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How many electric vehicles can one wind turbine charge?

A study on wind energy generation and electric vehicle demand correlation

Zongfei Wang, Patrick Jochem

Institute for Industrial Production (IIP) at Karlsruhe Institute of Technology (KIT)

Hertzstrasse 16, 76187 Karlsruhe Germany

zongfei.wang@partner.kit.edu

Summary

We propose an optimization model which schedules EV charging behaviors to maximally utilize wind energy and to alleviate the generation volatility. We compare the proposed charging strategy with other charging strategies. The performance is demonstrated by coupling the output of one wind turbine with an EV fleet. The simulated results show the necessity of smart charging strategy for wind energy integration and the challenge in alleviating wind generation volatility.

Keywords: battery electric vehicles, smart charging, renewable, optimization

1 Introduction

A growing number of countries have set targets to increase the market share of electric vehicles (EVs) and the integration of renewable energy into power system [1,2]. In this context, EVs are often expected to reduce carbon dioxide (CO_2) emission. However, such expectation depends on not only the electricity generation mix of the area but also the charging strategy of EVs. Considering the promising load shifting potential of EV [3], controlled charging can better utilize the renewable energy generation and lower CO_2 emissions [4].

[5] estimates the cost saving by the management of EV fleet based on a case study of California with high renewable integration. [6] develops a unit commitment and economic dispatch model to operate both conventional and wind generation unit under smart EV charging strategy to minimize operation cost. [7] applies fuzzy control theory and proposes a hierarchical controller to manage EV charging behaviors for wind power smoothing.

In this paper, we focus on tackling the uncertainties from EV during charging management for wind integration. We propose an EV charging scheduling model which aims to utilize more wind energy and to alleviate the volatility of wind generation. We demonstrate the proposed model with a simplified case where an EV fleet is supported by a local wind turbine. When wind generation is insufficient, EV charging demand will be supported by the grid. Compared with an instant charging strategy, we quantify the extra wind generation utilized by EVs. Compared with a myopic charging strategy which only aims to utilize more wind energy, we illustrate the function of wind volatility alleviation.

The remainder of this paper is organized as follows. Section 2 explains two controlled charging strategies and the respective optimization models. In section 3 we provide simulated results of wind energy utilization under different charging strategies. Section 4 concludes the paper.

2 Methodology

Two different controlled charging strategies are defined as follows and they both aim at utilizing wind energy for EV charging:

i. *Following charging strategy:* This charging strategy aims at having the total EV charging demand scheduled at the level of the wind turbine output so that wind energy can be utilized and its output volatility can be alleviated. With this objective, EVs that may arrive in the future should also be considered.
ii. *Myopic charging strategy:* This straightforward strategy only considers currently available EVs to maximize charging demand from wind energy. When possible, this myopic strategy will shift charging behaviour to periods with sufficient wind energy supply so that wind energy is maximally utilized and grid electricity use is limited.

2.1 Following charging strategy

The EV charging scheduling model we apply is based on [8], where the EV charging scheduling problem is formulated as a scenario-based two-stage linear programming model. The structure of the model is as shown in Fig.1. The objective of the model is to have the EV charging demand follow a target curve, which makes the model extensible for different applications. The model considers the uncertainties from future EVs' availability (i.e. arrival time and departure time) and their charging demand upon arrival (initial and final battery state of charge). The model optimizes charging behaviors for the next 24 hours with quarter-hour temporal resolution. Because new EVs will arrive in the future and join the optimization model, rolling window approach is applied and the model runs every quarter hour to update the charging scheduling solutions [9].

