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Investigating the charging potential of Plug-in Hybrid Electric Vehicles integrated with Sustainable buildings

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Abstract: One of the major challenges of the twenty-first century is developing technologies that reduce greenhouse gas emissions. One technology with the potential to address these challenges is plug-in (hybrid) electric vehicles (PHEVs). PHEVs derive much of their energy from the electric power grid rather than gasoline. If the projections of large PHEV penetration are true, they will put considerable additional stress onto existing power grids. It has been proposed that the appropriate scheduling of PHEV charging can reduce this stress through demand response. The PHEV charging scheduling has multiple facts. The focus of this paper is to develop algorithmic approaches to deal with the uncertainties associated with PHEV charging. The scheduling problem is modeled as a multi-stage online decision problem where input parameters of future charging requests and power grid status are not revealed when current charging decisions are made. We present two algorithms: consensus and expectation that use predictions about the future to make scheduling decisions.

Key Words: PHEV, Vehicle-to-Grid, Charging Scheduling, Online Optimization, Sustainable buildings

I.INTRODUCTION

Modern power grids are large, complex systems and managing them is challenging. Many power grid management tasks are modeled as scheduling problems, e.g., the maintenance of power grid components [21]. A classic and important scheduling grid management task is the unit commitment problem (see [13] for a survey). Various models and algorithms were developed for this problem including alternating current [7], direct current [27], and stochastic variations [11], [10]. The problem of unit commitment has become increasingly difficult in recent years as renewable energy has increased its share of generation mixes in today's grid, as described by a recent report [14]. The integration of renewable energy sources into the power grid is one of the features promised for next generation power grids (sometimes called smart grids). While intelligent unit commitment can address part of this problem, this paper considers another smart grid scheduling technology, demand-side management [25], in the presence of intermittent renewables. Demand-side management is a task where loads are scheduled to reduce peak power consumption and take advantage of cheap, clean renewable energy sources [18], [9]. For example, scheduling algorithms were proposed to manage deferrable loads based on forecasting [26]. A specific demand side scheduling problem involves charging batteries for plug-in (hybrid) electrical vehicles (PHEVs) [17].

The projected increase in PHEV adoption has the potential to add substantial loads to existing power grids. The vehicle to-grid (V2G) is a conceptualized system through which PHEVs interact with power grids. In a V2G system, PHEVs are used to balance load by charging during off-peak periods and discharging power when generation capacity is low. In a recent paper [24], a long-term planning location model was proposed to site battery exchange stations for optimal charging, discharging, and battery swapping. The counterpart of this problem is daily operation; the short term scheduling of electric vehicle charging to minimize the impact of additional demand on existing power grids [23], [19], [8], which this paper seeks to address.

In this paper, we consider the problem of centralized scheduling vehicle battery charging in the presence of renewable generation. PHEV charging is a multifaceted problem that includes communication between PHEVs and power grids, how to charge PHEVs with physical capacity constraints, and generation dispatch to minimize impact of additional loads from PHEV.

The focus and contribution of this paper are on developing stochastic online scheduling algorithms that deal with various uncertainties associated with battery charging through sampling future scenarios. More specifically, these uncertainties include states of PHEVs, i.e., arrival time of future requests for charging, departure times of PHEVs, required energy to charge future PHEVs, and the state of an electric power system (generation capacity and electricity cost). In addition to these uncertainties, scheduling decisions are made in real time. Therefore, scheduling algorithms need to be efficient and adjustable under computational time limits. Online optimization [16] and online stochastic optimization [28] have been applied to make real-time decisions under uncertainties and time constraints and its application is proposed here. In the literature, online stochastic scheduling problems have been studied in the context of package scheduling, job scheduling [12], [4], [1] with success proving evidence for its application to the problem discussed here.

The key contributions of this paper include developing a generalization of online stochastic optimization to problems with multiple decisions at every time step and designing efficient scheduling algorithms for PHEV battery charging.

II. ONLINE ALGORITHMS

The online algorithms are assumed to have access to a probability distribution characterizing the uncertainty about the future (generation capacity, electricity prices, PHEV requests). This distribution can be thought of as a black box that produces samples of possible futures. Given that the uncertainty in this problem does not depend on the decisions to schedule batteries, we are able to use the online stochastic optimization framework of [5], which offers some attractive computational advantages over approaches such as multi-stage stochastic programming.

