Green Energy Scheduling for Demand Side Management in the Smart Grid

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***Abstract*—Demand side management (DSM) is an essential property of smart grid systems. Along with increasing expectations related to power quality from customers, and as new types of loads emerge, such as electric vehicles, local (renewable) energy generation, and stationary and mobile energy storage, it is critical to develop new methods for DSM. In this paper, we first construct a more efficient and reliable communication infrastructure in smart grid based on cognitive radio technology, which is an essential component for enabling DSM. Then, we propose a distributed energy storage planning approach based on game algorithm in DSM, which helps users select the appropriate size of storage units for balancing the cost in the planning period and during its use. Since planning problems may lead to consumer discomfort, we propose a cost function consisting of the billing, generation costs, and discomfort costs to balance users' preferences with the payment. Furthermore, a game theory-based distributed energy management scheme is developed in DSM without leaking user privacy, which is used as inner optimization in our proposed distributed energy storage planning approach. In this energy management scheme, Nash equilibrium is obtained with minimum information exchange using proximal decomposition algorithm. Simulation results show superior performance of our proposed DSM mechanism in reducing the peak-to-average ratio, total cost, user's daily payment, and energy consumption in smart grid communication networks.**

***Index Terms*—Demand side management, green, energy scheduling, energy management, game theory, smart gird.**

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I. Introduction

A. Smart Grid Communication Infrastructure

SMART grid is a significant enhancement of the 20th century power grid, which uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network [1]–[3]. A reliable and effective communication infrastructure is essential to enable bi-directional information flow between energy generators (traditional energy generation and distributed renewable energy sources) [4] and users' side (commercial, industrial, and residential users) in the smart grid, aiming at controlling smart appliances at users' homes for reducing energy consumption [5], [6]. The smart grid communication infrastructure needs to cover an entire large geographical region connecting a huge set of nodes. The communication infrastructure can be considered as a multilayer structure including home area network (HAN), neighborhood area network (NAN), and wide area network (WAN), data centers, and automated integration of substation systems [7], [8]. HAN communicates with various intelligent appliances so as to facilitate efficient energy management and demand response. NAN acts as linking multiple HANs with local access nodes. WAN establishes communication between the NAN and the utility companies for information transmission. The smart grid communication infrastructure is a heterogeneous network with various complementary communication technologies, which require smart appliances to manage communication within every subarea or between different subareas. The smart grid appliance equipped with cognitive radio technology could support context awareness.

B. Demand Side Management

Smart grid communication infrastructure is a heterogeneous network with various complementary communication technologies [9], which is an essential component for enabling Demand Side Management (DSM). DSM acts as the control unit to counterpoise the process of energy demand and supply between users and energy suppliers in the smart grid. This counterpoise is implemented via combining energy management with reliable communication, which is meant to establish real-time and efficient connection between users and energy suppliers. Wireless communication technology is often used in DSM due to its wide coverage and low costs, but it has some inevitable shortages in the aspects of communication reliability and bandwidth. Thus, cognitive radio technology is used in our proposal for energy data transmission because it can significantly promote communication performance via allocating spectrum in a dynamic and adaptive manner [10].

With the emergence of new types of loads such as plug-in hybrid electric vehicles (PHEVs), which can significantly increase the average household load and drastically exacerbate the already high peak-to-average ratio (PAR) [11]. It is clear that novel solutions are necessary to design efficient DSM techniques while also smoothly incorporating these types of loads. In order to reduce energy consumption, changing users' consumption patterns is not the only solution. With the development of new appliances with controllable load, microgeneration, and energy storage, customers can change their role from static consumers into active participants [12]. Customers can shift the high-power household appliances to off-peak hours to reduce the PAR. Moreover, energy generation and storage units can provide customers more flexibility when scheduling their energy consumption. Distributed energy generation units alleviate the pressure to energy source at peak time and controllable energy generation units provide more possibility in energy scheduling. Customers can store energy ahead of time, and consume it during the peak hours so as to further reduce PAR of their power consumption from the grid.

As a powerful mathematical tool, game theory shows its great potential in designing efficient DSM schemes. The need for distributed operation of smart grid nodes, the heterogeneous nature of the smart grid and the need for low-complexity distributed algorithms which can efficiently represent competitive or collaborative scenarios naturally impel game theory to become a prominent approach [13], [14]. Game theoretic methods have been applied to design efficient DSM schemes in many studies. Some studies mainly focus on DSM in the smart grid system [15], [16], while others are concerned more on renewable energy source on the supply side, e.g., solar energy, wind energy, and hydro energy [17]. In several studies, the scheduling of distributed energy generation and storage units are the main focus [18], [19]. In works such as [20], appliances are usually treated as an aggregated load, which may not reflect the essence of shiftable appliances. In this paper, we consider a system model with local power generation and storage, and jointly consider the load scheduling including electric appliances, energy generation and energy storage units. Some studies (e.g., [21]) proposed a repeated game framework since the desired total energy consumption at each time slot can be assumed to be the same for every day. However, as the preference of the users regarding the operation of their appliances may change from day to day, the repeated game model may not suit our model. Thus, we propose a optimization scheme based on a cooperative game framework so that users can adjust their desired energy consumption each day for the next day.

Simply shifting all the appliances operating at a peak time to off-peak times may cause consumer-discomfort. For instance, the difference between the desired load and the actual load, and the waiting time of each appliance, are considered in [21] and [22], respectively, to measure the discomfort cost. We introduce discomfort cost as a quadratic function of the distance between the desired and the scheduled load, to describe user discomfort caused by load shifting [23]. The discomfort cost is minimized jointly with the billing, generation costs and discomfort costs to balance the desire of users with the payment.

In this paper, we investigate efficient DSM techniques to reduce the PAR of energy consumption from the grid, which, in the long run, can contribute in reducing fuel waste and greenhouse gas emission. Load control and management plays an important role in DSM. We analyze users' energy consumption situation, electricity price, weather conditions and many other aspects to determine optimal load control strategy in order to flatten the load curve. DSM at residential houses are designed to reduce consumption via offering energy-efficient device and persuading customers for energy-aware consumption. The consumers are encouraged to change their electricity loads in real-time based on a certain signal like electricity pricing information, in order to acquire short-term energy consumption reduction. DSM helps satisfying users' demands with less energy equipment by load shift and time of use (TOU). If we deploy more energy equipments other than DSM in practical to satisfy users' demands in peak hours, the capacity of these equipments will be wasted in off-peak hours. Hence, DSM promotes the equipments utilization. Efficient DSM could support smart functionalities in many fields, where locally generated energy can be consumed by local loads when available, so as to avoid long-distance power transmission and reduce fuel waste. A planning approach for user-side energy storage units and a green home energy management scheme with local power generation and storage, and user comfort considerations, are proposed. The major contributions of our work can be listed as follows:

- We construct a more efficient, reliable, and economical communication infrastructure for energy scheduling in the smart grid based on cognitive radio technology, where household appliances, energy generation, and storage units for users are planed one day in advance.
- In our proposal, consumers own the storage devices and select appropriate storage size to keep a balance between installation cost and savings. Additionally, the discomfort cost is introduced as a part of cumulative cost function to measure the influence caused by shifting appliances on the user, where the cumulative cost function is minimization goal in the energy scheduling problem. This helps users to adjust power mode and meanwhile do not have too much impact on user's expected life mode.
- We propose a game theory based distributed energy management scheme, where the proximal decomposition algorithm is developed for converging to the Nash equilibrium with minimum information exchange. This, not only protects users privacy to a certain extent, but also reduces the communication overhead significantly. Moreover, our proposed energy management scheme is used as inner optimization to calculate fitness function for each individual in genetic algorithm based distributed energy storage planning.

The rest of this paper is organized as follows. In Section III, we introduce the system model. We propose genetic algorithm for energy storage units in Section IV. Section V presents game theoretical approach for energy management. Simulation results are provided in Section VI and finally the paper is concluded in Section VII.

II. Related Work

A. Demand Side Management

DSM is a significant part of the smart grid, and efficient DSM techniques for the smart grid, constitute a widely researched area. Pedrasa *et al.* [12] presented a three-step management methodology for the control energy streams in (a group of) houses, where the steps include local prediction, global planning and local scheduling. Mohsenian-Rad and Leon-Garcia [22] designed a residential energy consumption scheduling framework for a real-time pricing environment. The framework attempts to achieve a desired trade-off between minimizing the electricity payment and minimizing the waiting time for the operation of each appliance, and finally leads to the reduction of both the users' payment and PAR of the grid. Logenthiran *et al.* [24] proposed a DSM strategy based on load shifting technique, and a heuristic-based evolutionary algorithm was developed for minimizing the peak load demandings. Hamid *et al.* [25] proposed a fuzzy multi criterion decision-making system for DSM of industrial consumers. Et-Tolba *et al.* [26] presented an architecture model for home energy management system. Liu *et al.* [27] introduced a multi-objective optimization problem for household energy management with consideration of both energy cost and inconvenience to the consumers. Veldman and Verzijlbergh [28] focused on impacts of electric vehicles (EVs) to distribution grids and assessed the financial impact of various EV charging strategies on distribution grids. Taneja [29] was interested in the effect of renewable generation on demand-side management where he constructed a model of distributed generation resource and assessed the role of substantial renewable generation resources in DSM. Ghazzai and Kadri [30] solved a unified optimization problem in DSM to implement collaboration among mobile operators for maximizing their profits while reducing the emission of carbon dioxide by networks. Diamantoulakis *et al.* [31] used the Stackelberg game to model the selfish interaction between the operators and the customers for efficient DSM, where the customers energy consumption behaviors are captured based on customers' acceptance prices. Zazo *et al.* [32] developed a realistic model to calculate a robust price in the smart grid for reducing users' monetary expenses and offering production cost estimation according to real demand variations, where convergent distributed algorithm is introduced in this scenario. Wang *et al.* [33] set up a Nash bargaining DSM framework to solve power distribution problem, achieving a balanced interest between energy supplier and demand side user. Ye *et al.* [34] investigated a real-time information based DSM system, where a centralized scheme and a game theoretical approach are proposed to reduce energy generation cost and PAR in smart grid. Gupta *et al.* [35] proposed a novel DSM strategy based on particle swarm optimization (PSO) algorithm for reducing peak demand and utility cost. Li *et al.* [36] set up a bidirectional infrastructure to deal with the DSM issue in a distributed manner for enhancing search efficiency, where a Newton approach is used for better Nash equilibrium and dual fast gradient method is employed for relieving users' discomfort.