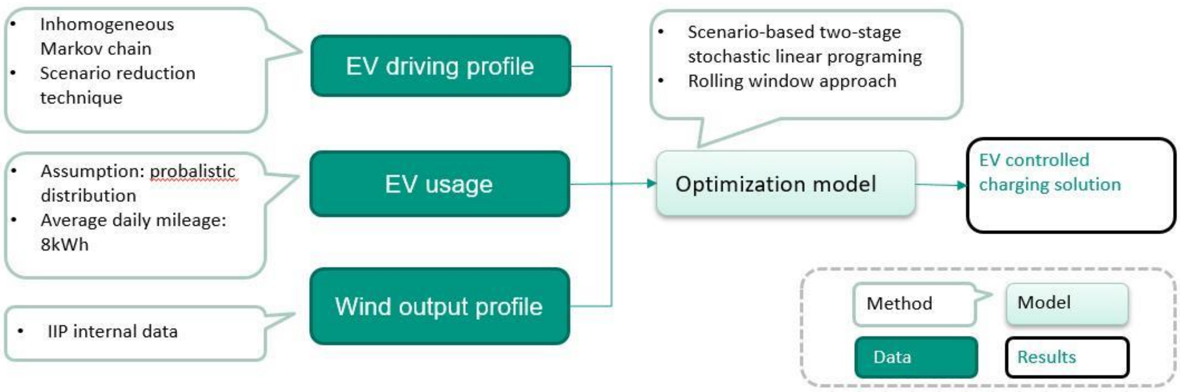

Figure 1: Model structure

In order to study the synergy between the generation of a wind turbine and a large amount of EVs (over 1000 EVs) over a time span of one month, we make some adjustments and simplifications to the original model above to shorten the calculation time.

In this paper, we take one empirically-based wind turbine output profile as the target curve so that the electricity for EV charging is more from wind energy. The objective formulation is as shown in eq. (1).

Minimize: $\sum_{t=i}^{t=W^i}(D_t^{grid}+D_t^{cur}) + \sum_{t=i+1}^{t=W^i}\left|(D_t-G_t^{wind})-(D_{t-1}-G_{t-1}^{wind})\right|$ (1)

Subject to:

$D_t^{grid}-D_t^{cur}=D_t-G_t^{wind} \qquad i\le t\le W^i$ (2)

Indices/Sets:

t	Time periods

Parameters:

i	Starting period of the optimization model
W^i	Ending period of the optimization model
G_t^{wind}	Wind turbine generation in period t [kW]

Variables (non-negative, in italic):

D_t	EV total charging demand in period t [kW]
D_t^{grid}	EV charging demand by the grid in period t [kW]
D_t^{cur}	Curtailed wind generation in period t [kW]

Eq. (2) shows the gap between EV total charging demand D_t and the current wind energy output G_t^{wind}. As objective (1) is a minimization problem and both charging demand by the grid D_t^{grid} and curtailed wind generation D_t^{cur} are non-negative variables, at least one of them is equal to zero. Therefore, the first summation of objective (1) aims at maximizing wind energy utilization and the second summation makes sure that EV charging demand could follow the output profile of the wind turbine. [10] explains the linearization of the second summation.

Furthermore, we simplify the model as a deterministic one and the number of future EV arrival is considered by its expected value instead of scenarios. The maximum charging power of EV is considered constant, regardless of EV's SOC [11]. The rest of the constraints are not adjusted, e.g. constraints for SOC and EV charging power.

The original model outperforms the simplified model when the actual number of EV arrival in the future greatly deviates from the expected value while the simplified model saves much computation time and the key findings are not affected.

2.2 Myopic charging strategy

In order to present the performance of the modified model above, we also propose another myopic optimization model which also aims at maximizing the EV charging demand by wind but in a more direct way. This reference model will only consider the currently available EVs for controlled charging and the follow objective is as shown in eq. (1a).

$$\text{Minimize:} \quad \sum_{t=i}^{t=W^i} c(t) * (D_t^{grid} + D_t^{cur}) \qquad (1a)$$

Parameters:

$c(t)$	Quasi price signal

Parameter $c(t)$ is not a real charging cost but just a time series of positive values which decrease over time. This myopic model only optimizes charging behaviors for the currently available EVs. With objective (1a) and parameter $c(t)$, this myopic will postpone the charging behaviors and limit charging power in early periods when EVs are charged with electricity from the grid and will charge EVs instantly and as much as possible when EVs use electricity from the wind turbine.

