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Decentralized PWM-based Charging Control for Plug-in Electric Vehicles

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Abstract— **Plug-in electric vehicles (PEVs) are becoming increasingly popular because of the environmental and economic benefits. However, high penetration of PEVs may overload the distribution network. In this paper, we propose a decentralized PWM-based algorithm to coordinate PEV charging. We first formulate the PEVs charging coordination problem as an optimization problem, with the objective to flatten the total demand curve as much as possible. Then, we design the control algorithm in two stages. In the first stage, we adopt the the water-filling-based algorithm proposed in our previous study, assuming the charging rate of PEVs takes a continuous value. In the second stage, the assumption is dropped by utilizing the pulse-width modulation (PWM) principle. The moving horizon idea is also introduced to alleviate the errors due to inaccurate forecast and quantization, as well as to tackle the random arrival time of PEVs. Moreover, each PEV only needs to calculate its own power allocation, and hence its implementation requires low computational capacity. Numerical simulations are given to demonstrate the effectiveness of our algorithm.**

I. INTRODUCTION

Electric vehicles have been enjoying a great popularity recently, because of the benefits of high efficiency and low exhaust fume emission. According to [1], the market share of electric vehicles would reach 70% in 2025 in the United States. However, large penetration of plug-in electric vehicles, including all-electric vehicles (such as Tesla and Nissan Leaf) and plug-in hybrid electric vehicles (such as Toyota Prius and Volvo V60 Hybrid), may pose challenges to the power grid. Plug-in electric vehicles (PEV) chargers impose a considerable load on the distribution network. Even with the lowest charging rate, AC Level 1 charging [2], PEVs can be charged at up to 16 A at 120 V, a load of 1.92 KW, while a typical household has an average load of less than 2KW. In other words, a single PEV being charged at the lowest charging rate could impose an instantaneous load as large as that imposed by an average household. Therefore, they may add to the current peak load or create new peak load, if not coordinated, which can cause overloading of transformers and voltage deviations from the normal value [3].

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There have been a multitude of studies dealing with this problem in a smart grid scenario. In [4], a decentralized charging control strategy is proposed, on the basis of non-cooperative games, but it makes a rather strong assumption that all PEVs have the same exit time, energy need, and maximum charging power. In [3], a control signal broadcasted by the utility company is used to update PEVs' charging profiles. This algorithm is proved optimal in both homogeneous and non-homogeneous cases. In our early work [5], we develop a decentralized water-filling-based algorithm to flatten the load curve of low-voltage transformers, which also achieves optimal charging scheduling. And this algorithm is developed further in [6] by introducing a protection mechanism. Water-filling has been widely used in other demand side management problems [7]–[10]. Inspired by the design of the Internet to avoid congestion, a decentralized algorithm is proposed in [11], which allocates a fair share of the resources by adjusting the charging power of each PEV to the network capacity. In [12], a dual coordination mechanism is presented, in which the charging needs are coordinated at two levels. The decentralized algorithms presented in [13] and [14] can capture efficiently the interaction of individual EV charging decisions and LMP-DLMP market clearing prices. Nevertheless, the aforementioned studies all assume that the PEV can be charged at any rate less than the maximum power of its charger, i.e. the charging power has a continuous value between zero and the maximum charging power. A PEV charger with a variable charge rate, which is referred to as a $smart\ charger$, may not be desirable for the following reasons:

- The efficiency of the charger would decrease if not running at full capacity. For example, the efficiency drops to 89% at 25% capacity from 96% at full capacity [15].
- This type of charger requires power electronics to modulate the power and can cause noise and harmonics which deteriorate the power quality of the network [16].
- This kind of charger is more sophisticated and therefore is more expensive.

As an alternative, the ordinary on-off type charger is considered to tackle the same problem with smart control schemes. The work in [17] presents an optimal centralized solution based on linear programming. But the heavy two-way communications are expensive to implement and the centralized nature of the algorithm makes it inapplicable to scalable networks. An algorithm proposed in [16] enables every PEV to have the same probability being charged in each time interval. However, this fair power dispatch method may make these PEVs with relatively high energy needs not fully charged. An algorithm based on the particle swarm optimization method is proposed in [18], but it is also centralized and not suitable for engineering practice.

