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Coordinated PEV Charging for Distribution System Management

July 2019

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U.S. DEPARTMENT OF ENERGY

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Executive Summary

Plug-in electric vehicles (PEVs) can help to reduce worldwide dependence on petroleum and carbon emissions. In the past a few years, PEVs have received considerable attention as an eco-friendly and cost-effective alternative to conventional gasoline vehicles. PEVs consume higher power from the grid during charging compared to conventional residential loads. Therefore, the emerging fleet of PEVs will introduce a considerable amount of additional load on power systems. On the other hand, a majority of PEVs are parked for more than 90% of the time, making them ideal for providing various services through Electric Vehicle Supply Equipment (EVSE), a.k.a. charging stations which are PEVs' connection points to the power system.

In this project, coordinated PEV charging methods are developed to provide distribution system services, considering PEV characteristics, realistic travel pattern, charging behaviors, and EVSE power rating and availability. The main efforts and contributions are summarized as follows.

- Mobility models and EVSE charging capability/availability are indispensable for evaluating PEV charging coordination strategies and developing PEV charging control. Many existing studies utilize simplified mobility models assuming that the entire vehicle fleet returns home in the evening and is parked at home until the next morning. Some other PEV models better represent diversified home arrival and departure time, but cannot capture varying charging flexibility and capability at different locations, and therefore are not appropriate to study the impacts of public EVSE on PEV load and utilization. In this work, a mobility and charging flexibility model is proposed to better represent the temporal availability and varying charging capability from PEV onboard charger and EVSE.
- Based on the mobility model, a generalized optimization method is proposed to evaluate different PEV charging coordination strategies. In the existing literature, different algorithms and methods need to be designed to evaluate each charging strategy from both vehicle owners' and the power system's perspective. With the optimization method proposed in this work, different charging control strategies can be studied and compared by only updating objective functions. Moreover, optimization tricks are provided to convert the optimization problems to equivalent linear programming problems, which can be efficiently solved with existing solvers.
- An innovative scheduling and control framework is proposed to enable smart PEV charging for grid services while meeting PEV owners' travel needs. In the proposed framework, each set of EVSE is equipped with a controller that estimates charging power and energy flexibility based on vehicle characteristics, EVSE power rating, battery energy state, and upcoming trip information. With the simplified charging flexibility model received from each EVSE controller, the central coordinator determines the optimal power allocation for a look-ahead time window for the given grid services. The proposed charging control can help reduce the computational complexity and communication requirement compared with existing methods. It is also scalable to the expanding PEV fleet and robust to uncertainties in upcoming vehicle trips and future system condition.
- The proposed charging strategy evaluation and smart charging control methods are applied to one of the prototypical feeders developed by the Pacific Northwest National Laboratory (PNNL) for case studies. Detailed trip information extracted from the National Household

Travel Survey (NHTS) is used to represent travel and parking patterns. Different scenarios are simulated to evaluate the performance of the proposed methods and understand how PEV mobility and public EVSE availability affect PEV load and potential grid services.

Acronyms and Abbreviations

DMS	Distribution Management System
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
NHTS	National Household Travel Survey
MPC	Model Predictive Control
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
TOU	Time-of-Use

Notation

$d_i(t)$	average tractive power consumption at wheels of vehicle i at time step t
$d_i^{\text{batt}}(t)$	battery power consumption in driving mode of vehicle i at time step t
$e_i(t)$	battery energy state of vehicle i at the end of time step t
$e_i^{\max}$	maximum battery energy of vehicle i
$e_i^{\min}$	minimum battery energy of vehicle i
$E_{\text{flex},i}^{\max}(t)$	maximum charging energy flexibility of vehicle i at the end of time step t
$E_{\text{flex},i}^{\min}(t)$	minimum charging energy flexibility of vehicle i at the end of time step t
h_i	average tractive energy per mile at wheels of vehicle i
H_w	central-coordinator look-ahead time horizon
$L(t)$	total system load at time step t including PEVs
$L_0(t)$	system load without PEVs at time t
$m_{i,k}$	distance traveled by vehicle i during trip k
$p_i^{\text{batt}}(t)$	change of battery energy state of vehicle i at time step t in parked mode
$p_i^{\text{grid}}(t)$	power exchange between vehicle i and its EVSE at time step t
$p_i^{\max}(t)$	maximum charging capability of vehicle i at time step t
$p_i^{\min}(t)$	minimum charging (maximum discharging) capability of vehicle i at time step t
$p_{i,l}^{\max}$	maximum charging capability of vehicle i at location l
$p_{i,l}^{\min}$	minimum charging capability of vehicle i at location l
$T_{i,l}$	duration of vehicle i parked at location i
$\Delta e_i^{\text{drive}}(t)$	battery energy used during trips that occur within the next t time steps by vehicle i
ΔT	time step size
η_i^{b2w}	battery-to-wheel efficiency of vehicle i

η_i^{g2v}	grid-to-vehicle charge efficiency of vehicle i
η_i^{v2g}	vehicle-to-grid discharge efficiency of vehicle i
$\mathcal{K}_{i,t}$	set of trips that start within the next t time steps by vehicle i
$\mathcal{T}_{i,k}$	set of time steps in trip k by vehicle i
$\mathcal{T}_{i,l}$	set of time steps when vehicle i is parked at location l

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1.0 Introduction

Plug-in electric vehicles (PEVs) refer to either plug-in hybrid electric vehicles (PHEVs)—that also contain an internal combustion engine—or pure electric vehicles (EVs). These vehicles are equipped with adequate battery energy storage to travel for several miles using (mostly) electricity, and are rechargeable from the electric grid. Hence, a portion of petroleum can be displaced by electricity. PEVs are identified as a key technology for reducing worldwide dependence on petroleum and carbon emissions [Tanaka et al., 2011]. In the past a few years, PEVs have received considerable attention as an eco-friendly and cost-effective alternative to conventional gasoline vehicles. Worldwide PEV sales have increased from 320 thousand in 2014 to 1.04 million in 2017 [InsideEVs, 2017], and the demand is expected to further accelerate [Office for Low Emission Vehicles, 2011]. The annual sales of PEVs in the U.S. have increased from 17.4 thousand in 2011 to 158.6 thousand in 2016 [InsideEVs, 2017]. By November 2017, the cumulative national PEV sales were about 700 thousand [PEV Collaborative, 2017]. In 2017, many automakers announced new PEV models in coming years. For example, General Motors Co. announced it would add 20 new battery electric and fuel cell vehicles to its global lineup by 2023, while Volkswagen announced it would spend $40 billion on electric cars, autonomous driving, and new mobility services by the end of 2022 [Davies, 2017]. Volkswagen will roll out 80 new electric cars by 2025, up from a previous goal of 30, and wants to offer an electric version of each of its 300 group models by 2030 [Cremer, 2017]. Volvo will build only electric or hybrid-electric cars beginning in 2019, making it the first big auto company to abandon gas-only cars [Ewing, 2017]. China, India, France, and the United Kingdom all have announced plans to phase out vehicles powered by combustion engines and fossil fuels between 2030 and 2040.

PEVs consume higher power from the grid during charging compared to conventional residential loads. The emerging fleet of PEVs will introduce a considerable amount of additional load on power systems. Many studies have been devoted to estimating PEV load and their potential negative impacts on power systems, e.g., [Wu et al., 2011b, Weiller, 2011, Shaaban et al., 2013, Hafez and Bhattacharya, 2016]. In fact, majority of PEVs are parked for more than 90% of the time [Wu et al., 2011a], making them ideal for providing various services at both transmission and distribution levels, including ancillary services [Peng et al., 2017], load leveling for distribution system upgrade deferral and energy cost saving [García-Villalobos et al., 2014], and renewable output smoothing [Dallinger and Wietschel, 2012, Gao et al., 2014]. All these services need to be provided through Electric Vehicle Supply Equipment (EVSE), a.k.a. charging stations which are PEVs' connection points to the power system. EVSE is available at residences of most existing PEV users and PEV flexibility can be fully utilized when they are parked at home. Therefore, existing residential EVSE at home enables most PEVs to provide frequency regulation service during the night. However, there is much less non-residential EVSE at work, public parking lots, retail chains, tourist destinations etc., compared to existing PEVs on road. Existing EVSE is not sufficient to connect all PEVs to the grid and additional EVSE investment is needed in order to fully utilize the flexibility of PEV charging for grid services.

Although current EVSE locations are placed for consumer utility yet they may coincide with a utility's distribution level infrastructure, and major consumer routes/patterns. This dispersion of access points, into a utility's distribution infrastructure, provides access to potentially deliver grid services. Furthermore, EVSE banks are likely owned by third parties. These access points, if provided supplemental data about the utility's constraints, could offer access points for third parties to provide/sell bulk grid services (including ancillary services such as capacity, balancing, or firming) and provide distribution level benefits. According to EERE's Alternative Fuels Data Center [Office of Energy Efficiency and Renewable Energy, 2017], there are 45.1 thousand charging outlets at 16.5 thousand charging stations in the U.S. capable of connecting only 6.4% of existing PEVs to the grid simultaneously. A summary of the total maximum potential assuming 6.6 kW unidirectional charging that can be provided by existing EVSEs for providing frequency regulation is shown in Table. 1. It can be seen that the maximum regulation potential from the existing EVSE is not enough to meet the frequency regulation requirements.

Table 1. PEV and EVSE number vs regulation requirement in California, Texas, and New York in 2016

State	Number of PEVs	Number of charging outlets	Typical regulation requirement (MW)	Total regulation potential from PEVs (MW)	Maximum regulation potential with existing EVSEs (MW)
California	257,937	16,066	600	851	53
Texas	17,031	2,650	450	56	9
New York	20,326	1,741	250	67	6

For example, in California, there are currently 16,066 charging outlets at 4,492 charging stations. The regulation requirement is around 600 MW in California. The total frequency regulation potential from 257,937 PEVs with 6.6 kW Level 2 bidirectional chargers is:

$$\underbrace{851 \text{ MW}}_{\text{total reg. potential}} = \underbrace{257,937}_{\text{Total PEVs}} \times \underbrace{3.3\text{kW}}_{\text{reg. capability per PEV}} \times \underbrace{1 \text{ MW}/1000 \text{ kW}}_{\text{unit conversion}}$$

However, the existing EVSEs in California can at most connect 16,066 PEVs to the grid. If all these EVSE are Level 2 chargers, we can obtain at most 53 MW regulation capacity through unidirectional charging.

$$\underbrace{53 \text{ MW}}_{\text{total reg. potential}} = \underbrace{16,066}_{\text{Total EVSE}} \times \underbrace{3.3\text{kW}}_{\text{reg. capability per PEV}} \times \underbrace{1 \text{ MW}/1000 \text{ kW}}_{\text{unit conversion}}$$

This is much less than the 600 MW requirement. A significant portion of regulation potential from PEVs cannot be realized during day time because of a lack of EVSE. Therefore, PEV mobility and charging flexibility model is required to account for EVSE availability in PEV impact assessment and charging control development.

