# Online Reservation and Deferral of EV Charging Tasks to Reduce Energy Use Variability in Smart Grids

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***Abstract*—Utilities face complex problems of peak demand and intermittent supply, made more pressing by the need to integrate large EV loads and distributed generation. The added flexibility of EV loads, which can charge at varying rates, together with forecasts of renewable availability can be used to reduce integration costs. We show that, in addition, the lookahead provided by requesting EVs to telegraph arrival times can be exploited to shave peaks. We propose a novel optimization theoretic approach to scheduling EV charging, that delays workload to minimize charging cost while meeting latency constraints. We present an online algorithm for dynamic deferral to determine a near optimal balance of workload delay and power use. We validate our algorithm on simulated EV workload, collected wind and solar power generation data from our micro-grid and publicly available electricity price traces from the grid. Results show that the algorithm gives 10-30% energy-savings compared to the naïve 'follow the workload' policy.**

## I. Introduction

There are two important challenges facing electricity generation and distribution companies - peak demand and time-varying supply-demand imbalance. Serving a large demand peak requires generation and distribution companies to build and maintain larger capacity and more expensive infrastructure, which is under-utilized in non-peak situations. As a particularly revealing example, it is estimated that a $5\%$ lowering of demand would have resulted in a $50\%$ price reduction during the peak hours of the California electricity crisis in 2000/2001 [9]. In addition, large power flow peaks lead to correspondingly larger losses and reduces the lifetime of overloaded hardware like transformers.

Changes in the nature of demand and supply, in particular the widespread and growing adoption of Electric Vehicles (EVs) and renewable energy sources, have required a paradigm shift in how utilities plan generation and distribution. EVs are large demand sources, a single EV can store and consume daily energy use equivalent of 3-5 homes [4], and are also much more unpredictable - both in terms of location and load size. Increased incorporation of renewable energy sources, like wind and solar, have exacerbated the problem of demand supply imbalance.

The adoption of new communication [15] and control [5] infrastructure in the smart grid allows for increased prosumer participation in grid operations. In order to limit peaks, minimize losses and reduce costs, utilities need to exploit the patience and flexibility of consumers and any available local storage. This begs the question: *how can this infrastructure exploit demand flexibility to ameliorate supply-demand uncertainity and reduce costs?*

In our work we focus on algorithms that shave peaks and efficiently allocate time varying demand to cheaper supply. In particular we focus on EVs. While there is much work in this area - see Section V and references therein - our work is distringusihed by two features:

- We demonstrate that the lookahead provided by requesting EVs to telegraph arrivals times, can be exploited to reduce costs. This information is often available in practice - for example, as people drive to EV charging stations - but has not been used in any prior work.
- We design computationally efficient algorithms, with provable gaurantees, that utilize this information and flexibilities in deferral to minimize the total energy cost for EV charging tasks.

Finally, we substantiate our theroretical claims through extensive simulations on data collected from a working microgrid in operation.

## II. Model Formulation

We start with discussion of a model in Section II that serves as a basis devising practical online algorithms discussed later in Section III.

We consider a charging station managing the EV-charging jobs of its customers. We assume that time is slotted $t \in \{1, 2, \ldots, T\}$ where $T$ is the total number of time slots in a billing period, which can be one day or one month depending on the billing policy. The EVs can be charged from the station but the energy price varies over time. The goal of the charging station is to minimize the energy consumption across all time slots in the billing period. Let $p_t$ be the unit energy price at time $t$.

We consider a sequence $J$ of EV charging jobs and denote the total number of jobs $|J| = n$. Each job $i \in J$ can be represented by a 4-tuple $(s_i, d_i, e_i, r_i)$, which indicates that this EV arrives at the beginning of time slot $s_i \in T$, departs at the end of time slot $d_i \in T$ and requires $e_i$ amount of energy to finish its request (we also refer to $e_i$ as the demand). The 4-th term $r_i \in T$ is the reservation time for the job $i$. Since a job can only be reserved in advance and EVs depart after they arrive, we have $r_i \leq s_i < d_i$. We also assume that each EV arrives with some amount of charge $v_i$ (we also refer to $v_i$ as the resource) which is known at the time of arrival $s_i$. This stored charge can be used to charge the other EVs when the electricity price is high in order to save total energy cost for meeting all the demands. But at the time of departure $d_i$, the amount of energy stored in the battery should be $(e_i + v_i)$.

