Incorporating Residential Smart Electric Vehicle Charging in Home Energy Management Systems

Preprint

Michael Blonsky, Prateek Munankarmi, and Sivasathya Balamurugan

National Renewable Energy Laboratory

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Incorporating Residential Smart Electric Vehicle Charging in Home Energy Management Systems

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***Abstract*—Electric vehicles (EVs) are expected to drastically increase residential electricity consumption and could provide a significant source of flexible demand. Aggregating smart EV charge controllers with other smart home devices through a home energy management system can lead to more optimal outcomes that benefit homeowners, utilities, and grid operators. Control strategies should consider occupant convenience by accounting for the need for fully charged EVs near the EV departure time. In this paper, we develop an EV charging framework that accounts for occupant convenience using OCHRE, a residential energy model, and foresee, a home energy management system. We simulate a community with high EV penetration and show that integrated, smart EV charging reduces peak demand and smooths night-time energy consumption. Simulation results show that the proposed control strategy nearly eliminates peak period EV charging and reduces the daily peak demand from EVs by 23%.**

I. Introduction

Demand for electric vehicle (EV) charging is an increasingly important factor when considering the design of the future electric grid. Globally from 2020 to 2030, the EV market share of new car sales is projected to increase from 2.7% to 28%, and total EVs on the road are projected to increase from 8.5 to 116 million vehicles [1]. By 2040, passenger EVs are projected to consume 1,290 TWh globally [1]. The U.S. Department of Energy indicates that 80% of EV charging is done at home due to the convenience and low cost of residential charging [2], which could cause a substantial increase in residential electricity demand.

There are many benefits of vehicle electrification, including reduced emissions, lower operating costs, and less dependence on fossil fuel resources. However, a rapid increase in electricity demand may cause issues in the design and operation of residential distribution networks. Increased demand from electrification lowers distribution voltages and may increase peak demand, both of which could lead to additional system upgrades [3]. Increasing peak demand is a particularly significant concern given the timing of EV charging (typically in the evening) when there is no coordination of EV charging and when faster (i.e., Level 2) charging is considered [4].

The coordination and control of flexible devices using home energy management systems (HEMS) can help alleviate these issues by shifting when electricity is used. Studies with HEMS consistently show cost savings to the occupant [5], [6], and peak power reductions [7]–[9]. The most common control technique used for HEMS is model predictive control (MPC) for thermostatically control loads including heating, ventilation, and air conditioning (HVAC) and water heating equipment [10].

Many studies have shown the benefits of residential EV charging control coupled with other controllable devices. Some papers use a coordinated approach for an aggregation of EVs within a region to reduce peak demand or provide ancillary services to the grid [11], [12]. Others include similar control strategies for commercial charging stations with multiple EV chargers [13]–[15]. Studies that focus on a single household tend to use mixed-integer linear program (MILP) optimization to dispatch flexible devices and a hard constraint for the EV state of charge (SOC) at the departure time [16]–[18]. Mirakhorli and Dong [19] use MILP for a HEMS that considers energy costs as well as soft constraints for indoor air temperature, hot water temperature, and EV SOC. To the knowledge of the authors, there are no studies of HEMS with residential EV charging that include costs in the objective associated with the convenience of having a fully-charged EV at or near the EV departure time.

In this paper, we integrate a novel EV charging control with an existing residential energy model, OCHRE [20], and an existing HEMS, **foresee**™ [5]. The HEMS uses quadratic programming to control an EV, HVAC system, water heater, photovoltaic (PV) system, and battery. It incorporates occupant behavior for the EV control by incurring a cost when the EV is not fully charged at or near the departure time. We simulate a community with a variety of building properties, equipment types, and vehicle charging levels and show the benefits of the HEMS control on occupant costs with a time-of-use rate and a demand charge. Specifically, our key contributions include:

- A detailed residential EV charging model that handles delayed charge control signals and that integrates with a comprehensive building model
- The integration of a demand charge and a cost term for user discomfort due to low EV SOC into a HEMS framework
- Simulation results showing an improvement in energy consumption profiles due to smart EV charging with the HEMS

We outline the energy modeling framework in Section II and the HEMS control architecture in Section III. Section IV shows the simulation results including a validation of the EV model. We conclude with additional considerations and areas for future work.

