Demand Side Management to Minimize Peak-to-Average Ratio in Smart Grid

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Abstract

In this paper, a demand side management (DSM) technique for minimizing the peak load of the electric grid is proposed. The grid optimization problem is formulated and analyzed to find the optimized strategies. A smart power system with multi-residential end-users connected to a single energy source is considered. The end-users attempt to minimize peak-to-average ratio (PAR) of the electric grid by using energy scheduler (ES) as well as their energy production and storage strategies. Some end-users possess renewable energy sources (RESs), distribution generators (DGs), storage devices or both. Users charge their storage devices at low-demand periods and discharge them at high-demand periods. Likewise, end-users produces electricity during the peak hours to minimize their energy cost.

1 Introduction

In recent years, much attention has been paid in optimization of energy consumption in smart grid. Demand side management (DSM) is one of the notable function in a smart grid that enables end-users to modify their demand for energy through various methods such as financial incentives and education [1–4]. The deployment of DSM will motivate the end-users to utilize less energy during peak hours, or to shift the time of energy use to off-peak times [1,5,6], which will help the utility company to reduce the peak load demand and reshape the load profile. Consequently, end-users will save money on electricity and society as a whole will conserve and use less electricity.

Generally, the performance of the DSM programs largely relies on the total amount of controllable load [1,6,7]. End-users consisting of adjustable loads, such as plug-in hybrid electric vehicles (PHEV), dishwashers, offer significant benefit to this end. In addition, end-users with storage devices and dispatchable energy sources (RESs), distribution generators (DGs), storage devices or both. Users charge their storage devices at low-demand periods and discharge them at high-demand periods [1–4,7–12]. Similarly, end-users with distribution generators (DGs) produce electricity during peak hours to minimize their energy cost [1,5,6,13,14].

Practically, to meet all energy demands from the end-users, the grid capacity should be designed such that it satisfies the peak power demand instead of just the average power demand [13]. However, the utility company supplying energy to the grid, prefers to use the least expensive sources of energy to generate electricity (which might not be enough to meet the required grid capacity), and use expensive energy sources only when the demand increases [3,4]. When costly energy sources are employed by the utility company, end-users will also pay high prices for the energy. Thus, by strategically engaging end-users in energy production, storage and shifting the energy consumption of their adjustable load appliances, the utility company will alleviate the use of expensive base load generators and both end-users and the utility will benefit from the strategy [1,6].

An effective energy scheduler (ES) is for the success of DSM system. Without effective ES for charging and discharging cycles of the storage devices, it is possible for all end-users with storage devices to try charging their devices at the same time when the energy cost is low. This will result to higher peak demand, which might endanger the power system. Likewise, ES is important for end-users with DGs to ensure that the energy supply and demand is balanced. The use of an effective ES for adjustable home appliances, distribution generators as well as storage devices is crucial towards the success of the smart grid network [9–12].

In addition, renewable energy sources (RESs) such as solar and wind turbines play an important role in reducing the total load. Conventional solar and wind turbines are non-dispatchable energy sources due to their periodic nature of the sunlight or wind, which cannot be predicted and controlled [7,8]. With a rapid advancement of battery technology, it is likely that storage devices will become an integral part of the means by which energy generated from RESs can be stored and utilized during peak hours [1].

This paper presents a distributed DSM algorithm using a game theoretical approach to minimize total energy costs as well as PAR in the future smart grid. We consider a multi residential setup where end-users possess adjustable loads, nonadjustable loads together with either storage devices and/or DGs as well as RESs. By using game theoretical approaches [14], a distributed ES algorithm where each end-user independently schedules his/her energy consumption, storage and production profile strategy is proposed. The ES runs on the end-users’ smart meters to provide the optimized energy strategies without disclosing the privacy of the end-users. The distributed algorithm minimizes the required signaling with the central unit [7].

