Load Scheduling and Dispatch for Aggregators of Plug-In Electric Vehicles

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***Abstract*—This paper proposes an operating framework for aggregators of plug-in electric vehicles (PEVs). First, a minimum-cost load scheduling algorithm is designed, which determines the purchase of energy in the day-ahead market based on the forecast electricity price and PEV power demands. The same algorithm is applicable for negotiating bilateral contracts. Second, a dynamic dispatch algorithm is developed, used for distributing the purchased energy to PEVs on the operating day. Simulation results are used to evaluate the proposed algorithms, and to demonstrate the potential impact of an aggregated PEV fleet on the power system.**

***Index Terms*—Electric vehicles, power demand, power system economics, smart grids.**

NOMENCLATURE

c_j	Rated power of charger type j.
e_i	Departure time (slot) for the first trip in the morning for PEV i.
$\mathcal{E}$	Overall energy required to charge all PEVs.
$\mathcal{E}_i$	Energy required to charge PEV i.
$\mathcal{H}_i$	Set of time slots where PEV i will be charged.
K	Number of slots within the charging period.
l_i	Charging time (number of slots) of PEV i.
$n(l,j,s,e)$	Number of PEVs with charging duration l, charger type j, arrival slot s, and departure slot e.
N	Number of PEVs under the aggregator's control.
N_1	Number of PEVs charged with energy purchased through long-term bilateral contracts.
N_2	Number of PEVs charged with energy purchased in the day-ahead market.
p_i	Charger power rating of PEV i.
$p_{i,k}$	Scheduled power for PEV i at time slot k.
$\mathcal{P}_k$	Total scheduled charging power at time slot k.
$R_{s+1,e}(\tau_k)$	Rank of τ_k for time slots between $s+1$ and e.
s_i	Arrival time (slot) for the last trip at night for PEV i.
ΔT	Duration of time slot.
τ_k	Wholesale electrical energy price in time slot k.

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I. INTRODUCTION

THE transportation sector accounts today for a significant portion of all nations' petroleum consumption and carbon emissions. For instance, in the U.S. in 2009, 94% of the transportation energy was obtained from petroleum, while 63% of the crude oil was imported [1]. This dependency on dwindling oil resources represents an ever-increasing risk to national security and poses grave environmental concerns. The electrification of transportation and, in particular, the development of plug-in electric vehicle (PEV) technology has been recognized as a key part of the solution to energy and environmental problems worldwide [2], [3]. PEVs—either plug-in hybrid electric vehicles or pure electric vehicles—are equipped with adequate battery energy storage to travel for several miles using (mostly) electricity, and are recharged from the electric grid, thus allowing electricity to displace a portion of petroleum.

The emerging fleet of PEVs will introduce a considerable amount of additional load on the power system. In the simplest case, this can be treated as a traditional (i.e., uncontrollable) load, being served whenever a PEV is plugged in, and billed at a normal retail rate. In [4], the power consumption from a fleet of uncontrolled light-duty PEVs has been estimated based on the travel pattern obtained from the 2009 National Household Travel Survey (NHTS) [5]. The analysis of [4] and other reports [6]–[16] have predicted that a significant amount of PEV charging will take place during peak hours when the wholesale electricity price is high. Moreover, the coincidence between peaks of PEV and non-PEV load will require investments in generation, transmission, and distribution, in order to maintain the reliability of the power system. Fortunately, PEVs are more flexible than traditional load, because the majority of PEV owners return home early in the evening, and may not have a preference about the exact time that their vehicles will be charged, as long as the batteries are full by the next morning. To utilize this flexibility, appropriate algorithms for charging control and management must be designed.

This control will be performed by PEV aggregators, which will be either existing utilities that will offer new financial contracts specific for PEV loads, or new for-profit entities that will participate in the wholesale electricity market. A broad array of aggregators is described in [17], and a conceptual framework to integrate the aggregated PEVs with vehicle-to-grid (V2G) capability into the grid is proposed in [18]. The PEV aggregator considered herein has a significantly large customer base so that it can purchase energy at wholesale. The aggregator could also provide ancillary services to the power system. This has been the focus of previous work, wherein the possible ancillary services that could be offered by aggregated PEVs have been reported [17]. For example, controlling PEVs with or without V2G capability to maximize the revenue from frequency regulation is discussed in [19] and [20], respectively.

In contrast to these previous approaches, where the objective is profit maximization from ancillary services, this paper focuses on the actions of an aggregator who wishes to maximize its energy trading-related profits. In this analysis, the contracts with the PEV owners stipulate that charging will only occur during off-peak hours, e.g., from 10 P.M. to 7 A.M., because most vehicles are not in use and the wholesale electricity price is generally low during this period. Aggregators coordinate and control PEV charging. PEV owners relinquish control of their batteries' state of charge, in exchange for a fixed reduced electricity rate. We are considering a risk-averse aggregator, who would purchase the bulk of its electricity through long-term bilateral contracts and/or by participating in the day-ahead markets (there are 24 hourly markets); the real-time market would be used for balancing purposes only. Specifically, it is assumed that this aggregator controls a fleet of $N = N_1 + N_2$ PEVs; N_1 PEVs are charged with energy purchased through bilateral contracts, while the remaining N_2 PEVs are charged with energy purchased in the day-ahead market. This split is arbitrary, and in the extreme case, either N_1 or N_2 could be zero. Setting $N_1 = 0$ would increase the aggregator's financial risk, so it might not be a prudent choice. Also, because the number of PEVs that subscribe to this aggregator can change on a daily basis, N_2 realistically cannot be zero, unless the aggregator updates its bilateral contracts daily, which is highly unlikely. In any case, it should be noted that this paper does not delve on the determination of the optimal split between N_1 and N_2, but rather on what happens once this split is given. Due to the assumption of a fixed retail rate, profit maximization is equivalent to minimization of the purchased energy cost. Therefore, this aggregator would take advantage of the flexibility of the PEV load, and would charge PEVs with the cheapest possible electricity, which typically occurs during off-peak hours at night. Also, in the presence of several competing aggregating entities, the reduction of energy cost would be necessary to gain market share.

