Data-driven Chance Constrained Programming based Electric Vehicle Penetration Analysis

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Abstract

Transportation electrification has been growing rapidly in recent years. The adoption of electric vehicles (EVs) could help to release the dependency on oil and reduce greenhouse gas emission. However, the increasing EV adoption will also impose a high demand on the power grid and may jeopardize the grid network infrastructures. For certain high EV penetration areas, the EV charging demand may lead to transformer overloading at peak hours which makes the maximal EV penetration analysis an urgent problem to solve. This paper proposes a data-driven chance constrained programming based framework for maximal EV penetration analysis. Simulation results are presented for a real-world neighborhood level network. The proposed framework could serve as a guidance for utility companies to schedule infrastructure upgrades.

1. Introduction

With the increasing attention on environment protection and development of battery technology, electric vehicles(EVs) are growing very quickly in the last few years. The global sales of EVs has increased significantly in last four years (Global EV Outlook 2018). The annual EV sales increase in 2018 in Canada was 79% and 81% in the US. Electric vehicles could help to reduce oil dependency and protect the environment compared with traditional internal combustion engine vehicles. Many countries and regions have proposed transportation development plan to promote the development of transportation electrification. It is expected that in China, EVs and PHEVs (plug-in Electric Vehicles) production capacity will reach two million in 2020 (China State Counil). And in Germany, the production capacity of EVs and PHEVs will reach one million in 2020 and five million in 2030 (German Goverment).

The EVs as a whole will cause a high power demand and impose significant impacts on the grid. The early adopters of EVs adopting similar behaviors could cause overloading problems for the neighborhood level network. Then for those networks, infrastructure upgrading will be required. It has been a pressing topic for the utility companies to analyze the maximal allowable EV penetration for certain networks to schedule the infrastructure upgrading. This paper aims to propose a framework to analyze the maximal EV penetration for a given neighborhood level network. The proposed framework could serve as guidance for the utility companies to devise infrastructure upgrading plans.

2. Related Work

The impacts of EV charging on power system has been discussed in several papers. In (Fernandez et al., 2011), the authors stated that 60% of electric vehicle penetration would lead to a 40% of power loss increase for off peak hours. The high EV charging demand may also require infrastructure upgrading for the power system which would impose a high cost. It would be helpful for the utility companies to learn the maximal EV penetration for an existing network. The penetration of electric vehicle has been discussed in several papers. In (Wu et al., 2017; Wi et al., 2013), EV charging scheduling strategies are discussed for buildings and homes. In (Wu et al., 2014), the authors analyzed the maximal EV penetration with considering both the customer satisfaction and charging constraints.

Implementation of chance constrained programming has been discussed in some recent papers. In (Ravichandran et al., 2018), a chance constrained programming based framework is used for energy scheduling in a microgrid. In (Bruninx et al., 2018), the chance constrained programming is used for the day-ahead scheduling of a power plant. In this paper, chance constrained programming has been implemented to learn the maximal EV penetration for a given neighborhood level network, in which we consider

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that some constraints like the total power consumption could be violated with certain probabilities.

Power transformers have inherent overloading capability. As shown in (Shahbazi et al., 2007), the authors mentioned that when operating within the transformer capacity, transformer overloading could provide economic benefit. In this paper, we treat the transformer peak power consumption as a soft constraint and allow it to be higher than the rated power consumption with a certain probability.

3. System Models

3.1. Base Load Consumption

It is assumed that there are two types of power consumptions in a neighborhood level network: base load power consumption and electric vehicle charging power consumption. The base load consumption refers to all types of power consumption except for EV charging consumption. The load profiles (Wu et al., 2014) for one summer day and one winter day of a neighborhood level network are shown in Fig.1. We can see that even with two Tesla model S (charging rate is 6.6kW) charging at the same time, the total peak power consumption will be doubled in this network for the winter day.

