# An Adaptive Smart Grid Management Scheme Based on the Coopetition Game Model

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**Recently, the idea of the smart grid has been gaining significant attention and has become a hot research topic. The purpose of this paper is to present a novel smart grid management scheme that uses game theory principles. In our proposed scheme, power appliances in the smart grid adaptively form groups according to the non-cooperative hedonic game model. By exploiting multi-appliance diversity, appliances in each group are dynamically scheduled in a cooperative manner. For efficient smart grid management, the proposed coopetition game approach is dynamic and flexible to adaptively respond to current system conditions. The main feature is to maximize the overall system performance while satisfying the requirements of individual appliances. Simulation results indicate that our proposed scheme achieves higher energy efficiency and better system performance than other existing schemes.**

**Keywords: Smart grid, coopetition game, group formation, demand-side management, scheduling algorithm.**

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## I. Introduction

Nowadays, energy demand is exponentially increasing in many countries. Therefore, the issue of power energy management has directly impacted economics, society, industrial development, and the environment. However, electrical infrastructure has remained unchanged for about 100 years. Experiences have shown that the 20th century power grid is ill-suited to the current power needs. For the 21st century, the concept of smart grid has become a common choice to face future challenges. To adaptively support electric power generation, transmission, distribution, and control, the smart grid transforms the old power system into a smart and intelligent power system [1], [2].

Traditional power systems are generally used to carry power from a few central generators to a large number of customers. In contrast, the smart grid uses two-way flows of electricity and information to create an advanced energy delivery network [2]. Therefore, it is capable of delivering power in more efficient ways and automatically responding to wide ranging conditions and events that occur anywhere in the grid. To adaptively implement the smart grid system, current research offers the fusion of electric power engineering technologies with network communications through smart meters, which are placed between the electricity provider and customers [1].

For the future smart grid, the main goal is to develop an adaptive demand-side scheduling algorithm that enables efficient management of the power supply and demand [3]. To satisfy this goal, developers always face technical challenges, such as pricing, regulations, adaptive decision making, appliances' interactions, and dynamic operation [4]. All of these issues are ripe for game theory. Game theory is a conceptual framework with a set of mathematical tools




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enabling the study of complex interactions among independent rational players. Due to its many appealing properties, the basic concept of game theory has become an interesting research topic in smart grid and communication systems [4].

Traditionally, games can be divided into non-cooperative and cooperative games. In non-cooperative games, players are in conflict with each other and do not communicate or collaborate. Their preferences can be expressed as a utility function and players try to ensure the best possible consequence according to the utility function. On the contrary, cooperative games are games in which players make binding commitments and find it beneficial to cooperate in the game. To reach an agreement that gives mutual advantage, players bargain with each other. In cooperative games, the main interest is to fairly distribute the outcome to each player according to their contributions [5], [6].

In 1996, A. Brandenburger and B. Nalebuff introduced a new game model called "coopetition game," which combined the characteristics of non-cooperative and cooperative games. The coopetition game model is understood to achieve greater and reciprocal advantages for every player, who can strengthen their competitive advantages through cooperation [7]-[9]. Specifically, the concept of coopetition describes the fact that most game players can achieve more success than they ever could working alone. Recently, it has been proven that the coopetition game model is efficient when it is applied to a business strategy in a dynamic industry field [7]-[9].

Based on the facts presented above, a new smart grid management scheme based on the coopetition game model is designed herein. To maximize the overall system performance while satisfying the requirements of the individual appliances, the proposed scheme consists of a competitive grouping algorithm and a cooperative scheduling algorithm. Therefore, the proposed approach is part competition and part cooperation. The grouping algorithm allows power appliances to constitute groups of interest. Groups are adaptively formed according to the non-cooperative hedonic game model. To jointly reach the objective, the scheduling algorithm is designed to schedule power appliances dynamically. In each group, multi-appliance diversity is exploited and flexible appliances are shifted in a cooperative manner. This distributed power scheduling approach can provide an effective solution to the current power generation and distribution problem. The important feature of the scheme is an ability to maintain energy efficiency as high as possible by adaptively responding to current system situations. Under widely different and diversified smart grid situations, the proposed coopetition approach is suitable to obtain a globally desirable system performance. Until now, it seems there have not been any studies on the coopetition control paradigm for the smart grid power management problem.

