EV Charging Algorithm Implementation with User Price Preference

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***Abstract*—In this paper, we propose and implement a smart Electric Vehicle (EV) charging algorithm to control the EV charging infrastructures according to users' price preferences. Charging boxes, equipped with bi-directional communication devices and smart meters, can be remotely monitored by the proposed charging algorithm applied to EV control center and mobile app. On the server side, ARIMA model is utilized to fit historical charging load data and perform day-ahead prediction. A pricing strategy with energy bidding policy is proposed and implemented to generate a charging price list to be broadcasted to EV users through mobile app. On the user side, EV drivers can submit their price preferences and daily travel schedules to negotiate with Control Center to consume the expected energy and minimize charging cost simultaneously. The proposed algorithm is tested and validated through the experimental implementations in UCLA parking lots.**

***Index Terms*—EV charging scheduling, load prediction, price preferences, pricing strategy**

I. Introduction

Electric Vehicle (EV) is considered as the innovative technology to gradually replace petroleum-driven vehicles that rely on diminishing reserves of crude oil [1]-[3]. Accordingly, many governments are now establishing clear deployment goals for EVs. The U.S. government, for instance, aims to achieve one million EVs on the road by the year 2015 [4], and up to 35% of total vehicles by 2020 [5]. Since the EV motors are powered by rechargeable battery sets, EVs need to be charged periodically. However, the increasing penetration of EVs will have a serious impact on the power grid in uncontrolled charging scenarios, or named "dumb" charging. For example, the emerging fleet of EVs will introduce considerable amount of addition load, which potentially increases peak demand or generates new peak, and increase demand side uncertainties to local distribution power system. Even a small penetration of EVs might result in the unacceptable disturbance in power grid. Therefore, smart charging strategies become significantly important to schedule EV charging behaviors intelligently and effectively.

There are a number of EV smart charging studies have been addressed to date (see e.g. [6]-[9]). The algorithm proposed in [6] introduced a method to maximize the electricity energy that is to be delivered to all the EVs in a fixed period of time. In [7], an operating framework for aggregators of EVs has been proposed, and a minimum-cost load scheduling algorithm is designed to determine the energy transaction strategy in the day-ahead market. The problem of optimizing EV charge strategy in order to reduce the energy cost and battery degradation is proposed in [8]. The intelligent EV scheduling method in [9] is based on the parking lot level to maximize the profit in grid power transactions. However, none of these studies considers charging behavior of EV users, and there is a lack of real-world implementations to support their algorithms through the testing EV infrastructures.

Many researches for "smart" algorithms to regulate EV charging behaviors have been proposed. Generally, they can be divided into three categories: centralized control [10], [11], [13], distributed control [12] and time of use (TOU) price based control [14], [15] on the side of utility and aggregator. However, these studies are non-practical, and they are conventionally based on static scenarios, where the model parameters (e.g. number of EVs, EV battery sizes, charging rates and schedule availabilities) are assumed to be known or fixed factors. On the other hand, vehicle arrival and departure are stochastic behaviors other than static assumptions. Additionally, lack of user interaction mechanism with price and schedule preferences undermines the validity of the simulation results.

In this paper, we model an aggregator to regulate all charging facilities in UCLA parking structures, which can perform bi-directional communication with a control center configured in the lab. Users are able to manage their charging sessions with price and schedule preferences through mobile App. This software system implementation is based on the charging hardware developed by UCLA Smart Grid Energy Research Center (SMERC) equipped with wireless communication modules, current multiplexing circuits and smart meters [16]. Thus real-time charging profile, such as charging rate and meter status, can be obtained by control center and user mobile App to perform charging controls. The algorithms on control center will be able to retrieve and pre-process the historical data into a proper format. ARIMA model is selected to model the real-world charging records in a fashion of time series. In the system model, we assume that

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Control Center is required to flatten the load curve based on day-ahead load prediction and generate corresponding price list for users to respond to. A simple price model is proposed to generate price according to the predicted load and the desired load curve. On user side, different price options (from highest to lowest) are available for selection, which indicates user's charging will start only the price value falls below the accepted one.

The objective of this paper is to introduce, utilize and implement the proposed smart EV charging strategy considering user's price preferences to demonstrate a user-friendly and grid-friendly EV charging infrastructure. The contributions of this paper can be summarized as the following. First, we implement a flexible charging scheme with control algorithms on both server side and user side. Second, we deploy a pricing policy with simple bidding strategy, considering aggregator's predicted charging load by ARIMA model and desired load profile. Third, the effectiveness of this algorithm to shift load from higher price period is validated by experiment data.

