Learning EV Placement Factors with Social Welfare and Economic Variation Modeling

Jingyi Yuan, Qiushi Cui, Zhihao Ma and Yang Weng
School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, Arizona, USA
Email: {jyuan46, qiushi.cui, zhihaoma, yang.weng}@asu.edu.

Abstract—The past few years have witnessed significant growth on the possession rate of electric vehicles (EV). Such growth urgently requires well-designed plans on charging station placement for sustainable EV growth. Existing solutions ignore many practical factors and lack a systematic method prioritizing them. Through constructive learning, we propose an urban EV charging station planning method with the deployment of levelized cost. This method incorporates four practical costs, considering the convexification of the constraints, economic parameter variation, and the interconnected electric and transportation networks. To better quantify the charging demand, the nested logit model is deployed. Meanwhile, we relate the public information of house prices with EV growth when assigning the weights. Furthermore, we also design the software that enables EV charging station placement. Numerical results reveal the trade-off in EV charging station placement, as well as a promising system-level optimization performance.

I. INTRODUCTION

Due to the societal demand on the environment and economical incentives from governments, electric vehicle (EV) ownership will hit 125 million by 2030 according to the International Energy Agency. Therefore, the EV charging station placement has been an active research area for intercity and urban infrastructure planning. In freeway charging infrastructure planning, EV charging station placement problem is tackled in a simple round freeway, whereas [1] proposes a capacitated-flow refueling location model to capture EV charging demands in a more complex meshed transport network. However, the work in both typologies shares the similarity of considering the driving range in the freeway. In contrast, the driving range constraints are not prominent in the urban area charging infrastructure planning since the charging stations are easily accessible. Therefore, researchers have considered various aspects dedicated to the charging station placement in urban area. For example, researchers manage to find the optimal ways to recharge electric buses with long continuous service hours under two scenarios: with and without limited batteries. However, they apply only to public bus systems. Urban traffic circulations and hourly load change of private EVs are considered in some work, but it is deficient in prioritizing a broad range of placement factors and estimating the social welfare behind the charging demand.

If zooming in on the specific techniques deployed and the realistic factors considered, the problem under study can be examined in various technical aspects. For example, researchers and engineers explore many realistic factors such as investment and energy losses, quality of service, service radius, etc. The work in [2] considers the EV integration impact on the grid. When the load profiles change, the electrical demand at particular points can exceed the rated value of the local T&D infrastructure. A study in the U.S. has put the value of deferring network upgrade work at approximately $650/kW for transmission and $1,050/kW for distribution networks. Besides the techniques in the previously mentioned papers, studies focusing on the infrastructure upgrade, therefore, seems necessary under large-scale EV integration. Some papers discuss infrastructure upgrade. For example, some researchers take into account the loading limits of transformers and distribution lines; while some consider minimizing the voltage deviation cost. However, realistic factors like the upgrade of protective devices are not addressed in the past.

The aforementioned urban planning and technical issues are mainly formulated as optimization problems. Considering the nature of the equations involved, these optimization problems contain linear programming as well as nonlinear programming problems. Based on the permissible values of the decision variables, integer programming and real-valued programming usually exist in the same EV charging station problem. Based on the number of objective functions, researchers propose both single-objective and multi-objective problems. Various, the optimization problems are sometimes considered on a game theoretical framework. Solutions to these optimization problems include greedy algorithm, genetic algorithm, interior point method, gradient methods, etc. However, these solutions do not consider the convexification of the constraints. Consequently, they are unable to guarantee a global optimum. In addition to sensitivity analysis, this paper analyzes the benefits of constraints convexification and compares the results with and without convexification.

The contributions of this paper include three points. Firstly, we design a novel way of quantifying charging loads, voltage regulation cost, and protective device cost, which is successfully incorporated in the optimization function. Secondly, the convexification preservation is realized in this optimization problem while the global optimum is also guaranteed. Thirdly, this paper introduces the levelized cost to account for the variation of time and money in urban EV charging station planning. The numerical results reveal that the error accumulation due to convexification is low on system level. Besides, we have investigated five scenarios on economic parameters and identified scenarios that require less charging stations.