This project studies PEV and EVSE utilization for distribution services considering different charging strategies and different levels of public EVSE availability. The distribution system used for evaluation, assumptions on PEV and EVSE configuration, and travel pattern that represents PEV mobility are described in Chapter 2. A comprehensive mobility and charging flexibility model is proposed in Chapter 3 to capture impacts of various factors on PEV load control, including PEV characteristics and temporal availability, driving energy consumption, and charging capability of EVSE at different locations. Chapter 4 presents PEV charging strategy evaluation. An optimization method is developed to evaluate different charging strategies by only updating the objective function. Optimization tricks are provided to convert the optimization problems to equivalent linear programming problems. Case study results are offered to provide insights on the performance of different charging strategies. In Chapter 5, a smart charging framework is developed for online charging control to provide grid services while meeting PEV owners' charging demand. The proposed charging framework is illustrated and evaluated using the same test systems in a few representative scenarios. Finally, concluding remarks and future work are offered in Chapter 6.

2.0 Testing System and PEV Fleet

2.1 Distribution system

In this analysis, the electric distribution system is modeled using one of the 24 prototypical feeders provided by PNNL. These prototypical feeder models contain the fundamental characteristics of radial distribution feeders found in the U.S., based on 575 distribution feeders from 151 separate substations from different utilities across the nation [Schneider et al., 2008, Schneider et al., 2009]. GridLAB-D [Pacific Northwest National Laboratory, 2018] is used as a simulation platform. The PNNL feeder named R1-12.47-4 (feeder No. 4 with 12.47 kV primary distribution voltage in climate region 1 (West Coast) is selected for evaluation. This feeder represents a distribution system in a heavy suburban area, where PEVs are expected to concentrate. Since California accounts for about 45% of cumulative national PEV sales through 2017 [PEV Collaborative, 2017], San Francisco weather is used so that the feeder exhibits the main characteristics of distribution systems in northern California. This feeder serves 793 end-user loads, which include 652 residential houses and 141 commercial buildings.

2.2 Number of PEVs

In this analysis, the number of vehicles associated with each residential house is determined based on the probability mass function (PMF) of a number of vehicles for a random household in the U.S. is obtained from [U.S. Dept. of Transportation, 2010], as shown in Table 2. The number of vehicles associated with each commercial building can then be estimated based on the building type and floor area and/or electric energy consumption. PEV penetration level is assumed to be 30%.

Table 2. Vehicles per Household

Veh/HH	0	1	2	3	4	5	≥ 6
Prob.	0.087	0.323	0.363	0.144	0.053	0.019	0.01

2.3 PEV configuration and EVSE

The electric driving range heavily depends on particular PEV models. In this study, it is assumed that the range follows a normal distribution with a mean of 80 miles and a standard deviation of 20 miles. A PEV's charging/discharging power limits depends on charging rates of EVSE at the parked location and the vehicle's onboard charger. PEV charging infrastructure standards and classifications are reviewed in [Rubino et al., 2017]. For residential EVSE, it can be a conventional outlet at 120 V/12 A, 16 A, or a separate circuit at 240 V with a higher current rating. For nonresidential EVSE, level 1, level 2, and fast DC charging are available, and level 2 dominates the EVSE infrastructure in the U.S. Popular onboard charger rates are 1.4 kW and 1.9 kW for level 1 and 3.3 kW and 6.6 kW for level 2, depending on the PEV model and battery size. In this analysis, for PEVs with an electric range of fewer than 40 miles, both the onboard charger and residential EVSE ratings are 1.9 kW. For PEVs with a larger electric range, both an onboard charger and residential EVSE ratings are 6.6 kW. Two scenarios of EVSE infrastructure availability are considered:

- **Scenario 1**: EVSE only at home;
- **Scenario 2**: EVSE everywhere (with 6.6 kW public EVSE).

The reality is most likely to be between these two extremes.

2.4 Travel pattern and mobility

Statistical information on driving energy consumption, arrival and departure times, and charging durations of the PEV fleet is important in the analysis of PEV load estimation and charging coordination. Such data can be obtained by monitoring the actual composition, travel pattern, and energy consumption of the fleet as the penetration of PEVs increases in the future. In this work, the 2009 National Household Travel Survey (NHTS) database [U.S. Dept. of Transportation, 2010] is used in conjunction with certain assumptions about EVSE locational availability and charging power capability to generate synthetic data. The survey collects information on the travel behavior of a national representative sample of U.S. households, such as mode of transportation, trip origin and purpose, and trip distance. The 2009 NHTS consists of 150,147 households and 294,408 light-duty vehicles (including car, van, SUV, and pickup truck). An example of vehicle travel information is shown in Table 3.

Table 3. NHTS Data Sample

Vehicle	Type	Origin	Start time	Destination	End time	Trip miles
Veh1	SUV	Home	07:35	Work	07:50	6
		Work	17:30	Home	17:45	6
Veh2	Car	Home	07:25	Work	07:54	17
		Work	15:45	Home	16:15	17
		Home	17:35	Library	18:05	12
		Library	19:00	Home	19:25	12

3.0 PEV Mobility and Charging Availability Model

The key characteristics that differentiate PEVs from static battery storage and other loads are their temporal availability and varying charging capabilities at different locations. PEV charging and discharging availability depend on whether the vehicle is parked and whether EVSE is available at the parking location. The charging/discharging levels depend on both the onboard charger and EVSE power ratings. Many existing studies utilize simplified mobility models assuming that the entire vehicle fleet returns home in the evening and is parked at home until the next morning, such as [Clement-Nyns et al., 2010] and [Wu et al., 2012]. However, many personal vehicles are away from home from late morning to early afternoon. Some vehicle trips take place from evening to midnight as well. In addition, the home-arriving time of a vehicle fleet is distributed throughout a day and there is no parking-at-home period for the entire fleet. The percentage of traveled vehicles parked at home and away from home in urban areas on an average weekday is shown in Figure 1. Some other PEV models better represent diversified home arrival and departure time, e.g. [Weiller, 2011] and [Shaaban et al., 2013], but cannot capture varying charging flexibility and capability at different locations, and therefore are not appropriate to study the impacts of public EVSE on PEV load and utilization. To overcome these shortcomings, a PEV mobility and charging flexibility model is proposed as follows.

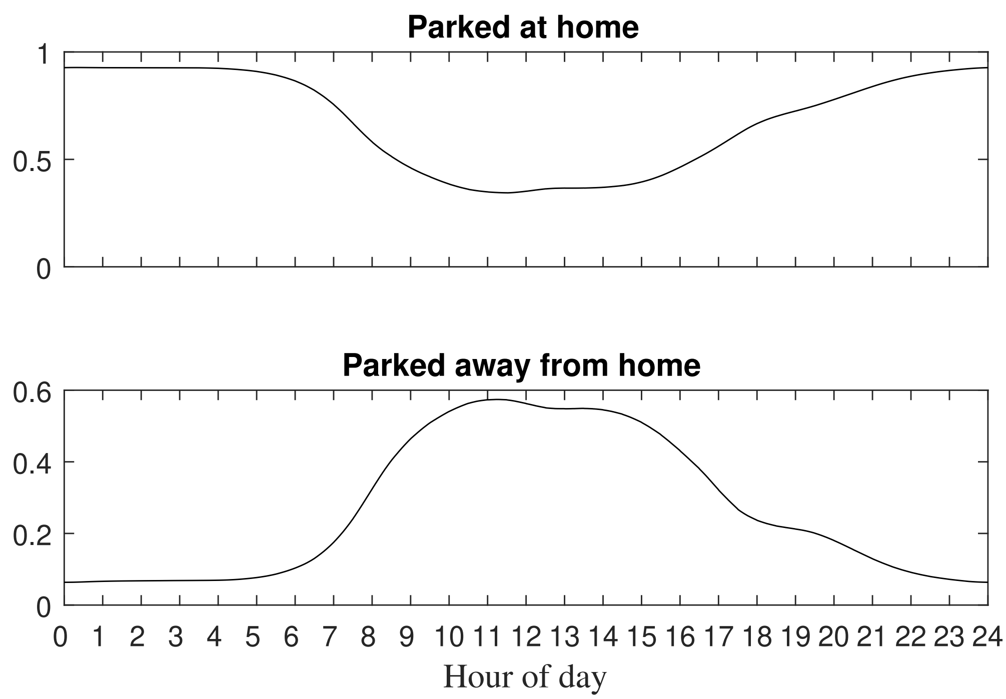

Figure 1. Percentage of vehicles in urban areas parked at different locations during weekdays

- In driving mode, the power consumption of vehicle i can be estimated as

$$d_i(t) = \begin{cases} \frac{h_i m_{i,k}}{T_{i,k}}, & \text{if } t \in \mathcal{T}_{i,k}, \\ 0, & \text{Otherwise,} \end{cases} \tag{1}$$

where h_i is the average tractive energy at wheels provided by battery and motor[(a)], $m_{i,k}$ is the miles traveled by vehicle i during trip k, $T_{i,k}$ is the duration of trip k by vehicle i, and $\mathcal{T}_{i,k}$ is the set of time periods in trip k by vehicle i. The power consumption from the battery of vehicle i can be estimated as

$$d_i^{\text{batt}}(t) = \begin{cases} \frac{d_i(t)}{\eta_i^{\text{b2w}}}, & \text{if } e_i(t) > 0, \\ 0, & \text{if } e_i(t) = 0, \end{cases} \tag{2}$$

where η_i^{b2w} is the ratio of energy from the battery over tractive energy at wheels, and $e_i(t)$ is the usable energy left in the battery of vehicle i at the beginning of period t. In this analysis, it is assumed that all the tractive energy comes from the battery in charge-depleting mode. Therefore, this ratio is the same as battery-to-wheel efficiency, which is assumed to be 0.73 based on the estimation in [Wu et al., 2011a], considering losses from battery discharging, power electronics, traction motor, mechanical transmission, etc. After all usable energy in the battery is exhausted, i.e., $e_i(t) = 0$, the operation of the PEV enters charge-sustaining mode, with all tractive energy derived from the fuel.