The proposed algorithm differs from the DSM scheme in [6,9,15], where ES is considered to a system with adjustable load appliances, without energy storage and distribution generators, the proposed scheme considers a setup with both storage devices, RESs as well as dispatchable generators.
Although, the algorithm in [7] integrate the storage devices, dispatchable energy sources as well as non-dispatchable energy sources, it does not incorporate energy shifting of adjustable appliances, which is crucial in minimizing PAR. The proposed algorithm includes the PAR constraint to limit the PAR in the optimization of energy consumption of adjustable appliances, energy production and energy storage. Simulation results show substantial minimization of the total energy cost and the PAR.

2 System Model

We consider $N$ users, and each end-user possess a smart meter communicating with several devices per user and the utility company through the advanced metering infrastructure (AMI). We assume that the price of energy supplied by the utility company is known in advance for a specified period of time $1, \ldots, T$. Each time slot of the scheduling horizon can represent e.g., one hour, with $T = 24$ corresponding to one day. For a user $n \in N$, let $K_n$ denote a set of adjustable load appliances. For each device $k \in K_n$, we define energy consumption scheduling vector $x_{n,k} \triangleq [x_{n,k}^1, \ldots, x_{n,k}^T]$, where $x_{n,k}^t$ denotes the corresponding one-hour energy consumption scheduled for device $k$ from user $n$, while the energy consumption for non-adjustable load at slot $t$ is denoted as $p_{n,0}^t$.

The user $n$ may also have a storage device (such as a battery). Let $p_{n,0}^t > 0$, $t = 1, \ldots, T$, be the energy available in a storage device at the end of slot $t$; and $p_{n,\text{max}}^t$ be the capacity of the storage device. The energy present at the beginning of the horizon is given by $p_{n,0}^0$. The storage device can either be charged or discharged during time slot $t$ [1]. Let $b_{n}^t$ denote the energy drained from or supplied to the battery at slot $t$. Here $b_{n}^t > 0$ represents that the battery is discharging while $b_{n}^t < 0$ represent that the battery is charging. The relation between the energy stored in the battery together with the charge/discharge variables are given by [1]

$$p_{n}^t = p_{n}^{t-1} + b_{n}^t, \quad t = 1, \ldots, T.$$  

(1)

The variable $b_{n}^t$ is constrained by the maximum charge and discharge as $b_{n}^{\text{dis}} < b_{n}^t < b_{n}^{\text{ch}}$, also the battery-supply energy is no more than the current energy consumption i.e., $b_{n}^t + \sum_k x_{n,k}^t + p_{n,0}^t \geq 0$. Each battery has efficiency $\eta_n \in (0, 1)$, meaning that if $p_{n}^{t-1}$ is stored at the end of the slot $t-1$, then the discharge at slot $t$ is limited by $b_{n}^t \geq -\eta_n p_{n}^{t-1}$.

With energy scheduler (ES), users can utilize energy storage devices to store energy during off-peak hours and discharge them during peak hours [1].

Some end-users own RESs and/or distributed generators (DGs). We denote the energy generated by the RESs and DGs of user $n$ per-time slot as $g_{n,r}^t$ and $g_{n,d}^t$ respectively. We set a function for end-users energy production cost as $C'(g_{n}^t)$ [8]. This function provides the costs for generating $g_{n}^t$ amount of energy at a time-slot $t$, with $C'(0) = 0$.

Let $g_{n}^{\text{max}}$ denotes the maximum energy produced by user $n$ over a time-slot $t$, then, per-slot energy production profile is constrained by [8]

$$0 \leq g_{n,d}^t \leq g_{n}^{\text{max}}.$$  

(2)

$g_{n}^{\text{max}}$ represents the amount of energy generated when user $n$’s energy source operates throughout the time-slot $t$. Moreover, the cumulative energy production should meet

$$\sum_{t=1}^{T} g_{n,d}^t \leq \lambda_{n}^{\text{max}},$$  

(3)

where $0 \leq \lambda_{n}^{\text{max}} \leq T \times g_{n}^{\text{max}}$. We define the non-dispatchable and the dispatchable energy production scheduling vector as $g_{n,r}^t = (g_{n,r}^t)_{T}^T$ and $g_{n,d} = (g_{n,d})_T^T$ respectively.