Let $x_{i,t}$ denote the charging/discharging rate of EV $i$ at time $t$. We use negative values of $x_{i,t}$ to denote discharging. EVs have maximum charging and discharging rate $E_C$ and $E_D$ at each time slot i.e. $-E_D \le x_{i,t} \le E_C$ for $t \in [s_i, d_i]$ and $x_{i,t} = 0$ for $t \in T - [s_i, d_i]$ . Then the total energy consumption at time $t$ is $x_t = \sum_{i=1}^{n} x_{i,t}$.

*Cost Model*

The goal of this paper is to minimize the total charging cost and maximize the renewable energy usage for charging EVs. The EV charging cost consists of two parts: charging cost and switching cost. *Charging cost* is the cost for charging the EVs which in our model is proportional to the amount of the charging requirement multiplied by the electricity price as a function of time:

$$C(x_t) = \alpha p_t x_t$$

where $\alpha$ is a constant and $x_t$ is the amount of charging accomplished in a time slot. We note that this model is general and allows for incorporation of parameters such as heat density, battery lifetime which make the optimization problem nonlinear. Our algorithms can, however, be applied since optimization is a single independent step.

*Switching cost* $\beta$ is the cost incurred for changing the total power demand. We consider the cost of both increasing and decreasing the charging requirements. Switching cost at time $t$ is defined as follows:

$$S_t = \beta |x_t - x_{t-1}|$$

where $\beta$ is a constant (e.g. see [18]) which comes from the ramp constraints in power generation.

We can formulate the offline energy cost minimization problem while satisfying all the EV demands by the following optimization:

$$\begin{aligned}
\min_{x_{i,t}} \quad & \alpha \sum_{t=1}^{T} p_t x_t + \beta \sum_{t=1}^{T} |x_t - x_{t-1}| && (1)\\
\text{subject to} \quad & \sum_{t=s_i}^{d_i} x_{i,t} \ge e_i && \forall i\\
& \sum_{k=s_i}^{t} x_{i,t} \ge -v_i && s_i < t < d_i, \forall i\\
& -E_D \le x_{i,t} \le E_C && \forall i, \forall t
\end{aligned}$$

Suppose the charging station is equipped with renewable generation plants (solar, wind, etc.). Let $R_t$ be the amount of renewable power generated at time $t$ which can be used to reduce the energy consumption from the grid. Then the power drawn from the grid is $z_t = x_t - R_t$. As we do not consider separate energy storage (other than the EV batteries) for renewable energy, we have $z_t \ge 0$. We can replace the variable $x_t$ with variable $z_t$ in the optimization objective of (1):

$$\begin{aligned}
\min_{x_{i,t}, z_t} \quad & \alpha \sum_{t=1}^{T} p_t z_t + \beta \sum_{t=1}^{T} |z_t - z_{t-1}| && (2)\\
\text{subject to} \quad & \sum_{t=s_i}^{d_i} x_{i,t} \ge e_i && \forall i\\
& \sum_{k=s_i}^{t} x_{i,t} \ge -v_i && s_i < t < d_i, \forall i\\
& -E_D \le x_{i,t} \le E_C && \forall i, \forall t\\
& z_t \ge x_t - R_t, z_t \ge 0 && \forall t
\end{aligned}$$

While this model requires a priori knowledge about all EV jobs, it serves as a basis for a more practical online algorithm discussed next.

## III. Online Algorithm

In this section, we consider the online case where at any time $t$ we do not have information about future EV jobs. We only know the reservation information $r_i$ about job $i$ before it is released at time $s_i$. In the online algorithm, we use this reservation information to reduce the total cost of charging/discharging. The interesting part of the online optimization is the incorporation of the reservation information in the formulation.