II. Residential Energy Model

In this section, we describe the methods used for residential energy modeling and the electric vehicle modeling. We use the OCHRE model and provide more details on the EV model and its controllability.

A. Building Model

The Object-Oriented, Controllable, High-Resolution Residential Energy (OCHRE) Model [20] is a physics-based residential energy model that integrates with home energy management systems. It includes controllable device models for HVAC equipment, water heaters, EVs, PV, and batteries. Below, we outline the key features of the model used in this paper; for more information, we refer the reader to [20].

OCHRE creates a white-box multi-node linear thermal model for the building envelope for each house. Parameters are derived from the thermal properties of the building materials. The building envelopes for each house simulated in this paper include a main indoor zone and an attic. The houses vary in insulation levels, number of occupants, building orientation, and type and size of equipment, all of which impact the dynamics of the zone temperatures.

The houses in the simulated community include many HVAC equipment types, including electric and gas furnaces, gas boilers, electric baseboards, and air source heat pumps. Air source heat pumps and all other cooling equipment use a biquadratic equation from [21] to dynamically calculate capacity and efficiency. The other HVAC equipment types are modeled with a constant heating capacity and heating efficiency. All HVAC equipment include a thermostat control with a deadband and are sized using Manual J [22]. Each house also includes either a gas or electric water heater. Some homes have a tank water heater with a thermostat control, and others have tankless water heaters that are modeled as ideal devices that instantly heat the hot water to the setpoint temperature.

The PV model is based on the System Advisor Model (SAM) [23], which uses multiple weather inputs to determine the PV generation profile. For the houses in this paper, PV system tilt angles are equal to the house's roof pitch, and orientations are randomly chosen to face east, southeast, south, southwest, or west. The battery model accounts for the battery state of charge and separate efficiency values for charging and discharging.

B. EV Charging Model

The EV model combines a standard battery model with a random parking event generator using residential parking survey data. The data set is taken from the Electric Vehicle Infrastructure Projection (EVI-Pro) [24] based on a vehicle travel study in California [25]. A parking event is characterized by three parameters: the arrival time k_0, departure time k_{end}, and arrival state of charge SOC_0. Events are sampled by day, with at least one event occurring on each day. EVI-Pro assumes that the EV is fully charged at the beginning of each day (i.e., the first departure time of the day). The set of events used for the random sampling varies by day according to the following parameters [24]:

- EV Type: Plug-in hybrid (PHEV) or Battery (BEV) options. PHEVs tend to deplete a larger percentage of their battery than BEVs, leading to lower values for SOC_0.
- EV Battery Capacity: EVs with larger batteries can drive further, but tend to use less energy relative to the battery capacity, leading to higher values for SOC_0. PHEVs are split into small and large sizes based on a threshold of 35 mile range (or 11.4 kWh capacity). BEVs are split based on a threshold of 175 mile range (or 56.9 kWh).
- Charging Level: Level 1 (1.4 kW) or Level 2 (3.6 kW for PHEV, 9.0 kW for BEV) options. EVs with Level 1 chargers tend to charge more often, leading to more parking events per day compared to the same EV with a Level 2 charger.
- Average Daily Temperature: EVs tend to use more energy on days with very high temperatures (due to air conditioning use) and days with very low temperatures (due to lower battery efficiency), leading to lower values for SOC_0. The data are split into 5°C increments from -20°C to 40°C.
- Day of Week: Weekday and weekend options. EV parking times follow different patterns for weekdays and weekends. Weekdays tend to have fewer parking events.

Fig. 1 and Fig. 2 show the distribution of weekday parking events in the EVI-Pro data set for a large PHEV and a small BEV, respectively. Both vehicles have about 34,000 days of parking events in the data set. The majority of parking events are overnight events with an arrival time between 4:00 PM and 8:00 PM and a departure time between 6:00 AM and 10:00 AM the next day. The arrival SOC is typically greater than 70% for BEVs; for PHEVs, the arrival SOC is significantly more variable, and 9% of events have an arrival SOC of 0%.

