Sensitivity Analysis of Incentive-Based Coordinated Charging Control of Plug-in Electric Vehicles

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Introduction
As Plug-in Electric Vehicles (PEVs) penetrate commercial vehicle markets at higher rates, power consumption in residential neighborhoods could increase drastically, causing a significant load increase on the distribution grid. Severe peak loads can be catastrophic for a distribution-level substation transformer, as sustained excess current could heat the transformer’s copper winding to the point of insulation failure, leading to local blackouts for the neighborhood that the substation supplies. One way to reduce the likelihood of such a failure occurring is through a coordinated charging scheme, such that large numbers of PEVs can be fully charged throughout the course of the night without exceeding the temperature constraints of the substation.

Methods
The decentralized, incentive-based control scheme explored herein utilizes a negotiation algorithm to iteratively solve the optimal control problem for each PEV individually. The technique, known as Model Predictive Control, is a computationally intensive form of optimization-based control. The distributed version solves the optimization problem for each PEV individually, thus reducing the computational burden, but also incurs an additional communication burden. This occurs because for every time step, each PEV transmits the locally optimal charging schedule to the transformer, and the transformer then responds with a price-signal schedule, as shown in Figure 2.

Results
The results displayed in Figure 3 show the Euclidean distance between the control signal at a given iteration and the control signal at the previous iteration. For this coordination scheme, a small Euclidean distance means that the negotiation process has converged to a near optimal price point.

Conclusions
With $\alpha = 1$, the Euclidean distance remained above 1 for over 100 iterations, but dropped to around $10^{-6}$ by 200 iterations. With $\alpha = 0.1$, the Euclidean distance remained above 1 for about 20 iterations, but only dropped to around $10^{-4}$ by 200 iterations. With $\alpha = 0.001$, the Euclidean distance dropped below 1 immediately, but failed to reach $10^{-2}$ after 200 iterations. This means that, for this scenario, $\alpha = 1$ yields the smallest Euclidean distance between two control signals, given that 200 iterations occurred. However, if time-constraints require a negotiation scheme to converge in 50 iterations, for example, a value $\alpha \approx 1$ would perform best.

Future Work
In the future, this research will be expanded to develop a “recipe” of tuning parameters to achieve good performance for a given maximum number of iterations.

Reference

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Centralized Coordination Scheme - charging control of many vehicles is determined by a centralized authority. Typically, these schemes have a large computational overhead, and required a large transfer of information between consumers and utilities.

Decentralized Coordination Scheme - charging control of an electric vehicle is determined by the PEV owner themselves, but may use information from a coordinator (e.g. dynamic pricing). A well-designed decentralized method has the potential to minimize the computational overhead required, and alleviate many privacy concerns.

Literature Review
There are many different methods currently being explored for coordinating the charging of electric vehicles. These methods generally fall into one of two categories: centralized or decentralized.

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