The total hourly energy profile for user $n \in N$ can be defined as

$$t_{n}^t \triangleq \sum_{k \in K_n} x_{n,k}^t + y_{n,0}^t + b_{n}^t - g_{n,r}^t - g_{n,d}^t,$$  

(4)

and the daily total load for user $n$ is defined as $I_n = [I_{n,1}, I_{n,2}, \ldots, I_{n,T}]$. It should be noted that, $t_{n}^t \geq 0$ if energy flows from the grid to user $n$, and $t_{n}^t \leq 0$ otherwise.

Many devices may have some maximum power levels $\gamma_{n}^{\text{max}}$ as well as the minimum power level $\gamma_{n}^{\min}$, this imposes the upper and lower-bound constraints on the ES vector $x_{n,k}$ for each device $[1]$, that is,

$$\gamma_{n}^{\min} \leq x_{n,k}^t \leq \gamma_{n}^{\max}, \quad \forall t \in \{\alpha_{n,k}, \beta_{n,k}\}. $$  

(5)

The total load for $N$ users at each hour of a day is given by

$$L_{t} = \sum_{n \in N} t_{n}^t.$$  

(6)

2.1 Peak to Average Ratio in Smart Grid

The peak to average ratio (PAR) minimization is a concern of the utility company but not a major concern of end-users. The PAR is a preferable design objective of the utility company because when the demand is higher, extra electric plant have to be deployed to generate more energy. Generally, these extra plants are costly. Thus, peak demand minimization reduces the utility capital cost requirements. We denote the average and the peak load of the smart grid network by $L_{av}$ and $L_{\text{max}}$, respectively. Thus,

$$L_{av} = \frac{1}{T} \sum_{t \in T} L_{t},$$  

(7)

and

$$L_{\text{max}} = \max_{t \in T} L_{t}.$$  

(8)

The PAR of the load represented by $\Lambda$, is given by

$$\Lambda = \frac{L_{\text{max}}}{L_{av}}.$$  

(9)

If we consider the maximum tolerable PAR to be $\Lambda_{\text{max}}$, then

$$\max_{t \in T} L_{t} \leq \Lambda_{\text{max}} L_{av},$$  

(10)

consequently, the following inequality is also true

$$L_{t} \leq \max_{t} L_{t} \leq \Lambda_{\text{max}} L_{av}.$$  

(11)

From (11), it is desired to have

$$L_{t} \leq \Lambda_{\text{max}} L_{av}.$$  

(12)
3 ENERGY MINIMIZATION PROBLEM

Let \( R^t(L_t) \) denote the energy cost over a time slot \( t \). This is the cost the utility company incurs to provide energy to the end-users or the cost that the utility company pays to buy electricity from end-users. We also consider that the price of the same load may differ at different time of the day \([5,6,9,15]\). The cost paid by end-user \( n \) to buy electricity \( l^t_n \) from the utility company (if \( l^t_n > 0 \)), or the cost paid to the end-user for selling the same energy load to the utility company (if \( l^t_n < 0 \)) is given by

\[
R^t(L_t) \frac{l^t_n}{L_t}.
\]  

(13)

The dispatchable energy production cost function is given by \( C^t(y) = \nu y \), where \( \nu \) is a constant \([8]\). The cumulative expenses incurred by user \( n \) over a period of analysis \( T \) is given by

\[
S(x_n, g_{n,d}, b_n) = \sum_{t=1}^{T} \left( R^t(L_t) \frac{l^t_n}{L_t} + C^t(g_{n,d}) \right).
\]  

(14)

We define the total cumulative expenses of all users as

\[
\Gamma(\mathcal{I}) = \sum_{n \in \mathcal{N}} S(x_n, g_{n,d}, b_n)
\]  