B. GAME Theory and Genetic Algorithm

Game theory is effective to analyze the competitive or collaborative behavior of these users and seek an equilibrium where all users are individually satisfied [37]. Here, we introduce some related models and approaches. Mohsenian-Rad *et al.* [38] presented a distributed demand-side energy management system, allowing each user adjusts response strategy according to the current total load and tariffs in the power grid. Atzeni *et al.* [18] proposed a DSM method focused on energy generation and storage units, where users optimize their load through adjusting their generation and storage scheduling. The problem was formulated as both a noncooperative game and a cooperative game [19]. Soliman and Leon-Garcia [15] presented an extension by considering storage units, which provides a generalized treatment of storage with a novel and more generalized cost function. Belhaiza and Baroudi [20] proposed a noncooperative game theoretic model to manage and optimize demand reponse in smart grid. Atzeni *et al.* [39] proposed a novel bidding strategy formulated as a generalized Nash equilibrium problem including global constraints that couple the users' strategies. A Time-of-use (TOU) pricing scheme was proposed using game-theoretic approach in [40]. Rasoul *et al.* [41] proposed a optimization method based on a game theory and non-cooperative game to reduce load and consumption in peak hours for DSM in smart grid equipped with PHEVs. Forouzandehmehr *et al.* [42] modeled the power system using differential equations and proposed a two-level differential game framework. Bu and Yu [43] modeled and analyzed the interactions between the retailer and electricity customers as a four-stage Stackelberg game. Maharjan *et al.* [44] introduced a heuristic approach to optimize the demand response performance in a large population of consumers that includes both residential and industrial consumers. Several studies has also investigated consumer discomfort. For example, Song *et al.* [21] introduced a repeated game framework and a critical peak pricing scheme in order to reduce peak-time billing and discomfort cost. Deng *et al.* [23] investigated the residential energy consumption scheduling problem and formulated a coupled-constraint game. GA is based on the natural selection mechanism, which means each species hunts for beneficial adaptations in a changeable environment. GA has been effectively applied in many optimization issues in power system. Aminifar *et al.* [45] developed an immunity GA to optimally place the phasor measurement units (PMU) in power grid, employing the local and prior knowledge related to the considered issue is the core idea. Mousavian and Feizollahi [46] built a novel investment decision model to optimize the placement of PMU for full observability of the electrical power system, where a problem-specific GA is proposed to decide the optimal investment strategy. Gerbex *et al.* [47] proposed a GA based method to locate multi-type FACTS devices in power network, where the locations of the devices, the types and the values are optimized. Hu *et al.* [48] proposed a multiobjective GA to extend optimization issues for DSM, which takes the objectives from two confliciting groups into account and offers compromise solutions. Awais *et al.* [49] proposed a novel GA based DSM algorithm in the smart grid, where residential load, commercial load and industrial load are taken into consideration. The load scheduling issue for different types of appliances is transformed into a cost minimization problem in the smart grid.

However, there is no study on the planning problem of user-side energy storage units. We focus on load shifting and the schedule of electric devices, including household appliances, energy generation and energy storage units. A discomfort cost is added to the cost function to measure the discomfort of users due to shifting appliances. We present a energy storage planning scheme based on GA. Also, a game theoretic energy management approach is proposed.

III. System Model

We consider a cognitive radio based smart grid communication system with multiple consumers. The communication infrastructure is equipped with a three-layer hierarchical structure, consisting of HAN, NAN, and WAN. Cognitive radio technology is used to guarantee a more efficient, reliable, and economical communication infrastructure in the smart grid. Cognitive radio communications in the license-free bands are adopted for coordination of heterogeneous wireless technologies in the HAN. Meanwhile, cognitive radio communications in the licensed band are adopted to access unused spectrum in the NAN and WAN. In HAN, a cognitive gateway behaves as a central node to connect between multiple smart appliances in the smart grid for bi-directional communication. In the forward direction, it can collect load information from smart appliances, and then it delivers them to a destination out of the HAN. At the same time, the cognitive gateway can distribute information to smart appliances in the backward direction. In NAN, load information from users is often transferred to the central unit, where the cognitive gateway in NAN is regarded as the cognitive radio access point to make single-hop links with the cognitive gateway acting as data aggregators in HAN. In WAN, the cognitive gateway in NAN acts as a cognitive node to communicate with the control center connected to cognitive radio base stations. Each consumer is equipped with a smart meter (SM) which can schedule energy consumption, and a central unit is deployed at the utility company. SMs are connected to and exchange information with the central unit. The system model is shown in Fig. 1. The list of symbols is shown in Table I.

We divide one day into H time slots. For example, we can assume $H = 24$, which means each time slot is 1 hour. Let $\mathcal{N}$ denote the set of users, and the number of users is n. We denote $\mathcal{A}_n$ as the set of appliances belonging to user $n \in \mathcal{N}$ and A_n as the number of appliances owned by user n. For each user $n \in \mathcal{N}$ and each appliance $a \in \mathcal{A}_n$, $e_{n,a} = [e^1_{n,a}, \ldots, e^h_{n,a}, \ldots, e^H_{n,a}]$ are the energy consumption

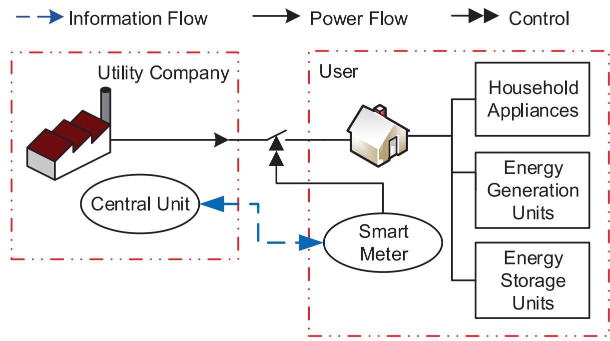

Fig. 1. System model of the smart gird.

vectors of appliance a, where $e^h_{n,a}$ represents the energy consumed by appliance a during time slot h. For each user n, $g_n = [g^1_n, \ldots, g^h_n, \ldots, g^H_n]$ and $s_n = [s^1_n, \ldots, s^h_n, \ldots, s^H_n]$ is the vector of energy generation and energy storage, respectively, where g^h_n is the amount of energy generated at time slot h and s^h_n is the amount of energy stored at time slot h. Here, the value of s^h_n can be either positive or negative where a positive s^h_n means the storage device is charged during time slot h and a negative s^h_n means the storage device is discharged during time slot h.

Therefore, the total load of user n during time slot h is defined as

$$l^h_n = \sum_{a \in A_n} e^h_{n,a} + s^h_n - g^h_n. \tag{1}$$

Appliances can be classified into two categories: shiftable appliances and non-shiftable appliances. Non-shiftable appliances cannot be scheduled while shiftable appliances can be organized and shifted. The desired total daily energy consumption of appliance a is denoted by $E_{n,a}$. Moreover, $t_{start,n,a}$ and $t_{end,n,a}$ are the starting and ending time of the interval that appliance a can be scheduled in. We do not try to cut down the daily energy consumption but concentrate on better organizing the shiftable appliances so as to reduce the cost. Hence, to any appliance $a \in \mathcal{A}_n$, the following conditions hold:

$$\sum_{h=t_{start,n,a}}^{t_{end,n,a}} e^h_{n,a} = E_{n,a}, \tag{2}$$

and

$$e^h_{n,a} = 0, \ \ \forall h \in [1, t_{start,n,a}) \cup \left(t_{end,n,a}, H\right]. \tag{3}$$

Appliances are also restricted by maximum and minimum operating power denoted by $e_{max,n,a}$ and $e_{min,n,a}$. They express the maximum and minimum amount of energy appliance $a \in A_n$ can consume during a single time slot if operating such that

$$e_{min,n,a} \le e^h_{n,a} \le e_{max,n,a}. \tag{4}$$

Storage units provide users with more flexibility when scheduling energy consumption. Users can store energy ahead of time, and consume it during peak hours. Upper and lower limits of the amount of stored energy should be set to characterize a storage device. Let $S_{max,n}$ and $S_{min,n}$ denote the

