Optimal Electric Vehicle Scheduling in Smart Home with V2H/V2G Regulation

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***Abstract*—Thepopularity of electric vehicle (EV) provides both challenges and opportunities. Although EV increases the load pressure to the grid, it can also serve as the potential storage to facilitate the demand response for residential customers. In this paper, we propose an optimal and automatic scheduling scheme to exploit the benefits of EV not only from residential side but also from utility companies. Specifically we consider that the EVs can achieve a two-way discharging, either supply the power usage of its house (i.e., V2H) when the electric price is high or sell back to the Grid (i.e., V2G) if the market price is more attractive. The objective is to minimize the total cost, including electricity expenditure and storage depreciation cost, while satisfying various practical constraints. Simulation results show our proposed scheme can not only lower the cost but also share part of the pressure from utility companies.**

***Index Terms*--Demand response, distributed storage, electric vehicle, real-time pricing (RTP), Vehicle to Home (V2H).**

I. Introduction

TODAY electricity demand increases sharply every year,while the development of power generation and transmission system increases at a much slower rate.To avoid power system failure,power generation and demand have to be balanced all the time. Therefore, power generation capacityis generally sized to peak demand. In other words, some power generation plantsoperate continuously to support base demand,while some plants operate only during peak period,called peaker plants. How can we reduce the number of peaker plants to reduce thehuge construction and maintenance waste while still balancing the demand and generation? Two effective approaches are the use of storage system and the implementation of demand response. The storage system can store energy during the off-peak period and then supply the energy to complement the generation during the peak period. The demand response can shift some demand from peak period to off-peak period to reduce the peak demand.

For decades, most energy storage researchfocused on bulk storage technologies to provide large-scale storage. However, due to the physical scale and cost, the bulk storage systems become less and less popular[1]. In the past ten years, small-scale storage devices havebeen developed rapidly, including advanced batteries, ultra-capacitors, high-efficiency fly-wheels, and superconducting magnetic storage. Those devices can increase efficiency, improve reliability, and increase asset value across the entire electricity grid, from power plants to customer premises [1]. With electric vehicle (EV) becoming popular worldwide, a growing number of companies consider it as potential storage system for residential household. For example Nissan demonstrated an off-grid self-sufficient smart home, “Leaf-to-home”[2]. The house was completely powered by solar panel and Nissan Leaf. It was shown that Leaf could completely power a typical Japanese home up to 2 days,or 20 hours for a typical US house[3].In general, EV needs to replace batteries every ten years, however, these replaced batteries still retain 70% of the capacity [4]. Noting that, GM and ABB came up the idea oftransformingdiscarded Chevy Volt batteries into energy piggy banksto serveas a distributed energy storage system for community. It is believed that this community storage system would benefit both industry and the community.

Although it is inevitable for EV to become more and more popular in the future, there still exists uncertainty. One of them is the massive charging. With the emerging smart grid that enables bidirectional communication between utilities and customers, real-time pricing (RTP) can be provided to customers for them to perform demand response. With the inclusion of storage system into household, the customers are given more flexibility. In this way, the home appliances need not to delay their operations to wait for a low price time. The customers not only save money but also experience little inconvenience.

Most of the research efforts on V2G have appeared in the last few years. In [5], authors studied relationship between

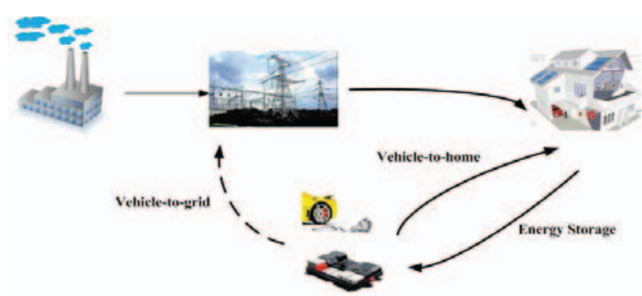

Figure 1. EV as distributed storage in smart grid

Lithium-ion battery cell degradation and benefits from“Vehicle to Grid” (V2G). Authorsanalyzedthe potential economic benefits including peak power, spinning reserves, and regulation services brought by three different types of EVs for power market in [6].[7–10] proposed different V2G scheduling schemesin either distributed model or centralized model. However, all above works focused on power market side instead ofresidential side. [11] investigated different approaches for residential demand response based on varied pricing,but none of them involve the distributed storage system.