The remaining of the paper is organized as follows: Section II explains the formulated problem. Section III discusses how is the social welfare embedded into the charging demand estimation. Section IV provides the details of the problem convexification. The numerical results is presented in Section V. Section VI concludes this paper.
II. PROBLEM FORMULATION

Fig. 1 use a flowchart to illustrate how we model the EV charging station placement. It considers the integrated electrical and transportation networks as well as their associated infrastructure costs. Therefore, the costs related to distribution expansion, voltage regulation, protective device upgrade, and EV station construction are incorporated in the objective function. This study is assumed to be conducted for urban cities with high EV integration in the future. Since a great amount of stations has to be installed in this circumstance, the EV charging station integration point could be at any bus along the distribution feeder as long as the operation constraints permit. The objective function also considers the variation of economic parameters. Factors like the time value and the uncertainty of the cost cannot be ignored sometimes since some costs in the objective function are related to an early stage of the project, and some are postponed to a later stage. Consequently, we propose the levelized cost coefficients. The idea comes from the levelized cost of energy, which is extensively studied in systemically analyzing comparable projects and renewable energy policy. The objective function is defined as:

\[
\text{minimize } C_{sta}^{lev} + C_{dis}^{lev} + C_{vr}^{lev} + C_{prot}^{lev},
\]

\[
(1)
\]

subject to

\[
x_i \in \{0, 1\}, \ i \in \Phi, \quad (2a)
\]

\[
y_i \in \mathbb{Z}^+, \ i \in \Phi, \quad (2b)
\]

\[
\sum_{i \in \Phi} q(y_i) \geq S, \ i \in \Phi, \quad (2c)
\]

\[
f(V_i, \delta_i, P_i, Q_i) = 0, \ i \in \Phi, \quad (2d)
\]

\[
0 \leq |I_j| \leq I_{max,j}, j \in \Psi, \quad (2e)
\]

\[
V_{min,i} \leq |V_i| \leq V_{max,i}, \ i \in \Phi, \quad (2f)
\]

where

\[
C_{sta}^{lev} = \sum_{i \in \Phi} \sum_{t=0}^{T} \left( \frac{1 + \alpha_1}{1 + \beta_1} \right)^t x_i + \sum_{t=0}^{T} \left( \frac{1 + \alpha_2}{1 + \beta_2} \right)^t y_i,
\]

\[
(3)
\]

\[
C_{dis}^{lev} = \sum_{i \in \Phi} \sum_{t=0}^{T} \left( \frac{1 + \alpha_3}{1 + \beta_3} \right)^t I_i (P_{line}^{line} + \Delta P_{line}^{line}) + \sum_{t=0}^{T} \left( \frac{1 + \alpha_4}{1 + \beta_4} \right)^t h(\Delta P_{sub}^{line}),
\]

\[
(4)
\]

\[
C_{vr}^{lev} = \sum_{i \in \Phi} \sum_{t=0}^{T} \left( \frac{1 + \alpha_5}{1 + \beta_5} \right)^t \sum_{i \in \Phi} \Delta V_i^2,
\]

\[
(5)
\]

\[
C_{prot}^{lev} = \sum_{i \in \Phi} \sum_{t=0}^{T} \left( \frac{1 + \alpha_6}{1 + \beta_6} \right)^t (C_{acq} + C_{inst} + C_{uninst} + C_{main}),
\]

\[
(6)
\]

where \( t \) is the year of the project, \( T \) is the total life of the project, \( \alpha_n (n = 1, \cdots 6) \) is the inflation rate, \( \beta_n (n = 1, \cdots 6) \) is the discount rate. The inflation rate denotes the increase in the price index. The discount rate originates from the net present value theory and can be understood as the return earned in alternative investments.

The objective function aims to minimize the total cost in four aspects (also viewed as four constraints), which are visualized in Fig. 2, and are zoomed in from the electrical network in Fig. 1.

The first term is the fixed cost of building a new station and of adding an extra spot in the existing charging station. The second one is related to the distribution line cost and the substation expansion cost. The expanded line capacity can be estimated to be proportional to the number of new charging spots to be installed:

\[
P_{0,i}^{line} + \Delta P_{i}^{line} = P_{0,i}^{line} + p_{ev} y_i, \ i \in \Phi.
\]

(7)

The second term considers the distribution system expansion cost, including substation capacity upgrade, branch capacity
upgrade, branch expansion, etc. An h function is employed to describe the net power increase according to the substation surplus capacity $P_{sur}$. The h function is defined as follows:

$$h(\Delta P_i^{sub}) = \begin{cases} 0, & \Delta P_i^{sub} < P_{sur}, \\ p_{ev} \sum y_i, & \Delta P_i^{sub} \geq P_{sur}. \end{cases} (8)$$

The third term represents the equivalent cost resulting from the impact of EV charging stations on the distribution network voltage profile, where $\Delta V_i = V_i - V_{i,ref}$. Since $Q = V^2 / X = \omega CV^2$, the amount of reactive power compensation is proportional to the bus voltage. Therefore the square of voltage deviation from the reference voltage at each bus is employed to evaluate the voltage regulation related cost.