(15)

where \( \mathcal{I} \) is an \( N \times T \) matrix representing the daily total load of all users, i.e., \( \mathcal{I} = \mathcal{I}_1, \ldots, \mathcal{I}_N \). The multi-residential load control task amounts to minimizing the cumulative expense of electricity, that is

\[
\min_{x_1, \ldots, x_N, g_1, \ldots, g_{N,d}} \Gamma(\mathcal{I}_1, \ldots, \mathcal{I}_N)
\]

subject to

\[
L_t \leq \Lambda_{max} L_{av},
\]

\[
\frac{\beta_n}{\alpha_{n,k}} x^t_{n,k} = E^t_{n,k},
\]

\[
\gamma_{n,k} \leq x^t_{n,k} \leq \gamma_{n,k}, \quad \forall t \in \{\alpha_{n,k}, \ldots, \beta_{n,k}\},
\]

\[
x^t_{n,k} = 0, \quad \forall t \notin \{\alpha_{n,k}, \ldots, \beta_{n,k}\},
\]

\[
b^t_{dN} < b^t_{n} < b^t_{ch}, \quad t = 1, \ldots, T,
\]

\[
p^t_n = p^{t-1}_n + b^t_n, \quad t = 1, \ldots, T,
\]

\[
b^t_n \geq -\eta_p n^{-1},
\]

\[
0 \leq g_{n,d} \leq g_{n,d}^{max},
\]

\[
\sum_{t=1}^{T} g^t_{n,d} \leq g^{max}_{n,d},
\]

\[
0 \leq \lambda_n^{max} \leq T \times g^{max}_{n,d}.
\]  

(16)

The PAR constraints limits the hourly load from all end-users to be less than \( \Lambda_{max} \times L_{av} \). Careful selection of \( \Lambda_{max} \) is required to ensure the feasibility of the optimization problem. It is not guaranteed that the imposed PAR constraint can be achieved, for example, \( \Lambda_{max} = 1 \) implies perfect flat load profile, which is practically impossible for a residential setup utilizing energy scheduler (ES) for their adjustable loads, storage devices and DGs. The constraints of the optimization problem in (16) are linear, thus, if the objective function is convex then the problem can be solved by using convex optimization techniques in a centralized fashion. Some modifications are required to solve the problem distributively. A distributed approach is desirable to address possible concerns regarding data privacy and integrity \([5]\).

4 DECENTRALIZED LOAD PROFILE MINIMIZATION

To mitigate the centralized approach, we propose a distributed algorithm using game theory to solve the optimization problem in (16). We assume the price that each user pays or receives is proportional to his/her daily energy load. For each end-user \( n \in \mathcal{N} \), let \( \xi_n \) represent the daily price charged by the utility company, or the amount of money that end-user \( n \in \mathcal{N} \) receives from the utility company for generating energy. Thus,

\[
\xi_n \propto \sum_{t} l^t_n, \quad \forall n \in \mathcal{N}.
\]  

(17)

By using the proportionality constant we can equate end-users’ energy consumption and their bills as

\[
\frac{\xi_n}{\xi_m} = \frac{\sum_{t=1}^{T} l^t_n}{\sum_{t=1}^{T} l^t_m}, \quad \forall n, m \in \mathcal{N}.
\]  

(18)

From (18), we have

\[
\xi_m = \xi_n \frac{\sum_{t=1}^{T} l^t_m}{\sum_{t=1}^{T} l^t_n}.
\]  

(19)

The total monetary expenses for all end-users can be expressed as

\[
\sum_{m \in \mathcal{N}} \xi_m = \sum_{m \in \mathcal{N}} \left( \xi_n \frac{\sum_{t=1}^{T} l^t_m}{\sum_{t=1}^{T} l^t_n} \right) = \xi_n \sum_{m \in \mathcal{N}} \frac{\sum_{t=1}^{T} l^t_m}{\sum_{t=1}^{T} l^t_n}.
\]  

(20)

From (20), we can express \( \xi_n \) as

\[
\xi_n = \frac{\sum_{m \in \mathcal{N}} \sum_{t=1}^{T} l^t_m \left( \sum_{m \in \mathcal{N}} \xi_m \right)}{\Phi_n} \sum_{m \in \mathcal{N}} \xi_m,
\]  