- In parking mode, the energy change rate of battery in vehicle i can be expressed as

$$p_i^{\text{batt}}(t) = \begin{cases} p_i^{\text{grid}}(t)/\eta^{\text{v2g}}, & \text{if } p_i^{\text{grid}}(t) < 0 \text{ (disch.)}, \\ p_i^{\text{grid}}(t)\eta^{\text{g2v}}, & \text{if } p_i^{\text{grid}}(t) \geq 0 \text{ (ch.)}, \end{cases} \tag{3}$$

where $p_i^{\text{grid}}(t)$ is the power exchange between vehicle and EVSE, η^{v2g} is the vehicle-to-grid discharging efficiency, and η^{g2v} is the grid-to-vehicle charging efficiency. Both efficiencies are assumed to be 0.9 considering losses from the battery, charger, and power electronics. The limits of $p_i^{\text{grid}}(t)$ are given in (4).

$$-p_i^{\min}(t) \leq p_i^{\text{grid}}(t) \leq p_i^{\max}(t), \tag{4}$$

where

$$p_i^{\max}(t) = \begin{cases} p_{i,l}^{\max} & \text{if } t \in \mathcal{T}_{i,l}, \\ 0, & \text{Otherwise} \end{cases} \tag{5}$$

$$p_i^{\min}(t) = \begin{cases} p_{i,l}^{\min} & \text{if } t \in \mathcal{T}_{i,l}, \\ 0, & \text{Otherwise} \end{cases} \tag{6}$$

where $p_{i,l}^{\max}$ and $p_{i,l}^{\min}$ are the maximum discharging and charging power, respectively, which depend on both vehicle onboard charger rating and EVSE availability and power rating at the parking location, and $\mathcal{T}_{i,l}$ is the set of time periods when vehicle i is parked at location l.

(a) In this study, the average tractive energy for different vehicle classes is 0.21 kWh/mile for cars, 0.33 kWh/mile for vans, 0.37 kWh/mile for SUVs, and 0.40 kWh/mile for pickup trucks.

- The dynamics of the battery energy state can be expressed as

$$e_i(t) = e_i(t-1) - d_i^{\text{batt}}(t)\Delta T + p_i^{\text{batt}}(t)\Delta T \tag{7}$$

where $e_i(t)$ is the battery energy state of vehicle i at the end of time period t, and Δt is time step size. Please note that $d_i^{\text{batt}}(t)$ and $p_i^{\text{batt}}(t)$ cannot be non-zero at the same time. The energy state needs to satisfy the constraint in (8).

$$e_i^{\min}(t) \leq e_i(t) \leq e_i^{\max}, \tag{8}$$

where $e_i^{\max}$ is the maximum usable energy stored in the battery, which depends on the vehicle's charge-depleting range, driving energy per mile, and a fraction of driving energy from battery in charge-depleting mode. The lower bound $e_i^{\min}$ is typically set at zero, but could be nonzero to reflect specific requirements from PEV owners for charging. In addition, for charging control and PEV load estimation, constraints on battery energy state at the end of scheduling horizon is needed, as shown in (9).

$$e_i(T) \geq e^{\text{req}}. \tag{9}$$

4.0 PEV Charging Strategy Evaluation

The expanding fleet of PEVs will introduce a considerable amount of load onto the power grid [Wu et al., 2011a, Fernandez et al., 2011]. Utilities face a growing challenge in determining charging behaviors of PEV customers regarding time, amount, and location of charging. Under the U.S. Department of Energy's Smart Grid Investment Grant program, six utilities evaluated operations and customer charging behaviors for in-home and public PEV charging stations with time-based charging rates, providing essential insights into peak-period charging habits of customers [U.S. Department of Energy, 2014]. Among other findings, the report concludes that the customers were aware and took advantage of time-based charging rates, and convenience in prescheduling charging sessions for off-peak periods was acknowledged. The willingness of customers to keep track of or participate in grid-favorable schemes opens up many more avenues for grid operators to use the flexibility in PEV charging, and provides an excellent opportunity for grid services. Different charging strategies are reviewed in [Mukherjee and Gupta, 2015], such as uncontrolled charging, energy cost minimization, and load leveling (cut the peak and fill the valley). Uncontrolled charging and time-of-use (TOU) charging (a special case of energy cost minimization) are today's practices for most PEVs. Coordinated charging for load leveling and renewable power smoothing can help to adopt high-penetration of PEVs into existing distribution systems, and even provide services such as distribution upgrade deferral, congestion mitigation, voltage management. These more advanced charging coordination are expected to be deployed in the near future. In the existing literature, PEV load estimation and scheduling methods vary with charging strategies. Significant efforts are required to develop a new method to evaluate any new control strategies and run comparisons with existing ones. This chapter proposes to estimate PEV load from different charging strategies by formulating and solving the same optimization problems only with different objective functions. Herein, the optimization problems for uncontrolled charging, TOU charging, and load leveling are presented as examples in Chapter 4.1. In Chapter 4.2, optimization tricks are provided in to convert the optimization problems to equivalent linear programming problems. Evaluation results for the test system are presented in Chapter 4.3.

4.1 Charging Strategy Evaluation Method

4.1.1 Uncontrolled charging

Uncontrolled charging represents a scenario where PEV charging energy is charged at a flat residential rate. It is assumed that PEV owners immediately plug their vehicles into EVSEs for charging as vehicles are parked, and no delayed charging is desired. PEVs are being charged until they are fully charged or unplugged for travel. No discharging is enabled. This is today's practice for the majority of PEVs. In order to represent uncontrolled charging behavior, the objective in (10) is formulated.

$$\mathbf{P}_1: \min_{e_i(t), d_i^{\text{batt}}(t), p_i^{\text{grid}}(t), p_i^{\text{batt}}(t)} \sum_t \sum_i (t-T) e_i(t) \tag{10}$$

The constraints include (2)–(4) and (7)–(9), where $d_i(t)$, $p^{\min}(t)$, and $p^{\max}(t)$ are input parameters and are calculated according to (1), (6), and (5), respectively. With the objective function in (10), for every t, starting charging immediately results in the largest feasible $e_i(t)$, and therefore minimizes the objective function. The obtained optimal solution represents the PEV load with uncontrolled charging.

4.1.2 Energy cost minimization

In this charging strategy, PEVs charging is scheduled to minimize total charging cost based on time-varying electric energy prices. Time-of-use rate is a special case of energy cost minimization, where the energy price $\lambda(t)$ is the same for all t within on-peak, mid-peak, or off-peak period. In this case, there are many optimal solutions with the same energy cost. The objective function in (11) is formulated to minimize the total charging energy cost.

$$\mathbf{P}_2 : \min_{e_i(t), d_i^{\text{batt}}(t), p_i^{\text{grid}}(t), p_i^{\text{batt}}(t)} \sum_t \sum_i \lambda(t) p_i^{\text{grid}}(t) \tag{11}$$

The constraints are (2)–(4) and (7)–(9), where $\lambda(t)$ is the energy price for period t. In order to capture the charging behaviors in real-world, the second component $\varepsilon[(t-T)e_i(t)]$ is added into objective function to reflect PEV owner' preference of early charging when the energy cost is the same, where ε is a very small positive number (e.g., 10^{-5}) so that the added term is small enough compared with the original objective function.

4.1.3 Load leveling

In this charging control strategy, PEV charging is coordinated so that the peak of the system load is minimized and the valley is filled evenly with PEV load, Such a strategy can help to not only reduce the charging cost of PEVs, but also to effectively reduce the annual peak load, and thereby defer distribution system upgrades. The objective function in (12) is formulated to represent this strategy.

$$\mathbf{P}_3 : \min_{e_i(t), d_i^{\text{batt}}(t), p_i^{\text{grid}}(t), p_i^{\text{batt}}(t)} \left[\max_t L(t) - \min_t L(t)\right] \tag{12}$$

where

$$L(t) = L_0(t) + \sum_i p_i^{\text{grid}}(t), \tag{13}$$

and $L_0(t)$ is the system load without PEVs. The constraints are (2)–(4) and (7)–(9).

4.2 Equivalent Linear Programming Problems

All the objective functions and constraints in $\mathbf{P}_1$–$\mathbf{P}_3$ are linear except the conditional expression in (2) and (3), and max and min operators in (12). Optimization tricks can be applied to convert $\mathbf{P}_1$–$\mathbf{P}_3$ into linear programming problems, which are described as follows.

- The constraint in (2) simply means that electric energy stored in the battery is used for vehicle driving before the battery is exhausted. An alternative way to represent is to set

$$d_i^{\text{batt}}(t) \leq d_i(t) \tag{14}$$

and add $-M\sum_t \sum_i d_i^{\text{batt}}(t)$ in to objective functions, where M is a sufficiently large positive number. Because of constraint (8), the optimal solution always lead to $d_i^{\text{batt}}(t) = d_i(t)$ when $e_i(t)$ is positive.

- Equivalent linear constraints of (3) are provided in [Wu et al., 2015].

$$p_i^{\text{grid}}(t) = p_i^{\text{g2v}}(t) - p_i^{\text{v2g}}(t) \tag{15}$$

$$p_i^{\text{batt}}(t) = p_i^{\text{g2v}}(t)\eta^{\text{g2v}} - p_i^{\text{v2g}}(t)/\eta^{\text{v2g}} \tag{16}$$

$$p_i^{\text{v2g}}(t), p_i^{\text{g2v}}(t) \geq 0 \tag{17}$$

$$p_i^{\text{v2g}}(t)p_i^{\text{g2v}}(t) = 0 \tag{18}$$

It has been shown in [Hao et al., 2018] that constraint (18) is unnecessary for the objective function in (11). This is also true for the objective function in (10), but not (12), because "wasting energy" ($p_i^{\text{v2g}}(t)p_i^{\text{g2v}}(t) \neq 0$) may help to raise the valley during off-peak hours and increase $\min_t L(t)$. Therefore, the objective function is modified as

$$\min\left[\max_t L(t) - \varepsilon_1 \min_t L(t) + \varepsilon_2 \sum_t \sum_i p_i^{\text{grid}}(t)\right] \tag{19}$$

where ε_1 and ε_2 are small positive numbers, and ε_2 is sufficiently small compared with the first term but sufficiently large compared with ε_1.