This paper has two main objectives.

1) To set forth algorithms that aggregators can use to schedule and dispatch the PEV load so that their energy cost is reduced (and ideally minimized), using information about the forecasted charging demand for the coming day. The proposed scheduling algorithm can be applied for negotiating long-term bilateral contracts, based on the offered electricity price (especially if this price is time-varying); or for participating in the day-ahead market, based on the forecasted electricity price. The proposed dispatch algorithm is used to distribute the purchased energy to the individual PEVs during the operating day. "Scheduling" and "dispatch" are familiar terms in power system analysis, applicable to generators in the context of unit commitment and economic dispatch, respectively. Herein, these terms are applied to the charging of PEV batteries. In particular, "dispatch" refers to the determination of the charging time for each PEV (dynamically, in real time) so that the actual aggregated power consumption follows the "scheduled" load curve purchased by the aggregator.
2) To identify how an aggregated PEV load would impact the power system, assuming that the aggregator would operate under the current electric energy market structure. The analysis shows that the PEV load can have an unusual stepped pattern, which could be detrimental to the proper operation of the power system. It also suggests that new market mechanisms might be necessary to provide load-leveling and load-smoothing incentives to aggregators.

The rest of this paper is organized as follows: Section II outlines assumptions made in this analysis. In Section III, potential issues with simple uncontrolled off-peak charging are presented. In Section IV, a scheduling algorithm is proposed for minimizing the expected electric energy cost according to the price variation and the charging demand. In addition, a dynamical dispatch algorithm is set forth. In Section V, simulation results are discussed. Finally, Section VI concludes the paper.

II. Analysis Assumptions

The proposed algorithms are developed and validated using the actual U.S. travel patterns as captured by the 2009 NHTS, and the simulation method of [4]. The NHTS statistical data represent the travel patterns of the U.S. light-duty vehicle (LDV) fleet,[1] and contain information on the travel behavior of a national representative sample of U.S. households, such as mode of transportation, trip origin and purpose, and trip distance. LDV travel accounts for 92% of the highway vehicle miles traveled [22], 76% of the energy consumed by highway travel modes [23], and 74% of the carbon dioxide emissions from on-road sources [24]. For the purposes of this analysis, the NHTS database is used to extract statistics of electric energy consumption, charging duration, and arrival and departure times, under reasonable assumptions of PEV drivetrain configurations and charger sizes. In the future, an aggregator will have access to more accurate statistics by monitoring the actual composition, travel pattern, and energy consumption of its own fleet.

The PEV charging infrastructure will be available at the garages or driveways of PEV owners' residences[2] and at some public locations, such as parking lots of commercial buildings and shopping malls. However, it is conceivable that, when charging at public locations, a PEV driver might be hesitant to permit controlled charging, especially if the driver needs to

[1]The U.S. fleet of light-duty vehicles consists of cars and light trucks, including minivans, sport utility vehicles (SUVs), and trucks with gross vehicle weight less than 8500 pounds [21].

[2]Most probably, people will not consider purchasing a PEV if they cannot charge their vehicle at home. Chargers are currently available for 120-V or 240-V circuits, both typically available at U.S. residences [25]. Often, PEV manufacturers and the U.S. federal government offer assistance and financial incentives for the installation of the required equipment [26].

ensure that the battery will be charged as much as possible, uninterrupted throughout the duration of the stop. (A notable exception is the charging that would occur during normal business hours, when employees' vehicles would remain plugged in at the parking lot of their workplace.) Therefore, for simplicity, in this analysis it is assumed that the proposed controlled charging program is associated only with home charging. Nevertheless, in case it becomes necessary to account for the charging at public locations as well, the proposed scheduling and dispatch methods would still apply.

The proposed methods require that the aggregator utilizes techniques for forecasting the day-ahead electricity price, such as the ones presented in [27]–[30]. Herein, it is assumed that day-ahead locational marginal price (LMP) can be forecasted with reasonable accuracy, and the error associated with the forecast is ignored. It is important to note that the LMP forecast's absolute value is not critical. Rather, for minimizing cost, it is the *ranking* of the hourly LMPs that is critical, and should be predicted as accurately as possible. In addition, it is assumed that aggregators' actions do not affect the relative ranking of hourly LMPs.

Finally, any charging constraints that would arise at the distribution level (e.g., from transformer overloading) or distribution system optimization [31] are ignored. This analysis is performed at the bulk power level, and it is further assumed that the aggregator can schedule arbitrarily large amounts of power. Extending this work to systems with detailed distribution feeder models is worthwhile, but is left for future study.

III. Uncontrolled Off-Peak Charging

Fig. 1 depicts the average percentage of vehicles parked at home through a day, calculated using the NHTS data. As can be seen, more than 90% of vehicles are parked at home between 9 P.M. and 6 A.M. Recognizing this opportunity, several charging strategies have been previously proposed for shifting the PEV load to off-peak hours, in order to utilize less expensive electricity and reduce the peak of the overall load. For example, all the vehicles begin charging at 10 P.M. in the "delayed charging" scenario of [7]; half of the vehicles are charged at 10 P.M. and half at 11 P.M. in the "night charge" scenario in [9]; vehicles are only charged between 12 A.M. and 6 A.M. in the "delayed night charging" scenario in [10]. These studies, however, do not take into account realistic travel patterns. So, herein, a similar scenario is considered using the travel pattern obtained from the 2009 NHTS, with charging only allowed between 10 P.M. and 7 A.M. During this period, PEVs will be charged whenever they are parked at home until their batteries reach full capacity. Computer simulations are performed using the method and parameters presented in [4].

