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Online Dynamic Scheduling for Charging PHEVs in V2G

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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 facets. 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. The performance of these algorithms is compared with algorithms that do not account for future uncertainty.**

***Index Terms*—PHEV, Vehicle-to-Grid, Charging Scheduling, Online Optimization, Uncertainties.**

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. Similar to this paper, scheduling PHEV charging has been recently modeled as optimization problems. Caramanis and Foster developed a stochastic dynamic programming method with finite look-head to model the economic impact of PHEVs to an energy market [8]. In another recent paper [26], the authors proposed heuristic algorithms that are similar to our greedy heuristics (see Section II for details) to manage deferrable loads and a rollout algorithm for incorporating forecasted demand into the decision making.

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, and kidney transplant exchange [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.

The rest of paper is divided into four sections. In Section II, the PHEV scheduling problem is formally stated. The deterministic and online problems are also described. Online algorithms are introduced in Section III. Section IV describes the experimental setting and a comparison of the different approaches. In Section V, we summarized our work and findings.

II. Problem Description

In this section, we introduce the nomenclature:

Index/Set

T	time horizon $\{0,\cdots,T\}$
I	set of PHEV battery requests

Deterministic Data

a_i	arrival time of request i, $a_i \in T$
d_i	departure time of request i, $d_i \in T$
l_i	number of charging slots required to fulfill request i
g_t	available slots for charging in period t
c_t	unit cost per slot for charging in period t
λ	unit penalty cost per unfulfilled slot

Variables

x_{it}	number of scheduled slots for request i in period t
y_i	integer variable on the number of unserved slots in request i

A V2G system is defined by a set of PHEVs, I. For a PHEV $i \in I$, (a_i, d_i, l_i) is a triplet specifying the state of vehicle i. The arrival time, a_i, is the starting time when the state of the PHEV i is revealed and the PHEV is available for charging. The departure time, d_i, is the time after which vehicle i is not available for charging and l_i is the total amount of energy needed to fully charge the battery. A PHEV stops charging once it is fully charged. If the battery is not fully charged prior to departure, a unit penalty cost λ is applied to the uncharged amount, and this penalty represents the environmental benefit of a PHEV not utilized due to partially charged battery. For the power grid in the V2G system, let g_t be the residual generation capacity. This is the total generation capacity subtracted by the non-PHEV base load. We define c_t as the cost of electricity at time t. In a discrete time horizon $\{0,\cdots,T\}$, the scheduling problem is to assign PHEVs to feasible time slots to charge their batteries with the lowest cost globally.

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.

In the **Deterministic** version of the scheduling problem, the state of all PHEVs and the power grid for all times is revealed at $t = 0$. The PHEV scheduling problem is formulated as the following linear program

$$z^0 = \min \quad \sum_t c_t \sum_i x_{it} + \sum_i \lambda y_i \tag{1}$$

$$\text{s.t.} \quad \sum_{a_i \le t \le d_t} x_{it} + y_i = l_i \quad \forall i \in I \tag{2}$$

$$\sum_i x_{it} \le g_t \quad \forall t \in T \tag{3}$$

$$1 \ge x \ge 0, y \ge 0. \tag{4}$$

This model is a variation of the transportation problem that is solved in polynomial time [20] and has an integral optimum [15]. We denote this model as TP and the optimal objective as z^0. We let $O(TP)$ be the run time for solving the transportation problem [1]. We use TP as a subproblem in the online stochastic version of the PHEV scheduling problem. For convenience, we define TP as a function $\text{TP}(I, g, c)$ which returns a solution γ (assignments to x and y) with cost $z(\gamma)$. Furthermore, the function $\text{TP}(\gamma, I, g, c)$ is used to solve the TP when given a partial solution γ. Finally, the notation $\gamma(t)$ is used to denote the decisions at time t in γ.

In the V2G, the states of the charging problem are not all known at $t = 0$ and are revealed as time progresses. Therefore, the scheduling of PHEV charging is an online problem. At time t, the parameters are known only for the vehicles arrived prior to t, i.e., $a_i \le t$, g_t and c_t. Decisions about which batteries to charge have to be made based on the current information available at time t. The benefit of delaying the charging of a vehicle is that the electricity prices may drop. The penalty for delaying the charging occurs when there is not enough capacity in the future or energy prices rise. However, even though the future is unknown, information in the form of forecasts and historical data is available to help develop predictions about the future.