- The $\max_t L(t)$ and $\min_t L(t)$ operators can be replaced by $L_{\max}$ and $L_{\min}$, respectively, and add the following constraints

$$L_{\max} \geq L(t),\ \text{for } t = 1,2,3\ldots \tag{20}$$

$$L_{\min} \leq L(t),\ \text{for } t = 1,2,3\ldots \tag{21}$$

The resulted equivalent linear programing problems are summarized as follows:

- Uncontrolled charging:

$$\mathbf{P}_1' : \min_{\mathbf{x}} \sum_t \sum_i [(t-T)e_i(t) - M\sum_t \sum_i d_i^{\text{batt}}(t)] \tag{22}$$

subject to constraints (14)–(17), (4), and (7)–(9), where

$$\mathbf{x} = [e_i(t), d_i^{\text{batt}}(t), p_i^{\text{grid}}(t), p_i^{\text{batt}}(t), p_i^{\text{g2v}}(t), p_i^{\text{v2g}}(t)].$$

- TOU charging:

$$\mathbf{P}_2': \quad \min_{\mathbf{x}} \sum_t \sum_i \{\lambda(t) p_i^{\text{grid}}(t) + \varepsilon[(t-T)e_i(t)] - M \sum_t \sum_i d_i^{\text{batt}}(t)\} \tag{23}$$

  subject to the same constraints and with the same decision variables as $\mathbf{P}_1'$.

- Load leveling:

$$\mathbf{P}_3': \quad \min_{\mathbf{x}} \{L_{\max} - \varepsilon_1 L_{\min} + \varepsilon_2 \sum_t \sum_i p_i^{\text{grid}}(t) - M \sum_t \sum_i d_i^{\text{batt}}(t)\} \tag{24}$$

  with (20) and (21) added to the constraints, and $L_{\max}$ and $L_{\min}$ added to the decision variables in $\mathbf{P}_1'$.

4.3 Charging Strategy Evaluation Results

Different charging strategies are evaluated using the proposed method for the test system described in Chapter 2 for representative average and peak summer days. For charging scenarios are considered:

SC1: uncontrolled unidirectional charging at home,

SC2: time-of-use unidirectional charging at home,

SC3: optimal coordinated bidirectional charging at home,

SC4: optimal coordinated bidirectional charging at all locations.

The feeder loading for different charging strategies for a peak summer day is plotted in Figure. 2, while the minimum voltage within the feeder is plotted in Figure 3, where

Some key observations and explanations are provided below:

- Uncontrolled charging increases system load but not significantly, because the vehicles' arrival time and charging start time are naturally distributed throughout a day. Nevertheless, the increased peak load cannot be ignored as PEV penetration, electric ranges and charging power increase.
- TOU charging causes a spike during off-peak hours because of charging synchronization around the beginning of reduced rate period. This kind of undesirable synchronization has been observed in some distribution systems in California. This strategy is only effective when PEV penetration is very low.
- Optimal coordinated charging can help to avoid increasing peak load, and can even reduce

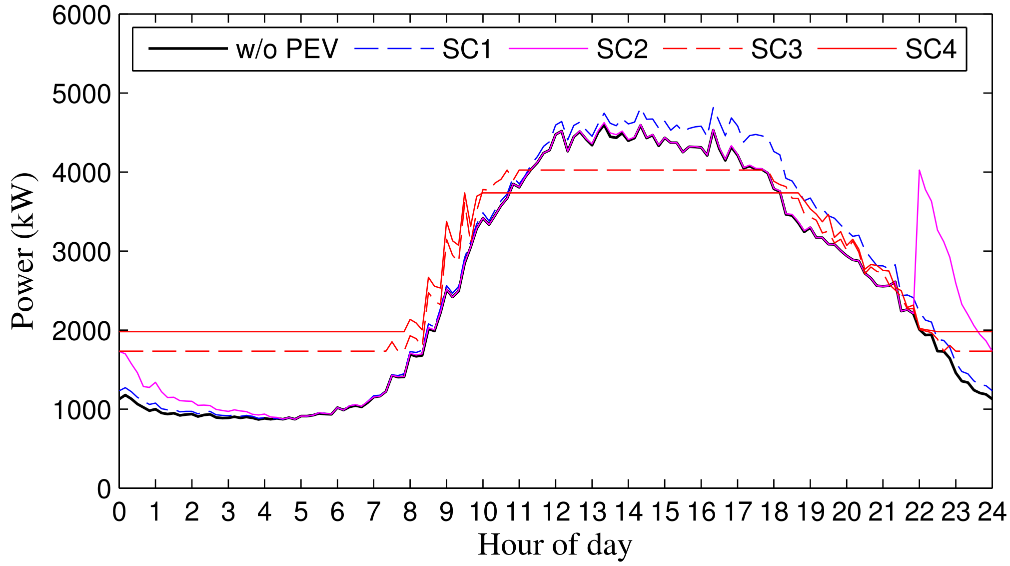

Figure 2. Feeder loading level

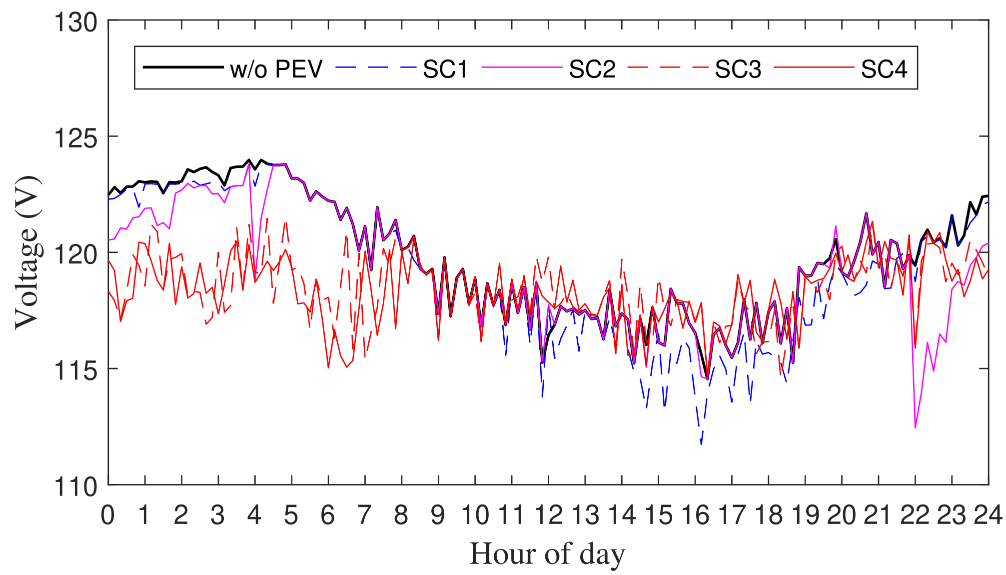

Figure 3. Minimum voltage within the feeder

peak with vehicle-to-grid (V2G) enabled PEVs. PEVs and EVSE with bidirectional charging capability can be used for load shifting when vehicles are not in use. This strategy can be leveraged to reduce energy cost or to absorb excessive renewable generation. More importantly, it can effectively reduce the annual peak load, and therefore avoid or defer distribution system upgrades. For example, the prototypical feeder has a daily peak around 3 MW except for a few hot summer days with peak load around 4.5 MW. Coordinated charging by using V2G capability can lower the peak by 1 MW.

- With V2G enabled home EVSE, an additional reduction in peak load from public EVSE is not significant. Therefore, other utilizations are important in making public EVSE economically viable.

- The ANSI standard C84.1 requires that the service voltage remains within five percent from the nominal value (114–126 V) at the customer level. Low-voltage violations are detected for uncontrolled and TOU charging scenarios, as can be seen in Figure 3. Reactive compensation needs to be modified in order to meet the voltage requirement in these two scenarios.
- Vehicle miles powered by electricity increase by 5% due to the availability of public EVSE in this analysis. This is another advantage of public EVSE, and the percentage could increase for a PEV fleet with smaller electric ranges.

The feeder losses and efficiency[a] are plotted in Figure 4 and Figure 5, respectively. Current magnitude in a feeder is proportional to system loading, and therefore adding PEV load tends to increase losses. Optimal charging shifts PEV charging to hours with low loading level, and help reduce losses in this case. Optimal charging decreases loss-to-energy ratio, and therefore increases efficiency. Uncontrolled and TOU increase loss-to-energy ratio, and therefore decreases efficiency.

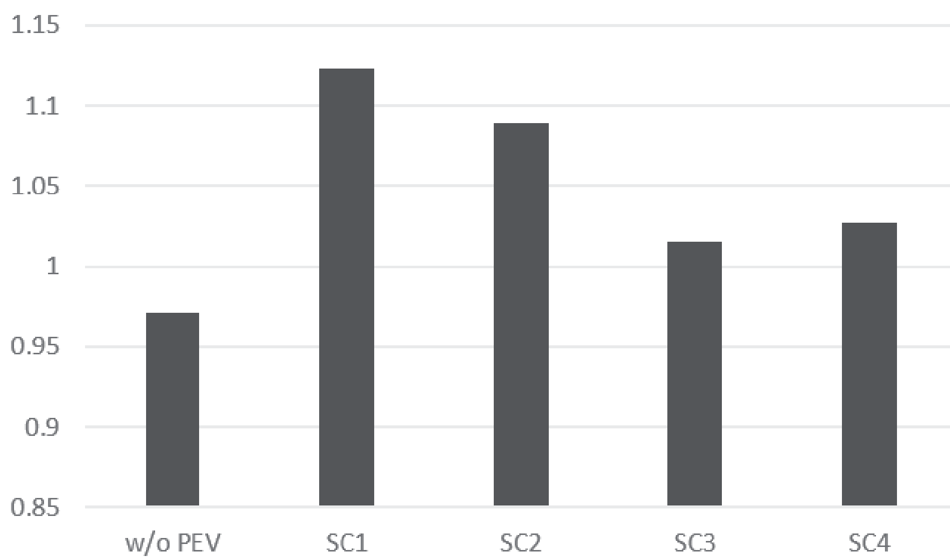

Figure 4. Feeder losses (MWh)

(a) Efficiency is defined as the ratio of total energy-loss over total energy.