The EV model tracks the EV battery SOC using:

$$\begin{aligned} SOC(k+1) &= SOC(k) + \frac{t_s \eta_{ev}}{\kappa_{ev}} P_{ev}(k) \\ SOC(k_0) &= SOC_0 \end{aligned} \tag{1}$$

where t_s is the time resolution, η_{ev} is the efficiency of charging, κ_{ev} is the battery capacity, and P_{ev} is the AC power input to the EV charger. When charging without any external control, the EV begins charging at k_0 at its maximum power, accounting for the power limits and SOC limits. The EV input power is calculated as:

$$P_{ev}(k) = \begin{cases} \min(\frac{\kappa_{ev}}{t_s \eta_{ev}}(1 - SOC(k)), P_{max}) & k_0 \le k < k_{end} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where P_{max} is the maximum EV charging power. Note that the maximum SOC is assumed to be 100%.

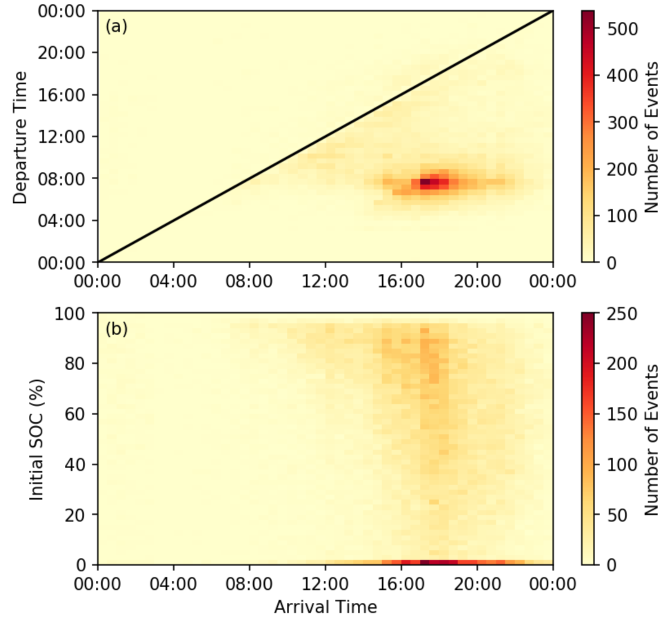

Fig. 1. Heatmap of parking events used for a PHEV with a large battery capacity and Level 1 charging on weekdays. Shows the distribution of arrival time of day with (a) departure time of day (events in the bottom right half correspond to overnight events) and (b) arrival SOC.

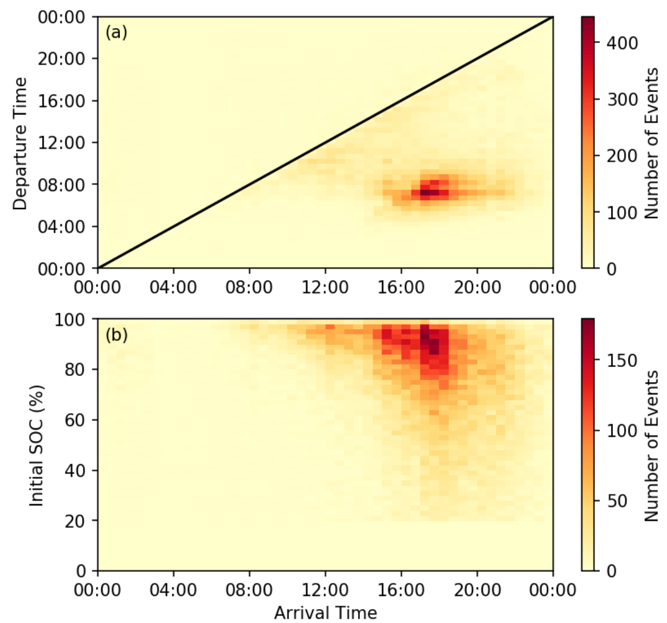

Fig. 2. Heatmap of parking events used for a BEV with a small battery capacity and Level 2 charging on weekdays. Shows the distribution of arrival time of day with (a) departure time of day (events in the bottom right half correspond to overnight events) and (b) arrival SOC.

The EV model can be controlled by directly setting P_{ev} or by updating k_0 in (2), which leads to a delay in the EV charging start time. Level 1 charge controllers are set to update k_0, and Level 2 chargers can update k_0 or directly set P_{ev}.

Each day of parking events is considered to be independent of the events before and after it. However, in some instances the departure time of one parking event is very close to, and may overlap with, the arrival time of the next event. The model checks for these overlaps and, when necessary, will move the departure time of a parking event earlier to ensure at least a 1-hour gap between each parking event.