Recently, several smart grid management schemes were developed. Zhu and others [10] proposed a distribution demand-side management scheme that uses the framework of dynamic games. In this scheme, a two-layer optimization framework is established. At the lower level, for each player (such as one household), different appliances are scheduled for energy consumption. At the upper level, the dynamic game is used to capture the interaction among different players in their demand responses through the market price. Bu and others [11] presented a novel game-theoretical decision-making scheme for electricity retailers in the smart grid. They modeled and analyzed the interactions between the retailer and electricity customers as a four-stage Stackelberg game. Lambotharan and others [12] developed a consumption scheduling mechanism for home area load management in the smart grid. The aim of this scheduling is to minimize the peak hourly load to achieve an optimal daily load schedule. It is able to schedule both the optimal power and the optimal operation time for power-shiftable appliances and time-shiftable appliances respectively according to the power consumption patterns of all the individual appliances. Logenthiran and others [13] proposed a demand-side management algorithm based on a load shifting technique for demand-side management of future smart grids with a large number of devices of several types. By using the day-ahead load shifting technique, this algorithm mathematically formulates as a minimization problem. Miorandi and others [14] designed a game-theoretical demand-side management scheme. Leveraging on concepts and results from evolutionary game theory, they have shown that in the first case there exists a phase transition in the eventual adoption of demand-side management. In the second case, at the opposite, the system converges toward a mixed equilibrium, in which only a fraction of the agents' population uses demand-side management. Most existing schemes were developed using dynamic programming or linear programming; these programming techniques cannot handle a large number of controllable devices from several types of devices that have several computation patterns and heuristics. Therefore, they handled only a limited number of controllable loads of limited types. Due to this reason, most existing literature is not suitable to apply to the real world.

The Autonomous Energy Consumption Scheduling (AECS) scheme in [15] is a game theoretic demand-side management algorithm for the future smart grid. The AECS scheme is a distributed energy management system that takes advantage of a two-way digital communication infrastructure. In this system, power appliances participate in the energy consumption scheduling game. The strategy in the AECS scheme requires each customer to simply apply its best response to the current total load and tariffs in the power distribution system. The Auctioning-based Smart Grid Scheduling (ASGS) scheme presented in [16] includes a decoupling approach that defines two objectives: utility cost minimization and customers' social welfare maximization. This approach provides a better description of electricity networks. Upon receiving the initially submitted load demands from customers, the utility generates an optimal load profile over time that minimizes its cost under the generation capacity constraint. Then, repeated auctions are adopted to allocate loads among customers in the system to maximize social welfare. The AECS and ASGS schemes have attracted a lot of attention and introduced unique challenges. Compared to these schemes [15], [16], the proposed scheme attains better performance in smart grid management.

This paper is organized as follows. Section II presents the proposed algorithms in detail. In section III, performance evaluation results are presented along with comparisons with the AECS and ASGS schemes proposed in [15] and [16]. Through simulation, the ability of the proposed scheme to achieve high accuracy and promptness in dynamic smart grid environments is shown. Finally, concluding remarks are given in section IV.

## II. Proposed Smart Grid Management Algorithms

In this section, the proposed smart grid management scheme is explained in detail. Based on the adaptive coopetition game model, power appliances in the smart grid form a group and create a schedule to approximate an optimal system performance.

### 1. Grouping Algorithm in Smart Grid

Electrical energy is an important material foundation of the economical and social development in the world. Due to the growth of higher electricity demands, the total electric energy consumption is still growing. However, most electrical energy is generated by burning a huge amount of fossil fuel, which causes environment degradation and global warming. To solve this problem, a lot of research has been conducted on renewable energy sources, such as wind turbines and solar panels. However, these renewable energy sources are characterized by their high intermittence. Therefore, their energy outputs are not always available where and when needed. To efficiently and reliably operate these renewable energy sources, a number of new challenges have been introduced [17].

A smart grid is defined as an electricity network that can intelligently integrate the power generators and consumers to efficiently deliver sustainable, economic, and secure electricity supplies. Currently, advances in technology enable the integration of renewable energy sources into the emerging smart grid. To combine renewable energy sources in the smart grid, the key issue is to mitigate the impact of frequency fluctuations within a power system.

In this paper, a new smart grid control algorithm with renewable energy sources is proposed. The main goal of the proposed algorithm is to match adaptively the requested energy power and the realized power production. To satisfy this goal, the power generation units are classified as renewable power units (RPUs; for example, sunlight, wind, and geothermal heat plants) or non-renewable power units (NPUs; for example, fossil fuels and nuclear power plants). With power units, power consumers (that is, electrical appliances) are clustered as a customer unit (CU) and measured by the smart meter. To maintain the power balance between power demand and supply, the entities of the smart grid (that is, RPUs and CUs) are self-organized into disjoint groups. Therefore, a power provider and end users can be grouped together. However, renewable power units are highly stochastic and often uncontrollable [18]. Therefore, in each group, it is difficult to balance between energy load and generation at all times. When the energy generation of RPUs cannot match the total CU requests of their corresponding groups, NPUs compensate for these power shortfalls and keep the power system stable. With the flexibility offered by NPUs, the power imbalance is reduced in each group. In this work, CUs can act as a single virtual energy consumer and the cooperative combination of the RPU and the NPU can act as a virtual power plant [19].