In this paper, we consider a realistic scenario in whicheach household has an EV or each community has a medium size storage system as shown in Fig 1.Smart meter[14] is installed in each house or community which can provide both day-ahead price(DAP) and RTP to customers in real time. We aim at exploiting benefits of distributed storage in demand response for residential customers while not bringing too much pressure on utility side because of the night charging. The problem is formulated as a cost minimization problem subject to a set of constraints, including the total power constraint. Since price prediction is required, here we assume a price prediction model that can provide future price, e.g. next three days. Our simulations, based on PJM market price data [12] and MECOLS [13], show that our proposed scheme can dramatically reduce the cost andshift load from peak to off-peak period

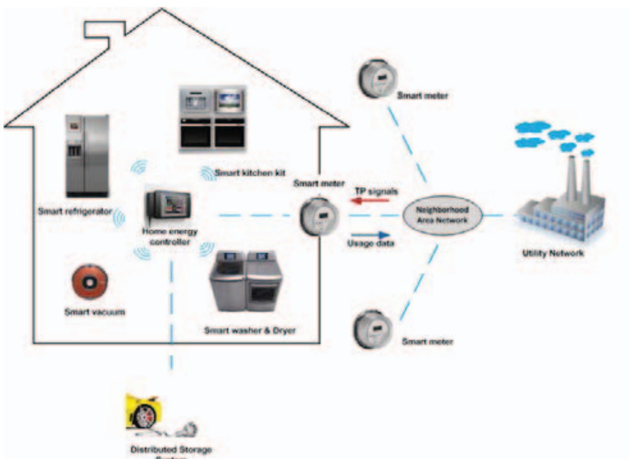

Figure 2. Smart home with storage system

The rest of paper is organized as follows. In Section II, the system architecture and problem formulation are provided. The EV daily usage and charging mode are presented in Section III. Section IV describes our scheduling scheme. Simulation results and case study are shown in Section V. Finally the conclusions are given in Section VI.

II. System Model

In this section, we first discuss the overall system architecture and then present assumptions of our problem formulation of optimal scheduling with distributed storage for smart homes.

A. System Architecture

A smart home that is equipped with an energy storage system, e.g. a plug-in electric vehicle (EV), is illustrated in Figure 2. The smart home is connected to the smart grid where the advanced metering infrastructure (AMI) provides bi-directional communication channels to support information exchange between utilities and customers. Utilities can read meter data from residential households and customers can receive pricing signals, including future predicted price. While previous works are interested in utilizing such real-time information at utilities, e.g. demand response request [16], we are interested in EV scheduling at customer side based on the price signal.

Within the smart home, all the appliances along with the energy storage system form a home area network based on either ZigBee [17] or WiFi. Due to the limited process ability of the smart meters and other considerations including security and privacy, an additional equipment, named home energy controller (HEC), is usually required to monitor the energy consumption and to schedule the home appliances and energy storage system operations when necessary. The scheduling will be based on the energy usage and the price signal while considering the priority of the loads and the characteristics of the home appliances and the energy storage system. It is preferred to have the HEC to generate the scheduling toward cost saving automatically, while the customer should be able to override certain parameters and decisions, possibly remotely.

B. Problem Formulation

We consider our optimalscheduling problem for smart homes. The objective is to reduce the cost for the customer without introducing inconvenience by meeting all the scheduling deadlines. Since the electricity price is not known as prior, it is prerequisite for either smart meter or some other kind of machines that have built-in algorithm to obtain a future price prediction before computing a schedule. Note that the scheduling would lead to changes in the customer's behavior in terms of the energy consumption profile. We assume thatsuch changes are too small to impact the electricity prices significantly so that we can decompose future price prediction from residential load scheduling.

We assume that after people coming back from outside, the normal procedures they need to do are as follow. The first step is to plug in the vehicle's charger whether or not it is going to charge immediately. Second is to set up the charging mode which we will discuss later. We also assume that after plugging in, the vehicle's battery become an ancillary storage system served as electric source which can discharge its remaining power to support all the home appliances. The switch between vehicle and grid are charged by the HEC according to the current mode after gathering all the electric price and usage data from smart meter so to achieve smart control.