The arrival SOC of the EV is also impacted by the previous charging event if a control signal impacts the SOC on departure. When the departure SOC is less that the maximum departure SOC, the arrival SOC is reduced by the same amount, if possible:

$$\begin{aligned} SOC^e_{max} &= \min(SOC^e_0 + \frac{t_s \eta_{ev}}{\kappa_{ev}}(k^e_{end} - k^e_0)P_{max}, 1) \\ SOC^{e+1}_0 &= \max(SOC'^{e+1}_0 - (SOC^e_{max} - SOC^e_{end}, 0) \end{aligned} \tag{3}$$

where e is the event index, SOC^e_{max} is the maximum possible departure SOC from the previous event, SOC^e_{end} is the actual departure SOC from the previous event, and SOC^{e+1}_0 is the updated arrival SOC for the next event.

The full procedure for the EV model is outlined in Fig. 3.

III. Control Architecture

This section outlines the architecture for controlling flexible loads in the OCHRE model. We give an overview of **foresee**, a HEMS, and then describe the EV control methodology in detail.

A. Home Energy Management System

foresee is a HEMS capable of coordinating various behind-the-meter (BTM) resources in residential homes including PV, batteries, HVAC equipment, and water heaters in response to a time-varying tariff or utility signal. **foresee** is formulated as a multi-objective MPC problem and determines the optimal schedule for all the BTM resources simultaneously. The details regarding the formulation of **foresee** can be found in [5] and [26].

Without EVs, the objective of **foresee** includes minimization of the total energy cost, user discomfort associated with indoor air temperature and hot water temperature, and battery degradation. Mathematically, the objective is represented as:

$$\min \sum_{t=k+1}^{k+n_k} J(t) \tag{4}$$

where k is the current time, n_k is the horizon length, and:

$$\begin{aligned} J(t) =& b_m \lambda(t) P_{house}(t) \\ &+ b_{air}\big((T_{air}(t) - T^{max}_{air})^2 + (T^{min}_{air} - T_{air}(t))^2\big) \\ &+ b_{wh}\big((T_{wh}(t) - T^{max}_{wh})^2 + (T^{min}_{wh} - T_{wh}(t))^2\big) \\ &+ b_{batt}\big(P_{ch}(t) + P_{dis}(t)\big) \end{aligned} \tag{5}$$

where $J(t)$ is the cost function at future time t, $\lambda(t)$ is the time-varying utility rate, $P_{house}(t)$ is the net power of the building, $T_{air}(t)$ and $T_{wh}(t)$ are the indoor air temperature and water heater tank temperature, $P_{ch}(t)$ and $P_{dis}(t)$ are the battery charging and discharging power, and $\{b_m, b_{air}, b_{wh}, b_{batt}\}$