III. 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.

To present the formal algorithms, we adopt the framework of [5]. The structure of the online algorithms is shown in

[1] The run time is polynomial, for example $O(n^3)$ with Hungarian algorithm.

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 $(\sum_{i:d_i=t} y_i)$, and y_i is used in the linear program (1)-(4) to account for uncharged units for each PHEV. More formally, the function AVAILABLEREQUESTS is defined as

AVAILABLEREQUESTS(t)
return $\bigcup i \in I_{t-1} \mid (d_i \geq t$ **and** $l_i > \sum_{j \leftarrow 0}^{t-1} x_{ij})$;

The function EXPIREDREQUESTS is defined by

EXPIREDREQUESTS(t)
return $\sum_{i \in I_t : d_i = t} \max(0, l_i - \sum_{j \leftarrow 0}^{t} x_{ij})$;

ONLINEOPTIMIZATION(T)
1 $z \leftarrow 0$;
2 **for** $t \in T$
3 **do** $I_t \leftarrow$ AVAILABLEREQUESTS$(t) \cup$ NEWREQUESTS(t);
4 $\quad i_t \leftarrow$ CHOOSEREQUESTS(I_t, t);
5 $\quad \gamma_t \leftarrow \gamma_{t-1}$;
6 $\quad$ **for** $i \in i_t$
7 $\quad$ **do** $\gamma_t \leftarrow \gamma_t \cup [x_{it} \leftarrow 1]$;
8 $\quad \gamma_t \leftarrow \gamma_t \cup [y_t \leftarrow$ EXPIREDREQUESTS$(t)]$;
9 $\quad z \leftarrow z + c_t |i_t| + \lambda y_t$;

Fig. 1. The basic structure of the online algorithms

Greedy 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 $|S(I,a)| \leq a$. For $i \in S(I,a)$, d_i is no larger than d_j for any $j \in I \setminus S(I,a)$. 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 from

CHOOSEREQUEST-G(I,t)
return argmax$|S(I, g_t)|$;

Fig. 2. Greedy algorithm

S with size $\leq a$.

CHOOSEREQUEST-LD(I,t)
$S \leftarrow \bigcup i \in I_t \mid d_i = t$;
return SUBSET(S, g_t);

Fig. 3. Latest delay online algorithm

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, γ_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 $\mathscr{I}$, generation capacity g, and electricity costs c out 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. The consensus score $m_g(j)$ is non-increasing. i.e., $m_g(j) \geq m_g(j')$ if $j' > j$. Lines 13-15 computes the set of batteries to schedule by accumulating the requests whose scores outnumber the score for leaving the remaining slots unfilled.

```
chooseRequest-C(I,t)
for i ∈ comb(I)
do m(i) ← 0;
for k ← 1...K
do ⟨𝒥,g,c⟩ ← sample(Δ);
    A ← I ∪ 𝒥;
    γ ← TP(γ_{t−1},A,g,c);
    m(γ(t)) ← m(γ(t)) + 1;
return argmax(i ∈ comb(I)) m(i);
```

Fig. 4. Consensus algorithm with combinations

```
chooseRequest-C(I,t)
for i ∈ I
do m_I(i) ← 0;
for j ∈ 0...g_t
do m_g(j) ← 0;
for k ← 1...K
do ⟨𝒥,g,c⟩ ← sample(Δ);
    A ← I ∪ 𝒥;
    γ ← TP(γ_{t−1},A,g,c);
    for i ∈ γ(t)
    do m_I(i) ← m_I(i) + 1;
    for j ← 0...g_t − |γ_t|
    do m_g(j) ← m_g(j) + 1;
Î ← ∅;
while |Î| < g(t) and max (i ∈ I \ Î) m_I(i) ≥ m_g(g_t − |Î|)
do Î ← Î ∪ argmax(i ∈ I \ Î) m_I(i);
return Î
```

