Predictive Scheduling for Electric Vehicles Considering Uncertainty of Load and User Behaviors

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***Abstract*—Un-coordinated Electric Vehicle (EV) charging can create unexpected load in local distribution grid, which may degrade the power quality and system reliability. The uncertainty of EV load, user behaviors and other baseload in distribution grid, is one of challenges that impedes optimal control for EV charging problem. Previous researches did not fully solve this problem due to lack of real-world EV charging data and proper stochastic model to describe these behaviors. In this paper, we propose a new predictive EV scheduling algorithm (PESA) inspired by Model Predictive Control (MPC), which includes a dynamic load estimation module and a predictive optimization module. The user-related EV load and base load are dynamically estimated based on the historical data. At each time interval, the predictive optimization program will be computed for optimal schedules given the estimated parameters. Only the first element from the algorithm outputs will be implemented according to MPC paradigm. Current-multiplexing function in each Electric Vehicle Supply Equipment (EVSE) is considered and accordingly a virtual load is modeled to handle the uncertainties of future EV energy demands. This system is validated by the real-world EV charging data collected on UCLA campus and the experimental results indicate that our proposed model not only reduces load variation up to 40% but also maintains a high level of robustness. Finally, IEC 61850 standard is utilized to standardize the data models involved, which brings significance to more reliable and large-scale implementation.**

Keywords—EV Scheduling; Predictive Control; IEC 61850; Renewable Energy Integration;

I. INTRODUCTION

Electric Vehicle and corresponding charging infrastructure have received much attention in recent years due to the lack of fossil fuel and pressure from government to reduce carbon emission[1]. The initiative from California government, 1 million zero-emission EVs are expected to be on road by 2020[2]. Accordingly, there will be more Electric Vehicle Supply Equipments (EVSEs) to be installed as the penetration of EV increases in the foreseeable future. Un-coordinated Electric Vehicle charging can create unexpected load in local distribution grid, which may degrade the power quality and system reliability[3]. Many pioneer researches[5],[10]-[14] on advanced charging infrastructure, including both software and hardware that are developed to facilitate the acceptance of EVs. However, it is still a challenging task to regulate numerous EV charging behaviors in real-time due to the following reasons: 1) the randomness of EV user behaviors, such as arrival time, departure time and energy demand; 2) complexity of stochastic models that describe the loads, renewables and EVs. Thus, more efforts should be made to design a real-time energy scheduling system that considers the above factors.

Previous researches have proposed several viable scheduling schemes for deferrable load control. An optimal distributed charging protocol is designed and implemented in simulations with a large number of EVs in [4]. Valley-filling and load-following strategies are proposed to provide grid-side regulations with deferrable EV load. However, these solutions assume static travel schedules for EV users without uncertainties, which is not true in reality. Price-based charging algorithm is designed and implemented with user preferences in [5]. Uncertainties of renewable generation and EV load are considered in [6]-[9]. [7] utilizes receding horizon scheduling techniques based on MPC to handle uncertainties of EV arrival and renewable generation periodically. In addition, in [7] a proof for optimality is provided given the Gaussian noise of baseload. However, the estimation for the short-term EV energy demand is derived from a simple assumption rather than from real-world EV energy consumption data, which undermines the problem formulation and the simulation results. The power consumptions for different EVSEs are also assumed to be un-correlated and no power sharing scheme exists. The EVSE[10] designed and manufactured by UCLA Smart Grid Energy Research Center (SMERC) has the capacity to allow multiple charging sessions at the same time by power-sharing and current-multiplexing circuit design. Event-based scheduling algorithms, considering random user behaviors are developed in [11]. Vehicle-to-Grid and Vehicle-to-Building services[12],[13] are developed for various EV energy consumption scenarios. Accordingly, smart EV charging algorithms are designed to support more complex functions that satisfy both EV energy demand and also provide grid-side services, such as load flattening and load following.

In this paper, we proposed a new real-time EV charging scheduling algorithm inspired by MPC, which is designed and simulated in a micro-grid scenario, including building load, solar generation and EV load. A dynamic load estimation and a predictive optimization module are implemented to handle the uncertainties in system. The contributions of this paper can be summarized as: 1) Current-multiplexing is considered in the problem formulation and accordingly a virtual load for each EVSE is modeled to simulate the uncertain short-term EV energy demand. 2) Dynamic estimation method based on K-nearest neighbor (KNN) are utilized for charging session parameters. 3) Online predictive optimization method based on MPC is formulated, considering the uncertainties of building load and user behaviors; 4) IEC 61850 is utilized to standardize

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the information exchange by modeling the data involved in this algorithm, which gives practical meaning to more reliable and large-scale implementation.