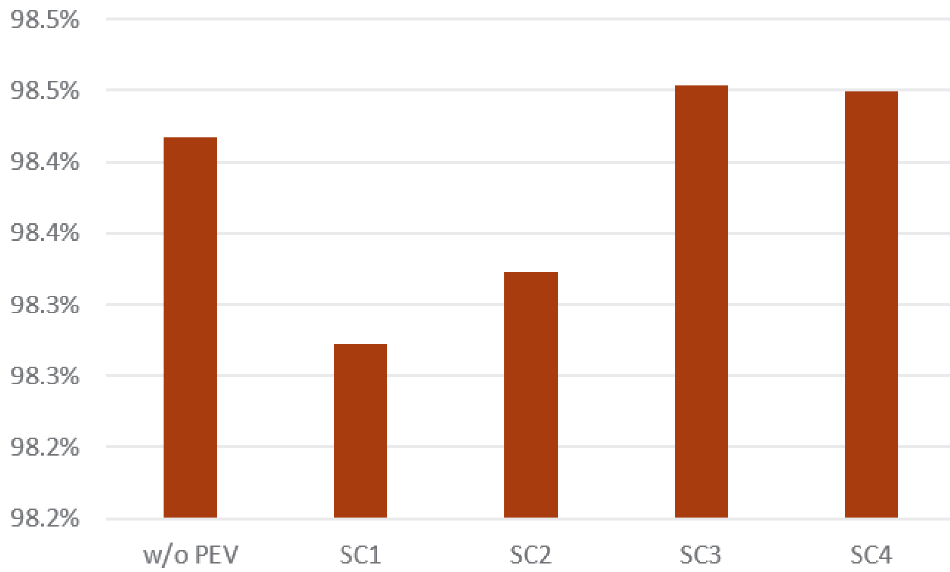

Figure 5. Feeder efficiency

5.0 PEV Charging Control Framework

A few charging coordination strategies are presented in the previous chapter. Some charging strategies can be realized through simple price-based charging control, which is though helpful in PEV load management at a mild penetration level, could cause an even bigger peak at night with a large number of PEVs. The development of advanced PEV charging coordination strategies that can adapt to changing system conditions and types of services with the least inconvenience to customers has been the subject of considerable study of late. In [Clement-Nyns et al., 2010], quadratic programming and dynamic programming techniques are used for charging coordination to minimize power losses in distribution systems. A priority-based method is proposed in [Wu et al., 2012] for PEV aggregators to schedule and dispatch charging load for energy cost minimization. Auction mechanisms are proposed in [Bhattacharya et al., 2014] to achieve efficient allocation of charging energy to PEVs. Based on scenarios of stochastic PEV connection to grid, an event-triggered scheduling scheme is proposed for load flattening in [Jian et al., 2015]. Fuzzy control and quadratic programming are used to determine optimal charging that minimizes both load variance and charging costs with weight factors in [García-Villalobos et al., 2016]. In [Ke et al., 2019], a real-time greedy-index dispatching policy is developed to control PEVs for providing frequency regulation service. While these methods can effectively solve the formulated charging coordination problems, the assumptions are oversimplified and many practical constraints are not considered. For example, many studies use simplified mobility models, assuming that the entire vehicle fleet returns home in the evening and is parked at home until the next morning. As a result, the proposed methods and algorithms may not be useful in practice. Furthermore, most of the existing studies are based on centralized control approaches, in which the modeling objective and constraints at the system level are straight forward. The obtained coordinated charging has definite advantages over the local charging strategy, as shown in [Mets et al., 2010] for load flattening. Nevertheless, centralized control approaches require a single control center to gather information on PEV configuration, charger power rating, battery energy state and preferred operating range, and upcoming trips for potentially thousands of vehicles and incorporate complicated mobility and charging availability models into the coordination problem. Such a centralized control strategy is often subject to several disadvantages, such as high requirement and cost in communication, substantial computational burden, and limited flexibility and scalability. Far less work has been done towards effective decentralized methods for grid services. In [He et al., 2012], a locally optimal scheduling scheme is developed for charging cost minimization with a performance close to a centralized scheduling method. In [Ma et al., 2013], a decentralized charging control is developed using concepts from non-cooperative games to achieve valley filling, assuming PEVs are weakly coupled via a common electricity price. In [Zeraati et al., 2019], consensus-based algorithms are proposed to effectively utilize PEV storage capacity for voltage management. Unlike centralized charging control methods, it is extremely challenging to adapt or modify existing distributed charging algorithms for problems with modified/additional objectives and constraints. In addition, these distributed control methods rely heavily on iterative algorithms that require speedy communication or fail to generate charging control signals within the required time. Moreover, communication network effects such as time delays and packet drops could fail distributed algorithms from practical applications [Yang et al., 2015]. To address these challenges, hierarchical charging has been proposed. In [Qi et al., 2014], the authors show that a hierarchical control structure has clear advantages over a completely centralized or decentralized control regarding computation and communication. The authors of [Xu et al., 2016] present a three-level hierarchical framework consisting of provincial, municipal, and charging station levels to facilitate PEV charging coordination in China. In [Luo et al., 2018], a three-level scheme is proposed to utilize PEV to hedge against wind-induced unit ramp cycling operation, where decentralized charging control is implemented at the bottom level. In these hierarchical charging systems, aggregators as intermediate layers are introduced to serve between a central coordinator at the transmission or sub-transmission level and individual PEVs. The charging scheduling and control at the bottom level are still either centralized or distributed, requiring aggregators to gather information on vehicles, charging equipment, and vehicle trips for a large number of vehicles and incorporate complicated mobility and charging availability models into the scheduling problem, significantly increasing computational and communication cost.

Inspired by [Radhakrishnan et al., 2016], this paper proposes a simple, but powerful, smart charging method, in which each vehicle reports charging requirements for its travel needs and discharging availability for supporting grid operations through the charging infrastructure known as electric vehicle supply equipment (EVSE). PEVs and EVSE are not aware of operating conditions and needs of the electric power systems. Each set of EVSE includes a local controller that gathers information on PEV configuration, EVSE power rating, battery energy state, and upcoming trips, to estimate its charging/discharging flexibility for a look-ahead time window, which is then sent to a central coordinator, either a PEV aggregator or distribution system operator. Based on the updated PEV flexibility and system information, the central coordinator then optimally coordinates PEV charging to support and improve distribution system operation or provide transmission level services while meeting PEV owners' travel needs. In this way, the central coordinator is relieved from having to take in detailed PEV mobility models. The process repeats in a model predictive control (MPC) fashion and can adapt to any updates on PEV owners' travel needs and power system conditions. Because the central coordination only needs to act when there are updates on charging demand from PEV customers, the communication and computation requirements are reduced. Please note that the proposed control framework is not a hierarchical system with layers representing PEV aggregation. It is a hierarchical control because the proposed EVSE controller forms an additional control layer. The main contributions of the proposed charging control framework are highlighted as follows.

- We develop a novel and scalable framework for PEV charging control to not only meet PEV owners' travel needs, but also to provide grid services. The proposed framework is based on a hierarchical control structure which has clear advantages over a completely centralized or decentralized control for PEV charging control regarding computation and communication. The use of MPC for scheduling services provides a superior control capable of accounting for various uncertainties.
- We propose a model to characterize PEV charging flexibility locally, taking into account various factors, including PEV and EVSE configuration parameters and travel needs. The proposed model is simple but is equivalent to the comprehensive mobility and charging availability model for charging control.
- The proposed hierarchical charging control framework enables a service model that makes

it convenient for PEV owners to participate in smart-grid services. The customer only needs to key-in energy needs and the associated deadline when a PEV is plugged in and does not need to keep track of time-based rates for reducing charging cost.

5.1 Smart Charging Control Framework

The charging coordination problem presented in the previous chapter, if directly solved, would require information on detailed trip information, battery characteristics, vehicle characteristics, and customer demand to be collected at a central authority, which is very challenging in practice. To overcome this, a novel smart charging architecture is proposed, as illustrated in Figure 6. In the proposed charging control architecture, a local controller residing at each EVSE starts up when a PEV is plugged in. The customer then has the option to enter how many miles' worth of charge they require or demand a percentage of energy state required by a particular time. The information is collected and processed to calculate a set of four parameters that are indicative of the charging flexibility and demands of each vehicle. The central coordinator receives the data from all EVSE and solves an optimal charging coordination problem. This paper considers load leveling. The following subsections will describe the charging control procedures, information flow, and computations involved in the proposed smart charging method.

5.1.1 EVSE Controller

In the proposed method, the charging flexibility of PEV i is characterized by its maximum and minimum charging power and energy limits for a predefined time slot H_w based on vehicle characteristics (e.g., vehicle weight and electric range), EVSE power rating, battery energy state, and upcoming trip information. Trading-off required charging energy for additional grid services is beyond the scope of this paper. Therefore, the customers' charging requirements should be satisfied at all times. The following calculations capture the upward and downward flexibility of each PEV regarding its bidirectional power flow capability and energy demands, in order to avoid sending all vehicle parameters and the comprehensive mobility model as described in (1)–(9) to the central coordinator.

- Power flexibility
  The maximum and minimum charging power flexibility depend on a PEV's onboard charger rating, whether the vehicle is parked, and the availability and power rating of EVSE at the parked location. The maximum charging power flexibility is simply $p_i^{\max}(t)$, which can be calculated using (5). Similarly, the minimum charging power flexibility $p_i^{\min}(t)$ can be calculated using (6).
- Energy flexibility
  The cumulative charging energy supplied to each vehicle needs to take into account driving energy demand and battery capacity. The maximum charging energy for PEV i during the next t time steps depends on the initial energy stored in the battery $e_i(0)$, the battery energy capacity $e_i^{\max}$, the grid-to-vehicle charging efficiency η_i^{g2v}, and the energy discharged from