Fig. 5. Consensus algorithm

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-anticipativity 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 ∈ comb(I)
2 do m(i) ← 0;
3 for k ← 1...K
4 do ⟨𝒥,g,c⟩ ← sample(Δ);
5     A ← I ∪ 𝒥;
6     for i ∈ comb(I)
7     do γ ← TP(γ_{t−1} ∪ i,A,g,c,i);
8         m(i) ← m(i) + z(γ)
9 return argmax(i ∈ comb(I)) m(i);
```

Fig. 6. Expectation algorithm using combinations

Once again this is an extremely computationally expensive algorithm. However, given the non-anticipativity constraints, the problem can equivalently stated as a two-stage stochastic program TP-E:

$$\min_{x_t} \quad c_t \sum_{i \in I(t)} x_{it} + \frac{1}{|K|} \sum_{k \in K} h(k, x_t) \tag{5}$$

$$\text{s.t.} \quad \sum_{i \in I_t} x_{it} \leq g_t \tag{6}$$

$$0 \leq x_{it} \leq 1, \quad \forall i \in I_t, \tag{7}$$

where

$$h(k, x_t) = \min_{x^k, y^k \geq 0} \quad \sum_{t_0 < t \leq T} c_t^k \sum_{i \in I_t \cup I^k} x_{it}^k + \sum_{i \in I_t \cup I^k} \lambda y_i \tag{8}$$

$$\text{s.t.} \quad \sum_{t+1 \leq t \leq d_i} x_{it}^k + y_i^k = l_i - x_{it}, \quad i \in I_t \tag{9}$$

$$\sum_{a_i \leq t \leq d_i} x_{it}^k + y_i^k = l_i, \quad i \in I^k \tag{10}$$

$$\sum_{i \in I_t \cup I^k} x_{it} \leq g_t, \quad t+1 \leq t \leq T \tag{11}$$

$$0 \leq x_{it}^k \leq 1, \quad i \in I_t \cup I^k. \tag{12}$$

In the first stage, decision x_t is made about which PHEVs in I_t are charged at time t (the current time). In the second stage, a transportation problem with the first stage decisions as parameters is solved for each sample path k, where I^k is the set of requests generated in $\mathscr{I}$. The second stage decision provides the charging schedule from $t+1$ to T with $T = \Delta + t$ for each scenario.

The two-stage model is still a transportation problem. Although the two-stage problem can be solved in polynomial time, the running time is higher than solving $|K|$ smaller transportation problem independently as seen in the consensus approach. In practice, to keep the running times roughly equivalent, $\frac{K}{|I|}$ is used for the number of samples. The final expectation algorithm is shown in Figure 7.

IV. Experiments

For our experimental setting, we use a V2G system that contains 1000 PHEVs. The time horizon has $T = 24$ discrete periods $\{0, \cdots, 23\}$. The arrival time a_i of a PHEV is a discrete

CHOOSEREQUEST-E(I,t)

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

return $\gamma(t)$;

Fig. 7. Expectation online algorithm

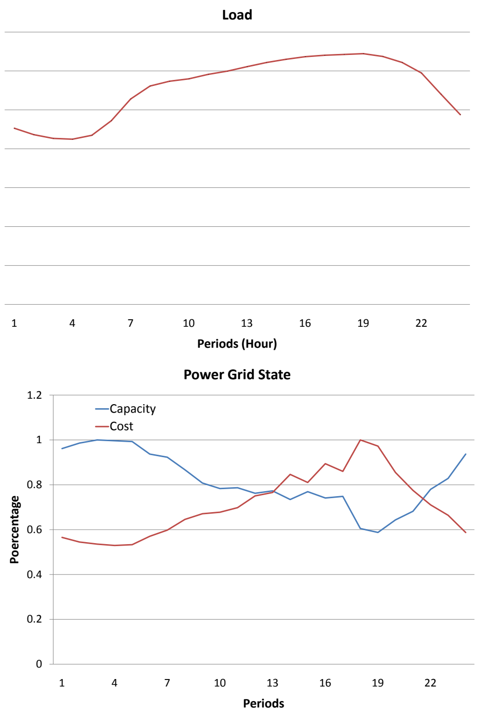


Fig. 8. Arizona base load. Averaged residual grid capacity and cost.