The rest of this paper is organized as follows: Section II discusses over system architecture. Section III introduces detailed problem formulation. Session IV discusses the experiment results and potential improvements. Finally, we conclude this paper in section V.

II. SYSTEM OVERVIEW

A. System Architecture

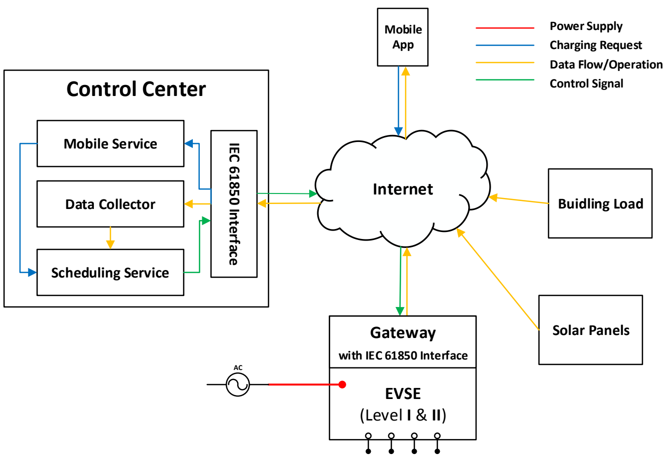

Fig. 1 System Overview

The proposed system architecture is illustrated in Fig. 1. In general, the system has 5 main components, i.e. EVSE, building load, solar generation, client mobile application and a control center. Real-time energy consumption data with user index and device ID are retrieved and transmitted through advanced communication networks [14] constructed within UCLA campus, and finally stored in a central database. EVSEs [5] are controllable by commands from scheduling service on server side or client mobile applications, via assigning different duty-cycles to different outlets that share the same power source from the grid. The mobile application can perform the remote control function for each EVSE in our system. Based on the real-time power data from all engaged buildings, solar generation sites, EVSEs and mobile charging requests, scheduling services are able to compute periodically for an optimal EV energy scheduling given dynamic estimation of short-term energy demand. The building load used here is from Cornell University Facilities Service[17] and the solar data is from UCLA Ackerman Union Solar Integration project[18]. To support reliable and large-scale implementation, IEC 61850 is implemented in EVSE gateways and the control center to encode/decode all the involved data and communication. This architecture has been tested by real EV users in UCLA and is friendly to more advanced charging algorithms.

B. EVSE with Current Multiplexing and Existing Algorithm

One distinguished feature of the EVSE developed by SMERC is power –sharing and current-multiplexing function. The power supply from grid can be split into multiple charging sessions based on users' preferences or control signals. The current assigned to each vehicle connected to the EVSE is proportional to the specified duty-cycle value in control signals. The duty-cycle ranges from 0 to 50% according to SAE J1772 standard. This design provides more flexibility for the algorithm to assign various current to different outlets due to varied energy demand and travel schedules. In current implementation, the existing charging algorithm is simply to check the real-time power consumption value and verify the connected vehicle is fully charged. Charging session will be closed and notification will be sent to users once the charging session is finished. By analyzing the monitoring records associated with each user's charging session, one can extract the historical data of energy demand and personal charging schedules, such as start time, end time and leave time, which will be utilized for the estimation of current charging session.

C. IEC 61850 Protocol and Integration

IEC 61850 is an international standard that provides a standardized framework that specifies the communication protocols, originally for power automation substation[15].The advantages include interoperability, free configuration and long-term stability[16]. A specialized IEC 61850 gateway is designed as communication interface for both control center and EVSE in our system. Data models, that include power information, EVSE status, charging requests and control signals, are all encoded as virtual components in xml-based messages to improve the system interoperability and reliability. Fig.2 is the schema view of communication and data modeling for EV system, based on IEC 61850 protocol.