To form CU groups, the methodology adopted in this paper is a hedonic game. This game model has previously been studied in economics to model a variety of settings ranging from multi-agent coordination to group formation in social networks [20], [21]. Hedonic games describe the situation in which the player's utility depends only on the identities of the members of the group. This is a general class of games that encompasses many matching problems. In this paper, it is assumed that there are $n$ CUs, that is, $\mathcal{N}=\{c_1,\dots,c_n\}$. CU groups are defined as set $\Pi=\{S_1,\dots,S_l\}$, s.t. $l << n$. Set $\Pi$ partitions the CUs' set $\mathcal{N}$, that is, $\forall k$, $S_{k,1\le k\le l}\subseteq\mathcal{N}$, are disjoint groups such that $\bigcup_{k=1}^{l}S_k=\mathcal{N}$ and $S_i\bigcap S_j=\varnothing, i\neq j$. For a CU (that is, $c_i$ and $c_i\in\mathcal{N}$), $S_\Pi(c_i)$ is denoted as group $S_k\in\Pi$, such that $c_i\in S_k$ [20], [21].

In each group, RPUs, NPUs, and CUs are connected and self-adapt to environmental changes, such as a change in the power demand and supply. When a group, $S_k$, is formed, $c_i$ in $S_k$ satisfies a certain payoff requirement and this requirement is defined by a utility function ($U_{c_i}$). This function induces a preference order $\succsim_i$ on groups in set $\Pi$. In hedonic games, the preference order ($\succsim$) is defined based on the payoff value. For example, let $A$ and $B$ be groups and $p$ be a player.

According to player $p$'s utility function ($U_p$), if $U_p(A) \geq U_p(B)$, it is denoted by $A \succsim_p B$ and $p$ prefers group $A$ to group $B$. In our proposed scheme, each CU has preferences over its own set and can compare and order its potential groups. When $c_i$ prefers group $S_k$ to group $S_m$ if and only if $U_{c_i}(k) \geq U_{c_i}(m)$, it is denoted by $S_k \succsim_i S_m$. Using the preference-based group formation process, the proposed grouping algorithm provides a solution (that is, group structure $\Pi$) of a hedonic game. In a distributed online manner, each CU takes a decision individually to join a specific group. After groups are formed, the smart grid situation is dynamically changed. To effectively adapt the current system conditions, formed groups should be reconfigured. Therefore, $c_i$ can decide to quit its current group, $S_\Pi(c_i) = S_k$, and join another group, $S_{k'} \in \Pi$, if and only if $S_k \bigcup \{c_i\} \succsim_i S_{k'} \bigcup \{c_i\}$.

The proposed grouping algorithm is composed of three stages: demand and supply estimation, group formation, and group reconfiguration. In the first stage, CUs and RPUs individually monitor their power demand and supply amounts throughout a time period. To implement the time-driven approach, the duration of one day is partitioned, that is, 24 hours. Let $\mathbb{D}_{c_i}$ denote the energy consumption vector of $c_i$ and $\mathbb{S}_{\text{RPU}_j}$ denote the energy provisioning vector of RPU$_j$.

$$\mathbb{D}_{c_i} = [D_i^1, D_i^2, ..., D_i^H] \text{ and } \mathbb{S}_{\text{RPU}_j} = [S_j^1, S_j^2, ..., S_j^H], \quad (1)$$
$$\text{s.t. } H = 24,$$

where $D_i^k$ (or $S_j^k$) is the amount of power demand (or supply) at the $k$-th hour in a day. These vector values are dynamically modified in a real-time online fashion. In the second stage, the proposed group formation procedure is triggered. In this work, each group consists of one RPU and some CUs. To implement a grouping algorithm, each RPU maintains another $\mathbb{G}$ vector. At the initial time of the grouping process, the values of $\mathbb{G}$ are assigned the same values of $\mathbb{S}$ (that is, $\mathbb{G}_{\text{RPU}_j} = \mathbb{S}_{\text{RPU}_j} = [\mathcal{S}_j^1 = S_j^1, \mathcal{S}_j^2 = S_j^2, ..., \mathcal{S}_j^H = S_j^H]$). For smart grid systems, it is an important issue to effectively distribute the power energy. Therefore, if an RPU has enough power energy, it is desirable that customers are enticed to get power energy from that RPU. In this work, according to $\mathbb{D}_{c_i}$ and $\mathbb{G}_{\text{RPU}_j}$, the $c_i$'s utility function ($U_{c_i}$) is given by

$$U_{c_i} = \sum_{k=1}^{H} (\mathcal{S}_j^k - D_i^k), \quad \text{s.t. } j \in \text{the set of RPUs}. \quad (2)$$