This rest of this paper is organized as the following. The system model, including different modules and their functions is discussed in section II. In section III, system load prediction based on time series analysis is discussed. In this part, the historical charging records is pre-processed and fitted into ARMA model. In section IV, a simple pricing strategy with bidding policy is utilized to produce price list based on the predicted EV load profile and the aggregator's favorable load curve. Finally, the experiment results are discussed in section V.

II. System Model

A. System Overview

In the implementation of this smart charging system, generally there are three key components: server side control algorithms, user side mobile App and smart charging hardware, as shown in Figure 1.

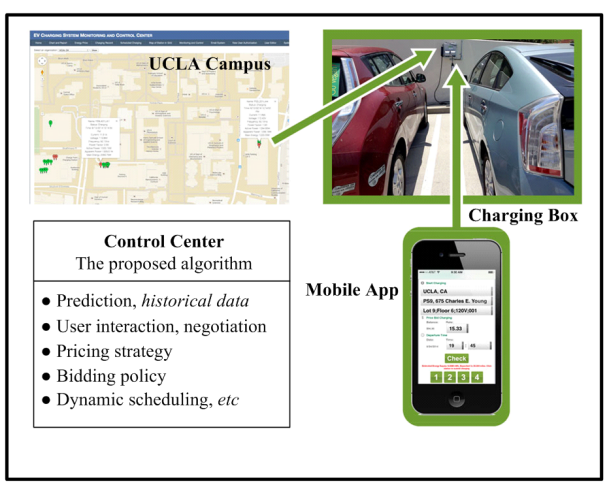

Figure 1. System Diagram

On server side, control center is able to monitor and regulate all charging behaviors. Historical charging records are fitted into ARIMA model for day-ahead load prediction. The predicted EV load is then applied into a pricing model to generate EV price list, with the desired system EV load curve considered. The interval for price list is set to one hour in this implementation. Power information and meter status for all charging boxes are automatically collected. The other functional module on server side is the controlling algorithm to dynamically regulate charging behaviors by splitting current or time quantum according to users' varied schedule preferences and price preferences.

On user side, a mobile app is deployed to enable users to manage charging sessions interactively. EV users, whose daily travel schedules may vary, are able to select charging profile, when they arrive in parking structures in campus. Then, after user selects charging facility, he/she will be able to select charging parameters and schedule preferences, including price options (from higher to lower) and estimated departure time listed in mobile App. The selected price is maximum price this user accepts, which indicates the charging will start when price falls below the accepted one. After selection of charging profile, the server will respond to this charging request and calculate the predicted energy supply based on users' preferences and charging time range. If users do not agree with this arrangement, it is free for them to modify the charging preferences. This negotiation mechanism will help EV user avoid high prices intervals automatically.

III. EV Charging Load Prediction

We average system-wide charging load on an hour basis for better prediction. As is shown in Figure 2, the system EV charging load indicates a periodicity property, i.e. the load has a similar pattern every other week and on each workday except Friday. However, the historical data is imperfect with data missing for certain time intervals and wrong value caused by hardware failure. Thus, data modification method is implemented to correct the data series.

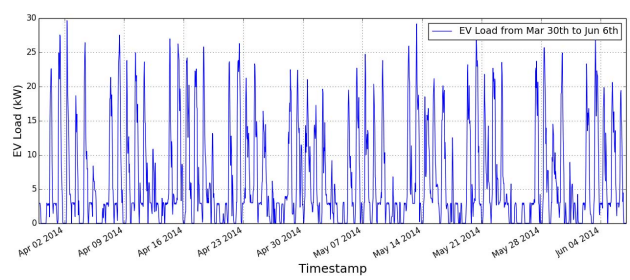

Figure 2. EV Load from Mar. 30th to Jun. 6th

Autoregressive moving average (ARMA), as a stationary time series model, is chosen to model the data and perform prediction. There are two parts in ARMA model, i.e. autoregressive (AR) part with order p, and moving-average (MA) part with order q. The general expression is,

$$X_t - \varphi_1 X_{t-1} - \cdots - \varphi_p X_{p-1} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \qquad (1)$$

And ε_t is a white noise with 0-mean and variance equal to σ_ε^2 . The procedures to handle historical charging load records are:

i. Error correction and data pre-process
ii. Determine orders for ARMA model, *i.e.* p and q
iii. Model Fit, *i.e.* calculate φ , θ values
iv. Model validation, *i.e.* error analysis

Since the raw data, even after modification, has non-stationarity property, differencing steps are necessary to transform into stationary time series. The seasonal factor is identified as 168 hours from plot, equivalent to one week, to remove data periodicity. Additionally, to make the model stable without incremental and decremental trend, Y_t is first-order differentiated with adjacent values in time series.

$$Y_t = X_t - X_{t-s} \tag{2}$$

$$W_t = \nabla^1 Y_t = Y_t - Y_{t-1} \tag{3}$$

Akaike and Bayesian Information Criteria (AIC, BIC) is utilized to evaluate the selections of model orders. The prediction results are shown in the figure below.

