OPTIMAL CHARGING MANAGEMENT OF ELECTRIC VEHICLE FLEETS UNDER UNCERTAINTY

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Overview and background

With an increasing market share in the car market, electric vehicles (EV) bring both problems and opportunities to the power system. For example, instant charging or uncontrolled charging will further increase the demand peak from conventional load and decrease power plant efficiency. While under controlled charging strategy, EV's load shifting potential can be utilized for renewable energy integration (Babrowski et al., 2014). The charging management of EV fleets becomes highly desirable.

In literature, this research area has been already well established. For instance, Sundström et al. (2012) develops a EV controlled charging model considering grid constraints. Their work focuses on describing the general framework of the problem and assumes perfect predictions for future trips. Wu et al. (2017) develops a EV charging management for a fast charging station. Their work considers uncertainties from EVs that may arrive in the future and assumes same charging duration for all EVs. This assumption is reasonable under their model setting but is difficult to extend to a general situation.

Motivation and Contribution

Based on these experienes, our work aims at developing a more general EV charging management model for practical applications which considers several uncertainties. We optimize the performance to the charging management model while minimizing EV users' inconvenience (EV usage and mileage). We consider the uncertainties from future EVs (EV availability and battery status). Our model is also easily extensible for different management purposes.

Methods

We formulate the EV charging management problem as a stochastic linear programming model. The model objective is to minimize the distance between the EV total charging demand and a pre-defined reference demand within a one-day period. With this objective, the true task of the model depends on the setting of this pre-defined 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. The model decides how to charge the EVs that are currently in charging service for the next 24 hours with a 15-minute time resolution. As upcoming EVs would also contribute to the total charging demand in the future, the model consider the uncertainties of the EVs that may arrive in future periods, i.e., their arrival time, departure time and electricity demand (i.e. battery state of charge).

The original EV usage data is from a field test project (iZeus, 2017). With this data, we simulate EV usage patterns from inhomogeneous Markov chains (cf. Widén et al., 2009). Simulated data are also used as scenarios to consider uncertainties. Scenario reduction technique is further applied to reduce the number of scenarios considered and to guarantee computing time (cf. Wang, 2010). As upcoming EVs would always join the charging fleet, we run the model in a rolling window fashion (every 15 minutes) to incorporate the latest information (He et al., 2012). For each optimization, only the solution for the first 15 minutes will be executed.

The proposed model is implemented in GAMS with CPLEX solver for optimizaiton.

Results and findings

In the model, we simulate EV usage patterns for a total number of 112 EVs. For these EVs, we compare results of two charging stragies. The 1st strategy is instant charging, which means EVs charge with maximum charging power upon arrival. The 2nd stragety is controlled charging. The specific target for this controlled charging strategy is to level the total charging demand. We achieve this by setting the pre-defined charging demand to zero for the whole day so that the model tries to diapatch the charging demand evenly throughout the day. Results are shown in Fig. 1.

The simulated result for the instant charging demand is in line with results from other literatures. As can be seen in Fig. 1, the number of parked and grid-connected EVs varies slightly over the day but the instant charging demand peaks significantly during early evening hours and drop to zero during night hours (as already known from literature). This is because most cars are already fully charged before midnight under instant charging strategy. Unfortunately, the evening peak leads, together with the conventional load pattern, to significant load peaks, which might harm the local distribution grid. The low demand during night-hours does not contribute to reduce current curtailment of wind feed-in. While in controlled charging, the model manages to dispatch the demand equally throughout day even under the uncertainties from future EVs. This result also serves as a quantitative example of the load shifting potential of EVs.

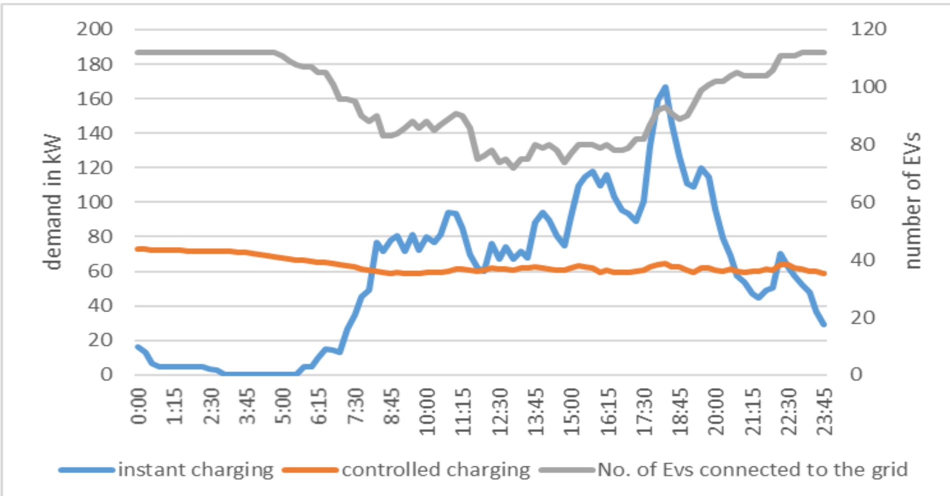

Fig. 1 Total charging demand of instant charging and controlled charging

Conclusions

Our work focuses on the charging management problem of EV fleets under uncertainties. We develop a scenario-based stochastic linear programming model, which considers the uncertainties of future arrival EVs in detail. The model aims to minimize the distance between the actual total charging deman and a pre-defined reference demand. This objective setting makes the proposed model easily extensible for different applications. We demonstrate the use of the model by comparison with the simulated result from instant charging strategy. Our results show the prospect of EV charging management.

References

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