At a point in the grouping time, each CU discovers its neighbor RPUs and selects an RPU to maximize its expected payoff according to (2). If the $c_i$ decides to join the $j$-th group, which contains the RPU$_j$, $\mathbb{G}_{\text{RPU}_j}$ vector values are reduced by $\mathbb{D}_{c_i}$ values. This group formation process is repeated sequentially until all CUs are grouped. When the grouping procedure finishes, the topology of the smart grid is represented by a collection of groups, which shape a two-level tree structure rooted at each RPU.

Due to the limitations in accuracy of forecasts, power energy yield from RPUs cannot be exactly predicted on a day-ahead market. In addition, the energy request of each power appliance is also dynamically changed. To adapt the current system situation, $\mathbb{D}$ and $\mathbb{S}$ vector values are adjusted periodically as follows.

$$\begin{cases} D_i^k = D_i^k + \alpha \times [D_i^{\text{current}} - D_i^k] \\ S_j^k = S_j^k + \beta \times [S_j^{\text{current}} - S_j^k] \end{cases} \quad (3)$$
$$\text{s.t. } k \in H \text{ and } 0 \leq \alpha, \beta \leq 1,$$

where parameters $\alpha$ and $\beta$ represent the learning rate to control the relative weights given to past and current information. Under diverse smart grid environments, a fixed value for $\alpha$ and $\beta$ cannot effectively adapt to the changing conditions. In this paper, we treat it as an online decision problem and adaptively modify $\alpha$ and $\beta$ values. When the power load difference ($D_i^{\text{current}} - D_i^k$) is small, the power load is uniformly distributed over time. Therefore, we can put more emphasis on power request history, that is, on $D_i^k$. In this case, a lower value of $\alpha$ is more suitable. However, if the power load distribution is non-uniform, due to temporal fluctuations, we should strongly depend on the recent amount of power load differentiation, that is, on ($D_i^{\text{current}} - D_i^k$). In this case, a higher value of $\alpha$ is more suitable. By the real-time monitoring, the value of $\alpha$ is adjusted based on the ratio of the current power differentiation to history, that is, $|D_i^{\text{current}} - D_i^k| / D_i^k$. The value of $\beta$ is also adaptively modified in the same manner, that is, $|S_j^{\text{current}} - S_j^k| / S_j^k$.

Based on the adaptively adjusted $\mathbb{D}$ and $\mathbb{S}$ information, each CU has a chance to reconsider the previous grouping decision and can change its own group. Therefore, the third stage of the grouping algorithm is developed as a group reconfiguration procedure. On a daily basis, each CU individually monitors the current modification of its own $\mathbb{D}$ vector and neighbor RPUs' $\mathbb{S}$ vectors. If a CU can improve its payoff (that is, the payoff in the newly formed group is strictly preferred over the previous group), the CU can leave the current group and join a new group. For example, $c_i$ performs a switch operation from current group $S_k$ to group $S_{k'}$ if the condition stated in (4) is satisfied.

$$U_{c_i}(c_i \in S_k) < U_{c_i}(c_i \in S_{k'}) \text{ iff } S_k \bigcup \{c_i\} \succsim_i S_{k'} \bigcup \{c_i\} \quad (4)$$

By using the group switching operation, CUs can be regrouped and group structure $\Pi$ is modified into a new grouping set, $\Pi' = (\Pi \setminus \{S_k, S_{k'}\}) \bigcup \{S_k \setminus \{c_i\}, S_{k'} \bigcup \{c_i\}\}$. This dynamic reconfiguration approach can make the smart grid more responsive to the current system situation.

## 2. Scheduling Algorithm in Smart Grid

Since energy cannot be stored efficiently on a large scale, the smart grid must perfectly balance the demand of all customers at any instant with supply. Therefore, next-generation smart grids will use new monitoring and control technologies to balance supply and demand over a region more effectively than what is done today. To improve energy efficiency, demand-side management (DSM) is one of the important functions and has been regarded as a promising technology in the smart grid. To accommodate the demand fluctuations over a daily cycle, DSM is developed to reshape the demand profile by shifting power consumption. Therefore, this technique can transfer as much of the flexible demand as possible away from the peak time into the period of lower activity without negatively impacting the system performance. However, most conventional DSM approaches are controlled in a centralized control manner and are too static to adapt to the real world situation due to the lack of automation [3].