The simulation results provide the average power consumption that is shown in Fig. 2(b). It can be observed that the resulting peak load per PEV is much higher than the uncontrolled charging scenario shown in Fig. 2(a). This happens because charging tends to concentrate at the beginning of the charging-allowed period, whereas it would be naturally distributed with time if left uncontrolled. This PEV load is also superimposed on

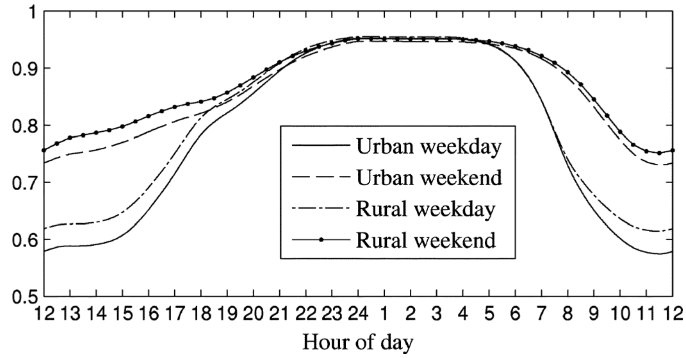


Fig. 1. Average percentage of vehicles parked at home in 2009.

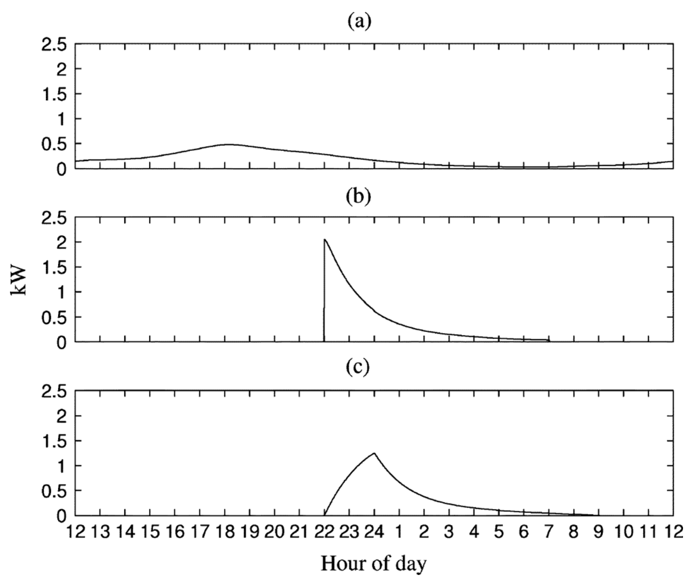


Fig. 2. Average power consumption per PEV (in an urban area on a weekday). (a) Uncontrolled charging. (b) Simple-delayed charging. (c) Modified delayed charging.

MISO's load curve in Fig. 3, for 1 million and 10 million PEVs (which amounts to about one third of the current LDV fleet size in the MISO area).

These findings contradict the conclusions of previous studies (which are obtained with simplified travel patterns) that suggest simple-delayed charging strategies are better than uncontrolled charging in terms of reducing the peak load. In addition, even though the cost of electric energy in this charging scenario would be probably reduced compared to uncontrolled charging, this is not necessarily the most economic way to charge the PEV fleet. The electricity cost could be further reduced by optimally shifting PEV charging to periods with the lowest LMP.

The adverse sharp peak can be avoided with a simple modification, namely, by uniformly distributing the charging start time over a predefined period (e.g., from 10 P.M. to 12 A.M.). This leads to lower peaks, as shown in Figs. 2(c) and 3(c). In fact, it might even be possible to solve the inverse problem of finding the distribution of charging start times that would generate some desirable load pattern. The aggregator would in turn reflect this distribution to the financial contracts with PEV owners. Although this method would be rather simple to implement, it would be static and inflexible, and it would not allow

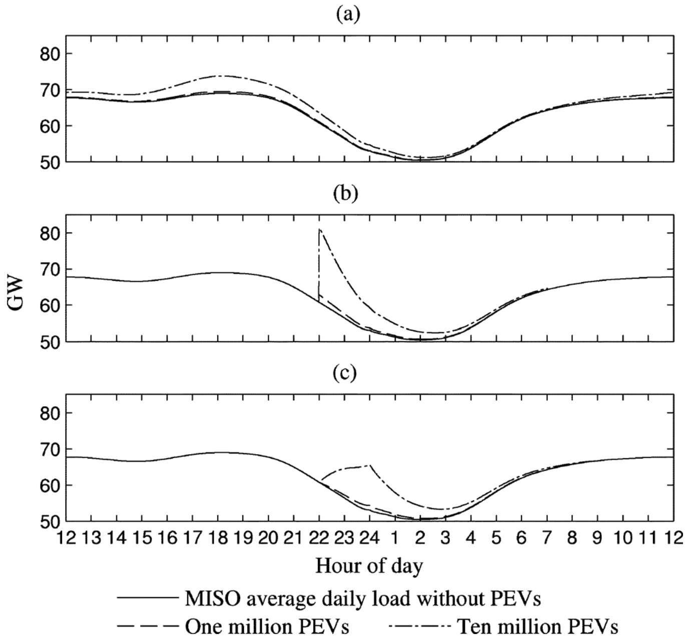


Fig. 3. PEV fleet power load superimposed on MISO load curve. (a) Uncontrolled charging. (b) Simple-delayed charging. (c) Modified delayed charging.

dynamic coordination among PEVs. Also, the peak of the aggregated load would not be synchronized with the lowest LMP, because this varies on a daily basis.

Other more advanced charging control algorithms have been proposed to fill the overnight valley, such as the decentralized control strategy described in [32]. However, flattening the overall load may increase the aggregators' energy cost in the wholesale electricity market. A different strategy is required to maximize the aggregators' profits from energy trading. This is described in the next section.

IV. Proposed Algorithms

In the proposed framework, aggregators control PEV charging during the off-peak period from 10 P.M. to 7 A.M. It is also assumed that they are contractually bound to maximize the state of charge of the batteries by the departure time declared by each PEV owner[3] (unless a battery cannot be fully charged overnight given its state of charge on arrival and the charger rating). The charging period is discretized into a finite number of slots. The proposed scheduling algorithm determines the amount of energy to purchase in each time slot, according to the price (either the bilateral contract price or the forecasted day-ahead LMP) and the PEV charging demands. On the operating day, aggregators need to dispatch the PEV load according to the committed load. The dispatch algorithm determines the time slots where each PEV will be charged.