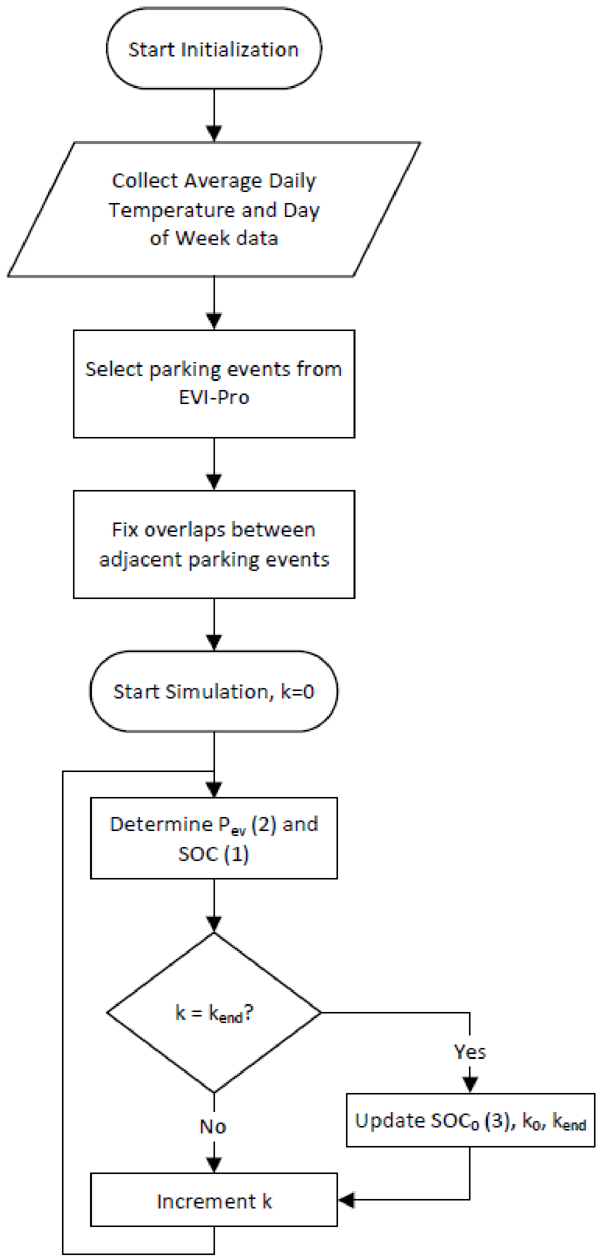

Fig. 3. Flow chart for EV model initialization and simulation.

are the weighting factors for multiple objective functions. The comfort bands for indoor air temperature and hot water temperature are represented by $(T_{air}^{min}, T_{air}^{max})$ and $(T_{wh}^{min}, T_{wh}^{max})$ respectively. The optimization problem is subject to house power constraints and constraints for each equipment. Constraints are described in detail in [5] and [26].

B. EV Charge Control

With EVs, the objective of **foresee** is modified to include minimization of the user inconvenience associated with a low EV SOC near the EV departure time. Mathematically, it can be represented as:

$$\min \sum_{t=k+1}^{k+n_k} J(t) + J_{ev}(t) \tag{6}$$

with:

$$J_{ev}(t) = \begin{cases} b_{ev}(1 - SOC(t)) \frac{t-k}{k_{end}-k} & k_0 \le t < k_{end} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where b_{ev} represents the weighting factor for the inconvenience of low EV SOC. The penalty term J_{ev} increases linearly as t approaches the departure time k_{end}, and also increases as the current time k approaches k_{end}. It is always non-negative because $t > k$ as shown in (6).

EV constraints include:

- EV model constraint: The EV model in (1) describes the relationship between SOC and EV charging power P_{ev}.
- EV charging power constraint:

$$\begin{cases} 0 \le P_{ev}(t) \le P_{max} & k_0 \le t < k_{end} \\ P_{ev}(t) = 0 & \text{otherwise} \end{cases} \tag{8}$$

  This limits the charging power $P_{ev}(t)$ between 0 and the maximum charging power P_{max} when the EV is available for charging in the home. When the EV is not available for charging, the EV charging power is set to 0.
- EV SOC constraint:

$$SOC_{min} \le SOC(t) \le SOC_{max} \tag{9}$$

  This maintains the EV SOC between minimum (SOC_{min}) and maximum (SOC_{max}) EV SOC limits.

For the EV control, **foresee** receives the current EV SOC and the arrival and departure times from the OCHRE model. It then computes the optimal charging setpoint $P_{ev}(k+1)$ and sends the setpoint to OCHRE to be implemented at the next time step.

C. Demand Charge Control

We add an additional term to the objective to reduce the peak demand of the home. This term is beneficial for incorporating the costs of a demand charge on the customer utility bill or for reducing peak demand for more efficient distribution system operations. The objective function is modified as below:

$$\min \sum_{t=k+1}^{k+n_k} J(t) + J_{demand} \tag{10}$$

with:

$$J_{demand} = b_m \max(\max_{t \in [k+1, k+n_k]} (P_{house}(t)) - P_{peak}(k), 0) \tag{11}$$

$$P_{peak}(k) = \max(P_{peak}(k-1), P_{house}(k)) \tag{12}$$

where $P_{peak}(k)$ is the maximum house demand for the demand charge period up to and including time k. Note that (11) uses forecasted values for P_{house}, whereas (12) uses actual house power to update the peak power at each time step.