In this paper, we propose a decentralized PWM-based control algorithm to coordinate PEV charging. This is the extended work of our previous study [5] by introducing the idea of pulse width modulation (PWM) to tackle the PEVs charging coordination problem using ordinary on-off type chargers. In order to abbreviate possible errors caused by inaccurate forecast of load demands and unpredictable arrival of new PEVs for charging, a moving horizon strategy is introduced to re-solve the PEVs charging coordination problem every step. The deviation of each PEV's state of charge after implementing the obtained coordination solution is analyzed for both the scenario without using moving-horizon and the one using moving-horizon. It shows the latter is much improved compared to the former. Finally, we summarize the advantages of our proposed algorithm as follows.

- It is decentralized with high scalability and low requirement for communication and computation.
- It is simple and suitable for engineering practice.
- The algorithm takes advantage of the pulse-charge method, which features a high battery-charging efficiency and a longer cycle life [19].

The rest of the paper is organized as follows. In Section II, the model of PEV charging, as well as relevant preliminaries, are introduced and the problem formulation is presented. In Section III, we design a decentralized PWM-based algorithm to address this problem. Numerical simulations are given in Section IV. Concluding remarks are given in Section V.

II. PRELIMINARIES AND PROBLEM FORMULATION

In this section, we first give the dynamic model of PEV charging and then introduce the charging methods of Lithium-ion batteries and the pulse-width modulation technique. Finally, PEV charging coordination problem is formulated as an optimization problem.

A. Dynamic Model of PEV Charging

The state of charge (SOC) of the Lithium-ion battery in a PEV at time k, denoted by $s(k)$, is defined as:

$$s(k) = \frac{C(k)}{C} \times 100\%, \tag{1}$$

with C representing the battery energy capacity (KWh) and $C(k)$ the remaining battery energy capacity at k.

The SOC update of the i-th PEV is given by

$$s_i(k+1) = s_i(k) + \frac{p_i(k) \cdot \Delta T}{C_i}\eta, \tag{2}$$

where $p_i(k)$ is the charging power at time k and ΔT is the sampling period. The efficiency coefficient $\eta \in (0,1)$ is

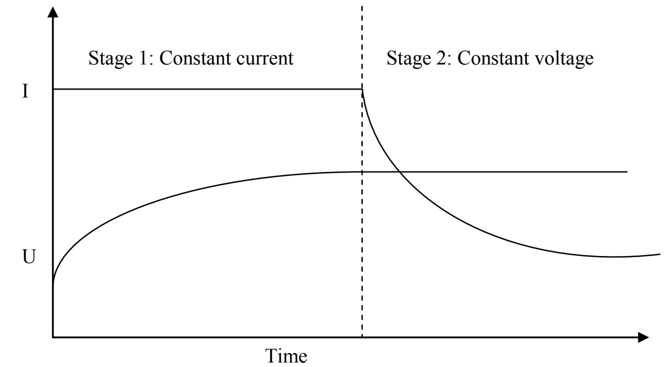

Fig. 1. CC-CV charging process of Lithium-ion batteries (I - current; U - voltage)

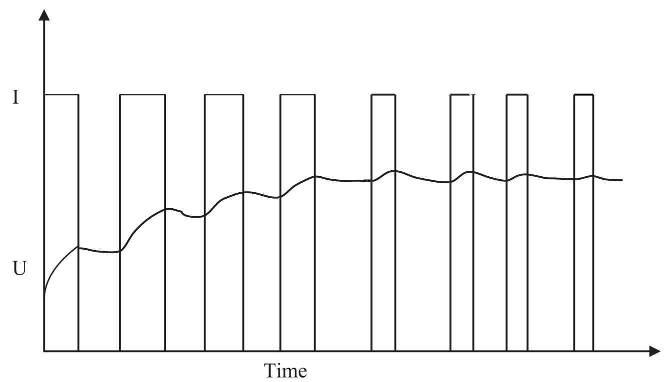

Fig. 2. Pulse charging process of Lithium-ion batteries (I - current; U - voltage)

assumed to be constant. Besides, the charger in this paper is an on-off type charger, and the rated power is denoted by $p_{i,r}$.

