyperbolic problems, volume 31. Cambridge university press, 2002.

[11] Feng Li, Ilhan Kocar, and Antoine Lesage-Landry. Rapid method for impact analysis of grid-edge technologies on power distribution networks. Technical report, Les Cahiers du GERAD G–2022–45, Groupe d'études et de recherche en analyse des décisions, GERAD, HEC Montréal, Canada, October 2022.

[12] Renzhi Lu, Seung Ho Hong, and Xiongfeng Zhang. A dynamic pricing demand response algorithm for smart grid: reinforcement learning approach. Applied Energy, 220:220–230, 2018.

[13] Jukka Saarenpää, Mikko Kolehmainen, and Harri Niska. Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption. Applied Energy, 107:456–464, 2013.

[14] Shengnan Shao, Manisa Pipattanasomporn, and Saifur Rahman. Grid integration of electric vehicles and demand response with customer choice. IEEE Transactions on Smart Grid, 3(1):543–550, 2012.

[15] Shengnan Shao, Tianshu Zhang, Manisa Pipattanasomporn, and Saifur Rahman. Impact of TOU rates on distribution load shapes in a smart grid with PHEV penetration. In IEEE PES T&D 2010, pages 1–6, 2010.

[16] Eric Sortomme, Mohammad M. Hindi, S. D. James MacPherson, and S. S. Venkata. Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. IEEE Transactions on Smart Grid, 2(1):198–205, 2011.

[17] Michael A Tamor, Chris Gearhart, and Ciro Soto. A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. Transportation Research Part C: Emerging Technologies, 26:125–134, 2013.

[18] Prakash R Thimmapuram and Jinho Kim. Consumers' price elasticity of demand modeling with economic effects on electricity markets using an agent-based model. IEEE Transactions on Smart Grid, 4(1):390–397, 2013.