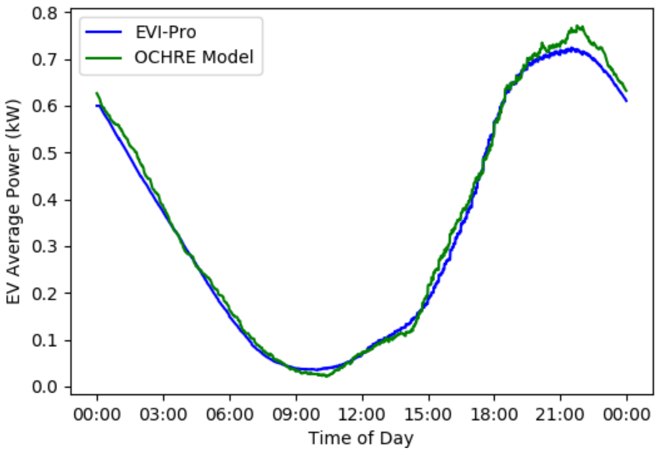

Fig. 4. Daily load profile comparison for a 50-mile PHEV with a Level 1 charger.

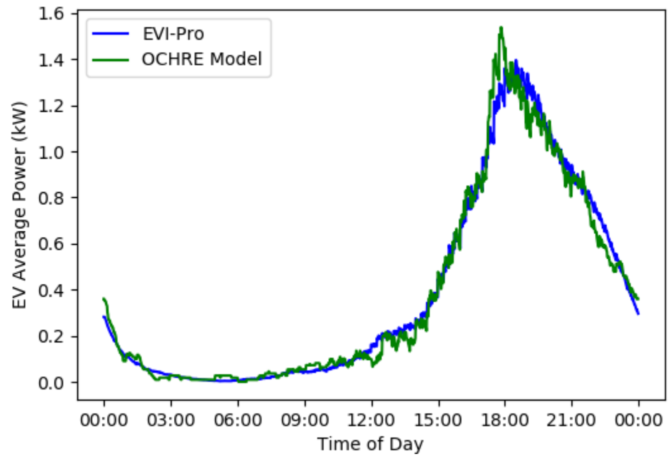

Fig. 5. Daily load profile comparison for a 100-mile BEV with a Level 2 charger.

IV. Results

This section presents results using the proposed model and controller. We first show validation results comparing the EV model with EVI-Pro. We then show simulation results with multiple control strategies to show their impacts on peak load reduction with a focus on EV peak demand.

A. EV Model Validation

We validate the OCHRE EV model to ensure that the daily load profile is similar to the profile from EVI-Pro. Profiles are generated for each vehicle type and size, charging level, ambient temperature bin, and day of week option (see Section II-B for details). OCHRE was run for 1000 days at 1-minute resolution. The weekday and ambient temperature were held constant for validation purposes.

Fig. 4 and Fig. 5 show the daily load profiles for a 50-mile PHEV with a Level 1 charger and a 100-mile BEV with a Level 2 charger during weekdays at 15°C, respectively. OCHRE estimates a slightly larger peak for both profiles, which is likely due to the effects of random sampling. The root-mean-square error is about 0.02 kW for the PHEV and 0.05 kW for the BEV.

B. Simulation Inputs

We simulate a community with high EV penetration under multiple control strategies to reduce peak demand from EVs. The simulations were run using Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) [27], an agent-based co-simulation framework. House models and HEMS were each simulated as separate agents and the house status and HEMS controls were communicated using the HELICS message bus.

Simulations were run for one week at a 1-minute time resolution. The HEMS operated at a 15-minute time resolution. Using the National Renewable Energy Laboratory's high-performance computing system [28], the baseline and the basic control scenarios took approximately 2 minutes and the HEMS-based scenarios took approximately 9 minutes to complete.

The simulated community consists of 50 residential homes, each with a different level of insulation and a different set of equipment. The house models were generated using ResStock™ [29], which contains probability distributions of residential building characteristics across the entire U.S. We use the distributions for an area near Washington D.C. to come up with a series of typical building models to represent the community. Each day of the simulation had an average daily temperature between 25 and 30 °C.

We assume the 50-home community includes 13 PHEV with Level 1 chargers and 12 BEV with Level 2 chargers. PHEV size ranges from 20 to 50 miles, and BEV size ranges from 100 to 250 miles. For the control scenarios with **foresee**, the Level 1 chargers were turned off when $P_{ev} < \frac{P_{max}}{2}$ and on when $P_{ev} \geq \frac{P_{max}}{2}$. The Level 2 chargers followed the control signal exactly.

PV and battery sizes were designed to simulate a community with high levels of DERs and minimal community-level grid export. The community includes a total of 162 kW of PV, split among 30 of the 50 homes. Batteries are included in 20 homes; 10 homes have a 3kW/6kWh battery and 10 homes have a 6kW/12kWh battery.