III. EV Daily Usage and Charging Mode

On the residential side, the main purposes of EV distribute in areas such as daily workplace, shopping, go to school and community activities. Its characteristics show as high randomness, short driving ranges and long stop period. Based on [14], for a conventional household the EV start charging at around 18:00pm after back from work and will keepidol until 7:00 in the morning. This 13 hours duration forms the night charging period that may increase load pressure on power grid

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but is also adjustable so that we set as one cycle time. According to the average daily driving distance probability distribution obtained from National Household Travel Survey (NHTS) [15] shown in Figure 3, nearly 70% are from 10-30 miles which we considered as our experiment data. After

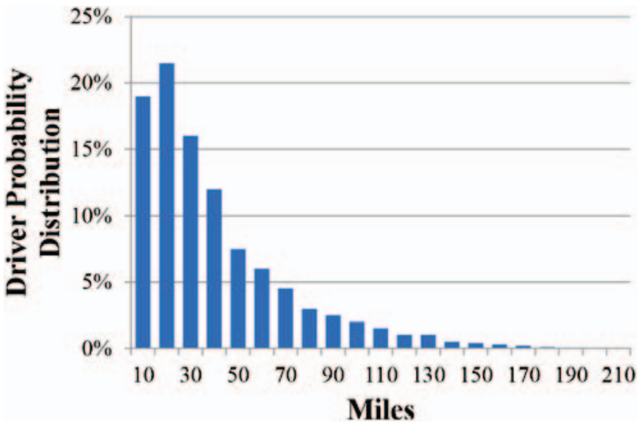

Figure 3. U.S. commuter daily driving distance probability distribution

checking and comparing series type of EV we decided to make assumption that the type we adopted has such energy consumption patterns, it equipped with average level 25 kWh battery that can provide 100 Miles driving range and its charging rate we set as 3.5 kWh. We also assume that the typical power factor is 90%for all the EVs.

As mentioned before, after plugging in, the charging mode should then be set up. Here in this article, three charging modecan be selected, named as fast charging, single-cycle charging and multi-cycle charging. For fast charging the EV would getting charged directly without any delay or data analyzing, until fully charged or being interrupted manually. The single-cycle charging means to start using EV's battery as a backup storage and allow it to switch from charging to discharging back and forth according to the data that received from smart meter, all process lasts one cycle duration. The multi-cycle charging are similar with single-cycle charging except the number of cycles, people can choose two day mode or three day mode to extend cycle duration.

If the two day mode is selected, the whole process will cover three days and contains two cycles.For the three day mode it will add one more day and cycle. It has been proved that the three day mode has a more significant improvement than the other. So we only focus on the former in the rest of the paper

Figure 4 shows how the charging demand change from hours during one single day. We can see that the peak period occurs during midnight when EVs' aggregate charging begin for the reason that owners are more willing to save their money bychoosingthe off-peak price period. Although right now the EV's off-peak charging will not add too much on the off-peak period, not to mention challenging the peak load period. But in the future it still can produce pressure on utility companies to stay alert in night. Our goal is to help the grid to average the load and, at the same time, bring more profit on residential side.

IV. Optimal Scheduling Based on Price Prediction

In this section, we formulate and solve the problem of optimal scheduling with distributed storage as an integer linear programming (ILP) problem. We first discuss our price prediction based on price history, and then approach different charging mode with scheduling constraints.

A. Future price prediction

In order to run our program, we need to first get the price data. Based on the existing works, the prediction for RTP can now be realized. But none of the publications talked about predicting the future price. So we have made assumption that since it's acceptable to allow some uncertainty without influencing too much on our algorithm, we decided to gather data from past years. After analyzing the data from [12] [23], we found that there are some regular patterns to follow. In