A. Scheduling

Consider an aggregator that is controlling a fleet of N_x PEVs, $x \in \{1, 2\}$, which are indexed by i. Let p_i denote the charger rating of vehicle i, which belongs to a set $\{c_1, \ldots, c_j, \ldots, c_J\}$, where c_j is the rating of charger type j among a number of charger types J. For a normal residential wiring installation, typical options for charging circuits [33] are shown in Table I, where "charger rating" denotes the nominal power consumption (continuous rated power) at the wall outlet. The "ratio" column shows that these are equally distributed within the hypothetical fleet of PEVs herein for simulation purposes. It is conceivable that there might exist commercial charger models with the capability to modulate the charging power from zero to a rated value based on an external control signal. Nevertheless, in the proposed minimum-cost scheduling and dispatch scheme, all PEVs are charged with either zero or maximum rate. In fact, optimal battery charging follows a varying power profile [34]. However, it has been found that modeling this profile in detail does not affect the simulation results significantly.

TABLE I
Charging Circuits

Charging circuit	Charger rating (kW)	Ratio
120 V, 15 A (Level 1)	1.4	1/3
240 V, 30 A (Level 2)	3.3 (limited by on-board charger)	1/3
	6	1/3

The charging period is discretized into K time slots, indexed by k, with the duration of each time slot equal to ΔT. The parameter ΔT is independent of the rate that market operations take place (e.g., on an hourly basis for the day-ahead market), and will be on the order of 1 min. Such a fine resolution might be necessary to ensure proper charging of the PEVs, i.e., to better accommodate vehicles that arrive or leave at arbitrary times, or whose charging time is not an integer number of hours. The charging time of PEV i, denoted by l_i, is defined as the number of time slots during which charging would take place with full rate p_i, under a simple-delayed charging scenario; in this scenario, vehicles are plugged in as soon as they arrive home, the only restriction on the charging is that it must take place within a prescribed time period, and there is no other advanced control whatsoever. Clearly, $0 \le l_i \le K$. The total energy required to charge all vehicles is $\mathcal{E} = \Delta T \sum_{i=1}^{N_x} p_i l_i$. Furthermore, let τ_k denote the price (either from the bilateral contract or the forecasted day-ahead LMP) during time slot k, and $n(l, j, s, e)$ denote the number of vehicles with charging time l and charger type j, which arrive home at time slot s and leave home at time slot e. (If a vehicle leaves home later than K, then set $e = K$.) Because a vehicle associated with the parameter set $\{l, j, s, e\}$ can be charged for at most $e - s$ time slots (the earliest that charging can start is the $s + 1$ slot), it follows that $l \le e - s$.

It is assumed that reliable estimates of $n(l, j, s, e)$ can be obtained from statistics, based on data that the aggregator can collect on a daily basis from its fleet of PEVs. Herein, such statistics are generated using the 2009 NHTS data set. For illustration purposes, we consider the trips of all urban vehicles that traveled on weekdays, and it is assumed that the driving patterns of PEVs are similar to those of regular automobiles. Elimination of the vehicles that did not travel on the survey date (ca. 35% of the total number of vehicles), as well as of those that for any reason

[3]It is conceivable that some PEV owners would try to ensure that their vehicle gets charged by reporting false (i.e., earlier than the actual) departure time. Hence, they must be incentivized to report their true departure time, or penalized when they consistently report false departure times. The design of such mechanisms would fall within the aggregator's responsibility, but is outside the scope of this paper.

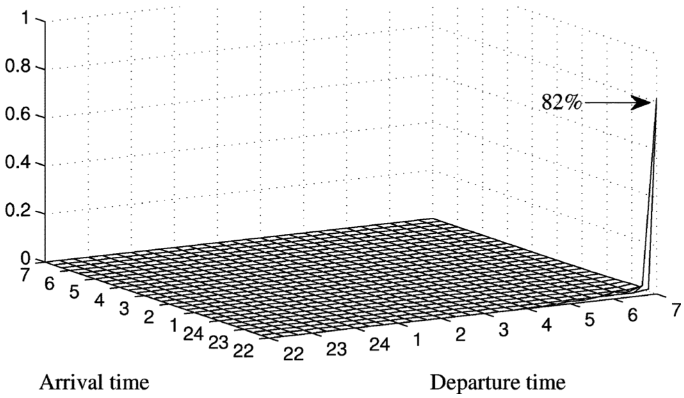


Fig. 4. Probability of vehicle arrival and departure time. Note: The vehicles in the 10:00–10:20 P.M. arrival time or 6:40–7:00 A.M. departure time category arrived home before 10:20 P.M. or left home after 6:40 A.M., respectively.

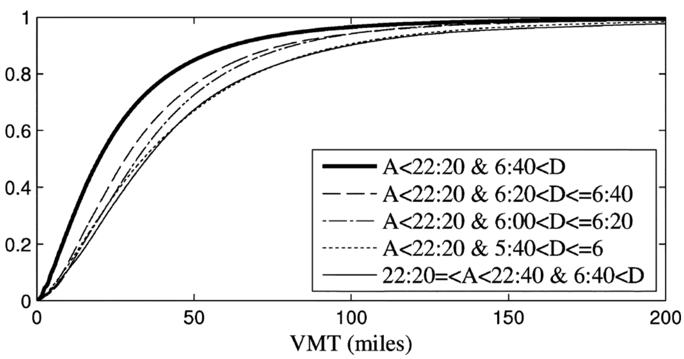


Fig. 5. CDF of daily VMT for several combinations of arrival and departure times.

did not return home at the end of the day (ca. 5.8% of the vehicles that traveled), yields a total of approximately 86 000 vehicles, whose trips are used to generate the statistics. First, each vehicle is categorized according to its arrival and departure time, using 20-min-long time slots. This results in the two-dimensional probability distribution shown in Fig. 4. As can be observed, the majority of vehicles (ca. 82%) arrive at home before 10:20 P.M., and leave home after 6:40 A.M., but several other bins contain substantial vehicle numbers as well. It is important to note that the travel patterns differ between these groups of vehicles. For example, further examination of the NHTS data reveals that vehicles that arrive home later at night and leave earlier in the morning usually travel longer distances than the rest (as is intuitively expected); this is depicted by the cumulative distribution functions (CDFs) of vehicle-miles traveled (VMT) shown in Fig. 5. Finally, the electrical energy required to charge the PEVs is computed using the above VMT information and the method described in [4]; some representative results from these statistics are illustrated in Fig. 6. The end result of these calculations is $n(l,j,s,e)$.