(21)

where

\[
\Phi_n = \frac{\sum_{t=1}^{T} l^t_n}{\sum_{m \in \mathcal{N}} \sum_{t=1}^{T} l^t_m} = \frac{\sum_{t=1}^{T} l^t_n}{\sum_{t=1}^{T} l^t_n + \sum_{m \in \mathcal{N} \setminus n} \sum_{t=1}^{T} l^t_m}.
\]  

(22)

\( \Phi_n \) is not constant for a daily energy due to the use of the the DGs as well as the uncertainty of the RESs (such as solar or wind turbine) in producing energy. Due to weather conditions, at some hours in a day, users with RESs might produce more power than their own energy demand and thereby feed their excess energy to the grid, which may lead to zero or negative aggregate load \( l^t_n \) for such a user \( n \).
From (21), it can be seen that, energy price for each user depends on his/her energy strategy and the strategies of other users. This lead to the game theory among the users. In this game, users are players and their strategies are their daily energy schedule. Next, we investigate different approaches of end-users in responding to the price values.

The cumulative cost of user \( n \), \( S(x_n, g_{n,d}, b_n) \) is proportional his/her daily load, that is,

\[
S(x_n, g_{n,d}, b_n) \propto \sum_{t=1}^{T} t^n. \tag{23}
\]

The utility company generate profit by setting the cost of electricity for the end-users \( \xi_n \) to be equal or slightly higher than the cumulative cost \([6, 15]\), i.e.,

\[
\xi_n \geq S(x_n, g_{n,d}, b_n), \tag{24}
\]

where the left hand side represents the total daily charge to the end-user \( n \), while the right hand side indicates the daily cumulative cost. Following the inequality in (24), we define

\[
\mu = \frac{\xi_n}{S(x_n, g_{n,d}, b_n)} \geq 1. \tag{25}
\]

For \( \mu = 1 \), the billing system is budget balanced and the utility company pays/charges the end-users equivalent amount corresponding to their cumulative costs. From (21) and (25), it is clear that regardless of the value of \( \mu \)

\[
S(x_n, g_{n,d}, b_n) = \Phi_n \sum_{m \in N} S(x_m, g_{m,d}, b_m). \tag{26}
\]

### 4.1 Equilibrium Among Users

Given the daily total load for user \( n \) as \( I_n \), we define the daily total load of other users as \( I_{-n} \) such that, \( I_{-n} = I \setminus I_n \). The problem can be formulated as a non-cooperative energy cost minimization game. In game theory, a non-cooperative game is one in which players make decisions independently \([14]\). The game essentially includes

- **Player**: a set of end-users \( n = 1, \ldots, N \)
- **Strategies**: energy scheduling vectors \( x_n, g_{n,d}, b_n \) for all end-users with adjustable load devices, dispatchable generators, battery or both.
- **Payoff functions**: \( P_n(I_n, I_{-n}) = -S(x_n, g_{n,d}, b_n) \), represents the user payoffs for the joint strategies.

To maximize payoff, end-users aim at minimizing the overall cost of energy. From (26), the payoff can be expressed as

\[
P_n(I_n, I_{-n}) = -\Phi_n \sum_{m \in N} S(x_m, g_{m,d}, b_m). \tag{27}
\]

Using (15), the payoff of user \( n \), can be expressed as

\[
P_n(I_n, I_{-n}) = -\Phi_n \Gamma(I). \tag{28}
\]

End-users attempt to optimize their energy strategies to minimize the cost paid to the utility company or maximize their profit. Using Nash equilibrium we can characterize how players play a game \([6, 15]\). The optimized performance with regard to energy cost minimization is achieved at Nash equilibrium of power consumption game. The Nash equilibrium of this game always exist. The energy consumption variable \( I_n, \forall n \in N \) are in a Nash equilibrium of the game if for every user \( n \in N \),

\[
P_n(I_n^*, I_{-n}^*) \geq P_n(I_n; I_{-n}). \tag{29}
\]

Once the energy scheduling game is at unique Nash equilibrium, non of the end-users would attempt to diverge from the schedule \( I_n^*, \forall n \in N \). Also, the user cannot influence the value of \( \Phi_n \) with the choice of their strategies.

