Data-driven Chance Constrain Programming based Electric Vehicle Penetration Analysis

Anonymous Authors[1]

Abstract

Transportation electrification is growing rapidly in recent years. The adoption of electric vehicles (EVs) could help to release the dependency on oil and reduce the greenhouse gas emission. However, the increasing EV adoption will also impose a high demand on the power grid and jeopardize the grid network infrastructures. For certain high EV penetration areas, the EV charging demand may lead to transformer overloading on peak hours which makes the maximal EV penetration analysis be an urgent problem. 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 the infrastructures upgrading plan.

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 is 79% and 81% in US. Electric vehicles could help to reduce oil dependency and protect the environment compared with traditional internal combustion engine vehicles. Many countries and regions proposed transportation development plan to promote the development of transportation electrification. It is expected that in China, EV and PHEV (plug-in Electric Vehicle) 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 would cause a high power demand and impose significant impacts on the grid. The early adopters of EVs would exhibit similar behaviors and 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 company 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 a guidance for the utility companies to decide the infrastructure upgrading plan.

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 for off peak hours and 15% of investment requirement for infrastructure upgrading. The high EV charging demand would require for the infrastructure upgrading for the power system which will 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), the authors propose a strategy for EV charging scheduling in large office building. In (Wu *et al.*, 2014), the authors analyzed the maximal EV penetration with considering the customers satisfactions.

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

Power transformers have inherent overloading capability.

[1]Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

Preliminary work. Under review by the International Conference on Machine Learning (ICML). Do not distribute.

As shown in (Shahbazi *et al.*, 2007), the authors mentioned that when operating within the transformer capacity, transformer overloading could provide economic benefit with transformer overloading. In this paper, we treat the transformer peak power consumption as a soft constraint and allow it 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 includes all types of power consumption except for EV charging consumption. The load profiles 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.

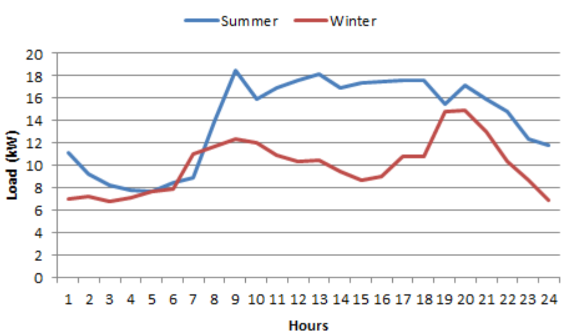

Figure 1. Base load consumption for a neighborhood network

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 EV departure time. We assume that there are N electric vehicles in every house and all the EVs in the neighborhood level network could charged with continuous charging rate (between zero and maximal charging rate).

3.3. Transformer Overloading

Transformer 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 transformers overloading are allowed with a low probability. We study the impacts of transformer overloading on maximal EV penetration for a certain neighborhood level network.

3.4. Short-term Load Forecasting

Day-head 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 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. 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. Reginal 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. Second step is to set up the hard constraints and soft constraints. The third step is 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 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 charing 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 SOC ($bsoc$) 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

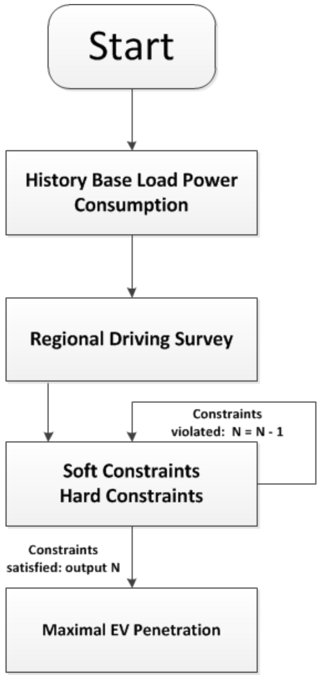

Figure 2. Penetration determining framework

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 ($\mathrm{SOC}_{\max}$) 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 ($tc[i][j] = pc^{\max}[i]$).

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

Total power consumption hard constraint: the total power consumption should be smaller than the upper bound $P_t^{\max 1}$ for every time slot.

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

Soft Chance Constraint: When transformer overloading is allowed, we use total power consumption as soft constraints. The total power consumption (sum of total base load: $pbt[j]$ and total EV charging load: $pct[j]$,) from the power system could go over the low-upper bound $P_t^{\max 2}$ with a probability of $1 - P_{pt}$.

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

5. Experimental Results

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

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. We can see that with the proposed controlled methods, we can have a significant increase (close to 10 times increase) of maximal EV penetration which shows the significance of EV charging scheduling. When transformer overloading 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 control strategies.

6. Conclusion and Future Work

The fast increasing 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 increased 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. In the future, we plan to investigate more networks with proposed framework, consider the impacts of renewable energy generation and different types of EVs.

References

Kenneth Bruninx, Yury Dvorkin, Erik Delarue, William Dhaeseleer, and Daniel S Kirschen. Valuing demand response controllability via chance constrained programming. *IEEE Transactions on Sustainable Energy*, 9(1):178–187, 2018.

China State Counil,. energy-saving and new energy automotive industry development plan. (2012). http://www.cev-pc.or.jp/event/pdf_n/japanese/7-2.pdf.

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

Luis Pieltain Fernandez, Tomás Gómez San Román, Rafael Cossent, Carlos Mateo Domingo, and Pablo Frias. Assessment of the impact of plug-in electric vehicles on distribution networks. *Power Systems, IEEE Transactions on*, 26(1):206–213, 2011.

German Goverment,. Electromobility in germany: Vision 2020 and beyond. report 1 (2013). http://www.worldwatch.org/node/6251.

Global EV Outlook 2018. Global ev outlook 2018 update, clean energy ministerial.(2018). https://www.connaissancedesenergies.org/sites/default/files/pdf-actualites/globalevoutlook2018.pdf.

Adhithya Ravichandran, Shahin Sirouspour, Pawel Malysz, and Ali Emadi. A chance-constraints-based control strategy for microgrids with energy storage and integrated electric vehicles. *IEEE Transactions on Smart Grid*, 9(1):346–359, 2018.

B Shahbazi, M Ashouri, MR Shariati, S Farzalizade, and M Makhdoomi. A new approach for transformer overloading considering economic terms. In *Power Engineering, 2007 Large Engineering Systems Conference on*, pages 54–57. IEEE, 2007.

Di Wu, Haibo Zeng, and Benoit Boulet. Neighborhood level network aware electric vehicle charging management with mixed control strategy. In *Electric Vehicle Conference (IEVC), 2014 IEEE International*, pages 1–7. IEEE, 2014.

Di Wu, Haibo Zeng, Chao Lu, and Benoit Boulet. Two-stage energy management for office buildings with workplace ev charging and renewable energy. *IEEE Transactions on Transportation Electrification*, 3(1):225–237, 2017.

Jian Xiong, Di Wu, Haibo Zeng, Shichao Liu, and Xiaoyu Wang. Impact assessment of electric vehicle charging on hydro ottawa distribution networks at neighborhood levels. In *2015 IEEE 28th Canadian Conference on Electrical and Computer Engineering (CCECE)*, pages 1072–1077. IEEE, 2015.