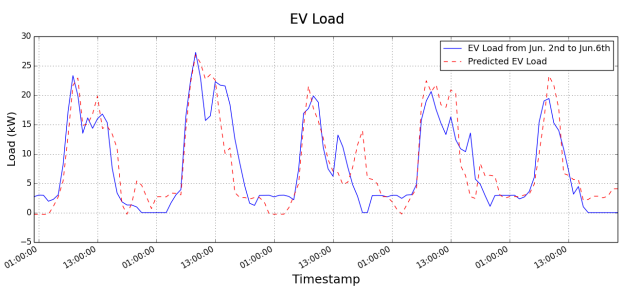

Figure 3. Actual Load vs Virtual Load on Jun. 3rd

IV. PRICING STRATEGY AND BIDDING POLICY

A. *Pricing strategy*

The purpose of designing an appropriate pricing strategy is to encourage EV users to shift their EV charging load to a preferable time range. Since charging facilities are installed in a university campus, charging behaviors are believed to have similar patterns in terms of arriving time, leaving time and energy required by faculty and students. It is assumed that varied persons may have different reactions towards price options, e.g. for a certain day, 20% of all customers are willing to pay the highest prices to charge enough energy as soon as possible. Another assumption is that electricity price is linearly related to system-wide load/demand, i.e. price increases as predicted demand increases. Thus, 24 prices, one for each hour, are generated day ahead, by taking both EV predicted EV charging load and desired load into consideration. The price is defined by:

$$P_i = P_b + \alpha(L_{pi} - L_{di}) \tag{4}$$

P_i denotes charging price in i_{th} hour of current day, P_b denotes the base price for the charging box selected, L_{pi} is predicted load value for i_{th} hour, L_{di} denotes the desired load value for i_{th} hour. α is a coefficient defined to reflect the relationship between load and price. We offer users with 5 price options, from highest to lowest, as a charging threshold, i.e. accepted maximum price. As an example, if charging aggregator's purpose is to dis-encourage EV users to charge between 1:00 PM and 3:00 PM.

B. *Bidding Policy:*

For each level I box, it has 4 outlets and only one input power source. Only one vehicle is allowed to charge due to the inner circuit design. Thus, the policy is to determine timing to switch from one vehicle to another according to users' preferences and priorities. An accepted price threshold is select before users submit charging, which is assumed to reflect how urgent he/she needs to charge. As a result, a charging session with higher price has higher priority and is able to consume more energy within every time quantum. The criteria for algorithm to switch charging session is

$$T_i \geq (\mathrm{P}_i / \sum_{i=1}^{n} P_i) \cdot \Delta T = \gamma_i \cdot \Delta T \tag{5}$$

Where T_i is continuous charging time since turned on last time, P_i the price selected by i_{th} user, ΔT is the time quantum, denoting the timespan of box control loop. γ_i is defined as priority coefficient according to bids provided by users for current charging box.

The scenario for level II is different since level II charging box has higher power supply with ability to multiplex current. The charging box selected for implementation has single power source (240V, 30A). Multiple outlets (stations) can charge at the same time but current for each outlet should be between 5A (10% duty cycle) to 30A (50% duty cycle). Accordingly, the algorithm will determine the energy sharing policy in a current multiplexing manner. To determine each participating vehicle's charging duty cycle (DC), a two-step process is conducted. The first step calculation will rule out the vehicles whose duty cycle values are lower than 10%, and second step will calculate again to reallocate the source current.

$$DC_i = I_{\max} \cdot (\mathrm{P}_i / \sum_{i=1}^{n} P_i) = I_{\max} \cdot \gamma_i \tag{6}$$

where priority coefficient γ_i is defined as $\gamma_i = \mathrm{P}_i / \sum_{i=1}^{n} P_i$.