TABLE I
LIST OF SYMBOLS

Notation	Description	Notation	Description
H	time slots in one day	n	the number of users
$\mathcal{A}_n$	the set of appliances belonging to user N	$\mathcal{N}$	the set of users
$e_{n,a}$	the energy consumption vector of appliance a	$e^h_{n,a}$	the energy consumed by appliance a during time slot h
g_n	the vector of energy generation	s_n	the vector of energy storage
g^h_n	the amount of energy generated at time slot h	s^h_n	the amount of energy stored at time slot h
l^h_n	the total load of user N during time slot h	$E_{n,a}$	the desired total daily energy consumption of appliance a
$t_{start,n,a}$	the starting time of the interval that appliance a belonging to user N can be scheduled in	$t_{end,n,a}$	the ending time of the interval that appliance a belonging to user N can be scheduled in
$e_{max,n,a}$	maximum operating power of appliance a belonging to user N	$e_{min,n,a}$	minimum operating power of appliance a belonging to user N
$S_{max,n}$	the maximum capacity of the storage device belonging to user n	$S_{min,n}$	the minimum capacity of the storage device belonging to user n
s^0_n	the initial power of the storage device belonging to user n	$s^h_{in,n}$	the charging profile of user n
$s^h_{out,n}$	the discharging profile of user n	$s^{max}_{in,n}$	the maximum amount of energy the storage device of user n is able to store during one time slot
$s^{max}_{out,n}$	the maximum amount of energy the storage device of user n is able to discharge during one time slot.	$g^h_{D,n}$	the energy generation of nondispatchable generators belonging to user n during time slot h
$C_g(g^h_{D,n})$	the cost function of dispatchable generators	$g_{max,n}$	the maximum energy production capacity of the dispatchable generators belonging to user n
$\bar{e}^h_{n,a}$	the desired energy consumption pattern of each appliance a during time slot h	$\omega_{n,a}$	the willingness of user n to shift appliance a
K_D	the weight factor for the discomfort cost	$\boldsymbol{l}_{-n,h}$	the load vector of all the users except user n at time slot h
VI($\mathcal{K}$,$\boldsymbol{F}$)	variational inequality problem	k_n	the size of the energy storage device owned by each user
F_{GA}	the fitness function	C_{DES}	the aggregated initial installation cost of all the users
Pr_{BU}	the installation price of base unit	P_{BU}	the size of the base unit
C_{UP}	the network upgrading cost	n_{branches}	the total number of branches in the grid
C_{0b}	the cost for upgrading branch b	C_{daily}	the aggregation of daily costs of all the users during an M-day period
$\boldsymbol{x}_n$	the strategy vector of each user n	$\boldsymbol{x}^h_n$	the corresponding strategy profile at time slot h of user n
$\mathcal{Q}_n$	the feasible energy scheduling profile set of user n	$C(\boldsymbol{x}_n,\boldsymbol{l}_{-n})$	the cost function of user n

maximum and minimum power level of the storage device belonging to user n respectively. Then we have

$$S_{min,n} \leq \sum_{t=0}^{h} s^t_n \leq S_{max,n}, \ \ \forall h \in \{0, \dots, H\}, \tag{5}$$

where s^0_n is the initial power level of the storage device. The charging and discharging profile of user n is denoted by $s^h_{in,n}$ and $s^h_{out,n}$ respectively, while $s^h_n = s^h_{in,n} - s^h_{out,n}$. A maximum charging rate is denoted by $s^{max}_{in,n}$ which indicates the maximum amount of energy the storage device of user n is able to store during one time slot. Also, we denote a maximum discharging rate by $s^{max}_{out,n}$ which indicates the maximum amount of energy, the storage device of user n is able to discharge during one time slot. Hence, we have

$$0 \leq s^h_{in,n} \leq s^{max}_{in,n} \ and \ 0 \leq s^h_{out,n} \leq s^{max}_{out,n}, \ \ \forall h \in \{1, \dots, H\}. \tag{6}$$

Energy generators are equipped at users' home. The generated energy can either flow to appliances to support their energy consumption, or be stored in the storage device. The generators fall into two categories: nondispatchable generators and dispatchable generators. Nondispatchable generators, such as solar panels and wind turbines, have fixed costs and users cannot take any strategies on the amount of energy it produces. Due to the uncertainty of these energy resources, we use the discrete time Markov chain (DTMC) to model the renewable energy [41].

Dispatchable generators, however, can schedule their energy generation and have a varied cost accordingly. We denote the cost function of dispatchable generators by $C_g(g^h_{D,n})$, where $g^h_{D,n}$ is the energy generated by the dispatchable generator belonging to user n and $C_g(0) = 0$. The dispatchable generator has an upper limit on its energy production capacity. We denote the maximum energy production capacity of the dispatchable generator belonging to user n as $g_{max,n}$. Then we have

$$0 \leq g^h_{D,n} \leq g_{max,n}, \ \ \forall h \in \{1, \dots, H\}. \tag{7}$$

The cost function includes three parts for every user: cost charged by the providers, energy generation cost and discomfort cost. We assume that the cost function is an increasing function of the total load, and is convex. A quadratic cost function, e.g., as in [38], satisfies both of the above assumptions, and is also widely accepted to model the cost charged by the providers to the consumers. We therefore consider a quadratic cost function

$$B_h(L_h) = K_h L^2_h, \tag{8}$$

where $\{K_h\}^H_{h=1} \in (0, 1)$, and K_h changes over time.

We introduce a discomfort cost to reflect the discomfort of users for shifting and rescheduling the appliances. The discomfort cost indicates the difference between the scheduled energy consumption pattern and the desired energy consumption pattern. The desired energy consumption pattern of each appliance $a \in A_n$ during time slot h is denoted by $\bar{e}_{n,a}^h$. As the higher is the difference between a user's planned or expected hour of operating an appliance and it's actual operating hour, the higher will be the discomfort. Moreover, if the user has to wait longer than a certain duration to operate an appliance, the rate of increase of the discomfort will be even higher. Thereby, we model the discomfort cost as a quadratic function, which is also a common practice. The discomfort cost can be defined as follows.

Definition 1: The discomfort cost is defined as

$$D(\mathbf{e}_n) = \sum_{h=1}^{H} \sum_{a \in \mathcal{A}_n} \omega_{n,a} \left(\bar{e}_{n,a}^h - e_{n,a}^h \right)^2, \tag{9}$$

where $\mathbf{e}_n = (e_{n,a})_{a=1}^{A_n}$ and $\omega_{n,a}$ represents the willingness of user n to shift appliance $a \in \mathcal{A}_n$. A large $\omega_{n,a}$ indicates that user n is less willing to shift appliance a for a lower billing.

Therefore, the cost function is defined as

$$C = \sum_{h=1}^{H} B_h\left(l_{n,h},\ \mathbf{l}_{-n,h}\right) + \sum_{h=1}^{H} C_g\left(g_{D,n}^h\right) + K_D \cdot D(\mathbf{e}_n), \tag{10}$$

where K_D is the weight factor for the discomfort cost. A large K_D indicates higher discomfort when shifting appliances. $\mathbf{l}_{-n,h}$ is the load vector of all the users except user n at time slot h.

IV. Genetic Algorithm for Energy Storage Units Planning

As mentioned before, storage units can help reduce the bill for the users by discharging during peak hours. However, the costs for initial installation may far exceed the billing reduction over a long time. Therefore, it becomes important to assess whether it is worthy for a specific user to install storage units and what size of the storage units is the most economical. In this section, we consider distributed energy storage units owned by residential users and analyse the planning problem balancing the cost in the planning period and during its use. Distributed energy storage unit can be considered as both a power consumer and a power producer. The storage size can not be dynamically changed based on everyday or every hour consumption, but the planning level optimization problem is necessary for optimizing a rather long term investment where the size is determined based on, e.g., peak renewable energy generation levels, average energy consumption levels etc. Despite optimizing the size of the storage unit, the dynamic and stochastic load characteristics (instantaneous) make it necessary to optimize the DRM performance at a finer time granularity. For a finer granularity DSM optimization (which can be considered as the dispatch level) the storage size is given, and one optimizes over through load shifting by use of local renewable generation, local storage and also power dispatch from the grid, together. We explicitly specify that the grid network architecture is given, and the load demands and power production are known in statistics, characterized by representative growing rates and daily variations [50].

In general, the planning problem can be formulated in terms of minimization of a cumulative cost function in the grid as follows:

$$\begin{aligned} \min\ & f_{obj}(\mathbf{X}, \mathbf{C}) \\ \text{s.t.}\ & \psi(\mathbf{X}, \mathbf{C}) = 0 \\ & \eta(\mathbf{X}, \mathbf{C}) \le 0, \end{aligned} \tag{11}$$

where f_{obj} is a cumulative cost we try to minimize in the grid, $\mathbf{X}$ is the system state vector, and $\mathbf{C}$ is the control vector. The grid network structure is assumed to be fixed and the branches between network nodes are known to us. The evaluation of the cumulative cost function mainly depends on the deployment and size of distributed energy storage units. Thus, every solution could be coded by a vector, whose size is equal to the amounts of network nodes. Each element of the solution vector contains information about whether or not to deploy the storage unit. 0 represents no distributed energy storage unit is installed in the node. $1, 2, \ldots, k_n$ represent the size of the energy storage unit installed in the node for every user. k_n is an integer, $n \in \mathcal{N}$. The deployment and the size of distributed energy storage units are stored in $\mathbf{C}$, which is the output of the optimization procedure. Such a non-linear and constrained optimization problem can be solved using GA. However, the daily variations in energy management may result in high computation complexity with GA. Hence, we propose a hybrid approach in this paper including GA and an inner algorithm for energy management optimization which is introduced in detail in the following sections. The proposed approach is presented in *Algorithm 1*. The space complexity of Algorithm 1 is $O(population)$. The GA randomly generates an initial population whose individuals are characterized by the pre-assigned size of distributed energy storage units. Once the initial population is created, the inner algorithm for energy management optimization is performed. The inner optimization output is used to calculate the fitness function for every individual in the population. If GA does not converge, it will generate a next population. Selection, crossover and mutation are performed in this phrase. In selection step, we adopt the "remainder stochastic sampling without replacement" strategy. In crossover step, we use "uniform crossover", where the crossover happens with a probability of 0.5. In mutation step, all the elements will choose a different value in a defined set to mutate in a small probability.