Except for the consideration of future EV arrival, all other constraints used for this myopic model are the same as the model discussed in Section 2.1.

Both following and myopic charging strategies are applied in the rolling window fashion. Every time each model only optimizes charging behaviors for the next 24 hours and neither of the two strategies has future information beyond that. Only the solutions for the first quarter hour will be implemented and then charging solution will be updated with latest information.

2.3 Flexible EV charging targets

It is also worth noting that in both models above we do not set fixed charging targets for EVs, as shown in eq. (3).

$$SOC_{m,t} \geq \mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}} \qquad \forall m, \mathrm{t} = \mathrm{dep}_{\mathrm{m}} \wedge \mathrm{t} \leq \mathrm{W}^{\mathrm{i}} \tag{3}$$

Indices/Sets:

m EVs currently available for charging scheduling

Parameters:

$\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ Starting period of the optimization model

$\mathrm{dep}_{\mathrm{m}}$ Guaranteed departure time of EV m

Variables (non-negative, in italic):

SOC_{m,t_t} Battery SOC of EV m in period t [%]

We assume that the departure time of the currently available EVs is known to the model. The scheduled SOC at departure time $SOC_{m,t}$ could be greater than the charging target of each EV $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ and this constraint only applies to EVs that will depart within the next 24 hours (the optimization horizon).

Based on the SOC upon arrival and available time to charging scheduling, $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ is individually set by each charging service and will not exceed 90%. According to [10], EV charging power decreases when SOC reaches a certain level. As a result, if $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ is strictly set to 100%, EVs will take much longer to charge EVs.

Considering the focus of this paper, when the total charging demand D_t is below the wind turbine output, SOC at departure time will try to reach 100% to maximally utilized wind energy. When wind output is insufficient, SOC at departure time $SOC_{m,\mathrm{dep_m}}$ will just reach $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ (less than 100%) to limit the use of electricity from the grid.

3 Results and discussions

3.1 Data

With inhomogenous Markov Chains [12, 13] and test field EV usage data from [14], we get the transition matrix for EV usage behaviors and we assume that the transition matrix of each EV for weekdays is the same and so is the matrix for weekends. Then we generate usage data for 1008 simulated EVs for one month and assume that EVs are available for controlled charging service when the parking time is longer than three hours. The battery capacity of each EV is assumed to be 17.6 kWh with a maximum charging power of 5 kW. The initial SOC upon arrival is assumed to be uniformly distributed between 30% and 80%. The charging target is individually assigned considering the initial SOC and parking time of each charging service and will not exceed 90%. The wind output profile [15] is a simulation result for a 3 MW wind turbine with quarter-hour resolution based on wind speed data in 2015.

3.2 Integration of wind generation

With simulated usage data of 1008 EVs, we first test how much wind energy can be utilized under instant charging strategy which serves as a reference scenario for the two controlled charging strategies discussed in section 2, i.e. following charging strategy and myopic charging strategy. For instant charging strategy, we assume that EVs will start charging upon arrival with maximum charging power until they reach 100% SOC or they start their next trips.

We select the simulated wind output profile in four representative months of 2015 (January, April, July and October) and apply the two controlled charging strategies for a time span of each month. Summarized results of the four months are listed in Table 1 and time series EV charging demand under the three charging strategies are presented in Fig.2. Please note that only results of the first 15 days of April are presented in this paper due to page limit. With rolling window approach, Fig.2 is an accumulation of the first period solutions of 1440 iterations (96 iterations for one day).