Usually, power-appliance services can be categorized into two classes: shiftable (S) and non-shiftable (NS). For S services, such as washing machines and electric vehicle chargers, we can schedule power requirements flexibly during the schedule-available period. Since S services need only to guarantee their deadlines, the S services are amenable to adaptation with variable power levels between service request time and deadline. For NS services, such as TVs and refrigerators, which have fixed power requirements during the operation period, a continuous supply of power should be ensured. Therefore, NS services should be executed immediately with a fixed power level. In our proposed scheme, S and NS services are mixed and service scheduling is carried out in a cooperative manner.

We define $\Psi_k$ as the set of requested services in the $k$-th group, $\Psi_k = \{sr_1, ..., sr_i, ..., sr_m\}$, where $m$ is the total number of requested services. Set $\Psi_k$ consists of two different service types: S and NS. If $sr_i$ is an NS type service, $sr_i$ is characterized by $\{a_i, r\_c_i\}$, where $a_i$ is the service start time and $r\_c_i$ is the requested power level; $a_i$ is the current time ($a_i$=$c_t$), and $r\_c_i$ is a fixed value during the service execution period. If $sr_i$ is an S type service, $sr_i$ is characterized as $\{a_i, d_i, t\_c_i\}$, where $a_i$ is the service request time, $d_i$ is the service deadline ($s_i$< $d_i$), and $t\_c_i$ is the total power energy for service $sr_i$. The assigned power level for service $sr_i$ at time $t$ ($PS_i(t)$) is defined as

$$PS_i(t) = \begin{cases} PS_i(t) = r\_c_i & \text{if } sr_i \in NS, \\ 0 \le PS_i(t) \le t\_c_i & \text{if } sr_i \in S. \end{cases} \qquad (5)$$

At the current time, the total power consumption in the $k$-th group ($TP_k(c_t)$) is defined as the sum of all assigned power levels for running services at the current time ($c_t$).

$$TP_k(c_t) = \sum_{i=1}^{m} PS_i(c_t), \quad \text{s.t. } sr_i \in \Psi_k, m = \| \Psi_k \|. \qquad (6)$$

The average power level ($APL$) during a day is defined as

$$APL = \frac{\int_1^H TP_k(t)\,dt}{H}, \text{ s.t. } H = 24. \qquad (7)$$

To potentially increase sustainability of the smart grid while lowering overall operational cost, the main goal of the scheduling algorithm is to minimize the $TP_k(c_t)$ while satisfying the constraints of all S services' deadlines. To satisfy this goal, we propose an adaptive online DSM scheduling approach, which dynamically switches power levels based on the accumulated workload. When the power is supplied with a low-level voltage, the service execution may be prolonged, but the energy efficiency is very high. On the other hand, when the power can be set with a high level, service requests can be completed sooner but at a higher cost. Therefore, we try to maintain each group's power level effectively while avoiding the adverse effect of running too slowly to meet the required deadline demands.

To provide energy efficiency, the online scheduling strategy is to minimize the difference between $TP_k(c_t)$ and $APL$. Therefore, we adaptively reschedule the start times and power levels of shiftable services. There are two kinds of adaptive service techniques: for degradation and for upgradation. When the degradation (or upgradation) policy is applied to the shiftable services at the current time, the assigned power energy ($PS_i(c_t)$) decreases (or increases). This adaptive rescheduling technique based on real-time feedback tries to balance the system load between the current and future times. Therefore, the proposed scheduling algorithm can avoid abrupt power level changes over time as much as possible. Based on these requirements, we can formulate the following optimization problem:

$$\begin{aligned} &\textbf{Minimize}: \min\left(TP_k(c_t) - APL\right) \text{ and} \\ &\qquad \min\left(\sum_{k=1}^{H} \max[S_j^k - \sum_{i=1}^{m} D_i^k, 0]\right) \\ &\textbf{subject to}: \int_{t_s}^{t_f} PS_i(t)\,dt = t\_c_i, \\ &\text{where } \; t_s \le t_f \le d_i, \text{ if } sr_i \in S, \\ &PS_i(t) = r\_c_i, \quad \text{if } \; sr_i \in NS. \end{aligned} \qquad (8)$$

The proposed scheduling algorithm, which is distributively executed in each group, can i) mitigate the impact of power imbalance to facilitate the integration of renewable energy, ii) complete services just before their deadlines, iii) reshape the


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energy consumption to reduce the overall operational cost, and iv) flatten the load over time by shaving the power peak.