Given τ_k and $n(l,j,s,e)$, a load scheduling that minimizes the wholesale energy cost is outlined below as Algorithm 1. (If τ_k represents the forecasted day-ahead price, then it is the expected energy cost that is minimized.) The basic idea is to charge each vehicle in the time slots where the lowest electricity price occurs. PEVs can only be charged when they are parked (at home), so for each vehicle i only the time slots between s_i and

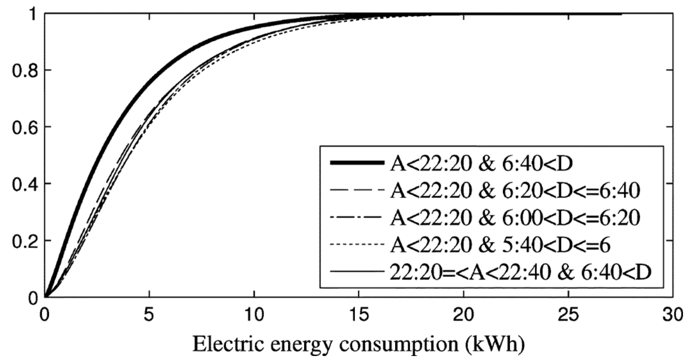


Fig. 6. CDF of daily PEV electric energy requirement for several combinations of arrival and departure times.

e_i need to be considered. The time slots are ranked by electricity price from low to high, and the l_i time slots associated with the least expensive electricity are selected for charging.

Algorithm 1 Min-Cost Load Scheduling

Input: τ_k for $1 \le k \le K$, and $n(l,j,s,e)$ for $1 \le s < e \le K, 0 \le l \le e-s \le K$ and $1 \le j \le J$.
for $k = 1$ **to** K **do**
  $\mathcal{P}_k \leftarrow 0$
end for
for $s = 1$ **to** K **do**
  for $e = s+1$ **to** K **do**
    Rank the price τ_k for $s < k \le e$ from lowest to highest. The ranking function is denoted by $R_{s+1,e}(\tau_k)$, and takes the values $\{1,\ldots,e-s\}$. If different time slots have equal τ_k, they are ranked according to the index k from low to high.
    for $m = 1$ **to** $e-s$ **do**
      Compute the power which should be purchased for the time slot with the m^{th} cheapest price among time slots $s+1$ to e, which is

$$\chi_m \leftarrow \sum_{j=1}^{J} c_j \sum_{l=m}^{e-s} n(l,j,s,e).$$

    end for
    for $k = s+1$ **to** e **do**
      Update the charging power $\mathcal{P}_k$ for time slot k:

$$\mathcal{P}_k \leftarrow \mathcal{P}_k + \chi_{R_{s+1,e}(\tau_k)}.$$

    end for
  end for
end for
return $\mathcal{P}_k$

Algorithm 1 solves the following linear program:

$$\min_{p_{i,k}} \quad \Delta T \sum_{i=1}^{N_x} \sum_{k=1}^{K} \tau_k p_{i,k} \tag{1}$$

$$\text{subject to} \quad \sum_{k=1}^{K} p_{i,k} = p_i l_i, \quad \text{for all } i \tag{2}$$

$$0 \le p_{i,k} \le p_i, \quad \text{for all } i, k \tag{3}$$

$$p_{i,k} = 0 \quad \text{for } k \le s_i \text{ and } k > e_i, \text{ for all } i. \tag{4}$$

The solution that is produced is (for all i)

$$p_{i,k} = p_i, \text{ for } k \text{ such that } R_{s_i+1,e_i}(\tau_k) \le l_i, \text{ and} \tag{5}$$

$$p_{i,k} = 0, \text{ otherwise.} \tag{6}$$

This solution corresponds to one of the extreme points on the boundary of the feasible region, and is optimal by construction. The algorithm outputs a schedule for the minimum-cost power purchase, $\mathcal{P}_k$. It is possible to use a commercial solver to obtain a numerical solution to this problem. However, this solution will not have a clear physical significance. On the other hand, the proposed algorithm, via the use of the ranking function R, provides a way to affect the shape of the PEV load, as will be demonstrated later.

It is interesting to observe that there might be other equally optimal solutions to this problem, yielding the same energy cost. For instance, consider a PEV i that has been parked at home since early in the evening, and that needs to charge for 90 min, so $l_i = 90$ if $\Delta T = 1$ min. Also, assume that the price remains constant for hour-long intervals (as usual for the LMP of the day-ahead market). Obviously, this PEV's charging will be spread over two hourly intervals (which could be non-adjacent), corresponding to the two lowest LMPs occurring between s_i and e_i, say, between 1–2 A.M. (the lowest), and 4–5 A.M. (the second lowest). Therefore, this PEV will get charged for all 60 slots between 1–2 A.M., but the remaining 30 slots can be selected arbitrarily from the 60 slots of the 4–5 A.M. period (there are $\binom{60}{30}$ combinations if the slots are not contiguous, or 30 different combinations of contiguous time slots). Alternatively, the PEV could be charged during the entire 4–5 A.M. period, but at reduced (half) power if this capability is provided by the charger, or for some other combination of time slots/power level if the battery charging tail end profile is considered. The proposed Algorithm 1 would use the first 30 slots of the 4–5 A.M. interval, because of its definition of the ranking function $\mathcal{R}$ (see step 7). Various other minimum-cost algorithms, each using a different slot selection algorithm, can be conceived. This flexibility could be used to provide regulation services to the power system [20].