B. Charging Method

Many battery-charging strategies are available now, such as constant-trickle-current, multi-step constant-current, and constant-current and constant-voltage (CC-CV) charging strategies [20]. Among the strategies aforementioned, the CC-CV is widely used, shown in Fig. 1. First, the PEV is charged with a constant current and when the battery voltage limit is reached, Stage 2 begins. In terms of SOC, the best functional range of Lithium-ion batteries is from 20% to 85%. Actually, when Stage 1 terminates, SOC can reach 85%. Thus, it is recommended to ignore Stage 2 [21]. However, the charging speed and efficiency of the CC-CV charging strategy are still too low to satisfy the user requirements, due to the lack of consideration about electrochemical characteristics. As a result, the pulse-charge strategy is presented to diffuse and distribute electrolytes ions more evenly to retardation of the polarization. The pulse-charge strategy is to provide the battery a pulsed current/voltage, instead of invariant CC/CV, as shown in Fig. 2, and to provide a rest period for the ions to diffuse and neutralize, which can increase the battery life cycle and reduce the battery-charging time [19].

C. Pulse-width Modulation Principle

PWM uses a rectangular pulse wave whose pulse width is modulated resulting in the variation of the average value of the waveform. If we consider a pulse waveform $f(t)$, with period T, a low value $y_{\min}$, a high value $y_{\max}$ and a duty cycle D, the average value of the waveform is given by

$$\begin{aligned}\bar{y} &= \frac{1}{T}\int_0^T f(t)dt \\ &= \frac{1}{T}\left(\int_0^{DT} y_{\max}dt + \int_{DT}^{T} y_{\min}dt\right) \\ &= D\cdot y_{\max} + (1-D)\cdot y_{\min}.\end{aligned} \tag{3}$$

Therefore, the average value of the signal $\bar{y}$ depends on the duty cycle D [22].

D. Problem Formulation

Suppose there are n PEVs and the utility company needs to negotiate with them to coordinate their charging over N time slots of length ΔT. We assume that the aggregate non-PEV power demand at time k, denoted by $Q(k)$, is known and that the i-th PEV needs to charge from its initial SOC $s_i(0)$ to target SOC $s_i^\star$ by the exit time $K_i(\leq N)$. Then the problem of flattening total power demand is formulated as

$$\min\ f(p) = \sum_{k=0}^{N-1}\left(Q(k) + \sum_{i=1}^{n} p_i(k)\right)^2, \tag{4}$$

which is subject to the following two constraints:

$$\sum_{k=0}^{K_i-1} p_i(k) = C_i\frac{s_i^\star - s_i(0)}{\Delta T\eta} \quad i = 1,2,\ldots,n \tag{5}$$

$$p_i(k) \in \{0,\ p_{i,r}\} \quad i = 1,2,\ldots,n. \tag{6}$$

Equation (5) means every PEV must be charged to its target SOC by the exit time specified by the owner while the second constraint indicates an on-off type charger.

III. MAIN RESULTS

In this section, based on our previous work in [5] and the PWM principle, a PWM-based control algorithm is designed in two stages.

A. The First Stage

Without loss of generality, we assume that $K_1 \leq K_2 \leq \ldots\ K_n \leq N$. If we relax the constraint in equation (6) into $0 \leq p_i(k) \leq p_{i,r}$, then this problem becomes a convex optimization problem similar to that in [5]. We adopt the water-filling-based algorithm to solve it.

In Algorithm 1, ε can be chosen to be a very small positive value and b_i is the energy need of the i-th PEV (normalized by ΔT), which is calculated by

