Optimal Charging Management of Electric Vehicle Fleets under Uncertainty

Zongfei Wang, Patrick Jochem, Wolf Fichtner*

Karlsruhe Institute of Technology
Institute for Industrial Production, Chair of Energy Economics
Hertzstrasse 16, Building 06.33, 76187, Karlsruhe, Germany
Phone: +49 721 608-44571, Fax: +49 721 608-44682, Email: zongfei.wang@partner.kit.edu

Abstract

Electric vehicles (EV) show huge potentials in terms of reducing greenhouse gas emissions. However, the integration of EV into power systems may also bring challenges, such as demand increase during peak hours. Therefore, charging behaviors of EV should be scheduled appropriately.

This paper proposes an optimization model to address the charging management problem of EV. The EV charging management problem is formulated as a stochastic linear programming model. The objective of the model is to minimize the distance between the EV total charging demand and a pre-defined reference demand curve within a one-day period. With this objective, the true task of the model depends on the setting of the reference demand, which makes the model easily applicable for different purposes. These reference demands might focus on integrating local renewables, arbitrage trading on different electricity markets or load management from the local grid perspective. As future arrivals of EV are uncertain but contribute to the total charging demand in future periods, the model considers these uncertainties by a stochastic term in their arrival time, departure time and electricity demand (i.e. state of charge). Hence, EV usage patterns are simulated with inhomogeneous Markov chains and scenario reduction technique is applied to reduce the number of scenarios considered and to guarantee feasible computing times. The simulation results demonstrate that the controlled charging strategy outperforms the uncontrolled charging in terms of demand decrease during peak hours and that the proposed model manages to distribute the EV charging demand throughout the day.

Keywords

Electric vehicles, Charging scheduling, Stochastic programming, Demand side management, Uncertainty

1. Introduction

Electric vehicles (EV) show huge potentials in terms of reducing greenhouse gas emissions and improving energy efficiency (Teixeira et al., 2018). Many countries take EV as a promising option for the transition of the energy system (Bauer et al., 2018; Bubeck et al., 2016; Du et al., 2017). In Germany, one of the energy transition targets is to have 40% less greenhouse gas emissions by 2020 compared to 1990 (BMWi, 2017). As a result of policy support, registrations of EV have been notably increased in recent years in many countries (IEA, 2017). The adoption of EV can help to achieve this target.

Large integration of EV may bring both challenges and benefits to the power systems (Jochem, 2016). When customers are of their own will to charge EV, this is often referred to as uncontrolled charging, uncoordinated charging or instant charging. Green et al. (2010) analyze the impact of EV on distribution networks. For uncontrolled charging, Schill et al. (2015) find that charging load will further increase the peak load, which may be a problem for grid capacity and power plant operation. Babrowski et al. (2014) and Kaschub et al. (2013) point out the potential and necessity of controlling the charging processes of EV.

Recent literature has also discussed about controlling EV charging behavior in diverse ways and for different purposes. Sarker et al. (2016) develop an optimization model for an EV aggregator to participate in day-ahead energy and reserve markets and considers the probability of acceptance and deployment. Sundström et al. (2012) optimize the charging behaviors for multiple EV while considering distribution grid constraints. The availability of EV is both assumed to be known in advance in Sarker et al. (2016) and Sundström et al. (2012). Jian et al. (2015) consider the stochastic EV connection with an event-triggered charging scheduling scheme. He et al. (2012) apply rolling window approach for real-time charging scheduling problem of multiple EV and compares the difference between a global EV charging scheduling optimization problem and a local one. The local optimum does not take future EV arrivals into consideration.

Upcoming EV have an influence on the total charging demand in future periods. However, in the real world future arrivals are hard to predict. Therefore, this paper contributes to the current literature in considering the uncertainties from future EV arrival with a scenario-based stochastic linear programming model. This proposed model optimizes charging scheduling problem for multiple EV in real-time and considers the uncertainty of EV information in the future, i.e., their arrival time, departure time and electricity demand (i.e. state of charge). Scenarios for EV usage patterns are simulated by inhomogeneous Markov chains. Scenario reduction technique is further applied to reduce the number of scenarios considered and to guarantee suitable computing times.

The rest of the paper is organized as follows. Section 2 presents the proposed model for optimal EV charging management. Section 3 explains the setting of parameters and scenarios. Section 4 demonstrates the proposed charging strategy with simulation results. Section 5 concludes the paper.