At each time $t$, we have unfinished tasks with released time $s_i \le t \le d_i$, $\forall i \in J$. We denote the unfinished (active) jobs at time $t$ by $J_t \subseteq J$ such that $s_i \le t \le d_i$, $\forall i \in J$. Let $D_t = \max_{i \in J_t}(d_i - t)$ be the maximum deadline of the active jobs at time $t$. Then at each step $t$, we apply the following online optimization on the active jobs for the interval $[t, t + D_t]$:

$$\begin{aligned}
\min_{x_{i,t}, z_t} \quad & \alpha(p_t z_t + \sum_{j=t+1}^{t+D_t} \tilde{p_j} z_j) + \beta \sum_{j=t}^{t+D_t} |z_j - z_{j-1}| && (3)\\
\text{subject to} \quad & \sum_{j=s_i}^{d_i} x_{i,j} \ge e_i && \forall i \in J_t\\
& \sum_{k=s_i}^{j} x_{i,t} \ge -v_i && s_i < j < d_i, \forall i \in J_t\\
& -E_D \le x_{i,j} \le E_C && \forall i \in J_t, t \le j \le t + D_t\\
& z_t \ge x_t - R_t, z_j \ge 0 && t \le j \le t + D_t
\end{aligned}$$

where $\tilde{p_j}$ is the predicted electricity price for $j > t$. After solving optimization (3) at time $t$, we only use the values $x_{i,t}$, $z_{i,t}$ to determine the charging/discharging of each vehicle and discard the other values. For the next time slot $t+1$, we apply optimization (3) again.

*Incorporation of reservation information*

To utilize the prior knowledge of reservation, we simplify the formulation (3) by dropping the index $i$ from the variable $x_{i,t}$. We use the terms $E_i$ and $V_i$ to denote the average demand and resource for job $i$ in the interval $[s_i, d_i]$,

$$E_i = \frac{e_i}{d_i - s_i} \qquad V_i = \frac{v_i}{d_i - s_i}$$

We now incorporate reservation information by dropping index $i$ in the formulation (3).

Let $J_t^s \subseteq J_t, J_t^r \subseteq J_t, J_t^d \subseteq J_t$ be the sets of jobs that have start time $s_i = t$, reservation time $r_i = t$, and end time $d_i = t$, respectively for $i \in J$. Suppose $L_t^s = \sum_{i \in J_t^s} e_i$ be the total load demand from the grid at time $s = t$. The information about this load curve is revealed at the time of reservation. Let $L_t^r = \sum_{i \in J_t^r} e_i$ and $L_t^d = \sum_{i \in J_t^d} e_i$ be the reservation and deadline curves respectively at time $t$. Similarly, $V_t^s = \sum_{i \in J_t^s} v_i$ and $V_t^d = \sum_{i \in J_t^d} v_i$ be the resource curves corresponding to arrival and deadlines of EVs respectively at time $t$.

Thus we have three fundamental constraints on the amount of task done for all $t$:

(C1) Deadline Constraint: $\sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j$

(C2) Release Constraint: $\sum_{j=1}^{t} x_j \leq \sum_{j=1}^{t} L_j^s$

(C3) Discharge Constraint: $\sum_{j=1}^{t} V_j^s - \sum_{j=1}^{t} V_j^d \leq x_t$

Condition (C1) says that all the charging tasks done up to time $t$ cannot violate deadline and Condition (C2) says that the charging tasks done up to time $t$ cannot be greater than the total released EV workload up to time $t$. Condition (C3) illustrates that total discharging at any time cannot exceed the available resources. Using these constraints we reformulate the optimization (3) as follows:

$$\min_{x_t, z_t} \quad \alpha(p_t z_t + \sum_{j=t+1}^{t+D_t} \tilde{p_j} z_j) + \beta \sum_{j=t}^{t+D_t} |z_j - z_{j-1}| \quad (4)$$

$$\text{subject to} \quad \sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j, \quad \sum_{j=1}^{t+D_t} x_j = \sum_{j=1}^{t+D_t} L_j^s$$

$$z_t \geq x_t - R_t, \quad \sum_{j=1}^{t} V_j^s - \sum_{j=1}^{t} V_j^d \leq x_t$$

$$z_j \geq 0 \qquad t \leq j \leq t + D_t$$

After solving this optimization problem, at each time slot $t$, we charge the EVs with maximum charging rate $E_C$ according to the EDF (Earliest Deadline First) policy; if there is a tie in the deadline, we charge in the descending order of $(E_i - V_i) > 0$ if $\exists i \in J_t$. We also discharge the EVs with maximum discharging rate $E_D$ according to the EDF policy; if there is a tie in the deadline, we discharge in the descending order of $(V_i - E_i) > 0$ if $\exists i \in J_t$. Then we calculate new $E_i$ and $V_i$ for the remaining part of the active jobs ($i \in J_t$) for the interval $[t+1, d_i]$.