Green energy storage units are assumed to be integer multiples of a base unit. Assuming the base unit as *BU*. The GA fitness function includes costs of initial installation, costs of network upgrading and the total cost during daily use. The fitness function is given as

$$F_{\text{GA}} = C_{\text{DES}} + C_{\text{UP}} + C_{\text{daily}}, \tag{12}$$

where

$$C_{\text{DES}} = \sum_{n \in \mathcal{N}} Pr_{\text{BU}} \cdot k_n P_{\text{BU}}, \tag{13}$$

$$C_{\text{UP}} = \sum_{b=1}^{n_{\text{branches}}} C_{0b}, \tag{14}$$

$$C_{\text{daily}} = \sum_{m=1}^{M} \sum_{n \in \mathcal{N}} {\alpha_n}^{m-1} C_{m,n}, \tag{15}$$

Algorithm 1: Energy Storage Units Planning Algorithm

Input: Pr_{BU}, P_{BU}, n_{branches}, $\{C_{0b}\}_{b=1}^{n_{\mathrm{branches}}}$, $\{\alpha_n\}_{n \in \mathcal{N}}$, and $\mathbf{X}_{\mathrm{his,m,n}}$

Output: $\mathbf{k}^*$

calculate the upper bound with the energy management algorithm;
$i = 0$;
generate initial population;
repeat
  if $i \geq 1$ **then**
    generate the next population;
  end
  inner optimization with the energy management algorithm for each individual;
  evaluate fitness function for each individual;
  $i = i + 1$;
until GA converges;

where C_{DES} denotes the aggregated initial installation cost of all the users $n \in \mathcal{N}$, Pr_{BU} is the installation price of base unit and P_{BU} is the size of the base unit. C_{UP} is the network upgrading cost, n_{branches} is the total number of branches in the grid and C_{0b} denotes the cost for upgrading branch b. The details on the upgrading cost evaluation can refer to [51]. C_{daily} denotes the aggregation of daily costs of all the users $n \in \mathcal{N}$ during an M-day period. The cost of user n in day m, $C_{m,n}$, can be calculated using Eq. (10) with the history energy consumption patten $\mathbf{X}_{\mathrm{his},m,n}$. $0 < \alpha_n < 1$ shows the degree in which the energy consumption patten of earlier days is valued to user n.

The GA is constrained by the maximum number of base units which can be deployed for one user, i.e., for any $n \in \mathcal{N}$, it should satisfy $k_n \leq K_{max}$, K_{max} is constrained by economic and technical conditions. $S_{maxuse,n}$ is denoted as the maximum potential usage of each storage in the energy management algorithm. Therefore, we can write the upper bound of the GA as

$$k_n \leq \min\Big(K_{max},\ S_{maxuse,n}/BU\Big),\ \forall n \in \mathcal{N}. \tag{16}$$

For the individuals in GA, we use Algorithm 2 to study the inner optimization for energy management each day and then calculate the fitness function to evaluate the termination criterion of the GA. Evaluating fitness function is actually a process of looking for the minimal fitness function, where the newly calculated fitness function needs to be continuously compared with the minimum fitness function calculated before.The GA ends with the termination criterion that the best fitness function value remains constant over an assigned number of generations, or when the maximum number of iterations is reached. The output of the GA indicates the optimal size of energy storage device for every user.

Having considered distributed energy storage units owned by residential users and analyzed the planning problem to reduce bills, we are motivated to take users' privacy into consideration. In the next section, we propose a game-theory-based distributed energy management algorithm concerning the privacy issues.

V. Game Theoretical Approach for Energy Management

We build a game-theory-based distributed energy management model, where users adjust their energy consumption strategies to achieve the Nash equilibrium in the game theory. It is designed to be beneficial for every user's own interest and privacy as well as cutting down peak load in the grid. In this section, we define and derive Nash equilibrium, and introduces a distributed energy management algorithm to obtain the Nash equilibrium of the game based on proximal decomposition algorithm and the best response algorithm.

A. Problem Formulation

We define the strategy vector of each user n as

$$\mathbf{x}_n = (\mathbf{e}_n, \mathbf{g}_n, \mathbf{s}_n), \tag{17}$$

and the corresponding strategy profile at time slot h of user n is

$$\mathbf{x}_n^h = \left(\mathbf{e}_n^h, g_n^h, \mathbf{s}_n^h\right)^{\mathrm{T}}. \tag{18}$$

The feasible energy scheduling profile set of user n can thus be expressed as

$$\mathcal{Q}_n = \{\mathbf{x}_n : \text{Constraints}(2), (3), (4), (5), (6) \text{ and } (7),\ \forall h \in H\}. \tag{19}$$

For convenience, we rewrite the total load of user n during time slot h (Eq. (1)) in a vector form as

$$l_n^h = -g_{ND,n}^h + \boldsymbol{\delta}_l{}^{\mathrm{T}} \mathbf{x}_n^h, \tag{20}$$

where the auxiliary vector $\boldsymbol{\delta}_l = (1, \ldots, 1, -1, 1, -1)^{\mathrm{T}}$. Also, the discomfort cost (Eq. (9)) is rewritten as

$$D = \sum_{h=1}^{H} \left(\bar{\mathbf{x}}_n^h - \mathbf{x}_n^h\right)^{\mathrm{T}} W_n \left(\bar{\mathbf{x}}_n^h - \mathbf{x}_n^h\right), \tag{21}$$

where $\bar{\mathbf{x}}_n^h = (\bar{e}_{n,1}^h, \ldots, \bar{e}_{n,a}^h, \ldots, \bar{e}_{n,A_n}^h, 0, 0, 0)$ is the desired energy scheduling pattern of user n in time slot h and where the $(A_n + 3)$-dimensional diagonal matrix $\mathbf{W}_n$ is formed as $\mathbf{W}_n = \mathrm{Diag}(\omega_{n,1}, \ldots, \omega_{n,A_n}, 0, 0, 0)$.

Then, the cost function of user n can be written as

$$\begin{aligned} C(\mathbf{x}_n, \mathbf{l}_{-n}) = &\sum_{h=1}^{H} K_h \Big(l_{-n}^h - g_{ND,n}^h + \boldsymbol{\delta}_l{}^{\mathrm{T}} \mathbf{x}_n^h\Big)\Big(-g_{ND,n}^h + \boldsymbol{\delta}_l{}^{\mathrm{T}} \mathbf{x}_n^h\Big) \\ &+ \sum_{h=1}^{H} C_g\Big(\boldsymbol{\delta}_g{}^{\mathrm{T}} \mathbf{x}_n^h\Big) + K_D \sum_{h=1}^{H} \Big(\bar{\mathbf{x}}_n^h - \mathbf{x}_n^h\Big)^{\mathrm{T}} \\ &\times W_n\Big(\bar{\mathbf{x}}_n^h - \mathbf{x}_n^h\Big), \end{aligned} \tag{22}$$

where $\mathbf{l}_{-n}$ is the load of all other users except user n, l_{-n}^h is the aggregated load of all other users except user n at time slot h, and $\boldsymbol{\delta}_g$ is an ausiliary where an auxiliary vector is introduced as $\boldsymbol{\delta}_g = (0, \ldots, 0, 1, 0, 0)^{\mathrm{T}}$.

To this end, the elements of the energy scheduling game among users is defined as follows.

- Players: All users in set $\mathcal{N}$
- Strategies: Each user $n \in N$ selects its green energy scheduling vector $x_n \in Q_n$ to minimize its cost
- Payoffs: $f(\mathbf{x}_n, \mathbf{l}_{-n}) = C(\mathbf{x}_n, \mathbf{l}_{-n})$ for each user $n \in \mathcal{N}$.

B. Nash Equilibrium Derivation

In order to analyze the properties of the Nash equilibrium of the proposed energy scheduling game, we reformulate the game as a variational inequality (VI) problem [28]. A VI problem is defined as follows.

Definition 2: Given a closed and convex set $\mathbf{F} : \mathcal{K} \subseteq \mathbb{R}^n$ and a mapping $\mathbf{F} : \mathcal{K} \rightarrow \mathbb{R}^n$, the VI problem, denoted as VI($\mathcal{K}, \mathbf{F}$), consists of finding a vector $\mathbf{x}^* \in \mathcal{K}$ (called the solution of the VI) such that

$$\left(y - \mathbf{x}^*\right)^{\mathrm{T}} \mathbf{F}\left(\mathbf{x}^*\right) \geq 0. \tag{23}$$

The following Lemma describes the equivalence between a game and a VI problem.

Lemma 1: Given the game $\mathcal{G}\langle \mathcal{Q}, f\rangle$, suppose that for each player n

i) the strategy set $\mathcal{Q}_n$ is closed and convex;

ii) the payoff function $f_n(\mathbf{x}_n, \mathbf{x}_{-n})$ is continuously differentiable in $\mathbf{x}$ and convex in $\mathbf{x}_n$ for every fixed $\mathbf{x}_{-n}$.

Then, the game $\mathcal{G}$ is equivalent to VI($\mathcal{Q}, \mathbf{F}$), where $\mathbf{F}(\mathbf{x}) = (\nabla_{\mathbf{x}_n} f(\mathbf{x}))_{n=1}^{Q}$.

Therefore, the equivalence between the energy scheduling game and the VI problem is given in the following theorem.