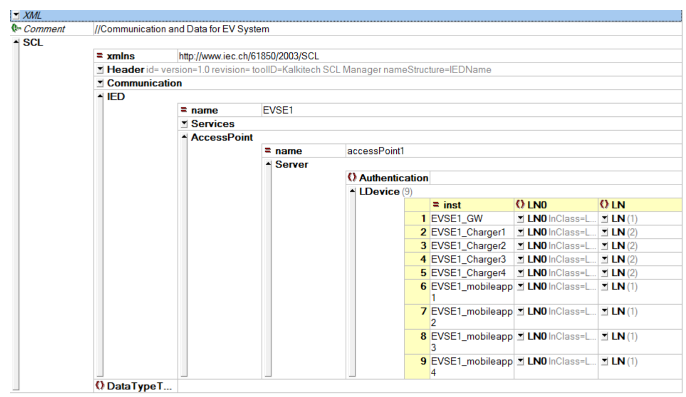

Fig. 2 Communication & Data Modeling using IEC61850

III. PROBLEM FORMULATION

A. Dynamic Parameter Estimation

The optimization method in this paper is inspired by MPC, which is an online optimization method and computes optimal scheduling across fixed steps in the future periodically, however just realize the first element in the schedule results. The procedure continues in every step, taking the updated system states into consideration. In our system, the optimization program needs to involve the estimations of leave time and energy consumption values for all the active charging sessions. Thus, proper estimation methods play a significant role in improving the system performance. The leave time and energy consumption values are estimated dynamically, using the following methods.

1) Session Parameter Estimation

Each charging session, with a number of properties values, such as user index, device ID and start time, finish time, leave time and energy consumption, are stored as a record in database. We model each record associated with a charging session as a tuple:

$$s \coloneqq (u_n, t_s, t_f, t_l, e, d)$$

where u is the user index for this session, d is the EVSE ID or power source ID. t_s, t_f denotes the start time and finish time for the charging session, respectively; t_l is the leave time; e denotes the energy consumption. K-nearest neighbor (KNN) method is utilized to estimate e and t_f. In general, KNN calculates the weighted mean of neighbor values, who are among top k smallest distances with input value. In our case, the start time and stay duration in qualified sessions with top k smallest distances with current session value are extracted from database and averaged with weights.

$$dis_{i,j} = \left\| s_i.t_s - s_j.t_s \right\| \tag{1}$$

$$w_i = \frac{dis_{k+1,j} - dis_{n,j}}{dis_{k+1,j} - dis_{1,j}} \tag{2}$$

where $dis_{i,j}$ denotes the distance between session s_i and session s_j; w_i *denotes weight of the* ith *session* s_j.

$$\hat{e}_n = \frac{1}{k} \cdot \sum_{i=1}^{k} w_i \cdot (s_i.e) \tag{3}$$

$$\hat{t}_{n,f} = t_{n,s} + \frac{1}{k} \cdot \sum_{i=1}^{k} w_i \cdot (s_i.t_l - s_i.t_s) \tag{4}$$

where $\hat{e}_n$ and $\hat{t}_{n,f}$ are estimations of energy consumption and stay duration; k denotes the total number of qualified sessions.

2) Virtual Load Estimation

Since the hardware we are modeling in this paper has the power sharing and current multiplexing function, it means that the charging schedules for vehicles connected to the same power source will interact with each other. If taking uncertainties of future EV energy demands into consideration, the proposed system models an additional virtual EV load for each power source to account for the potential deviation. For each EVSE, historical data are extracted to construct the estimation of future EV load demand. Two steps are needed for dynamic virtual load estimation, i.e. total demand estimation and real-time update for remaining demand. Total demand after time t can be computed offline for all charging sessions in one specific EVSE:

$$D_t^k = \frac{1}{M} \cdot \sum_{i=1}^{i=M} s_i.e \tag{5}$$

where the qualified session s_i is subject to $s_i.t_s = t$ and $s_i.d = k$.

Real-time EV energy demand will be updated based on current active charging sessions in power source k and their estimated energy consumptions. The update for virtual load is illustrated in the following equation:

$$t_{v,f}^k = \max(s_i.t_f) \tag{6}$$

$$e_v^k = \max(0, D_t^k - D_{t_f}^k - \sum_{i \in N} s_i.e) \tag{7}$$

The virtual load charging rate $r_v^k(t)$ for power source k is modeled as a regular EV load and will be input into the overall optimization problem.

$$0 \le r_v^k(\tau) \le r_v^{max}.\eta, \qquad \forall \tau \in [t, t_{v,f}^k] \tag{8}$$

$$\sum_{\tau=t}^{t_{v,f}} r_v^k(\tau) = e_v^k \tag{9}$$

B. Load Modeling with Uncertainties

1) Building Load and Solar Generation

The power consumption for the building and solar power generation cannot be exactly known in advance and there exists little variation between different days. In this paper, wiener filter and historical data are combined as a simple load predictor.