Going beyond online formulation in (4), we can reduce the switching cost even more by looking beyond $D_t$ slots. We do that by accumulating some EV charging tasks from periods of high loads and execute that amount of EV tasks later in valleys without violating constraints (C1) and (C2). Note that by accumulation we do not violate deadline at each slot, as we execute a portion of the accumulated workload by swapping with the newly released workload by EDF policy. To determine the amount of accumulation and execution we use the load $L_t^s$ curve. Thus the online algorithm looks ahead using the reservation curve $L_t^r$ to determine the amount of charging/discharging. We determine the amount of accumulation and execution by controlling the set of feasible choices for $x_t$ in the optimization. By having a lower bound on

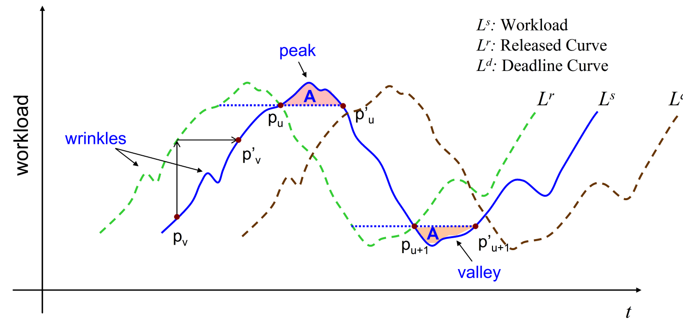



Fig. 1. The curves $L_t^s$ and $L_t^r$ and their intersection points. The peak from the $L_t^s$ curve is cut and used to fill the valley of the same curve.

$x_t$ for the valley (low workload) and an upper bound for the high workload, we control the execution in the valley and accumulation in the peak. Thus in the online algorithm, we have two types of optimizations: Local Optimization and Global Optimization. Local Optimization is used to smooth the 'wrinkles' (we define *wrinkles* as the small variation in the workload in adjacent slots e.g. see Figure 1) within $D_t$ consecutive slots and accumulate some workload. On the other hand, Global Optimization accumulates workload from the peak and fills the valleys with the accumulated workload.

### A. Local Optimization

The *local optimization* is applied over future $D_t$ slots and finds the optimum capacity for current slot by executing no more than $L_t^s$ workload. Let $t$ be the current time slot. At this slot we apply a slightly modified version of online optimization (3) in the interval $[t, t + D_t]$. We apply the following optimization LOPT($L_t^s$, $L_t^d$, $L_t^r$, $z_{t-1}$) to determine $x_t, z_t$ in order to smooth the wrinkles by optimizing over $D_t$ consecutive slots. We restrict the amount of execution to be no more than the $L_t^s$ workload while satisfying the deadline constraint (C1).

$$\min_{x_t, z_t} \quad \alpha(p_t z_t + \sum_{j=t+1}^{t+D_t} \tilde{p_j} z_j) + \beta \sum_{j=t}^{t+D_t} |z_j - z_{j-1}| \quad (5)$$

$$\text{subject to} \quad \sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j, \quad \sum_{j=1}^{t+D_t} x_j = \sum_{j=1}^{t+D_t} L_j^s$$

$$z_t \geq x_t - R_t, \quad \sum_{j=1}^{t} V_j^s - \sum_{j=1}^{t} V_j^d \leq x_t$$

$$z_j \geq 0 \qquad t \leq j \leq t + D_t$$

After solving the local optimization, we get the value of $x_t, z_t$ for the current time slot. For the next time slot $t + 1$ we solve the local optimization again to find the values for $x_{t+1}, z_{t+1}$. Note that the deadline constraint (C1) and the release constraint (C2) are satisfied at time $t$, since from the formulation $\sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j \leq \sum_{j=1}^{t} L_j^s \leq \sum_{j=1}^{t} L_j^r$.

### B. Global Optimization

The *global optimization* is applied to accumulate workload from the peak (*peak optimization*) and execute in the valley (*valley optimization*). Before giving the formulation for the peak/valley optimization, we need to detect a peak/valley.