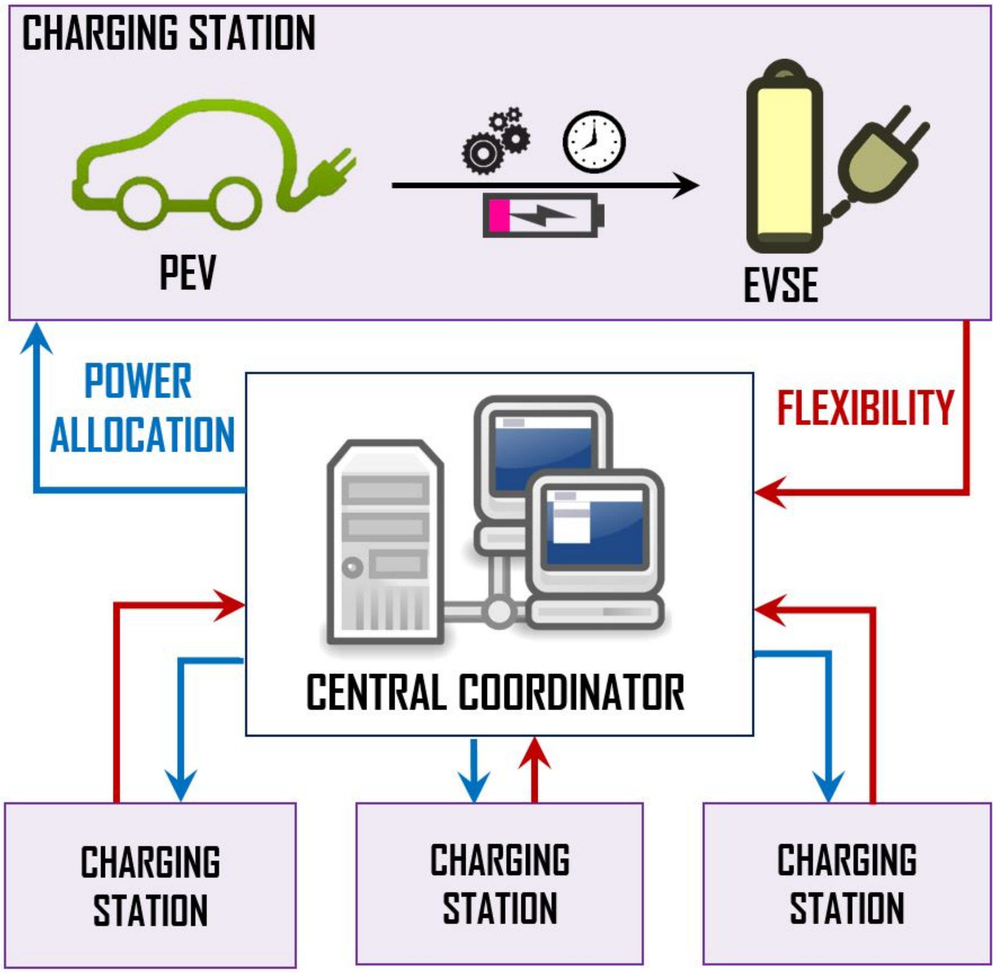

Figure 6. Smart charging architecture.

the battery during trips that occurs within the next t time steps $\Delta e_i^{\text{drive}}(t)$.

$$E_{\text{flex},i}^{\max}(t) = e_i^{\max} - e_i(0) + \Delta e_i^{\text{drive}}(t)\,, \tag{25}$$

where $t = 1, \cdots, H_w$. Similarly, the minimum charging energy for PEV i during the next t time steps can be calculated as

$$E_{\text{flex},i}^{\min}(t) = e_i^{\min} - e_i(0) + \Delta e_i^{\text{drive}}(t)\,. \tag{26}$$

Note that when the right-hand side in (26) is positive, i.e.,

$$\Delta e_i^{\text{drive}}(t) > e_i(0) - e_i^{\min}\,, \tag{27}$$

it means the remaining energy in the battery at the current time step, $e_i(0)$, is insufficient for the next t time steps. On the other hand, when the right-hand side in (26) is negative, it means there is more than enough energy in the battery for vehicle trips and the vehicle can be discharged to support grid operation. The energy discharged from the battery during trips that occur within the next t time steps can be expressed as

$$\Delta e_i^{\text{drive}}(t) = \sum_{k \in \mathcal{K}_{i,t}} e_{i,k} \tag{28}$$

where $e_{i,k}$ is the energy consumption from the battery by vehicle i during trip k, and $\mathcal{K}_{i,t}$ is the set of trips that start within the next t time steps by vehicle i. Note that $e_{i,k}$ depends on not only the miles vehicle i travels in trip k, but also the initial battery energy state and the time available for charging within the next t time steps, as expressed in (29).

$$e_{i,k} = \min\left(h_i m_{i,k}/\eta_i^{\text{b2w}}, E_i(t_{i,k}^{\text{start}})\right) \tag{29}$$

where $h_i m_{i,k}/\eta_{\text{b2w}}$ is the required energy consumption from the battery by vehicle i during trip k, and $E_i(t_{i,k}^{\text{start}})$ is the maximum energy that can be stored in the battery of vehicle i at the starting time of trip k. $E_i(t_{i,k}^{\text{start}})$ should be less than the battery energy capacity $e_i^{\max}$. It should be also less than the battery energy at $t_{i,k}^{\text{start}}$ if vehicle i would be charged at the maximum rate for the entire parked period between two trips, i.e.,

$$E_i(t_{i,k}^{\text{start}}) = \min\left(e_i^{\max},\ e_i(t_{i,k-1}^{\text{end}}) + \eta_i^{\text{g2v}} p_{i,l}^{\max} T_{i,l}\right) \tag{30}$$

where $e_i(t_{i,k-1}^{\text{end}})$ is the energy left in the battery at the end of trip $k-1$, $p_{i,l}^{\max}$ is the maximum charging rate at location l where vehicle i is parked between trips $k-1$ and k, and $T_{i,l}$ is the parked duration.

The input, output, and flexibility characterizing procedures at the EVSE controller are summarized in Algorithm 1, which is an event-driven algorithm.

Algorithm 1 EVSE controller: characterizing flexibility

Input: h_i, $e_i^{\max}$, η_i^{b2w}, η_i^{g2v}, $p_{i,l}^{\max}$, and $p_{i,l}^{\min}$ (PEV and EVSE parameters) read by EVSE controller, $e_i^{\min}$, $m_{i,k}$, and $t_{i,k}^{\text{start}}$ (input from PEV owners), and a predefined H_w

Output: $p_i^{\max}(t)$, $p_i^{\min}(t)$, $E_{\text{flex},i}^{\max}(t)$, $E_{\text{flex},i}^{\min}(t)$

1: *Initialization*: $e_i(0) \leftarrow$ energy state at current time step
2: Calculate $p_i^{\max}(t)$ using (5) and $p_i^{\min}(t)$ using (6)
3: Calculate $\Delta e_i^{\text{drive}}(t)$ based on (28)–(30)
4: Calculate $E_{\text{flex},i}^{\max}(t)$ using (25) and $E_{\text{flex},i}^{\min}(t)$ using (26)
5: **return** $p_i^{\max}(t)$, $p_i^{\min}(t)$, $E_{\text{flex},i}^{\max}(t)$, $E_{\text{flex},i}^{\min}(t)$
6: **loop**
7:     **if** updates in PEV energy demands **then**
8:         Repeat 1-5
9:     **end if**
10: **end loop**

5.1.2 Central Coordinator

The central coordinator receives the power and energy flexibility information from EVSE controllers and determines the optimal allocation of electric power based on operating conditions and needs of the power system. These flexibility bounds are used to construct constraints in the optimal power allocation problem periodically solved by the central coordinator. The objective could be load leveling, peak load shaving, energy cost minimization, voltage management, or any other applications that support grid operation. The decision variables are the individual PEV charging/discharging power level from the grid $p_i^{\text{grid}}(t)$. There is no need for the central coordinator to receive and consider the comprehensive mobility model and many PEV and EVSE parameters, which significantly reduces computation and communication requirements.

The charging coordination problem for load leveling is formulated in (31).

$$\min_{p_i^{\text{grid}}(t),L(t)} \quad [\max L(t) - \min L(t)] \tag{31a}$$

s.t.:

$$L(t) = L_0(t) + \sum_i p_i^{\text{grid}}(t) \tag{31b}$$

$$p_i^{\min}(t) \le p_i^{\text{grid}}(t) \le p_i^{\max}(t), \qquad \forall i \tag{31c}$$

$$E_{\text{flex},i}^{\min}(t) \le \sum_{\tau=1}^{t} \eta(\tau) p_i^{\text{grid}}(\tau)\Delta T \le E_{\text{flex},i}^{\max}(t), \quad \forall i \tag{31d}$$

$\forall t = 1, \cdots, H_w$, where $\eta(\tau)$ is η_i^{g2v} when $p_i^{\text{grid}}(\tau) \ge 0$, and $1/\eta_i^{\text{g2v}}$ when $p_i^{\text{grid}}(\tau) \le 0$. Constraints (31c) and (31d) capture the flexibility bounds sent by each EVSE controller. This problem can be readily converted to a standard linear programming problem [Wu et al., 2018] and solved efficiently with existing solvers. The optimization is performed by a central coordinator in a MPC manner. At each time step, the solution $p_i^{\text{grid}}(t)$ for the next step is sent back to each EVSE for it to follow.

5.2 Smart Charging Control Evaluation Results

This subsection evaluates the proposed smart charging control method using the setup presented in the previous subsection. For comparison, a base case is first studied to represent today's uncontrolled charging practice, in which PEVs are charged whenever they are plugged in until they are fully charged or unplugged for travel. Uncontrolled charging is used as the basis for evaluating the proposed method including the following cases.

- Uncontrolled charging
- Smart charging with knowledge of all trips during the day
- Smart charging with knowledge of imminent trips only
- Smart charging with varying scheduling window sizes

In all the smart charging scenario, the step size is 10 minutes. The charging flexibility updates at each EVSE and central coordination occur every 30 minutes with different look-ahead time windows.

5.2.1 Uncontrolled charging

In the uncontrolled charging case, PEVs are charged whenever they are plugged in until they are fully charged or unplugged for travel. No discharging is enabled. The non-PEV load together with the total system load including PEV load for both EVSE infrastructure scenarios is plotted in Figure 7 for a typical summer peak day. As can be seen, most charging occurs during peak hours, resulting in high charging cost. The system peak demand increases by 6.50% in the "EVSE only at home" scenario and 6.90% in the "EVSE everywhere" scenario. This may entail investment in upgrading the distribution system to maintain reliable operation. The difference between the peak demand (maximum load) and base load (minimum load) is increased by 7.97% for the "EVSE only at home" scenario and 8.40% for the "EVSE everywhere" scenario. Additional public EVSE helps to shift driving energy derived from conventional fuel to electricity for PEVs with small batteries compared with their travel needs. Charging at public EVSE also raises the peak demand slightly but does not affect the magnitude of base load.