Table1: Total charging demand under three charging strategies

	Following	Myopic	Instant
Total charging demand (MWh)	1329.33	1335.68	1424.59
Charging demand by wind (MWh)	1130.14	1132.57	907.26
Charging demand by wind ratio	85.02%	84.79%	63.69%
Unutilized wind ratio	55.00%	54.91%	63.87%
100% wind charging periods ratio	62.65%	73.87%	57.50%

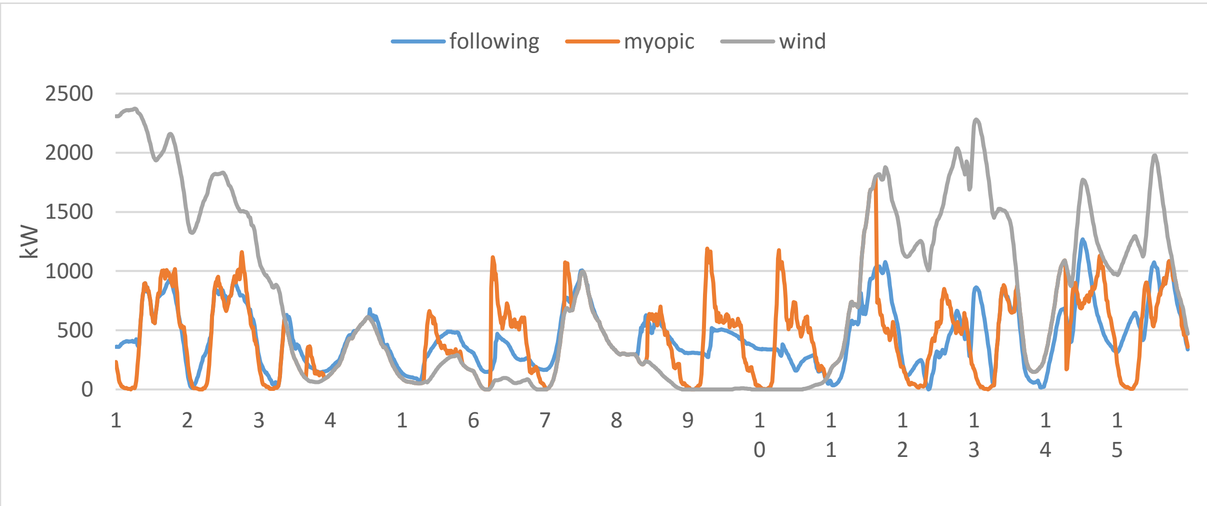

Figure2: Time series charging demand under three charging strategies (15 days)

In the four representative months of 2015, the average output of the 3 MW simulated wind turbine is about 0.85 MW and the total output is about 2511.67 MWh. In Table 1, the total charging demand under following and myopic charging strategies is lower than that under instant strategy because the two controlled charging strategies have no incentive to charge to full SOC during periods with insufficient wind energy supply. Despite less total charging demand, two controlled charging strategies make use of more wind energy for EV charging to satisfy charging targets and limit to the use of grid electricity.

Although their capabilities of utilizing wind energy are similar, the two controlled charging strategies schedule charging behaviors in different ways. In day 9 and 10 of Fig. 2, the myopic strategy postpones charging behaviors as late as possible when wind energy supply is insufficient and only charges EVs to satisfy their charging targets. As a result, a peak charging demand happens before a larger amount of EVs depart during similar periods (morning hours to workplace). When there is enough wind energy output and no postponed charging behaviors, the myopic strategy will behave like instant charging strategy, e.g. in day 1 and 2 of Fig. 2. In contrast, the following strategy tries to follow the shape of the wind energy output (e.g. in day 12 and 13) and tries to evenly schedule charging tasks when wind energy output is low (e.g. in day 9 and 10).

3.3 Alleviation of wind generation volatility

According to Table 1, the total wind energy supply is about 88% more than the total EV charging demand. However, even under the two controlled strategies where wind energy utilization is maximized, more than half of the total wind energy are unutilized.

The unutilized wind generation under two controlled charging strategies of Fig.2 is shown in Fig.3 and negative value means the amount of electricity charged by the grid. As discussed in Section 2.1, the following charging strategy considers information of EVs that will arrive in the future. In order to show the error of such estimation, Fig. 3 additionally shows a perfect foresight scenario where charging behaviors with one month are optimally scheduled to follow the wind output profile with full EV information in the optimization period. This perfect foresight serves as the upper bound of the following charging strategy.