Let $p_1, p_2, \ldots, p_n$ be the sequence of intersection points of $L_t^r$ and $L_t^s$ curves on the $L_t^r$ curve (see Figure 1) in nondecreasing order of their x-coordinates ($t_p$ values). Let $p'_1, p'_2, \ldots, p'_n$ be the corresponding sequence of points on $L_t^s$ (see Figure 1). We discard all the intersection points (if any) between $p_u$ and $p'_u$ from the sequence such that $t_{u+1} \geq t'_u$. Note that at each intersection point $p_u$, the curve from $p_u$ to $p'_u$ is known. To determine whether the curve $L_t^s$ between $p_u$ and $p'_u$ is a peak or a valley, we calculate the area $A = \sum_{t=t_u}^{t'_u}(L_t^s - L_{t_u}^s)$.

*1) Peak Optimization:* If $A$ is positive, then we regard the curve between $p_u$ and $p'_u$ as a *global peak* though it may contain several small peaks and valleys. If the curve between $p_u$ and $p'_u$ is a global peak, we accumulate some (possibly all) of the workload by not executing more than the $L_t^s$ workload while satisfying the deadline and release constraints (C1) and (C2). For each $t$, we apply the following optimization POPT($L_t^s$, $L_t^d$, $L_t^r$, $z_{t-1}$) in the interval $[t, t+D]$ to find the value of $x_t, z_t$ where $t_u \leq t \leq t'_u$.

$$\begin{aligned}
\min_{x_t, z_t} \quad & \alpha(p_t z_t + \sum_{j=t+1}^{t+D_t} \tilde{p_j} z_j) + \beta \sum_{j=t}^{t+D_t} |z_j - z_{j-1}| \quad (6)\\
\text{subject to} \quad & \sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j, \quad \sum_{j=1}^{t+D_t} x_j \leq \sum_{j=1}^{t+D_t} L_j^s\\
& z_t \geq x_t - R_t, \quad \sum_{j=1}^{t} V_j^s - \sum_{j=1}^{t} V_j^d \leq x_t\\
& z_j \geq 0 \qquad t \leq j \leq t + D_t
\end{aligned}$$

*2) Valley Optimization:* If $A$ is negative, then we regard the curve between $p_u$ and $p'_u$ as a *global valley* though it may contain several small peaks and valleys. If the curve between $p_u$ and $p'_u$ is a global valley, we execute some (possibly all) of the accumulated workload by executing up to the $L_t^r$ workload while satisfying the release constraint (C2). For each $t$, we apply the following optimization VOPT($L_t^s$, $L_t^d$, $L_t^r$, $z_{t-1}$) in the interval $[t, t+D]$ to find the value of $x_t, z_t$ where $t_u \leq t \leq t'_u$.

$$\begin{aligned}
\min_{x_t, z_t} \quad & \alpha(p_t z_t + \sum_{j=t+1}^{t+D_t} \tilde{p_j} z_j) + \beta \sum_{j=t}^{t+D_t} |z_j - z_{j-1}| \quad (7)\\
\text{subject to} \quad & \sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j, \quad \sum_{j=1}^{t+D_t} x_j \leq \sum_{j=1}^{t+D_t} L_j^r\\
& z_t \geq x_t - R_t, \quad \sum_{j=1}^{t} V_j^s - \sum_{j=1}^{t} V_j^d \leq x_t\\
& z_j \geq 0 \qquad t \leq j \leq t + D_t
\end{aligned}$$

Note that the deadline constraint (C1) and the release constraint (C2) are satisfied at time $t$, since $\sum_{j=1}^{t} L_j^d \leq \sum_{j=1}^{t} x_j \leq \sum_{j=1}^{t} L_j^s$. We apply the valley optimization (7) or peak optimization (POPT) for each $t_u \leq t \leq t'_u$ and local optimization (5) for each time slot $t$. Algorithm 1 summarizes the procedures for our online algorithm. For each new time slot $t$, Algorithm 1 detects a peak or valley by checking whether the curves $L_t^r$ and $L_t^s$ intersect. If $t$ is inside a peak, Algorithm 1 applies peak optimization (POPT); if $t$ is inside a valley, Algorithm 1 applies valley optimization (VOPT); local optimization (LOPT), otherwise.