### 4.2 Distributed Algorithm

Suppose all other end-users fix their corresponding energy schedule \( I_{-n} \), then the end-user \( n \) can maximize his/her own payoff by solving the local optimization problem:

\[
\max_{x_n, g_{n,d}, b_n} P_n(I_n; I_{-n})
\]

subject to

\[
I_n + \sum_{m \in N \setminus n} I_m \leq \Lambda_{max} \frac{\sum(I_n + \sum_{m \in N \setminus n} I_m)}{T} \tag{30}
\]

\[
\sum_{t=\alpha_{n,k}}^t x_{n,k} = E_{n,k},
\]

\[
\gamma_{\alpha_{n,k}}^{\min} \leq x_{n,k}^t \leq \gamma_{\alpha_{n,k}}^{\max}, \quad \forall t \in \{\alpha_{n,k}, \ldots, \beta_{n,k}\},\n\]

\[
x_{n,k}^t = 0, \quad \forall t \notin \{\alpha_{n,k}, \ldots, \beta_{n,k}\},
\]

\[
b_{n}^{\min} < b_{n}^{h} < b_{n}^{\max}, \quad t = 1, \ldots, T,
\]

\[
p_n = p_{n}^{t-1} + b_{n}^{h}, \quad t = 1, \ldots, T
\]

\[
b_{n}^{h} \geq -\eta p_{n}^{t-1}
\]

\[
0 \leq g_{n,d}^{t} \leq g_{n,d}^{\max}
\]

\[
\sum_{t=1}^{T} g_{n,d}^{t} \leq \lambda_{n}^{\max},
\]

\[
0 \leq \lambda_{n}^{\max} \leq T \times g_{n,d}^{\max}\tag{30}
\]

At Nash equilibrium, the PAR constraint is equivalent to that in (16). The instantaneous PAR constraint is given by

\[
I_n + \sum_{m \in N \setminus n} I_m \leq \Lambda_{max} \frac{\sum(I_n + \sum_{m \in N \setminus n} I_m)}{T} \tag{31}
\]

We assume that each end-user has a predetermined amount of energy consumption and active end-users have limited capacity of generating power for a particular day, thus, end-users influence on the value of \( \Phi_n \) is minimum regardless of the uncertainty of the RESs in generating power. Consequently, the value of \( \Phi_n \) can be assumed to be constant for a daily consumption. The minimization of the cost function
can be expressed as

$$\min_{x_n, g_{n,d}, b_n} S(x_n, g_{n,d}, b_n) + \sum_{m \in N \setminus n} S(x_m, g_{m,d}, b_m) = \Gamma(I)$$

subject to

$$I_n + \sum_{m \in N \setminus n} I_m \leq \lambda_{\text{max}} \frac{\sum(I_n + \sum_{m \in N \setminus n} I_m)}{T}$$

$$\sum_{t=\alpha_{n,k}}^{\beta_{n,k}} x_{n,k}^t = E_{n,k},$$

$$\gamma_{n,k}^{\text{min}} \leq x_{n,k}^t \leq \gamma_{n,k}^{\text{max}}, \quad \forall t \in \{\alpha_{n,k}, \ldots, \beta_{n,k}\},$$

$$x_{n,k}^t = 0, \quad \forall t \not\in \{\alpha_{n,k}, \ldots, \beta_{n,k}\},$$

$$b_{n}^{\text{dis}} < b_{n}^{t} < b_{n}^{\text{ch}}, \quad t = 1, \ldots, T,$n_d^0 \leq I_{n,d} \leq I_{n,d}^{\text{max}}$$

$$0 \leq g_{n,d} \leq g_{n,d}^{\text{max}}$$

$$\sum_{t=1}^{T} g_{n,d}^t \leq \lambda_n^{\text{max}},$$

$$0 \leq \lambda_n^{\text{max}} \leq T \times g_{n,d}^{\text{max}}.$$  \hfill (32)

The optimization problem in (32) is equivalent to (16). Unlike (16), the problem in (32) can be solved distributively. The following is the proposed algorithm to solve the optimization problem in (32) distributively.