$$b_i = C_i\frac{s_i^\star - s_i(0)}{\Delta T\eta}.$$

Algorithm 1 Water-filling-based optimization algorithm

Input: ϵ, $p_{i,r}$, b_i and K_i, $k = 0,1,\ldots,N-1, i = 1,2,\ldots,n$

Output: $p_i(k), k = 0,1,\ldots,N-1, i = 1,2,\ldots,n$

1: **for** $i = 1,2,\ldots,n$ **do**
2: PEV$_i$ gets $Q(k)$ from the utility company, $k = 0,1,\ldots,N-1$
3: Initialize $\alpha_{\min} = \min_k Q(k)$ and $\alpha_{\max} = \max_k Q(k) + p_{i,r}$
4: **while** $\alpha_{\max} - \alpha_{\min} > \varepsilon$ **do**
5: Choose $\alpha = (\alpha_{\min} + \alpha_{\max})/2$
6: Compute $p_i(k) = \mathcal{P}[\alpha - Q(k)], k = 0,1,\ldots,N-1$
7: **if** $\sum_{k=0}^{K_i-1} p_i(k) > b_i$ **then**
8: set $\alpha_{\max} = \alpha$
9: **else if** $\sum_{k=0}^{K_i-1} p_i(k) < b_i$ **then**
10: set $\alpha_{\min} = \alpha$
11: **end if**
12: **end while**
13: PEV$_i$ reports $p_i(k)$ to utility company, $k = 0,1,\ldots,N-1$
14: Utility company computes $Q(k) \Leftarrow Q(k) + p_i(k), k = 0,1,\ldots,N-1$
15: **end for**

$\mathcal{P}[\cdot]$ is the projection operation, i.e.,

$$\mathcal{P}[x] = \begin{cases} p_{i,r} & x > p_{ir}, \\ x & 0 \leq x \leq p_{i,r}, \\ 0 & x < 0. \end{cases}$$

Remark 1: This algorithm is decentralized in the sense that every PEV computes its own power and the utility company only needs to do small amounts of communication and computation

Remark 2: Algorithm 1 is termed as water-filling because the final result looks much like the natural phenomenon of water-filling: before water-filling $Q(k)$ is the original water surface and becomes the eventual water level after the water-filling (see step 14). The eventual $Q(k)$ is the optimal total demand curve.

B. The Second Stage

In the second stage, we come back to the original problem, where the charger is an on-off type, i.e. $p_i(k)$ can only take $p_{i,r}$ or 0. We adopt a much smaller time interval κ, with $\Delta T = M \cdot \kappa$. According to the PWM principle, the duty cycle of the i-th PEV during the period from $k \cdot \Delta T$ to $(k+1)\Delta T$, denoted by $D_i(k)$ can be calculated by

$$D_i(k) = \frac{p_i(k)}{p_{i,r}}$$

Therefore, the charger is on for $m_i(k)$ intervals of length κ and $m_i(k)$ is an integer obtained by rounding off $M \cdot D_i(k)$. The $m_i(k)$ intervals of each PEV are chosen randomly from the M intervals, to avoid oscillation caused by many chargers turning on or off at the same time, and to approximate

Algorithm 2 PWM-based algorithm

Input: $M, \kappa,\ p_{i,r}$, and $p_i(k),\ k = 0, 1, \dots, N-1$
Output: $p_i(k \cdot \Delta T + m \cdot \kappa)$, $m = 0, 1, \dots, M-1$

```
m_i(k) = round(p_i(k)/p_{i,r})
Select m_i(k) integers randomly from 0 to M − 1 and
  put them into a set 𝓜.
for m = 0, 1, ..., M − 1 do
  if m ∈ 𝓜 then
    p_i(k·ΔT + m·κ) = p_{i,r}
  else
    p_i(k·ΔT + m·κ) = 0
  end if
end for
```

Algorithm 3 PWM-based algorithm with moving horizon

Input: $\epsilon,\ M,\ \kappa,\ p_{i,r},\ b_i$ and $K_i, i = 1, 2, \dots, n$
Output: $p_i(k \cdot \Delta T + m \cdot \kappa)$, $m = 0, 1, \dots, M-1,\ i = 1, 2, \dots, n$

```
Use Algorithm 1 to get p_i(k), p_i(k+1), ..., p_i(k+N−1)
Keep p_i(k) and discard p_i(k+1), ..., p_i(k+N−1)
Use Algorithm 2 to get p_i(k·ΔT + m·κ), m =
  0, 1, ..., M − 1, i = 1, 2, ..., n
Shift the horizon from k to k+N−1 to k+1 to k+N
Update Q(k), b_i, and n
Carry out the process repeatedly.
```

the optimal total demand curve achieved using the water-filling-based algorithm. Algorithm 2 is given to describe this methodology.

Remark 3: Algorithm 2 is decentralized, because each PEV only needs its own information for calculation.

Remark 4: This PWM method makes the charging process similar to that using the pulse-charge strategy by allowing a rest period, so the battery can enjoy the benefits of higher charging efficiency and longer lifespan.