2. Model formulation

2.1 Centralized charging scheduling

The model proposed in this paper schedules the EV charging behaviors in a centralized way, which means that an entity or an aggregator schedules the charging for a group of EV. This aggregator might be the electricity utility itself or a third party that can benefit by providing such kind of demand side management service (cf. Ensslen et al., 2018). The aggregator collects EV information, optimizes EV charging strategy and communicate with EV to manage corresponding charging solutions. A centralized model can include EV connected to one location, e.g. one charging infrastructure or one charging station.

2.2 Implementation assumptions

The EV considered fall into two categories: EV that are currently connected to the grid and EV that will arrive in the future. As discussed, the uncertainties of the model stem from the *future* EV. The following assumptions are made for the formulation of the model:

1) Upon arrival, EV are connected to the grid and will inform the aggregator about their departure time.
2) The departure time is guaranteed by EV users and the actual departure time cannot be earlier than the guaranteed departure time.
3) Upon arrival, EV also inform the aggregator about their desired battery state of charge (SOC).
4) This desired SOC is guaranteed by the aggregator.

Although EV users will have less convenience by guaranteeing their departure time, the assumptions above can be reasonable when profitable charging tariff is offered (cf. Ensslen et al. 2018).

2.3 Objective function

The objective function (1) aims to have the total EV charging demand operated at a certain level (cf. eq. 1).

$$Minimize\text{: } \sum_{t=i}^{t=W^i} \pi_\omega * \left|D_{t,\omega} - D_t^{pref}\right| + \sum_{t=i+1}^{t=W^i} \pi_\omega * \left|(D_{t,\omega} - D_t^{pref}) - (D_{t-1,\omega} - D_{t-1}^{pref})\right| \quad (1)$$

Indices/Sets:

$m(EV^i)$	EV that are available for charging at period i
t	Time periods
ω	Scenarios for EV arrival patterns

Parameters:

i	Starting period of the optimization model
W^i	Ending period of the optimization model
π_ω	Probability of scenario ω
D_t^{pref}	Preferred total EV charging demand in period t [kW]

Variables:

$D_{t,\omega}$	EV total charging demand assumed in period t in scenario ω [kW]

In eq. 1, the first term is the distance between the total charging demand $D_{t,c}$ and the preferred charging demand D_t^{pref}. The second term is the difference of that distance in two consecutive periods. With these two terms in eq. 1, the model minimizes the total distance between the total charging demand and the preferred charging and also tries to avoid changes over time. Please note that all variables in this paper are non-negative variables.

2.4 Constraints for total EV charging demand

The constraint in eq. 2 limits the total EV charging demand.

$$D_{t,\omega} = \sum_{m\in EV^i} P_{m,t} + \sum_{s\geq i+1} P'_{s,t,\omega} \qquad i \leq t \leq W^i, \forall\omega \qquad (2)$$

Indices/Sets:

s	Time periods (arrival periods for future EV)

Variables:

$P_{m,t}$	Charging demand of currently-connected EV m in period t [kW]
$P'_{s,t,\omega}$	Charging demand in period t of future EV from period s in scenario ω [kW]

As categorized in Section 2.2, the *currently-connected EV* refer to EV that are currently connected to the grid and are being scheduled by the model. Obviously, all information about these EV are deterministically considered by the model. The *future EV* refer to EV that the model assumes to arrive in a future period within the optimization horizon. The information about future EV are all considered by scenarios.

For the starting period i, the total charging demand $D_{t,\omega}$ is only from *currently-connected EV* $P_{m,t}$. For future periods, $D_{t,\omega}$ also considers the demand $P'_{s,t,\omega}$ by *future EV*. Although *currently-connected EV* are considered individually, *future EV* are considered in an *aggregated* way. Index s marks all EV that arrive in this future period s. Index t is for a charging period of this aggregated EV.

2.5 Constraints for currently-connected EV

Eq. 3-7 constrain the charging processes of *currently-connected EV*.

$$SOC_{m,t} * Cap = SOC_{m,t-1} * Cap + P_{m,t} * e * \Delta t \qquad m \in EV^i, i+1 \le t \le W^i \tag{3}$$

$$SOC_{m,t} * Cap = SOC_m^{ini} * Cap + P_{m,t} * e * \Delta t \qquad m \in EV^i, t = i \tag{4}$$

$$SOC_{m,t} \le SOC^{max} \qquad m \in EV^i, i+1 \le t \le W^i \tag{5}$$

$$SOC_{m,t} \ge SOC_m^{target} * (1 - AA_m) \qquad m \in EV^i, t = W^i \tag{6}$$

$$P_{m,t} \le P^{max} * A_{m,t} \qquad m \in EV^i, i+1 \le t \le W^i \tag{7}$$

Parameters:

Cap	Battery capacity of an EV [kWh]
e	EV charging efficiency [%]
Δt	Length of a time interval [hour]
SOC_m^{ini}	Initial SOC of EV m before charging [%]
SOC^{max}	Maximum SOC of EV [%]
SOC_m^{target}	SOC target of EV m when charging ends [%]
P^{max}	Maximum EV charging power of an EV [kW]
$A_{m,t}$	Availability of EV m in period t [binary]
AA_m	Availability of EV m after W^i [binary]

Variables:

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

Eq. 3 and 4 present the SOC change in two consecutive periods. Eq. 5 limits the SOC in any period t with a maximum value. Eq. 6 guarantees that the charging target of each EV m is met. However, this does not apply to EV whose departure time is later than the ending period W^i of the optimization model. AA_m is a binary indicator for EV availability beyond W^i. AA_m is equal to 1 when EV m is still available after W^i. Eq. 7 limits the charging power of each EV. $A_{m,t}$ is a binary indicator for EV m in period t. $A_{m,t}$ is equal to 1 when EV m is available in period t.

2.6 Constraints for future EV

Eq. 8 to 12 constrain the charging process of *future EV*.

$$SOC'_{s,t,\omega} * Cap * \alpha_{s,\omega} = SOC'_{s,t-1,\omega} * Cap * \alpha_{s,\omega} + P'_{s,t,\omega} * e * \Delta t \qquad i+1 \le t \le W^i, i+1 \le s < t, \forall\omega \quad (8)$$

$$SOC'_{s,t,\omega} * Cap * \alpha_{s,\omega} = SOC'_0 * Cap * \alpha_{s,\omega} + P'_{s,t,\omega} * e * \Delta t \qquad i+1 \le t \le W^i, s = t, \forall\omega \quad (9)$$

$$SOC'_{s,t,\omega} \le SOC^{max} \qquad i+1 \le t \le W^i, i+1 \le s \le t, \forall\omega \quad (10)$$

$$SOC'_{s,t,\omega} \ge SOC_s^{target} \qquad t = W^i, s \ge i+1, \forall\omega \quad (11)$$

$$P'_{s,t,\omega} \le P^{max} * \alpha_{s,\omega} \qquad i+1 \le t \le W^i, i+1 \le s \le t, \forall\omega \quad (12)$$

Parameters:

$\alpha_{s,\omega}$	Number of EV that are estimated to arrive in future period s in scenario ω
SOC'_0	Initial SOC for EV that are estimated to arrive in future periods [%]
SOC_s^{target}	SOC target of EV from future period s when charging ends [%]

Variables:

$SOC'_{s,t,\omega}$	Forecast of SOC in period s in period t in scenario ω [%]

The future estimated charging demand from EV is aggregated for each future period s. $\alpha_{s,\omega}$ is the estimated number of *future EV* and varies among scenarios. Similar to Eq. 3 and 4, Eq. 8 and 9 show the SOC change in two consecutive periods for future EV. Eq. 10 limits the maximum SOC level of these vehicles. Eq. 11 sets a charging target for this aggregated SOC and Eq. 12 limits the overall charging power demand.

2.7 Rolling window approach

As EV will arrive at all time and the charging of newly arrived EV should also be scheduled, the proposed model runs on a rolling window basis. The model optimizes for a fixed time span and iterates with updated parameters. Therefore, only the solution for the starting period of the model will be actually implemented.

3. Parameter setting

3.1 Temporal setting

The model optimizes for a fixed time span of 24 hours with quarter hour resolution and iterates quarter hourly. The rolling horizon is set to 24 hours because the total amount of energy that needs to be charged greatly varies among different windows, which will have a negative impact on the performance of the model.

3.2 EV setting
3.2.1 EV usage pattern

The model uses real EV usage data from a field test (iZeus 2017) to simulate EV availability data and to generate scenarios $\alpha_{s,\omega}$. The model applies inhomogeneous Markov chains to capture the probability of EV state change in two consecutive periods (Iversen et al., 2017; Widén et al., 2009). As shown in Eq. 13, p_{jk} denotes the probability of a state change from state j in period t

to state k in period $t+1$. $M(t)$ is called transition matrix which includes the probability of all state changes. EV are more likely to remain parking or charging at night than during day time so its probability of state change is time-dependent. Therefore, the model uses inhomogeneous Markov chains instead of homogeneous.