C. *Billing Policy*

The final cost for participating users consists of not only expense for purchasing electricity but the fee for occupying the charging service priority. Thus, the final cost for each user can be expressed in a simple model with electricity price for specific hour, P_i and current user's priority ratio, γ_i :

$$C = \sum_{k=k_0}^{k_l} \eta_k \cdot \Delta t \cdot P_k \cdot R_k = \sum_{k=k_0}^{k_l} (1 + \beta \cdot \gamma_k) \cdot \Delta t \cdot P_k \cdot R_k \tag{7}$$

Where C denotes the final cost, η_i is the cost factor considering priority to occupy power source in k_{th} timeslot. For simplicity, we apply $\eta_k = 1 + \beta \cdot \gamma_k$ to include both the cost for purchasing electricity and priority service fee. β denotes priority price coefficient and is set to 0.1 tentatively in experiment. P_k is the price for k_{th} timeslot and R_k is the charging rate in i_{th} timeslot. In both level I and level II charging scenarios, priority coefficient γ_k can be obtained by calculating the ratio of current user's bid among all players in certain charging box.

D. *Algorithms for Implementation*

Implemented algorithms on server side are capable of regulating charging sessions with dynamic arriving time, departure time and varied price preferences. For explanation, the simplified versions of implemented algorithms are illustrated below:

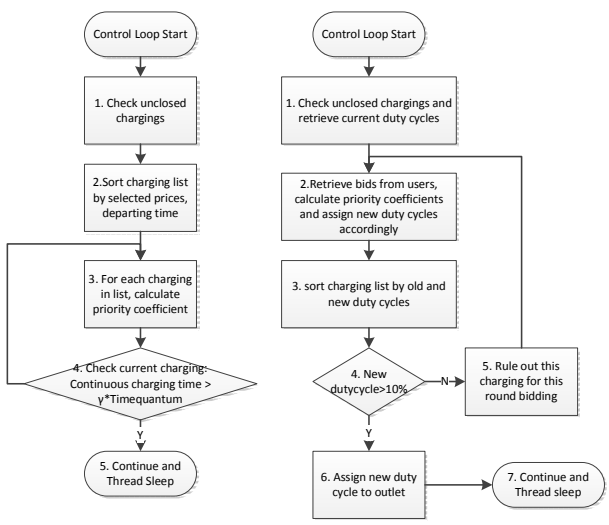

Figure 4. Simplified Level I and Level II Algorithm

For level I box, after each control loop starts, algorithm will select active charging sessions for current box from database, and sort them by their accepted prices and departure time. Only the charging sessions, whose prices agree with user price preferences, can be retrieved. It is assumed that EV drivers, with higher accepted prices and earlier departing time, are in more urgent need for energy and will be given higher priorities than others. To guarantee the energy assigned among users in each time quantum is proportional to their priorities, algorithm calculates priority coefficient γ_i and the continuous charging time T_i in each control loop. If current charging session has used up its portion of charging time in current time quantum, algorithm will switch from this charging to a lower one from charging session list. For level II box, priority coefficients and corresponding duty cycle are calculated in a two-step manner. In the first step, charging session will temporarily be disabled if the duty cycle calculated is lower than 10% or user accepted price is lower than current price. Then, after ruling out the unqualified charging sessions, algorithm will re-allocate the power source to each remaining session, proportionally to its priority coefficient. The charging sessions will be closed if current is lower than threshold or schedule deadline is reached.

V. Result Analysis

To explain the energy sharing and scheduling mechanism, charging records for typical days are retrieved from database for analysis. For level I charging box, records for July 5th, 2014 are selected since there are 4 users submitted their charging sessions with different price preferences. The highest price is 15 cents/kWh, which happens around 13:30 PM.