**Algorithm 1:** Performed by every end-user $n \in N$

1. Initialize $I^0$ randomly, and calculate the corresponding cost function $\Gamma(I^0)$
2. Initialize counter $c = 1$ and set $\Gamma(I^c) = \Gamma(I^0) - \epsilon_0$
3. While $\Gamma(I^c) < \Gamma(I^{c-1})$ do
   1. Generate a random sequence $\vartheta$ for $N$ users
   2. For $n \leftarrow 1$ to $N$ do
      1. $I_n = I(\vartheta(n), \cdot)$ and $I_{-n} = I \setminus I_n$
      2. Optimize $\Gamma(I_n, I_{-n})$ under the PAR constraint and update $I_n$
      3. Convey a control message to make $I_n$ known to all smart meters and update $I$
   4. Increment the counter, $c \leftarrow c + 1$
   5. Update the cost function $\Gamma(I^c) = \Gamma(I_n, I_{-n})$
4. End

From algorithm 1, end-users minimize the optimization problem in (32) based on the random order sequence $\vartheta$ by optimizing their load scheduling for adjustable loads $x_n$, storage devices, dispatchable generators or both, such that the objective function $\Gamma(I)$ is strictly decreasing, i.e., $\Gamma(I^c) < \Gamma(I^{c-1})$.

Each user minimizes the cost function with respect to $I_{n,d}^t$, $\forall t \in T$, while the load of the other users (i.e., $\sum_{m \in N \setminus n} I_{m,d}^t$, $\forall t \in T$) is fixed. User $n$ broadcasts its new load $I_{n,d}^t$, $\forall t \in T$ (without giving detailed information about his/her storage strategies, generators strategies, or energy consumption of his/her appliances) provided that the objective function is decreasing. The energy consumption schedule for users $I$, is updated and the next user in the generated sequence minimizes the objective function in (32) with respect to its local load. This process is repeated until none of the users can improve its payoff by scheduling his/her load. The parameter $\epsilon_0$ is a small fraction value for adjusting the cost function at the beginning of the algorithm to make the first two cost functions, $\Gamma(I^c)$ and $\Gamma(I^{c-1})$ different.

Each end-user reveals his/her strategy to all other users, the Nash equilibrium exists if no users change their strategy, despite knowing the actions of the other users [14]. The algorithm terminate when there is no change in cost function. Each user is making the best decision taking into account the decisions of the others, thus users are in Nash equilibrium.

5 Simulation Results

We evaluate our distributed DSM optimization in a scenario consisting of $N = 1000$ users each having random devices between 15 to 25 non-adjustable loads, 15 to 25 adjustable loads. Non-adjustable loads have a fixed schedule and consume energy continuously. The adjustable loads include electrical appliances with flexible schedule such as plug-in hybrid electric vehicles (PHEVs), dish washers, and clothes dryers.

Fig. 1 depicts the aggregate energy consumption per time-slot $t$ when ES and energy storage as well as production strategies are deployed. From the figure it is clear that with the constrained PAR algorithm, ES minimizes the PAR, which implies that, the utilization of the ES can help to shave off the peak load. By employing ES together with other energy strategies such as energy storage and/or dispatchable energy generators, the PAR and the daily cost of energy can be further minimized. Fig. 2 shows that users utilizing both ES and storage devices schedule their storage devices to be charged during low-price off-peak hours and discharge stored energy during peak hours to further minimize their consumption cost. Also, users with DGs produce...
power only when the cost of buying energy from the utility company is higher than that of generating energy with their dispatchable energy sources.

6 Conclusion

We presented a demand Side management (DSM) technique using a game theoretical approach for efficient energy and energy utilization in multi residential buildings. The proposed distributed algorithm optimizes the cumulative cost to minimize the cost of electricity as well as the peak-to-average ratio (PAR) of the power system. Simulation results demonstrated that, with our proposed scheme both PAR and total energy price can be substantially minimized.

References