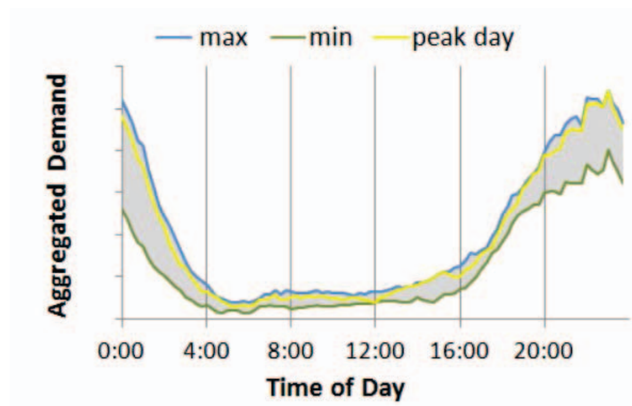

Figure 4. Charging demand on a single day

figure 5, we compare usage and price data from different scenario like summer vs winter, weekday vs weekend. We can see from these graphs that hourly usage in winter are usually higher than in summerbecause of the heater and the RTP are usually not constant during weekend for resident's behavior. We have to say that we didn't see any relationship between market price and power usage, we guess that is because among utility companies the price are dynamic so it depends more on a demand-supply balance and that is not our concern.

B. Scheduling for Energy Storage System

When the energy storage system is available, we can define its state of charge (SOC) in terms of energy at the time slot $h$as s^h . Clearly, the SOC at any time cannot exceed the capacity of the storage system, denoted by S_{max}. Moreover, to avoid over-discharging that may damage the storage system, the SOC should not drop below certain lower bound, denoted by S_{min} , which we set as 20% remaining. Therefore, the following constraints should be satisfied.

$$S_{min} \le s^h \le S_{max}, \forall 1 \le h \le H. \tag{1}$$

On the other hand, the SOC at the current time slot is determined by the SOC and the charging/discharging at the previous time slot. Denoting the charging/discharging energy at the time slot by c_h and d_h respectively, this relationship is formulated as follows,

$$s^{h+1} = s^h - d^h + K_c * c^h, \forall 1 \le h \le H-1, \quad (2)$$

where K_c , named the charging efficiency, represents the possible energy loss during charging which we set as 0.9. Furthermore, we denote the upperbound on charging and discharging by C_{max} and D_{max} respectively, i.e.,

$$c^h \le C_{max} \text{ and } d^h \le D_{max}, \forall 1 \le h \le H. \quad (3)$$

Since the EV may be used outside of the smart home, e.g. as a plug-in EV, it may start with certainSOC S_o at the beginning of each cycle and may require to charge to a certain SOC S_H at the end, i.e.,

$$s^1 = S_o \, , s^H - d^H + K_c * c^H = S_H. \quad (4)$$

Note that when the energy storage system could be offline during the whole scheduling interval, e.g. when the EV leaves home, one can formulate the necessary constraints by applying Eq. (1) to (4) to each of the continuous interval that the system is online.

C. The Overall ILP Formulation

As the remaining battery power values are dynamic from ranges and not constant, we take some typical values set as constrains. In Table I.We can see that a fully charged car will remain 80% or 70% battery energy after driving back from their workplace and can take out about 30% of its remaining energy to participate in this game, either charging, discharging or even sell back to grid, depending on the price data provided from the smart meter. We can also learn that two day mode is suitable for those who have to drive 30 miles out of the 100 mile driving range. In the three-day mode since we have to keep the remaining energy of battery upon a certain level, at the end of day 2 we have to set the upper level k_3 the same with k_2 to avoid deep discharging to satisfy S_{min} which means if the battery no longer charging it will not discharging neither.

Table I. Battery energy remaining under two day and three day mode

Day	SOC		
	k_1	k_2	k_3
One	100%	70%	50%
Two	50%	20%	100%

Day	SOC		
	k_1	k_2	k_3
One	100%	80%	60%
Two	60%	40%	40%
Three	40%	20%	100%

Based on the above discussions, we formulate the following optimization problem,

$$Problem\ I: min \sum_{h=1}^{H} (P_h * z^h + De * d^h) \ s.t. \quad (5)$$

$$z^h = c^h - K_d * d^h, \quad \forall 1 \le h \le H, \quad (6)$$

$$z^h \le E_{max}, \forall 1 \le h \le H, \quad (7)$$

All scheduling constraints from Eq. (1) to Eq. (4).

Here d^h contains both home usage and sell back energy discharged. De represents the degradation coefficient caused by frequent charging/discharging operations. Because only affine functions with decision variables are involved. Therefore, we define our problem as an integer linear programming problem (ILP). Although ILP problems are NP-hard in general, recent advances in ILP solution techniques make it possible to solve large ILP problems in practice. Since confirmed by our experimental results, our ILP formulation can be solved very efficiently by commercial ILP solvers. We further comments that our formulation is less likely affected by scaling issues since we do not expect the number of variables of our ILP formulation to be increased dramatically, which usually leads to much longer solution time and much more memory usage, as both the number of appliances and the granularity of price prediction will not increase dramatically in future.