Figure - 1. In this figure, line 1 initializes the objective function to 0. Lines 2-9 define the loop for executing the decision making at each time step t. Line 3 collects all the PHEV requests that can be scheduled at time t. This includes any available requests from t -1 and new requests that arrive at time t. Line 4 chooses a set of requests to charge at time t. This is the point where different online algorithms may be implemented to determine the choice of requests to schedule (the function CHOOSEREQUEST). This part of the algorithm is also an important generalization of the framework of [5], as it returns a set of requests to schedule instead of a single request. As discussed here, this feature makes some of the traditional online algorithms more complex. Lines 5-8 update the schedule. Finally, line 9 updates the objective function by adding the expense for charging batteries and the cost for the departure of any uncharged batteries. Notice that Y(t)is the sum of uncharged units in period t (∑åi:di=t yi), and yi is used in the linear program (1)-(4) to account for uncharged units for each PHEV. More formally ,the function AVAILABLEREQUESTS is defined as

AVAILABLE REQUESTS(t) –
The function EXPIREDREQUESTS is defined by
EXPIREDREQUESTS(t) –
ONLINE OPTIMIZATION(t)
1 z →0;
2 **for** t $\in T$;
3**do** I ← AVAILABLEREQUESTS(t) $\cup$NEWREQUESTS(t);
4 I ← CHOOSEREQUESTS(I ; t);
5 $\gamma \leftarrow \gamma - 1;$
6**for** I $\in$ i;
7 **do** $\gamma \leftarrow \gamma \cup [x(it) - 1];$
8 $\gamma \leftarrow \gamma \cup [y \leftarrow EXPIREDREQUEST(t)];$
9 $z \leftarrow z + c_{|i|} + \lambda * y;$

Fig. 1. The basic structure of the online algorithms

Our first online algorithm implements CHOOSEREQUESTS in a greedy fashion, scheduling as many batteries as possible at a time t, with a preference on earliest departure time. This algorithm is similar to the Earliest Deadline First algorithm described in the paper [26]. We define S(I,a) be a subset of I such that |S(I,a)| ≤ a. For i $\in$ S(I,a), di is no larger than dj for any j $\in$ I \ S(I,a). The notation argmax|S(I,a)| returns a subset with the maximal size.

Latest Delay Our second online algorithm implements CHOOSEREQUESTS by waiting as long as possible to schedule requests. More formally it is presented in Figure-3 where SUBSET(S,a) returns a maximal-sized set of elements.

CHOOSEREQUEST-G(I, t)

1. **return** argmax|S[I,g(t)]|;

Fig. 2. Greedy algorithm

S with size ≤ a.

CHOOSEREQUEST-LD(I , t)

1 S ← $\cup\, i \in I(t) \;|di == t;$
2 **return** SUBSET[S , g(t)];

Consensus Our third algorithm adopts the idea of consensus from [4]. In the consensus algorithm, at a time t a number of samples of possible futures are considered. Each sample is solved and the decision that occurs the most often at time t is chosen. This algorithm can be thought of as maximizing the probability of achieving an optimal solution to the future. The biggest difference between the consensus algorithm of [4] and [5] is that they make a single decision at a time step. Here we must choose a set of decisions. The simplest way to generalize the consensus algorithm to sets of decisions is to consider all possible combinations of decisions on individual PHEV charging and evaluate them according to the consensus idea (it treats each combination, $\gamma(t)$, of decisions as a single decision). This is described more formally in Figure 4. In this figure, lines 1-2 initialize the consensus scores for the combinations to 0. Lines 3-7 generate K samples and determine the optimal solution to each sample. Line 4 generates a sample of future requests $\emptyset$, generation capacity g, and electricity costs to a user-specified time horizon Δ. Line 5 creates a set of PHEV requests. Line 6 solves the battery scheduling problem .Line 7 increments the consensus score for the combination of batteries scheduled at time t.

This algorithm needs K to be prohibitively large in order to accurately score the consensus across all the combinations. Instead, we approximate consensus as seen in Figure 5. In this approximation, there are two consensus scores, one on each individual PHEV and one on the number of unused slots of the grid. In this figure, lines 1-2 initialize the consensus scores of individual PHEV battery requests to be 0. Lines 3-4 initialize the consensus scores for the number of slots to leave unfilled in the grid to be 0. Lines 6-12 generate K samples and determine the optimal solution to each sample. Line 6 generates a sample tuple of future requests. Line 7 creates a set of PHEV requests. Line 8 solves the battery scheduling problem using TP. Lines 9-10 compute increments of the consensus score for the charging requests scheduled at time t. Lines 11-12 increment the consensus score for the number of slots unused at time t.