$$M(t) = \begin{bmatrix} p_{11}(t) & p_{12}(t) & p_{13}(t) \\ p_{21}(t) & p_{22}(t) & p_{23}(t) \\ p_{31}(t) & p_{32}(t) & p_{33}(t) \end{bmatrix} \qquad p_{jk}(t) = P(X_{t+1} = k | X_t = j) \tag{13}$$

The field test records usage data of 28 EV for 6 months. Four usage patterns are generated from one transition matrix so that there are in total 112 EV included in the modelling. A relatively large amount of EV helps to demonstrate the performance of the model. With inhomogeneous Markov chains, simulated usage patterns from the same transition matrix are of high diversity. Therefore, one scenario of $\alpha_{s,\omega}$ stems from availability patterns of 112 EV. A total number of 500 scenarios are generated for the proposed model. Fig. 1 shows the number of parking EV of the 500 scenarios within a day. As can be seen, most EV are available for charging before 6 a.m.. The number of parking EV reaches the minimum in the middle of the day. Fig. 1 presents the uncertainty of EV usage pattern. In order to consider such uncertainty, the scenario-based model should include as many scenarios as possible. However, rolling window approach requires the timeliness of the solution. Therefore, scenario reduction technique is needed to reduce the computation time while maintaining the diversity of scenarios. A fast forward selection method is applied to select a limited amount of representative scenarios out of a large scenario set (Feng et al., 2013; Wang 2010). After applying this scenario reduction technique, the model considers only 10 representative scenarios with weighted probabilities out of the 500 scenarios.

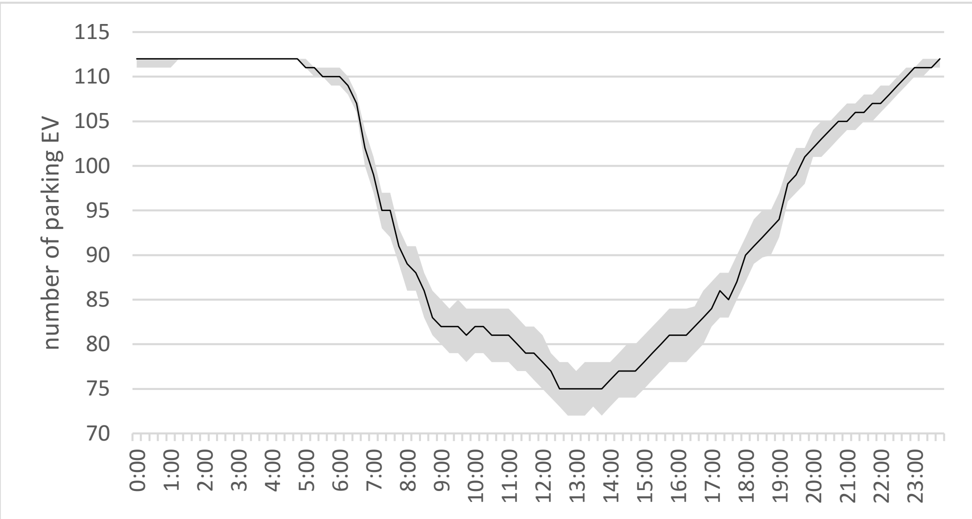

Fig. 1. Number of parking EV in 500 scenarios (with median – curve; 25% & 75% quantile – shade)

3.2.2 EV specifications

The specifications used in the model follows the specifications of the test EV (Daimler Smart) of the field test used in Section 3.2.1. EV specifications of the proposed model are as follows:

Parameter	*Setting*	*Parameter*	*Setting*
Cap	17.6 kWh	e	90%
P^{max}	5 kW	SOC_m^{ini}	$U(15\%, 75\%)$

SOC_m^{target}	90%	SOC^{max}	100%
SOC_0'	45%	SOC_s^{target}	$\min(SOC_0' + (W^i - s) * 3\%, 90\%)$

SOC_0' is assumed to be the average of SOC_m^{ini}. Considering the remaining periods of future EV towards the end of the rolling window, SOC_s^{target} is set as shown above so that this target can be completed appropriately. As solutions for the *future EV* will not be implemented, they only contribute to the quality of the solution for the *currently-connected EV*.

4. Results and discussions

For comparison, two charging strategies are presented here as follows:

1) Instant charging: EV users will charge their EV upon arrival with maximum charging power until their charging targets are satisfied.
2) Controlled charging: With the proposed model, all charging behaviors are centrally managed in order to distribute the EV charging demand evenly throughout the day.