Theorem 1: The energy scheduling game is equivalent to the VI problem VI($\mathcal{Q}$, F), where

$$\mathbf{F}(\mathbf{x}) = \left(\nabla_{\mathbf{x}_n} f(\mathbf{x})\right)_{n=1}^{\mathcal{Q}}. \tag{24}$$

Proof: The Hessian matrix of the payoff function can be written as follows with block elements

$$\begin{aligned} \nabla^2_{\mathbf{x}_n^{h_1}\mathbf{x}_n^{h_2}} f(\mathbf{x}_n, \mathbf{l}_{-n}) &= \boldsymbol{\delta}_g \boldsymbol{\delta}_g{}^{\mathrm{T}} C_g''\left(\boldsymbol{\delta}_g{}^{\mathrm{T}} \mathbf{x}_n^{h_1}\right) \\ &\quad + 2K_{h_1} \boldsymbol{\delta}_l \boldsymbol{\delta}_l{}^{\mathrm{T}} + 2K_D \mathbf{W}_n, \quad h_1 = h_2 \\ \nabla^2_{\mathbf{x}_n^{h_1}\mathbf{x}_n^{h_2}} f(\mathbf{x}_n, \mathbf{l}_{-n}) &= 0, \qquad h_1 \neq h_2, \end{aligned} \tag{25}$$

where $\mathbf{0}_n$ denotes the n-dimension zero matrix. Since all the eigenvalues are nonnegative, the Hessian matrix is positive semidefinite. Thus, the payoff function $f(\mathbf{x}_n, \mathbf{x}_{-n})$ is continuously differentiable in $\mathbf{x}$ and convex in $\mathbf{x}_n$ for every fixed $\mathbf{x}_{-n}$. Also, the strategy set $\mathcal{Q}_n$ of every user n is evidently closed and convex. According to *Lemma 1*, we can obtain the VI reformulation. ■

Theorem 2: The energy scheduling game has a nonempty and compact solution set.

Proof: Following from the existence of a solution of the VI, in addition to conditions i) and ii) in *Lemma 1*, if strategy set $\mathcal{Q}_n$ of each player n is compact, then the game has a convex and nonempty solution set. With the first two conditions proved before, since the constraints are all defined as linear inequalities, the third condition readily satisfies. ■

Next, we will discuss about the uniqueness of the Nash equilibrium. The Nash equilibrium is not unique. However, all the Nash equilibriums share some properties. For each user n, given any two optimal strategy vector $\mathbf{x}_n^* = (\mathbf{e}_n^*, \mathbf{g}_n^*, \mathbf{s}_n^*)$, $\mathbf{x}_n^{**} = (\mathbf{e}_n^{**}, \mathbf{g}_n^{**}, \mathbf{s}_n^{**})$, the following are true

$$\sum_{h=1}^{H} C_g\left(g_{n,h}^*\right) = \sum_{h=1}^{H} C_g\left(g_{n,h}^{**}\right), \tag{26}$$

$$e_{n,h}^* + s_{n,h}^* - g_{n,h}^* = e_{n,h}^{**} + s_{n,h}^{**} - g_{n,h}^{**}, \ \forall h \in \{1, \ldots, H\}, \tag{27}$$

$$D_n\left(\mathbf{e}_n^*\right) = D_n\left(\mathbf{e}_n^{**}\right). \tag{28}$$

Thus, for each time slot h, the total load of user n, l_n^h is constant among all the Nash equilibrium solutions. Then, the aggregated load of all other users except user n, l_{-n}^h is constant among all the Nash equilibriums. As a result, although each user has an infinite number of optimal strategy vectors to be chosen, all the strategies lead to the same value in payoff function.

Algorithm 2: Distributed Energy Management Algorithm

```
Input: {ϵ_i}_{i=0}^∞, {ρ_i}_{i=0}^∞, and τ > 0
Output: x*
choose any feasible starting point x^(0); set i = 0;
repeat
    Choose any feasible start point s^(0); j = 0;
    repeat
        For each user n,;
        y_n^(j+1) = argmin f_n(y_n, l_{-n}) + (τ/2)||y_n^(j) − x_n^(i)||;
        j = j + 1;
    until ||l^(j) − l^(j−1)|| < 10^−2;
    Find z^(i) such that ||z^(i) − y^(i)|| ≤ ϵ_i;
    x^(i+1) = (1 − ρ)x^(i) + ρ_n z^(i);
    i = i + 1;
until ||l^(i) − l^(i−1)|| < 10^−2;
```

C. Distributed Implementation of Energy Management

We now focus on how to reach unique Nash equilibrium of our energy scheduling game. Best response algorithms are usually utilized to obtain the Nash equilibrium solutions of games. However, the strict or strong convexity of the payoff functions, which is required for the convergence in best response algorithms, is not satisfied in our case. In order to overcome this defect, we introduce the proximal decomposition method whose convergence is guaranteed under some milder conditions [52]. We consider a regularization of VI($\mathcal{K}, \mathbf{F}$), given by VI($\mathcal{K}, \mathbf{F} + \tau(\mathbf{I} - \mathbf{y})$), which is strongly monotone with a sufficiently large τ. The regularized VI is equivalent to the following game.

$$\begin{aligned} \min_{\mathbf{x}_n} \ & f_n(\mathbf{x}_n, \mathbf{x}_{-n}) + \frac{\tau}{2}\left\|\mathbf{x}_n - \mathbf{x}_n^{(i)}\right\| \\ \text{s.t.} \ & \mathbf{x}_n \in \mathcal{Q}_n. \end{aligned} \tag{29}$$

The solution of the game can be computed using the best response algorithm. Hence, based on the proximal decomposition algorithm and together with the best response algorithm, Algorithm 2 is proposed to solve our problem.

TABLE II
INFORMATION EXCHANGE IN GREEN ENERGY MANAGEMENT IMPLEMENTATION

Public information		τ, $\{K_h\}_{h=1}^H$
User's private information		$\mathbf{x}^{(i)}$, $\mathbf{s}_n^{(j)}$, $C_g(\mathbf{s}_n^{(j)})$, $D(\mathbf{s}_n^{(j)})$
Central unit to users	Initialization	① τ, $\{K_h\}_{h=1}^H$
User n to other users	Initialization	② $l_n^{(0)}$
	Run time	④ $l_n^{(j)}$
Other users to user n	Initialization	③ $\mathbf{l}_{-n}^{(0)}$
	Run time	⑤ $\mathbf{l}_{-n}^{(j)}$

Here, we should guarantee that $\sum_{i=0}^{\infty} \epsilon_i < \infty$ and $\rho_i \in [R_m, R_M]$ with $0 < R_m \le R_M < 2$. As a special case, we can set $\epsilon_i = 0$ and $\rho_i = 1, \forall i$ for simplicity.

Now our concern is the value of τ. The following theorem shows the relationship between the value of τ and the convergence of *Algorithm 2*.

Theorem 3: Algorithm 2 converges when

$$\tau > (N-1)(A+3)\ \max K_h. \tag{30}$$

Proof: We denote $\mathbf{F}(\mathbf{x}) = (\nabla_{\mathbf{x}_n} f(\mathbf{x}))_{n=1}^{\mathcal{Q}}$ and let $\mathbf{J}_{\mathbf{x}_n}\mathbf{F}_n(\mathbf{x})$ be the Jacobi matrix of $\mathbf{F}(\mathbf{x})$ (i.e., the Hessian matrix of f_n). The aforementioned algorithm globally converges if the matrix

$$\Upsilon_{\mathbf{F},\tau} = \Upsilon_{\mathbf{F}} + \tau \mathbf{I} \tag{31}$$

is a P-matrix [23]. Here,

$$[\Upsilon_{\mathbf{F}}]_{ij} = \begin{cases} \alpha_i^{min}, & i = j \\ -\beta_{ij}^{max}, & \text{otherwise} \end{cases} \tag{32}$$

where

$$\alpha_i^{min} = \inf_{\mathbf{z} \in \mathcal{Q}} \lambda_{least}\big(\mathbf{J}_{\mathbf{x}_i}\mathbf{F}_i(\mathbf{z})\big) \text{ and } \beta_{ij}^{max} = \sup_{\mathbf{z} \in \mathcal{Q}} \big\|\mathbf{J}_{\mathbf{x}_i}\mathbf{F}_j(\mathbf{z})\big\| \tag{33}$$

with $\lambda_{least}(\mathbf{A})$ being the least eigenvalue of $\mathbf{A}$.

For our problem, we can write the Jacobi matrix $\mathbf{J}(\mathbf{x})$ as

$$\begin{aligned} \mathbf{J}_{nn}(\mathbf{x}) &= 2\boldsymbol{\Delta}_l^{\mathrm{T}}\mathbf{K}\boldsymbol{\Delta}_l + \boldsymbol{\Delta}_g^{\mathrm{T}}\mathbf{D}_{C_g''(\mathbf{x}_n)}\boldsymbol{\Delta}_g + 2K_D\mathbf{W}_n \\ \mathbf{J}_{nm}(\mathbf{x}) &= \boldsymbol{\Delta}_l^{\mathrm{T}}\mathbf{K}\boldsymbol{\Delta}_l, \quad n \neq m \end{aligned} \tag{34}$$

where we introduce two H-dimensional diagonal matrixes $\mathbf{K}$ and $\mathbf{D}_{C_g''(\mathbf{x}_n)}$ such that $\mathbf{K} = \mathrm{Diag}(K_1, \ldots, K_H)$ and $\mathbf{D}_{C_g''(\mathbf{x}_n)} = \mathrm{Diag}(C_g''(x_n^1), \ldots, C_g''(x_n^H))$, and where two auxiliary matrixes are introduced that $\Delta_l = [\mathbf{I}_H, \ldots, \mathbf{I}_H, \ -\mathbf{I}_H, \mathbf{I}_H, -\mathbf{I}_H]$ and $\Delta_g = [\mathbf{0}_H, \ldots, \mathbf{0}_H, \mathbf{I}_H, \mathbf{0}_H, \mathbf{0}_H]$. Then, we have $\alpha_i^{min} \geq ??0$ and $\beta_{ij}^{max} \le (A+3)\ \max K_h$. Hence, in order to meet the requirement that $\Upsilon_{\mathbf{F},\tau}$ is a P-matrix, it should hold that $\tau > (N-1)(A+3)\ \max K_h$. ■