### 3. Main Steps of Proposed Scheme

Due to the dynamics of smart grid environments, traditional DSM approaches are impractical to justify realistic system operations. In this paper, we adopt a coopetition paradigm by employing self-organizing grouping and flexible online scheduling algorithms. Therefore, our smart grid management scheme defines the phenomenon that differs from competition or cooperation and stresses two aspects (that is, cooperation and competition) of CUs. According to the grouping algorithm, self-concerned CUs can form groups in a competitive manner. In each group, scheduling is executed in a cooperative fashion. This combined approach suggests that a judicious mixture of collaboration and competition is advantageous in smart grid environments.

Based on the notion of coopetition game model, the proposed algorithms are developed to support a decentralized smart grid system substantially powered by various forms of intermittent RPUs and stable NPUs. By a sophisticated combination of grouping and scheduling algorithms, our proposed scheme dynamically adapts to the current system condition and can effectively approximate an optimal system performance. Usually, the traditional optimal and centric algorithms have exponential time complexity. However, our distributed online algorithm has only polynomial time complexity. The main steps of the proposed smart grid management scheme are given next.

**Step 1.** At the initial stage, CUs and RPUs are self-organized into disjoint groups. Each CU discovers its neighbor RPUs and selects a specific RPU to maximize its expected payoff according to (2).

**Step 2.** After a CU joins a group, its corresponding $\mathbb{G}$ vector values are modified. In a distributed online manner, this group formation process is repeated recursively until all CUs are grouped.

**Step 3.** To adapt to the current system situation, $\mathbb{D}$ and $\mathbb{S}$ vector values are adjusted periodically based on (3). In addition, the leaning parameters $\alpha$ and $\beta$ are dynamically adjusted as $|D_i^{\text{current}} - D_i^k| / D_i^k$ and $|S_j^{\text{current}} - S_j^k| / S_j^k$, respectively.

**Step 4.** In each group, the proposed scheduling algorithm is triggered in a distributed manner.

**Step 5.** When a new NS service is requested in each group, this request is accepted without scheduling and executed immediately to guarantee required constraints.

**Step 6.** When a new S service is requested in each group, the proposed algorithm schedules this request to minimize $(TP_k(c_t) - APL)$ while satisfying the deadline requirement.

**Step 7.** Every *unit_time*, $TP_k(c_t)$ value in each group is monitored constantly for load balancing over time, and running services are dynamically rescheduled to approximately solve the optimization problem in (8).

Step 7.1. S services are sorted in decreasing order based on their deadlines.

Step 7.2. If $S_j^k - \sum_{i=1}^{m} D_i^k > 0$ ($c_t$ is in the $k$-th time period), we select the $sr_i$ ($sr_i \in S$) having the earliest deadline and the $PS_i(c_t)$ is upgraded by the power unit ($PU$). Sequentially, the next service is selected and power is upgraded in the same manner until $S_j^k - \sum_{i=1}^{m} D_i^k \leq 0$.

Step 7.3. If $TP_k(c_t) - APL > 0$, currently executing S services are adaptively rescheduled. The executing $sr_i$ ($sr_i \in S$) with the latest deadline is selected, and the $PS_i(c_t)$ is degraded by the $PU$ while satisfying the deadline requirement. Sequentially, the next service is selected and power is degraded in the same manner until $TP_k(c_t) - APL \leq 0$.

**Step 8.** On a daily basis, the group reconfiguration procedure is triggered by considering the adaptively adjusted $\mathbb{D}$ and $\mathbb{S}$ information. According to (4), a CU can leave the current group and join a new group.

**Step 9.** The system constantly self-monitors the current situation; proceed to Step 3.

## III. Performance Evaluation

In this section, the effectiveness of the proposed scheme is validated through simulation. Using a simulation model, the performance of the scheme is compared with two existing smart grid management schemes: the AECS scheme [15] and the ASGS scheme [16]. The assumptions implemented in the simulation model are as follows.