The first strategy is fulfilled by a simulation model that uses the same EV usage pattern as in the proposed optimization model but charges EV upon arrival with maximum charging power. For the second strategy, D_t^{pref} is set according to Eq. 14. As it is not possible to have charging demand at zero throughout the day, the 2nd term of the objective function (cf. Eq. 1) tries to have as few load-changes as possible, which is supported by Eq. 14, which intends to have a low and flat load throughout the whole modelling period. The two charging strategies are implemented on the same parameters for EV availability and SOC status. Results are shown in Fig. 2.

$$D_t^{pref} = 0 \qquad \forall t \qquad (14)$$

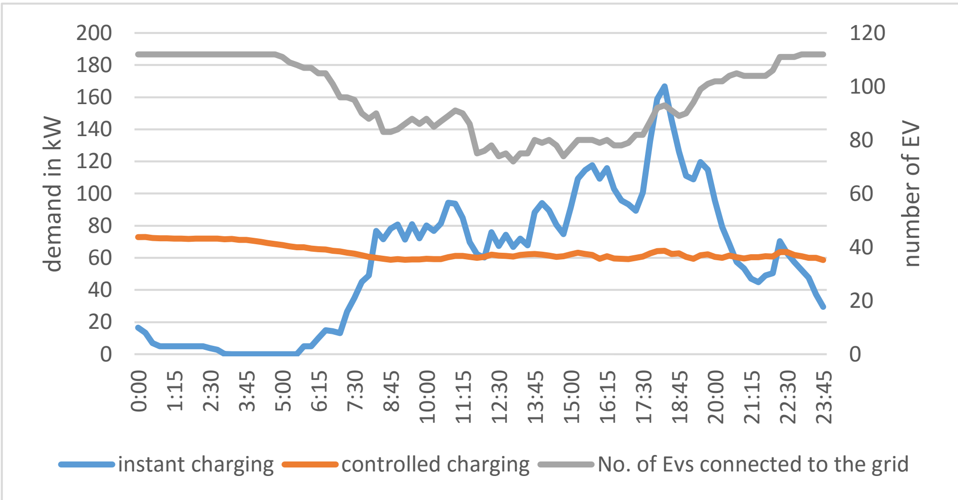

Fig. 2 Total charging demand of instant charging and controlled charging

Fig. 2 also shows the availability of these 112 EV considered by the two charging strategies. As can be seen, less EV are connected to the grid during daytime. However, the instant charging demand increases the load dramatically to a peak of over 160 kW and drops to almost zero at night. The simulation result for the instant charging demand is in line with results from other literature (e.g. Tehrani et al., 2015; Brady et al., 2016; Schäuble et al, 2017). This is because EV users prefer to charge their EV right after work and most EV are already fully charged before midnight under instant charging strategy. To make matter worse, this evening EV peak leads –

together with the conventional load pattern – to significant load peaks, which might harm the local distribution grid.

In the controlled charging strategy, the proposed model manages to dispatch the demand more evenly throughout day and cuts peak demand by two – even under the uncertainties from future arrivals. By contrast, in the instant charging strategy, there is almost no charging demand during night hours. Even though the number of parking EV decrease by about 35% during daytime, the proposed model still manages to utilize the flexibility of EV and shift a large amount of charging demand to night hours. This result also serves as a quantitative example of the load shifting potential of EV. It shows that EV have huge potentials to shift their charging demand to night hours.

5. Conclusions and future work

This paper focuses on the charging management problem of EV fleets under uncertainties. A scenario-based stochastic linear programming model is proposed and it considers the uncertainties of future arrival EV in detail (availability pattern and SOC status). Based on empirical driving data of EV, the scenarios are generated by inhomogeneous Markov chains. Scenario reduction technique is further applied to reduce the number of scenarios in the model and to improve model efficiency.

The model aims to minimize to distance between the actual total charging demand and a pre-defined reference load. This objective setting makes the proposed model extensible for different applications. In this paper, the use of the model is demonstrated by the flattening the total EV charging demand throughout the day and the results are compared with the simulation result from the instant charging strategy. The results highlight the prospect of EV charging management and show the promising load shifting potential of EV.

As premises for the use of the proposed model, the user acceptance of the proposed charging strategy is assumed and situations where users leave early than their guaranteed departure time is not expected. In data processing, this paper assumes the initial SOC is uniformly distributed with a certain range, which is a simplification of the real world. Vehicle-to-grid technology (V2G) is not included in this paper. With V2G, integer variable shall be introduced into the model, which will increase the model complexity. The limitations above may be taken into account in the future study.

Future work may also focus on further applications of the proposed model with different pre-defined curves. Possible research topics may include peak shaving for conventional household demand, the participation in control reserve market, the integration of renewable energy and the option of V2G.

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