Facilitated with bidirectional communications, smart meters act as energy schedulers. The information exchanged in the DSM mechanism can be sorted by transfer direction and is listed in Table II. Fig. 2 shows how the proposed energy management mechanism is implemented based on Algorithm 2. ① represents information flow from central unit to users in the initialization phase. ② and ④ represent information flow from user n to other users in the initialization phase and operational phase, respectively. ③ and ⑤ represent information flow form other users to user n in the initialization phase and operational phase, respectively. We discuss the implementation under the

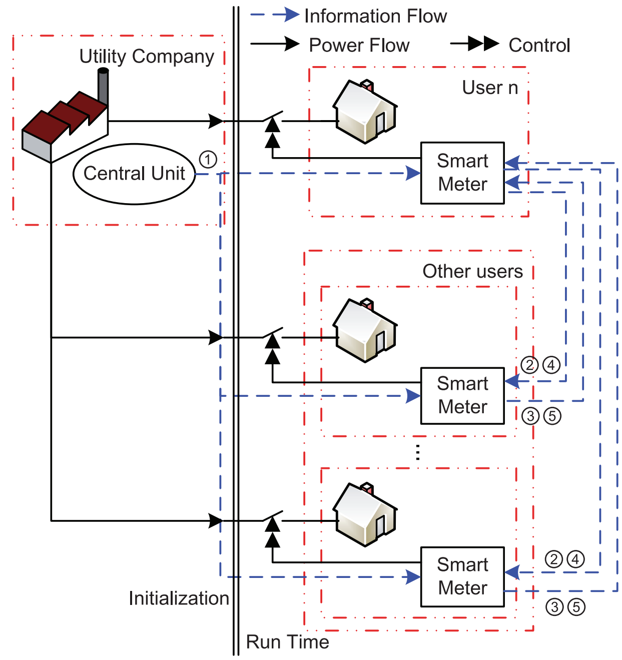

Fig. 2. Implementation of DSM.

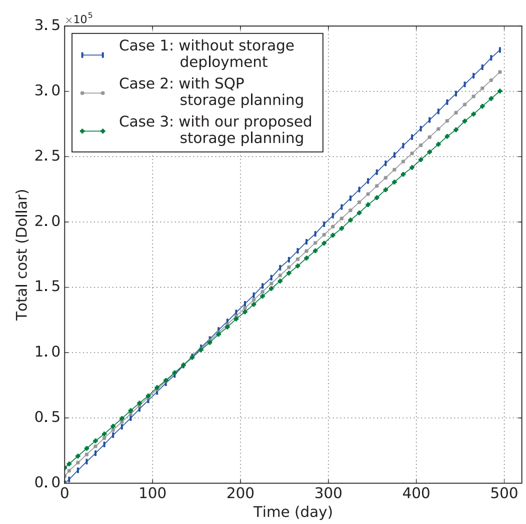

Fig. 3. Total cost for 100 users among different deployment cases of energy storage units.

condition $\epsilon = 0$ and $\rho = 1$ in order to ensure that no user's scheduling details need to be communicated to the grid. The implementation of Algorithm 2 can be divided into two phases: initialization phase and operational phase. In the initialization phase of the outer loop, the central unit chooses proper τ and broadcasts $\{K_h\}_{h=1}^H$ and τ to every user. Meanwhile, each user randomly chooses an initial strategy $\mathbf{x}_n^{(0)}$. As the mechanism then goes to the initialization of the inner loop, each user randomly initializes $\mathbf{z}_n^{(0)}$ as the initial strategy of the regularized game and announces its corresponding load. Then the run time phase of the inner loop begins. In the operational phase, every user solves (29) for current optimal energy consumption pattern according to the collected load information of all users and their own energy consumption pattern constraints.

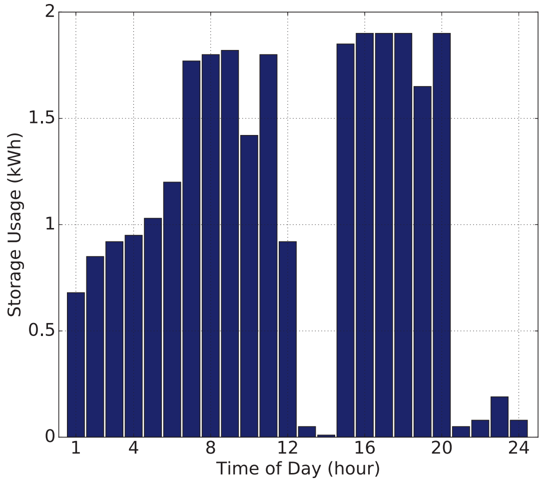

Fig. 4. Daily storage usage for 100 users.

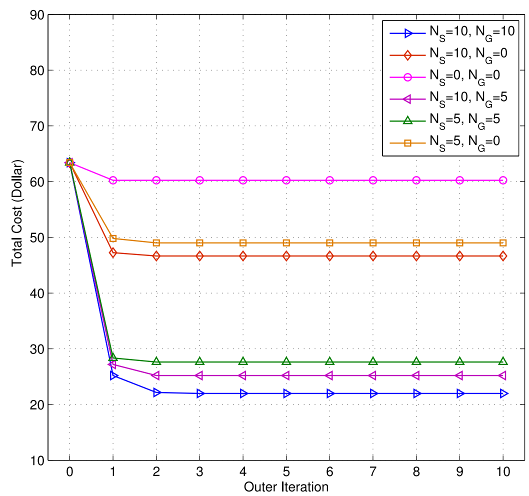

Fig. 5. Convergence of outer loop iterations of Algorithm 2.

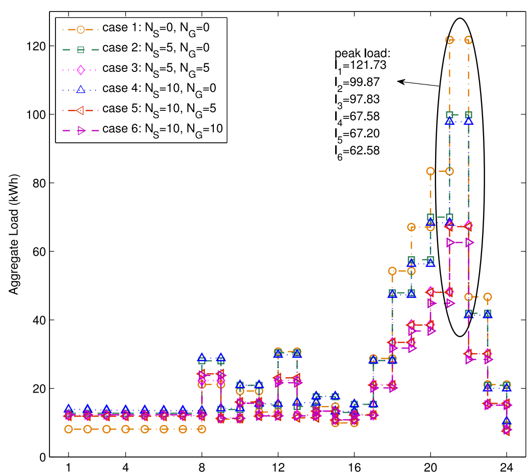

Fig. 6. Aggregated load comparing among different amount of energy generation and storage units.

Then, the current total load information is broadcast to all users again. Users who have acquired new load information, update optimal energy consumption pattern and broadcast in real-time. The Nash equilibrium is reached when the update does not change compared to its previous value. Users only need to broadcast the aggregated value and not the detailed scheduling vectors of each of their appliances. This, not only protects users privacy to a certain extent, but also reduces the communication overhead significantly.

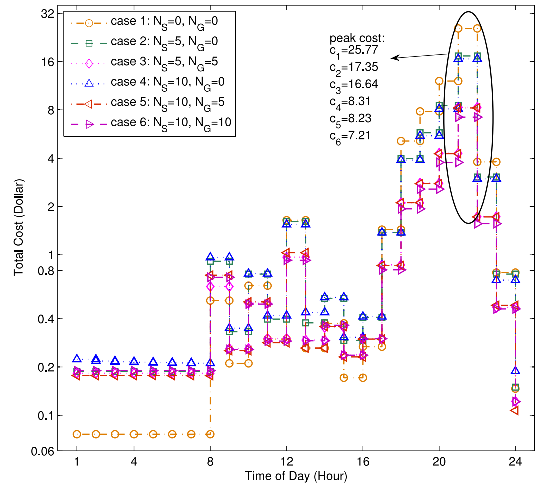

Fig. 7. Total cost comparing among different number of energy generation and storage units.

TABLE III
PAR AND TOTAL COST FOR 100 USERS WITH DIFFERENT NUMBER OF GENERATION AND STORAGE UNITS

PAR / Total Cost		Number of generation units		
		0	5	10
Number of Storage Units	0	4.61 / 619	- / -	- / -
	5	3.78 / 479	3.38 / 258.3	- / -
	10	3.69 / 466.7	3.37 / 257.7	3.22 / 236.5

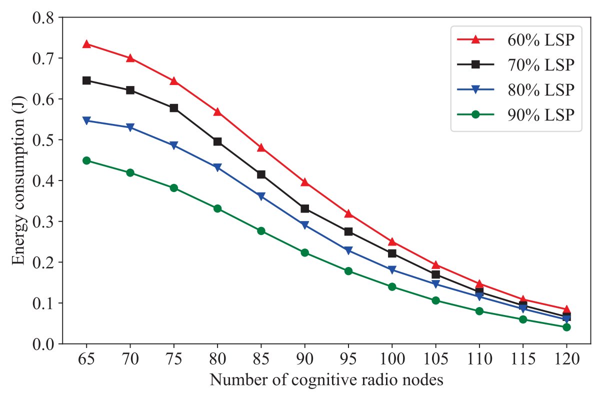

Fig. 8. Energy consumption during a single-hop operation against the number of cognitive radio nodes.