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 of requested slots to be charged is selected uniformly at random from 0 to $d_i - a_i$. In this model, the PHEV states are generated independently.

In this V2G system, without loss of generality, we assume that the maximum capacity of the grid is fixed and we adopt a load curve from the state of Arizona (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 24 periods and the average cost, which is proportional to $1/g_t$.

We generated 100 independent cases for 1000 PHEVs and the 24-period grid states and ran the five algorithms for each case. For **Consensus** and **Expectation** algorithms, 5 samples are generated at each period to simulate the future. Linear programs are solved by using Cplex 11.

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

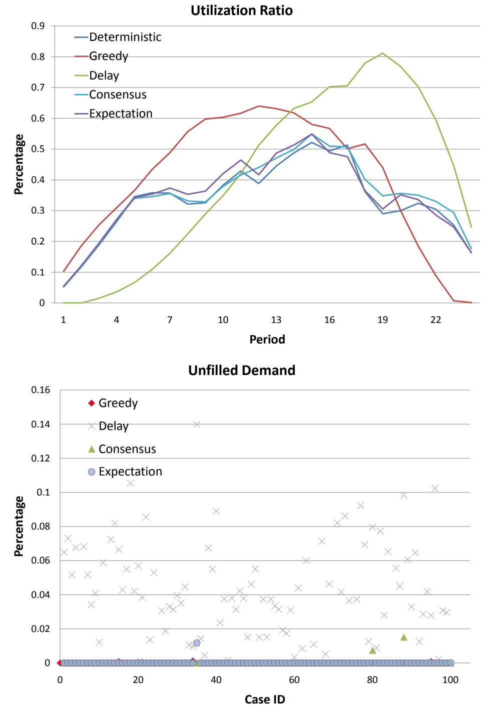


Fig. 9. In scenario 1, utilization ratio at each period and percentage of unfilled demands.

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. In Fig.9, **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 produces unfilled 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 have few cases where small percentages of slots are unfilled. It is important to note that since the penalty cost for unfilled slots is high, the objective value is 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). A log plot is used to show the results due the magnitude differences in the plots. The results are shown in Fig. 10.

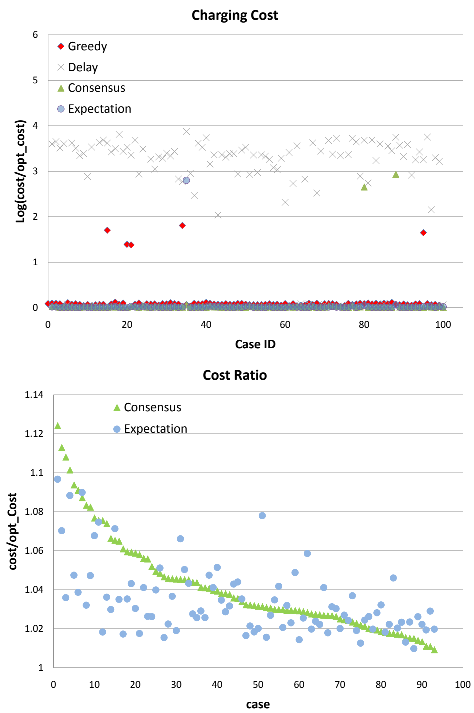


Fig. 10. In scenario 1, comparison of charging costs and comparison of cost ratio between Consensus and Expectation.

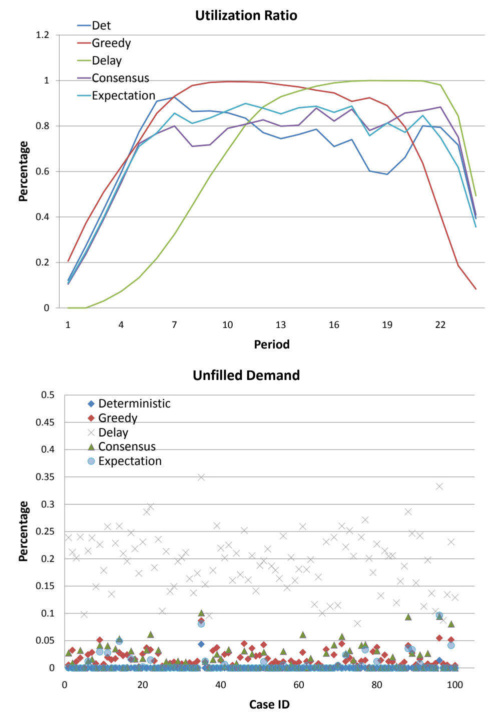


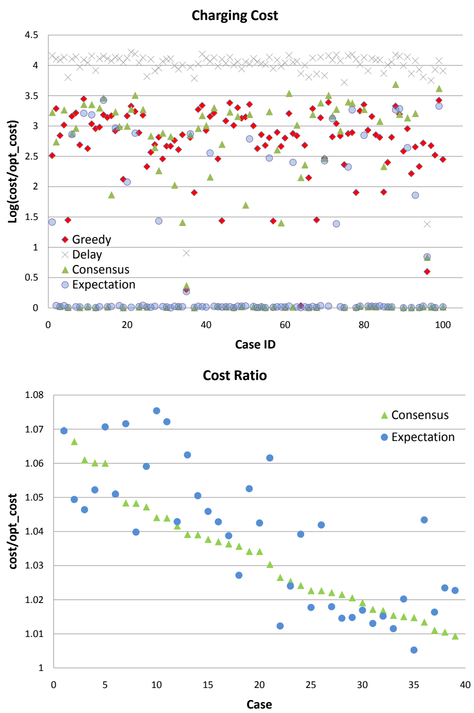
Fig. 11. In scenario 2, utilization ratio at each period and percentage of unfilled demands.

A closer look at Fig. 10 shows that **Greedy** has slightly higher total charging cost than the online algorithms in those cases without unfilled demands. In order to analyze the impact of charging costs, we also report the results for those cases where the algorithms are able to satisfy all demands. These competitive ratios show that the **Greedy** scheduling has a 20% increase in charging cost. The **Consensus** and **Expectation** algorithms have a 4% and 3% increase in cost, respectively. After removing all cases with unfilled demand and plotting the cases by decreasing order of cost ratio for **Consensus**, Fig. 10 shows **Expectation** produces lower charging cost in many cases. **Expectation** provides the strongest results, but requires slightly more computation that **Consensus**. Overall, generating 5 samples is sufficient for the two online algorithms to perform nearly as well as the deterministic case. This is due to the structure of the probability distribution, which has small variance and allows for strong performance guarantees [5].