C. Baseline Results

A baseline scenario was run to show the community power with no controls. Fig. 6 shows the total community power by end use for three simulation days, two weekdays followed by one weekend day. Air conditioning accounts for most of the load, and PV generation significantly reduces daytime load, but not enough to cause net export of the community.

Fig. 7 shows the total community power with a basic delayed EV charge control. The EV charging was delayed by up to 5 hours to reduce load during the peak period from 2 P.M. to 7 P.M. The EV power shifted from the afternoon to the evening to reduce the peak load. The on-peak maximum

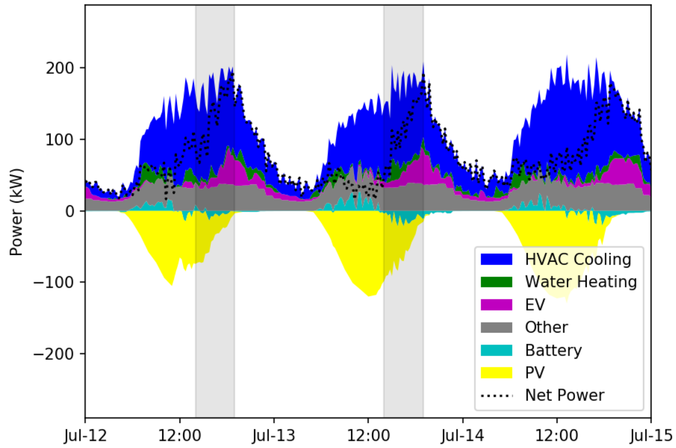

Fig. 6. Stacked plot of total community power by end use for the baseline scenario without controls. Net power combines all loads, PV, and battery power.

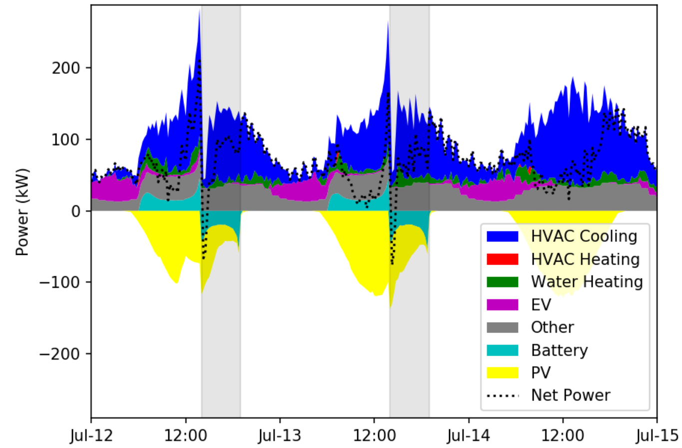

Fig. 8. Stacked plot of total community power by end use for the scenario with **foresee** controls and a TOU rate. Net power combines all loads, PV, and battery power.

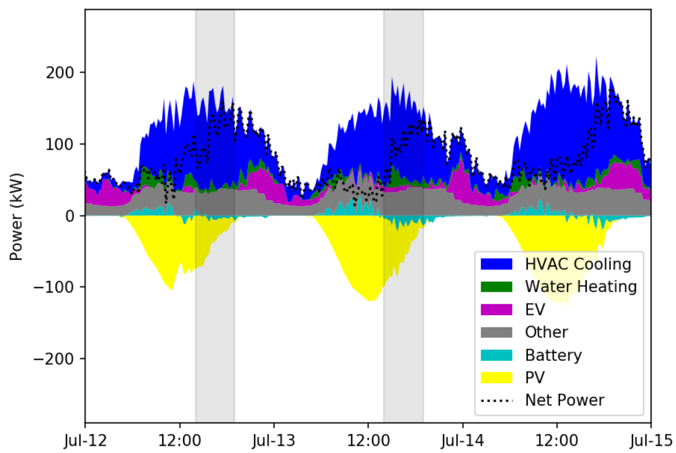

Fig. 7. Stacked plot of total community power by end use for the basic EV delay scenario. Net power combines all loads, PV, and battery power.

demand (averaged across all days of the simulation) reduced from 178 kW to 156 kW. However, the average daily EV peak demand increased from 43 kW to 45 kW (see Fig. 9), indicating that this control scheme may lead to a spike in demand in the evening.