$$P_b(t) = P_b^e(t) + \overline{P_b(t)} \tag{10}$$

$$\overline{P_b(t)} = \overline{P_d(t)} - \overline{P_s(t)} \tag{11}$$

where $\overline{P_b(t)}$ denotes the average value of base load at the time t, which is the difference between average building power consumption value $\overline{P_d(t)}$ and the average solar generation value $\overline{P_s(t)}$. $\overline{P_d(t)}$ and $\overline{P_s(t)}$ can be simply obtained by averaging historical data for time t. The assumption for wiener filter is that the estimation error can be accumulated by previous steps[8] and thus, real-time error calculation is performed by:

$$P_{b,t}^e = \sum_{i=1}^{i=T} \xi(i) \cdot f(t-i), \quad \forall t \in [1, T] \tag{12}$$

where $P_{b,t}^e$ is the error between real base load and predicted average baseload at time t. ξ is an identically distributed random variable with *zero* mean and variance σ^2. f is the impulse response of a causal filter, with following form:

$$f(t) = \begin{cases} 0, & t < 0 \\ a^{-t}, & t \ge 0 \end{cases} \tag{13}$$

Thus, the prediction error for current time t is only the summation of the previous estimation errors with different weights. Note that $f(0) = 1$.

2) EVSE Model

Due to the characteristics of our EVSE design, more than one vehicle can share the power source at the same time, which means each charging session has separate constraints. For each connected vehicle, we use $r_n = \{r_{t_s}, r_{t_s+\Delta t}, r_{t_s+2\cdot\Delta t}, \dots, r_{t_f}\}$ to denote the power consumption rates from session start time t_s to session finish time t_f. Δt is the time step we use in this paper. The constraint for each charging session:

$$0 \le r_v^k(t) + r_n^k(t) \le r_k^{max}.\eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}] \tag{14}$$

where $r_n^k(t)$ is the power consumption rate for vehicle n, which is connected to power souce k, at time t. r_k^{max} is the maximum power supply for power source k; η is the safety coefficient for this power source. $\hat{t}_{n,f}$ denotes the estimated finish time for vehicle n.

For each power source (EVSE), the same limitation of total power consumption also applies:

$$0 \le r_v^k(t) + \sum_{n \in N_k} r_n^k(t) \le r_k^{max}.\eta, \forall t \in [t_{n,s}, \hat{t}_{n,f}] \quad (15)$$

where N_k denotes the number of active charging sessions for power source k.

3) User Model

Each charging session in our system is labeled with a number of properties, such as user ID, session start time $t_{n,s}$, session finish time $t_{n,f}$, vehicle leave time $t_{n,l}$ and the session energy consumption e_n. At the beginning of each charging session, estimation algorithm will calculate the predicted energy consumption $\hat{e}_n$ and the real energy consumption should be larger than the predicted value, but less than battery capacity E_n:

$$\hat{e}_n \le e_n\left(t_{n,f}\right) \le E_n \quad (16)$$

As the time goes on, energy consumption is accumulated at each time interval:

$$e_n(t) = e_n(t - \Delta t) + r_n(t) \cdot \Delta t, \quad \forall t \in [t_{n,s}, \hat{t}_{n,f}] \quad (17)$$

C. Receding Horizon Control

At each time interval, the scheduler on control center will call optimization program to compute for an optimal EV charging schedule, considering the estimated travel schedules and energy consumption values for all active charging sessions. To minimize the overall load fluctuations, the optimization problem, referring to [8], is modeled as:

Obj:

$$\min \sum_{\tau=t}^{\tau=T} (P_b(\tau) + \sum_{n \in N} r_n(\tau) - \frac{1}{T-t+1} \cdot (P_b(\tau) + \sum_{n \in N} r_n(\tau)))^2 \quad (18)$$

$s.t.$ $(8)(9),(14)-(17)$

After the algorithm initiation, the baseload that consists of building load and solar generation, and EV demand will be estimated. At each time interval, parameters for all active charging sessions in system will be extracted from database, and virtual load will be estimated to solve the optimization program. Only the first element in scheduling results $r_n(t)$ is used to control specific EVSE and then algorithm moves forward to next time interval. This procedure repeats until the end of the day. The whole algorithm is summarized in Algorithm 1:

Algorithm 1: Predictive EV Scheduling Algorithm (PESA)

Calculate baseload $\overline{P_{b,t}}$ by averaging historical data
Estimate EV demand for each EVSE: D_t^k, using $(1)(2)(5)$
$t = 1$
Do
  Estimate $P_b(t)$ with error using $(10)-(13)$
  For each vehicle $n \in N$:
    Estimate leave time $\hat{t}_{n,f}$ and energy consumption $\hat{e}_n$ for vehicle n, using $(3)(4)$
  End
  Estimate virtual load parameters, using $(1)(2),(6)-(9)$
  Solve problem (18) ,subject to $(8)(9),(14)-(17)$
  For each vehicle $n \in N$
    Implement $r_n(t)$
  End
  $t = t + 1$
While $t \le T$

IV. Results and Discussion

In this section, results from PESA is discussed, based on comparisons with those algorithms without considering uncertainties. The overall load variation is utilized as metric for performance evaluation of PESA. Potential improvements are also discussed.