The relative ranking of hourly day-ahead LMPs will probably not be affected under a mild PEV penetration level, say, within the next five to ten years. However, this could occur under higher PEV penetration levels. In this case, the aggregator would use a modified min-cost scheduling algorithm, whose basic idea is as follows: First, PEV load will be scheduled during the cheapest hour of day, until the price becomes equal to the second cheapest price. After this point, additional PEV load will be distributed between these two hours of the day. If the PEV load makes the price reach the level of the third cheapest price, then any additional PEV load will be distributed over these three hours, and so forth. The use of advanced day-ahead LMP forecasting algorithms, such as the ones in [27]–[30], will be again necessary.

B. Dispatch

The purpose of the proposed dispatch algorithm (Algorithm 2) is to distribute the purchased energy to the PEVs, with as little deviation from the schedule ($\mathcal{P}_k$) as possible. It is assumed that the aggregator does not engage in arbitrage. The charger ratings (p_i) of all PEVs controlled by the aggregator are known beforehand. The algorithm keeps running throughout the nightly charging period, and dynamically updates the list of PEVs and their charging time slots. The plug-in time (s_i) and required energy ($\mathcal{E}_i$) are communicated by PEV i to the aggregator as soon as it is plugged in. Simultaneously, the PEV owners report their expected departure time (e_i). For the vehicles that are expected to depart after the end of the charging period, the departure time is set to K. The charging duration (l_i) is calculated based on the above information, from $\mathcal{E}_i = \Delta T l_i p_i$. Decisions are made dynamically in real time for each arriving PEV, which is assigned the next l_i least expensive time slots, as long as these slots still have available power. At time slot k, if $k \in \mathcal{H}_i$, the aggregator charges PEV i with rate p_i. It should be noted that Algorithm 2 is not an optimization algorithm. However, its design is related to Algorithm 1, because it also uses the same ranking function R.

Algorithm 2 Dispatch

Input: $\mathcal{P}_k$ for $k = 1, \ldots, K$, and p_i for $i = 1, \ldots, N_x$.
loop
  if PEV i arrives at home and gets plugged in **then**
    Receive $\{\mathcal{E}_i, s_i, e_i\}$. Calculate l_i.
    Rank the time slots $\{k : s_i+1 \le k \le e_i \text{ and } \mathcal{P}_k > 0\}$ according to τ_k, from lowest to highest. The rank of slot k is denoted by $R_{s_i+1,e_i}(\tau_k)$.
    $\{\mathcal{P}_k \le 0$ corresponds to the case where the purchased power at time slot k has been exhausted.$\}$
    $\mathcal{H}_i \leftarrow \{k : R_{s_i+1,e_i}(\tau_k) \le l_i\}$.
    $\mathcal{P}_k \leftarrow \mathcal{P}_k - p_i$, for all $k \in \mathcal{H}_i$.
  end if
end loop

V. Simulation Results

Fig. 7 depicts the average load per PEV (i.e., all PEVs under contract, including those do not travel or return home) that would be obtained from Algorithm 1 with a hypothetical day-ahead LMP variation. The algorithm is run using 1-min-long time slots, while the price changes on an hourly basis. As can be observed, at the beginning of each hour, the PEV load has a relatively large spike that decreases with time, due to those PEVs that finish charging before the hour is over. This load shape is quite different from a traditional load variation. If the penetration of PEVs becomes significant, these abrupt step changes (both upwards but also downwards at the start of each hour) could be problematic for frequency regulation and transient system stability. Perhaps a better solution for the power system would be to average the PEV load throughout the hour. To achieve this, for example, the ranking function $\mathcal{R}$

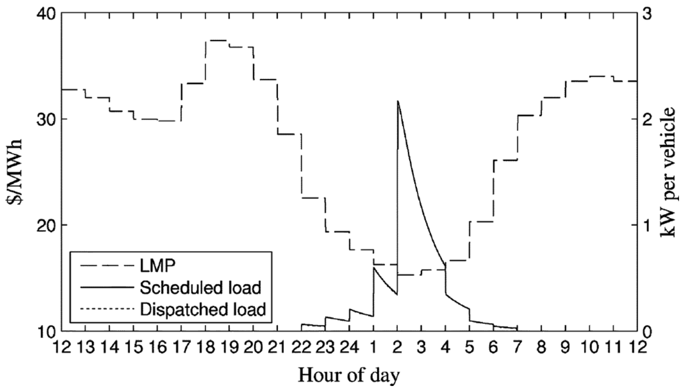


Fig. 7. LMP and PEV scheduled load obtained by Algorithm 1. Also shown is the PEV load dispatch obtained by Algorithm 2, which is almost identical to the scheduled load curve.

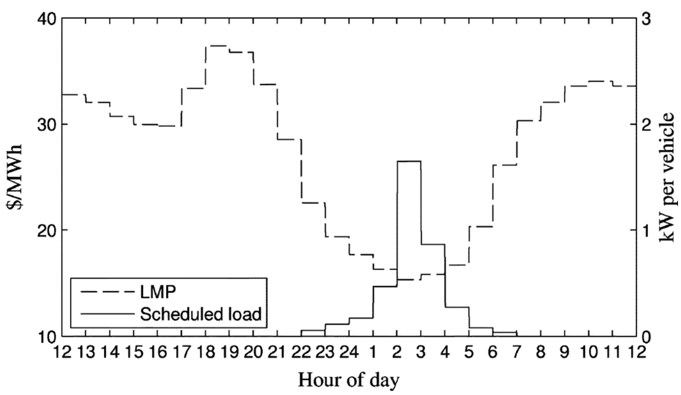


Fig. 8. LMP and hourly PEV load obtained by a modified Algorithm 1 that uses an alternate ranking function, which has no preference for the earlier time slots.

could be modified so that there is no preference for earlier time slots. This yields the load profile shown in Fig. 8.

