Real Time Smart Charging of Electric Vehicles by Second Order Cone Program

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● Context

The electrification of transport, particularly the increasing adoption of electric vehicles (EVs), is expected to impose significant demands on the electricity infrastructure in the near future [1]. The timing of peak demand for EV charging often aligns with peak household consumption, especially during evening hours when most people return home from work and plug in their EVs. This synchronization can indeed lead to an increase in total peak load on the electricity grid. This simultaneous surge in demand poses significant challenges for grid operators, particularly in regions where grid capacity is already constrained [2]. Electric vehicle smart charging (EVSC) provides opportunities for better managing and incorporating this additional electricity demand within the boundaries of the existing grid. EVSC strategies are also relevant for groups of EVs embedded within a distribution network, where charging needs to be coordinated to prevent network constraints from being violated [3].

In this project we are looking to propose smart charging strategies. Mathematically, these strategies can be formulated as a constrained optimization problem. The constraints are the capacity of the charging station, power limitations, charging time limits, and prioritization of earlier arrivals. The objective could be maximizing energy delivered to vehicles, minimizing charging costs, minimizing waiting times, minimizing peak demand, or a combination of these. It is assumed that vehicle arrival and departure times are unknown ahead of operation. To address this problem, the smart charging strategies schedule charging based on the vehicles which have already arrived at a station, and are updated online by solving an optimization problem, so that the charging schedules are adjusted as new vehicles arrive. If vehicle arrival information was available ahead of operation, this information could be directly incorporated into the smart charging strategies.

● State of the art

Optimization based EVSC strategies can be roughly divided into the following four categories:

1) Linear program (LP) strategies, which use a linear model for the relationship between battery charging power and state of charge (SoC) [4, 5, 6].
2) Non-convex optimization strategies, which use a nonlinear relationship between battery SoC and maximum charging rate [7, 8, 9].
3) Problem-dependent heuristic strategies, including rule-based control, stochastic algorithm, and fuzzy expert systems [10, 11, 12].
4) Metaheuristic strategies, including particle swarm optimization, evolutionary algorithm, and colony optimization [13, 14, 15].

The advantages of LP strategies are: i) they are scalable; ii) there exist several fast and reliable LP solvers. However, the linear battery model is an overly simplistic assumption that can hinder the EVSC performance. On the other hand, using a nonlinear model can lead to an optimal result. However, there is no guarantee that the solution is globally optimal as the optimization problem is non-convex. In addition, the computational complexity grows exponentially with the number of vehicles, limiting scalability.

Recently, it was shown [16] that the problem of optimal charge scheduling across multiple vehicles, considering the nonlinear battery characteristics, can be formulated as a convex second order cone program (SOCP). This is a huge advantage over the non-convex formulation, as the solution is globally optimal. However, it is assumed that the solution of the SOCP is available in real time, which is not trivial, especially for a large-scale SOCP.

● Objectives

In this project we are interested to continue the work in [16]. We aim to provide a real-time solver that can calculate as quickly as possible the solution of a large-scale SOCP problem resulting from the charge scheduling across multiple vehicles. We will focus on the so-called operator splitting methods (OSMs), which belong to first-order optimization algorithms. The basic idea of these methods is to decompose a complex optimization problem into a series of simpler sub-problems. The main disadvantage of OSMs is that they generally require more iterations to converge to an optimal solution with a given tolerance than other optimization algorithms such as interior point methods. The advantage of OSMs is that under certain conditions, the operations required at each iteration are very simple. The operations can also be parallelized. Hence, the use of OSMs may be preferable especially for a large-scale problem. We will first start with the alternating direction method of multipliers (ADMM), which is one of the most popular OSMs.

● Expected outcomes

1. A Matlab/Python SOCP solver toolbox;
2. A journal paper.

● References

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