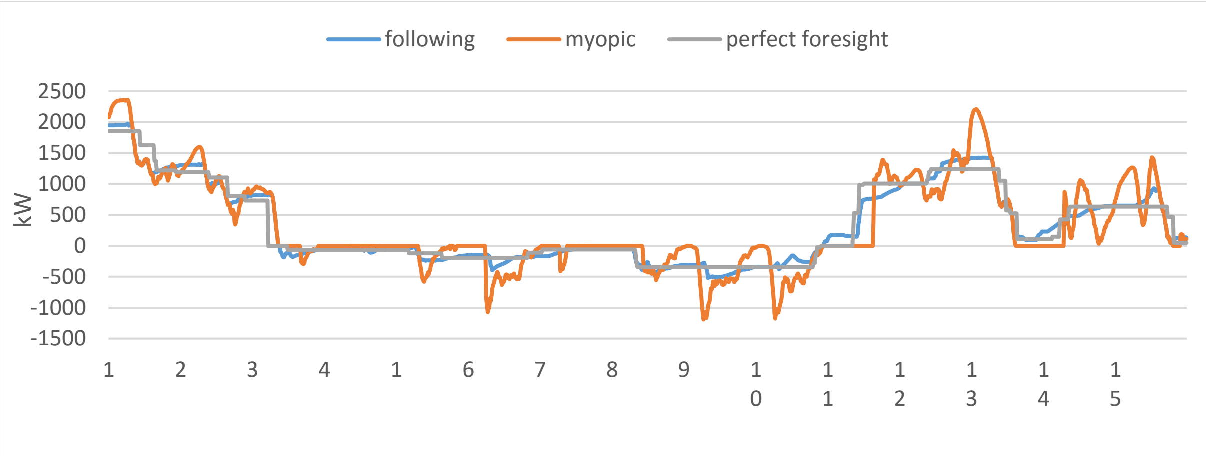

Figure 3: Alleviation of wind generation volatility under two controlled charging strategies (15 days)

As the myopic charging strategy has no further constraints for allocating EV charging demand, postponed charging with grid supply can result in charging demand spike (e.g. in day 9 and day 10 of Fig. 3) and the volatility of unutilized wind energy may not be alleviated (e.g. in day 12 and day 13 of Fig. 3). Since total EV charging demand tries to follow the wind output profile under following charging strategy, such volatility can be alleviated and the unutilized wind generation could be better integrated into the grid.

The performance gap between the following strategy and the perfect foresight scenario result from the modelling and the estimation and for future EVs' information, i.e. their arrival and departure time and initial and target SOC. If uncertainties from future EVs could be better modelled beyond the current following charging strategy model, the perfect foresight model would be the upper bound one could reach.

4 Conclusions

This paper aims at promoting the utilization of wind energy for controlled EV charging. We propose a linear programming optimization model to maximize the utilization of wind generation by the charging demand of local EVs. We test how much generation of a 3 MW wind turbine can be utilized by charging 1008 EVs. Compared with the instant charging strategy, we show that the propose model could increase the amount of charging demand by wind significantly. The proposed model can also alleviate the volatility of unutilized wind energy for better integration into the grid, which is demonstrated by comparison with a charging strategy which only considers maximizing the wind energy utilization. With a perfect foresight scenario, we show the upper bound of such alleviation. Further alleviation is limited by the number of EVs and their parking time. The option of vehicle-to-grid [16] might bring more possibilities to the field of renewable integration and emission reduction and would be the focus of our future work.

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Authors

Zongfei Wang is a PhD candidate in the Institute for Industrial Production of Karlsruhe Institute of Technology. He received M.Sc.Eng degree in electrical engineering from Arizona State of University in 2014, and Bachelor of Eng. degree in electrical engineering from Harbin Institute of Technology in 2012. His research interests include smart charging of electric vehicles and renewable energy integration.

Patrick Jochem is a research group leader at the KIT-IIP, -DFIU, -KSRI, and chair of energy economics. In 2009, he received his PhD in transport economics form KIT. He studied economics at the universities of Bayreuth, Mannheim and Heidelberg in Germany. His research interests are in the fields of electric mobility and ecological economics.