Algorithm 2 (dispatch) is applied to a set of trips randomly generated based on the NHTS data, different than the one used for the scheduling algorithm. In particular, the departure of PEVs at times different from the reported ones is modeled as a Gaussian error term: $e_i^{\mathrm{true}} = e_i + \mathcal{N}(0, \sigma)$. A 10-min standard deviation is chosen. Since most of the vehicles leave after 7 A.M., such errors are quite insignificant. Even for those PEVs that depart before 7 A.M., an earlier departure may not cause a problem, because their charging might be complete before their actual departure time. The dispatch obtained by Algorithm 2 is shown in Fig. 7 together with the scheduled load that was previously determined from Algorithm 1. The two curves are almost identical.

Aggregators would have to purchase the estimated average hourly power consumption as hourly energy blocks in the day-ahead market (or by a long-term bilateral contract). Hence, it could be argued that any aggregator would level its hourly load in order to match its actual consumed power with the amount purchased. This would minimize the deviation of its real-time load from the purchased power, reducing (and ideally eliminating) potential penalties or losses incurred from being forced to participate in the real-time markets.

Nevertheless, even this "flatter" load variation is atypical. Even without the pronounced spikes at the beginning of the hour, the step changes—if large enough—could cause problems to system frequency regulation. As mentioned in the Introduction, PEV fleets can be used to provide regulation services to the system to alleviate generation-load unbalance [17]–[20], whereas the PEV load shape obtained by the min-cost scheduling algorithm will require additional regulation at the beginning of each hour from other sources. (This becomes apparent once the maximization of energy trading-related profits becomes an objective. Previous work on PEV-related frequency regulation has not identified this issue.) Power systems routinely handle MW-level step changes in load, for example, from large industrial customers. The potential problem described here stems from the sheer impact of a large aggregate PEV load (such as several million PEVs in the MISO system that would cause hourly steps on the order of hundreds of MW) coupled with its controllability. This will tend to synchronize the step changes at the beginning of the hour among all aggregators in the system, especially if the prices are calculated on a zonal rather than a nodal basis, or for metropolitan areas with a single LMP where large concentrations of PEVs would exist. This phenomenon could be made less pronounced by purchasing the bulk of the energy via long-term bilateral contracts.[4] Also, the difference of LMP prices at different nodes throughout the power system could be beneficial, unless the correlation of LMP time variation is significant throughout the system. A more accurate analysis that will use LMP calculations obtained from an optimal power flow formulation is left for future study, which should take into account the impact of the additional PEV load on the LMP levels, whose relative ranking is assumed to be predefined in this analysis. But regardless of the calculated LMP levels, the resulting waveform of aggregated PEV power load will probably still have a similar staircase shape, with the bulk of the energy consumed during the hour of lowest LMP.

Aggregators also have the option to bid a price-sensitive load curve in the day-ahead market, but this complicates the scheduling process considerably. To see why this is so, consider the case where the contract between the aggregator and the PEV owners stipulates that PEVs must be maximally charged overnight. Assume that during hour h, high prices lead to some PEV load not being served. This lost energy must be acquired during hour $h+1$ or later. However, the price-sensitive bids are submitted one day in advance, and cannot be modified. This will force an aggregator to acquire the energy deficit in the real-time market, and will increase its financial risk. (Even so, it is not clear at which hour it would be advantageous to purchase the deficit.) So, bidding price-sensitive loads might be a problematic strategy.

The currently implemented two-settlement market structure has been devised with the traditional slowly varying bulk power system load in mind, which has relatively minor real-time deviations. But an emerging controllable PEV fleet represents an important new constant-energy load paradigm, which requires a certain amount of electric energy over a specific period of time, and for which the exact time and rate of power consumption

[4]Applying Algorithm 1 to a bilateral long-term contract with a single off-peak price yields an average power consumption that is identical to the curve of Fig. 2(b). A large step change in load would still occur, but only once.

are not critical to the end-user. Our results seem to suggest that perhaps the existing market mechanisms should be modified, in order to provide the appropriate incentives to the PEV aggregators, so that the power system operation is not compromised. For example, it might be beneficial to smoothen the PEV load variation; however, a hypothetical aggregator today would have no incentive to do so, and in fact it might be penalized for deviating significantly from the purchased load level. Perhaps new regulations that impose maximum ramp up/down rates to aggregated PEV loads are necessary, in addition to the ones already in place for generating units. Alternatively, it might be beneficial to use the PEV load to fill the overnight valleys of the overall system load; this has been previously suggested to be one of the major benefits of PEV integration with the power system. Apparently, this will not be the case if aggregators participate in the wholesale energy markets, because the obtained load will not have the required pattern that will exactly level the load curve. The design of appropriate market-based mechanisms remains an open research question.

VI. Conclusion

This paper set forth algorithms for the scheduling and dispatch of electric power by aggregators of PEV fleets, whose main objective is the maximization of energy trading profits. The aggregators are assumed to operate in the current wholesale electric energy market framework. The algorithms were developed by taking into account realistic vehicle travel patterns from the NHTS database. The impacts of such fleets on the bulk power system were estimated with computer simulations. A major implication of our findings is that current market regulations and policies associated with PEV load have to be revised, to avoid causing problems to the power system, and to incentivize its utilization in a synergistic manner in order to improve the overall system operation, especially for aggregators without interest in ensuring power system reliability.

References

[1] "Annual energy review," Energy Information Administration, U.S. Dept. of Energy, Washington, DC, Tech. Rep. DOE/EIA-0384(2009), 2010.

[2] J. T. Chambers *et al.*, "Fleet electrification roadmap. Revolutionizing transportation and achieving energy security," Tech. Rep., Nov. 2010, Electrification Coalition.

[3] N. Tanaka *et al.*, "Technology roadmap: Electric and plug-in hybrid electric vehicles," International Energy Agency, Tech. Rep., Jun. 2011.

[4] D. Wu, D. C. Aliprantis, and K. Gkritza, "Electric energy and power consumption by light-duty plug-in electric vehicles," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 738–746, May 2011.