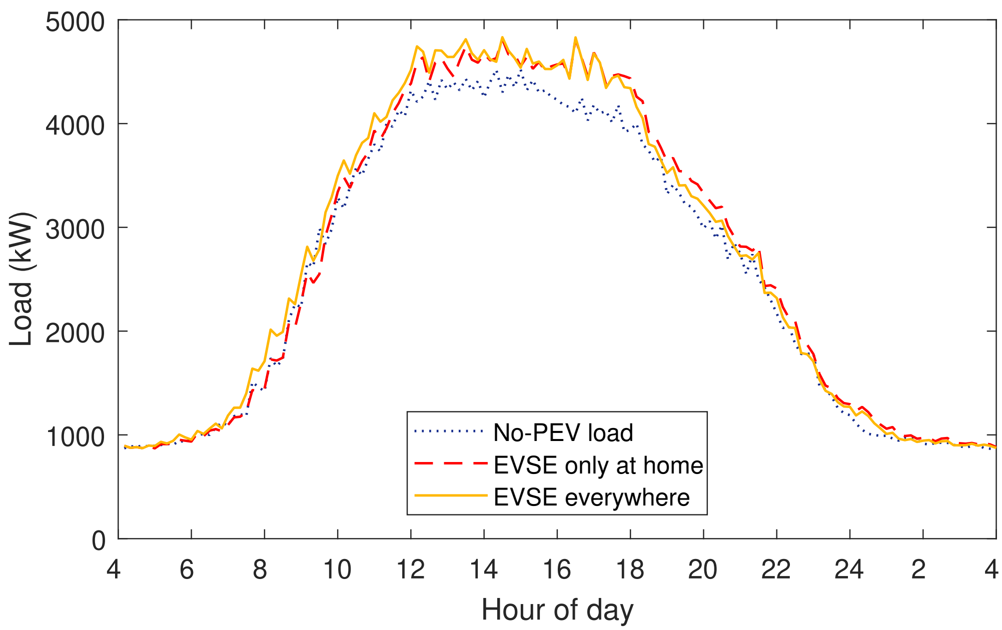

Figure 7. System load from uncontrolled charging

5.2.2 Perfect knowledge

In this case, each PEV owner predicts its trips for the entire operating day and abides by their predictions. The prediction horizon for the EVSE controller and the time window for the central scheduler (H_w) are both 24 hours. Using the smart charging method presented in Chapter 5.1, optimal charging coordination is simulated for the two EVSE scenarios. The results are plotted in Figure 8.

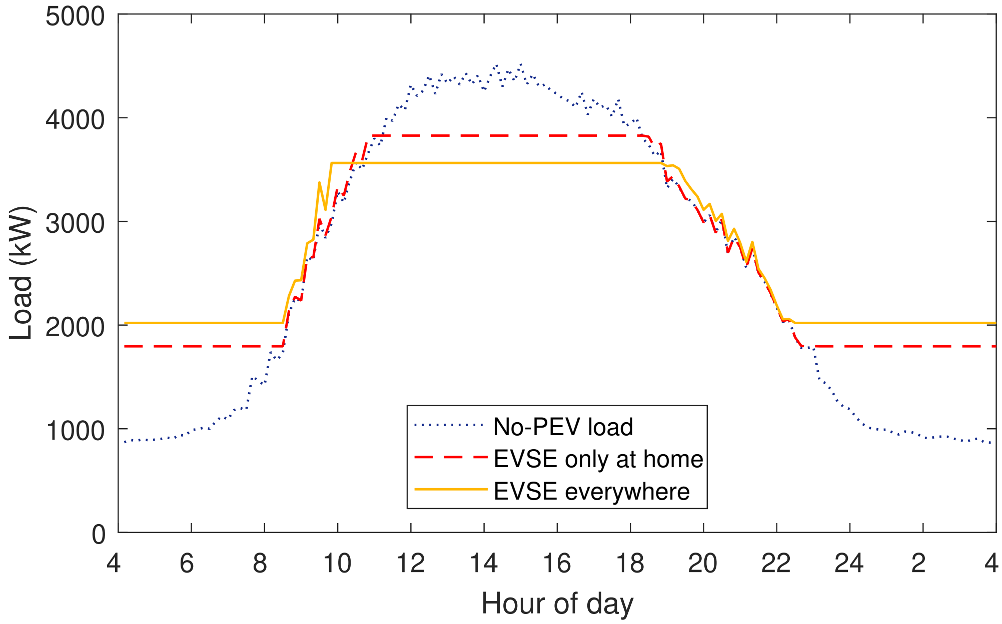

Figure 8. System load from smart charging with perfect knowledge

Compared with uncontrolled charging, smart charging takes advantage of charging flexibility and delays a significant amount of charging to off-peak hours. In addition, with the V2G capability, vehicles that are not in use for travel can be discharged during peak hours to shift some non-PEV load to off-peak hours. The proposed smart charging can be used to reduce energy cost or to absorb excess renewable generation. More importantly, it can effectively reduce the annual peak load, and thereby avoid or defer distribution system upgrades. For example, the prototypical feeder has a daily peak around 3 MW except for a few hot summer days with peak load around 4.5 MW. Uncontrolled charging increases the peak by about 300 kW, while smart charging by using V2G capability only at home lowers the peak by 700 kW. Smart charging with public EVSE further reduces system peak load by another 300 kW. The peak demand is reduced by 15.15% for the "EVSE only at home" scenario and 21.15% for the "EVSE everywhere" scenario compared with the non-PEV load. In other scenarios, the loading level during off-peak hours is effectively raised. The difference between the peak demand and base load is reduced by 44.37% for the "EVSE only at home" scenario and 57.79% for the "EVSE everywhere" scenario compared with the non-PEV load. Compared with uncontrolled charging, public EVSE has much greater impacts on system loading in smart charging.

The total driving versus charging power from the entire PEV fleet are plotted in Figure 9, and cumulative driving versus charging energy are plotted in Figure 10. As can be seen from Figure 9, majority of PEV driving occurs from 7 am to 8 pm. Therefore, cumulative driving energy in Figure 10 increases during this period. With smart charging control, most PEV charging occurs between 11 pm and 8 am, and hence cumulative charging energy in Figure 10 increases; most discharging occurs between 11 am and 7 am, and hence cumulative charging energy in Figure 10 decreases. The total charging energy meets the driving needs over the entire day.

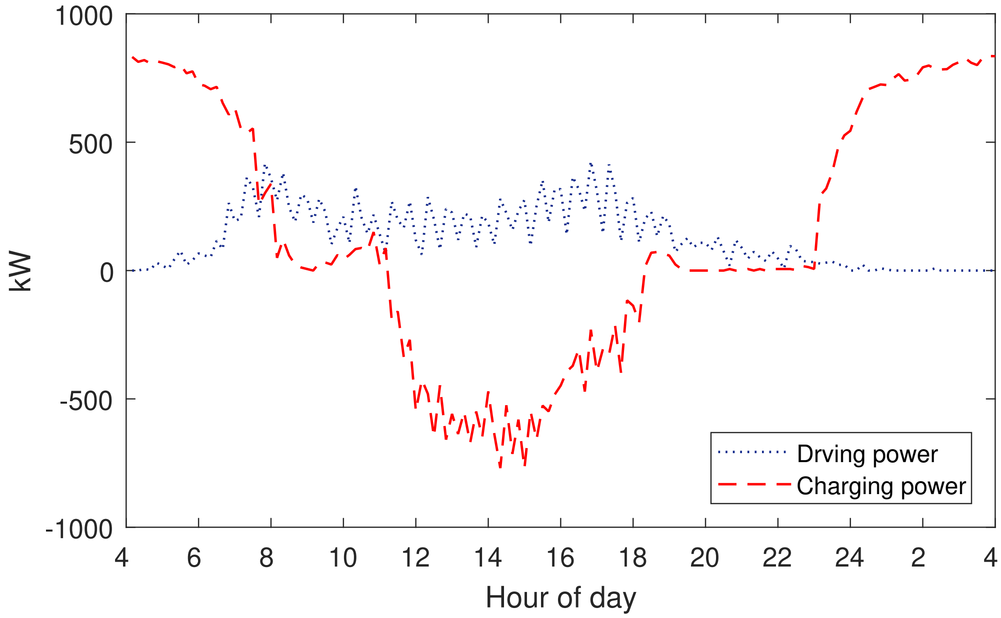

Figure 9. Driving power vs. charging power

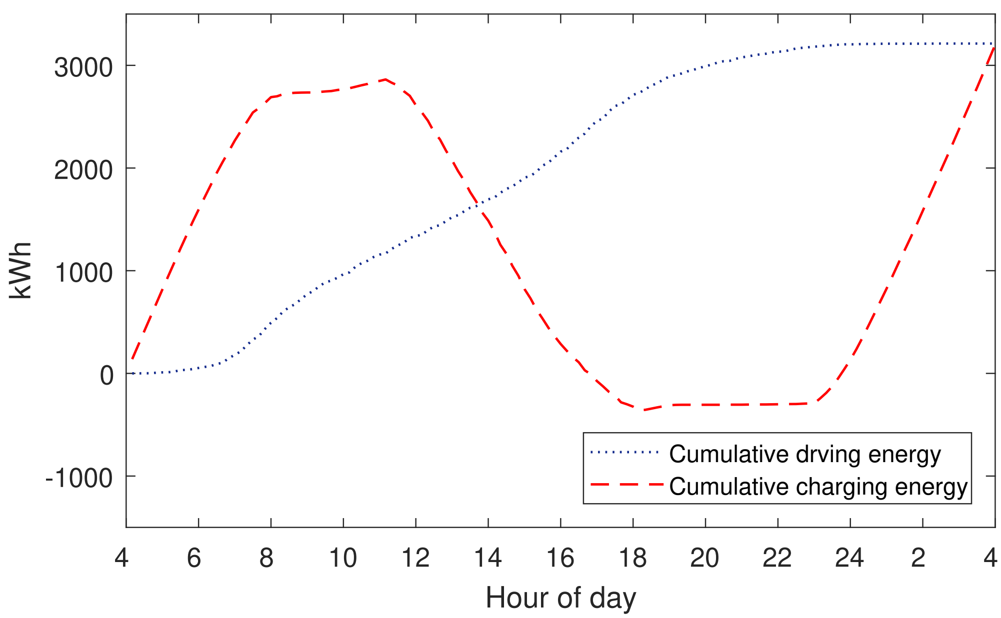

Figure 10. Cumulative driving energy vs. cumulative charging energy

5.2.3 Imminent knowledge

In practice, customers cannot be expected to report their entire day's travel activity and energy needs and adhere to it precisely. It is more reasonable to assume that each customer only reports the trip information or charging needs for the very next trip. The flexibility beyond the next trip is assumed to be zero when making charging control decision. We have repeated the simulation using the proposed smart charging where the charging flexibility is characterized based on only the very next trip information for both EVSE scenarios. The updated results are plotted in

Figure 11. In perfect knowledge case, most PEVs can be discharged during peak hours and are expected to be charged later. In this case, with charging flexibility information only from current time step to the departure time of next trip, many PEVs are not discharged during peak hours in order to meet required charging energy within limited parking period. Without discharging operation during peak hours, the capability of PEV fleet to raise load during off-peak hours also decreases. Therefore, the system peak demand is much increased compared with the perfect knowledge case. Nevertheless, compared with the non-PEV load, the peak demand is still reduced by 5.93% in the "EVSE only at home" scenario and 7.21% in the "EVSE everywhere" scenario. The difference between the peak demand and base load is reduced by 21.24% for the "EVSE only at home" scenario and 21.79% for the "EVSE everywhere" scenario compared with the non-PEV load. This is still very impressive and is indicative of the benefits of including PEV charging flexibility in grid operations even with limited knowledge of future charging demands. The peak demand together with the difference between peak demand and base load are summarized in Table 4.