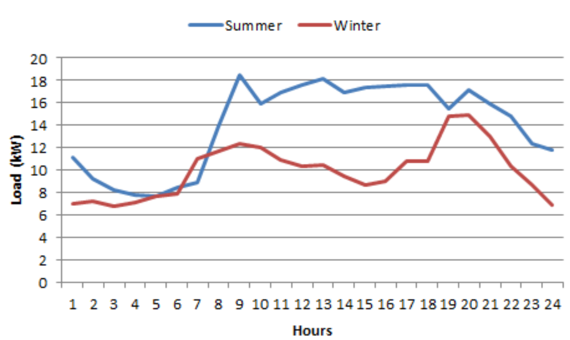

Figure 1. Base load consumption for a neighborhood network

3.2. Electric Vehicles Charging Load

The EV charging power consumption can be treated as a kind of flexible power consumption (Clement-Nyns et al., 2010). The charging demand only needs to be finished before the departure time. We assume that there are N electric vehicles in every house and all the EVs in the neighborhood level network could be charged with continuous charging rate (between zero and maximal charging rate).

3.3. Transformer Overloading

Transformers are designed with inherent overloading capability. The controlled transformer overloading could be used to mitigate the high EV adoption. In this paper, we assume that the neighborhood level transformer overloading is allowed with a low probability. The impact of transformer overloading on maximal EV penetration for a certain neighborhood level network is studied.

3.4. Short-term Load Forecasting

Day-ahead base load consumption forecasting is used for the EV penetration analysis. The hourly base load power consumption and hourly temperature of last three days are used as features to predict the hourly base load power consumption in the next day (24 hours). Support vector regression (SVR) is chosen as the model for short-term base load forecasting.

4. EV Penetration Assessment Framework

4.1. Chance Constrained Programming Framework

The framework to determine the maximal EV penetration for a given neighborhood level network is shown in Fig. 2. For this problem, we have two types of constraints: hard constraints which should be satisfied for every time slot and soft constraints which could be violated with certain probabilities.

There are mainly three steps to study the maximal EV penetration for a given network. The first step is to prepare historical base load power consumption, and regional survey for customers driving habits. Historical base load power consumption data could be used to implement day-ahead base load forecasting. Regional survey data could be used to learn the driving habits inlcuding leaving home time, arriving home time, and daily driving distance for the residents in the neighborhood. The second step is to set up the hard constraints and soft constraints. The third step is to solve the optimization problem until the maximal EV penetration for a given neighborhood level network is found. The objective and constraints are discussed as follows.

4.2. Objective Function

The objective function is the maximal allowed EVs in a certain network: N_{max_ev}.

$$\max\ N_{max\_ev} \tag{1}$$

4.3. Constraints with Transformer Overloading

Charging power limit: the charging consumption for the EV i at time slot j, $pc[i][j]$ should be smaller than the maximal charging power defined by the EV specification $pc^{\max}[i]$.

$$\forall i, \forall j, pc[i][j] \leq pc^{\max}[i] \tag{2}$$

SOC requirement: Equation (3) describes that the battery

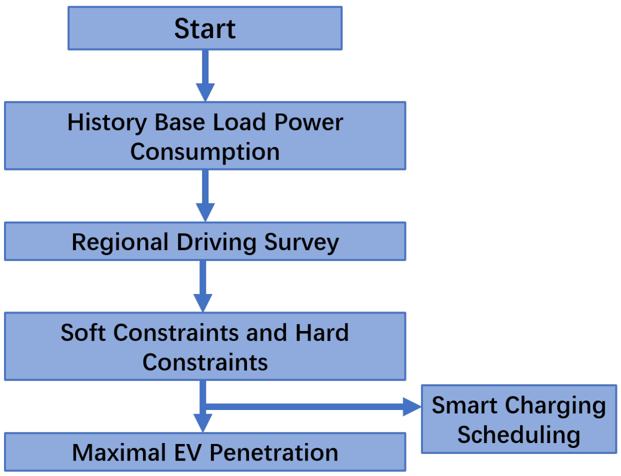

Figure 2. Penetration determining framework

SOC ($bsoc$, battery state of charge) is increased with the amount of charged energy where $E[i]$ is battery capacity and $\eta_e[i]$ is charging efficiency. Equation (4) requires that in the end, all EVs should be charged with a minimum amount of energy $bsoc^{\min}[i]$. Equation (5) constrains that the EV $bsoc$ should be smaller than the upper limit ($bsoc^{\max}$) for all time slots.