Remark 5: PWM brings about harmonics and fast switching can help to overcome harmonics. In terms of the effects of pulse frequency on batteries, it is not certain which frequency is optimal as it depends on the parameters of the battery [23], [24]. Also, the switch frequency in our algorithm is not fixed as some "on" states may come successively, but the benefits, i.e. higher charging efficiency and longer lifespan, due to the rest period still exist. So in practice, we can choose a relatively high switching frequency.

C. PWM-based Algorithm With Moving Horizon

The aforementioned algorithms have some drawbacks: the forecasted $Q(k)$ may become inaccurate throughout such a long period and the round-off operation brings quantization errors. So in this section, we introduce the moving horizon idea to deal with these problems and the size of the horizon is N. The modified PWM-based algorithm with moving horizon is described in Algorithm 3, in which b_i is updated by measuring its current SOC and the quantization errors due to PWM compensated. Moreover, the total number n may change over time because PEVs may come and leave the network at any time. The idea of moving horizon is simply described as follows. At time k the future power allocation $p_i(k), p_i(k+1), \dots, p_i(k+N-1)$ is calculated using this algorithm. But only the first element of the optimal sequence, i.e. $p_i(k)$, is applied. At the next time instant, the horizon is shifted from $[k, k+N-1]$ to $[k+1, k+N]$ and then the optimization problem is re-solved again. The process is carried out repeatedly.

D. Error Bounds Analysis

As we have mentioned, the round-off operation in the PWM algorithm may affect the completion of charging, so the equality constraints, described by equation (5), may not be satisfied. Consequently, moving horizon is adopted for compensation. But the errors (undercharge or overcharge, in terms of energy, defined in equation (7)) still exist and theoretically they come from two sources — PWM and the convergence condition in Step 4 of Algorithm 1.

$$Error_i = \Delta T \sum_{k=0}^{K_i-1} p_i(k) - \frac{C_i(s_i^\star - s_i(0))}{\eta} \quad i = 1, 2, \dots, n \tag{7}$$

The error bounds caused by PWM in any charging interval of ΔT is described by

$$\theta_i = \pm\frac{1}{2} \cdot \frac{p_{i,r}\Delta T}{M} = \pm\frac{1}{2} p_{i,r} \cdot \kappa. \tag{8}$$

In equation (8), $\pm\frac{1}{2}$ is due to the round-off (round-up and round-down) operation. It can be seen that θ_i is determined by the rated power of PEV$_i$ and the switch frequency of the charger.

The other error results from ε in Step 4 of Algorithm 1. Suppose that $\hat{\alpha}$ is the accurate value of α. Then it is certain that $\hat{\alpha} \in (\alpha_{\min}, \alpha_{\max})$. In the last round of the "While" loop, after setting $\alpha_{\max}$ to be α or setting $\alpha_{\min}$ to be α, the loop stops, because it satisfies $\alpha_{\max} - \alpha_{\min} \le \varepsilon$, which means $\alpha - \alpha_{\min} \le \varepsilon$ or $\alpha_{\max} - \alpha \le \varepsilon$. Recalling $\hat{\alpha} \in (\alpha_{\min}, \alpha_{\max})$, we get $|\alpha - \hat{\alpha}| < \varepsilon$. Thus, the error caused by the convergence condition in any charging interval of ΔT is in the range $(-\varepsilon \cdot \Delta T,\ \varepsilon \cdot \Delta T)$

1) Error Bounds Without Moving Horizon: Without moving, the errors (caused by PWM and ε) in every ΔT interval may accumulate as well as cancel each other out. Considering that the maximum charging time for PEV$_i$ is $K_i \cdot \Delta T$, we obtain that the error after the whole charging process lies in the range $(-K_i(|\theta_i| + \varepsilon \cdot \Delta T),\ K_i(|\theta_i| + \varepsilon \cdot \Delta T))$.

2) Error Bounds With Moving Horizon: With moving horizon, the parameters in Algorithm 3 are updated when the horizon shifts, so the errors will not accumulate. The error after the whole charging process depends on the last charging interval of ΔT, so it belongs to $(-|\theta_i| - \varepsilon \cdot \Delta T,\ |\theta_i| + \varepsilon \cdot \Delta T)$.

IV. CASE STUDIES

In this section, we compare the demand curves without coordination, using smart chargers to coordinate and using on-off type chargers through simulation. Charging completion is shown as well.