CHOOSEREQUEST-C(I, t)-

1 **for** i $\in$ COMB(I);
2**do** m(i) $\leftarrow$ 0;
3**for** k $\leftarrow$ 1............K;
4 **do** $\langle\emptyset,\ g, c\rangle \leftarrow SAMPLE(\Delta)$;
5 A $\leftarrow I \cup \emptyset$;
6 $\leftarrow TP(\gamma - 1, A, g, c)$;
7 $(\gamma(t)) \leftarrow m(\gamma(t)) + 1$;
8 **return** arg max($i \in COMB(I)$) m(i);

In this paper, we assume that the underlying power grid is well designed and the only capacity constraint is on the power generation. As long as there is enough total power, it can be delivered to satisfy the load from PHEVs. The absence of physical constraints and stability issues of a power grid allows us to focus on dealing with the uncertainties related to PHEV charging; we leave grid constraints for future work.Also, PHEVs are assumed to be charged at a single rate, e.g., the level-2 charging rate (240VAC, single-phase, 40Amp). This constant rate is modeled as a unit called a slot for measuring energy. For any given period, a PHEV can consume only one slot of energy for battery charging. In turn, battery demand l(i) and generation capacity g(t) are also measured in units of slot.

CHOOSEREQUEST-C(I; t)

1 **for** i $\in$ I;
2 **do** m(I) 0;
3 **for** j $\in$ 0............g(t);
4 **do** m (j) $\leftarrow$ 0;
5 **for** k ←1.............K;
6 **do** $\langle\emptyset, g, c\rangle \leftarrow SAMPLE(\Delta)$;
7 A $\leftarrow I \cup \emptyset$;
8 $\gamma \leftarrow TP(\gamma(t-1),\ A, g, c)$;
9 **for** i $\in \gamma(t)$;
10 **do**m(i) $\leftarrow$ m(i) + 1;
11 **for**j $\leftarrow$ 0......g(t) - |$\gamma(t)$|;
12 **do**m(j) $\leftarrow$ m(j) + 1;
13 I $\leftarrow \emptyset$;
14 **While**$|I| < g(t)\ and \max(i \in I \backslash m(i))$;
15 **do**I $\leftarrow I \cup argmax(i \in I) m(I)$;
16 **return**I ;

In the consensus algorithm, the computing time is |K|O(TP) for solving |K| transportation problems. Expectation Our fourth algorithm captures the uncertainty using expectation [12] instead of consensus. The expectation approach can be formulated as a multi-stage stochastic program [6]. However the sample paths are independent from period t and there are no non-Anticipatively constraints after the period t. Thus the online expectation approach can be used [12]. Once again the expectation approach, as stated, is designed to make a choice about a single decision at any time step. Similar to consensus, the simplest generalization of expectation is to evaluate all possible combinations of decisions as seen in Figure 6. Lines 1-2 set the expectation scores for the combinations of I to be 0. Lines 3-8 compute the expected value for each combination for K samples (Line 3). The number of samples is smaller than consensus in order to keep the running time of the algorithm roughly equivalent (the time complexity arises from the number of times TP is executed). Line 4 generates the samples and line 5 creates the set of battery requests to consider. Lines 6-8 consider each combination of battery requests to schedule at time t and calculates the optimal solution given that schedule for time t.

CHOOSEREQUEST-E(I, t)

1 **for** i $\in$ COMB(I);
2 **do** m(i) ← 0;
3 **for** k ← 1...........K;
4 **do** $\langle\emptyset, g, c\rangle \leftarrow SAMPLE(\Delta)$;
5 A $\leftarrow I \cup \emptyset$;
6 **for** i $\in$ COMB(I);
7 **do** $\gamma \leftarrow TP[\gamma(t-1) \cup i,\ A, g, c, i]$;
8 m(i) $\leftarrow$ m(i)+z(γ);

9 **return** argmax(i ∈ COMB(I))*m(i);

IV. EXPERIMENTS

For our experimental setting, we use a V2G system that contains 1000 PHEVs. The time horizon has T = 24 discrete periods (0 .....23). The arrival time a(i)of a PHEV is a discrete random variable uniformly distributed between 0 and 23. Given an arrival time, the departure time is a discrete uniform variable between a(i) and 23. Each PHEV driver is assumed to be rational in their charging request. Thus, the number ofrequested slots to be charged is selected uniformly at random from 0 to di – a(i). In this model, the PHEV states are generated independently.