In the second scenario, we consider the same 100 cases and reduce the residual capacity by half. This scenario can be also interpreted as a power grid where there is a large number of PHEVs. Overall the utilization ratios become higher. The pattern of utilization ratios in Fig. 11 is similar to those in the previous scenario, although there are periods where residual capacities are fully used by the **Greedy** and **Latest Delay** algorithms.

Since the generation capacity is small compared to the number of PHEVs, even in the **Deterministic** model there are 2 cases with unfilled slots (Fig. 11). Although the **Latest Delay** still has the highest percentage of unfilled slots, **Greedy**, **Consensus**, and **Expectation** have 98, 60, and 37 cases, respectively where not all charging requests can be fulfilled (Fig. 11). The average cost ratios, cost over optimal cost, are 910, 807, 216 for **Greedy**, **Consensus** and **Expectation**, respectively. Under this scenario, the **Expectation** algorithm provides considerably better charging schedules than the **Consensus** algorithm (with higher computational requirements). In Fig. 12, the 39 common cases for **Consensus** and **Expectation** without unfilled demand are plotted by cost ratios. Among these remaining cases, **Consensus** has lower ratios, albeit with fewer cases with fully satisfied demands. One possible explanation for this behavior is that in the **Expectation** algorithm there is only one set of non-anticipative constraints at period t. This set of constraints makes the scheduling more reserved against unfilled demands, which can induce the scheduling of battery charging at some higher cost compared to **Consensus**. In terms of fulfilling demand, one possible reason for the performance of **Consensus** is that the method adopted to approximate **Consensus** compares the consensus of individual PHEV charging to the consensus of unused grid capacity. This introduces a bias towards selecting not to use grid capacity.

The third scenario is derived from the first scenario. It multiplies the residual generation capacity at each period by a uniform(0,1) random variable. It mimics a large penetration of variable renewable energy sources in a grid. This scenario has considerably more variance than the previous scenarios because of the independence assumption among periods. On average, this scenario has the same total (summing over 24 periods) residual generation capacity as the second scenario, but has large fluctuations between periods. For all algorithms, there exist periods where the utilization ratios reach 100%.