- The arrival process for new service requests is Poisson with rate $\rho$ (calls/s), and the range of the offered load is varied from 0 to 3.0.
- The performance measures obtained on the basis of 50 simulation runs are plotted as a function of rate $\rho$ (calls/s).
- There are 500 CUs (that is, $n = 500$) and 50 RPUs (that is, $l = 50$). Therefore, a total of 50 groups are formed.
- There are sufficient NPUs. The cost of power generation in the NPU is proportional to the amount of energy.
- To represent various services, eight different services are assumed and generated with equal probability.
- The durations of S and NS services (that is, service execution time) are exponentially distributed with different

Table 1. Service characteristics and system parameters.

| Traffic class | Application | Power requirement max (min) | Execution time average |
|---|---|---|---|
| NS | Television | 32 (32) W | 180 min |
| | Refrigerator | 256 (256) W | 180 min |
| S | Transmitter | 16 (16) W | 30 min |
| | Battery charger | 64 (32) W | 30 min |
| | Electric heater | 128 (64) W | 180 min |
| | Dishwasher | 256 (128) W | 180 min |
| | Electric condenser | 384 (128) W | 300 min |
| | Electric car charger | 512 (128) W | 120 min |
| Parameter | Value | Description | |
| *unit_time* | 1 min | Intervals of time length for dynamic service scheduling | |
| *PU* | 2 W | Power changing unit for rescheduling | |
| Parameter | Initial | Description | Values |
| $\alpha$ | 1 | Control parameter for weighted average for $\mathbb{D}$ vector | $0 \leq \alpha \leq 1$ |
| $\beta$ | 1 | Control parameter for weighted average for $\mathbb{S}$ vector | $0 \leq \beta \leq 1$ |

means for different devices.

The performance of the smart grid usually depends on the energy cost, system stability, and appliance's payoff, which belongs to the field of quality of experience. In this paper, performance measures obtained through simulation are normalized energy cost, power balance over time, S service deadline miss ratio, and so on. Table 1 shows the service types and system parameters used in the simulation [22], [23].

The schemes in [15] and [16] introduced unique challenges to efficiently solve the DSM problem. As mentioned earlier, the performance of the proposed scheme is compared to the performances of these schemes to confirm the superiority of the proposed approach.

Figure 1 shows the normalized energy cost of each scheme. From the simulation results obtained, it can be seen that all the schemes have similar trends. However, due to the adaptive service scheduling strategy, the power generation of NPUs can be minimized. Therefore, the proposed scheme has lower energy cost than the preexisting schemes from low to heavy service load distributions.

Figure 2 shows a comparison of power balancing performance among the three schemes. In this paper, power balancing is defined as a normalized value, which indicates the relative stability of the system power level. If the power level for service execution is fixed over time, it can be said that the power balance is 1. As the offered load increases, the stability

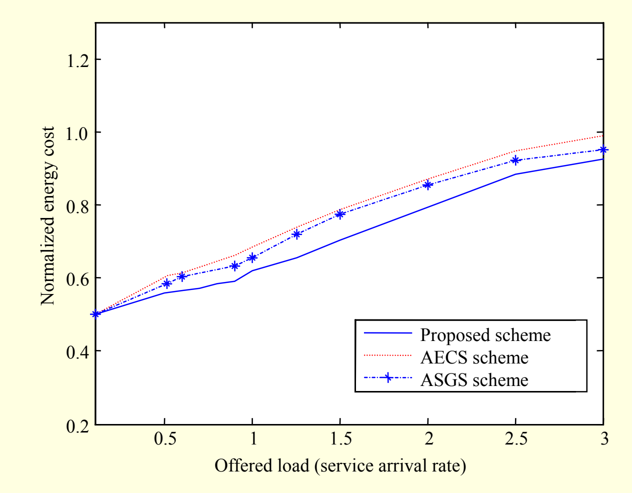


Fig. 1. Normalized energy cost.

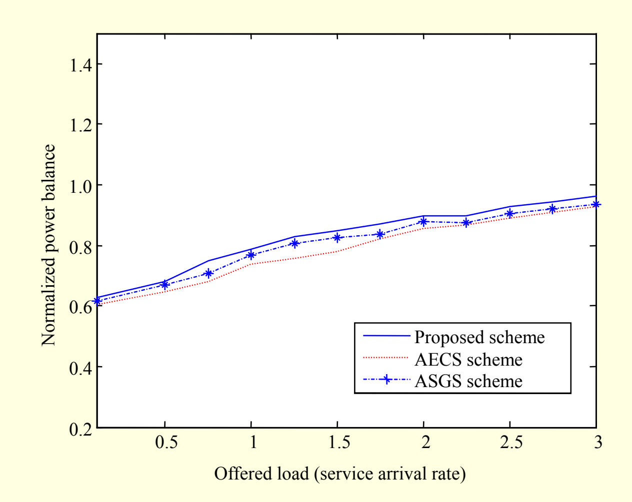


Fig. 2. Normalized power balance.

of the power level increases linearly with the dynamic scheduling technique. Under various service load intensities, our scheme is able to maintain a stable power balance, which is a highly desirable property for real-time smart grid management.