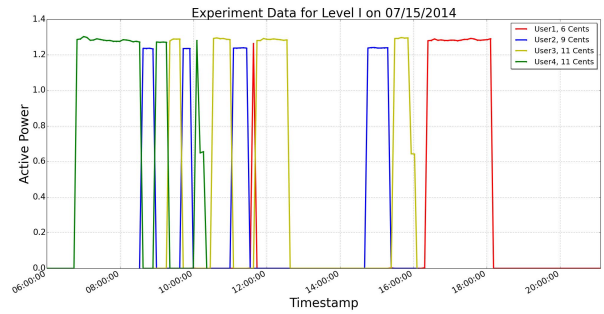

Figure 5. Level I Experiment Data

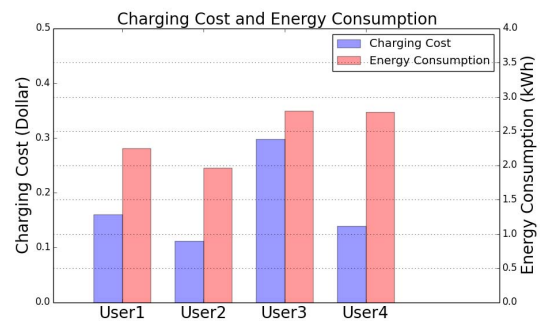

Figure 6. Level I Cost vs Energy Consumption

According to experiment data shown above, the first user (user4) started charging around 7:00 AM in the morning with 11 cents/kWh and finished charging around 10:30 AM. After a while, user2 and user3 joined the energy sharing program and occupied charging periods, which are proportional to their priority coefficients. The last user, user1, selected the lowest price of the day around noon. Thus, his/her charging was disabled soon after charging session initialization and re-activated after 16:00 PM when system price signal is lower than his/her accepted price. Since her/his duration of stay in campus is longer than other users, it is wise of her/him to wait until price is lower in latter hours and avoid higher price period. Charging cost plot implies that users may save charging cost by placing a proper price. Moreover, experiment results also suggest that users' schedules with price preferences is potentially grid-friendly because the charging load for higher price period, usually also higher system load period, can be shifted to time intervals with lower the system pressure.

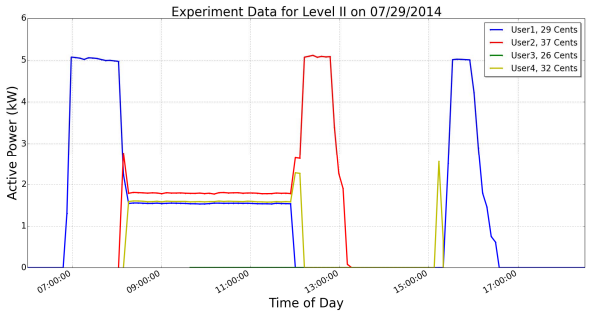

Figure 7. Level II Experiment Data

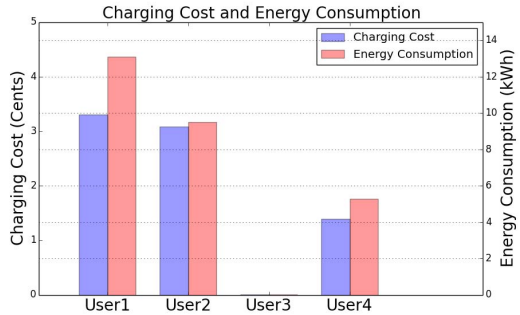

Figure 8. Level II Cost vs Energy Consumption

For level II charging box, multiple vehicles can consume power from a single power source simultaneously. Charging records on July 29th, 2014, when the highest price is 37 cents/kWh, are retrieved from database. As is shown in following Figures, 4 active charging sessions are submitted by users. The first user (user1) selected a medium price (the third highest price) from the five price options offered by aggregator around 7:00 AM. When he is the only consumer for that box, his priority coefficient γ_i is 1 and he was assigned with the maximum duty cycle. For circuit stability reason, maximum duty cycle for this box is set to 45%. Around 8:15 AM, additional 2 users with higher prices submitted their charging sessions for that box. Accordingly, the current is multiplexed for each user proportionally to γ_i. Around 12:00 PM, as the system price increases to a level which is higher than both user1 and user4's accepted prices, their charging sessions are disabled temporarily. Thus, user2 with the highest price could consume all power supply until it finished charging. User1 and user4 halted their charging and waited for price to drop down. Finally user1 finished his charging around 17:00 PM. User3 was unable to obtain any power supply, because the system price was never lower than her/his accepted price even she/he submitted charging schedule as from 9:00 AM to 12:00 PM. From the experiment results, charging sessions with higher price tend to charge at a higher rate and consume more energy than other users in the same period. Moreover, for users with longer time of stay in campus, a better price or bid strategy exists to charge enough energy, while save charging cost. The cost and energy consumption comparison is plotted in Figure 9.

VI. Conclusion

In this paper, we implemented a price-based smart charging algorithm in a university campus. ARIMA was applied to model the historical charging records and perform day-ahead prediction. We deployed a pricing strategy with bidding policy to determine EV charging price, considering predicted load and system desired load curve. We implement server side controlling algorithm to dynamically regulate charging sessions for a single box according to price and schedule preferences. Stochastic modeling of users' charging behaviors, EV energy transaction market and control strategy design will be carried out for future publications.

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