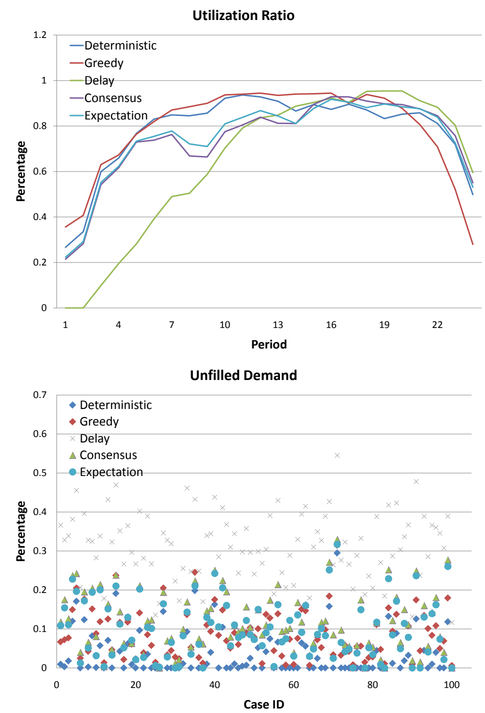


Fig. 12. In scenario 2, comparison of charging costs and comparison of cost ratio between Consensus and Expectation.

Fig. 13. In scenario 3, utilization ratio at each period and percentage of unfilled demands.

This is not reflected in Fig. 13 due to the averaging across 100 cases. Interestingly, **Greedy** has a similar average utilization ratio to the **Deterministic** case. The reason is that if capacity fluctuates widely, one good practice is to charge as many slots as one can, which is the **Greedy** algorithm. From a theoretical perspective, this probability distribution no longer has the properties required for **Expectation** and **Consensus** to have performance guarantees and this is reflected their performance.

Fig. 13 also shows that the number of unfilled battery slots is considerable higher than the second scenario (despite the same average residual capacity). In general, **Greedy** produces lower cost charging schedules than the online algorithms in Fig. 14. The cost ratios are 1049, 1748, and 1306 for **Greedy**, **Consensus** and **Expectation**, respectively. After increasing the sample size to 10 the average cost ratios of **Consensus** and **Expectation** are reduced to 1736 and 1268. However, the computational time increases from 2072 to 4174 seconds in **Consensus** and from 2325 to 6035 for **Expectation**. Clearly, larger samples help to improve performance, but they substantially increase computational requirements. The fact that the high variance makes the theoretical performance guarantees poor and the empirical results sub-optimal suggests that future work using ideas from robust online stochastic optimization to hedge against the worst case variance [2] might be appropriate.

V. Conclusion

In this paper, we investigated the scheduling problem of PHEV charging in a V2G system. We formulated 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

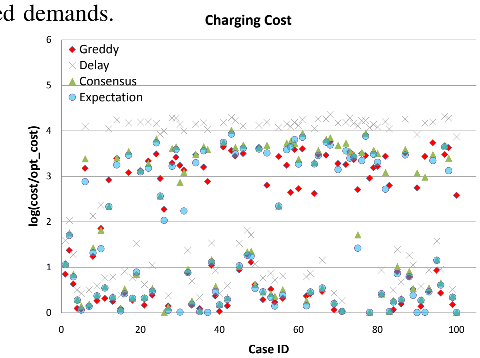


Fig. 14. Comparison of charging costs in scenario 3.

associated with future states of PHEV battery charging and the power grid. In a simulated V2G system, it was 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 be greedy about charging in order to ensure most PHEVs are charged.

There are several future directions to be explored. Decentralized charging scheduling models are 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.

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