**Algorithm 1**

```
global ← 0; flag ← 0; z_0 ← 0
for each new time slot t do
    if global = 0 and L^r intersects L^s then
        Calculate Area A = Σ_{t=t_u}^{t'_u} (L^s_t − L^s_{t_u})
        global = t'_u − t_u
        if A < 0 then
            flag ← −1 {valley}
        else if A > 0 then
            flag ← 1 {peak}
        end if
    end if
    if global = 0 then
        x[t], z[t] ← LOPT(L[1 : t], L^s[1 : t], L^d[1 : t], z_{t−1})
    else if flag = 1 then
        x[t], z[t] ← POPT(L[1 : t], L^s[1 : t], L^d[1 : t], z_{t−1})
        global = global − 1
    else if flag = −1 then
        x[t], z[t] ← VOPT(L[1 : t], L^s[1 : t], L^d[1 : t], z_{t−1})
        global = global − 1
    end if
end for
```

We now analyze the competitive ratio of the online algorithm with respect to the offline formulation (2). We denote the charging cost of the solution vectors $X = (x_1, x_2, \ldots, x_T)$ and $Z = (z_1, z_2, \ldots, z_T)$ by $cost_c(X, Z) = \alpha \sum_{t=1}^{T} p_t z_t$, switching cost by $cost_s(X, Z) = \beta \sum_{t=1}^{T} |z_t - z_{t-1}|$ and total cost by $cost(X, Z) = cost_c(X, Z) + cost_s(X, Z)$. We have the following lemma.

**Lemma 1.** $cost_s(X, Z) \leq 2\beta \sum_{t=1}^{T} z_t$

*Proof.* Switching cost at time $t$ is $S_t = \beta|z_t - z_{t-1}| \leq \beta(z_t + z_{t-1})$, since $z_t \geq 0$. Then $cost_s(X, Z) \leq \beta \cdot \sum_{t=1}^{T}(z_t + z_{t-1}) \leq 2\beta \sum_{t=1}^{T} z_t$ where $z_0 = 0$. □

Let $X^*$ and $Z^*$ be the offline solution vectors from optimization (3). The following theorem proves that the competitive ratio of the online algorithm is bounded with respect to the offline formulation (3).

**Theorem 2.** $cost(X, Z) \leq \frac{(\alpha P_{max} T + 2\beta)}{\alpha P_{\min} T} cost(X^*, Z^*)$.

*Proof.* Since the offline optimization assigns all the workload in the $[1, T]$ interval, $\sum_{t=1}^{T} x_t^* = \sum_{t=1}^{T} L_t \leq \sum_{t=1}^{T}(z_t^* + R_t)$, where we used $z_t^* \geq x_t^* - R_t$ for all $t$. Hence $cost(X^*, Z^*) \geq cost_c(X^*, Z^*) = \alpha \sum_{t=1}^{T} p_t z_t^* \geq \sum_{t=1}^{T} p_t(L_t - R_t) \geq \alpha P_{\min} T \sum_{t=1}^{T}(L_t - R_t)$.

In the online algorithm, we set $z_t \geq x_t - R_t$ and $\sum_{j=1}^{t} x_j \leq \sum_{j=1}^{t} L_j$ for all $t \in [1, T]$. Hence by lemma 1, we have $cost(X, M) = cost_c(X, M) + cost_s(X, M) \leq \alpha \sum_{t=1}^{T} p_t z_t + 2\beta \sum_{t=1}^{T} z_t \leq \alpha \sum_{t=1}^{T} p_t(L_t - R_t) + 2\beta \sum_{t=1}^{T}(L_t - R_t) = (\alpha P_{max} T + 2\beta) \sum_{t=1}^{T}(L_t - R_t)$. □

## IV. Evaluation

### A. Simulation Setup

*1) Cost Benchmark:* A common approach for power usage in EV stations is to follow the workload curve. In this policy, the amount of power usage at each time is determined by the amount of released workload. This is a conservative estimate as it meets all the deadlines. We compare the total energy cost from Algorithm 1 with the 'follow the workload' ($x = L^s$) strategy (FTW) and evaluate the energy reduction.

*2) Cost Function Parameters:* We used a time slot length of 10 minutes because of the granularity of the available renewable traces. The values of $\alpha$, $\beta$ are chosen 1 and 10 respectively.

*3) EV Data:* EVs arrive at the charging station with poission inter arrival rate. Reservation interval, deadline, charging demand and available resource for each EV task are generated by poission distribution with different rates.

*4) Electricity Price:* There are two types of electricity markets: day-ahead market and real-time market. For the purposes of our simulation, we use traces from the real-time market as they exibit significant volatility with high frequency variation. Electricity price in this market varies on a 5-minute or 15 minute basis. We collected the publicly available real time electricity prices from the Independent System Operator (ISO) located at New England (ISO-NE).