D. HEMS Control

We next run a scenario with the same community, using **foresee** as the control system. The HEMS uses (6) with a time-of-use (TOU) rate from the local area with a peak period from 2 P.M. to 7 P.M on weekdays and a peak-to-off-peak price ratio of 4.875 [30]. Regarding the user-preferences in **foresee**, cost-saving had highest preference ($b_m = 0.35$) followed by EV discomfort ($b_{ev} = 0.27$), air temperature discomfort ($b_{air} = 0.19$), hot water discomfort ($b_{wh} = 0.13$), and battery degradation ($b_{batt} = 0.06$).

Fig. 8 shows the results of this scenario for the same three days. The HVAC and battery profiles change considerably, and the EV profile shifts to later in the evening. The EV tends to charge when the HVAC and other load powers are low to reduce any demand spikes. The peak demand increases due to HVAC load before the peak period, but the on-peak maximum demand decreases considerably, from 178 kW in the baseline case to 120 kW in the HEMS case.

A comparison of the EV profiles from all scenarios is shown in Fig. 9. The baseline scenario has a considerable EV usage during the peak period, and all control scenarios are able to shift that consumption to later in the day. The HEMS scenarios (TOU and Demand) shift the consumption later than the basic delay control, and are able to reduce the daily average on-peak maximum demand from 12 kW (in the basic control case) to 1.2 kW.

The HEMS scenarios also reduce the average daily peak demand due to EVs (at 15-minute resolution) from 45 kW to 34 kW, a 23% reduction. This reduction is critical when considering an increase in residential EV adoption. As EV charging becomes a significant portion of residential energy consumption, smoother EV charging profiles will reduce peak demand and allow for more efficient grid operations.

E. Demand Charge Control

We run a fourth scenario with **foresee** controls using an additional demand charge term as described in (10). We use the same TOU rate and a demand charge of $10 per kW. As shown in Fig. 9, the EV profile is very similar to the profile from the HEMS scenario without a demand charge. There were some differences in the results at the beginning of the simulation, but fewer differences near the end of the simulation.

The demand charge does not have a significant effect on the EV controls because EV consumption does not often coincide with the peak demand. Residential peak demand tends to occur in the afternoon in the summer when air conditioning loads are high, and EV charging tends to occur later in the evening. Once the peak demand P_{peak} is set at a high level, the demand charge term J_{demand} does not significantly impact the control strategy. It is likely that this control would have a larger effect

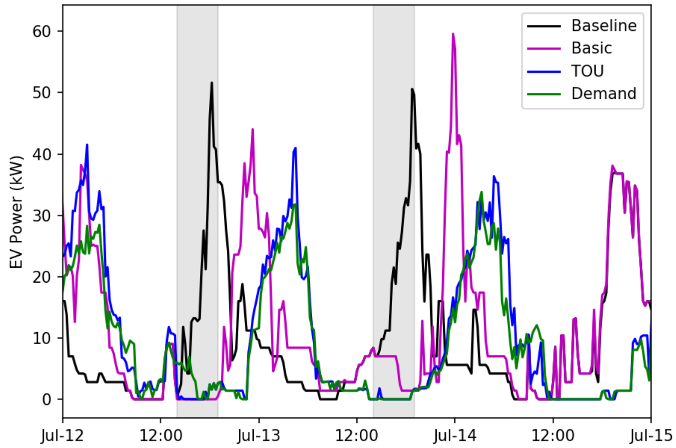

Fig. 9. Total EV power in the community for all scenarios.

on EV charging when EV loads contribute more to the peak demand, for example during times and locations with less HVAC demand.

V. Conclusion

In this paper, we develop a framework for modeling and controlling residential smart EV chargers. The EV charging model accounts for vehicle and charging parameters, ambient conditions, and dependencies between adjacent charging events. The EV control architecture integrates with **foresee** and accounts for the inconvenience cost of having a low state of charge close to the departure time. Simulation results show that the proposed controller reduces peak period energy consumption and lowers the peak demand associated with EV charging.

We note that EV charging, as well as other residential load controllers, depends significantly on occupant behavior and other stochastic variables that are difficult to estimate in real-world applications. We recommend field testing and validation to better understand the control performance when some variables, for example EV arrival SOC and departure time, are less certain. Additional improvements to the modeling and control framework include accounting for uncertainty in these variables, incorporating real device constraints, and testing the framework under different occupancy and climate conditions.

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