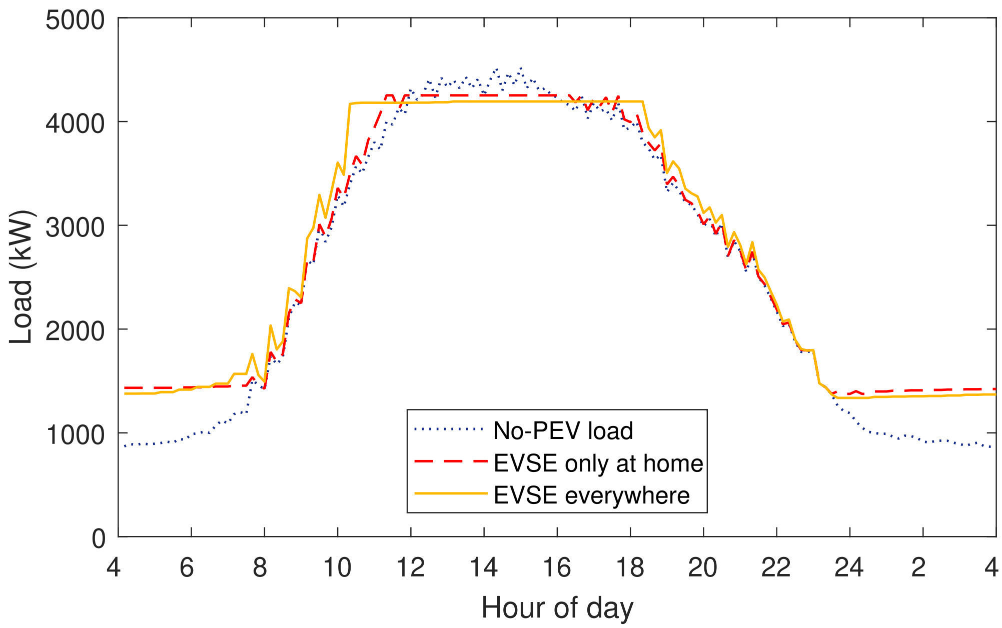

Figure 11. System load from smart charging with imminent knowledge

5.2.4 Smart charging with varying look-ahead window

The choice of the look-ahead window size H_w, which represents how far into the future the charging coordination is performed, affects the performance of the proposed smart charging method. Smart charging of PEVs has been simulated for both EVSE infrastructure scenarios with varying values of H_w as the MPC look-ahead window for an entire day for the "EVSE only at home" scenario. The peak demand reduction percentage is plotted in Figure 12, and the reduction percentage of the difference between peak demand and base load is plotted Figure 13. Both are with respect to non-PEV load. It shows that with an increase in prediction horizon, the solution becomes more optimal until it reaches a saturation point beyond which no more savings can be obtained. This trend is indicative of a sweet spot for the selection of H_w beyond which

Table 4. Peak demand and difference between peak (maximum) and base load (minimum)

Case	**Scenario**	**Peak demand**		**Peak minus base load**	
		(kW)	change (%)	(kW)	change (%)
Uncontrolled charging	1	4814	6.50	3944	7.97
	2	4832	6.90	3960	8.40
Smart charging perfect knowledge	1	3827	-15.33	2032	-44.37
	2	3563	-21.17	1542	-57.79
Smart charging imminent knowledge	1	4252	-5.93	2877	-21.24
	2	4194	-7.21	2857	-21.79

additional information on PEV flexibility and system, and increased computational complexity and communication burden are unnecessary.

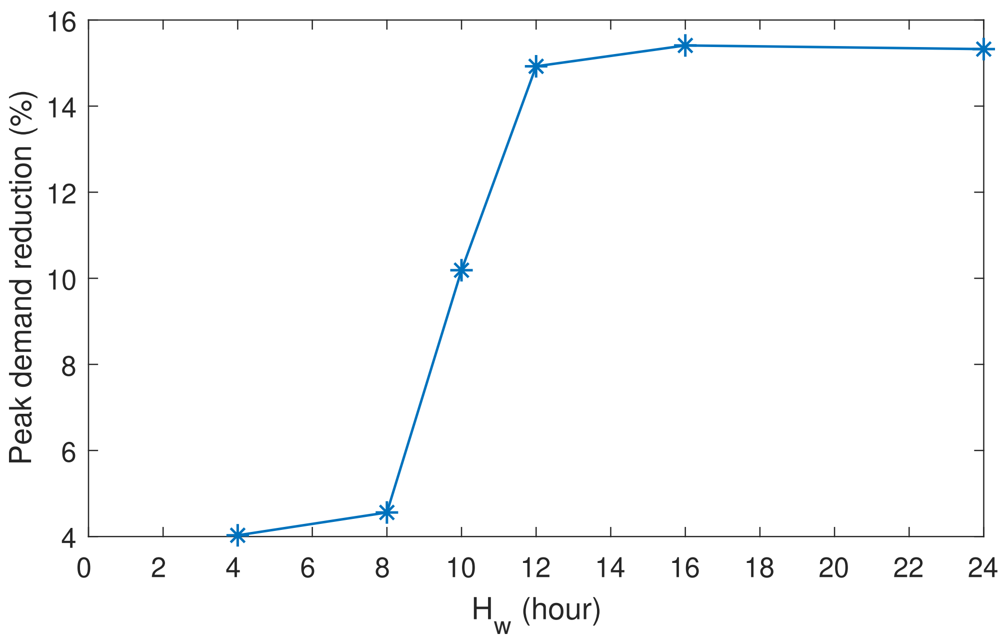

Figure 12. Peak demand reduction percentage with varying H_w in scenario 1

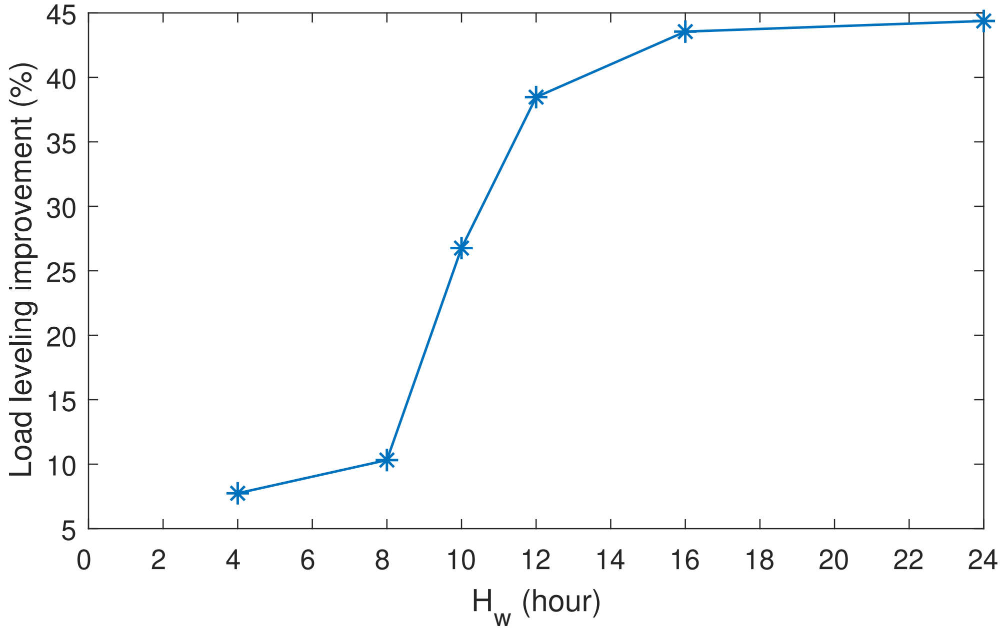

Figure 13. Load leveling improvement percentage with varying H_w in scenario 1

6.0 Conclusions and Future Work

In this project, we have proposed a PEV mobility and charging availability model to capture PEV characteristics, EVSE charger rating, driving energy requirement, and parked and departure times, etc. Based on the mobility and charging availability model, optimization-based method are proposed for offline evaluation of PEV charging coordination strategies. The proposed method is used to study the loading condition of a distribution system with a medium penetration of PEVs, considering different charging strategies and different levels of public EVSE availability. Insights on different charging strategies and public EVSE utilization are provided. It is found that flexibility from PEVs can be effectively utilized to shape system load through coordinated charging. The addition of public EVSE as a supplement to home charging can further reduce peak load, but to a limited extent for a medium congested system.

In addition, we have developed a simple yet powerful control method for effectively coordinating PEV charging/discharging to provide grid services. The proposed method consists of two types of control agents: local EVSE controllers and a central coordinator. Each local EVSE controller takes in information on PEV, EVSE, and customers' driving needs to construct a simple charging flexibility model, which is equivalent to the comprehensive mobility and charging availability model for charging control. The central coordinator takes the flexibility models and formulates and solves the optimal charging power allocation problem. Compared with the existing methods based on the comprehensive mobility model, the proposed method can help to reduce computational complexity at the central coordinator and communication requirements between the EVSE and the central coordinator. It is also robust to uncertainties in system load and charging demand, and scalable as numbers of PEV and EVSE increase. The case studies using a practical test system and realistic travel patterns showed that the proposed method can effectively coordinate PEV charging for load management while meeting PEV owners' travel needs. The flexibility potential from a PEV fleet and the capability for load leveling depend on PEV owners' participation in smart charging program. Developing incentive mechanisms and business framework for PEV owners to participate in a smart charging program is one of our future plans. Another interesting task is to evaluate the technical and economic performance of the proposed method for various single and multiple grid services. Additionally, a stochastic optimization will be performed in the future to explicitly use uncertainty information on system load and PEV trips for PEV charging coordination.

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