$$\forall i, \forall j,\ bsoc[i][j] = bsoc[i][j-1] + \eta_e[i] \cdot pc[i][j] \cdot T \cdot \frac{100}{E[i]} \tag{3}$$

$$\forall i, \forall j \quad bsoc[i][j] \geq bsoc^{\min}[i] \tag{4}$$

$$\forall i, \forall j \quad bsoc[i][j] \leq bsoc^{\max}[i] \tag{5}$$

The timing constraint: EVs can only be charged when they are parked at home ($tc[i][j] = pc^{\max}[i]$).

$$\forall i, \forall j, \quad 0 \leq pc[i][j] \leq tc[i][j] \tag{6}$$

Soft Chance Constraint: When transformer overloading is allowed, we use total power consumption as soft constraint. The total power consumption (sum of total base load: $pbt[j]$ and total EV charging load: $pct[j]$) could be larger than the low-upper bound $P_t^{\max 1}$ with a probability of $1 - P_{pt}$.

$$\forall j, \quad Prob\{pct[j] + pbt[j] \leq P_t^{\max 1}\} \geq P_{pt} \tag{7}$$

Total power consumption hard constraint: the total power consumption should be smaller than the upper bound $P_t^{\max 2}$ for every time slot.

$$\forall j, \quad pct[j] + pbt[j] \leq P_t^{\max 2} \tag{8}$$

5. Experimental Results

The proposed optimization framework is used to evaluate a real-world neighborhood level network in Ottawa in Canada. The survey data discussed in (Xiong et al., 2015) is used to build the arrival, and departure pattern for the EVs. We assume that the required bsoc $bsoc^{\min}$ is 85 and maximal bsoc $bsoc^{\max}$ is set as 95. The soft constraint for the total power consumption is 50 kW ($P^{\max 1}$) and hard total power consumption is 60 kW ($P^{\max 2}$). The violation probability $(1 - P_{pt})$ is 20% or 30%. Honda Fit is used for evaluation, for which the maximal charging rate is 6.6 kW and battery capacity is 20 kWh. The proposed framework could also be treated as a charging scheduling method as well as a method for EV penetration analysis. The maximal EV penetration for four scenarios are analyzed: start EV charging when arrived home (ASAP), zero violation (No overloading), 20% and 30% probability of soft constraint violation.

Table 1. Maximal EV Penetration Analysis

Scenarios	Winter	Summer
ASAP	4	5
No overloading	45	43
20% overloading	48	47
30% overloading	53	50

The optimization problem is modeled in Java and solved by the IBM ILOG CPLEX Optimizer 12.0. All simulations are run on a laptop with an Intel i7 CPU and 16 GB memory. The experimental results are shown in Table.1. We can see that without any control, for the given neighborhood the maximal EV penetration could only be 4 and 5 for the two days. With the proposed control framework, we can have a significant EV penetration increase (close to 10 times increase) which shows the importance of EV charging scheduling. When transformer overloading allowed, we can further increase the maximal EV penetration for a given neighborhood level network. This shows that the proposed framework can successfully demonstrate the maximal EV penetration for different overloading scenarios.

6. Conclusion and Future Work

The fast increase of electric vehicle adoption will bring a high power demand on the power system especially for peak power consumption hours. The infrastructure upgrading for neighborhood level network has been a pressing problem to support the continually increasing power demand. This paper proposed a data-driven chance constrained programming framework to analyze the maximal EV penetration in which the transformer overloading is considered as a soft constraint. Experimental results show that the maximal EV penetration for one neighborhood level network could be significantly increased with soft constraints considered. In the future, we plan to implement more case studies with the proposed framework and consider different kinds of soft constraints.

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