TABLE I
PARAMETERS OF THE 200 PEVS

NO.	Max Power	Energy Need	Arrival Time	Exit Time
1-40	6.00	30.0	1	84
41-80	5.25	22.5	1	98
81-120	5.85	30.0	8	105
121-160	6.90	37.5	43	98
161-200	6.00	30.0	50	126

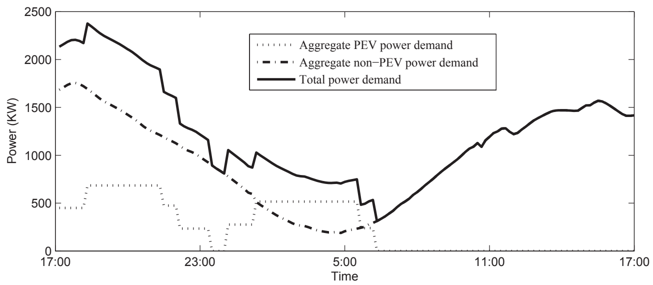

Fig. 3. Power curves without coordination

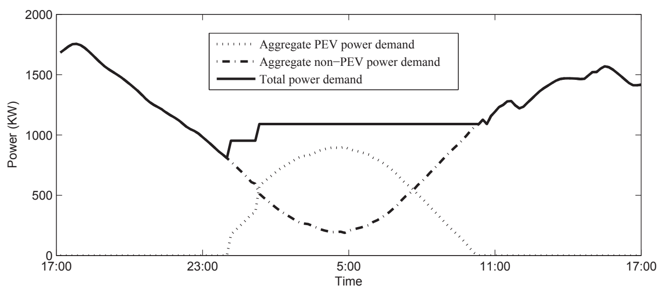

Fig. 4. Power curves with coordination

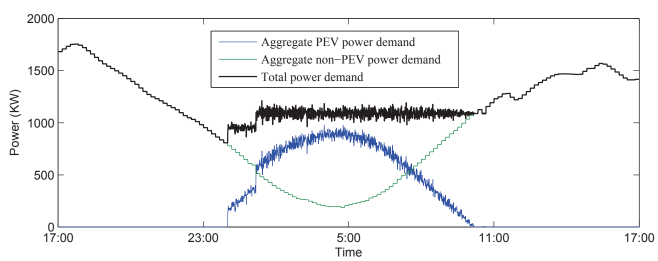

Fig. 5. Power curves with coordination and PWM

We consider 200 PEVs here and the simulation parameters are given in Table I. The aggregate non-PHEV power demand $Q(k)$ is given by the dash-dot curve in Fig. 3, which is from [25]. In the example, the starting time is assumed to be 17:00 hours, and the sampling period ΔT is 10 minutes. We set M to be 20, so κ is half a minute. ε is set to be $|\theta_i|/\Delta T$ to make the simulation results more clearly. The unit for power is KW and unit for energy is KWh.

A. Illustration of Flattening Total Demand Curve

Fig. 3 shows that all PEVs start charging as soon as they arrive home, if not coordinated. And because of this, the original peak load is increased. If all the loads are served by a 2000 KVA transformer, the increased peak load can be devastating to it.