The fourth term is associated with the protective device upgrade since the original placement of the recloser was function in this paper. We assume there is no relocation during and directional overcurrent relays with synchronized recloser model considers the fuses, reclosers, overcurrent relays, and maintenance costs are constant at each current range. One protection cost decomposition is shown at the top of Fig. 2.

III. NESTED LOGIT MODEL AND CHARGING DEMAND ESTIMATION

To quantify the charging load $D_{i,k}$, we include the nested logit model [4] to predict and quantify the charging demand $D_{i,k}$. We have a particular interest in social welfare such as the influence of the EV owner preference, charging prices, and maintenance costs are constant at each current range. One protection cost decomposition is shown at the top of Fig. 2.

As for the charging demand estimation, let $w = 1, 2, \ldots, N_{EV}$ denote the total electricity that the $w^{th}$ EV owner purchases from the charging station ($N_{EV}$ is the total number of EVs). The total predicted charging demand of bus node $i$ of service provider $k$ is modeled as:

$$D_{i,k} = \sum_{w=1}^{N_{EV}} w \hat{\theta}_{i,k}^w. (14)$$

IV. PROBLEM CONVEXIFICATION

Following the proposed problem formulation, this section discusses the way of convexifying the nonlinear terms in the objective function. By convexifying the optimization constraints, we can achieve (1) the guarantee of a global minimum solution in both small and large electric systems, and (2) a decreased computational time.

A. Convexify the Problem

We adopt the AC power flow linearization method in [6] to convexify constraint (2). This paper does not focus on AC power flow linearization. Besides, other constraints in (2) are linear. Therefore, we place greater emphasis on the constraints from the objective function.

1) Constraint (3): It is a linear combination of the number of stations and the number of spots, indicating it’s convexity.

2) Constraint (4): The first part of this constraint is linear, whereas the second part of this constraint is not as indicated in (8). However, the piece-wise linear function (8) becomes linear when the substation surplus capacity (assuming to be 1 MW in this paper) is exceeded. As long as there are more than 1MW/0.041MW ≈ 23 spots to be built downstream of the entire substation, this constraint is linear.
3) Constraint (5): In this constraint, the optimization variable \( x_i \) is linearly related to the net active power injection \( P_i \) at bus \( i \) in power flow calculation:

In this constraint, the variable \( V_i \) is a nonlinear function of the optimization variable \( x_i \), which is linearly related to the net active power injection \( P_i \) at bus \( i \) in power flow calculation:

\[
P_{i,inj} = P_{i,gen} - P_{i,load} - x_i P_{EV}, \quad i \in \Phi,
\]

but the variable \( V_i \) is a nonlinear function of the optimization variable \( x_i \). Utilizing the AC power flow linearization technique as elaborated in [6], we can easily establish the linear relationship between the optimization variable \( x \) and the bus voltage. It is convex and a global optimum is guaranteed.

4) Constraint (6): Given the assumption of this constraint, the protection cost is a summation of four piece-wise step functions, including the costs of acquisition, installation, uninstallation, and maintenance. We linear the step functions with straight lines according to the realistic device price [3].

B. Sensitivity Analysis

The errors, according to the above analysis, are small and have little influence on the sensitivity of the problem. For example, the constraint (3) is linear by itself. The constraint (4) is also linear when below or above a certain number of charging spots. The constraint (5) has a maximum error of 0.26% if the deployed voltage regulator regulates the bus voltage between 0.95 and 1.05. The constraint (6) does not present a significant cost change among each two adjacent current ranges based on the protection cost data. Therefore the protection cost can be assumed as a constant when the continuous current setting is within a range of operating currents [3].

C. Feasibility Analysis

To evaluate the feasibility of the solution, it is recommended to plug the solution back to the AC power flow and the main optimization problem as a validation. The solution evaluation comes in twofold. Firstly, if the solution is within the feasible region of the main optimization problem, no corrective action is required. Secondly, if the solution is within the infeasible region, we recommend using a weighted constraint violation metric to quantify the error. We formulate all the inequality constraints in (2) in the format of \( b_{i,min} \leq a_i(x) \leq b_{i,max}, \quad i = 1, \ldots, r \), where \( r \) is the number of constraints. Then for a solution \( x^* \) obtained from the convexified problem, the constraint violation metric \( V_c \) is defined as follows:

\[
V_c = \sum_{i=1}^{r} [a_i(x^*) - b_{i,max}]_+ + \sum_{i=1}^{r} [b_{i,min} - a_i(x^*)]_+, \quad (16)
\]

where the operator \([\cdot]_+\) keeps the value inside the bracket unchanged when it is non-negative, and output zero when it is negative. The weight of each constraint is at the utility or DSO’s discretion. To simplify this problem, we assume each term weights 1.