We now illustrate our model for predicting the electricity price $\tilde{p}_j$ in the future time slots $j \in [t+1, t+D]$. There are several electricity price prediction models (e.g. ARIMA, EWMA [8] etc.) based on time series prediction which often ignore seasonal/historical components. To capture the hourly and weekly trends, we use two different methods to estimate the mean and variance of the electricity. In other words, we model future prices within a 24-hour time-frame by Gaussian random variables with known means, which are the predicted prices, and some estimated variance. The mean for the Gaussian distribution is predicted by the widely used moving average method for time series. The variance for the Gaussian distribution is estimated from the history by the weighted average price prediction filter proposed in [11]. In this model, variances are predicted by linear regression from the previous prices from yesterday, the day before yesterday and the same day last week. By using two different methods for mean and variance, we exploit both the temporal and historical correlation of renewable generation. To facilitate the future price prediction, we denote the set of the time slots in a 24-Hour time frame by $\mathcal{K} \subset T$. Let $\tilde{\mu}_\kappa[\chi]$ and $\tilde{\sigma}_\kappa[\chi]$ be the predicted means and standard deviations for each time slot $\kappa$ on day $\chi$. Then the mean of the prediction model for Gaussian distribution is obtained as follows:

$$\tilde{\mu}_\kappa = \varepsilon_0 + \sum_{j=0}^{D} \varepsilon_{\kappa-j} p_{\kappa-j}, \quad \forall \kappa \in \mathcal{K}$$

Here, $\varepsilon_j$ are the coefficients for the moving average method which can be estimated by training the model over the previous day prices. The variance parameter $\tilde{\sigma}_\kappa[\chi]$ is estimated from the history using the following equation:

$$\tilde{\sigma}_\kappa[\chi] = k_1\sigma_\kappa[\chi-1] + k_2\sigma_\kappa[\chi-2] + k_7\sigma_\kappa[\chi-7], \quad \forall i \in n, \forall \kappa \in \mathcal{K}$$

Here, $\sigma_\kappa[\chi-1]$, $\sigma_\kappa[\chi-2]$ and $\sigma_\kappa[\chi-7]$ denote the previous standard deviation values $\sigma_\kappa$ on yesterday, the day before yesterday and the same day last week, respectively. We use the optimal daily coefficients for the price prediction filter from [11] for estimating $\tilde{\sigma}_i^\kappa[\chi]$. Figure 2 illustrates the real time electricity prices from (ISO-NE) for Wednesday (15th February, 2012), the day before wednesday and the same day last week and chose $k_1 = 0.837$, $k_2 = 0$ and $k_7 = 0.142$.

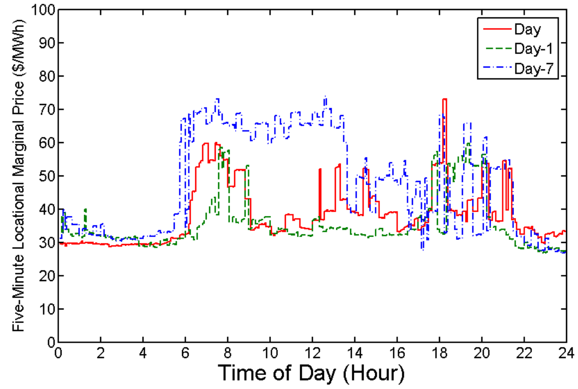
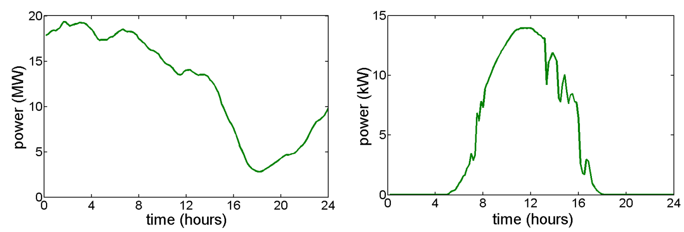



Fig. 2. Illustration of five minute locational marginal electricity prices in real time market on 26th, 25th and 19th October, 2011 from Independent System Operator located at New England (ISO-NE).




(a) Wind (b) Solar

Fig. 3. Illustration of the renewable power (a) wind traces on 01 August 2006 (b) solar traces on 01 August 2012 used in the simulation.

*5) Renewable Power:* We simulated on collected traces from two renewable energy sources: solar and wind.