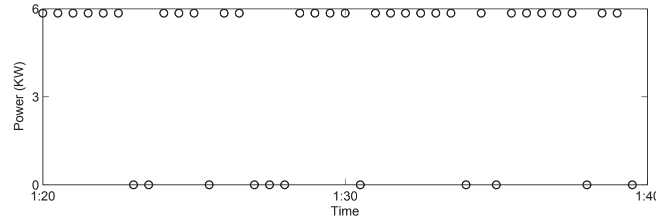

Fig. 6. On/off state changes of a PEV

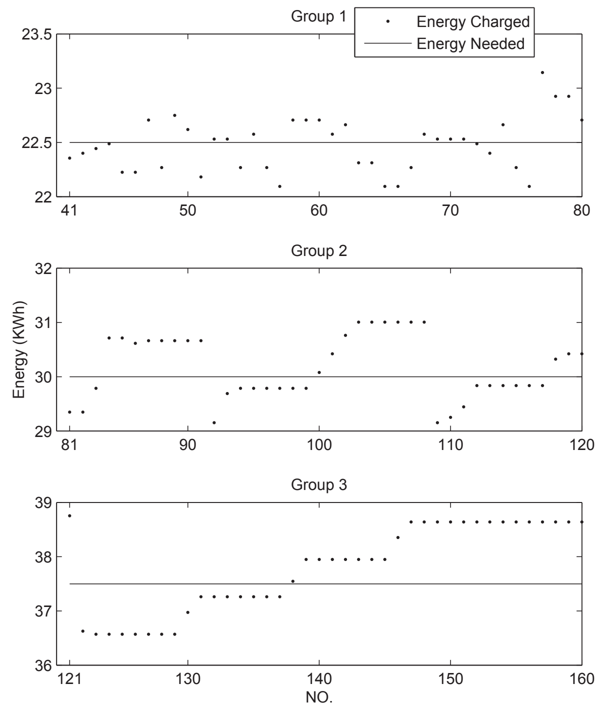

Fig. 7. Charging completion without moving horizon

Fig. 4 illustrates the power curves where the charging of PEVs is coordinated using the water-filling-based algorithm. It can be seen that the PEV demand is shifted to the valley period, when aggregate non-PEV demand is relatively low.

We get Fig. 5 using the PWM-based control algorithm proposed in this paper. In this simulation, the charger may change its on/off state every 30 seconds, due to the introducing of PWM. As a result, there is some fluctuation, but it reflects what the realistic power grid looks like. Also, the total demand curve and aggregate PEV demand curve are rather similar to those in Fig. 4, which shows the effectiveness of our algorithm.

Fig. 6 is a segment the on/off states of some PEV. The circles on top indicate the "on" state, corresponding to the rated power. For example, from 1:20 hours to half a minute before 1:30 hours, there are 14 "on" states and 6 "off" states and they randomly distribute on the time axis.

B. Illustration of Satisfying Charging Needs

In the previous section, we showed the effectiveness of our algorithm in achieving the objective to flatten total demand

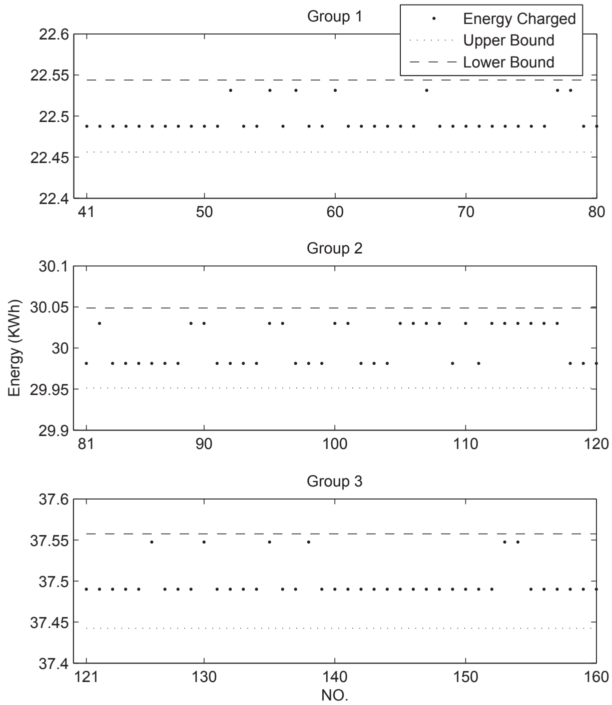

Fig. 8. Charging completion with moving horizon

curve and in this section, charge completion with and without moving horizon is shown. We consider 3 groups of PEVs — group 1 (PEV NO. 41 to 80), group 2 (PEV NO. 81 to 120), and group 3 (PEV NO. 121 to 160). From Fig. 7 we can see some PEVs have a big energy gap because the quantization errors accumulates throughout the charging process. In contrast, when moving horizon is introduced, the errors are within the $2|\theta_i|$ bounds, shown in Fig. 8 and it is because a closed loop is formed. So our control algorithm can achieve satisfactory charging completion.

V. CONCLUSIONS

With the increasingly high penetration rate, PEV charging need to be coordinated, otherwise the distribution network is likely to be threatened. In this paper, we formulate the charging control problem into an optimization problem and a decentralized PWM-based control algorithm is given, which is simple, fast, and suitable for engineering practice. No assumption about a *smart charger* is needed because of the introduction of PWM. Simulation results demonstrate satisfying charge completion as well as achievement of the objective. Future work would include some practical experiments.

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