VI. NUMERICAL RESULTS

In this section, we present simulation results and study the performance of our proposed DSM mechanism. We use the MATLAB optimization toolbox, and the genetic algorithm toolbox as optimization tool. All the simulations are conducted using MATLAB in a Sony server equipped with 4-core CPU,

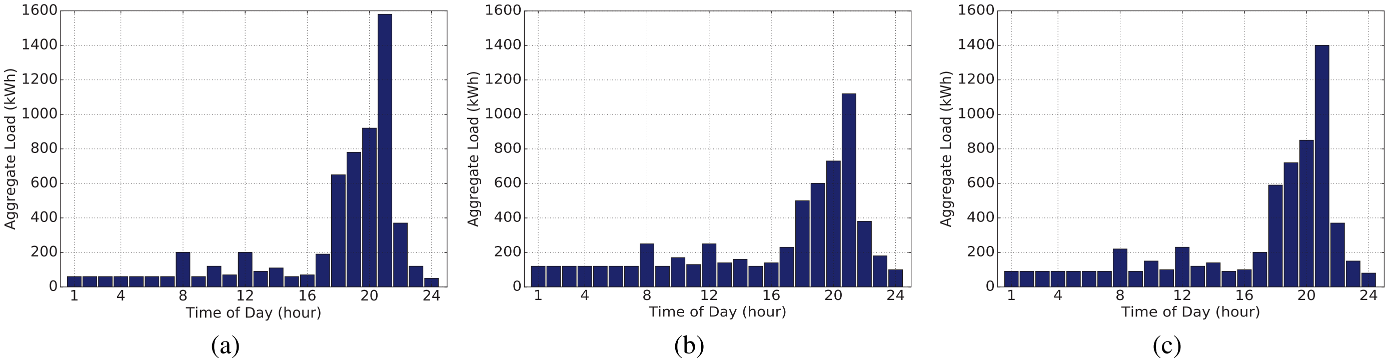

Fig. 9. Comparison between 100 users' different energy consumption patterns. (a): Aggregate load without DSM mechanism. (PAR = 6.27) (b): Aggregate load with our proposed DSM mechanism. (PAR = 4.38) (c): Aggregate load with day-ahead DSM mechanism. (PAR = 5.48).

16 GB memory, and Mango DB, which can enable a stable simulation environment. Computational complexity is defined as $n_{outer}*n_{inner}*N*n_{optimize}$, where $n_{outer} \leq 2$ and $n_{inner} \leq 10^2$. In the first part, the performance of the energy storage planning algorithm is presented. Subsequently, a detailed analysis of the energy management algorithm is presented in the second part. We firstly present the performance of the whole system and for individual consumers. Then the impact of the number of energy generation and storage units is analysed. Besides, how the value of discomfort weighting coefficient affects the performance of the proposed DSM mechanism, is also analysed.

We consider a scenario where one day is divided into $H = 24$ time slots and there are $N = 100$ users in our system. Each user has between 10 to 20 nonshiftable appliances, such as refrigerator and lightning, and also 10 to 20 shiftable appliances, which may include washing machine, dishwasher, PHEV etc. Users randomly select their appliance set while considering that higher energy consumption is more likely to occur in day-time hours. The pricing scheme involves two times: day-time hours, i.e., from 8:00 in the morning to 12:00 at night and night-time hours, i.e., from 12:00 at night to 8:00 in the next morning [38]. The grid coefficient K_h is such that $K_{day} = 1.5K_{night}$. The initial average price is 0.1\$/kWh. We assume that all the dispatchable energy generation units are the same type and a linear cost function $C_g(g) = K_g g$ is adopted. The maximum energy production capacity of a single generation device g_{max} is set as 0.4kWh. Similarly, storage units are assumed to be lithium-ion batteries [53]. Each user's storage device is assumed to be the multiple of a base unit. The maximum power level of each base unit is set as 0.024kWh and the minimum power level S_{min} is assumed to be 0kWh.

A. Performance of Storage Planning

In this section, we compare the total cost after energy storage planning and without storage deployment. The long-term energy consumption patterns of each user is generated respectively according to a set of 20 patterns with similar characteristics subjected to a uniform distribution.

As shown in Fig. 3, although a relatively large cost is devoted at first in the case with storage planning, less costs are paid in the subsequent days. As a result, the total cost in the case with energy storage planning become less than the other case after 169 days. In the long run, Our proposed storage planning scheme could save up nearly \$54 for 100 users per day, and the sequential quadratic programming (SQP) based storage planning scheme [50] could save up tp nearly \$36 for 100 users per day. Considering a ten-year lifetime, the case with our proposed storage planning scheme for 100 users would save up to nearly \$197100 in total, which is 33% higher than SQP based storage planning. Fig. 4 illustrates the energy storage usage for 100 users during one day. We can observe that energy storage units gradually charge to the maximum level and discharge in the peak hours so that the cost is effectively reduced.

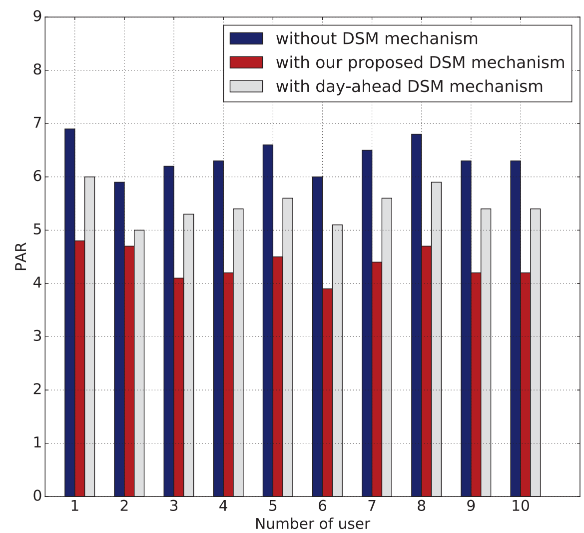

Fig. 10. PAR for each user in different DSM mechanisms.

B. Impact of Generation and Storage Units

In this subsection, we compare the simulation results in six cases with different amount of energy generation and storage units. N_S and N_G are denoted as the amount of energy storage and generation units, respectively. We investigate 6 different cases when N_S and N_G are set to 0, 5, 10. Fig. 5 shows the relationship between the number of outer loop iterations and

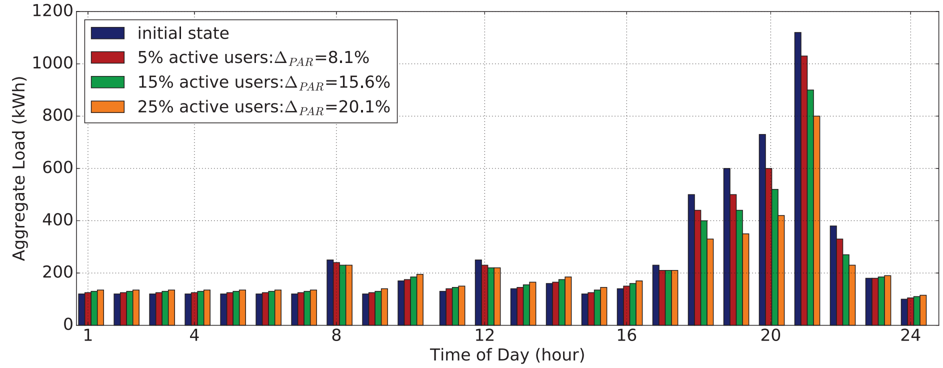

Fig. 11. The comparison of aggregate load between different active users. (Δ_{PAR}=decrease in PAR).

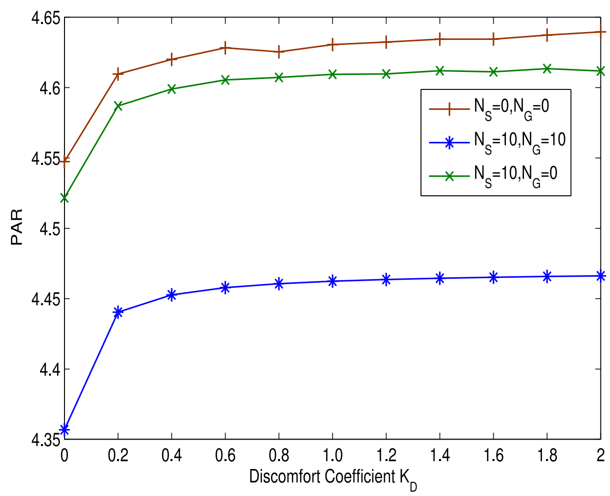

Fig. 12. PAR vs. Discomfort weighting coefficient K_D.

optimized total cost when the amount of energy storage and generation units differs. It demonstrates that these 6 cases tend to converge after twice iterations. Fig. 6 shows the aggregated load at each time slot when the number of users equipped with storage and generation units varies. Compared among different number of storage units with the same number of generation units, we can see that peak load decreases and the trend tends to be smooth when the number of storage units increases. Similarly, the increase in the number of generation units when the number of storage units is fixed, decreases the peak load and the whole trend tends to be smooth across the day. Fig. 7 shows some similar characteristics in total cost when the number of energy generation and storage units varies. In general, an increasing number of energy generation and storage units both lead to a lower cost.

C. PAR Analysis for DSM

The PAR and total cost is given in TABLE III. It can be seen that when the number of storage units is fixed, the PAR and the total cost reduce with increase in the number of generation units. Also, with increase in the number of storage units, both PAR and total cost reduce, when the number of generation units is fixed. Our results do numerically verify that the number of energy generation and storage units has a great impact on both PAR and total cost.

D. Cognitive Radio Communication Analysis

Fig. 8 illustrates energy consumption during a single-hop operation against different numbers of cognitive radio nodes, where the link success probability (LSP) varies from 60% to 90%. In Fig. 8, we can see that the higher LSP is, the lower is energy consumption. As the number of cognitive radio nodes increases, energy consumption during a single-hop operation reduces further. When the number of cognitive radio nodes reaches 120, energy consumption during a single-hop operation with different LSP decreases to the lowest, around 0.07 J. Thus, the utilization of cognitive radio technology in the smart grid communication network can effectively reduce energy consumption.