V. SIMULATION AND CASE STUDY

In this section, simulation results are presented and performance of our proposed residential control scheme with storage system is evaluated. In order to evaluate the performance of proposed scheme in real world, all simulation settingsare from the practical data. We consider a single household with various home appliances, either schedulable or non-schedulable.We ignore the charging/discharging switch time and energy lost and assume it can be done without any

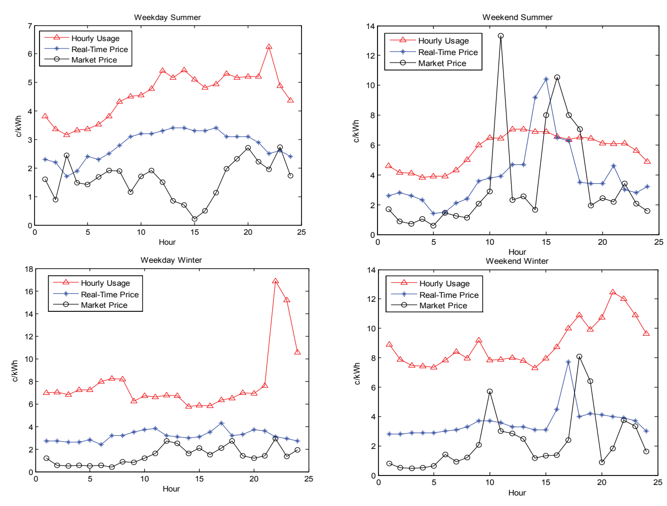

Figure 5. Usage and price comparison of different seasons and days

delay.

Our simulations are based on U.S. Household Electricity Report data [13]. RTP are from ComEd RealTime Saving [Online] [23]. Market Price are from PJM Preliminary Regulation Summary [12]. All data are from 2013.In figure 5, each of the subfigure represents data collected from summer and winter, weekday versus weekend, different seasons combined with different days from left to right, top to bottom,

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respectively. For convenience, we combine only four consecutive days' data from weekday-summer as our simulation input for the reason that it would be more representative, as shown in figure6. We thought that it will bemore intuitive to observe the price trend curves of Real-Time price and market price. This group of data are chosen from July, 2013. We didn't gather lots of data and average them because we need different curves and if it became

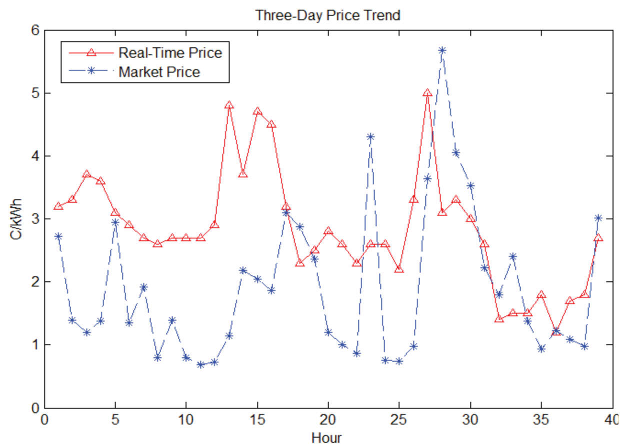

Figure 6. The combined cycle's price curve

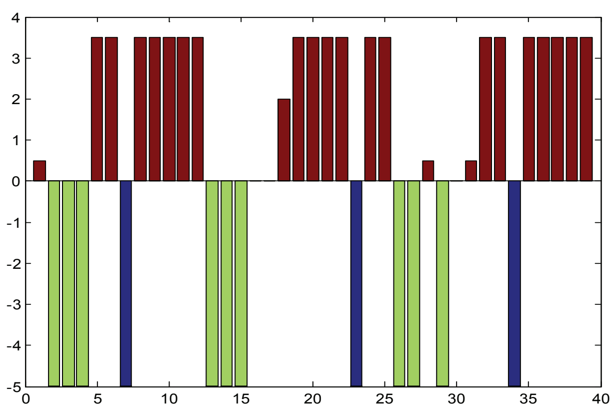

Figure 7. Hourly PHEV energy consumption

constant our mode analysis are meaningless.