V. COMMERCIALIZED SOFTWARE AND NUMERICAL RESULTS

After the explanation on the convexification and feasibility, this section firstly demonstrates the commercialized software for our industrial partner. Secondly, the benchmark platform is shown. Then, a comparison is made to highlight the benefits of problem convexification. We illustrate the sensitivity in terms of the optimization variables, and in the end, we show the impact of the economic parameter variation.

When assigning the weights in the objective function, we consider the impact of public data such as house prices, census records. Fig. 3 provides the visualization of EV charging data in several residential areas in California. We zoom in around the Bay Area and show bar plots of average house price in selected zip codes. The correlation between yearly load and house value is shown in the top-right corner, meaning the house price is in positive correlation with the charging load. Many other factors also contribute to the total charging energy, e.g., EV possession rate and population.

A. Commercialized Software

To commercialize the proposed method, we design a charging station placement software, as shown in Fig. 4. This software has five main functions: network loading, parameter setting, linearization, optimization, and placement. The purpose of this software is for our partner utility to plan the charging station placement. It is already tested in many benchmark systems from our partner utility.

B. Interconnected Transportation and Electric Network

The planning of the EV charging stations is taken into consideration in an interconnected transportation and electric network. We employ the benchmark Sioux Falls network and the IEEE 123-bus distribution system and visualize their interconnection in Fig. 5. The urban traffic networks have 24 transportation nodes and 76 links. To couple the electrical and distribution networks, we first adjust some node locations of the transportation network while maintaining the same node connectivity, and then merge the two networks by assuming only the centroid transportation nodes are directly overlapping with selected electrical nodes. The remaining electrical nodes that not shown are assumed to be connected to the transportation network through the nearest geographical locations.

C. Cost Parameters

The fixed costs for each EV charging station is assumed to be \( c_{1,i} = 163,000 \) ($)[1]. The land use costs are
charging current is assumed to be 44 kW. According to [9], given the base power of 100 MVA, the charging power for each charging spot is 44 kW, which can be utilized by charging station. The rated 1 MVA capacity which can be utilized by charging station. The rated 1 MVA is assumed to be 120 ($/(kVA·km)) and the substation expansion cost is assumed to be $788/($/kVA) [8].

The charging demand $D_{i,k}$, that each spot satisfies, follows the constraint (2c) and the nested logit model, the coefficients of which are estimated from the preference survey data. We assume the distribution feeder has 1 MVA surplus substation capacity which can be utilized by charging station. The rated charging power for each charging spot is 44 kW [1]. The voltage regulation coefficient $c_3$ is assumed to be 50,000 ($)$ according to [9], given the base power of 100 MVA. Per car, the charging current is assumed to be 44 kW/√3/12.5 kV=2 A.

**D. Benefits of Problem Convexification**

Efforts are exerted on the convexification of the nonlinear constraints, the purpose of which is to guarantee a global optimum without jeopardizing the cost evaluation. Table I illustrates the comparison between the scenario that convexifies all the constraints and the one does not.

<table>
<thead>
<tr>
<th>Constraints</th>
<th>Without convexification</th>
<th>With convexification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of cases that failed to find a global minimum</td>
<td>19.8% (50)</td>
<td>0.0% (0)</td>
</tr>
<tr>
<td>Average total cost in cases with a global minimum ($)</td>
<td>$7.92 \times 10^7$ (8)</td>
<td>$7.96 \times 10^7$ (11)</td>
</tr>
<tr>
<td>Average total cost in cases with a local minimum ($)</td>
<td>$8.47 \times 10^7$ (3)</td>
<td>Unavailable</td>
</tr>
<tr>
<td>Computational time in cases with a global minimum (sec)</td>
<td>112.4 (8)</td>
<td>105.6 (11)</td>
</tr>
<tr>
<td>Computational time in cases with a local minimum (sec)</td>
<td>2,115.7 (3)</td>
<td>Unavailable</td>
</tr>
</tbody>
</table>

Note: the numbers in the brackets denote the numbers of tests under the corresponding constraints.