E. PAR Analysis for DSM

Fig. 9(a) illustrates aggregate load without DSM mechanism, Fig. 9(b) illustrates aggregate load with our proposed DSM mechanism, and Fig. 9(c) illustrates aggregate load with day-ahead DSM mechanism [18]. In the scenario without DSM mechanism, users adopt the initial expected energy consumption pattern directly without taking control over energy generation and storage. Day-ahead DSM mechanism [18] provides optimal energy generation and storage strategy, where the optimization process is modeled as a noncooperative Nash game based on the proximal decomposition algorithm. A distributed and iterative scheme converging to the Nash equilibrium is presented, which allows minimum information exchange and protects users' privacy. Comparing the results in Fig. 9(a) and Fig. 9(b), we can see that the peak load has been greatly reduced while the off-peak loads generally increase at different levels after our proposed DSM mechanism is deployed. The PAR value of 100 users without DSM mechanism is 6.27, and is reduced to 4.38 after using our proposed DSM mechanism. In fact, due to the existence of local energy generation device, both aggregate load and peak load from the grid are reduced. Similarly, in Figs. 9(b) and 9(c), it is clear that the reduction in PAR using our proposed DSM mechanism is much higher than the case of day-ahead DSM (16.1% higher). Our proposed DSM mechanism shows

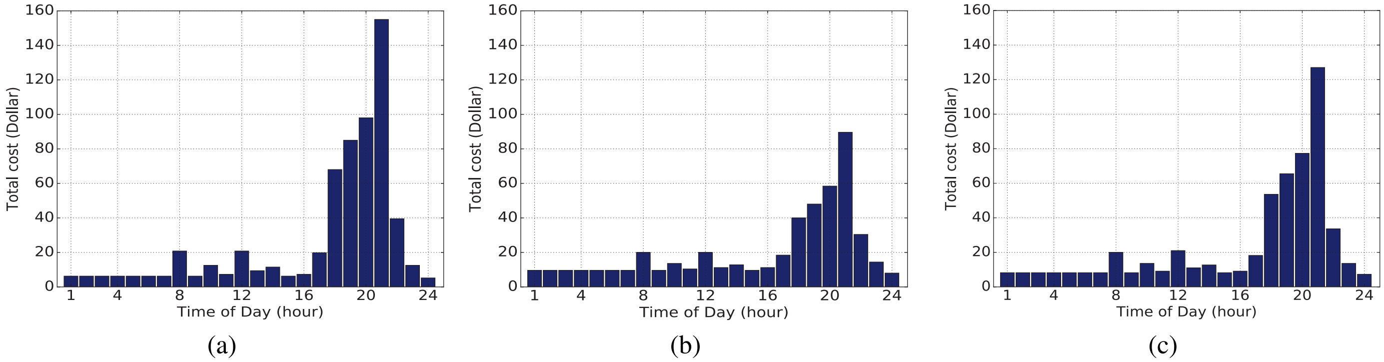

Fig. 13. Comparison between 100 users' different energy consumption patterns. (a): Total cost without DSM mechanism (total cost = \$633.9). (b): Total cost with our proposed DSM implementation (total cost = \$491.7). (c): Total cost with day-ahead DSM mechanism (total cost = \$557.2).

superior performance in PAR compared to both the cases: without DSM and the day ahead DSM.

The PAR for each user without DSM mechanism, with our proposed DSM mechanism, and with day-ahead DSM mechanism is shown in Fig. 10. The average PAR without DSM mechanism and day-ahead DSM mechanism are 6.38 and 5.48, respectively, after deploying our proposed DSM mechanism, the average PAR reduces to 4.37, a reduction of about 31.5%.

Fig. 11 illustrates the aggregate load among different active users. The number of active users are set as 5, 15, 25 among our 100-user capacity scenario, which corresponds to having 5%, 15%, and 25% of active users, respectively. From Fig. 11, we see that as the number of active users increases, the aggregate load curve becomes progressively more flattened, reducing the load during peak hours and raising the load during valley hours. Specifically, the initial PAR value decreases from 4.38 to 4.03 with 5 active users (i.e., 8.1% less), to 3.69 with 15 active users (i.e., 15.6% less), to 3.46 with 25 active users (i.e., 20.1% less). It means the more active users are, the higher is the PAR reduction.

We further investigate the impact on the grid when consumers have different preferences on whether or not to shift their appliances for a better price. Firstly, each user's willingness on shifting a certain appliance $\omega_{n,a}$ is chosen randomly with an average of 0.5, so that the discomfort weighting coefficient K_D of each user can directly reflect the user's preference. We run our proposed algorithm when K_D is set to different values and three cases are investigated with different amounts of energy generation and storage units. Fig. 12 shows that in all the three cases, PAR increases when K_D increases and when we choose a sufficiently high value of K_D, PAR tends to float around 4.46, 4.60 and 4.64, for the combinations $N_S = 10$ and $N_G = 10$, $N_S = 10$ and $N_G = 0$, and $N_S = 0$ and $N_G = 0$, respectively. That's because when users show less willingness to shift their appliances, there is little scope left to reduce PAR by shifting the load.

F. Cost Analysis for DSM

Fig. 13 presents total cost without DSM mechanism, with our proposed DSM mechanism, and with day-ahead DSM mechanism, respectively. Total cost during peak hour is greatly reduced with our proposed DSM implementation due to shifting of the load to other time slots, and reasonable utilization of energy generation and storage units also offer help to cut down the total cost. In Fig. 13(a) the total cost in one day is \$633.9. It reduces to \$491.7 in Fig. 13(b) (i.e., 22.43% less), and reduces to \$507.2 in Fig. 12(c) (i.e., 19.99% less). Our proposed DSM mechanism has the lowest cost, compared to the day-ahead DSM mechanism and without DSM mechanism, thus greener.

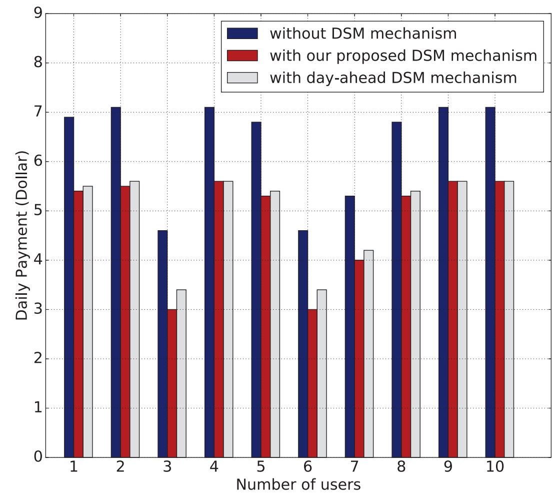

Fig. 14. Daily payment for each user in different DSM mechanisms.

Since each user also aims to reduce its peak load to save the cost as does the system, the proposed DSM mechanism based on Algorithm 2 is not only beneficial to the whole system for the reduction of total cost and PAR but also helpful to each user. Fig. 14 illustrates daily payment for each user without DSM mechanism, with our proposed DSM mechanism, and with day-ahead DSM mechanism, respectively. We can see that all users have a reduction in their payment, as the average cost before scheduling is \$6.34 which decreases to \$4.92, i.e., 22.43% with our proposed DSM mechanism. In day-ahead DSM mechanism, the average cost for every user is \$5.07, i.e., 20.03% less than what would have been incurred by the user's initial desired energy consumption pattern without DSM mechanism. The cost reduction brought by the day-ahead DSM mechanism is smaller than our proposed DSM mechanism.

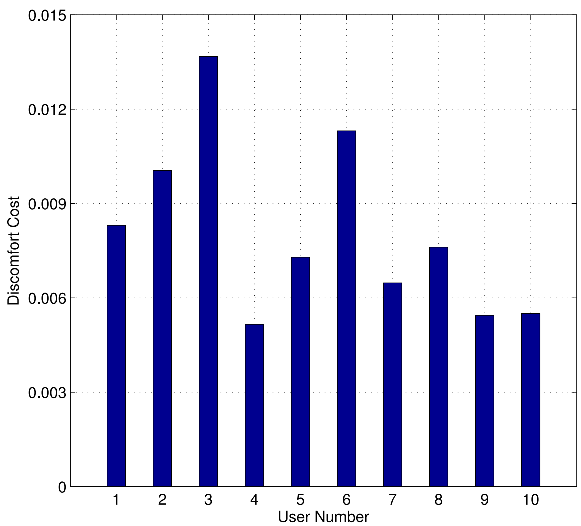

Fig. 15. Weighted discomfort cost for each user with our proposed DSM mechanism.

Fig. 15 shows that users' weighted discomfort costs vary from 0.005 to 0.013 and just an average of 0.008 unit of discomfort cost is produced with our proposed DSM mechanism. Our proposed DSM mechanism can effectively reduce daily payment and PAR for every user without causing significant discomfort for them, thus greener.

VII. Conclusion

In this paper, we first establish a cognitive radio based communication infrastructure in smart grid for green home energy scheduling which accommodates various household appliances, energy generation and storage units. Then, GA is proposed for the planning problem of energy storage units in DSM, where the cost function consists of the billing, generation costs and discomfort costs. Moreover, we develop game theory based energy management algorithm without the leakage of any user privacy in DSM. Finally, extensive simulations are conducted to evaluate the performance of our proposed DSM mechanism, from the aspects of performance of storage planning, impact of generation and storage units, cognitive radio communication analysis, PAR analysis for DSM, and cost analysis for DSM.

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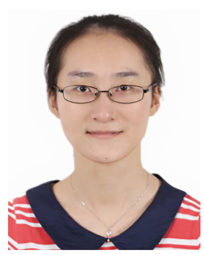

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