We ran our simulation based on a group of typical data in summer shown in figure 6 and we take the three-day mode as an example. The results are shown below. In figure 7, the red, green and blue bars representEV's battery power that charging, discharging to home appliances and discharging back to grid, respectively. Maximum charging/discharging constrains are set as 3.5 kWh and 5kWh, respectively. It is shown that the EV charges (upon zero axis) when the RTP is low and discharges (below zero axis) when the RTP is high and the charging level also follows the price trend inversely. In other words, the storage serves as an alternative energy source when it is expensive to buy the electricity from utilities. And we also find that when the market price are much higher than the RTP at certain hours, no matter what status the battery is in the previous hour, it will sell as much as its remaining energy back to grid and that is exactly what we expected.

In figure 8, the SOC of PHEV are shown. Basically we can see the trend is almost the same with one-day optimization but still exists some different hours. Since we have set the lower bound to prevent over-discharging, the minimum value keeps as 5 kWh. In practice, frequent switching from charging to discharging and also between two different kinds of discharging can lead to extra energy waste and sometimes failure, which exceed our discussion range. The result here

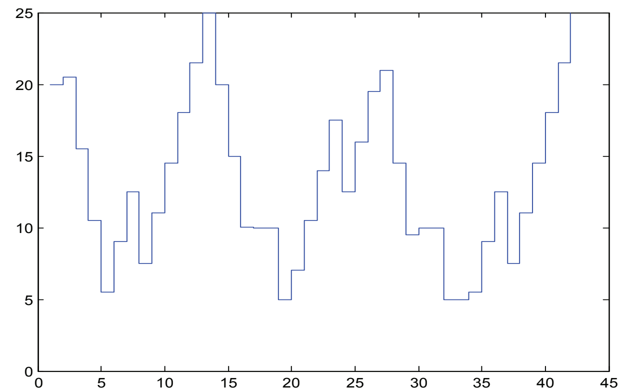

Figure 8. Hourly PHEV's SOC

shows it can average EV's charging pattern to further mitigate the pressure on generators.

Finally we plot the comparison of total cost among non-optimization, single-day optimization and our three-day

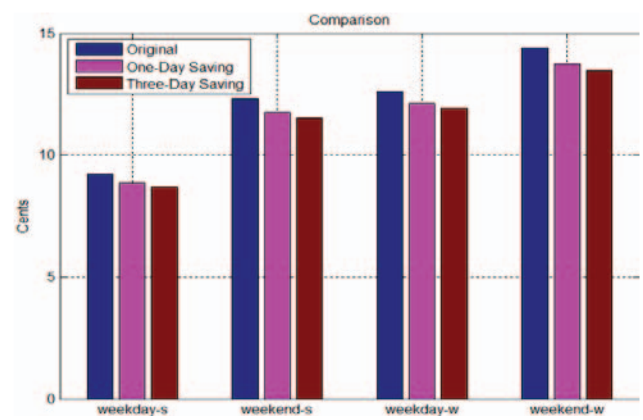

Figure 9. Comparison of daily electric cost in different scenario

optimization modein Figure 9. Here both non-optimization and single-day optimization have ran three times. It is shown that our model did decrease the cost compare to those two other situations and this benefit will definitely encourage customers to take part in the optimal scheduling so that to realize an improved better Vehicle to Smart Home structure.

VI. CONCLUSION AND FUTURE WORK

With EV's fast development and two-way communications that realized by smart grid, residential customers are provided with moreopportunities and flexibilities to perform the demand response. In this work, we have proposedoptimization-based EV scheduling scheme to help customer save their electricity bill while contributing to save

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energy and help utility side. To improve the performance, a future price prediction model is still needed to perform our scheme. Simulation and case study show that our three-day optimization is better than other schemes and can dramatically reduce the cost. Moreover, with the scheduling, the peak EV charging demand during midnight is averaged to a lower level and will become more flexible. We didn't give out the two-day mode scheduling simulation result for the reason that the result is less obvious on price saving but still better than one day optimization.We also ran our simulation several times based on different types of data and the results we showed was just one situation example. In the future, we need to consider the impact caused by the changes of PHEV's charging pattern on electric market as improvement and find a way to smooth frequency PHEV charging/discharging switches.

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