There are 23 cases tested in this section under different EV flows and station capacity limits in order to obtain the percent of cases that failed to find a global minimum. Since the initial points also affect whether the optimization objective function converges to a global minimum or not, 11 initial feasible points are, therefore, tested for each case to obtain the overall percentage of cases that failed to find a global minimum. As a result, 50 tests in total fail to converge to their corresponding global minimums. As is seen from Table I, $50/(23 \times 11) = 19.8\%$ of cases failed to find a global minimum due to the non-convexity constraints. Not surprisingly, all of the cases with convexified constraints successfully find the global minimum.

The fact of convexifying the constraints does not affect much of the total cost. In Table I, the demonstrated case is with the EV flow of 5,185 EVs/h and 25-spot limit per station. In this case, the solutions of 3 tests reach local minimums, and 8 tests reach global minimums. The total costs without and with convexification are calculated using equation (1) and averaged over their corresponding numbers of tests. Through an extensive investigation, the highest error is accumulated but does not exceed 4.4% as the number of EVs per hour increases. As a result, the influence due to error accumulation on the system-level performance is limited.

**E. Sensitivity Validation of Optimization Variable**

One of the optimization coefficients is analyzed here. Fig. 6 shows the charging station distribution from bus 2 to 123. Given the 122 potential stations, theoretically, the maximum station capacity in the whole system is $122 \times 25 = 3,050$ spots. However, the reality can be that the EV flows per hour have not been saturated to the point that each available station

$^1$The error is defined as the cost difference with and without convexification divided by the cost without convexification.
needs to be fitted with a maximum of 25 spots. A 30% capacity indicates 3,050 × 0.3 = 915 spots. It is a feasible scenario for the medium voltage distribution network as evidenced in [1].

By observing the overall placement results in the 123-bus system, the following conclusions are drawn: (1) the constraint on voltage regulations pushes the EV charging station placement towards the end of the distribution feeder, and (2) the cost derived from the constraint on the protective device is less when the EV charging stations are located near the feeder trunk.

F. Impact of the Economic Parameter Variation

It is also presented here how the optimization variables alter when the economic parameter variation is considered in equation (1). An analysis is applied to the levelized cost coefficients model using the inflation rate of 1%, 2%, and 5%, discount rate of 5%, 7.5%, 10%, and 15%, as well as project time of 1, 5, and 20 years. We have designed five scenarios to show the influence of the economic parameter variation. The time value of the cost coefficients \( c_{n, i, t} \) (\( n = 1, \ldots, 5 \)) is taken into account as the duration of the project changes. The corresponding results are shown in Fig. 7, where four stages are identified in the figure. It is interesting to see the subtle deviation from the base case affected by the economic parameters as the EV flow increases. For example, scenario 2 and 3 consider the time-sensitive costs given the project periods of 20 and 5 years. They share at least five crossover points during each level of the EV flows. Behind these two scenarios are two different objective functions that consider the different time value of money.

VI. CONCLUSIONS

The proposed objective function utilizes the levelized costs of distribution expansion, EV station, voltage regulation as well as protective device costs in EV charging station planning. We cast new light on introducing available public data such as house price and census records into this optimization problem. The convexification and sensitivity analysis show that our approach is not only universally applicable but also has a small approximation error for prioritizing the most urgent constraint in a specific setup. Finally, the proposed method provides recommendations for the DSOs on future EV charging station planning. Since this work is related to EV charging station planning, future work could incorporate an optimal charging strategy on this determined EV infrastructure.

Fig. 6. The station distribution of the entire system when the coefficient \( c_5 \) changes. The x-axis represents the bus number from 2 to 123. The spot limitation of each station in this network is 25. The y-axis demonstrates five groups of sensitivity analysis. Assuming the number of EV flows per hour requires only 30% of the maximum station capacity in the whole system.

Fig. 7. The number of charging stations under five different scenarios when considering the economic parameter variation. The first scenario assumes that the levelized cost is not involved. The second scenario is the base case for the levelized method, where \( \alpha_1 = 5\% \), \( \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 3\% \), \( \beta_2 = 15\% \), \( \beta_3 = \beta_4 = \beta_5 = 5\% \), and \( T = 20 \). Scenario 3 is the same as the second scenario except for \( T = 5 \). Scenario 4 is the same as the second scenario except for \( \alpha_1 = 1\% \). Scenario 5 is the same as the second scenario except for \( \beta_1 = 15\% \).

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