The curves shown in Fig. 3 represent the normalized power generation amount of the NPUs. To optimize the system performance, the RPU generation energy should be used effectively while minimizing the use of NPU generation energy. In the proposed scheme, power appliances are grouped to adaptively match the requested energy power and the power production of RPUs. Therefore, the power generation from NPUs can be minimized.

Figure 4 shows a comparison in terms of normalized difference between *TP* and *APL*. It is also an important performance metric to evaluate the system stability. When the

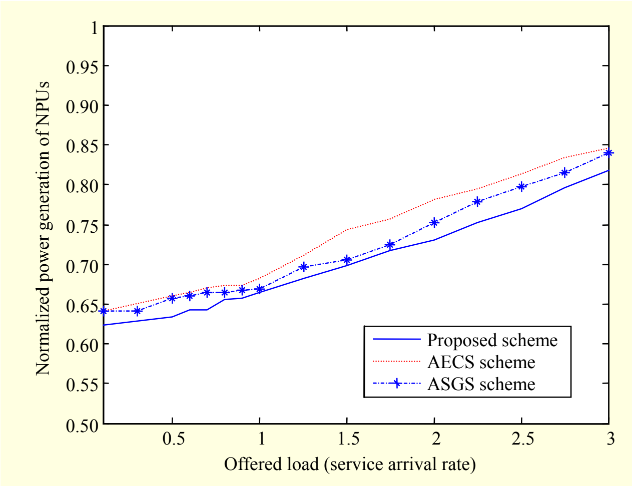


Fig. 3. Normalized power generation amount of NPUs.

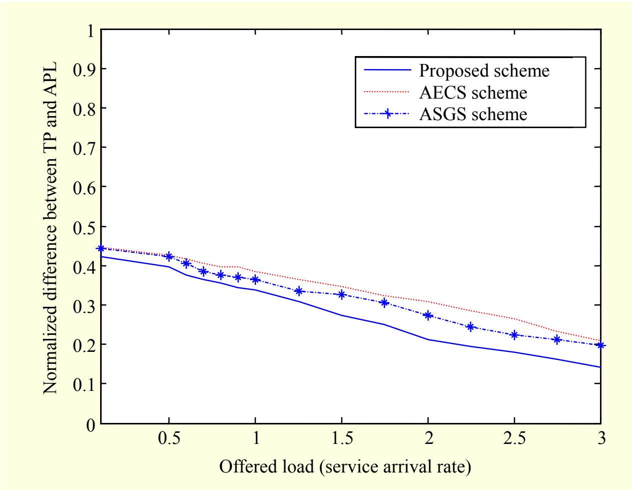


Fig. 4. Normalized difference between *TP* and *APL*.

service arrival rate is low, there are few services to be scheduled. Therefore, the difference is huge. However, as the service arrival rate increases, the proposed scheduling algorithm schedules the running services adaptively, and the difference between *TP* and *APL* can decrease. Due to the adaptive online approach, it can be seen that the proposed scheme performs better than the other schemes.

The simulation results shown in Figs. 1 through 4 demonstrate that the proposed coopetition game model generally exhibits a better performance under vastly different service load situations than the performances of the schemes introduced in [15] and [16]. The design goal is to minimize energy cost while guaranteeing service requirements. To satisfy this goal, adaptive grouping and scheduling algorithms are developed and practically applied to smart grid management based on a real-time online manner. Through the simulation experiments, the performance superiority of the proposed scheme is confirmed.

## IV. Summary and Conclusion

The smart grid is the next-generation power system that incorporates power infrastructures with communication network technologies. However, due to the dynamic power demands and intermittent renewable energy resources, demand-side management is a key factor in enhancing system performance. In this article, a new smart grid management scheme was proposed by jointly employing the grouping and scheduling algorithms. Based on the basic concept of the coopetition game, the proposed approach can obtain an excellent solution for a complex smart grid situation. Therefore, power generation cost can be minimized while satisfying the requirements of individual appliances. In addition, the proposed algorithm is designed in a distributed online fashion without a central controller. This approach is suitable for ultimate practical implementation in real-world smart grid operations. The simulation results indicate that the dynamics of our proposed scheme lead to an effective solution while effectively handling the energy consumption fluctuations.

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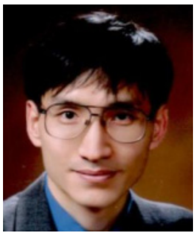

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