CHOOSEREQUEST-E(I, t)

1 $\gamma \leftarrow$ TP-E(I , t);

2 **return** γ(t);

In this V2G system, without loss of generality, we assumethat the maximum capacity of the grid is fixed and we adopt a load curve (Fig. 8) to simulate the base load for each period. Residual capacity is obtained by subtracting simulated base load from the maximum capacity and then scaled proportionally to 1000 PHEVs. Fig. 8 shows the average residual capacity g(t)for 12 periods and the average cost, which is proportional to 1 / g(t) .

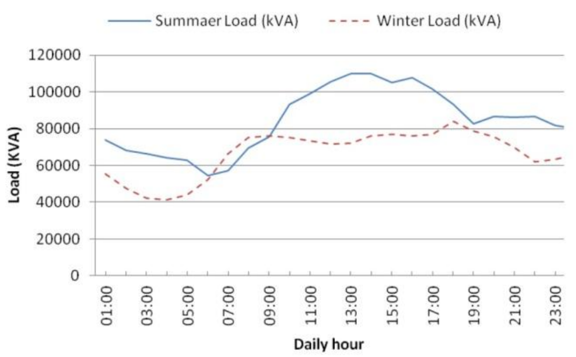

Fig.1. Averaged residual grid capacity and cost.

If we generate 100 independent cases for 1000 PHEVs and the 12-period grid states and ran the five algorithms for each case. For Consensus and Expectation algorithms, 5 samples will be generated at each period to simulate the future. In the first scenario, we assume that the residual capacity is large enough to satisfy all charging demand in any period. The average residual capacity and average cost over 100 cases are shown in Fig 8. The utilization ratio is used to compare the charging schedules. The utilization ratio is the total number of slots charged at period t divided by the residual capacity in the period. High utilization ratios indicate that the grid is at its capacity limit.

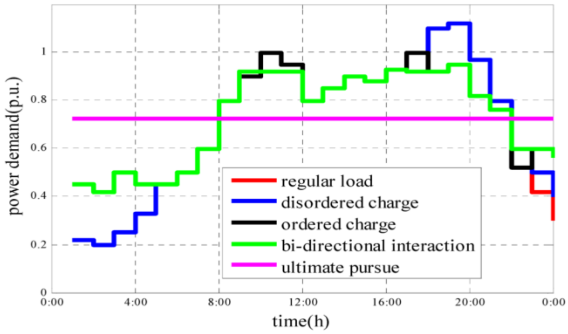

Fig.2 utilization ratio at each period and percentage of unfilled demands.

In Fig.2, Latest Delay and Greedy have highly unevenly distributed utilization ratios and exhibit peaking behavior. Latest Delay has high utilization ratios during the late periods and Greedy has high ratios in the middle periods when the residual capacity drops. The other three methods behave similarly and spread the loads across a range of periods since the cost is inversely proportional to the grid capacity. In this scenario, the residual capacity is large enough such that there are no unfilled batteries in the Deterministic case. Fig. 9 shows the percentage of unfilled slots of the batteries as a function of the total number of requested slots for each of 100 cases. As expected, the Latest Delay algorithm producesunfilled slots in a large number of cases since the algorithm is likely to push the grid to its limit (discussed above) and it has no alternative to rearrange schedules. The other three algorithms will have few cases where small percentages of slots are unfilled. It is important to note that since the penalty cost for unfilled slots will be high, the objective value will be dominated by the penalty cost. The Deterministic model has the lowest total cost since it optimizes the charging scheduling with all the future information known. This is a theoretical lower bound for the best possible performance of an online algorithm. To compare the cost of battery charging, we compute the ratio of cost obtained from each algorithm to optimal cost (competitive ratio).

V. CONCLUSION

In this paper, we investigated the scheduling problem of PHEV charging as a V2G system. We formulated here, the deterministic problem as a linear program, discussed two greedy heuristics, and introduced two online optimization algorithms, Consensus and Expectation to deal with the uncertainties associated with future states of PHEV battery charging and the power grid. In a simulated V2G system, it is shown that under low variance conditions, Expectation and Consensus are strong candidates for centralized control of PHEV charging, however, in high variance situations, it is best to take in consideration about charging in order to ensure most PHEVs are charged to avoid the optimal charging conditions.

VI. FUTURE OUTCOMES

There are several future directions to be explored. Decentralized charging scheduling models are well needed to account for selfish charging behaviors of PHEVs who may be unlikely to accept centralized control. Recent work has suggested online stochastic optimization can be used in a decentralized framework [22]. In addition, certain price schemes can be developed to achieve overall social welfare under decentralized environments which will be likely benefited towards maintaining balance between ecology and technology in the roads.

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