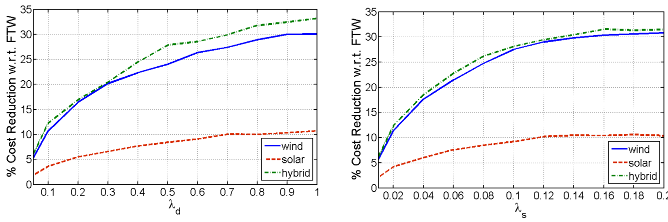
*Wind traces:* The wind power generation data over time is taken from the publicly available western wind dataset from National Renewable Energy Laboratory (NREL) website. Figure 3(a) shows the wind power generated over time in 10 minutes granularity for 24 hours on 01 August, 2006. For our simulation, we normalize the power data with the workload to capture the variation in the wind power to align with the workload variation.

*Solar traces:* We use the solar power generation data from the PV panels at UC San Diego campus. Figure 3(b) shows the variation in the solar power traces over 24 hours on 01 August 2012. Note that we do not use the solar thermal generation as it requires significant infrastructure for a solar thermal plant. Since solar thermal plants typically incorporate a day's thermal storage [10], we cannot apply variation mitigation techniques via workload deferral. Similar to wind traces, we normalize the solar data to match the workload.

*Hybrid traces:* Since wind and solar trends are quite different, we combine the two traces and present analysis for a hybrid system. We generate hybrid power traces by combining 10% solar and 90% wind power at any time and show that this hybrid system gives better cost reduction than with solar or wind traces alone.

## B. Analysis of the Simulation

We analyze total cost reduction for wind, solar and hybrid traces and recommend the system with the best cost savings.




(a) Deadline (b) Reservation

Fig. 4. Energy cost reduction for different values of (a) $\lambda_d$ for solar, wind and hybrid traces with arrival rate $\lambda_r = 0.2$ and reservation interval $\lambda_s = 0.2$, (b) reservation interval $\lambda_s$ for solar, wind and hybrid traces with inter-arrival time $\lambda_r = 0.2$ and deadline $\lambda_d = 1.0$.

*1) Savings with deadline:* We vary the deadline by changing the interval $\lambda_d$ in the poission distribution. The total cost savings from the online algorithm increases with the increase in the flexibility of deadline. However, larger deadlines can increase the total cost due to prediction errors. Figure 4(a) shows the cost reduction from our algorithm with $\lambda_d$ with respect to FTW algorithm for solar, wind and hybrid traces. Since solar power is not available at night, solar traces gives less cost savings. However, we can use the solar traces at day-time to reduce the variation in wind traces which results in more cost savings as found with the hybrid traces.

*2) Savings with reservation:* The energy reduction increases with the increase in the flexibility in reservation time. Figure 4(b) shows the cost reduction from our algorithm with different reservation intervals $\lambda_s$ with respect FTW algorithm for solar, wind and hybrid traces. For the hybrid system we get more energy savings with respect to only using wind and solar generation.

## V. Related Work

Our work builds upon a significant background work on algorithm for scheduling EVs with bounds on computational efficiency and quality of results.

Soares et. al. [14] extend day ahead markets to schedule EV charing. Bitar and Low [2] study the performance of Earliest Deadline First algorithms when EVs are presented with higher prices for earlier deadlines. Gan et. al. [7] and Subramaniam et. al. [16] study real time algorithms that optimize charging profiles. Park et. al. [12] develop algorithms that recommend charging locations and slots based on travel route and EV charge requirements. In [13], Qin et. al. study scheduling algorithms that minimize waiting time. In contrast to our work, Tang et. al. [17] design optimal schedules without lookahead forecasts. Zhang et. al. [19] study schedules that are robust to uncertainties in EV arrival and price.

In support of our work, Chen et. al. [3] show that optimal policies in certain grid structures are *valley filling*, like the policies we design. Valley filling algorithms are also studied in [6], [20].

There has also been much work on distributed versions of the EV scheduling algorithm. In [1], (dual) prices are broadcast to EVs to maximize utility while respecting capacity constraints.

## VI. Conclusion

We have presented an algorithm for EV integration into the smart grid that uses the flexibility of charging/discharging reservation information along with task deferral while mitigating the variation in renewable power generation. Our simulation shows around 30% cost savings by utilizing these flexibilities with renewables incorporated into a hybrid system of solar and wind.

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