A. Experiment setup

Real-world charging records from users in UCLA campus are utilized for our experiment setup. One day in March, 2015 is randomly selected as a test day. There are totally 21 charging sessions from multiple users on test day, associated with all Level II EVSEs. We set the time interval for all data preprocessing and PESA to 15 minutes, which is long enough considering our problem size and performance requirement. The standard variance σ of ξ is set to *2* according to our observation and a is set to *0.4* in the wiener filter. Safety coefficient η is set *0.9*. CVX package[19] is used for solving the optimization problem in each step.

B. Scheduling Results and Future Improvements

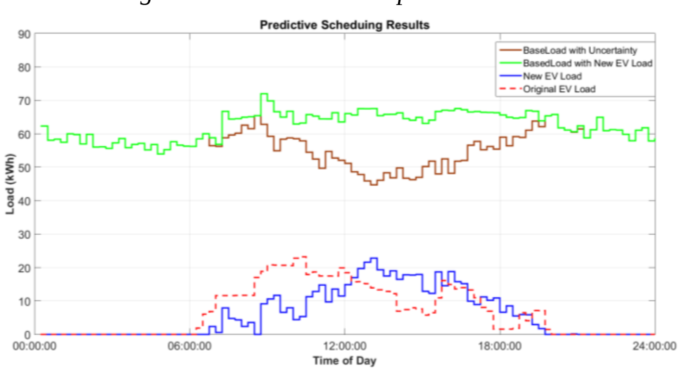

Fig. 3 Predictive Scheduling Results

In Fig.3, the brown step curve is the base load generated by $(10)-(13)$ on the test day and the red dotted curve is the original EV load caused by the real-world charging behaviors. PESA is performed every 15 minutes and only the first schedule elements from the output is implemented. The blue curve is the new energy consumption schedules created by

PESA. Visually, there is a portion of EV load is shifted from around 9:00 AM to 2:00 PM. Thus, the total load with EV, solar generation and building load is updated as the green curve in Fig.3. Thus, PESA's ability for valley filling is demonstrated.

Quantitatively, equation (18) can serve as a numerical metric load variation. After applying the updated EV load, the variation values for system loads with and without PESA are compared in Table I. Scheduled EV load with PESA can reduce the load variation drastically by more than 40%.

Table I Comparison of Load Variation

	With PESA	Without PESA
Load Variation	40.1413	70.7471

However, it should be noted that there is a slight difference between original total EV energy consumption and the new total EV consumption, which is reflected by the areas under the red-dotted curve and the blue curve, respectively. This deviation, caused by uncertainties of user behaviors, can be used as another criteria for performance evaluation. We define Average Schedule Error Rate (ASER) to represent this deviation:

$$ASER = \frac{1}{L} \cdot \sum_{n}^{L} \frac{e_n - e_{n,c}}{e_n} \cdot 100\% \qquad (19)$$

where e_n is the original energy consumption for one charging session. $e_{n,c}$ is the energy consumption obtained from PESA. L denotes the number of charging sessions on a particular EVSE. Smaller ASER values denote less deviations and higher levels of satisfactions of energy demand from EV users. For each level II EVSE in experiment, single ASER is calculated as well as the overall value in Table II.

Table II ASER Values for Different EVSEs

EVSE ID	EVSE 1	EVSE 2	EVSE 3	EVSE 4	Overall
ASER(%)	7.4061	24.6687	1.6531	19.6281	14.9745

After comparing different ASER values for different EVSEs, we find that, for EVSE 2 and EVSE 4, there are users, whose travel schedules and energy demands have quite large deviations from their historical routines, *i.e*, they leave unexpectedly at a much earlier time than before or demand much higher energy than usual. Even though the overall deviation level represented by ASER values are acceptable, users, whose daily charging behaviors are beyond estimations, will undermine the overall scheduling results. To solve this problem completely, the resemblance between current charging session and historical sessions should be estimated dynamically based on more information extracted from live system.

V. Conclusion

In this paper, a predictive EV scheduling algorithm(PESA) is developed, accounting for the uncertainties of building load, renewable generation and EV load. PESA reduces the system load variation and maintains high level of satisfaction for energy demand from EV users. Bayesian inference method has the potential to be used as an adaptive estimator for biased user behaviors and research efforts will be invested into that direction to improve performance.

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