[5] "National Household Travel Survey (NHTS)," U.S. Dept. Transportation, Federal Highway Administration [Online]. Available: http://nhts.ornl.gov/download.shtml

[6] P. Denholm and W. Short, "An evaluation of utility system impacts and benefits of optimally dispatched plug-in hybrid electric vehicles," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-620-40293, Oct. 2006.

[7] K. Parks, P. Denholm, and T. Markel, "Costs and emissions associated with plug-in hybrid electric vehicle charging in the Xcel Energy Colorado service territory," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-640-41410, May 2007.

[8] M. Kintner-Meyer, K. Schneider, and R. Pratt, "Impacts assessment of plug-in hybrid vehicles on electric utilities and regional U.S. power grids. Part 1: Technical analysis," *J. EUEC*, vol. 1, no. 4, 2007.

[9] S. W. Hadley and A. Tsvetkova, "Potential impacts of plug-in hybrid electric vehicles on regional power generation," Oak Ridge National Laboratory, Oak Ridge, TN, Tech. Rep. ORNL/TM-2007/150, Jan. 2008.

[10] S. Letendre and R. A. Watts, "Effects of plug-in hybrid electric vehicles on the Vermont electric transmission system," in *Proc. Transport. Res. Board 88th Annu. Meet.*, Washington, DC, Jan. 2009.

[11] "Alternate route: Electrifying the transportation sector. Potential Impacts of plug-in hybrid electric vehicles on New York State's electricity system," New York Independent System Operator, Tech. Rep., Jun. 2009.

[12] S. Meliopoulos, J. Meisel, G. Cokkinides, and T. Overbye, "Power system level impacts of plug-in hybrid vehicles," Power Systems Engineering Research Center (PSERC), Tech. Rep., Oct. 2009.

[13] A. Hajimiragha, C. A. Cañizares, M. W. Fowler, and A. Elkamel, "Optimal transition to plug-in hybrid electric vehicles in Ontario, Canada, considering the electricity-grid limitations," *IEEE Trans. Ind. Electron.*, vol. 57, no. 2, pp. 690–701, Feb. 2010.

[14] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, "Evaluations of plug-in electric vehicle distribution system impacts," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, Minneapolis, MN, Jul. 2010.

[15] M. Mahalik, L. Poch, A. Botterud, and A. Vyas, "Impacts of plug-in hybrid electric vehicles on the electric power system in Illinois," in *Proc. IEEE Innov. Technol. Efficient Reliable Electr. Supply (CITRES)*, Waltham, MA, Sep. 2010, pp. 341–348.

[16] R. Sioshansi, R. Fagiani, and V. Marano, "Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system," *Energy Policy*, vol. 38, no. 11, pp. 6703–6712, Nov. 2010.

[17] K. Fell *et al.*, "Assessment of plug-in electric vehicle integration with ISO/RTO systems," KEMA, Inc. and ISO/RTO Council, Mar. 2010 [Online]. Available: http://www.isorto.org

[18] C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid (V2G) implementation," *Energy Policy*, vol. 37, no. 11, pp. 4379–4390, Nov. 2009.

[19] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–72, Jun. 2010.

[20] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, "Demand dispatch," *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 20–29, May/Jun. 2010.

[21] "Fuel economy of the light-duty vehicle fleet," U.S. Energy Information Administration [Online]. Available: http://www.eia.doe.gov/oiaf/aeo/otheranalysis/aeo_2005analysispapers/feldvf.html

[22] "Highway Statistics 2006," U.S. Dept. of Transportation, Federal Highway Administration, Table VM-1 [Online]. Available: http://www.fhwa.dot.gov/policy/ohim/hs06/htm/vm1.htm

[23] "National transportation statistics," U.S. Dept. Transportation, Bureau of Transportation Statistics, Table 4–6 [Online]. Available: http://www.bts.gov/publications/national_transportation_statistics/html/table_04_06.html

[24] Transportation Statistics Annual Report 2008 U.S. Dept. of Transportation, Bureau of Transportation Statistics, Table 1-1-1 [Online]. Available: http://www.bts.gov/publications/transportation_statistics_annual_report/2008/html/chapter_01/table_01_01_01.html

[25] "Characterizing consumers' interest in and infrastructure expectations for electric vehicles: Research design and survey results," Electric Power Research Institute, Tech. Rep. 1021285, May 2010.

[26] P. Fairley, "Nissan gets into the electric vehicle charging business," [Online]. Available: http://staging.spectrum.ieee.org/energywise/energy/the-smarter-grid/nissan-gets-into-the-electric-vehicle-charging-business

[27] T. Niimura, "Forecasting techniques for deregulated electricity market prices," in *Proc. Power Syst. Conf. Expo.*, Atlanta, GA, Oct. 2006.

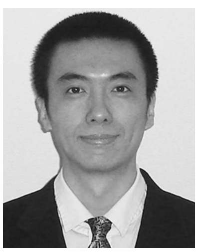
[28] G. Li, C.-C. Liu, C. Mattson, and J. Lawarree, "Day-ahead electricity price forecasting in a grid environment," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 266–274, Feb. 2007.

[29] N. Amjady and F. Keynia, "Day-ahead price forecasting of electricity markets by mutual information technique and cascaded neuro-evolutionary algorithm," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 306–318, Feb. 2009.

[30] L. Wu and M. Shahidehpour, "A hybrid model for day-ahead price forecasting," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1519–1530, Aug. 2010.

[31] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011.

[32] Z. Ma, D. Callaway, and I. Hiskens, "Decentralized charging control for large populations of plug-in electric vehicles: Application of the Nash certainty equivalence principle," in *Proc. IEEE Int. Conf. Control Appl. (CCA)*, Yokohama, Sep. 2010, pp. 191–195.
[33] "Comparing the benefits and impacts of hybrid electric vehicle options," Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 1000349, Jul. 2001.
[34] D. Danilov and P. H. L. Notten, "Adaptive battery management systems for the new generation of electrical vehicles," in *IEEE Veh. Power Prop. Conf. (VPPC)*, Dearborn, MI, Sep. 2009, pp. 317–320.



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